Proposal for a health surveillance and research framework around Brussels Airport

Preface

This report is the result of a collaborative effort between VITO, Sciensano and PIH, commissioned by Department Health of the Flemish Ministry on Welfare, Public Health and Family Matters, to investigate the health impacts of environmental stressors around Brussels Airport. The project aims to provide a comprehensive framework for surveillance and research around the national airport to inform policy decisions and protect the well-being of communities living near the airport.

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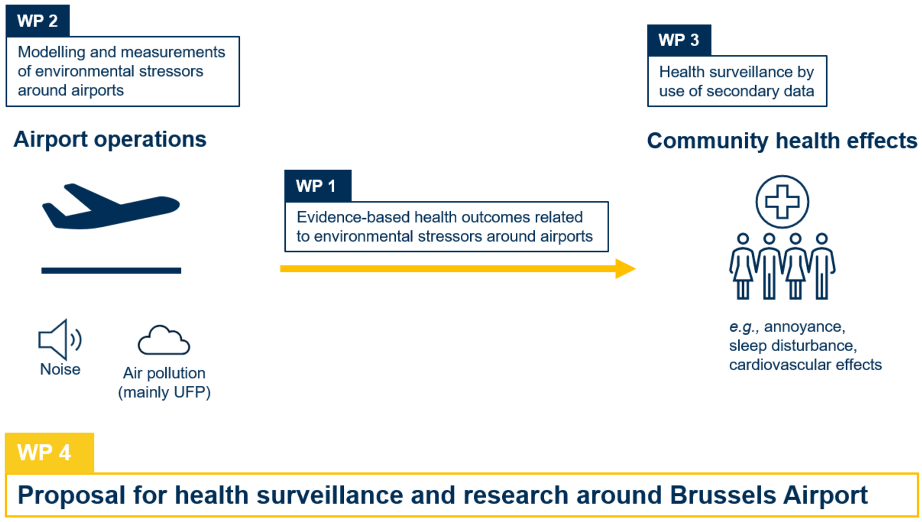
Reading guide

This report proposes a comprehensive health surveillance and research framework for the Brussels Airport region. The report is built from four workpackages, preceeded by a summary:

The framework is detailed in Work Package (WP) 4, which builds upon the foundation laid by three preceding WPs:

- WP 1: Comprehensive review of health outcomes linked to environmental stresssors around other airports.
- WP 2: An in-depth analysis of environmental stressor modelling and measurement (with a focus on noise and ultrafine particles) around airport, including data specific to the Brussels Airport region.
- WP 3: An exploration of how existing (secondary) health data can be leveraged for effective health surveillance in the area.



Notice

This report was mainly elaborated before the publication of opinion Nr 9741 'The health impact of aircraft noise and pollutant emissions in the vicinity of Brussels airport' of the Superior Health Council (SHC) (Superior Health Council, 2024). However, the opinion of the SHC, highly relevant to this study, was carefully considered during the finalization process of this report.

Steering group

This project received guidance from a steering group with members from the Flemish authorities (Departement Zorg, Departement Omgeving, Vlaamse MilieuMaatschappij), Brussels authorities (LeefMilieuBrussel) and Bond Beter Leefmilieu (BBL). The project team expresses its appreciation to the steering group for their valuable contributions, insights and discussion during steering group meetings.

Summary

Proposal for a health surveillance and research framework around Brussels Airport

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Brussels Airport is a major European aviation hub for both passenger and cargo air traffic, playing a key role in the region's economy and connectivity. However, the airport's operations (including aircraft movements, ground operations and associated road traffic) generate environmental stressors such as noise and air pollution, raising concerns about the health of nearby residents.

The environmental stressors of primary concern are aircraft noise and ultrafine particles (UFP). Aircraft noise is a well-known stressor that has been linked to various health issues, including sleep disturbance, cardiovascular and mental health problems as well as cognitive impairment in children. UFPs, on the other hand, are a relatively new area of concern. These tiny particles, less than 0.1 µm in aerodynamic diameter, are emitted in large quantities by aircraft engines and can penetrate deep into the lungs and potentially other organs, including the brain and placenta. This deep penetration raises concerns about the potential for both pulmonary and extrapulmonary health problems. The focus on aircraft noise and UFP is justified by several factors. First, airport operations are identified as primary contributors to ambient levels of noise and UFP in surrounding communities, whereas their contribution to standard air pollutants (e.g., $PM_{2.5}$, NO_2) appears relatively minor compared to emissions from road traffic, agriculture and industry. Second, although the adverse health effects of aircraft noise are well-established (based on health research studies around other airports, see further), data specific to the Brussels Airport region is lacking. Lastly, UFP, recognised as an emerging pollutant of concern, lacks established regulations and a comprehensive understanding of its health effects compared to the regulated standard air pollutants (e.g., $PM_{2.5}$, NO_2). Therefore, investigation of the health impacts of UFP and aircraft noise around Brussels Airport is of utmost importance (see further). In addition to noise and UFP, hazardous air pollutants (HAPs), including substances of very high concern related to airport operations, have also been identified as potential health concerns. However, a preliminary assessment performed in this study, based on modelling approaches extrapolated from benzene modelling, including assumptions and emission rates from literature, indicates that the modelled exposure levels in residential areas are generally well below health-based guidelines for these substances. Therefore, the health effects of HAPs are considered less of a priority for health concern than noise and UFP at this stage. Nevertheless, to ensure a comprehensive understanding of the potential health risks associated with airport operations, it is advised to advance the understanding of exposure to HAPs by refining modelling approaches (e.g., to account for the complexity of chemical processes), by performing measurements in the environment (ambient air) and by conducting human biomonitoring measurements for some HAPs (e.g., benzene) in the vicinity of Brussels Airport. This multifaceted approach will provide more accurate and reliable estimates of HAP exposure levels and their potential impact on the health of nearby residents.

The current understanding of the potential health impacts of the operations at Brussels Airport relies primarily on theoretical impact assessments, such as the Environmental Impact Assessment (EIA, In Dutch: milieueffectenrapport or MER) and the E-HIS study for air traffic noise. The E-HIS tool estimated that in 2019, 205 000 individuals experienced severe annoyance due to aircraft noise from Brussels Airport, resulting in 4 100 disability-adjusted life years (DALYs). Additionally, 97 000 individuals were estimated to suffer from sleep disturbances, leading to 6 850 DALYs. In terms of cognitive effects, learning delay (children) was calculated, resulting in 74 DALYs. Furthermore, 2 900 cases of ischemic heart disease were calculated to be related to noise pollution from the airport, totalling 1 170 DALYs.

These assessments utilize modelled noise levels (L_{den} and L_{night}[1]) specific to the region around Brussels airport. The above estimated health burden is based on the application of exposure-response functions derived from other airports on the noise levels around Brussels Airport. However, relying on such a semi-theoretical approach has limitations. First, airport operations, local air quality patterns and population demographics can vary significantly between airports, making it challenging to directly apply findings (such as exposure-response functions) from one airport to another without considering the unique characteristics of each location. For example, the specific flight paths, time window of night flights, aircraft types and meteorological conditions at Brussels Airport may lead to different noise and UFP exposure patterns compared to other airports. Second, theoretical models may not fully capture the complexity of real-world exposure scenarios. Factors such as co-exposure to other environmental stressors, time-activity patterns and exposure or effect modifiers (e.g., noise insulation or individual sensitivity to noise) can significantly influence an individual's actual exposure to noise and air pollution. For instance, people having better noise insulation in their homes may experience lower exposure levels than predicted by the models, and people with low sensitivity or high tolerance for aircraft noise could experience less impact despite the exposure.

Therefore, a tailored health surveillance and research framework is needed to specifically investigate the health impacts of Brussels Airport's operations on nearby residents. This framework should consider the unique characteristics of Brussels Airport, including its specific emission sources, local air quality patterns and population demographics. Ideally, it would incorporate a combination of different research approaches, such as health surveys, exposure assessments and in-depth monitoring studies, to gather comprehensive data on both exposure and health outcomes as well as residents' background variables. In addition, to better understand the impact of noise on the health of the surrounding population, this framework should also include an assessment of different noise metrics. While the traditional L_{den} (day-evening-night) and L_{night} metrics provide valuable information, they may not fully capture the specific characteristics of aircraft noise that are most relevant to the health outcome under study. For example, metrics that assess the frequency and intensity of noise peaks, such as the maximum sound level (L_{Amax}) or the number of events exceeding a certain threshold (number above threshold, NAT), could provide additional insights into the disruptive nature of aircraft noise. Furthermore, the intermittency ratio which quantifies the "eventfulness" of noise by measuring how much loud events stand out from the background noise, could be another valuable metric to consider. By incorporating these additional noise metrics (), researchers and policymakers can gain a more nuanced understanding of how different aspects of aircraft noise affect health and well-being. In contrast to the readily available highly time and spatial resolved noise maps for L_{den} and L_{night} for the Brussels Airport region, these additional noise metrics are not yet readily available and may require additional data collection and modelling efforts. This information can then be used to develop more targeted and effective noise mitigation strategies, ultimately with the aim of improving the quality of life for residents living near Brussels Airport.

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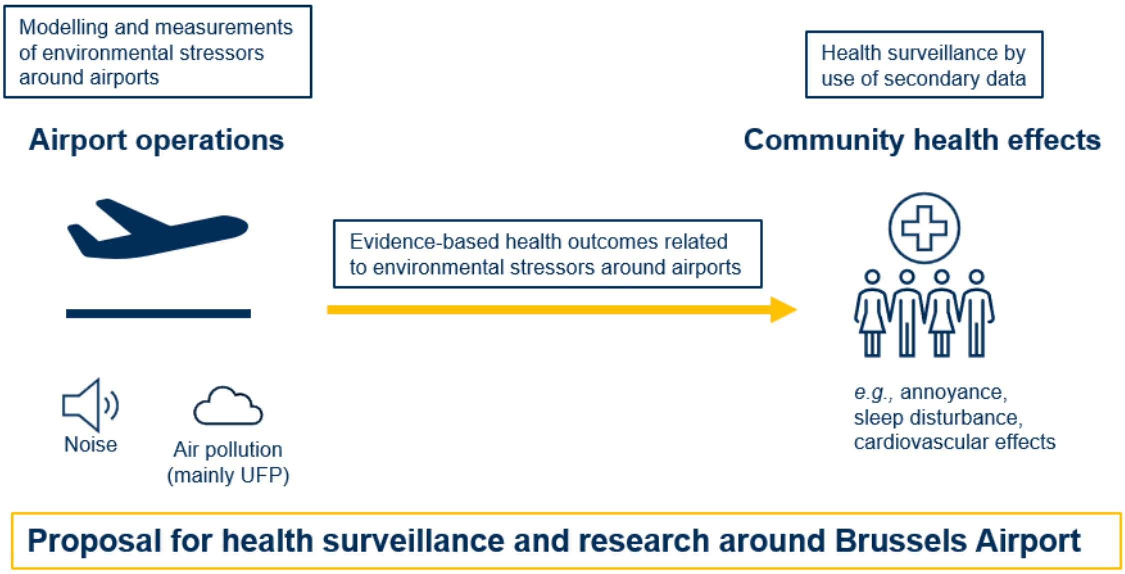
[1] L_{den} combines the following the A-weighted equivalent continuous sound level indicators: L_{day} (daytime noise, typically 7:00 – 19:00 averaged over the whole year), $L_{evening}$ (evening noise, typically 19:00 – 23:00, averaged over the whole year) and L_{night} (nighttime noise, typically 23:00 – 7:00, averaged over the whole year). A 5 dB(A) penalty is added for the evening period to reflect the increased annoyance during these hours. A 10 dB(A) penalty is added for the nighttime period to reflect the importance of sleep and the greater annoyance caused by noise at night.

Building on existing knowledge

This report integrates findings of different interrelated work packages that collectively provide a comprehensive overview of the current state of knowledge regarding the health impacts of airport-related environmental stressors as visualised below.



Firstly, a review was made of existing literature identifying well-established health outcomes linked to noise pollution and air quality, particularly UFP, mainly concerning airport operations (*Table 1*). Given the evidence from research around other airports, it is recommended to focus health surveillance and research in the region of Brussels airport on these outcomes.

Table 1: Evidence-based pollutant – outcome pairs

Pollutant–outcome pair	Health outcome indicators
Aircraft noise – effects on sleep	Physiologically measured awakenings in adults
	Self-reported awakenings in adults
	Self-reported sleep disturbance in adults (source specified)
	Sleep disturbance and/or awakenings in children
Aircraft noise – cardiovascular effects	Ischemic heart disease
	Hypertension
	Stroke
	Arterial stiffness
Aircraft noise – annoyance	Annoyance
Aircraft noise – cognitive impairment	Reading and oral comprehension, assessed with standardized tests, in children
Aircraft noise – adverse birth and pregnancy outcomes	Preterm delivery
	Gestational diabetes
Aircraft noise – quality of life, well-being and mental health	Interview measures of depression and anxiety
	Depression mediated by annoyance
Aircraft noise – metabolic outcomes	Diabetes
	Obesity

Pollutant–outcome pair	Health outcome indicators
UFP (long-term) – cardiovascular effects	Increased use of cardiovascular medication
	Mortality from cardiovascular disease (specifically observed for cardiac arrhythmias)
UFP (short-term) – intermediate mechanisms	Systemic inflammation
UFP (short-term) – respiratory effects	Exacerbation and medication use for respiratory complaints in children
	Decreased lung function (vulnerable subgroup: asthma)
UFP (long-term) – birth outcomes	Preterm birth
	Small for gestational age
	Congenital anomalies

While there is a wealth of information available on the exposure levels to environmental stressors such as noise and UFP around Brussels Airport, there is a significant lack of data on the actual health impacts on the surrounding population. This knowledge gap hinders a comprehensive evaluation of the real-world impact of these stressors. To address this, the report proposes a multi-tiered approach for health surveillance and research around Brussels Airport, encompassing surveillance programs based on existing secondary data, large-scale primary data collection and in-depth monitoring studies. Each tier offers distinct advantages and addresses specific research questions, contributing to a comprehensive understanding of the health impacts of airport operations. The proposed multi-tiered approach aims to establish a robust health surveillance system that not only monitors environmental conditions but also tracks health outcomes in the exposed population over time.

A multi-tiered approach

Surveillance based on secondary data

Health surveillance programs based on secondary data, or data that is already routinely collected for other purposes, offer a cost-effective way to monitor health trends and potential associations with environmental stressors like those produced by an airport. In the case of Brussels Airport, this could involve analysing health data from national registries (e.g., the national mortality registry, the Belgian Cancer Registry) and other routinely collected databases (e.g., hospital discharge data, the Intermutualistic Agency database) that cover the entire Belgian population or a substantial proportion of it.

By analysing these data at a small geographical level, such as statistical sectors (basic territorial unit for the dissemination of statistics in Belgium at a finer level than the municipal level), researchers can compare the health outcomes of communities living near the airport with those living further away in less or non-exposed areas, or they can study gradients within the area around the airport that are based on environmental data (e.g., noise or UFP contours). This allows for identifying potential areas of concern where residents may be experiencing a higher burden of illness due to airport-related stressors. For example, if a higher prevalence of cardiovascular diseases is observed in communities near the airport / near the airstrips compared to those further away, this could suggest a potential link between airport-related stressor exposure and cardiovascular health, particularly when the analyses account for relevant competing risk factors and socioeconomic background variables of the communities under study.

Secondary data can be used in two distinct ways: for ecological studies at an aggregated level and cross-sectional or panel studies at an individual level. Ecological studies examine population-level health data in relation to average exposure levels within specific geographical areas. This approach is valuable for identifying broad trends and potential areas of concern. Also, it is eminently suited for repeated analyses over a time to follow up time trends or impact of policy actions, since the data are routinely collected and the high quality of the collected data (according to international standards, i.e., International Classification of Disease (ICD) coding). Yet, the major weakness of ecological studies is that it cannot establish individual-level causal relationships. One major challenge is the ecological fallacy, which arises when inferences about individuals are made based on aggregated data. For instance, observing a higher rate of respiratory problems in a community near the airport does not necessarily mean that every individual in that community is experiencing issues due to airport-related air pollution. Individual factors, such as smoking habits or pre-existing conditions, can also contribute to these outcomes. When using secondary data at the individual level it is important to account for these individual factors and other potential confounders, such as socioeconomic status, age and sex, to isolate the specific effects of airport-related stressors on health as much as possible. This can be achieved for some health databases (detailing information regarding these factors) through various statistical methods, such as regression analysis or causal inference techniques, which allow researchers to control for the influence of these confounding variables and estimate the independent effect of airport-related stressors on health outcomes.

Cross-sectional or panel studies, on the other hand, collect individual-level data on both exposure and health outcomes, allowing for a more detailed analysis of the relationship between airport-related stressors and health. By analysing individual-level data from secondary data sources, researchers can account for individual differences in susceptibility and exposure, providing better insights in potential cause-and-effect relationships. However, accessing individual-level data often requires specific data requests and lengthy approval processes due to privacy concerns. In contrast, ecological studies, which rely on aggregated data, are less prone to these data accessibility and privacy issues.

This project involved a thorough evaluation of databases useful as secondary data sources to investigate relevant health effects related to noise and UFP exposure. The evaluation considered the databases' coverage, time series and available indicators (prevalence, incidence, mortality, medication use, etc.). In conclusion, the project identified several suitable databases for health surveillance around Brussels Airport (see *Table 2*) each with its strengths and limitations.

Table 2: List of secondary data sources and possible endpoints for health surveillance and research around Brussels Airport.

Data source	Health endpoint*	Indicator
Mortality Registry	All-cause mortality	Standardized mortality ratio
	Cause-specific mortality, e.g., cancer mortality, cardiovascular mortality, stroke mortality	Standardized mortality ratio
Belgian Cancer Registry	Total cancer incidence	Standardized incidence ratio
	Specific cancer incidence, e.g., breast cancer	Standardized incidence ratio
IMA/Farmanet	Hypertension	Frequency use of hypertensive medication
	Sleep disturbance	Frequency use of sleep medication
	Depression	Frequency use of anti-depressants
	Asthma	Asthma prevalence

Data source	Health endpoint*	Indicator
Hospital discharge data	Total cardiovascular disease, stroke	Standardized morbidity ratio
	Asthma	Standardized morbidity ratio
	Diabetes	Standardized morbidity ratio
Perinatal registry	Low birth weight, preterm birth	Standardized incidence ratio
Intego	Blood pressure	Average values
	Hypertension, diabetes, obesity	Incidence

* Selected health endpoints based on evidence from research around other airports

The use of secondary data for health surveillance also has limitations. Existing health registries may not capture all relevant health outcomes related to airport operations. For example, while data on hospitalization and medication use can provide insights into physical health conditions, they may not capture outcomes like sleep disturbance, annoyance or mental health issues, which are also known to be affected by airport-related stressors, but do not necessarily lead to general practitioner visits or hospitalization.

Therefore, while secondary data surveillance offers a valuable basis for monitoring health trends and identifying potential areas of concern, it should be complemented with other research approaches, such as large-scale primary data collection and in-depth monitoring studies, to gain a more comprehensive understanding of the health impacts and disease burden of airport operations.

Large-scale primary data collection

To overcome the limitations of secondary data, this report proposes conducting large-scale primary data collection through questionnaires. This approach allows for the collection of detailed individual-level data on self-reported health outcomes, noise annoyance, sleep disturbance, stress and other relevant factors, including demographic, socioeconomic status, lifestyle factors and residential history. Following respondents over time would furthermore give rise to a unique and tailored general population cohort. By collecting this comprehensive data, researchers can gain a deeper understanding of the health impacts of airport-related stressors on individuals living near Brussels Airport.

One of the key advantages of primary data collection is the ability to link self-reported health outcomes with modelled noise and UFP exposure data (at the home, work and/or school address of the residents, as a proxy for personal exposure). These exposure models can estimate noise levels at specific locations based on factors like flight paths, aircraft types, meteorological conditions and local topography. By linking this modelled exposure data with individual-level health data, researchers can establish site-specific exposure-response functions, which quantify the relationship between exposure levels and the probability of experiencing adverse health effects. This information is crucial for identifying vulnerable subgroups within the population, such as those living in areas with higher noise levels or those with specific demographic characteristics (e.g., age, socioeconomic status) that may make them more susceptible to the negative health effects of noise or UFP. Additionally, by collecting detailed information on individual health conditions and lifestyle factors through questionnaires, researchers can identify individuals with pre-existing health conditions that may be exacerbated by noise or UFP exposure. This information can then be used to develop targeted interventions and policies to protect public health and specifically the health of these vulnerable subgroups.

In addition to self-reported data, the report suggests incorporating non-invasive measurements to complement the questionnaires. These measurements could include self-sampling for biomarker analysis, such as cortisol levels in hair or saliva, which can indicate stress responses associated with noise exposure, or inflammatory markers in urine (e.g., CC16) which can indicate airway inflammation related to UFP exposure. Additionally, wearable devices like smartwatches or fitness trackers could be used to collect data on sleep patterns, heart rate variability and physical activity, providing further insights into the physiological and behavioural impacts of airport-related stressors.

By combining questionnaires with modelled noise and UFP exposure data and biological measurements, researchers can establish a more comprehensive and nuanced understanding of the health impacts of airport operations on nearby residents.

In-depth monitoring studies

In-depth monitoring studies are proposed to delve deeper into the causal relationships and underlying biological mechanisms linking airport-related stressors to specific health outcomes. These studies would involve a smaller, targeted group of participants compared to large-scale surveillance, allowing for more intensive data collection and the use of high-precision technologies.

For instance, an in-depth sleep study could use actimetry in combination with electrocardiography to objectively measure sleep patterns, arousals and awakenings in relation to nighttime noise exposure. This approach goes beyond self-reported sleep disturbances and provides physiological data on the actual impact of noise on sleep quality. Additionally, advanced sound sensors could be deployed inside and outside participants' homes to capture detailed noise data, including sound pressure levels, frequency content and the timing of the noise events. This would allow researchers to correlate specific noise events with sleep disruptions and assess the impact of different noise characteristics on sleep quality. The specific protocol for this study has been validated in a pilot project within the PIO program (in Dutch: Programma Innovatieve Overheidsopdrachten).

Similarly, in-depth studies could investigate the impact of UFP exposure on inflammatory responses and lung function. This could involve collecting blood samples from participants at regular intervals to measure inflammatory markers, such as C-reactive protein and interleukin-6. Additionally, spirometry tests could be conducted to assess lung function. While personal UFP monitoring would be ideal, it is currently not feasible due to high costs and uncertainties associated with the technology. Therefore, modelled UFP exposure at the address level should be used as a proxy for personal exposure. By combining these different data sources, researchers can gain a more comprehensive understanding of the biological pathways through which UFP exposure may affect health.

Such in-depth monitoring studies would provide valuable insights into the causal relationships between airport-related stressors and specific outcomes, as well as the underlying biological mechanisms. This information can inform the development of targeted interventions and policies to mitigate the adverse health effects of airport operations. For example, while a causal link between nighttime noise exposure and sleep disruptions has already been established in literature, there is currently no evidence specific to the Brussels Airport region. By investigating the relationship between various noise metrics, such as those assessing noise peaks or the intermittency ratio, and sleep disturbance in this specific context, policymakers can gain valuable insights into the most impactful noise characteristics. This information can then be used to develop more targeted and effective noise mitigation strategies. For instance, if noise peaks during specific nighttime hours are found to be particularly disruptive, policymakers could consider implementing stricter noise regulations or curfews during those specific time windows or promoting the use of noise-reducing measures in homes near airports.

Additional considerations

Citizen science: a complementary approach to health surveillance and research

Citizen science projects offer a complementary approach to health surveillance and research around Brussels Airport by actively involving the public in data collection and analysis. This approach could leverage readily available tools like smartphone apps and wearable devices to gather large-scale data on noise exposure, sleep patterns, physical activity and other relevant health outcomes. This data can then be combined with modelled noise exposure data and other relevant information to assess the impact of airport operations on health and well-being. By participating in data collection, citizens gain a better understanding of the issue and contribute to finding solutions, fostering collaboration between the community, researchers and policymakers.

However, it is important to acknowledge that the primary responsibility for monitoring and addressing the health impacts of airport operations lies with the relevant authorities and stakeholders, not with individual citizens. While citizen science can provide valuable complementary data, it should not be seen as a replacement for rigorous scientific research and evidence-based policymaking.

Strategies for ensuring representativeness and validity in health data collection

Ensuring the representativeness and validity of data collected through various research approaches is crucial for understanding the health impacts of airport operations on surrounding communities. This involves implementing strategies to encourage participation from diverse groups and mitigate potential biases.

For studies utilizing secondary data sources (e.g., health registries), it is important to select comprehensive data sources that cover the entire population or a substantial portion of it. Statistical methods can be employed to account for potential confounding factors (if present) and analyse the data at a granular level to identify areas with higher exposure levels and potential health disparities. Collaboration with relevant authorities and institutions is necessary to address data accessibility and privacy concerns.

In large-scale primary data collection through questionnaires, stratified sampling techniques can ensure adequate representation of different demographic groups and exposure levels. Additionally, measures such as reminders, incentives and follow-up calls can minimize non-response bias.

For in-depth monitoring studies involving smaller, targeted groups, partnering with local healthcare providers or community organizations can help identify and recruit eligible participants. Offering compensation and minimizing participant burden can improve recruitment and retention rates.

Additionally, targeted outreach efforts, clear instructions, user-friendly tools and incentives can encourage participation from diverse groups. Addressing potential biases, such as self-selection bias and technological barriers (e.g., limited access to smartphones or wearable devices), can be achieved through weighting techniques and alternative data collection methods.

By implementing these strategies across different research approaches, researchers can ensure that the data collected reflects the experiences and health outcomes of the entire community living near the airport, leading to more robust and reliable findings.

Recommendations and future directions

This report provides a comprehensive framework for health surveillance and research around Brussels Airport. While the framework outlines the general approach, the specifics, such as which exposure-outcome pairs to investigate and the detailed study approaches, will be determined in subsequent phases of the project. This process should involve a thorough evaluation of existing data sources (for now covered in WP3), consultation with relevant stakeholders (e.g., community members, airport authorities, health officials) and prioritization of research questions based on the specific needs and concerns of the local community. Additionally, it should also involve the development of detailed research protocols for both primary and secondary data. These protocols should outline the research question(s), study area, methodologies, data access procedures, communication plans and other relevant aspects.

This report advocates for a multifaceted approach to future research and surveillance efforts around Brussels Airport, integrating diverse research designs and data sources to comprehensively understand the health impacts of airport-related stressors comprehensively. This approach should consider the combined effects of multiple exposures, such as noise and UFP exposure, as their interaction may amplify adverse health outcomes.

The primary goal of this framework is to establish a baseline understanding of the current health situation of residents living near the airport. This will involve collecting environmental exposure data (noise and UFP) and data on various health outcomes (such as cardiovascular and respiratory health, sleep disturbance, annoyance and (mental) well-being) and comparing them with residents in less exposed areas. This will help identify health disparities and areas of concern that require further investigation. Additionally, this framework aims to establish a long-term surveillance program to monitor the community's health over time, assess the effectiveness of mitigation measures and identify any emerging health concerns. By continuously monitoring the health of the community, stakeholders can proactively address any potential risks and ensure residents' well-being.

Future research should investigate the impact of emerging aviation technologies and fuels, such as sustainable aviation fuels (SAFs), on air quality and public health. While these technologies hold promise for reducing emissions, their potential health effects remain unclear and require thorough investigation. A deeper understanding of the emission and dispersion of UFP, particularly in relation to different aircraft types and operational modes, is also crucial for developing effective mitigation strategies.

By implementing the proposed framework, including surveillance programs based on secondary data, large-scale primary data collection and in-depth monitoring studies, robust evidence can be generated to inform decision-making and develop targeted interventions. This evidence-based approach will enable the development of strategies to mitigate the adverse health effects of airport operations and protect the well-being of communities living near Brussels Airport, ensuring that the airport's economic benefits are balanced with the imperative of safeguarding public health.

Report Work Package 1

Evidence-based health outcomes related to environmental stressors around airports

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Aims and objectives of Work Package 1

Work Package (WP) 1 aims to achieve the following objectives:

- Identify **health outcomes** that are associated with **airport-related environmental stressors** based on **scientific evidence**;
- Identify **gaps in research** that need to be addressed to establish the link between airport-related stressors and health outcomes;
- Provide **input for relevant research questions and surveillance approaches** to assess the **health impact** of Brussels Airport on nearby communities.

To achieve these objectives, we have analysed the available scientific literature and knowledge on **airport-related stressors** and their **impact on health**. We have extracted relevant information from previously published extensive reviews and integrated science assessments. Additionally, detailed information regarding study approaches and methods is collected in a searchable database (Excel file) and discussed in this report to propose relevant research and surveillance approaches (input for WP4).

In **Chapter 1**, we provide an overview of the **scientific evidence** linking airport-related environmental stressors to health effects and provide an answer to the following questions:

- Which health outcomes are associated with one or more of the airport-related environmental stressors? What is the strength[1] and the quality[2] of this evidence?
- What are key evidence gaps for research linking airport operations and health? Where is the evidence weak? Which exposure-health outcomes pairs require further investigation?

In **Chapter 2**, we discuss **research methods and approaches** that have been used to study the link between airport activities and community health. In addition, we highlight important aspects to consider when designing such a study.

Notice

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[1] The strength of evidence relates to the certainty of the study findings. It reflects the degree of confidence in the conclusions drawn from the research. It addresses the question of how convincing or compelling the findings are supporting a particular hypothesis.

[2] The quality of evidence of a study refers to how well the research was designed, conducted and analyzed, which ultimately affects the reliability and validity of the findings (e.g., GRADE scoring system). It addresses the question of whether the study was conducted in a manner that allows confidence in the validity of its findings.

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List of acronyms

1 Community health effects related to airport operations

Airport operations impose a dual environmental burden in the form of **air** and **noise pollution**. It is crucial to understand the types of pollutants emitted and how exposure to air and noise pollution affects surrounding communities to develop effective strategies to mitigate their adverse impact.

Most airport emissions come from aeroplanes, especially combustion gases and fine particles formed from burning jet fuel and from the idling or taxiing of planes on taxiways. Air pollution levels at and around airports are further impacted by emissions resulting from traffic associated with airport operations, auxiliary power units, ground power units and ground support equipment within airports as well as vehicle traffic going to and from the airport. Air pollutants from airport operations include a variety of pollutants with varying quantities of emissions. The air pollutants of most concern related to airport operations (aircraft and road traffic activity) include particulate matter (PM; classified by size as PM_{10}, $PM_{2.5}$ and ultrafine particles (UFP)), ozone (O_3), carbon monoxide (CO), nitrogen oxides and dioxide (NO_x and NO_2), sulphur oxides (SO_x) and lead (Pb) (Kim, 2015). These pollutants are categorized as **standard air pollutants**, which are known to cause harm to human health and the environment and are monitored and regulated by the European Union (EU), except for UFP and black carbon (both part of $PM_{2.5}$). Several studies have shown that airport-related activities significantly contribute to elevated UFP levels downwind from runways during take-off and landing (Hudda et al., 2014; Keuken et al., 2015; Peters et al., 2016). Their potential health risks and the lack of established regulations and comprehensive understanding compared to standard air pollutants classify UFP as an **emerging pollutant**. Furthermore, some **hazardous air pollutants** (HAPs) (e.g., benzene and naphthalene and other substances considered as substances of very high concern are also related to airport operations (see *Section 1.1.2.3 Hazardous air pollutants (HAPs)* and output WP2). Up to now, not much is known about the levels and effects of these pollutants in neighbourhoods around airports and the limited knowledge focuses on emissions rather than on exposure and health impact. **Noise pollution** is another major concern for communities located near airports where aeroplanes generate a lot of noise during take-off and landing. Noise pollution refers to the persistent environmental noise that exceeds safe levels for human health. Studies have shown that people are generally more sensitive to aircraft noise compared to road or railway noise at similar decibel levels (Gély & Márki, 2022). This heightened sensitivity is reflected in the stricter noise guidelines implemented by the World Health Organization (WHO) for aircraft noise (45 dB(A) L_{den}, 40 dB(A) L_{night} (details on noise indicators see *Section 2.1.1.1 Choice of metric*)) compared to road traffic noise (53 dB(A) L_{den}, 45 dB(A) L_{night}) (WHO Regional Office for Europe, 2018).

There have been numerous studies that prove air pollution exposure can cause respiratory and cardiovascular issues (see *Section 1.1.2 Air pollution health effects*). However, it proves challenging to directly link airport-specific contributions to air pollution with specific health outcomes for two main reasons. First, **airport emissions** are a **relatively small contributor** to overall air pollution levels (except for UFP). Second, pollutants released by airports are **rather similar** in composition to those from traffic and other combustion sources (except for UFP), making it difficult to isolate their specific effects. Likewise, different noise sources, such as air traffic and road traffic, can also contribute to similar health problems like sleep disturbances, annoyance, cardiovascular issues and potentially cognitive difficulties.

Table 1 visually depicts the **distinct environmental health evidence profiles of airport emissions**. Airport activities are considered primary contributors to ambient levels of noise and UFP in surrounding communities. Conversely, their contribution to standard air pollutants, such as $PM_{2.5}$, O_3

and NO_2, appears relatively modest (see output WP2 for more details). The influence of airport operations on HAP emissions and immissions remains an area of ongoing investigation. As discussed below, a wealth of health effect studies exists for both general and aviation-specific noise exposure, providing a robust understanding of its harmful effects. However, the health consequences of UFP exposure are not yet fully understood, although research is ongoing and expanding (also see UFP report[3]). Standard air pollutants, on the other hand, have been extensively studied, with a well-established link to a significant disease burden. Since airport operations contribute little to overall ambient levels of these standard air pollutants, they are primarily considered co-exposures when evaluating health risks around airports.

Table 1: Environmental evidence profiles of environmental stressors in general and airport-specific settings.

Stressor	Contribution airport	Availability of health studies		Burden of disease	
		General	*Airport*	General	*Airport*
Noise	Significant	Abundant	*Abundant*	Large	*Large*
UFP	Significant	Growing	*Growing*	Unknown	*Unknown*
Standard air pollutants (e.g., $PM_{2.5}$, NO_2)	(rather) Limited	Abundant	*Mainly as co-exposure*	Large	*(rather) Limited*
HAPs	Under study*	Limited to abundant (depending on the specific compound)	*None*	Limited to abundant (depending on the specific compound)	*Unknown*

*The contribution of airport-related operations to HAP levels in ambient air is assessed as part of WP2.

Such distinct evidence profiles of airport-related stressors underscore the relevance for surveillance of effects related to noise around Brussels Airport, and the need for further research on the health effects of airport-related UFP and noise exposure (although effects are well recognised, further research is needed to better understand the mechanisms and impact of mitigation measures). Additionally, investigation into the combined effects of aircraft noise and UFP exposure on human health would provide valuable insights for developing effective mitigation strategies around airports.

The following sections highlight the **potential adverse health effects** of the identified airport-related stressors on nearby communities. These stressors, primarily noise and air pollution from airport operations, can have both direct and indirect effects on human health. A direct effect of aircraft noise includes sleep disturbance which in turn can negatively impact cognitive function and learning abilities (i.e., indirect effect). Likewise, UFPs can directly irritate the lungs and airways leading to respiratory problems while exposure to UFPs can also weaken the immune system, making individuals more susceptible to respiratory infections (i.e., indirect effect).

In general, evidence-based health indicators can be considered within one or several of the following areas:

- **(Patho)physiological functioning:** This includes measures like self-reported health complaints, blood pressure changes, performance impacts and sleep disruptions (awakenings);

[3]See report 'gezondheidseffecten-UFP-vliegverkeer' at Milieugezondheidskundig aandachtsgebied Luchthavens | Zorg (zorg-en-gezondheid.be)

- **Well-being:** This category explores how airport-related factors might influence perceived overall health, risk perception (i.e., feelings of being at risk due to airport proximity) and general annoyance levels;
- **Medical resource use:** This examines potential links between airport-related stressors and healthcare utilization, such as hospital admissions and medication usage.

Important criteria for the interpretation of these health indicators are (i) (biological) **plausibility** of possible effects, (ii) evidence for an **exposure-response relation** based on scientific literature, (iii) **number of people potentially affected** and (iv) **public concern**.

We here focus on **health impacts** that are **(likely) caused by airport-related stressors**. While both toxicological and epidemiological data play a role in risk assessment, in this report we only consider epidemiological studies as they reflect real-world exposure conditions, allow direct observations of health outcomes and can account for confounding factors that might both influence exposure and effect risks. Most information presented is deduced from the WHO systematic reviews, Integrated Science Assessments (ISA) by the Environmental Protection Agency (EPA) and other relevant reports on health effects from noise and air pollution exposure. *Appendices I* and *II* provide more details about noise and air pollution, respectively. The Grading of Recommendations Assessment, Development and Evaluation (GRADE) approach was used in these reports and rates the **quality of evidence** as '*high'*, '*moderate*', '*low*' or '*very low*', with implications for the need for further research. This rating is based on the study designs, consistency and other data features on a given question. It was developed for clinical medicine and has been adapted for use with environmental health exposures (Morgan et al., 2016). While structured, GRADE is not a deterministic approach that delivers an automatic answer. Instead, it is applied to bodies of evidence, considering all eligible data. Accordingly, studies of differing quality are considered together, and reviewers must ultimately judge the direction of the evidence (harmful effect or no effect). GRADE encourages transparency and consistency, but its strict methods mean it is typically difficult to obtain high quality evidence for environmental health risks. **Moderate quality evidence** is considered **sufficiently robust,** but *low* or *very low* quality evidence can still be informative and highlight potential health risks and areas that require further investigation with more robust research methods. *Appendices I* and *II* summarise the overall quality of evidence and direction of effect (whether the stressor is harmful or has no effect), drawing together the conclusions on the quality of evidence from the existing reviews and integrating new evidence where applicable. In the text below, we only focus on the health outcomes with a defined **harmful effect**.

1.1 Evidence bases for health outcomes related to airport operations

The current knowledge regarding the health consequence of exposure to significant airport-related stressors (i.e., aviation noise, UFP) remains incomplete and **the evidence for several key areas lacks robustness**. In general, researchers evaluate evidence using aspects like study design, strength of association, consistency, biological plausibility and addressing biases. Nevertheless, airport research presents some unique hurdles in assessing the quality and strength of evidence. Separating the effects of airport emissions from general background pollution proves a major challenge which weakens the link between exposure to airport-related stressors and health problems. **In addition, airport layouts, emissions and weather all vary significantly, hence findings from one airport might not apply to others**. The general approach to scoring the evidence could be adapted when evaluating evidence for airport-related stressors. Since randomised control trials are impractical around airports, it is better to focus on well-designed observational studies with strong methodologies that minimise bias and account for confounding factors. In addition, studies might not directly measure health outcomes but could assess indirect effects like sleep disruption or noise annoyance which can support a causal pathway. Other important aspects to consider are consistency across studies and biological plausibility. Research on UFP is a relatively new field compared to aircraft noise and standard air pollution (e.g., $PM_{2.5}$, NO_2). Accordingly, there are fewer studies available, and the evidence base is still evolving.

As listed below and detailed in *Appendices I* and *II*, across all outcomes where there is evidence of a harmful effect, the large majority is of *low* or *very low* quality (except for the standard pollutants). This *low* quality is primarily driven by the fact that most studies use a **cross-sectional design**, and many have **small sample sizes** which limits their power. Moreover, the smaller the effect, the more difficult it is to gain evidence that allows us to be certain of the effect. It is important to consider the potential **cumulative health burden** at the population level. Even if single effects of airport-related stressors on various health outcomes are small, the widespread exposure of large populations could translate into significant public health concerns. However, detecting this population-wide impact with certainty can be statistically challenging.

It is crucial to recognise that all considered health outcomes have **causes beyond airport operations**. Environmental, social, lifestyle and genetic factors all play a role in morbidity and mortality. The relative importance of airport-related stressors in the overall disease burden will vary depending on the specific health outcome. For chronic diseases with a low attributable risk to airport-related stressors, the overall impact on population morbidity and mortality might be minimal, even with widespread exposure to elevated levels of these stressors. This implies that research and surveillance efforts should prioritize outcomes where airport-related stressor exposure is likely to have a significant impact at the population level (or at least at subpopulation levels, like vulnerable groups). However, it is important to acknowledge that even rare effects on individuals, which may be difficult to detect through large-scale research or surveillance programs, cannot be neglected.

1.1.1 Aircraft noise health effects

Aircraft noise exposure can trigger negative health outcomes via direct (e.g., sleep disturbance) and indirect (e.g., disruption of intended activities) pathways that trigger **stress** responses (see *Figure 1(a)*). In turn, stress triggers cortical activation and involves the activation of the hypothalamic-pituitary-adrenal axis and the sympathetic nervous system, leading to a release of stress hormones (i.e., cortisol, catecholamines) and subsequently to the induction of inflammation and oxidative stress (see *Figure 1(b)*). Stress reactions, including higher glucocorticoid and catecholamine levels, lead to higher blood pressure which in turn can impair the function of endothelial nitric oxide synthase and increase oxidative stress in the vasculature, thereby reducing vascular nitrogen oxygen bioavailability. All these alterations lead to endothelial dysfunction and to a super sensitivity of the vessels to stress hormone-induced vasoconstriction (Babisch, 2003; Ising & Braun, 2000; Münzel et al., 2021). While this general stress response is a physiological acute adaptation to stress, **chronic exposure** can lead to unhealthy changes in the body (i.e., pathophysiological alterations) such as the manifestation of cardiometabolic risk factors, such as diabetes, high plasma cholesterol levels and high blood pressure, and subsequently to cardiovascular disease (e.g., myocardial infarction, heart failure, stroke). Although the conscious experience with noise may be the primary source of stress during daytime, the unconscious response during nighttime sleep is thought to play a particularly important role in the effects of noise on health. Typical urban noise levels, including a variety of noise sources (e.g., road and aircraft noise, leisure noise), have been shown to disrupt sleep patterns, ranging from changes in sleep stages to full awakenings. Recent studies further suggest that **nighttime aircraft noise** can increase biological risk factors for various diseases. These risks include, among others, oxidative stress and elevated blood pressure. Disrupted sleep itself is also linked to major chronic diseases like cardiovascular disease and diabetes (Münzel et al., 2014).

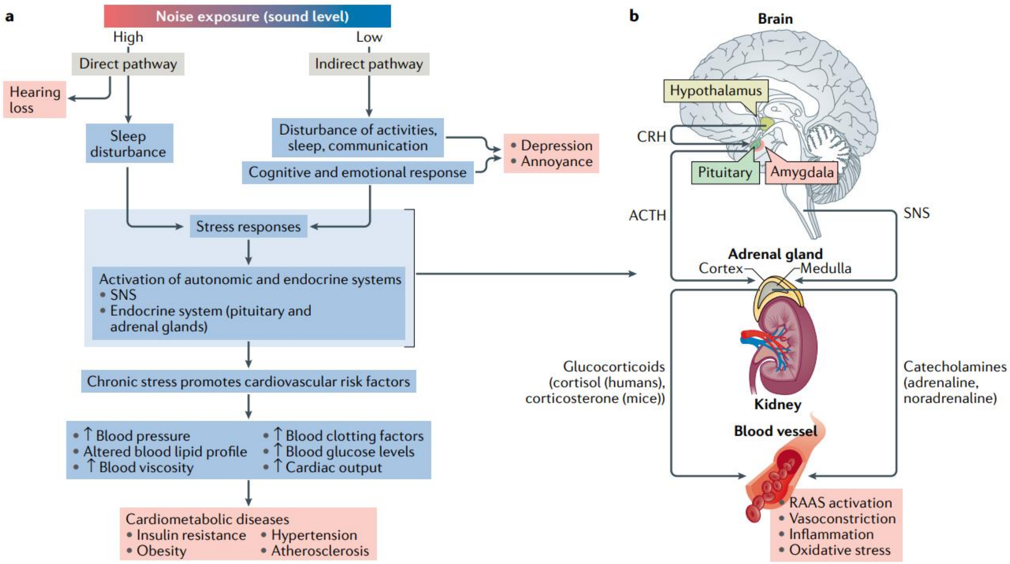

Figure 1: Noise-stress concept and its impact on human health. (a) Noise reaction model for the direct (auditory) and indirect (non-auditory) effects of noise exposure. (b) Neuronal activation (arousals) induced, for example, by noise exposure triggers signaling via the hypothalamic-pituitary-adrenal axis and sympathetic nervous system (SNS). In the hypothalamic–pituitary–adrenal axis, the hypothalamus releases corticotropin-releasing hormone (CRH; also known as corticoliberin) into the pituitary gland, which stimulates the release of adrenocorticotropic hormone (ACTH) into the blood. ACTH induces the production of glucocorticoids by the adrenal cortex, and the activation of the SNS stimulates the production of catecholamines by the adrenal medulla. The release of glucocorticoids and catecholamines, in turn, leads to the activation of other neurohormonal pathways (such as the renin-angiotensin-aldosterone (RAAS) system) and to increased inflammation and oxidative stress, which can ultimately have adverse effects on cardiovascular function and molecular targets. Reprinted with permission from (Münzel et al., 2021).

Prolonged exposure to environmental noise is one of the **major environment-related causes of ill health** in Europe. Although the levels of noise generated by transport sources are generally too low to cause biological damage to the ear, it is well established that, if exposure is long-term and exceeds certain levels, noise can lead to non-auditory health effects such as annoyance, sleep disturbance, negative effects on the cardiovascular and metabolic system as well as cognitive impairment in children as detailed in *Appendix I* and listed below. Current scientific literature demonstrates associations between long-term aircraft noise exposure and ischemic heart disease, annoyance, reading and oral comprehension in school children as well as sleep disturbance during the night. Research suggests a **vicious cycle**: noise disrupts sleep, which limits the body's ability to recover from stress, making one more susceptible to the damaging effects of stress on the heart, circulatory system and other organs. **Accordingly, chronic stress from noise pollution forms a major contributor to circulatory and cardiovascular diseases** (McEwen, 2008; Münzel et al., 2014; Recio et al., 2016). Interestingly, as mentioned above the body's stress response to noise can be automatic, even if you don't consciously find the noise annoying (Basner et al., 2014). This means low-level noise one might not even notice, may still negatively influence one's health.

Table 2 provides an overview of the health outcomes with a **reported harmful effect** due to aircraft noise exposure and the related quality of evidence. The health outcomes without reported harmful effects were not included in this overview but were discussed in *Appendix I.* The health outcomes which were prioritized for the definition of the WHO noise guidelines (WHO Regional Office for Europe, 2018) are given in bold (details can be found in *Appendix I*). While the effects are mentioned one by one in *Table 2,* it is noted that some effects are related one to another (cfr. underlying mechanisms) (see further in the text).

Table 2: Overview and quality of evidence for different outcomes with a reported harmful effect of aviation noise.

Outcome	Quality of evidence of harmful effect*
Cardiovascular and metabolic outcomes	
Arterial stiffness	Low
Cortisol levels	Very low
Diabetes incidence	Low
Heart rate	Very low
Hypertension incidence	Low
Ischemic heart disease incidence	Low
Asymptomatic heart damage	Very low
Obesity	Very low**
Stroke incidence	Moderate
Sleep-related outcomes	
Physiologically measured awakenings in adults	Moderate
Self-reported sleep quality and sleep coping behaviours	Very low
Self-reported awakenings	Very low
Self-reported sleep disturbance in adults (source not specified)	Very low
Self-reported sleep disturbance in adults (source specified)	Moderate
Cognitive outcomes	
Assessment of student distraction	Very low
Impairment assessed through Standardized Achievement Tests	Moderate
Reading and oral comprehension	Moderate
Short- and long-term (episodic) memory	Moderate
Birth outcomes	
Congenital malformation	Very low***
Low birth weight	Very low***
Preterm birth	Very low***
Quality of life, mental health and well-being outcomes	
Depression prevalence mediated by annoyance	Low
Hyperactivity	Low
Interview measures of depression and anxiety	Low
Medication intake to treat anxiety and depression	Very low
Well-being	Very low
Cancer	
Incidence of breast cancer	Low
General health outcomes	
General physical health of children mediated by annoyance	Low
Annoyance	Moderate

*Health effects for which no harmful effects were demonstrated are not included in this table

**No GRADE assessment but harmful effects reported in narrative review (van Kamp et al., 2020)

***No GRADE assessment but harmful effects reported in narrative review (Nieuwenhuijsen et al., 2017)

Cardiovascular health – While some studies suggest a connection between aircraft noise exposure and an increased risk of cardiovascular diseases, including hypertension, ischemic heart disease and stroke, the evidence is still developing. The associations observed between aircraft noise exposure and cardiovascular diseases need cautious interpretation. Individual responses to noise can vary depending on personal factors such as age, health status and noise sensitivity. Further research is needed to solidify the understanding of this relationship. Recent studies highlight the importance of nighttime noise exposure and its potentially stronger association with cardiovascular risk.

Metabolic health – Noise exposure might also influence metabolic health through stress hormones released in response to noise. Such hormonal changes could potentially affect insulin and glucose regulation. Currently, research on the effects of aircraft noise on metabolic diseases like diabetes or body parameters such as body mass index (BMI) and waist circumference is scarce, making it difficult to draw any firm conclusions.

Sleep-related outcomes – Studies in adults reveal that aircraft noise disrupts sleep, primarily by causing awakenings, as measured by physiological monitoring (i.e., objective). However, self-reported sleep quality (i.e., subjective), while also affected by noise, might not always align with these physiological measurements. The impact of aircraft noise on sleep in children remains poorly understood. The strength of the observed noise-induced sleep disruption depends heavily on how both noise exposure and sleep outcomes are assessed. Again, solely relying on average noise levels does not accurately predict physiologically measured and self-reported sleep outcomes. To gain a more accurate picture, the number of individual noise events and their maximum intensity should be considered too.

Cognitive health – A growing body of research suggests that aircraft noise exposure can negatively impact cognitive function, with children being particularly vulnerable. Moderate quality evidence exists suggesting a connection between aircraft noise exposure and impaired reading comprehension in children. The evidence of aircraft noise exposure on cognitive function in adults is less clear. Limited studies suggest a possibility that existing age-related cognitive decline in the elderly might be further exacerbated by noise exposure.

Birth outcomes – The current knowledge of the potential link between aircraft noise exposure and adverse birth outcomes remains limited. Given the long-term health consequences associated with adverse birth outcomes, further research is crucial to establish any definitive connections between these two factors.

Quality of life, mental health and well-being – Research investigating the association between aircraft noise exposure and mental health outcomes remains scarce. While newer studies suggest a potential negative impact of aircraft noise on well-being, quality of life, and even diagnosed depression, the overall findings on mental health are still inconsistent and require further exploration.

Cancer – A few studies have shown that transportation noise may also be a risk factor for the development of cancer but the findings for aircraft noise are inconclusive.

General health – The limited research available suggests no effect of aircraft noise on self-reported general health but an indirect effect of aircraft noise on the physical well-being in children (mediated by annoyance, see below).

Annoyance – Aircraft noise annoyance represents one of the most comprehensively studied and well-validated consequences of noise exposure potentially serving as an early warning for negative health impacts. As such, it is frequently employed as a key metric in noise impact assessments and serves as a basis for regulatory frameworks. Since increasing aircraft noise exposure levels are linked to greater annoyance, evidence suggests a potential link between increasing aircraft noise annoyance and various adverse health outcomes as detailed below. Annoyance is a complex experience with cognitive, emotional and behavioural aspects. This multifaceted nature and complexity suggest a potential link, or even a contributing factor, to various health outcomes. It is important to note that the relationship can be bidirectional. Existing health issues, particularly mental health problems, can also influence how people experience noise annoyance. Individuals with compromised coping mechanisms due to health problems may be more susceptible to the disruptive effects of noise, possibly leading to higher annoyance rates.

Interestingly, research shows that only about a third of noise annoyance is directly related to the loudness of the noise itself (measured by L_{den} or L_{Aeq}, detail on noise metrics see *Section 2.1.1.1 Choice of metric* and *Appendix I*). The other two-thirds are influenced by other factors not related to the sound itself, called **non-acoustical factors**. These factors can be broadly categorized as (i) personal and social factors which relate to your own personality, attitudes towards noise and social situation and (ii) contextual and situational factors which involve the specific situation where the noise occurs (e.g., the time of day or feeling like you have no control over the noise sources) (Bartels et al., 2022).

Recent studies support the theory that annoyance plays an **indirect role** in the relationship between aircraft noise exposure and (mental) health outcomes. For individuals experiencing annoyance due to aviation noise, there was an association with specific health problems including hypertension (Babisch et al., 2013; Baudin et al., 2020; Eriksson et al., 2010), the prevalence of depression and anxiety (Benz & Schreckenberg, 2019), mental health-related quality of life (Schreckenberg et al., 2017) and general physical health in children (Spilski, Rumberg, et al., 2019). However, this link was not observed for all health outcomes under study. For example, studies found no evidence of annoyance mediating the relationship between aircraft noise and cortisol levels (Baudin et al., 2020) and blood pressure (Carugno et al., 2018). The mediating role of annoyance is further discussed below (see *Section 2.2 Considerations when designing studies*).

Figure 2 gives an overview of the various health outcomes related to aircraft noise exposure and depicts the underlying mechanisms and role of noise annoyance.

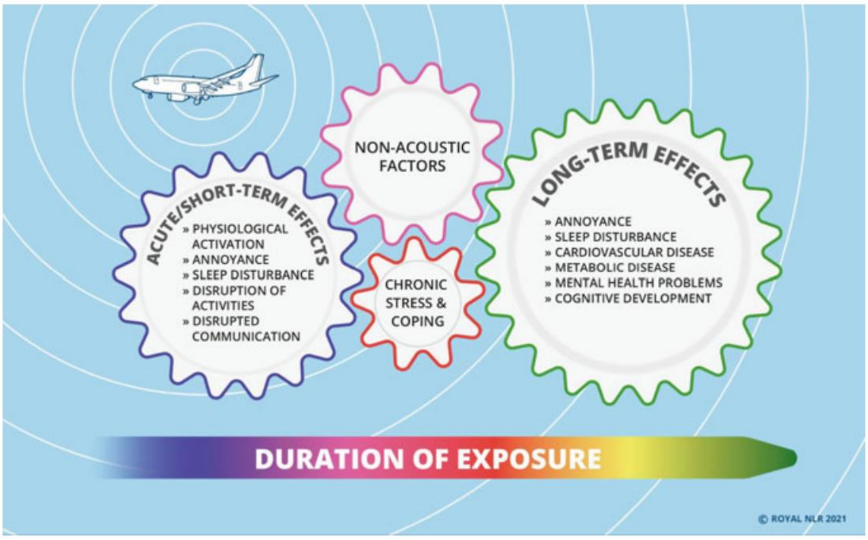

Figure 2: Health effects of aircraft noise exposure and the role of annoyance, from (Kranjec et al., 2019) under a Creative Commons Attribution 4.0 International license.

1.1.2 Air pollution health effects

1.1.2.1 Ultrafine particles (UFP)

While the research on the health impacts of UFP is accumulating (details in UFP report[3] and *Appendix II*), the WHO has **not yet established health advisory values for UFP exposure** below which negative health effects are not anticipated. This means that the current epidemiological evidence while growing, is not yet robust enough to derive precise health-based exposure thresholds for UFP. With that, there are currently **no air quality guidelines** specifically focused on ambient UFP concentrations. In recognition of the potential health risks associated with UFP, the WHO has recognised UFP as an **emerging pollutant** and formulated four 'good practice statements' on UFP exposure (WHO, 2021):

1) Quantify ambient UFP in terms of **particle number concentration** (PNC) for a size range with a lower limit of ≤ 10 nm and no restriction on the upper limit.
2) Expand the common air quality monitoring strategy by integrating **UFP monitoring** into existing air quality monitoring. Include size-segregated real-time PNC measurements at selected air monitoring stations in addition to, and simultaneously with, other airborne pollutants and characteristics of PM.
3) Distinguish between low and high PNC to guide decisions on the priorities of UFP source emission control. Low PNC can be considered < 1000 particles/cm^3 (24-hour mean). High PNC can be considered > 10 000 particles/cm^3 (24-hour mean) or 20 000 particles/cm^3 (1-hour).
4) Utilize emerging science and technology to advance approaches to the assessment of exposure to UFP for application in epidemiological studies and UFP management.

Below we summarize the health effects of UFP exposure (detailed in *Appendix II* and UFP report[3]). First, to make a substantiated statement about the effects of UFP on health, it is necessary to consolidate the knowledge from different studies. To this end, we largely based ourselves on three consolidation reports: (i) the Integrated Science Assessment (ISA) on particulate matter published by the US Environmental Protection Agency (EPA) in 2019 (U.S. Environmental Protection Agency, 2019), (ii) the report 'Risico's van ultrafijnstof in de buitenlucht' (Risks of ultrafine particles in the outdoor air) published by the Dutch Health Council (Gezondheidsraad, 2021) and (iii) the multi-year research program of the Dutch National Institute for Public Health and the Environment (RIVM) on the health risks of UFP around Schiphol airport (N. Janssen et al., 2022). To assess the strength of the connection between UFP exposure and various health outcomes, the reports rely on a robust methodology established by the US EPA. This methodology considers several key factors, including **consistency**, **biological plausibility** and **uncertainties**. Greater weight is placed on the evidence derived from **long-term exposure studies** as they offer a **more robust picture** of the potential health consequences of chronic UFP exposure compared to short-term studies or experimental research, which often provide supportive evidence. The US EPA's causality determinations offer a clear framework for interpreting the strength of evidence. This framework includes five causality determinations, namely 'causal relationship', 'likely to be a causal relationship', 'suggestive of, but not sufficient to infer, a causal relationship', 'inadequate to infer the presence or absence of a causal relationship' and 'not likely to be a causal relationship'. For evaluation of the health effect of short-term UFP exposure from air traffic, we adopt the terminology and framework used in the RIVM report on acute health effects around Schiphol Airport (N. A. H. Janssen et al., 2019).

Important to note is that epidemiological studies investigating the health effects of UFP exposure often face **limitations in accurately and reproducibly assessing UFP exposure levels**. This contributes to a high degree of uncertainty in these findings, which would typically result in *low* or *very low-quality* evidence according to the GRADE scoring system. Accurately assessing UFP exposure presents significant challenges, including (i) **spatial and temporal variability**, (ii) **lack of standardization** and (iii) **confounding factors**. UFP concentrations can **fluctuate considerably within short distances and time periods** as the particles quickly condensate and coagulate to form bigger particles. Studies relying on a limited number of measurement points may not capture this variability and might misrepresent individual exposure levels ('exposure misclassification'). Currently, there is **no single, universally accepted definition or standardized measurement method** for UFP. This inconsistency makes it difficult to compare findings across different studies and draw definitive conclusions. Epidemiological studies investigating the health effects of UFP exposure often **neglect the influence of other pollutants that co-occur with UFP** in the environment, such as black carbon and NO_2. Failing to account for these confounding factors makes it challenging to isolate the specific effects of UFP exposure. Given the limitations in exposure assessment, we here prioritize '**strength of evidence'** as presented in the table below, rather than the overall quality rating based on uncertainty. By focusing on the strength of the evidence rather than also on the quality, we can highlight the weight and consistency of observed associations between UFP exposure and potential health effects, while acknowledging the limitations in exposure assessment. *Table 3* summarizes the main outcomes and related strength of evidence following short- and long-term exposure to UFP in total and specifically from air traffic.

In general, the observed health effects for UFP mainly originating from air traffic align with established research on the general impacts of UFP. While the RIVM study provides valuable insights into potential health effects related to UFP from air traffic at Schiphol Airport, these findings cannot directly be extrapolated to Brussels Airport. Among others because the surrounding environments differ significantly, with a much higher population density near Brussels Airport compared to Schiphol Airport. Therefore, a dedicated study specifically examining the impact of UFP on nearby communities in Brussels Airport is paramount to establish a clearer understanding of the local health impacts of UFP from air traffic.

Table 3: Strength of evidence of health effects related to short-term and long-term exposure to UFP in general and UFP specifically related to air traffic.

Outcome	Strength of evidence	
	UFP general	UFP air traffic*
Short-term		
Cardiovascular health	Suggestive	Indications for effects
Metabolic health	Inadequate	Not assessed
Respiratory health	Suggestive	Effects found
Cognitive health	Suggestive	Not assessed
Total mortality	Inadequate	Not assessed
Long-term		
Cardiovascular health	Suggestive	Suggestive
Metabolic health	Inadequate	Inadequate
Respiratory health	Suggestive	Inadequate
Cognitive health	Suggestive	Suggestive
Birth outcomes	Suggestive	Suggestive
Total mortality	Suggestive	Inadequate
Cancer	Inadequate	Inadequate

*Terminology and framework adopted from the RIVM report on acute health effects around Schiphol Airport (N. A. H. Janssen et al., 2019).

Below, we summarize (more details can be found in *Appendix II*) the potential health consequences of exposure to UFP in general and specifically related to air traffic. While research is ongoing, some effects with suggestive strength of evidence (particularly for cardiovascular health and birth outcomes) require further attention in airport-related health research.

Cardiovascular health – A growing body of studies *suggests* a link between UFP and cardiovascular health problems. Studies have observed an increase in medication use for heart conditions and arrhythmias in populations exposed to UFP from air traffic. Additionally, short-term exposure appears to trigger inflammatory responses in the body, which could further contribute to cardiovascular issues. Future research needs to solidify this connection, particularly for long-term effects, and pinpoint the specific mechanisms by which UFP exposure might impact the heart and circulatory system.

Metabolic health – The current evidence regarding UFP and metabolic health, such as diabetes, is *inconclusive.* While some studies hint at a possible connection, more research with larger and more diverse populations is required to confirm or refute this potential association. Additionally, it is crucial to isolate the effects of UFP exposure from the influence of other co-pollutants in the environment.

Respiratory health – Long-term exposure to UFP from air traffic appears to have *minimal impact* on overall respiratory health. However, short-term exposure can exacerbate existing respiratory problems, particularly in individuals already suffering from respiratory conditions. Notably, children with pre-existing respiratory issues seem to be more susceptible to the negative effects of UFP exposure. Future studies should aim to differentiate between short-term and long-term effects and explore potential preventative measures, especially for vulnerable populations.

Cognitive health – Current evidence is *inadequate* to determine a link between UFP exposure and adverse effects on the neurological system. A recent study suggests a potential association between prenatal UFP exposure and autism spectrum disorder. However, the long-term effects of UFP on the neurological system require further investigation with larger and more diverse populations. Studies specifically designed to explore this link are essential for a clearer understanding.

Birth outcomes – While research is still developing, recent research *suggests* a potential association between long-term exposure to UFP and adverse birth outcomes, such as preterm birth and low birth weight. This potential link appears to be more significant for UFP from air traffic compared to UFP exposure from other sources (e.g., road traffic).

Total mortality – Recent research *suggests* a link between long-term UFP exposure and overall mortality (deaths from all natural causes). Contrary, for UFP specifically from air traffic *no indications* of a connection were found, but more research in larger populations is needed.

Cancer – Current evidence is *inadequate* to link UFP exposure to cancer. Both studies on general UFP exposure and UFP exposure from air traffic show inconsistent links to some cancers resulting in inconclusive findings. Further investigation within larger and more diverse populations is needed.

While the above studies hint at a **potential association between airport-related UFP exposure and cardiovascular health and birth outcomes**, the evidence for a definitive causal relationship remains suggestive and requires further investigation. **Future research with robust methodologies and larger sample sizes** is crucial to solidify our understanding of these potential health risks. One critical aspect of robust research design is the **careful control for co-pollutants**, as other airborne contaminants may also play a significant role in these health outcomes. More specifically, we need to refine our understanding of the specific mechanism by which UFP might impact health and isolate the effects of UFP exposure from the influence of other co-pollutants (especially co-pollutants arising from other sources than aircraft).

1.1.2.2 *Classic air pollutants*

Table 4 lists the short- and long-term health outcomes which were prioritized to inform the formulation of the updated air quality guidelines published in 2021 by WHO (more details in *Appendix II)*. Note a focus on mortality since the WHO is still working on the estimated morbidity from classic air pollutants (Estimating the Morbidity from Air Pollution and its Economic Costs, EMAPEC).

Table 4: Overview and quality of evidence for different health outcomes prioritized by the WHO related to short-term and long-term exposure to the following classic air pollutants: PM_{10}, $PM_{2.5}$, NO_2, O_3, SO_2 and CO.

Pollutant	Outcome	Quality of evidence
Short-term		
PM_{10}	All-cause mortality	High
$PM_{2.5}$		High
NO_2 (24h)		High
NO_2 (1h)		Moderate
O_3		High
SO_2 (24h)		High
SO_2 (1h)		Low
PM_{10}	Cardiovascular mortality	High
$PM_{2.5}$		High
PM_{10}	Respiratory mortality	High
$PM_{2.5}$		High
SO_2 (24h)		Moderate
SO_2 (1h)		High
PM_{10}	Cerebrovascular mortality	High
$PM_{2.5}$		High
O_3 (8h or 24h)	Emergency department visits and hospital admissions due to asthma	High
O_3 (1h)		Moderate
NO_2 (24h)		High
NO_2 (1h)		Low
SO_2 (24h)		Moderate
SO_2 (1h)		Moderate
CO	Emergency department visits and hospital admissions due to myocardial infarction	Moderate
Long-term		
PM_{10}	All-cause mortality	High
$PM_{2.5}$		High
NO_2		Moderate
O_3 (annual)		Low
O_3 (peak)		Moderate
PM_{10}	Respiratory mortality	High
$PM_{2.5}$		Moderate
NO_2		Moderate
O_3 (annual)		Low
O_3 (peak)		Low
PM_{10}	Chronic obstructive pulmonary disease mortality	Moderate
$PM_{2.5}$		High
NO_2		High
$PM_{2.5}$	Acute lower respiratory illness mortality	High
NO_2		Moderate
PM_{10}	Lung cancer mortality	High
$PM_{2.5}$		High

Pollutant	Outcome	Quality of evidence
PM_{10}	Circulatory disease mortality	Moderate
$PM_{2.5}$		High
PM_{10}	Ischemic heart disease mortality	Moderate
$PM_{2.5}$		High
PM_{10}	Stroke mortality	Low
$PM_{2.5}$		High

1.1.2.3 Hazardous air pollutants (HAPs)

A significant **knowledge gap** exists regarding the health impacts of chronic, low-level HAP exposure on communities living near airports. Unfortunately, to the best of our knowledge, there are no studies directly investigating the impact of low-level HAPs on the health of communities near airports. This lack of data creates a major hurdle in definitively linking HAP exposure to specific health problems within these communities. Unlike other airport-related stressors, where stronger causal relationships can be established the current limitations make it difficult to definitively prove cause and effect for HAPs. Nevertheless, we can use information from other sources (not specifically related to the airport) to perform a preliminary assessment of the risks of HAPs. For the 18 most concerning HAPs linked to airport activities, most existing knowledge comes from controlled animal studies and occupational studies (some come from general population epidemiology but not in the neighbourhood of airports). Animal studies provide a controlled environment to investigate the effects of HAP exposure on animal models. However, extrapolating these findings directly to human health effects requires caution. In addition, occupational studies examine the health of workers who are exposed to higher levels of stressors in their workplaces (exemplar study on occupational exposure of airport personnel to polycyclic aromatic hydrocarbons (Cavallo et al., 2006)). While valuable, these results may not translate perfectly to the lower exposure levels experienced by communities near airports. Notwithstanding these considerations, comparing HAPs exposure levels around airports with health-based reference values for chronic inhalation (*Table 5)* gives ***a first indication of the potential risk of HAPs for residents around airports.***

Table 5 highlights the potential health effects (and its corresponding health-based reference values) of the 18 most concerning HAPs linked to airport activities (see output WP2). The listed health effects are based on reviews by EPA, WHO and the Centres for Disease Control and Prevention, along with other reference documents used in the Flemish protocol for selecting health based reference values (De Brouwere et al., 2020)). When selecting and applying health-based reference values, one should consider both non-threshold effects (carcinogenicity) and threshold effects. For non-threshold effects, a health-based reference value is defined as the level corresponding to an excess risk of 1 per 10^{-6} (for lifelong continuous exposure). For substances causing both non-threshold effects (carcinogenicity) and threshold effects, both values should be considered (*Table 5)*.

Although the intrinsic hazard properties of HAPs arising from airport operations are of concern, the modelled exposure levels (at relevant places, in residential areas) are in general (far) below the health-based guidelines; leading to a **preliminary conclusion** that exposure to HAPs around Brussels airport is of less concern than exposure to UFP and noise around airports (except for benzene, see discussion in WP 2). This preliminary conclusion is based on modelled exposure levels in relation to health-based guidance values (see report WP2). Nevertheless, this is a **preliminary conclusion which needs to be further confirmed by** monitoring levels of HAPs around the airport (in addition to the preliminary conclusion based on modelled levels of HAPs).

Table 5: Health-based guidance values and critical effects for hazardous air pollutants most prevalent in airport operations (miscellaneous sources)[a].

HAP (CAS number)	Health guidance value (HGV)	Based on (critical effect)	Reference
Acetaldehyde (75-07-0)	160 µg/m³	*Non-cancer effects in the nervous and respiratory system*: degeneration of olfactory epithelium	(De Brouwere et al., 2020) for acetaldehyde based on ANSES 2014
Acrolein (107-02-8)	0.8 µg/m³	*Non-cancer effects in the respiratory system*: nasal lesions	(ANSES, 2013)
Benzene (71-43-2)	3 µg/m³	*Non-cancer effects in the immune system:* decreased lymphocyte count	Flemish HGV for benzene based on ANSES, 2014 (VITO, 2017a)
	0.038 µg/m³	*Cancer effects in the hematologic system:* leukaemia	
1-3-Butadiene (106-99-0)	2 µg/m³	*Non-cancer effects in the reproductive system:* ovarian atrophy	(IRIS EPA, 2002)
Crotonaldehyde (4170-30-3)	5 µg/m³	*Non-cancer effects in the hepatic system:* increased incidence of hepatocellular carcinomas and hepatic neoplastic nodules in rats	(EU LCI, 2022)
Ethylbenzene (100-41-4)	260 µg/m³	*Non-cancer effects in the developmental system and hepatic and urinary system*: developmental toxicity and liver and kidney toxicity, respectively	Flemish HGV for ethylbenzene (default analyse), based on (ATSDR, 2010)
Formaldehyde (50-00-0)	100 µg/m³ (based on non-cancer effects but protective for cancer effects)	*Non-cancer effects in the gastrointestinal and urinary system*: reduced weight gain, histopathology in rats	(De Brouwere et al., 2020) for formaldehyde based on WHO (2010)
Isopropyl benzene (98-82-8)	1 700 µg/m³	*Non-cancer effects in the endocrine and urinary system:* increased kidney weight in female rats and adrenal weights in male and female rats	(EU LCI, 2022)
Methanol (67-56-1)	2 000 µg/m³	*Non-cancer effects in the developmental and nervous system:* reduced brain weight in rat pups at 6 weeks of age	(IRIS EPA, 2013)
1-methyl naphthalene (90-12-0)	[§]14 µg/m³ (based on non-cancer effects)	*Non-cancer effects in the respiratory system:* pulmonary alveolar proteinosis	Read across from 2-mehtyl naphthalene
2-methyl naphthalene (91-57-6)	[§]14 µg/m³ (based on non-cancer effects)	*Non-cancer effects in the respiratory system:* pulmonary alveolar proteinosis	RfD from (IRIS EPA, 2003)

HAP (CAS number)	Health guidance value (HGV)	Based on (critical effect)	Reference
m-xylene and p-xylene (108-38-3 and 106-42-3)	217 µg/m^3	*Non-cancer effects in the nervous system:* impaired motor coordination (decreased rotarod performance)	Flemish HGV for xylene based on ATSDR, 2007, 2014 (VITO, 2017c)
Naphthalene (91-20-3)	3 µg/m^3 (based on non-cancer effects)	*Non-cancer effects in the respiratory system:* hyperplasia and metaplasia in respiratory and olfactory epithelium, respectively	(De Brouwere et al., 2020)for naphthalene based on US EPA (1998) 2014
o-xylene (95-47-6)	217 µg/m^3	*Non-cancer effects in the nervous system:* impaired motor coordination (decreased rotarod performance)	Flemish GAW for xylene based on ATSDR, 2007, 2014 (VITO, 2017c)
Phenol (108-95-2)	20 µg/m^3	*Non-cancer effects in the hematologic and hepatic system:* red blood cell and liver effects *Non-cancer effects in the nervous system:* CNS effects	(UBA, 2011)
Propionaldehyde (123-38-6)	8 µg/m^3	*Non-cancer effects in the nervous and respiratory system:* atrophy of olfactory epithelium	(IRIS EPA, 2008)
Styrene (100-42-5)	260 µg/m^3 (based on non-cancer effects but protective for cancer effects)	*Non-cancer effects in hematologic and hepatic system:* red blood cell and liver effects *Non-cancer effects in the nervous system:* CNS effects	Flemish HGB for styrene based on WHO (2000) (VITO, 2017b)
Toluene (108-88-3)	5 000 µg/m^3	*Non-cancer effects in the nervous system:* neurological effects in occupationally exposed workers *Non-cancer effects in the urinary system:* increased kidney weight	Flemish HGV for toluene based on US EPA IRIS (2005)

a: miscellaneous sources: if available, health-based values derived for Flanders using in-depth protocol GAW (for ambient air)) or derived using in-depth protocol for indoor air used; otherwise, default analysis or ad hoc selection of health-based value was used.

*, based on the 'lowest concentrations of interest' (LCI) concept (*Agreed EU-LCI Values (December 2022)*, n.d.)

§no inhalation RfC available. Value derived from oral RfD (0,005 mg/kg.day) via route-to-route extrapolation (70 kg bodyweight and 20 m^3 respiratory volume)

HGV: health guidance value

2 Research approaches and considerations

This section outlines the **tools and strategies** researchers use to investigate the connections between airport-related stressors and health outcomes. We will examine the various metrics used to quantify airport-related stressors, such as noise levels and UFP concentrations, and different methods to measure health outcomes (with a focus on health outcomes with moderate or low strength/quality of evidence). Further, we will discuss different approaches employed in past research and the strengths and weaknesses of different study designs. Moreover, novel approaches from recent research or highlighted by researchers during interviews will also be discussed as input for WP4. Lastly, we will discuss how research designs and methods can be adapted to fill the evidence gaps identified in the previous section. For example, we might explore methods to investigate the potential links between aircraft noise and neurodegenerative diseases (pioneering) or refine methodologies for studying the effect of aircraft noise on sleep (surveillance) or the combined effects of noise and UFP exposure on cardiovascular disease. By exploring these various research approaches and methods, we can (i) gain a deeper understanding of the potential health impacts of airport operations, (ii) identify areas for future research and (iii) recommend methods for surveillance (follow-up) specific for the Brussels Airport region.

2.1 Paired data on exposure and health outcomes

When conducting environmental health research or surveillance, understanding the link between exposure to environmental factors and the resulting health outcomes is paramount. Accordingly, it is crucial to collect paired data on exposure and health outcomes to link specific exposures with specific health effects in the same individual. Methods for exposure assessment and effect assessment are described in separate sections below.

2.1.1 Assessment of exposure to airport-related stressors

Understanding the health effects of airport-related stressors like aircraft noise and UFP requires **reliable methods to assess exposure**. However, variations in how researchers approach this assessment can lead to differences in the collected data and interpretation of the exposure-health results.

2.1.1.1 Choice of metric

The **choice of metric** is crucial when assessing exposure to airport-related stressors. This becomes evident when comparing chemical stressors like air pollutants and physical stressors like noise pollution. Assessment of **chemical stressors** presents a relatively straightforward approach. For air pollutants, the employed metric, usually expressed in the same unit (mass per volume of ambient air, i.e., micrograms per cubic meter, $\mu g/m^3$), depends on the study design reflecting short-term exposure (e.g., 24 hours or even shorter) or averaged over a longer time (yearly average). It is important to note that UFPs are very small and lightweight. Because of this, they barely contribute to the overall mass concentration of PM ($\mu g/m^3$). However, what UFPs lack in weight, they make up for in quantity. Accordingly, UFP dominates the total number of particles present in the air. That is why UFP concentrations are typically measured as **particle number concentrations** (i.e., the total number of particles per cubic centimetre) rather than mass concentrations. Currently, there is no universally accepted standard for the minimum size of particles measured as UFPs. While the WHO recommends a lower limit of 10 nm (WHO, 2021), studies often employ different cut-off points due to technical limitations. This inconsistency might impede the assessment of UFPs near airports where emissions contain a substantial number of smaller particles (<20 nm range).

Noise pollution requires a **different approach**. Noise from diverse sources is often presented in A-weighed decibels (dB(A)) using metrics like L_{den} (day-evening-night level) and L_{night} (night level (e.g., air traffic, road traffic, etc.). In addition, **aircraft noise** is characterized by a **sequence of short-lived** but **very high noise peaks** (i.e., bursts of intense noise) with **quiet periods** in between, whereas road traffic noise, especially on busy roads (major noise source around Brussels Airport), exhibits a quasi-continuous noise pattern without major peaks or valleys. Because of these fundamental differences in noise characteristics, simply adding dB(A) levels from various sources would not accurately represent the overall noise experience.

The A-weighting filter offers a standardized and consistent approach to filter out extremely low and high frequencies, to which human auditory perception is less sensitive. However, it might underestimate low-frequency sounds that penetrate buildings more easily and might disrupt sleep potentially leading to an underestimation of the true annoyance caused by aviation noise. On the other hand, C-weighting attempts to capture a wider frequency range including low-frequency noise in the environment. Important to note, changes in C-weighted readings do not necessarily reflect changes in low-frequency noise itself because C-weighing considers high frequencies as well. The A-weighting filter, while widely used as a standardized and consistent way to measure noise levels, has limitations in capturing the full spectrum of noise annoyance, particularly regarding low-frequency sounds. The C-filter might offer a more comprehensive approach but needs cautious interpretation. Ultimately, the choice of weighting filter depends on the specific context and the aspects of noise exposure being evaluated.

Noise metrics (calculated from raw noise time series) can be classified as (i) **cumulative/time-averaged metrics** which assess the total noise impact from multiple aircraft movements over a specific period (e.g., a day), (ii) **single-event metrics** which focus on the noise generated by a single aircraft passing and (iii) **hybrid metrics** that combine elements of both cumulative and single-event metrics, providing a more nuanced picture of noise exposure. An overview of these different metrics is provided in *Appendix I*.

The European Noise Directive (END) mandates **strategic noise mapping** using L_{den} to assess annoyance from noise exposure over 24 hours, considering a whole year, and L_{night} to assess sleep disturbance caused by noise exposure during nighttime hours (Directive 2002/49/EC). L_{den} and L_{night} are also the main indicators used in the WHO 2018 recommendations for the European region (WHO Regional Office for Europe, 2018). Using **standardized metrics** like L_{den} and L_{night} allows for **comparisons** between noise studies and effective evaluation of noise interventions. L_{den} combines the following L_{Aeq}-indicators[4]: L_{day} (daytime noise, typically 7:00 – 19:00, $L_{Aeq,7\text{-}19h}$ averaged over the whole year), $L_{evening}$ (evening noise, typically 19:00 – 23:00, $L_{Aeq,19\text{-}23h}$ averaged over the whole year) and L_{night} (nighttime noise, typically 23:00 – 7:00, $L_{Aeq,23\text{-}7h}$ averaged over the whole year) which are representative for the average sound levels for that part of the day, considering the whole year. A 5 dB(A) penalty is added for the evening period to reflect the increased annoyance during these hours. A 10 dB(A) penalty is added for the nighttime period to reflect the importance of sleep and the greater annoyance caused by noise at night. While these metrics are standardized and facilitate comparisons,

[4] $L_{Aeq,T}$ is the **A**-weighted **eq**uivalent continuous sound level given over a specific period (T). It considers fluctuating noise levels by considering both the intensity and duration of the sound.

they might not capture all aspects of noise impact. These metrics focus on **average sound pressure levels**, potentially missing the disruptive nature of individual noise events, like overflying aircraft. For a more accurate picture, scientists use more sophisticated methods that consider both **the intensity and pattern of noise from diverse sources**. *Appendix I* provides a background on the different noise indicators.

Aircraft noise can significantly impact communities living near airports. However, relating noise annoyance to objective metrics remains difficult as **human perception differs from sound level meters**. The penalties applied to evening and nighttime periods for L_{den} and L_{night}, respectively, attempt to address this gap, but the technical way noise is measured (i.e., L_{Aeq}-based metrics) is often **not easily understood and interpreted** by affected communities. The L_{Aeq}-based metrics **average** noise levels over extended periods, failing to capture the daily variations in flight patterns and the resulting noise experience for residents in real life. Moreover, the metrics treat all noise events equally, regardless of the number of flights or their intensity. This can result in misleading comparisons between communities and individuals. For instance, a community with infrequent loud flights might have the same L_{Aeq}-value as another community with many quieter flights. This discrepancy can lead to a sense of **distrust** and feeling that the data **does not reflect the reality** residents experience. Lastly, the forecast L_{Aeq}-values produced for airports do not give communities a clear picture of what to expect in terms of aircraft noise exposure and the potential impact of this on their quality of life.

A recent review by the Independent Commission of Civil Aviation Noise (ICCAN) highlights that the **most suitable noise metric depends on the specific health outcome being studied and the underlying mechanism** of how noise is thought to cause harm (Independent Commission on Civil Aviation Noise, 2020). If the focus lies on **cumulative chronic stress** caused by overall noise levels, **average sound pressure metrics** based on L_{Aeq}, like L_{den}, might be used. L_{den} considers noise levels throughout the day, with penalties for evening and nighttime noise, reflecting its greater disturbance potential. Accordingly, L_{den} is a primary indicator in assessing annoyance caused by aircraft noise. On the other hand, L_{night} focuses specifically on noise levels during nighttime hours, aiming to capture sleep disturbance. When the concern is focused on **short-term disruptions** like sleep or cognitive issues, studies might also utilize **event-related indicators** such as maximum sound level metrics (L_{Amax}[5]), the number-above metrics (e.g., NAT,65 – number of events exceeding 65 dB(A)) or measures of intermittency (Spilski, Bergström, et al., 2019).

Different studies emphasize that L_{Aeq}-indicators (including L_{night}) are inadequate for accurately representing the effects of nighttime aircraft noise on sleep. As discussed above, L_{Aeq} is an exposure indicator that focuses on average noise levels, neglecting the disruptive nature of individual noise events. To address this limitation, researchers have begun incorporating physiologically measured awakening using methods like polysomnography into their studies as effect indicators (Basner et al., 2006, 2019), and investigated which are suitable noise metrics associated with polysomnography outcomes. **Polysomnography** is a sleep monitoring technique that objectively measures brain activity, muscle activity, eye movements and breathing patterns during sleep. This approach provides valuable data on actual awakenings experienced by participants, both those they remember and those they do not. By utilizing physiological measures (i.e., the probability of awakenings), researchers gain a more health-focused perspective on sleep disruption compared to relying solely on acoustic energy

[5] L_{Amax} is the maximum A-weighed sound pressure level used to describe the peak noise level generated by an aircraft flyover event. It does not capture the total noise energy of an event as it only reflects a single point in time and does not consider the number of noise events.

indicators like L_{night}. The researchers suggest that two key aspects of aircraft noise contribute to sleep disturbance:

- **Frequency of noise events**: The number of aircraft noise events forms a major risk factor for awakenings. In these studies, the measured awakenings lasted briefly (15-45 sec) and were not always remembered by participants yet are related to long-term cardiovascular effects.
- **Intensity of individual noise events**: The peak noise level (L_{Amax}) and sound exposure level[6] (SEL) of each aircraft passage can be used to describe single noise events. These exposure metrics proved to be important in determining how long a person stays awake after being awakened and whether they remember the awakening later. A longer period of awake and the memory of being awakened can contribute to additional annoyance.

Researchers propose an innovative approach that combines exposure and effect metrics. A recent study combines physiological data on awakenings, i.e., **awakening indices**, as effect metrics with information about the specific noise events that caused them (i.e., exposure metrics) (Hauptvogel et al., 2021). This information can be represented in a dose-response curve, along with noise measurements at a specific location (i.e., acoustical immission at a given location in the vicinity of the airport). By combining these elements, researchers can create a more powerful tool for understanding and protecting communities around airports from the disruptive effects of aircraft noise.

In the above context that residents are more sensitive to specific features of aeroplane overflights (e.g., maximum noise level, the duration of the noise and the number of (loud) aircraft passages) rather than on the global noise immission, the SiRENE study introduced the **intermittency ratio** (IR) as a new exposure metric to quantify the **eventfulness** of noise, that is how much loud events stand out from the background noise levels. A high IR indicates loud events interrupting an otherwise quiet background, while a low IR suggests a higher baseline noise level. The study found that for L_{night} levels up to around 50 dB(A), participants living in environments with a low IR (i.e., higher background noise) reported significantly lower sleep disturbance (%HSD) than participants living in environments with a comparable L_{night} but a higher IR (Brink et al., 2019). In other words, these findings suggest that intermittent aviation noise, characterized by loud events interrupting a quiet background, may be more disruptive to sleep compared to consistent background noise at similar decibel levels. Additionally, the impact of aircraft noise appeared to vary based on the **degree of urbanization**. For a given L_{night} level, %HSD was highest in rural areas, lower in towns and suburbs and lowest in cities, indicating that people living in rural environments might be more sensitive to aircraft noise compared to those residing in urban areas (see also *Section 2.2.4 Exposure/effect modifiers)*.

A German study re-analysed data from 37 000 people living near 7 airports in Switzerland and Germany and investigated how well aircraft annoyance and sleep disturbance could be predicted based on different noise metrics and airport characteristics (Haubrich et al., 2020). Traditionally, aircraft noise annoyance is measured by the percentage of people highly annoyed (i.e., %HA). This study examined if using noise metrics that consider frequency (e.g., the logarithmic number of aircraft noise events above a certain threshold value: ‘number above threshold’, log(NAT)) and airport-specific characteristics (e.g., the number of night flights) could improve predictions of %HA and sleep disturbance (i.e., %HSD). The study showed that using these additional noise metrics in the model

[6] SEL is the sound exposure level and reflects the total sound energy of a single noise event accounting for both intensity and duration. It represents the sound level that would be experienced if all the sound energy of the event were compressed into one second.

improved the prediction of both %HA and %HSD. For %HA prediction, the model with $L_{Aeq,24h}$ and log(NAT_{24h},70) achieved the best fit, surpassing even the model using L_{den}. Also, regarding the prediction of HSD, the 2-predictor model with the best goodness of fit, the model with $L_{Aeq,22\text{-}6h}$ and log($NAT_{22\text{-}6h}$,80) proves to be statistically superior to the best 1-predictor model (with $L_{Aeq,22\text{-}6h}$ as the sole predictor). It can be summarized that for both HA and HSD, the addition of a frequency-related acoustic predictor with a higher maximum level threshold (log(NAT_{24h},70) for HA and log($NAT_{22\text{-}6h}$,80) for HSD) to the predictor L_{Aeq} improves the prediction quality. Among the airport characteristics, '**fleet mix'** had a particularly significant interaction with noise levels. It is a concept used to account for the distinct levels of various aircrafts operating in an airport. A higher fleet mix ratio is indicative of an airport with on average noisier aeroplanes. The study showed that for airports with fewer noisy aircraft (i.e., low fleet mix ratio), acoustic predictors (e.g., L_{Aeq}, L_{den}) had a stronger influence on %HA. This effect weakened at airports with more noisy aircraft (i.e., high fleet mix ratio). In other words, the **type of aeroplanes used at an airport plays a bigger role in annoyance when the overall noise level is lower,** implying that in airports with a moderate noise level, the effect on %HA and %HSD is likely to be underestimated when only relying on the standard noise metrics (e.g., L_{den}/L_{night}). In addition, the study showed that every additional night flight per year was linked to significant increases in the likelihood of sleep disturbances which highlights the disruptive effect of nighttime noise on sleep. Several other airport characteristics also influenced sleep disturbance. Airports undergoing major changes (e.g., construction) and a rising number of night flights were associated with higher sleep disturbance. As expected, the noise metric L_{den} performed better than other variations of L_{Aeq} for annoyance prediction. However, combining L_{den} with the number of noise events yielded the most accurate prediction. For sleep disturbance prediction, the best model combined noise levels during sleep hours (22-6h) with the number of noise events during these hours. **This study demonstrates that considering both the specific characteristics of an airport and the frequency of noise events significantly improves the prediction of aircraft noise annoyance and sleep disturbance**.

Beyond average noise levels, a holistic approach

In conclusion, while traditional L_{Aeq}-type metrics provide a general picture of noise exposure, they might miss crucial details about the character of aircraft noise that residents find disruptive. This includes the **frequency and intensity of individual noise events**. Frequency-based metrics like '**number above threshold**' (NAT) offer insights into the frequency of disruptive events exceeding a certain decibel level. However, this approach can be overly simplistic. Grouping events based on a single threshold discards valuable information. A loud event just below the threshold can be as disruptive as one slightly above it. Additionally, the chosen threshold itself can significantly influence the data. A high threshold might miss disruptive events altogether, while a low threshold could include irrelevant background noise. This skews the overall picture of noise exposure for a community. Moreover, supplementing L_{Aeq}-type metrics with metrics considering eventfulness, like '**intermittency ratio**' (IR), can be beneficial. This ratio considers the relative energy of individual noise events compared to the overall noise level and provides a more nuanced understanding of how disruptive individual flights are, even if they don't reach a specific threshold (Brink et al., 2019).

Ultimately, **effective communication** between communities and stakeholders requires clear and understandable noise metrics that accurately reflect the reality residents experience. Utilizing a **combination of metrics that capture both average noise levels and the disruptive nature of individual noise events** is crucial for a comprehensive assessment of aircraft noise impact, both given communication and surveillance and in setting up research studies investigating the impact on noise on health (e.g., potential research in the region of Brussels Airport).

2.1.1.2 Measured vs modelled

Two primary approaches to assessing noise and air pollution exposure are **direct measurement** and **modelling** (also see output WP2).

Measurement involves using specialized equipment to **collect real-world data** on noise or air pollution levels (e.g., sound level meters or UFP monitors, respectively) at specific locations near the airport. This approach provides a direct snapshot of the environmental conditions that residents experience. While direct measurement provides valuable ground-level data, it is not feasible to measure at every location within a community. This is where **modelling** comes in. Modelling utilizes computer simulations to **estimate** noise and air pollution levels across a broader area, offering a **large-scale view** of potential exposure patterns, including highly spatially resolution data (e.g., 100 x 100 m grids) which can never be reached by monitoring data; such highly spatially resolution data offer a powerful proxy for personal exposure at address level of individuals (instead of using data for monitoring devices further away from their residents). While convenient and cost-effective, modelling has limitations. Real-world factors like the intricate interaction of buildings with noise or the unpredictable nature of weather patterns can be challenging to fully capture in such simulations. It is remarked that monitoring and monitoring data are complementary (e.g., monitoring data are used for calibration or validation of models (see WP 2).

Another limitation to consider in stressor exposure assessment is the use of **address-based measures**. Residential exposure might not always accurately reflect an individual's actual exposure to noise and air pollution (i.e., **exposure misclassification**), particularly for daytime levels. People's **activity patterns** play a crucial role here. Residents may be exposed to stressors while away from home due to, for example, work commutes or spending time in other locations. In addition, the amount of time spent at home varies depending on, for example, work schedules. In this regard, nighttime exposure to aircraft noise (L_{night}) is less prone to exposure misclassification. As discussed above, sleep is crucial for health and most people spend more time indoors, often in their bedrooms, during nighttime hours. However, to accurately assess nighttime exposure, it is essential to distinguish between noise levels in the indoor versus outdoor environment, and within the indoor environment: differentiation between bedroom and noise levels in living rooms or other common areas. In addition, the degree of window and façade insulation, along with the location of rooms within a building relative to the noisy and quiet sides, can also contribute to exposure misclassification. Noise mapping typically focuses on noise levels at the most exposed façade when residents might spend significant time at shielded sides of their residence (see also *Section 2.2.4 Exposure/effect modifiers*). Currently, no models are capable to predict reliably indoor noise levels. Noise exposure is therefore mainly based on monitoring data (indoor or outdoor), or on modelled data (outdoor). Outdoor modelled exposure noise is therefore often pruned to misclassification when serving as a proxy for an individual's actual exposure (which happens mainly indoors).

To gain a more detailed understanding of **individual exposure**, researchers can employ personal noise dosimeters or air pollutant samplers. These wearable devices track an individual's exposure to noise and air pollution throughout their day. This approach reveals how exposure varies based on daily activities and location, providing **valuable insights** into individual overall experiences. A significant drawback of personal monitoring is the **cost and complexity** associated with dosimeters and samplers. These devices can be expensive to purchase and maintain, often limiting the number of participants in such studies, and often putting a burden on the participants (carrying a device). Additionally, interpreting the collected data can be complex, requiring specialized knowledge to accurately translate the readings into meaningful information.

In conclusion, a comprehensive understanding of airport-related stressor exposure in a community often requires a **combined approach**. **Direct measurement** data provides a crucial foundation, capturing **real-world conditions** at key locations. In addition, **modelling** complements this data by offering insights into **exposure patterns** across a wider area. Finally, considering factors like activity patterns helps refine the understanding of how residents are truly exposed to noise and air pollution from airport operations. By employing this holistic approach, one can gain a more complete picture of the potential health impacts on communities surrounding airports. Below we provide an overview on exposure assessment to aircraft noise and air pollution and a more detailed discussion is provided in the output of WP2.

2.1.1.2.1 Aircraft noise

Aircraft noise is assessed through a comprehensive approach, integrating both noise **monitoring** and noise **modelling** techniques.

Aircraft noise is usually **recorded** by specialized sound monitors that are strategically placed at key locations surrounding airports to record levels accurately. These monitors capture the dynamic variations in noise intensity, providing valuable data for assessing the volume and impact of aircraft noise on local communities. Following the recording phase, **noise metrics** are computed from the gathered data. These metrics serve as quantitative indicators of noise levels and help assess the extent of noise pollution in affected areas. Unlike other environmental parameters where a single universal metric might suffice, aircraft noise requires a nuanced approach. Different situations demand different noise metrics tailored to capture specific aspects of noise exposure accurately.

Noise modelling is a well-established and efficient method for estimating external noise levels across a geographical area. Most of the latest epidemiological studies investigating the health impact of noise exposure rely on source-propagation noise models to estimate noise levels at specific points, typically building facades or at a lattice of receptor points used to generate noise maps (Vienneau et al., 2019). While using the exact address of each participant's residence is considered as the gold standard, this approach is not always feasible. Some studies rely solely on participants' postal code as a proxy for residence location and estimate noise at the centre of such an area (Evrard et al., 2015; Franssen et al., 2004). Another approach involves using existing noise maps and assigning noise levels based on the grid cell where a participant's address falls (e.g., (Baudin et al., 2020; van Kempen et al., 2012). While this method offers more precise location data compared to area-level postal codes, it still lacks the granularity of using exact addresses. Both approaches have a risk of exposure misclassification, which may result in attenuated risk estimates (Vienneau et al., 2019).

A commonly used model for the creation of noise contour maps in the EU is the Integrated Noise Model. These **noise contour maps** depict areas exposed to different noise levels, providing valuable insights for airport authorities and regulators. Accordingly, the European Noise Directive mandates strategic noise mapping using metrics like L_{den} and L_{night} to assess noise annoyance and sleep disturbance, respectively. Moreover, the obtained contours could be used to select participants based on exposure categories. Flight patterns, aircraft types and local topography are all factored into the simulations. By considering these elements, models estimate how noise from aviation propagates and is experienced at ground level hence providing an estimation of the population potentially affected by various noise levels. While noise modelling offers a **valuable large-scale view**, it cannot replace the need for on-the-ground verification. This is where noise monitoring comes in. This data serves as a crucial **validation** tool, ensuring the modelled noise levels align with real-world conditions. While noise modelling primarily focuses on outdoor noise estimates, monitoring can provide location-specific data, including indoor noise levels. This is particularly important in social and health research.

For instance, studies investigating sleep-related or cognitive health outcomes require accurate data on noise experience inside participants' homes. Outdoor measurements alone might not be sufficient to capture this crucial information. Building materials, insulation as well as individual window opening habits significantly influence how much noise penetrates indoors (also see *Section 2.2.4 Exposure/effect modifiers*). Residents exposed to higher outdoor noise levels might take steps to mitigate indoor noise, such as installing double glazing or roof insulation. Therefore, some studies include indoor noise measurements (for example, (Clark et al., 2010; Nassur et al., 2019; Van Kempen, 2006)) to gain a more holistic picture of actual exposure experienced by participants. Moreover, focusing solely on outdoor measurements can be misleading. Individuals who are exposed to higher outdoor noise might install insulation and thereby experience a greater reduction in indoor noise compared to those with lower outdoor noise who do not install insulation. Important to note, measuring indoor noise to assess long-term exposure is not recommended. Indoor noise levels are typically lower than those outdoors, making them susceptible to interference from everyday activities and appliances within a home or building which can lead to inaccurate measurements that do not reflect actual exposure to aircraft noise over time.

By employing a combination of noise modelling, outdoor monitoring and, when necessary, indoor monitoring, researchers can gain a more comprehensive understanding of the noise burden on communities surrounding airports. This multi-layered approach not only provides valuable data for informing noise mitigation strategies but also strengthens the foundation for social and health research investigating the potential health impacts of aviation noise.

2.1.1.2.2 Air pollution

Understanding the health impact of airport-related air pollution necessitates a holistic approach to exposure assessment, particularly for UFP due to their unique characteristics. Similar to noise assessment, **direct measurement** using specialized equipment is crucial for capturing **real-world** air quality data near airports. However, for UFP, some specific considerations come into play. While conventional air quality monitors routinely measure standard air pollutants like NO_x, $PM_{2.5}$ and O_3, monitoring of ambient UFP levels requires specialized instruments. These measurements focus on measuring particle number concentration (particles per cubic centimeter) rather than the mass concentration (micrograms per cubic meter) because, despite their low mass, UFPs are plentiful. Strategically placed monitors near the airport can capture variations in UFP concentrations across the area. But factors like wind patterns and proximity to runways can significantly influence UFP dispersion as detailed in the UFP report[3] and above (see *Section 1.1.2.1*

Ultrafine particles (UFP)).

Air quality modelling complements direct measurement by providing insights into broader exposure patterns. It also provides highly spatially resolution data (e.g., 100 x 100 m grids) which can never be reached by monitoring alone. This data can offer a powerful proxy for personal exposure at the address level of individuals, rather than relying on data from monitoring devices further away from their residence.

Like noise pollution, understanding exposure goes beyond simply measuring air pollutant concentrations because of the influence of time-activity patterns or indoor levels (building materials and ventilation systems might influence indoor air pollutant concentrations). A combination of direct measurement, modelling and potentially even personal exposure monitoring (although very expensive) can provide the most robust assessment of UFP exposure in communities surrounding airports.

2.1.2 Measuring health outcomes

Understanding the health consequences of living near airports necessitates a **multifaceted approach** to measuring the health outcomes experienced by these populations. Airport operations generate stressors like aircraft noise and UFP, and researchers employ a variety of methods to assess the impact of these stressors on human health. The primary objective in environmental health studies is often to establish a clear connection between environmental exposure and health outcomes. To accurately determine this relationship, it is paramount to have detailed, individual-specific data that ties particular exposures directly to health effects (i.e., **paired data**). Understanding the health impacts of airport-related stressors on nearby communities requires careful consideration of **study design**. In general, four types of environmental epidemiology studies can be used, namely longitudinal studies, case-control, cross-sectional or ecological studies. As summarized in Table 6Table 6, each approach offers unique advantages and disadvantages, and researchers must weigh these factors to select the most appropriate method for investigating a specific health outcome. **Longitudinal studies** are ideal for establishing causality but require considerable time and resources. Common types of longitudinal studies include (i) cohort studies which follow a specific group of people (i.e., cohort) who share a common characteristic or exposure (e.g., born in the same year, exposed to a particular substance) over time to observe the development of outcomes or events, (ii) panel studies are similar to cohort studies as the same individuals or units (e.g., households) are repeatedly observed but the group is not necessarily defined by a shared characteristic, (iii) trend studies observe a population as a whole at different points in time, rather than following specific individuals and (iv) repeated cross-sectional studies where data is collected from different non-overlapping groups (different samples) representing the population at different points in time. Most of the studies considered in this work package have a cross-sectional design. Unlike longitudinal studies that track individuals over time, **cross-sectional studies** provide a snapshot at a specific point but cannot definitively demonstrate exposure-response relationships. Unlike cross-sectional studies that provide a broad picture at a single point, **case-control studies** delve deeper, focusing on identifying factors that might have caused a specific outcome. Case-control studies offer an efficient approach for rare outcomes, but like cross-sectional studies, they cannot definitively establish exposure-response functions. Unlike the above studies that focus on individuals, **ecological studies** provide population-level insights based on aggregated health indicators and averaged exposures. Ultimately, the best design depends on the specific health outcome under investigation and the research objectives.

Table 6: Study design strengths and weaknesses.

Study design	Strengths	Weaknesses	GRADE starting level	Exemplar studies	Indicative population size range
Longitudinal (e.g., cohort and panel studies)	+ Strongest evidence for causality + Tracks changes in modifying factors and outcomes (e.g., cortisol levels) over time	- Time-consuming (years) - Large sample sizes needed to detect subtle effects - Expensive	High	(Bozigar et al., 2024; Clark et al., 2013), (N. Janssen et al., 2022)	Registry data: 111 000 – 1 400 000 Clinical measurements: 140 – 1 250 Postal surveys: >70 000 Questionnaires interview: 700 – 1 250
Cross-sectional	+ Rapid and cost-effective + Suitable for short-term outcomes (e.g., sleep disturbance or cognitive effects)	- Lacks causality evidence (snapshot in time)	Low	(Baudin et al., 2021; Floud et al., 2013)	Registry data: 35 000 – 550 000 Clinical measurements: 90 – 5 000 Postal surveys: 2 800 – 12 000 Questionnaires interview: 1 200 – 6 000
Case-control	+ Efficient for rare health outcomes	- Susceptible to selection and recall bias - Not ideal for generic health outcomes	High	(Seidler et al., 2016)	Registry data: 19 000 – 140 000 cases vs 350 000 – 850 000 controls Clinical measurements: 75 cases vs 75 controls
Ecological	+ Cost-effective + Avoids selection bias (no individual participant recruitment) + High population coverage	- Descriptive only, no individual-level data	Very low	(Evrard et al., 2015; Hansell et al., 2013)	Registry data: 12 000 – 1 900 000

In general, to assess health outcomes in **environmental epidemiology studies,** three types of data are often used:

- **Health registry data:** Prevalence or incidence data for generic or specific health outcomes (e.g., hospital admissions or chronic disease rates) based on health registers from populations living near airports provide valuable information. For instance, researchers might access data from administrative health databases (i.e., registries) to investigate the prevalence of certain conditions in communities around airports (also see output WP3).
- **Human biomonitoring:** Some health outcomes also require data collection during the study itself, as these factors might not be routinely tracked elsewhere. Effect monitoring in study participants includes measuring **biomarkers**, which could be (i) indicators of exposure or (ii) (early effect) biological indicators of a health condition. Biomarkers of exposure could include urinary S-phenyl mercapturic acid or black carbon load for benzene and black carbon exposure, respectively. To the best of our knowledge, there are currently no biomarkers of exposure available for noise or UFP exposure. Some biomarkers can be collected through minimally invasive means like saliva samples for cortisol analysis, a stress hormone, or through blood draws for C-reactive protein measurement, an indicator of inflammation. Changes in these markers can provide insight into the body's response to environmental stressors and potential early signs of health problems (i.e., intermediate mechanisms), this can also be complemented with sleep monitors. Moreover, clinical measurements, such as blood pressure measurements, electrocardiography (ECG), polysomnography and spirometry, could serve as complementary tools in human biomonitoring studies as they provide additional insights into potential health effects associated with environmental exposures. For example, high blood pressure can be ascertained through three methods: (i) participant-reported diagnosis from surveys, (ii) reported use of medication to manage the condition (registry-based) or (iii) direct measurement during the study. These measurements can be taken by study staff using blood pressure cuffs or with self-administered equipment. This allows researchers to not only identify individuals with diagnosed hypertension but also capture those who might be managing the condition with medication without a formal diagnosis. It is important to note that diagnoses can also be measured without directly involving participants.
- **Surveys:** Some health outcomes are more subjective and necessitate input from the participants themselves. These outcomes often relate to aspects of daily life that might not be reflected in medical records. Many measures of quality of life, well-being or annoyance rely primarily on **self-reported data**. Fortunately, the field benefits from the existence of validated questionnaires that ensure consistency and reliability across studies (e.g., General Health Questionnaire, Pittsburgh Sleep Quality Index). Compared to physiological measures (e.g., polysomnography to assess sleep quality), questionnaires are generally **cheaper and easier** to implement in large studies but may not reflect actual physiological disturbances as measured by objective methods.

Which type of data to use, depends on the study design and research question. By combining these different methods in various study designs, researchers can build a more comprehensive picture of the potential health consequences of living near airports. For example, sleep quality is a research area where self-reported measures (i.e., psychological assessment of sleep) could be collected via questionnaires. These questionnaires can address sleep during the previous night or over a longer period. Compared to physiological measures (e.g., polysomnography), questionnaires are generally cheaper and easier to implement in large studies. Despite their advantages, it is important to acknowledge that self-reported sleep quality through questionnaires may not always perfectly reflect actual physiological sleep disturbances measured by objective tools like polysomnography. Polysomnography records brain waves, the oxygen level in blood, heart rate, breathing and eye and leg movements during sleep. The use of polysomnography is considered to be the most accurate methodology for obtaining objective physiological data that can allow for changes in sleep stages and awakenings to be observed. However, polysomnography is expensive and time-consuming and it is an invasive method that requires the attachment of multiple sensors which might be considered uncomfortable and potentially influence sleep patterns and hence the observation. The use of actimetry has previously been used in sleep studies as a proxy for sleep-wake activity (also see *Section 2.1.3 Combined exposure and health measurements*). Actimetry or actigraphy is a non-invasive method of monitoring human rest-activity cycles. A small actigraph unit or actimetry sensor is a small wristwatch-like device. Although it is not as accurate as polysomnography because it measures rest-activity patterns rather than brain activity, this method is less expensive and allows for a larger sample size of data to be collected. People's perceptions of their sleep quality can be influenced by numerous factors, such as stress, anxiety, or expectations. Therefore, researchers often recommend using a combination of physiological and psychological measures to gain a more comprehensive understanding of sleep quality in exposed populations.

By employing a diverse set of methods, researchers can gain a more complete picture of the health consequences associated with airport-related stressors. Combining diagnoses, self-reported experiences, objective measures and standardized tools allows for robust and comparable data collection, ultimately strengthening our understanding of how environmental factors like aircraft noise and UFPs influence human health.

The increasing use of harmonized and standardized methods across studies is a positive development. This trend not only facilitates comparisons but also opens the door for meta-analyses, which can provide stronger evidence for the health impacts of airport-related stressors.

2.1.3 Combined exposure and health measurements

Within the ‘Programma Innovatieve Overheidsopdrachten (PIO)’ of the Flemish Government, the Department of Environment financed a pilot project to develop a methodology to measure nightly noise exposure and its impact on sleep disturbance. The project was performed by UGent and PIH and the scientific report is available online (Dekoninck et al., 2023). The main focus of the protocol was the user-friendliness and the use of non-invasive but accurate technology. It included simultaneous indoor and outdoor noise monitoring to discriminate between indoor and outdoor noise (events) known to affect sleep quality. To detect potential arousals and awakenings, actimetry and heart rate were monitored on-body. At the start of a monitoring period, the subject completed a general questionnaire. After each monitored night (one week of data collection), a short questionnaire on sleep quality was completed to monitor sleep and noise perception.

The protocol was validated in two waves, including in total 17 adolescents (12–17-year-old), selected from the general population without specific noise burden. For 7 nights, they installed an indoor noise sensor near the bed, connected to a wireless outdoor noise sensor that was attached to the bedroom window. On the noise monitor, indicators were calculated in a resolution of 10 seconds and 15 minutes. These indicators are transmitted to a central data platform. The physical impact of noise on human sleep was assessed by ECG and accelerometry with the Bittium Faros. This 2-channel device was easy to install, collected a full ECG, provided motion data though the accelerometer and measured heart rate variability. These medical data are stored locally at the Bittium Faros and exported by the nurse after the retrieval of the sensor hardware. The questionnaire data included validated questions on annoyance (SLO, Schriftelijk Leefomgevingsonderzoek), questions on sleep quality (Pittsburg Sleep Quality Index) and daily questions on sleep disturbance and nightly noise.

An extensive set of noise indicators and physical indicators is calculated for further analysis. A preliminary analysis on the 9 participants in the second wave showed that devices deliver high quality noise data and biometry data. Noise indicators included standardized calculations (L_{Aeq}) at 10-second and 15-minute intervals. The main purpose of simultaneous noise monitoring indoors and outdoors is to be able to relate and isolate outdoor noise events to indoor disturbances. Spectral content is available and will allow detailed evaluation of source type, matching the deployment of the measurement hardware. The biological impact of environmental noise during sleep is visible in the ECG data and this is evaluated through the heart rate variability parameters. The biological response occurs 30 to 90 seconds after the noise event. A biological response to environmental noise can be expressed as a cardiac arousal (reaction without movement) or a combined cardiac and motility arousal (the subject starts moving and might awaken at full). Within the pilot study, we showed that a faster and stronger response can be detected through the heart rate variability (HRV) parameter LF/HF ratio (low frequency/high frequency) compared to the heart rate only response. This parameter is sensitive to both cardiac arousals and motility arousals. This indicator relates to the activation of the autonomous nervous system, a component of the biological stress axis. It therefore also has the potential to relate to the biochemical stress responses. The findings extend to the current practices which focus mainly on motility arousals and subjective sleep responses only.

Within the pilot study, the young and healthy subjects were exposed to rather low noise exposure, since no prior selection to higher noise exposure was included. The approach through the activation of the autonomic nervous system proved valid in these low exposure conditions. In an elderly population, we expect lower HRV responses due to impaired health, with environmental noise as a component of the long-term deterioration of the cardiovascular health. In studies with higher noise burden and impaired subjects, it is expected that – due to the proven sensitivity in low exposure - the technical setup, the proposed post-processing and analysis will enable advanced detection of the biological responses to environmental noise with high accuracy.

In conclusion, a measuring set was developed to monitor nightly indoor and outdoor noise simultaneously with sleep quality and arousals. This method was validated in randomly selected adolescents with low noise exposure. Its utmost purpose is to use this protocol in areas with elevated noise burden (e.g., around airports) and by doing so, collect state-of-the-art data to assess the impact of elevated nightly noise exposure on human health.

2.2 Considerations when designing studies

Understanding the health effects of airport-related stressors requires careful study design. Below is a breakdown of key points to consider.

2.2.1 Population and study area

Studies on airport health impacts typically include populations across all age categories. To maximise exposure contrast, studies often employ stratified sampling. This process involves dividing the population around the airport into subgroups (strata) based on **exposure levels**. One common way to define strata for airport health research is by using **noise contours**. Noise contours are maps that depict areas exposed to various levels of aircraft noise, typically measured in L_{den}. For instance, a study might define strata based on 5 dB(A) categories of L_{den}: <50, 50-54, 55-59 and ≥60 dB(A). By creating strata based on exposure levels, researchers ensure they include participants who are exposed to a range of stressor levels (high and low). This **exposure contrast** strengthens the study's ability to detect associations between airport-related stressors and health outcomes.

While noise contours are a helpful tool, other factors can also influence health. In this regard, studies often consider additional variables called covariates when selecting participants within each stratum. These covariates might include, among others, age, gender and socioeconomic status. By selecting participants within each exposure stratum while ensuring a good distribution of important covariates, researchers create groups that are more comparable except for their level of exposure. This helps to isolate the effects of airport-related stressors (such as aircraft noise and UFP) on health outcomes and reduces the influence of confounding variables.

2.2.2 The interaction between noise and air pollution effects and the issue of possible mutual confounding

Understanding the health impacts of noise and air pollution separately is a complex task, and it becomes even more intricate when we consider their combined effects. People are exposed to both throughout the day, not just separately or in specific locations. For example, aircraft noise at home, air pollution exposure during commute and road traffic noise exposure during leisure activities all contribute to an individual's overall exposure.

For aviation, noise exposure comes from various sources, namely the engines, the aircraft frame and ground operations like take-off and landing. Air pollution from aviation, on the other hand, primarily stems from the engines themselves. A crucial aspect of **disentangling the health effects of different stressors** (e.g., noise and air pollution) is understanding the **correlation** between these exposures. Strong correlations make it difficult to isolate the impact of each factor. Conversely, weak or inconsistent correlations might allow for geographical separation of the exposures, facilitating the study of their individual health effects. The correlations between noise and air pollution vary enormously between studies but are generally found to be moderate (S. A. Stansfeld, 2015). Such correlations may not only be influenced by factors related to pollutant measurement, but they may also reflect the differing dispersion patterns of different stressors. For example, noise is influenced by intervening buildings and geographical features, while air pollution is also dependent on weather conditions like wind speed and direction. Furthermore, air pollution and noise exposure often show collinearity with other health risk factors like socioeconomic status, stress and adverse lifestyle factors. **Co-pollutant models** can be used to assess the independent and combined various airport-related stressors on health outcomes. Regression analysis is commonly used in co-pollutant models as it considers all the exposure data simultaneously to estimate the association between each pollutant and the health outcome while accounting for the potential influence of other pollutants.

Numerous studies reveal independent associations between aircraft noise and air pollution with cardiovascular health. Some studies found the effects of aircraft noise on self-reported myocardial infarction (Floud et al., 2013) and cardiovascular disease hospital admissions (Correia et al., 2013; Hansell et al., 2013). Importantly, these associations remain after accounting for air pollution levels of PM_{10} (Hansell et al., 2013), NO_2 (Floud et al., 2013) and $PM_{2.5}$ and ozone (Correia et al., 2013). In addition, no significant confounding effect of air pollution ($PM_{2.5}$ and/or NO_2) on the link between aircraft noise and hypertension was found in several studies (Evrard et al., 2015; Nguyen et al., 2023). Still, the bigger picture of how noise and air pollution interact to influence cardiovascular health remains unclear. Likewise, the RANCH project explored the combined impact of noise and air pollution on children's cognitive development. While some studies within this project found connections between aircraft noise and cognitive functions like reading comprehension, memory and attention in 9–11-year-old children (Clark et al., 2012), the impact of air pollution was less clear. One study showed the effects of NO_2 on memory span length (van Kempen et al., 2012) while the other (Clark et al., 2012) shows no effects of air pollution on reading comprehension, memory and attention. This suggests potential differences in how noise and air pollution affect the developing brain (S. Stansfeld & Clark, 2015). Interestingly, even though both exposures might contribute to cognitive issues, their pathways could be distinct. In this regard, a recent experimental study in mice also suggests that studying the health effects separately might underestimate the true risk since noise and air pollution have apparent **additive health effects** on the cardiovascular system and brain (Kuntic et al., 2023). Noise primarily affects the body through psychological stress, possibly leading to high blood pressure and a heightened response from the nervous and hormonal systems. PM exposure via inhalation on the other hand primarily damages the lungs through inflammation and oxidative stress, which can potentially spread to other organs through the bloodstream. When combined, aircraft noise and air pollution (urban particulate matter) appear to cause additional damage which could significantly increase the risk and severity of common chronic diseases (e.g., diabetes, ischemic heart disease and neurodegeneration). This concerning interaction found in experimental research is further confirmed by a human study, suggesting this combined effect might be a real threat to public health. An initial study around Los Angeles International Airport found that exposure to aircraft-related UFP independently increased the risk of preterm birth after accounting for aircraft noise exposure (Wing et al., 2020). However, the researchers acknowledged that airports also attract heavy traffic, potentially impacting nearby communities with additional air pollution. In a follow-up study, they specifically investigated the role of airport-related noise and its interaction with road traffic-related air pollution on preterm birth risk (Wing et al., 2022). While all women in the study area were exposed to elevated levels of UFP from aircraft (due to proximity to the airport), the researchers found that the strongest associations between airport-related noise and preterm birth occurred in mothers who were also exposed to elevated levels of traffic-related air pollution. This suggests a synergistic effect – the combined impact of aircraft noise and traffic-related air pollution is greater than the sum of their individual effects. In other words, in this study, they found that exposure to both stressors together significantly increases the risk of preterm birth compared to exposure to either one alone. This research highlights the **importance of considering the combined effects of environmental stressors**, particularly around airports. While aircraft UFPs pose a clear risk, their presence does not negate the additional threat posed by traffic-related air pollution. Future studies and public health initiatives need to account for this potential synergy to effectively protect the health of communities living near airports.

Besides different stressors (e.g., noise and UFP) from a similar source (airport), the same stressor could also originate from various sources. A recent study examined how people perceive annoyance from combined transportation noise sources (i.e., road traffic, aviation and railway noise) (Marquis-Favre et al., 2021). Interestingly, they found that the overall annoyance was not significantly higher than the annoyance caused by the single strongest noise source. This aligns with previous research on combined transportation noise where **aircraft noise was judged to be the most annoying** (Wothge et al., 2017). In other words, the most dominant noise source seems to be the main driver of annoyance, even when other noise sources are present. This finding supports the 'strongest component model' for predicting total annoyance from combined noise sources (further discussed in *Section 2.2.6 Assessment of annoyance due to multiple sources*).

2.2.3 Identification of vulnerable groups concerning the effects of airport-related stressors on health

The risk of an adverse health outcome is not equal among everyone exposed to the same level of the same pollutant. Each person has a unique mix of other exposures and individual characteristics, including stage of life or underlying health conditions, which shape their own risk or susceptibility. While most research on airport operations focuses on the average population's experience, only a few studies have focused on so-called **vulnerable groups**, who are considered more susceptible to adverse effects of airport-related stressors and a higher-than-expected risk for developing particular diseases (Habre et al., 2018; S. Stansfeld & Clark, 2015; Van Kamp & Davies, 2013; Wing et al., 2020). Environmental health inequalities may arise not only because of exposure differentials. The health impacts of noise also depend on individual susceptibility and the ability to recover from such impacts. Vulnerability to the health effects of airport operations is a complex interplay of several factors including physical and mental health, life stage, lifestyle and habits, socioeconomic status and environmental characteristics. By acknowledging the existence of vulnerable groups and the complex interplay of vulnerability factors, researchers, policymakers and airport authorities can design more targeted solutions by developing effective noise mitigation strategies, improving air quality measures and engaging nearby communities.

2.2.3.1 Physical and mental health

Existing health conditions, both physical and mental, can influence how individuals cope with noise exposure and air pollution. Respiratory problems, for instance, can be exacerbated by air pollution. In this regard, short-term exposure to UFP related to air traffic was linked to exacerbation of existing airway complaints in children (N. A. H. Janssen et al., 2019) and increased systemic inflammation in adults with asthma (Habre et al., 2018). Additionally, a recent study indicates an increased risk for recurrence in patients diagnosed with acute coronary syndrome exposed to aircraft noise (Olbrich et al., 2023). Furthermore, people with **noise sensitivity** are more likely to experience negative health effects from noise exposure such as sleep disturbance, headaches and stress.

2.2.3.2 Life stage

Age plays a significant role. Children, pregnant women and the elderly are often considered vulnerable due to the developmental stage or changing physiology. While not necessarily more prone to annoyance from noise, **children** might be more susceptible to long-term cognitive and cardiovascular health problems due to both noise exposure and air pollution. Their developing bodies and lack of coping mechanisms make them vulnerable to the cumulative effects of these environmental stressors. For example, children have smaller airways and breathe two to three times faster than adults, making them more susceptible to respiratory issues potentially exacerbated by air pollution as specifically shown for UFPs in a study in schoolchildren around Schiphol airport (N. A. H. Janssen et al., 2019). Moreover, childhood is a critical period of cognitive development, characterized by rapid brain maturation and the acquisition of essential cognitive skills, including language processing, reading and comprehension. Disruptions to cognitive development during this sensitive period may have lasting consequences for academic achievement, social functioning and future career prospects. Another aspect to consider, children's activities are often concentrated in local areas including their homes, nearby playgrounds, schools and backyards. These locations might be closer to flight paths or airport operations compared to workplaces frequented by adults. **Adolescence**, particularly puberty, is another crucial life stage characterized by rapid physical, hormonal and psychological changes. Similar to children, adolescent's brains are still undergoing significant development. This ongoing neurodevelopment makes them potentially more susceptible to the disruptive effects of chronic noise exposure on sleep patterns, cognitive function and emotional regulation. **Older adults** may be at increased risk for cancer-related health effects because they have had a longer time to accumulate DNA damage. Additionally, they might have pre-existing health conditions like cardiovascular or neurodegenerative diseases, which can be further aggravated by noise and air pollution. In addition, older people typically spend more time at home or have lived in a property exposed to noise or air pollution for many years. Lastly, **pregnant women and newborns** are also considered a particularly vulnerable group given the developing systems of foetuses and newborns and the long-term health consequences associated with adverse birth outcomes.

2.2.3.3 Lifestyle and habits

Factors like sleep patterns, work schedules (shift workers) and overall lifestyle choices can influence noise sensitivity and exposure to air pollution. For example, people who spend more time outdoors might have higher exposure to air pollution while shift workers may be at an increased risk of experiencing negative impacts from exposure to environmental noise because their sleep structure is already under stress. Shift workers may also need to sleep during the day when environmental noise levels are higher.

2.2.3.4 Socioeconomic status

Lower socioeconomic status (SES) might limit access to, among others, quality housing (including acoustic insulation and/or air purifiers) or green spaces increasing vulnerability to both noise and air pollution (Dreger et al., 2019). Moreover, lower-income communities may be disproportionately located near airports due to lower housing costs. Research shows that both individual SES and the average SES of their neighbourhood independently affect health (Diez Roux & Mair, 2010). In this regard, people of higher SES living in lower-SES neighbourhoods have more resources at their disposal, allowing them to mitigate the health hazards associated with their environment (Science for Environment Policy, 2016). For example, they might be able to invest in better insulation for their homes to reduce noise pollution from traffic or airports.

2.2.3.5 Environmental characteristics

The surrounding environment, including existing noise levels, green spaces and prevailing wind patterns, can significantly influence the overall impact of both noise and air pollution from airport operations.

2.2.4 Exposure/effect modifiers

From a statistical point of view, all exposure-modifying factors and other potential effect modifiers can be treated as interaction terms in the statistical analyses or stratified analyses. Examples of exposure/effect modifying factors are discussed below:

Behavioural and dwelling characteristics

- <u>Room orientation, window opening habits and ventilation</u>: People living in rooms facing away from the airport or who habitually keep windows closed are likely exposed to less noise. Statistically, these factors can be treated as interaction terms in the analysis, revealing whether they influence the strength of the association between exposure and health outcomes. For instance, the negative health effects of noise might be weaker in subgroups with limited airport-facing windows or closed windows. Additionally, individuals who keep their windows closed more frequently could be a particularly interesting group to examine in sensitivity analyses, exploring how their unique exposure patterns might influence the overall findings. For example, a study on the link between aircraft noise exposure and hypertension near French airports collected information on house characteristics (e.g., window opening, insulation of roof and/or windows) yet this was not included in the final models as it did not impact the effect estimate (Evrard et al., 2017). Ventilation practices (natural or mechanical) can also be considered as potential modifiers, particularly for air pollution exposure.

- Building characteristics and insulation levels: The materials used in construction can significantly impact noise transmission. Buildings with heavier, denser materials (e.g., brick or concrete) offer better insulation compared to lightweight structures (e.g., wood). Moreover, air gaps and leaks around windows, doors and ventilation systems can acts as pathways for noise entry. In addition, the type of window acting as a barrier between residents and aircraft noise might form a crucial aspect in understanding how noise exposure translates to health effects. The impact of window type (i.e., single glazing, double or triple glazing) on noise reduction could be assessed by including for example window type as a factor in the statistical analysis. For example, a prospective patient cohort study showed that aircraft noise exposure deteriorates the long-term outcome after acute coronary syndrome (Olbrich et al., 2023). Here, they found a stronger effect for patients without noise-proof windows in their homes. Another factor that could significantly impact noise reduction is wall and roof insulation. The type and thickness of insulation can significantly impact noise reduction. Insulation materials with fibrous or porous structures absorb sound waves, while denser materials dampen vibrations, reducing noise transmission. Thicker insulation layers generally offer greater sound attenuation.
- Noise reduction habits: The use of earplugs during sleep is another factor that can modify the impact of noise exposure. Researchers should assess this habit through questionnaires and consider it in the analysis.

Environmental factors

- Building height, floor level and local topography: The height of surrounding buildings, the floor level of an apartment and local topographical features can influence both noise exposure and air pollution dispersion. Statistically, these factors can be incorporated as covariates in the analysis, potentially revealing distance-related gradients in health effects. For example, stronger effects on lower floors or closer to the airport, with air pollution potentially more concentrated in valleys or specific wind patterns.

Exposure duration

- Length of exposure (years of residence): Studies suggest that the duration of exposure to both noise and air pollution can modify their health impact. Statistically, this can be explored by stratifying the analysis, meaning they divide the study population into subgroups based on years of residence. The DEBATS studies exemplify this approach. Here, they limited some analyses to participants who had lived at their current address for at least five years and had not moved recently (e.g., (Baudin et al., 2021; Lefèvre et al., 2017). This strategy helps to control for potential influences of residential history on the observed relationship between aircraft noise exposure and health. For instance, it allows us to assess whether habituation to noise might play a role in health outcomes.

Socioeconomic status

- Type of housing and socioeconomic status**:** The type of housing (e.g., apartment, detached house) and socioeconomic status might be indirectly related to exposure levels and vulnerability. While not directly measured exposure modifiers, they can be considered potential effect modifiers, statistically exploring whether they influence the observed relationships between environmental exposures and health outcomes. For instance, lower socioeconomic communities might have less access to green spaces or higher-quality windows, potentially increasing their vulnerability to environmental exposures.

One crucial aspect in evaluating aircraft noise is recognising the distinction between the objective sound generated by aircraft (i.e., exposure metric) and the subjective experience of annoyance it may cause to individuals within the community (i.e., effect metric). Therefore, while objective measurements provide essential data, understanding the subjective perception of noise is equally vital for developing effective mitigation strategies and fostering community engagement. In contrast to the subjective nature of annoyance, sound pressure level serves as an objective measure of acoustic pressure. This physical parameter quantifies the intensity of sound waves and can be objectively measured using sound monitors. By providing an accurate representation of sound intensity, sound pressure level offers valuable insights into the acoustic environment and forms the basis for objective assessments of noise exposure. In summary, aircraft noise monitoring involves a comprehensive approach that integrates objective measurements with subjective perceptions to assess its impact on local communities accurately. By leveraging advanced monitoring technologies and understanding the complexities of noise perception, stakeholders can work towards minimizing the adverse effects of aircraft noise and promoting a healthier and more harmonious living environment.

As discussed previously, the SiRENE study introduced urbanization and the intermittency ratio (IR) (see above *Section 2.1.1.1 Choice of metric*), a metric that captures how much individual aircraft noise events stand out from the background noise, as possible effect modifiers for the relation between aircraft noise and sleep disturbance (Brink et al., 2019). This study found that for similar L_{night} levels, participants living in environments with a low IR (constantly noisy background) reported significantly lower sleep disturbance. This suggests that **consistent background noise might be less disruptive than intermittent loud events** (i.e., peaks). The impact of aircraft noise also varied based on the degree of **urbanization**. For a given L_{night} level, sleep disturbance was highest in rural areas, lower in towns and suburbs and lowest in cities. This suggests residents in quieter rural areas might be more sensitive to the disruptive nature of intermittent aircraft noise compared to those living in urban areas with more constant ambient noise. The observed effect modifications by intermittency and urbanization seem to be interrelated which could be explained by **noise insulation** or **habituation**. Noise levels were estimated at the exterior façade of participants' homes. Individuals residing in areas with lower IR (i.e., high baseline noise) or higher urbanization (potentially experiencing more ambient noise) might be more likely to invest in soundproofing measures for their homes. This improved insulation could mitigate the disruptive effects of intermittent aircraft noise on sleep. Moreover, the constant presence of background noise in urban environments or areas with low IR may lead to a degree of habituation. This habituation could make individual noise events less noticeable, reducing their impact on sleep compared to rural areas with quieter backgrounds. The NORAH study proposed to use **imperviousness** (i.e., the level of sealed spaces, such as buildings, in a given area) instead of the degree of urbanization to study possible effects of environmental exposures on children's well-being and health (Spilski, Rumberg, et al., 2019). Impervious space offers a more precise measure of a residential environment's quality for children's well-being compared to broad urbanization categories (i.e., rural, suburban and urban). While urbanization often implies high population density, it does not necessarily capture the availability of green spaces (for recreation) and other factors (e.g., bioclimate, sunlight exposure, etc.). Like the above study, in areas with less impervious space (i.e., more natural and open areas), exposure to aircraft noise might be a dominant stressor due to the quieter background.

Researchers could assess a possible exposure/effect modifier, for example use of earplugs during sleep, through questionnaires and consider it in the analysis. This could be done through various statistical approaches. Individuals who habitually use earplugs could be excluded from the analysis to isolate the effect of noise on those who do not use them. Moreover, earplug use could be included as an interaction term to see if it modifies the relationship between measured noise exposure and health outcomes. For instance, the negative effects of noise on sleep might be significantly weaker for those who use earplugs regularly. Lastly, the study population could also be divided into subgroups based on earplug use (users vs. non-users- and health outcomes compared within each group. This stratified analysis could reveal if earplugs truly mitigate the negative health effects of noise exposure.

Challenges in effect modification studies include **power limitations** and **separation** of the effects. Many studies are not specifically designed to investigate effect modification which can lead to a lack of statistical power, meaning studies might not be able to detect if these factors even truly modify the impact of exposures. In addition, a key challenge lies in disentangling the independent health effects of noise and air pollution as they often co-occur (see above). Statistical techniques like mediation analysis can be employed to attempt to separate these effects. It should be noted that random errors in measuring factors like noise sensitivity and annoyance can weaken the observed effect modification. For example, someone who is generally noise-sensitive might answer a questionnaire about noise annoyance slightly differently on days due to factors unrelated to noise exposure (e.g., feeling tired, or stressed).

It is crucial to recognise that the impact of these factors (confounding and effect modification) can be influenced by several aspects of the study design itself:

- **Study type**: Whether it is a cross-sectional survey, a longitudinal cohort or an intervention trial can affect how these factors influence the results;
- **Outcome measurement**: Self-reported health outcomes can be subjective, while objective clinical measures like blood pressure offer a more precise assessment;
- **Timing of assessment**: The order in which noise and air pollution exposure and health outcomes are measured can influence the observed relationships. Ideally, exposures should be assessed before or during the measurement of the health outcome to establish a temporal sequence. Moreover, considering the influence of seasonal factors on exposure levels, it is important to acknowledge the potential impact of study timing on the results.

A nuanced approach, considering not just established confounders but also individual susceptibility, psychological aspects and work and lifestyle factors, will lead to a more comprehensive understanding of the impact of environmental exposures on health. Furthermore, exploring interactions with airport-related stressors and health effects is paramount to identifying susceptible subgroups and setting priorities for prevention.

2.2.5 Sensitivity analyses

Sensitivity analyses help to assess how robust the study findings are and whether slight changes in the analysis methods or study population might alter the results. For example, an analysis can be restricted to participants who participated in all follow-up visits. This helps to ensure consistency in exposure assessment and reduces potential bias introduced by missing data. In addition, one could opt to only analyse data from participants who had lived in their dwellings for more than five years and did not move during the follow-up period. This allows us to investigate the hypothesis that prolonged exposure to an environmental stressor might lead to a greater risk of specific health problems. By limiting the study to long-term residents, researchers can explore habituation. For example, when Nassur et al. (2017) restricted their analysis to participants who lived at their address for at least five years, the association between noise exposure and feeling tired in the morning became non-significant, while the association with short sleep duration remained significant. These findings suggest that people might be habituated to some aspects of noise over time.

2.2.6 Assessment of annoyance due to multiple sources

A recent study investigates how people perceive annoyance from multiple transportation noise sources like road, rail and aeroplane traffic (Marquis-Favre et al., 2021). Previously, researchers proposed various models to predict total annoyance from combined noise sources, but these models were rarely assessed using real-world data. This study aimed to address this gap by (i) analysing annoyance data collected from urban residents exposed to two or three transportation noise sources and (ii) evaluating ten existing total annoyance models. The study found that models based on individual noise source annoyance (i.e., perceptual models) performed better than models based on a single noise level index (i.e., psychosocial models). This suggests people's annoyance is more intricately linked to how they perceive each noise source, rather than just a combined decibel level. While the strongest noise source significantly influenced the overall annoyance (i.e., dominant source effect), the study also revealed the importance of interactions between noise sources. The 'strongest component model' worked well for predicting average annoyance ratings while perceptual models with interaction terms (like mixed models) provided a more comprehensive explanation by accounting for how each noise source and their interactions contribute to annoyance. Furthermore, a perceptual linear regression model showed promise for situations with more than two noise sources, as it considers the contribution of each source. By highlighting the importance of perception and interaction effects, this study offers valuable insights for future research on combined noise sources and how they influence annoyance.

2.2.7 Noise annoyance as a mediator and noise sensitivity as a moderator

Recent DEBATS studies (Baudin et al., 2021; Kodji et al., 2023) investigated noise annoyance as a mediator and noise sensitivity as a moderator in the association between noise and self-reported health using Baron and Kenny's recommendations (Baron & Kenny, 1986). A mediator variable (M) (e.g., aircraft noise annoyance) serves to clarify the nature of the relationship between the independent variable (X) (e.g., aircraft noise levels) and the dependent variable (Y) (e.g., self-reported health). In other words, mediating relationships occur when a third variable plays a key role in governing the relationship between the other two variables. The results from three regression models are compared to assess a possible mediator:

- Model 1: Evaluate the association between mediator (M) and independent variable (X) to establish if X has a significant effect on M;
- Model 2: Evaluate the association between the dependent variable (Y) on the independent variable (X) to assess the total effect of X on Y;
- Model 3: Evaluate the association between the dependent variable (Y) on both the independent variable (X) and the mediator (M) to help determine if the effect of X on Y is partially or fully explained by M.

To conclude mediation, two key criteria should be met:

- Significant effect in Model 1: X (e.g., aircraft noise levels) must have a statistically significant effect on M (e.g., aircraft noise annoyance);
- Reduced or eliminated effect in Model 3: the effect of X (e.g., aircraft noise levels) on Y (e.g., self-reported health) in Model 3 (*direct effect*) should be weaker (ideally, non-significant) compared to Model 2 (total effect). This suggests that M (e.g., aircraft noise annoyance) is part or all of the original relationship between X and Y.

A moderating variable changes the strength or direction of an effect between two variables X and Y. A moderation analysis explains how the interaction between the independent variable X (e.g., aircraft noise levels) and the moderator variable (W) (e.g., noise sensitivity) influences the dependent variable Y (e.g., self-reported health). Interaction terms are included in the regression model. Typically, the model includes the main effects of X and W, along with their interaction term (X*W). A significant interaction term (X*W) indicates that the effect of X on Y depends on the level of W. Researchers then need to explore how the relationship between X and Y changes at different values of W.

It is important to ensure a sufficient sample size to reliably detect mediation or moderation effects as also highlighted by Baudin et al. (2021) who stated that the detection of the moderating role of annoyance would require approximately four times as many participants as compared to the model without the interaction (Baudin et al., 2021).

2.2.8 Dose-response relationships

Regression analysis is a statistical analysis technique used to estimate the connection between one or more predictors (i.e., airport-related stressors like UFP or aviation noise) and various health outcomes (e.g., respiratory illness rates or sleep disturbance). Regression analysis goes beyond simply identifying an association. It provides a measure of the strength of the relationship, allowing researchers to establish dose-response curves. Moreover, it can control for different acoustical and non-acoustical variables to isolate the specific effect of airport-related exposure on health outcomes. Linear regression is used for continuous health outcomes, for instance, to assess how changes in UFP levels from the airport relate to changes in blood pressure measurements. When the health outcome is binary (e.g., presence or absence of health outcome), logistic regression is used to estimate the odds of someone experiencing a negative health outcome (e.g., severe annoyance) based on their level of exposure to airport-related stressors.

The dose-response relationship between airport-related stressors and health effects is often assumed to be linear: with an increase in exposure, the effect also increases. However, a dose-response curve can also have another form in which there is, for example, at higher exposure levels a flattening or decrease in health effects seen (non-linear relationships). Possible non-linear effects can also be modelled by adding a so-called 'natural cubic spline' function to a regression model. A 'spline' consists of several concentrated, usually third-degree polynomials. The more nodes, the more flexible the estimation of the curve. RIVM presented findings on dose-response relationships for aircraft noise annoyance and sleep disturbance in the Netherlands using this method (van Poll et al., 2023).

2.2.9 Sample size and power calculations

A crucial element of robust research design is ensuring an adequate sample size. Accordingly, sample size calculations, along with power analysis, play a key role in determining the strength and reliability of the findings of a study. Larger sample sizes allow for more precise estimations of the true effects of airport stressors on health outcomes. Smaller samples can lead to wider confidential intervals, making it difficult to determine if observed associations are statistically significant. Moreover, adequate sample sizes are more likely to represent the entire community around the airport (under the condition of recruitment strategy).

Sample size directly impacts the study's statistical power which refers to the probability of detecting a true association between exposure and health effects, if one exists. Low power increases the risk of missing a real effect (i.e., type II error). Sample size calculations are influenced by (i) the anticipated magnitude of the health effect being investigated (larger expected effects require smaller sample sizes to be detected with sufficient power), (ii) the desired level of significance (alpha) which is typically

0.05, (iii) the study design and (iv) anticipated variation in the data (higher degree of variability in the exposure levels and health outcomes necessitates larger sample size). Power analysis, often conducted alongside sample size calculations, helps researchers determine the minimum sample size needed to achieve a desired level of power which is typically 80% or higher. This ensures a high probability of detecting a true relationship between airport stressors and health if it exists.

In practice, it is unusual that authors report explicitly what their studies were powered to detect, but it can be particularly important where a study reports multiple outcomes. An example is the study by Rojek et al. (2019) on indicators of cardiac health, which reported over 40 combinations of outcome and population stratum (Rojek et al., 2019). The authors reported that the study was powered to detect a difference in pulse wave velocity (PWV), and reported indicators related to asymptomatic heart damage alongside PWV. Among those indicators of asymptomatic heart damage, some had significant associations with the noise level, and some did not. It is possible that the study lacked the power to detect meaningful differences in some or all of those indicators. A study may in practice be powered for secondary outcomes, but it is good practice to specify a primary outcome and calculate the necessary sample size concerning that outcome.

The smaller the absolute effect you wish to detect, the greater power is needed: to detect a difference of 30% vs 33% prevalence of an indicator requires more power than to detect a difference of 30% vs 40% prevalence. Likewise, smaller relative effects require greater power: to detect a difference of 3 percentage points between 30% and 33% requires greater power than to detect a difference of 3 percentage points between 10% and 13%. Power is related to sample size, and to get more precise estimates or detect smaller effects, larger sample sizes are needed. Several statistical software packages and online calculators are available to facilitate sample size and power calculations for various study designs (e.g., G*Power).

2.2.10 Bias

Even the most well-designed studies can be susceptible to **bias**, possibly leading to inaccurate or misleading conclusions. For example, even after accounting for some factors that might influence both the exposure and the health outcome (e.g., age, income), there might be other unmeasured variables that confound the relationship between airport-related stressors and health which can lead to misleading results resulting in **uncontrolled or residual confounding**. In addition, **recall bias** occurs when participants inaccurately recall past events or exposures. In airport health research, people might overestimate or underestimate their noise exposure or past health problems. For example, people who are currently experiencing sleep problems might be more likely to recall past sleep disturbances even if they were not as severe which could lead to an overestimation of the association between noise and sleep problems. Moreover, **selection bias** can occur when the study population does not accurately reflect the entire target population of interest. In airport health studies, this might happen if people who are more (or less) bothered by airport-related operations, such as aviation noise, are more likely to participate. This can skew the results and make it difficult to generalize the findings to the whole community around the airport. By comparing the characteristics of participants with the characteristics of the non-responding inhabitants in the affected zone, researchers can assess if there were major differences in age or socioeconomic status (i.e., non-responder analysis). Finding no major discrepancies suggests a potentially representative sample among those who responded. Another strategy to mitigate selection bias could be to blind participants to the study's purpose. Keeping the specific aim of the study hidden from participant until later in the questionnaire can reduce the chance of altering their responses based on their own biases or expectations. This strategy proves particularly important when investigating noise annoyance, as participants might be more likely to report annoyance if they know that it is the focus of the study. However, blinding study purpose can conflict with creating trust and participation (note: in Flemish environmental health research conducted by VITO, PIH and Sciensano, the technique of blinding has never been used).

3 Input for Work Package 4

Airports play a vital role in our globalized world, but their operations can come at a cost to the health of nearby communities. As explored in Chapter 1, exposure to aircraft noise and air pollution, including UFP, has been linked to a range of health problems. Next, Chapter 2 provides an overview of research approaches and strategies for investigating the link between these airport-related stressors and health outcomes. Both chapters provide valuable input to explore opportunities for future research in the region of Brussels Airport as will be detailed further in WP4.

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Appendix I – Aircraft noise health effects

1 Evidence-based health indicators for aircraft noise exposure

The strongest base of evidence regarding exposure-response relationships between noise and health has been published by the World Health Organization (WHO) Regional Office for Europe in the form of a guidance document Environmental noise guidelines for the European region (WHO Regional Office for Europe, 2018). The WHO guidelines are based on systematic reviews of studies with an observational study design published between 2000 and August 2015. This and reviews by the UK Department for Environment, Food and Rural Affairs (DEFRA) were updated (specifically aircraft noise exposure) by the Aviation Noise Impact Management through novel Approaches (ANIMA) consortium with studies up to August 2018 (Benz et al., 2022) and by a rapid evidence assessment of the Independent Commission on Civil Aviation Noise (ICCAN) of the UK Government including studies published from March 2019 to April 2020 (Grollman et al., 2020). In *Appendix I*, we consider the quality of evidence relating aircraft noise to given health outcomes provided by these reviews. For some outcomes, there was evidence from one of the updates and the WHO reviews. For these outcomes, ICCAN took the conclusion of the WHO and/or Defra reviews as the starting level for the quality of evidence, applied the GRADE process to the additional evidence from the updated review and decided whether to revise the GRADE rating (i.e., ICCAN synthesis). The Defra-RIVM review (van Kamp et al., 2020) did not conduct GRADE assessments but they included the conclusions of that review regarding the direction of effect.

For the development of the environmental noise guidelines by the WHO, a selection of health outcomes was identified as either **critical** or **important** for developing recommendations on the health impacts of environmental noise (*Appendix I Table 1*). Cardiovascular disease, annoyance, effects on sleep, cognitive impairment and hearing impairment and tinnitus were rated as critical health outcomes. Adverse birth outcomes, quality of living, metabolic outcomes and well-being and subjected (self-rated) health were rated as important outcomes. The outcome measures given in bold were prioritized in terms of their representativeness, validity, impact of disease and disability weights (DWs)[1] associated with the health outcome measure. These priority outcome measures were used to derive the guideline exposure levels. For cardiovascular disease, the **incidence of ischemic heart disease** (including angina pectoris and/or myocardial infarction) and **hypertension** were prioritized. Except for self-reports, these are objective measures for cardiovascular disease which affect a large proportion of the population, have important health consequences and can lead to more severe diseases and/or mortality. For effects on sleep, the **percentage of the population highly sleep-disturbed** (%HSD) is defined as the most meaningful, policy-relevant measure of this health outcome. Self-reported sleep disturbances are a very common problem in the general population: they affect the quality of life directly and may also lead to subsequent health impediments. Effects on sleep may also be in the causal pathway to cardiovascular disease. This measure is not a proxy for physiological sleep quality parameters, but it is an important outcome in its own right. The **percentage of the**

[1] DWs are ratings that vary between 0 and 1, in which 0 indicates no disability and 1 indicates the maximum amount of disability. The rates are derived from large population surveys in which people are asked to rank a specific disease for its impact on several abilities. The DWs have been proven useful in calculating the burden of disease.

population highly annoyed (%HA) forms the most objective measure of annoyance. Large proportions of the population are affected by noise annoyance, even at relatively low exposure levels. Annoyance may be in the causal pathway to cardiovascular disease. **Reading and oral comprehension** were acknowledged as the most meaningful outcome measures as they can affect vulnerable individuals, namely children, and have a significant impact later in life. **Permanent hearing impairment** is another health outcome that can affect children and have a significant impact later in life.

Appendix I Table 1: Health outcomes prioritized by the WHO as "critical" or "important" health outcomes for the establishment of the environment noise guidelines.

Health outcome	Health outcome measure
Critical health outcomes	
Cardiovascular disease (L_{den})	Self-reported or measured prevalence, **incidence**, hospital admission or mortality due to: - **Ischemic heart disease** (DW = 0.405) - **Hypertension** (DW = 0.117) - Stroke
Effects on sleep (L_{night})	- **Percentage of the population highly sleep-disturbed (%HSD)**, self-reported, assessed with a standardized scale (DW = 0.07) - Polysomnography measured outcomes (probability of additional awakenings) - Cardiac and blood pressure outcome measures during sleep - Motility-measured sleep outcomes in adults - Sleep disturbance in children
Annoyance (L_{den})	- **Percentage of the population highly annoyed (%HA)**, assessed with standardized scale (DW = 0.02) - Percentage annoyed, preferably assessed with a standardized scale
Cognitive impairment (L_{den})	- **Reading and oral comprehension, assessed with tests** (DW = 0.006) - Impairment assessed with standardized tests - Short- and long-term memory deficit - Attention deficit - Executive function deficit (working memory capacity)
Hearing impairment and tinnitus (L_{Aeq})	- **Permanent hearing impairment**, measured by audiometry (DW (for mild severity level (threshold at 25 dB) for childhood onset) = 0.015)
Important health outcomes	
Adverse birth outcomes (L_{den})	- Preterm delivery - Low birth weight - Congenital anomalies
Quality of life, well-being and mental health (L_{den})	- Self-reported health and quality of life - Medication intake for depression and anxiety - Self-reported depression, anxiety and psychological distress - Interviewer-assessed depressive and anxiety disorders - Emotional and conduct disorders in children - Children's hyperactivity - Other mental health outcomes
Metabolic outcomes (L_{den})	Prevalence, incidence, hospital admission or mortality due to: - Type 2 diabetes - Obesity

1.1 Cardiovascular and metabolic outcomes

Noise is an important **risk factor** for **chronic diseases**. Noise exposure activates **stress reactions** in the body, possibly leading to increases in blood pressure, a changing heart rate and a release of stress hormones. In addition, the cardiovascular and metabolic effects related to noise exposure may also be a consequence of a reduction in **sleep quality**, caused by noise exposure during the night, among other additional or interrelated mechanisms. These chronic effects can lead to premature mortality.

Appendix I Table 2 summarizes the quality of evidence for the cardiovascular and metabolic effects of aircraft noise exposure.

Appendix I Table 2: Summary of quality of evidence for cardiovascular and metabolic outcomes, from (Grollman et al., 2020).

Outcome	Quality of evidence – *direction of effect*			
	WHO review (2018)	Defra-RIVM review (2020)	ICCAN review (2020)	ICCAN synthesis (2020)
Arterial stiffness			Low quality – *harmful effect*	
Blood pressure			Very low quality – *no effect*	
Blood pressure in children	Very low quality – *no effect*			
Cortisol levels			Very low quality – *harmful effect*	
Diabetes incidence	Low quality – *no effect*	No GRADE - *harmful effect*	Low quality – *harmful effect*	Low quality – *harmful effect*
Diabetes prevalence	Very low quality – *no effect*			
Heart rate			Very low quality – *harmful effect*	
Hypertension incidence	Low quality – *no effect*	No GRADE – *harmful effect*		Low quality – *harmful effect*
Hypertension prevalence	Low quality – *no effect*			
Incidence of central obesity		No GRADE – *harmful effect*		
Ischemic heart disease incidence	Very low quality – *harmful effect*	No GRADE – *harmful effect*	Low quality – *harmful effect*	Low quality – *harmful effect*
Ischemic heart disease mortality	Low quality – *no effect*			
Ischemic heart disease prevalence	Very low quality – *no effect*			
Asymptomatic heart damage			Very low quality – *harmful effect*	
Obesity (change in BMI)	Low quality – *no effect*			
Obesity (change in waist circumference)	Moderate quality – *harmful effect*			
Obesity (incidence of overweight)		No GRADE – *harmful effect*		
Obesity (weight gain)		No GRADE – *harmful effect*		

Outcome	Quality of evidence – *direction of effect*			
	WHO review (2018)	Defra-RIVM review (2020)	ICCAN review (2020)	ICCAN synthesis (2020)
Self-reported diagnosis of arrythmia			Very low quality – *no effect*	
Self-reported diagnosis of diabetes			Very low quality – *no effect*	
Self-reported diagnosis of heart disease			Very low quality – *no effect*	
Self-reported diagnosis of hypertension			Very low quality – *no effect*	
Stroke incidence	Very low quality – *harmful effect*		Moderate quality – *harmful effect*	Moderate quality – *harmful effect*
Stroke mortality	Moderate quality – *no effect*	No GRADE – *harmful effect*		Moderate quality – *no effect*
Stroke prevalence	Very low quality – *no effect*			

1.1.1 Cardiovascular outcomes

The main cardiovascular health effects discussed in the WHO environmental noise guidelines were **hypertension**, **ischemic heart disease** and **stroke** (Kempen et al., 2018). New studies show that aircraft noise exposure may increase the risk of hypertension, especially during the **nighttime**. Researchers highlight that the evidence concerning aircraft noise and heart disease needs cautious interpretation and further research. The studies investigated either the prevalence or the incidence of diseases associated with aircraft noise exposure. **Prevalence** describes the occurrence of a disease in a higher aviation noise-exposed population relative to the occurrence of the disease in a less exposed population. The aviation noise-induced **incidence** of a disease, however, refers to the occurrence of new cases of this disease in a highly exposed population compared to new cases in an unexposed or less exposed population.

Hypertension is an important medical condition, which is also a significant **risk factor** for other cardiovascular diseases and is the leading cause of cardiovascular mortality. The association between noise exposure and hypertension has been explained by the physiological **stress response** that may be triggered by noise exposure, resulting in activation of the sympathetic and neuroendocrine systems, which in turn leads to increased levels of stress hormones, which is itself associated with higher heart rate and blood pressure (also see *Figure 2*, *main text*). The initial WHO review (Kempen et al., 2018) concluded that there was *low quality evidence* supporting an *association* between aircraft noise and the *incidence of hypertension* mostly due to a high risk of bias, in large part attributable to selection bias or determination of hypertension status through self-reporting only. The Defra-RIVM (van Kamp et al., 2020) and ANIMA review (Benz et al., 2022) added evidence from two cohort studies showing a harmful effect of aviation noise, with evident importance of exposure during the night (Saucy et al., 2021; Schmidt et al., 2021), and one case-control study showing no effect (Zeeb et al., 2017). The ICCAN update concludes that given the finding of an effect in those two cohort studies, **the *evidence may point toward a harmful effect* and that given the inconsistency, the quality of the evidence remains *low*.** A recent review also confirmed this strength and quality of evidence (Sivakumaran, Ritonja, Waseem, AlShenaibar, et al., 2022b). Studies with additional methodological improvements (e.g., longitudinal design) would be needed to further reduce inconsistencies and improve the quality. Two recent cohort studies further strengthen the link between aircraft noise exposure and hypertension incidence (C. S. Kim et al., 2022; Kourieh et al., 2022) whereas no association with aircraft noise and hypertension (stable across several sensitivity analyses) was observed among post-menopausal women (Nguyen et al., 2023). The latter study did observe elevated risk among certain subpopulations such as those who lived in areas with fewer other sources of ambient noise.

From the reviewed studies, the WHO observed that the increased risk for **ischemic heart disease** (IHD, also known as coronary artery disease) was statistically associated with increased exposure to aviation noise. It was observed that aircraft noise was associated with the prevalence, incidence and mortality caused by IHD. However, only the association with the *incidence of IHD* was found to be small but statistically significant. The review authors conclude that the evidence of this finding is considered *very low* (most studies were of ecological or cross-sectional design). In addition, the ANIMA update states that *the relationship between aircraft noise exposure and risk of myocardial infarction or mortality from IHD needs cautious interpretation and that further research is required on this theme*. The heart diseases are all in all **multi-factorial** determined and the impact of aircraft noise is relatively small. However, it becomes relevant given that in a population even health effects of small size sum up to a considerable number of people suffering from severe health problems. The Defra-RIVM review concluded there was a small harmful effect but did not assess the quality of evidence. The meta-analysis by (Vienneau et al., 2019) also concluded there was evidence of a non-significant harmful effect. Given the increased size of the evidence base and consistency of the results, on the one hand, but also the high risk of bias in contributing studies on the other hand, ICCAN concluded that there is ***low quality evidence of a small harmful effect of aircraft noise on the incidence of IHD*.** A recent pooled study of nine Scandinavian cohorts indicated an association between aircraft noise and ischemic heart disease, particularly when angina pectoris cases were excluded, but without a clear exposure-response relation (Pyko et al., 2023).

Aircraft noise exposure was identified to be associated with an increase in both the prevalence and incidence of **stroke**. None of these associations observed in ecological and cross-sectional studies were statistically significant. Moreover, no association between air traffic noise and mortality due to stroke were defined in the initial WHO review (Kempen et al., 2018). The review authors rated the related quality of evidence *very low*. The lack of statistical significance could be related to the small number of people who are exposed to the highest levels of aviation noise. The ANIMA review (Benz et al., 2022) included four publications on cerebrovascular disease including different types of stroke. Overall, they found no conclusive evidence concerning an association between aircraft noise exposure and stroke as also confirmed by an RIVM scoping review of new evidence (van Kamp et al., 2020). A meta-analysis on aircraft noise and the risk of stroke found a small (1.3%), marginally significant increased risk of stroke per 10 dB increase in aircraft noise exposure (pooled RR=1.013, 95% CI 0.998 to 1.028) (Weihofen et al., 2019). ICCAN performed a GRADE assessment on this meta-analysis and concluded that there is ***moderate quality evidence* of a *small harmful effect* of aircraft noise on the *incidence of stroke*** (Grollman et al., 2020). For stroke mortality, they consider the findings of the WHO to stand and conclude there is *moderate quality evidence* of <u>*no effect*</u> *on stroke mortality*. A recent pooled study of nine Scandinavian cohorts reported that only moderate exposure to aircraft noise was positively associated with stroke incidence (40-50 dB(A) vs. little or no exposure) and that there was no evidence of an increased risk among those with high exposure (Roswall et al., 2021).

Recently, a study compared residents of Krakow, Poland in areas exposed to high and low aircraft noise and investigated a range of cardiovascular outcomes, namely blood pressure, arterial stiffness and a range of echocardiographic indicators selected for association with asymptomatic organ damage

(Rojek et al., 2019). ICCAN performed a GRADE assessment on this study and concluded that there is *low quality evidence* of a *harmful effect* of aircraft noise on *arterial stiffness.* Given mixed results within the study, they concluded *very low quality evidence* of the *harmful effect* of aircraft noise on *asymptomatic heart damage*. In addition, the natural relationship between pulse wave velocity (PWV) and age, previously skewed by aircraft noise exposure, was restored (Wojciechowska et al., 2022).

Several studies assessed the effect of aircraft noise on *heart rate.* Due to conflicting results within and across studies and differences in population, the evidence for a *harmful effect* was of *very low quality.* A recent review confirmed the strength and quality of evidence of this finding (Sivakumaran, Ritonja, Waseem, AlShenaibar, et al., 2022b). The ICCAN concluded *very low quality* for the *harmful effect* of aircraft noise on *cortisol levels* as it was based on only one cross-sectional study with mixed results (Baudin et al., 2019). A recent review confirmed that air traffic noise exposure may have *little to no effect* on cortisol levels and the quality of evidence is *very low* (Sivakumaran, Ritonja, Waseem, AlShenaiber, et al., 2022).

Recent studies (mainly in experimental animals) have investigated the potential link between aircraft noise exposure and **endothelial function** (Bayo Jimenez et al., 2023; Kvandová et al., 2023; Münzel et al., 2023). This is important because the endothelium forms a thin lining inside our blood vessels and heart that plays a crucial role in vascular health. Endothelial cells release substances that control blood flow and pressure and prevent blood clots. When the endothelium malfunctions (i.e., endothelial dysfunction), it cannot function properly, potentially leading to diseases like stroke and heart attacks. Conditions like hypertension, diabetes and smoking can contribute to this dysfunction. Endothelial dysfunction is often an early sign of atherosclerosis, a chronic condition where the artery walls thicken and stiffen, reducing blood flow and increasing the risk of heart attack and stroke.

Even though cardiovascular risk estimates for aircraft noise are found to be much lower than the ones found for known individual lifestyle risk factors for the development of cardiovascular diseases, individual lifestyle risk factors can be influenced by individual behaviour, and therefore, are not comparable. Also, protection from health consequences of traffic noise exposure is a governmental and management task and an individual does not have a direct influence over it.

As there are still uncertainties in scientific evidence, the precautionary principle is recommended. Decisions can be made based on the best available data and future studies should also focus on vulnerable groups, effect modifiers, sensitive hours of the day, coping mechanisms, differences between noise sources, possible confounding with air pollution and differences between objective (noise level) and subjective (noise perception) exposure.

Though the evidence supporting the association between aircraft noise exposure and cardiovascular health outcomes is substantial, there is still **heterogeneity** among studies in estimating the effect size. There are many reasons for heterogeneity among epidemiological studies due to different study designs, differences in exposure of observed populations and differences in exposure, confounder and outcome assessment. Especially unfavourable for the evaluation of the evidence of noise effects exposure is the use of different noise metrics, as the quantification of the noise exposure requires a common unit. The question, regarding which noise indicator is the most relevant in describing the relationship between aircraft noise exposure and health effects, is a recurring theme.

Aircraft noise exposure may increase the risk of cardiovascular diseases, although the evidence available may currently be contested. Subjective and objective factors may influence individual responses to aviation noise. It is through further research that a better understanding of the relationship between noise exposure and cardiovascular disease risk and mortality may be revealed.

New studies add information on the importance of nighttime exposure to noise, and the number and the level of individual noise events, therefore they should be considered in more detail.

1.1.2 Metabolic outcomes

Besides cardiovascular disease, diabetes also has a great public health significance as it is one of the largest public health challenges today. Potential mechanisms behind the effect of noise on diabetes include reduced insulin levels and sensitivity due to increased levels of cortisol and disturbance of sleep, as well as changed levels of appetite-regulating hormones due to sleep disturbance.

For the incidence of **diabetes**, the WHO review (Kempen et al., 2018) concluded there was *low quality evidence* of *no effect of aviation noise*. The Defra-RIVM review (van Kamp et al., 2020) did not assess the quality of evidence but reported there was *inconsistent evidence* between high quality studies, with two cohort studies respectively indicating a harmful effect and no effect. Vienneau et al. (2019) conducted a meta-analysis that included the studies from the WHO and Defra-RIVM reviews and concluded there was evidence of a harmful effect (a fairly large effect too, with a pooled RR=1.20, but a wide 95% CI of 0.88 to 1.63) but that this was not statistically significant (Vienneau et al., 2019). ICCAN performed their GRADE assessment on the meta-analysis, considering that it was the most thorough treatment of the evidence available. As the contributing studies had high-quality designs (being all cohorts or case-control studies) the evidence started at high quality but was downgraded for inconsistency and lack of precision. They conclude that there is *low quality evidence* of a *harmful effect* of aircraft noise on the *incidence of diabetes* (Grollman et al., 2020). A recent study in Switzerland on the effects of long-term transportation noise on mortality and diabetes type 2 only found evidence for a significant association with railway and road traffic noise but not aircraft noise (Vienneau et al., 2022).

The initial WHO review (Kempen et al., 2018) suggested a possible link to **obesity**. In recent years, three studies investigated this connection further. Two studies on obesity/overweight yielded mixed results but due to inconsistencies across the studies and a lack of precision in the results, the overall quality of evidence is considered to be *low*. A very recent study in two nationwide cohorts of female nurses in the United Stated, showed an association between higher aircraft noise exposure and higher body mass index (BMI; used as proxy for obesity), adding evidence to the aviation noise-obesity-disease pathway (Bozigar et al., 2024).

The potential impact of aircraft noise on metabolic health, particularly diabetes type 2, is a growing area of research. However, current evidence is still inconclusive. Therefore, no firm conclusions can be drawn from the current evidence. More research is needed on the topic of metabolic diseases.

1.2 Sleep-related outcomes

Sleep serves to facilitate vital functions in our body. Noise fragments sleep, reduces sleep continuity and reduces the total amount of sleep time, which can have impacts on alertness, performance at work and quality of life. Sleep restriction causes, among other things, changes in glucose metabolism and appetite regulation, impaired memory consolidation and dysfunction in blood vessels. Long-term sleep disturbance can lead to cardiovascular health issues.

Appendix I Table 3 summarizes the quality of evidence of sleep-related outcomes by aircraft noise exposure.

Appendix I Table 3: Summary of quality of evidence for sleep-related outcomes, from (Grollman et al., 2020).

Outcome	**Quality of evidence – *direction of effect***			
	WHO review (2018)	**Defra-RIVM review (2020)**	**ICCAN review (2020)**	**ICCAN synthesis (2020)**
Physiologically measured awakenings in adults	Moderate quality *– harmful effect*		Low quality – *harmful effect*	Moderate quality *– harmful effect*
Self-reported sleep quality			Very low quality *– harmful effect*	
Self-reported sleep coping behaviours			Very low quality *– harmful effect*	
Self-reported awakenings			Low quality – *harmful effect*	
Self-reported sleep disorder			Very low quality *– no effect*	
Self-reported sleep disturbance in adults (source not specified)	Very low quality – *harmful effect*			
Self-reported sleep disturbance in adults (source specified)	Moderate quality *– harmful effect*	No GRADE – *harmful effect*	Low quality – *harmful effect*	Moderate quality *– harmful effect*

For *self-reported sleep disturbance* in adults where noise was specified in the survey instrument, the WHO review (Basner & McGuire, 2018) showed that there was *moderate evidence* of a *harmful effect* of aviation noise. The Defra-RIVM review (van Kamp et al., 2020) found additional studies on self-reported sleep disturbance; the authors did not report whether or not noise was specified in the survey instrument. The authors described the results as "not consistent, primarily due to methodological differences between the studies, nevertheless pointing in the same direction", which we consider to be consistent enough with the findings of the WHO review. The ICCAN review found two further papers reporting on this outcome (Brink et al., 2019; Rocha et al., 2019), both of which were cross-sectional and one of which had a moderate risk of bias. Both papers found a harmful effect. The ICCAN review concluded that the *quality of evidence remains moderate* for the *harmful effect* of aircraft noise on *self-reported sleep disturbance in adults where noise was specified in the survey*. A recent review paper on environmental noise and its effects on sleep confirmed the strength and quality of the evidence (Smith et al., 2022). Interestingly, the authors indicate that populations exposed to higher levels of aircraft noise might be more susceptible to sleep disturbance than previously reported.

For cortical awakenings measured by **polysomnography** (physiologically measured awakening), the WHO review concluded there was *moderate quality evidence of a harmful effect*. Polysomnography involves multiple monitors attached to the body to measure brain, eye, muscle and other signals. It is the state of the art for objective measures of sleep but is expensive, logistically difficult to implement and relatively invasive. The study by Basner et al. (2019) involved using a less invasive single monitor of heart activity and movement that participants could apply themselves (Basner et al., 2019). Since the authors report that the agreement between this method and polysomnography was near perfect, the ICCAN authors found it appropriate to consider this evidence together as "physiologically measured awakenings". The study by Basner et al. (2019) was a small cross-sectional study that on its own could only offer low quality evidence. Nonetheless, the ICCAN review concluded that given the strong result consistent with the finding of the WHO review, it would be appropriate to maintain the finding of *moderate quality evidence of a harmful effect of aircraft noise on physiologically measured awakenings*.

ICCAN reported a *harmful effect* on *self-reported sleep quality* (Basner et al., 2019; Rocha et al., 2019; Smith et al., 2020) and *self-reported sleep coping behaviours* (Rocha et al., 2019) but concluded that the evidence was of *very low quality*. The conclusion was based on cross-sectional studies with some inconsistencies. The evidence of a *harmful effect* on *self-reported awakenings* was estimated to be of *low quality* but was only based on one cross-sectional study (Smith et al., 2020). Moreover, they reported *no effect* of aircraft noise on *self-reported sleep disorder*, but the quality of evidence was of *very low quality* as it was based on one cross-sectional study (Rocha et al., 2019) with moderate risk of bias. Important to note that the studies included for this assessment are all pilot studies and are not powered to elucidate precise associations or effects, hence the results are only indicative.

Physiological measurements reveal sleep disturbances due to aircraft noise exposure, mainly represented by awakenings. Self-reported measures of sleep outcomes are affected by aircraft noise exposure, too, but do not necessarily reflect physiologically measured sleep outcomes. The magnitude of the effect of aircraft noise exposure on sleep is influenced both by the assessment of exposure variables and sleep outcomes. Average sound pressure levels are insufficient predictors of both physiologically measured and self-reported sleep outcomes. The number of noise events and maximum levels should be considered, too.

Whether a noise event can cause an awakening does not only depend on its acoustic properties (e.g., loudness, duration, speed of volume increase) but also on situational and personal factors (Bartels et al., 2022). **Situational factors** include (i) the time asleep: as sleep progresses, the body's natural sleep drive weakens, making one more susceptible to waking from noise, especially in early mornings, (ii) the sleep stage: deep sleep stages are less likely to be disrupted by noise than lighter sleep stages and (iii) the background noise: aircraft noise is more likely to wake you up if it stands out significantly from the surrounding background noise. **Personal factors** such as age can influence sleep. As we age, sleep patterns change. Deep sleep decreases, making older adults potentially more susceptible to waking from aircraft noise, although research on this is limited. Children, conversely, are less likely to be woken up compared to adults by the same noise level. According to current research, gender does not seem to significantly influence how likely you are to wake up from aircraft noise, nor does it appear to affect how much sleep disturbance people report. In addition, people who are more noise sensitive to noise in general might be more bothered by aircraft noise and experience more sleep disturbance from it. However, more research is needed to understand the exact link between noise sensitivity and physiological sleep measurements.

Whilst the effects of aircraft noise on sleep in adults are well studied, with impacts including reduced sleep duration, decreased self-reported quality, changes in sleep architecture with decreased proportions of deep sleep and increased sleep fragmentation, the impacts of such noise on infants remain poorly understood. A recent study investigated the relationship between nocturnal transportation noise (i.e., road, rail and airplane noise) and actimetry-derived habitual sleep behaviour across the first year of life (Blume et al., 2022). Overall, the researchers found no significant link between nighttime noise and infant sleep across the first year. However, an interesting interaction emerged; infants with siblings showed no sleep disruption from noise while infants without siblings did experience shorter sleep durations with higher noise levels. Possibly infants might have a natural protection against external disturbances like noise during their first year or those living in quieter areas (without siblings) might be more sensitive to noise disruptions.

1.3 Cognitive outcomes

Noise exposure has been considered in the research associated with impairment to **cognitive function**. Children have the propensity to be especially vulnerable as their cognitive functions are less automatized and, thus, more prone to disruption in comparison to adults (Klatte et al., 2013). Noise in classrooms affect children in many ways, including lowering their motivation, reducing speech intelligibility, listening comprehension and concentration, producing annoyance and disturbance and increasing restlessness. As a result, children exposed to noise at school may experience poorer reading ability, memory and performance. Cognitive impairment could also be linked to noise exposure at home during night-time hours, which can cause low mood, fatigue and impaired task performance the next day. Noise at home may also be linked to hyperactivity and inattention problems, which can cause lower academic performance. In addition, the elderly could be considered as susceptible population group, as a decline in cognitive functions is already considered to be a normal consequence of aging (Glisky, 2007). A decrease in cognitive function in elderly, in addition to the expected decrease from aging, is assumed to be associated with environmental noise exposure through noise annoyance (Lee et al., 2016).

Appendix I Table 4 summarizes the quality of evidence for cognitive outcomes by aircraft noise exposure.

Appendix I Table 4: Summary of quality of evidence for cognitive outcomes, from (Grollman et al., 2020).

Outcome	**Quality of evidence – *direction of effect***			
	WHO review (2018)	**Defra-Arup review (2020)**	**ICCAN review (2020)**	**ICCAN synthesis (2020)**
Assessment of student distraction		Very low quality – *harmful effect*		
Attention	Low quality – *no effect*			
Executive function deficit (working memory capacity)	Very low quality – *no effect*			
Impairment assessed through SATs	Moderate quality – *harmful effect*			
Reading and oral comprehension	Moderate quality – *harmful effect*	Very low quality – *harmful effect*		Moderate quality – *harmful effect*
Short- and long-term (episodic) memory	Moderate quality – *harmful effect*			

All studies identified through the WHO review (Clark & Paunovic, 2018) had **child** populations and most focused on aircraft noise exposure. In order to define the association between children's cognitive abilities and aircraft noise exposure, a range of cognitive domains was evaluated. The WHO review concluded that there was *moderate quality evidence of a harmful effect of* aircraft noise on *reading and oral comprehension*. The Defra-Arup review (Clark et al., 2020) included four studies and concluded there was *very low quality evidence of a harmful effect*. The authors of the latter wrote that they had made their assessment based on a smaller number of studies some of which had methodological weaknesses leading to downgrading and recommended that the findings of the WHO review stand. The ICCAN review considers therefore that the WHO finding stands and that there is ***moderate quality evidence of a harmful effect of aircraft noise on reading and oral comprehension*.** The effect of aircraft noise on reading comprehension, which serves a good marker for children's general cognitive ability, and which influences subsequent attainment and life chances, is confirmed as well established in a recent meta-analysis (Clark et al., 2021).

In conclusions, several reviews (Clark et al., 2021; Clark & Paunovic, 2018; Dohmen et al., 2022) show that there **are indications that aircraft noise exposure could cause cognitive impairment in children**. These indications appeared for some cognitive domains stronger (e.g., reading comprehension) than for others. **Sound insulation of schools** proved to be an effective intervention method in some studies (Hygge et al., 2002; Sharp et al., 2014). Additionally, some studies indicated that exposure to environmental noise (e.g., road traffic noise) might not only affect children's cognition but also cognitive functioning in elderly (Tzivian, Dlugaj, Winkler, Hennig, et al., 2016; Tzivian, Dlugaj, Winkler, Weinmayr, et al., 2016; Tzivian et al., 2015).

1.4 Hearing impairment and tinnitus

The evidence on aircraft noise exposure and hearing impairment and related effects is a few decades old and does not specifically explore impacts on people outside of occupational settings. Hearing impairment is mainly associated with exposure to environmental noise in case of very loud or persistent listening to music and other leisure activities like fireworks, sports events etc. There is no convincing evidence that aircraft noise would cause hearing impairment in the general public. Further research may increase knowledge of the relationship between aircraft noise exposure and hearing, although there is a suggestion that it is unlikely to be an important factor in hearing impairment amongst the adult population. However, more research is needed to verify the possible impact on children. Extensive efforts to reduce aircraft noise exposure to prevent annoyance and sleep disturbance should further reduce the probability of risks of hearing impairment.

1.5 Birth and pregnancy outcomes

The WHO review observed indications for the association between aircraft noise exposure and **adverse birth outcomes** such as preterm birth, low birth weight and congenital abnormalities, but the evidence supporting these findings was assessed as of *very low quality* (Nieuwenhuijsen et al., 2017). Further investigation of the association is needed. The ANIMA or ICCAN update did not identify any new study investigating the association between aircraft noise and adverse birth outcomes.

A recent study around Los Angeles International Airport investigated the role of airport-related noise and its interaction with traffic-related air pollution on preterm birth risk (Wing et al., 2022). While all women in the study area were exposed to high levels of UFP from aircraft (due to proximity to the airport), the researchers found that the strongest associations between airport-related noise and preterm birth occurred in mothers who were also exposed to high levels of traffic-related air pollution suggesting a synergistic effect of aircraft noise and traffic-related air pollution.

Appendix I Table 5 summarizes the quality of evidence for adverse birth outcomes by aircraft noise exposure.

Appendix I Table 5: Summary of quality of evidence for birth outcomes, from (Grollman et al., 2020).

Outcome	Quality of evidence – *direction of effect*			
	WHO review (2018)	Defra-Arup review (2020)	ICCAN review (2020)	ICCAN synthesis (2020)
Congenital malformation	Very low quality – *no overall effect stated in GRADE assessment, but harmful effects reported in narrative review*			
Low birth weight	Very low quality – *no overall effect stated in GRADE assessment, but harmful effects reported in narrative review*			
Preterm birth	Very low quality – *no overall effect stated in GRADE assessment, but harmful effects reported in narrative review*			

Potential mechanisms are maternal sleep disturbance and stress, which may increase heart rate and stress hormone levels, and elevated blood pressure. High maternal cortisol levels may reduce foetal growth and gestational hypertension is associated with small-for-gestational age. From 20 weeks of gestation, the foetus can produce an independent stress response to external stimuli, which may further restrict growth.

Knowledge of the potential relationship between aircraft noise and adverse birth outcomes is deficient. Understanding any connections between the two factors requires further research due to the importance of the long-term morbidity that they can cause.

A recent review investigated the potential link between noise exposure during pregnancy and stress-related obstetric complications, such as pre-eclampsia, gestational diabetes and gestational hypertension (Sivakumaran, Ritonja, Waseem, AlShenaibar, et al., 2022a). Out of 11 000 studies reviewed, only six met the inclusion criteria and reported on relevant obstetric outcomes. Only one study examined aircraft noise (Thacher et al., 2021), whereas the others focused on road traffic noise. This study found increased odds of gestational diabetes mellitus among those exposed to ≥ 50 dB of aircraft noise. Nevertheless, the quality of evidence was considered *low*. This review highlights the gap in knowledge regarding the impact of noise on pregnancy outcomes and warrants further research on this topic.

1.6 Quality of life, mental health and well-being outcomes

The WHO review included seven studies and the Defra-Arup review included four studies on self-reported quality of life (QoL) or health. Both reviews concluded there was *very low quality evidence of no effect of aircraft noise* on *self-reported QoL or health*. The ICCAN review concludes that there was no new evidence on this outcome so that conclusion stands. A recent DEBATS study investigated noise annoyance as a mediator and noise sensitivity as a moderator in the association between noise and self-reported health (Kodji et al., 2023). The study suggests that the adverse effect of aircraft noise on self-reported health status could be mediated by noise annoyance. Moreover, noise sensitivity might moderate the health effects of noise, with a stronger association observed in men who reported to high noise sensitivity. The authors acknowledge the need for further research using causal interference methods to identify the causal effects of noise exposure, mediators and moderators.

The WHO review included one study and concluded there was *very low quality evidence* of a *harmful effect* of aircraft noise on *interview measures of depression and anxiety*. The Defra-Arup review included two studies and concluded that this should be upgraded to *low quality evidence* considering new data from cohort studies. The ICCAN review concluded that there is no new evidence so the conclusion of *low quality evidence* of a *harmful effect* of aircraft noise on interview measures of depression and anxiety stands.

Regarding evidence for psychological health in children, the WHO review concludes that there was *low* quality evidence for a *harmful effect* for hyperactivity and *low* quality evidence for *no effect* for conduct and emotional disorders. A recent meta-analysis agrees with these conclusions in terms of strength of the evidence (Clark et al., 2021). While some studies show an increase in psychological symptoms in children, these effects tend to be of a small magnitude and do not reflect a shift to psychological illness per se. However, there are still concerns for population health due to (i) widespread exposure may cause a large portion of the population to experience increased symptoms, (ii) cumulative effects on children which might have more serious consequences later in life and (iii) the recurring nature of mental health issues (Clark et al., 2007).

The ICCAN review concluded that there was *very low quality* evidence of *no effect* for a link between aircraft noise and well-being of children, self-reported diagnosis of chronic headaches/migraine, children's medication intake and children's physical diseases. ICCAN reported *no effect* on *depression prevalence* but a *harmful effect* on *depression mediated by annoyance*, both based on *low quality* evidence.

Appendix I Table 6 summarizes the quality of evidence for mental health and well-being effects linked to aircraft noise exposure.

Appendix I Table 6: Summary of quality of evidence for quality of life, mental health and well-being outcomes, from (Grollman et al., 2020).

Outcome	**Quality of evidence – *direction of effect***			
	WHO review (2018)	**Defra-Arup review (2020)**	**ICCAN review (2020)**	**ICCAN synthesis (2020)**
Wellbeing of children			Very low quality – *no effect*	
Depression prevalence			Low quality – *no effect*	
Depression prevalence mediated by annoyance			Low quality – *harmful effect*	
Emotional and conduct disorders in children	Low quality – *no effect*			
Hyperactivity	Low quality – *harmful effect*			
Interview measures of depression and anxiety	Very low quality – *harmful effect*	Low quality – *harmful effect*		Low quality – *harmful effect*
Medication intake to treat anxiety and depression	Very low quality – *harmful effect*			
Self-reported QoL or health	Very low quality – *no effect*	Very low quality – *no effect*		Very low quality – *no effect*
Well-being		Very low quality – *harmful effect*		

Outcome	Quality of evidence – *direction of effect*			
	WHO review (2018)	Defra-Arup review (2020)	ICCAN review (2020)	ICCAN synthesis (2020)
Self-reported diagnosis of chronic headaches/migraine			Very low quality – *no effect*	
Children's medication intake			Very low quality – *no effect*	
Children's physical diseases			Very low quality – *no effect*	

The authors of the reviews emphasize the difficulty in drawing conclusions from the studies for several reasons: the small number of studies, the differing study designs and the wide variation of methods for both noise measures and outcome measurements. All these aspects **hamper** the **comparability**. They also state that studies do not consider confounding factors such as history of mental well-being, and other factors. The small number of studies does not allow the derivation of exposure-response relationships and risk estimates. The variation in outcome measures limits the comparison of results and especially measures to assess health-related quality of life. Moreover, psychological symptoms must be differentiated from those detecting manifest disorders, as they do not necessarily lead to the development of severe disorders. In this regard, previous reviews have concluded that environmental noise predicts annoyance, as well as psychological symptoms, but not clinically definable psychiatric disorder, suggesting that noise exposure might be associated with milder conditions, such as those measured by symptom scales (Guski et al., 2017; S. Stansfeld & Clark, 2011). For example, it has previously been hypothesized that aircraft noise might not cause hyperactivity per se but that it may make an existing tendency towards hyperactivity worse or more obvious. This argument may also apply to other psychological health outcomes. Furthermore, the exact pathway through which noise affects mental health needs further exploration as the effects may not be direct. Noise annoyance itself can trigger stress responses, potentially leading to long-term negative impacts on mental well-being. Moreover, noise exposure might act as an additional stressor, interacting with other environmental and psychosocial stressors (e.g., childhood poverty) to influence mental health (Evans & De France, 2022). The possibility of further confounding by air quality remains as this has also been shown to be associated with children's cognition and mental health (Forns et al., 2017; S. A. Stansfeld, 2015).

There is a shortage of studies exploring aircraft noise and mental health. The available evidence is relatively weak and further research would improve understanding of exposure-response relationships and risk estimates.

1.7 Cancer

It is hypothesized that noise may affect carcinogenesis through sleep disruption which leads to suppression of melatonin secretion. Melatonin is a hormone regulating circadian rhythm and offering protection against free radicals and cell damage. It is also known to have various anti-carcinogenic properties, such as promoting DNA repair and inducing antioxidant defence (K. Kim et al., 2013; Liu et al., 2013; Viswanathan & Schernhammer, 2009). Additionally, chronic exposure to aircraft noise can activate the sympathetic nervous system and the hypothalamus-pituitary-adrenal axis, leading to elevated cortisol levels (i.e., glucocorticoid involved in immune suppression), cell death (i.e., apoptosis) and the formation of new blood vessels (i.e., angiogenesis); all factors that potentially can promote tumour development (Armaiz-Pena et al., 2013; Volden & Conzen, 2013).

Appendix I Table 7 summarizes the quality of evidence of cancer linked to aircraft noise exposure.

Appendix I Table 7: Summary of quality of evidence for cancer, from (Grollman et al., 2020).

Outcome	**Quality of evidence – *direction of effect***			
	WHO review (2018)	**Defra-Arup review (2020)**	**ICCAN review (2020)**	**ICCAN synthesis (2020)**
Incidence of breast cancer		Low quality – *harmful effect*		

The Defra-Arup review (Clark et al., 2020) concluded a *harmful effect* of aircraft noise on the *incidence of breast cancer* but the evidence was of *low quality*. This was based on a case-control study in Germany that did not find associations between road or railway noise and breast cancer, but a weak positive association was noted for aircraft noise (Hegewald et al., 2017). Two recent pooled studies on Nordic cohorts found no association between long-term aircraft noise exposure and the incidence of breast cancer (Thacher et al., 2023) and colon cancer (Roswall et al., 2023).

1.8 General health outcomes

The ICCAN review reported that there was *no effect* of aircraft noise on *self-reported general health* and *self-reported diagnosis of stomach ulcer*, both based on *very low quality*. In addition, they found no direct effect of aircraft noise on *general physical health of children*. However, they found significant indirect effects of aircraft noise on *physical well-being in children*, mediated through annoyance based on *low quality* evidence.

Appendix I Table 8 summarizes the quality of evidence for general health outcomes linked to aircraft noise exposure.

Appendix I Table 8: Summary of quality of evidence for general health outcomes, from (Grollman et al., 2020).

Outcome	**Quality of evidence – *direction of effect***			
	WHO review (2018)	**Defra-Arup review (2020)**	**ICCAN review (2020)**	**ICCAN synthesis (2020)**
Self-reported general health			Very low quality – *no effect*	
Self-reported diagnosis of stomach ulcer			Very low quality – *no effect*	
General physical health of children			Low quality – *no effect*	
General physical health of children mediated by annoyance			Low quality – *harmful effect*	

1.9 Annoyance

Aircraft noise **annoyance** is a complex issue that affects people in different ways. It involves a combination of how the noise disrupts one's daily life (behavioural), how it makes one feel (emotional) and how one thinks about it (cognitive). The behavioural aspect includes actions one takes to minimize the noise (e.g., closing windows), the emotional aspect involves feelings like anger and frustration towards the noise source and the cognitive aspect refers to the feeling of helplessness or lack of control over the situation. Interestingly, research shows that only about a third of noise annoyance is directly related to how loud the noise actually is (measured by L_{den} or L_{Aeq}). The other two-thirds are influenced by other factors not related to the sound itself, called **non-acoustical factors** (Bartels et al., 2022).

1.9.1 Non-acoustical factors

These non-acoustical factors can be broadly categorized into two groups of personal and social factors or contextual and situational factors as discussed below.

1.9.1.1 Personal and social factors

Attitudes, concerns and expectations belong to the most important non-acoustic factors influencing annoyance. If one believes airports are important to the local economy, they are likely less bothered by the noise. On the contrary, fears of health problems from noise or fear of plane crashes increase annoyance. These fears and negative attitudes can contribute even more to aircraft noise annoyance than de average indicators of noise level (e.g., L_{den} or L_{Aeq}). Moreover, annoyance is higher in individuals who expect noise to get worse in the future and in individuals who value a quiet and healthy environment over economic issues when it comes to airport-related decisions. In addition, **noise sensitivity** is considered as a stable personality trait which can make some people more sensitive to noise in general and hence make them more annoyed by aircraft noise. Noise sensitivity seems to be linked to a personality trait where people are more prone to negative emotions like anger, anxiety or tension. Interestingly, noise sensitivity is one of the biggest factors influencing how annoyed people get by aircraft noise, even more so than the attitudes discussed above. Additionally, the **ability to cope and coping strategies** of an individual are important non-acoustic factors that determine the way of living with noise exposure. Beyond these individual coping abilities, how people perceive control over the noise situation is also influenced by their **trust** in the airport. Residents are more likely to feel empowered and less annoyed if they trust the airport to be (i) proactive in minimizing unnecessary noise and (ii) open and honest in communication. **Fairness** also plays a crucial role. When residents feel the airport is treating them fairly and addressing their concerns seriously, it can significantly reduce annoyance.

A recent study shed light on several factors influencing how noise affects people. Closed windows, especially high-quality ones, not only block noise but also give residents a sense of control over their noise environment (i.e., subjective coping tool for noise). As discussed above, this feeling of control can reduce annoyance even when windows are open, and some noise enters. In addition, people who are more concerned about the environment are significantly more likely to report annoyance from aviation noise, even after accounting for other factors. This suggests a heightened awareness and sensitivity to noise as a potential environmental hazard (Preisendörfer et al., 2022). Another study showed that, unlike studies in adults, the acoustical aspects of noise exposure (e.g., number of aircraft overflights and maximum sound pressure levels) did not significantly influence short-term annoyance in children. Other non-acoustical factors, such as attitudes toward air traffic (e.g., aircraft are dangerous, fear of plane crashes, aircraft are useful) and noise sensitivity, were more impactful (Quehl et al., 2021).

1.9.1.2 Contextual and situational factors

These involve the specification situation where the noise occurs, like the time of day or feeling like you have no control over the noise sources. Moreover, the **degree of urbanisation and background noise exposure** is expected to influence annoyance. Studies suggest that people in rural areas tend to be bothered by aircraft noise the most, followed by suburban, urban, commercial and industrial areas. People in rural areas generally expect a peaceful environment with minimal noise. On the other hand, urban residents are already accustomed to a higher level of background noise, so aircraft noise may not be as disruptive. Studies have shown that **access to greenery and recreational areas** can reduce annoyance from traffic and train noise. However, the relationship with air traffic noise is more complex. While green spaces can be a positive coping strategy for those affected by aircraft noise, some research suggests that having greenery around might increase annoyance from aeroplanes because it is perceived as more disruptive in quiet, residential areas. Additionally, people living in greener areas might have a higher expectation of peace and quiet, making aircraft noise seem even more intrusive. Moreover, having **access to a quiet side or room** inside a house can be a helpful coping mechanism. Aircraft noise can become more annoying when it **suddenly changes** (e.g., increased aircraft noise due to the opening of a new runway or an unexpected quiet period during the COVID-19 pandemic). Also, people seem to be bothered more by noise during certain times of the day (i.e., evening and night) and when it interferes with their activities (e.g., during leisure time in weekends). These activity patterns explain why people can have different levels of annoyance with the same amount of noise exposure.

1.9.2 Mediation through annoyance

New studies support an **indirect role of annoyance** in the relationship between aircraft noise exposure and health outcomes. That is, for people who experienced annoyance due to aviation noise, there was an effect on the health outcome. Some of these outcomes expected to be influenced by annoyance were hypertension (Babisch et al., 2013; Baudin et al., 2020; Eriksson et al., 2010), prevalence of depression (Benz & Schreckenberg, 2019), mental health-related quality of life (Schreckenberg et al., 2017) and general physical health of children (Spilski et al., 2019). There was no role of annoyance in mediating the relationship between aircraft noise and cortisol levels (Baudin et al., 2019) or blood pressure (Carugno et al., 2018).

A few studies showed a link between mental health and well-being-related measures and noise annoyance. Baudin et al. (2018) found a higher risk for psychological distress for people being extremely annoyed by noise in comparison to a lower risk for people being less annoyed (Baudin et al., 2018). The researchers found in another study an association between aircraft noise annoyance and the use of anxiolytics (medication for anxiety disorders), implying a mediating role of annoyance for the link of aircraft noise exposure to mental health outcomes (Baudin et al., 2021). Moreover, a recent meta-analysis found that those experiencing high levels of noise-induced annoyance (from all noise sources) had a 1.23 times higher risk for depression. Moreover, they indicated an approximately 55% higher risk of anxiety and an almost 119% higher risk of mental health problems in highly noise-annoyed people (Gong et al., 2022).

As shown earlier, aircraft noise did not have a direct effect on mental health-related quality of life (Schreckenberg et al., 2017) and diagnoses of depression (Benz & Schreckenberg, 2019), but in both studies, an indirect effect via annoyance was found. The results suggest that aircraft noise exposure decreases mental health-related quality of life and predicts the development of depression one year later via noise annoyance. Both studies further indicate that there is a reciprocal association, i.e., that diagnoses of depression and poorer mental health-related quality of life also contributed to higher ratings of annoyance a year later. This indicates that vulnerability due to physiological and/or psychological health issues may limit resources to cope with noise which can contribute to higher annoyance.

Due to different methods to assess noise annoyance as well as different health outcomes and measures, it is difficult to draw consistent conclusions. However, evidence indicates that annoyance contributes to adverse mental health outcomes.

1.9.3 Measuring annoyance

While a wealth of evidence connects self-reported annoyance to aircraft noise exposure, it is crucial to recognize the subjective nature of the response. Because annoyance is an individual experience, it cannot be directly measured with the same objectivity as noise levels themselves. The most common way to assess annoyance from noise pollution is a standardized one-question survey recommended by the International Commission of Biological Effects of Noise (ICBEN) (Fields et al., 2001) to assess airport residents' long-term annoyance: "Thinking about the last 12 months or so, how much did aircraft noise as a whole bother, disturb or annoy you?". Typically, and in line with the ICBEN recommendations, annoyance ratings have been given on 5-point verbal scales and 11-point numerical scales. By dichotomising the answers in values of high (1) and not high (0) annoyance, the percentage of respondents highly annoyed related to computed average noise levels provides exposure-response curves that inform noise policy. However, the established exposure-response relationships often vary significantly between studies. Researchers have explored other factors beyond noise levels that might influence annoyance but have not yet been able to create a reliable mathematical model to predict annoyance largely because of non-acoustical factors as described above. While this method offers consistency across studies, it has limitations. It does not account for what moment during the day the annoyance is experienced (morning vs. night). Moreover, people tend to remember recent or very early experiences more vividly, which can skew their responses over a 12-month time frame (i.e., recall bias). Also, the term "annoyance" can encompass various feelings like loudness, fear, anger or depression. A single ICBEN question might not capture these nuances. Future research could improve annoyance assessment by adding more specific questions alongside the ICBEN scale to better capture the multifaceted nature of annoyance caused by aviation noise.

1.10 Health risk associated with aircraft noise exposure

The European Environment Agency (EEA) and WHO assessed the health risk associated with aircraft noise exposure the health outcomes that have been demonstrated a reasonable causal relationship between noise exposure and adverse health effects as shown in *Appendix I* Table 9.

Appendix I Table 9: Relationships between noise and health effects used by EEA and WHO. The relative risk (RR) and odds ratio (OR) is shown with the 95% confidence interval. If defined the established dose-response function is also provided.

Health outcome measure	Population	Quantitative risk for adverse health // impact function	Quality of evidence (GRADE)	Reference
Cardiovascular disease				
Incidence of ischemic heart disease	Whole population	RR=1.09 (1.04; 1.15) per 10 dB(A) increase in L_{den}	Very low (downgraded for risk of bias, upgraded for dose-response)	(Kempen et al., 2018)
Incidence of hypertension	Whole population	RR=1.00 (0.77; 1.30) per 10 dB(A) increase in L_{den}	Low (downgraded for risk of bias and because only one study is available	(Kempen et al., 2018)
Effects on sleep				
%HSD (highly sleep disturbed)	Whole population	OR=1.94 (1.61; 2.33) per 10 dB(A) increase in L_{night} // %HSD[1]=(16.7885 - 0.9293 * L_{night} + 0.0198 * L_{night}^2)/100	Moderate (downgraded for study limitations, inconsistency; upgraded for dose-response, magnitude of effect)	(Basner & McGuire, 2018)
Cognitive impairment				
Reading and oral comprehension	Children	1-2-month delay per 5 dB(A) increase in L_{den} // 1/(1 + exp(- (ln(0.1/0.9) + (ln(1.38)/10 × (L_{den} - 50)))) if $L_{den} \geq 50$ dB and 0.1 if $L_{den} < 50$ dB	Moderate (downgraded for inconsistency)	(Clark et al., 2006; Kempen et al., 2018)
Annoyance				
%HA (highly annoyed)	Whole population	OR=4.78 (2.27; 10.05) per 10 dB(A) increase in L_{den} // %HA=(-50.9693 + 1.0168 * L_{den} + 0.0072 * L_{den}^2)/100	Moderate (downgraded for inconsistency)	(Guski et al., 2017)

[1]Based on self-reports on survey questions that explicitly refer to aviation noise, related to aircraft sound levels L_{night}

2 Metrics used to assess aircraft noise exposure

Understanding how aircraft noise is measured is crucial for assessing its impact on communities. Therefore, it is important to explore the basic principles of acoustics and how sound is measured and represented. **Sound** and **noise** are not the same. Sound is a term from physics and refers generally and neutrally to noises emitted by a cause (i.e., source). These sounds are propagated in the air by pressure and density fluctuations (vibrations). These fluctuations can be determined using the sound pressure level (SPL) which characterizes the **amplitude** or peak level of the sound wave. Higher SPL indicates a stronger sound pressure, often perceived as a louder noise. SPL is measured in units called **decibels** (dB). Noise generally refers to undesired sound that is perceived as an annoyance, impairs well-being and, depending on the loudness and duration, can even make people ill. Unlike sound, noise is not objectively measurable but purely subjective. This means that every person perceives sounds differently.

Not all sound frequencies are perceived equally by the human ear. We are generally more sensitive to sounds in the middle-frequency range (roughly 2 to 5 kHz) than those at very low or very high frequencies. To account for this variation in human hearing perception, sound levels are often measured using the **A-weighted scale**, denoted as dB(A). This scale essentially filters out the extremely low and high frequencies that we hear less intensely. However, it might underestimate low-frequency sounds that penetrate buildings more easily and might disrupt sleep potentially leading to an underestimation of the true annoyance caused by aviation noise. On the other hand, C-weighting attempts to capture a wider frequency range including low-frequency noise in the environment. Important to note, changes in C-weighted readings do not necessarily reflect changes in low-frequency noise itself because C-weighing considers high frequencies as well. The A-weighting filter, while widely used as a standardized and consistent way to measure noise levels, has limitations in capturing the full spectrum of noise annoyance, particularly regarding low-frequency sounds. The C-filter might offer a more comprehensive approach, but needs cautious interpretation. Ultimately, the choice of weighting filter depends on the specific context and the aspects of noise exposure being evaluated.

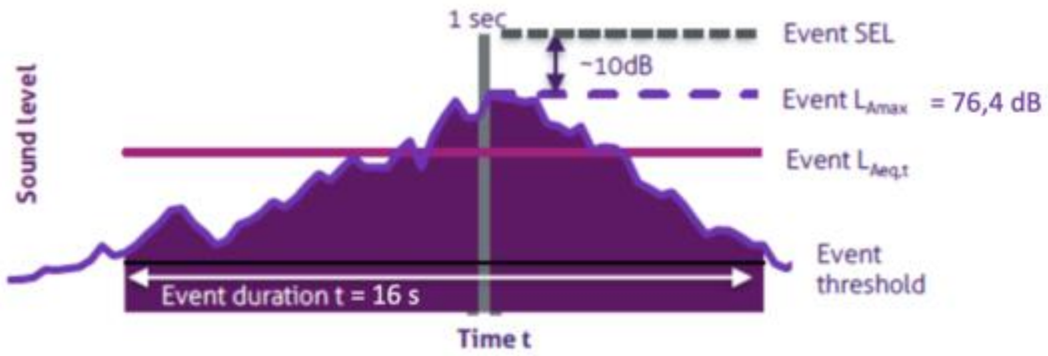
Unlike a linear scale, decibels are **logarithmic**. This means a small increase in dB signifies a relatively significant change in sound intensity. For instance, 10 dB is perceived as **10 times louder** than 0 dB, and 20 dB is a **100-fold increase** in intensity compared to 0 dB. This logarithmic scale reflects how our ears perceive loudness – small changes at low volumes are more noticeable than at high volumes. While SPL captures the peak sound pressure level, it does not consider the **duration** of the noise event. **Sound exposure level** (SEL) addresses this by factoring in both the **maximum sound level** and the **duration** for which the sound pressure exceeds a specific threshold. This provides a more comprehensive picture of the total noise energy an aircraft event generates. SEL proves particularly useful for comparing noise exposure from aircraft flyovers of varying lengths.

Noise metrics are essentially calculations that translate the effects of noise into understandable values and can be classified as (i) **single-event metrics** which focus on the noise generated by a single aircraft, (ii) **cumulative/time-averaged metrics** which assess the total noise impact from multiple aircraft movements over a specific period (e.g., a day) and (iii) **hybrid metrics** that combine elements of both cumulative and single-event metrics, providing a more nuanced picture of noise exposure. An overview of these different metrics is provided below.

2.1 Single noise event metrics

L_{Amax} is the maximum A-weighed sound pressure level reached during a measurement period (i.e., a single snapshot of noise such as a single flyover), measured in decibels (dB) with an A-weighting to reflect human hearing sensitivity. L_{Amax} or L_{A0} corresponds to the maximum noise level and L_{Amin} or L_{A100} corresponds to the minimum noise level. Likewise, the indicators L_{A5} and L_{A90} correspond to the noise levels reached or exceeded during 5% and 90% of the measuring time, respectively. The indices L_{A1} and L_{A5} are often used to represent transient and intermittent levels (e.g., aircraft noise). Conversely, the indices L_{A90} and L_{A99} characterize the quietest moments of the measurement period and are representative of the background noise.

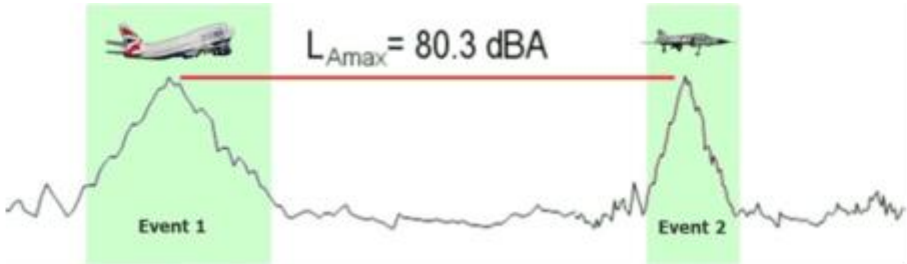
During the time of an aircraft flyover (16 seconds in the example below *Appendix I Figure 1*), the noise level starts at background noise levels, rises to the peak level (L_{Amax} = 76.4 dB(A)) as the plane passes overhead and returns to the background level again. Background or ambient noise encompasses all the everyday sounds in an environment except the specific source of interest (in this case, aircraft overflights). This can include chirping birds, wind blows or passing cards. To distinguish aircraft noise from this background, a threshold level needs to be set which serves as a cut-off point to differentiate between ongoing ambient noise and the specific noise event of, for example, an aircraft passing overhead.



Appendix I Figure 1: Example of different flyover sound measures, from (Understanding Aviation Noise, n.d.).

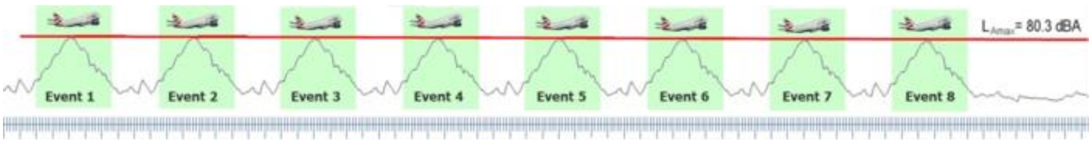
However, L_{Amax} has limitations:

1) **Limited information:** L_{Amax} only reflects a single point in time (i.e., instantaneous intensity), not the entire noise event as it does not provide information about cumulative noise exposure (sound energy of the event). Imagine two aircraft events with the same L_{Amax} (peak of 80.3 dB(A) in the example below *Appendix I Figure 2*). Event 1, a heavy aircraft, might last longer and be perceived as more annoying than Event 2, a light aircraft that passes quickly. L_{Amax} does not reflect this.



Appendix I Figure 2: Limitations of L_{Amax}, from (Understanding Aviation Noise, n.d.).

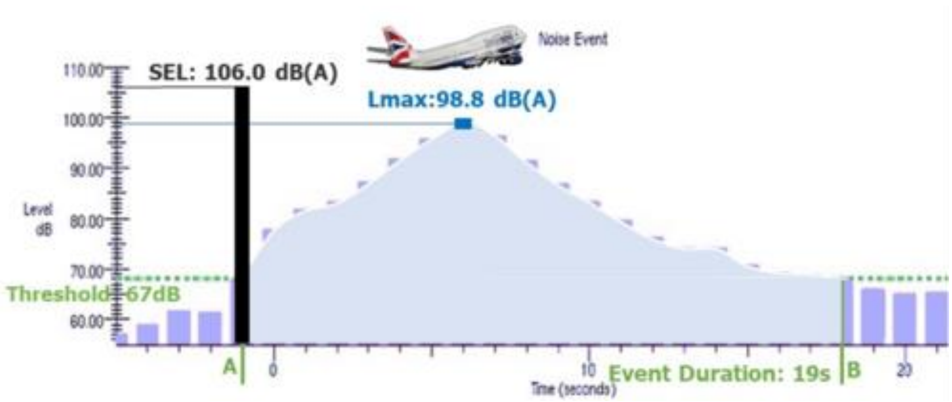
2) **Frequency does not matter:** L_{Amax} does not consider the number of noise events. If you measure L_{Amax} for an hour and only one aircraft flies over at 80.3 dB(A), that is the recorded L_{Amax}. But what if there were eight aircraft overflights at 80.3 dB(A) in that hour? L_{Amax} remains the same even though people would likely be more annoyed by the higher number of events.



Appendix I Figure 3: L_{Amax} ignores number of events, from (Understanding Aviation Noise, n.d.).

L_{Amax} serves a useful starting point, but for a better understanding of aircraft noise exposure, we need additional information. More specifically, information concerning the sound energy level reflecting the cumulative exposure since L_{Amax} does not capture the total noise energy of an event. While two events might have the same peak level, the one that lasts longer delivers more noise energy and might be perceived as more disruptive.

Sound Exposure Level (SEL) solves the first problem of L_{Amax} (i.e., limited information). It reflects the total sound energy of an entire noise event, from the moment it rises above a set threshold (67dB(A) in the example below, *Appendix I Figure 4*) to when it falls back below (a total of 19 seconds in the example). Imagine compressing the entire event's sound energy into a single second. This makes SEL valuable because it allows to compare aircraft noise events of very different durations. SEL essentially normalizes the duration to one second, enabling a fair comparison. However, it is important to remember that SEL does not capture the peak intensity (i.e., instantaneous intensity) despite being expressed in dB(A).



Appendix I Figure 4: SEL captures total sound energy for fair comparison, from (Understanding Aviation Noise, n.d.).

The SEL indicator complements the L_{Amax} indicator to compare aircraft noise events. Since SEL is normalized to one second, its value will always be higher than L_{Amax} for events lasting longer than one second (SEL is 106 dB(A) compared to $L_A$max of 98.8 dB(A) in the example). The black line in *Appendix I Figure 4* represents the same total sound energy as the blue area (the 19-second event). In essence, SEL captures the entire event's 'noise punch' as if delivered in one second.

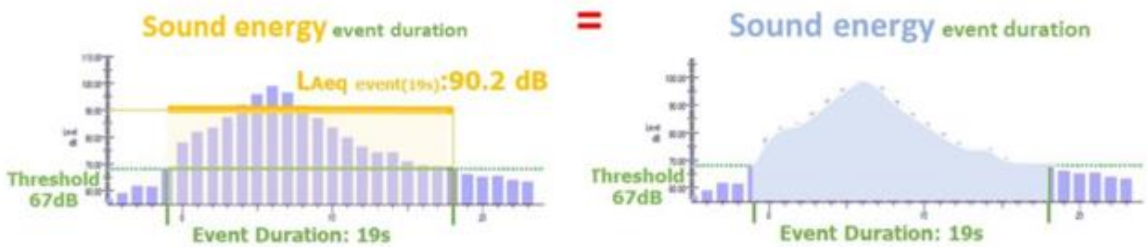
An overview of different single noise event metrics is given below in *Appendix I Table 10.*

Appendix I Table 10: Single noise event metrics, from (Love, 2023).

Metric	Definition	Presence in EU legislation and policy	Use
%HA	Percentage of the population **highly annoyed** by noise, assessed using a standardized scale. A self-reported metric which is a function of L_{den}	WHO environmental noise guidelines for the European Region. Evoked for EU regulation to measure health outcome	An objective measure of the health outcome of noise disturbance
%HSD	Percentage of the population **highly sleep disturbed** by noise, assessed using a standardized scale. A self-reported metric which is a function of L_{night}	WHO environmental noise guidelines for the European Region. Evoked for EU regulation regarding sleep disturbance	Policy-relevant measure of the health outcome of noise on sleep and subsequent sleep and health impacts
L_{Amax}	The A-weighted **Maximum Sound Level** from an aircraft event. A meaningful metric when given a response time	Only when used with a timeframe	Used for health research, correlations found to be linked with sleep disturbance and other effects of aircraft noise
SEL	**Sound Exposure Level**, an indicator which shows the total amount of time noise exceeds a given threshold	Used as part of other metrics	Used alongside L_{Amax} to directly compare individual aircraft noise events of different durations
PNdB	**Perceived Noise Decibel**, considers a singular aircraft noise event by comparing sound pressure level, including tonality, with perceived noise	/	Forms EPNdB
EPNdB	**Effective Perceived Noise Decibel**, is a measure of noise of individual aircraft flyover. Represents the integrated noisiness over a ten-second period	Used in the provision of different aircraft noise certifications	Reflects perception of aircraft noise, useful for compensation schemes

2.2 Time-averaged metrics

Equivalent Sound Level (L_{Aeq}) is the indicator that is good for solving both problems of L_{Amax} (i.e., limited information and frequency does not matter). L_{Amax} only captures the peak noise, not the entire event. L_{Aeq}, on the other hand, considers the total sound energy throughout a specific timeframe. Think of it like the average 'dose' of noise delivered over that period, not just the highest point. The yellow are in the example below (*Appendix I Figure 5*) represents this total sound energy of the time-varying noise (blue area) during the same period (19 seconds in example).

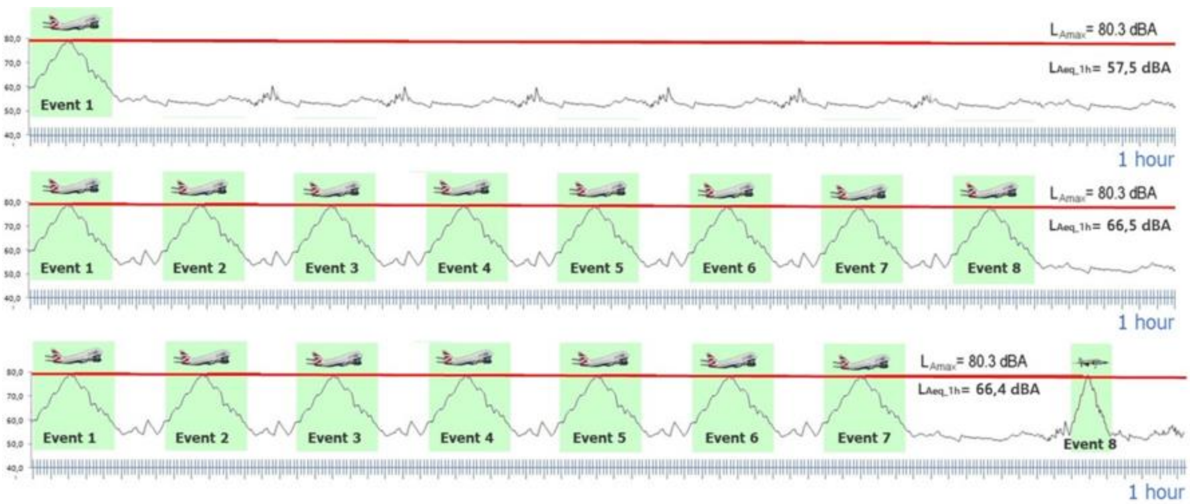


Appendix I Figure 5: L_{Aeq} captures both duration and energy, from (Understanding Aviation Noise, n.d.).

L_{Aeq} is not a simple average of noise intensity during a period of time. It is an amount of noise energy and focuses on the total sound energy. L_{Aeq} can be measured over various durations: one second, an hour, a day or even a year. 'L' stands for 'Level', 'A' indicates A-weighting for human hearing sensititivy and the subscript specifies the time frame. The sound energy in one minute is castly different from that in an hour or a year. Therefore, the specific time period is always needed in the subscript. L_{Aeq_1h}, for example, considers the sound energy of each event within an hour and the total number of events during that period. This provides a comprehensive picture of the noise exposure experiences over that one-hour timeframe.

Imagine we set up a sonometer to accurately measure airport noise for a one-hour period:

- Scenario 1: A single aircraft flies overhead during the hour. The sonometer wil show: LA_{max} = 80.3 dB(A) (i.e., peak noise level of aircraft passing), L_{Aeq_event} = 71.5 dB(A) (i.e., average sound energy of that single event) and L_{Aeq_1h} = 57.5 dB(A). L_{Aeq_1h} reflects the total noise exposure over the entire hour, considering both the single event's energy and the long periods of quiet between flights. As there was only one short event, the overal noise level (i.e., L_{Aeq_1h}) is significantly lower than the peak (L_{Amax}).
- Scenario 2: Eight identical aircrafts fly over during the hour. L_{Amax} remains 80.3 dB(A) because all aircrafts have the same peak noise level. L_{Aeq_event} stays at 71.5 dB(A) as the average energy per event remains the same. L_{Aeq_1h} increases to 65.5 dB(A) as with more aircrafts, the overall noise exposure increases even though the peak level and individual event energy remain constant.
- Scenario 3: Seven identical aircrafts and one different aircraft with a lower peak noise level (70 dB(A)) fly over during the hour. The highest peak level (L_{Amax}) remains at 80.3 dB(A). L_{Aeq_event} now has two values, $L_{Aeq\_event1-7}$ = 71.5 dB(A) for the identical aircrafts and L_{Aeq_event8} = 70 dB(A) for the different aircraft. The overall noise exposure is now slightly lower than the scenario 2 due to the quieter aircraft, L_{Aeq_1h} is around 65.4 dB(A).
- Scenario 4: Imagine 40 identical aircrafts fly over. The peak level does not change, L_{Amax} = 80.3 dB(A). The average energy per event remains constant, L_{Aeq_event} = 71.5 dB(A). With so many events, the overall noise exposure is significantly higher, approaching the peak level of eacht event, L_{Aeq_1h} reaches 71.5 dB(A).



Appendix I Figure 6: L_{Aeq} reveals the impact of multiple noise events, from (Understanding Aviation Noise, n.d.).

L_{Aeq_1h} is a valuable indicator because it considers both the number of noise events (i.e., frequency) and the sound energy of each event (i.e., intensity). This provides a more comprehensive picture of how aircraft noise affects an environment over time.

An overview of different metrics based on time-averaged/cumulative noise is given below in *Appendix I Table 11*.

Appendix I Table 11: Metrics based on time-averaged/cumulative noise, specifically L_{Aeq}-based metrics, from (Love, 2023).

Metric	Definition	Weighing	Presence in EU legislation and policy	Use
$L_{eq,T}$	**Equivalent Continuous Sound Level**, represents the sound pressure level that would be produced by a constant noise level with the same amount of noise energy, during the same period. It is measured in dB and usually measured over a 24-hour period (i.e., $L_{eq,24h}$)	/	Metric requires a time frame for it to become meaningful, forms the basis of all L_{eq}-derivates	Forms the basis for other metrics when given a time frame
$L_{Aeq,T}$	**A-weighted Equivalent Continuous Sound Level**, given over a specific time. It is more reliable than Leq as it accounts for differences in how people hear noise	Using A-weighted curve	Metric is used flexibly to reflect annoyance across different periods of the time (e.g., day, week or year). Noise sensitive periods, such as the night period, can be easily analysed	Used for modelling noise around an airport
$L_{Aeq,16h}$	**A-weighted Equivalent Continuous Sound level** over a **16-hour period**, when determining an average summer day between June 16th and September 16th (07h-23h)	Using A-weighted curve	/	Used for modelling noise around an airport
$L_{Aeq,8h}$	**A-weighted Equivalent Continuous Sound level** over an **8-hour period**, when determining an average summer night between June 16th and September 16th (23h-7h)	Using A-weighted curve	/	Used for modelling noise around an airport
$L_{Aeq,6.5h}$	**A-weighted Equivalent Continuous Sound level** between **23h30 and 6h**	Using A-weighted curve	/	Used for modelling noise around an airport
L_{night}	**Nighttime L_{Aeq}** (8h, typically 23h-7h) measured on an annual basis to give a measure of the annual night noise impact	Using A-weighted curve	European standard to express noise level over the night period (EC Directive 2002/49/EC)	Important metric for sleep disturbances from aircraft noise
L_{day}	**Daytime L_{Aeq}** (12h, typically 7h-19h), measured on an annual basis to give a measure of the annual day noise impact	Using A-weighted curve	European standard to express noise level over the day period (EC Directive 2002/49/EC)	Some evidence for a link with health effects
$L_{evening}$	**Evening time L_{Aeq}** (4h, typically 19h-23h), measured on an annual basis to give a measure of the annual evening noise impact	Using A-weighted curve	European standard to express noise level over the evening period (EC Directive 2002/49/EC)	/
L_{dn}	Accounts for noise over the 24h day and night period, noise between 22h-7h is weighted by a 10 dB penalty before averaging	Using A-weighted curve	Used by the European Environment Agency	Metric for the EEA for noise threshold for health and wellbeing
L_{den}	**Annual A-weighted Equivalent Continuous Sound Level** combining Lday, Lnight, Levening, then weighted by a 5 dB penalty for the evening period and 10 dB for the night period, to give a single measure for annual noise impact	Using A-weighted curve	European standard (EC Directive 2002/49/EC) used in noise contour mapping and noise impact assessments	European standard for noise contour maps and impact assessments

2.3 Health impact noise metrics

Metrics focused on the health impacts of aircraft noise can be classified as single event metrics, cumulative/time-averaged noise metrics or a hybrid of both and are given in *Appendix I Table 12*.

Appendix I Table 12: Health impact noise metrics, from (Love, 2023).

Metric	Definition	Presence in EU legislation and policy	Use
%HA (time-averaged)	Percentage of the population **highly annoyed** by noise, assessed using a standardized scale. A self-reported metric which is a function of L_{den}	WHO environmental noise guidelines for the European Region. Evoked for EU regulation to measure health outcome	An objective measure of the health outcome of noise disturbance
%HSD (time-averaged)	Percentage of the population **highly sleep disturbed** by noise, assessed using a standardized scale. A self-reported metric which is a function of L_{night}	WHO environmental noise guidelines for the European Region. Evoked for EU regulation regarding sleep disturbance	Policy-relevant measure of the health outcome of noise on sleep and subsequent sleep and health impacts
N_x (hybrid)	**Number of events** that lead to noise levels being higher than x dB (e.g., N70, N65 or N60) This metric also needs a time frame.	WHO environmental noise guidelines for the European Region	Used occasionally in noise contour mapping and community compensation schemes
$N_{50}A_{70}$ Population indicator (hybrid)	Number of people exposed to more than 50 events per day, above 70 dB	Noted in European Aviation Environmental Report (2022)	Highlights vulnerable populations to aircraft noise disturbance around the airport

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Appendix II – Air pollution health effects

1 Evidence-based health indicators for air pollution exposure related to airport activities

Air pollution poses a major threat to human health and the environment. This report focuses on three key categories of air pollutants near airports:

- Standard air pollutants: well-established threats like $PM_{2.5}$ and NO_2 are closely monitored and regulated due to their known health risks. However, airport operations contribute little to ambient standard air pollution levels.
- Emerging pollutants: UFPs, a growing area of concern, are very small particles that may penetrate deep into the lungs, posing potential health risks. Airport operations contribute significantly to ambient UFP levels.
- Hazardous air pollutants (HAPs): although not directly linked to core airport operations, minimal amounts of HAPs may be present from aviation fuels and maintenance. These pollutants can cause serious health problems and require careful monitoring and mitigation strategies.

1.1 Ultrafine particles (UFP) as emerging air pollutants

The body of evidence regarding the burden of proof of health effects caused by UFP is growing and discussed in detail in the UFP report. To make a substantiated statement about the effects of UFP on health, it is necessary to consolidate the knowledge from different studies. To this end, we largely based ourselves on three consolidation reports: (I) the Integrated Science Assessment (ISA) on particulate matter published by the US Environmental Protection Agency (EPA) in 2019 (U.S. Environmental Protection Agency, 2019), (ii) the report 'Risico's van ultrafijnstof in de buitenlucht' (Risks of ultrafine particles in the outdoor air) published by the Dutch Health Council in 2021 (Gezondheidsraad, 2021) and (iii) the multi-year research program of the Dutch National Institute for Public Health and the Environment (RIVM) on the health risks of UFP around Schiphol airport (N. Janssen et al., 2022). To assess the burden of proof, the reports are based on the methodology used by the EPA which involves weighing the scientific evidence from experimental and epidemiological studies based on consistency (do multiple studies show similar results?), biological plausibility and uncertainties (such as chance of bias, exposure assessment, adjustment for confounders, etc.). The strength of the evidence from long-term studies weighs the most in the assessment; conclusions from short-term studies or experimental studies are often considered as supportive. The strength of evidence for a causal relationship between chronic UFP exposure and adverse health effects is according to the EPA's ISA. The five causality determinations include 'causal relationship', 'likely to be causal relationship', 'suggestive of, but not sufficient to infer, a causal relationship', 'inadequate to infer the presence or absence of a causal relationship' and 'not likely to be a causal relationship'. For the assessment of the acute UFP effects, the wording from the RIVM report on the short-term health effects of UFP around Schiphol Airport is used (N. A. H. Janssen et al., 2019).

Important to note is that epidemiological studies investigating the health effects of UFP exposure often face limitations in accurately assessing exposure levels. This contributes to a high degree of uncertainty in these findings, which would typically result in *low* or *very low* quality evidence according to the GRADE scoring system. There are two key challenges in UFP exposure assessment: (i) UFP concentrations can vary significantly within a short distance. For example, in studies of short-term effects, the exposure to UFP is often characterized based on only one or two central measurement points which might not capture this variability and accurately represent individual exposure levels, and (ii) there is no single, universally accepted definition or standardized measurement method for UFP. This inconsistency can make it difficult to compare findings across different studies. Furthermore, epidemiological studies often neglect the influence of other pollutants that co-occur with UFP, such as black carbon or NO_2. Without accounting for these co-pollutants, it becomes difficult to isolate the specific effects of UFP exposure. Given these limitations, this section emphasizes the “strength of evidence” as presented in the tables below, rather than the overall quality rating based on uncertainty. By focusing on the strength of the evidence rather than on the quality, we can highlight the weight and consistency of observed associations between UFP exposure and potential health effects, while acknowledging the limitations in exposure assessment.

Cardiovascular health – Studies *suggest* a link between UFP from aviation and cardiovascular health problems. A recent long-term cohort study (N. Janssen et al., 2022) conducted near Schiphol airport identified a *probable association* between chronic exposure to UFP from air traffic and *increased use of medication (incidence) for heart disease*, as well as *mortality due to cardiac arrhythmias*. No association was found with medication use for hypertension and mortality from cardiovascular disease (primary endpoint) and ischemic heart disease, stroke and cerebrovascular disease (secondary endpoints). In addition, they found a clear association with several measures examined in the Health Monitor (Gezondheidsmonitor, GGD), namely with heart attack and (medication use for) hypertension. In addition, there was a possible association with medication use for heart disease (prevalence) and stroke. Supporting these findings, short-term exposure studies conducted around Schiphol (Lammers et al., 2020) and Los Angeles Airport (Habre et al., 2018) demonstrated that UFP exposure can lead to *prolongation of the QTc interval* (an indicator of altered electrical activity in the heart) and *increased acute systemic inflammation*, respectively. These observed biological responses align with established cardiovascular concerns associated with UFP exposure. Furthermore, studies investigating ambient UFP (not solely from air traffic) have revealed associations with elevated risk of mortality from ischemic heart disease (Ostro et al., 2015) and increased risk of hypertension, heart failure and myocardial infarction (Bai et al., 2018).

Metabolic health – Currently, there is *inadequate* evidence for a potential link between long-term exposure to aviation-related UFP and metabolic disorders, such as diabetes. The study of long-term exposure around Schiphol Airport found *no association* between UFP exposure and *medication use for diabetes or mortality from the disease.* Within the population of Health Monitor participants, there was instead a clear relationship, both for self-reported diabetes and medication use for diabetes (N. Janssen et al., 2022). There is also a lack of unequivocal results on the effects of UFP in general on the metabolic system. Recent studies suggest a possible connection between higher UFP exposure and increased diabetes risk (Bai et al., 2018; Sørensen et al., 2022) or markers of insulin resistance (Zhang et al., 2021). Another study found a link between UFP and childhood overweight and obesity in school children (De Bont et al., 2019). It’s important to note that only one of these studies accounted for a possible effect of other important components of air pollution (Bai et al., 2018). Furthermore, research on short-term UFP exposure and metabolic health effects is currently lacking.

Respiratory health – *No indications* of long-term health effects of UFP from aviation on the respiratory system were found. The recent study examining long-term exposure to UFP from air traffic near Schiphol Airport (N. Janssen et al., 2022) found *no association with respiratory mortality, medication use for respiratory disease or self-reported respiratory problems in children and adults*. This suggests that chronic exposure to aviation-related UFP might not significantly impact overall respiratory health. In contrast, short-term exposure to UFP around Schiphol Airport may *exacerbate existing airway complaints* and *increase medication use for these conditions* (N. A. H. Janssen et al., 2019). Another study of short-term exposure to UFP around Los Angeles Airport found an association between UFP road traffic and *decreased lung function* and UFP air traffic and *increased systemic inflammation in adults with asthma*, which could further impact respiratory health (Habre et al., 2018). Although the evidence for long-term effects remains inconclusive, short-term exposure appears to be a potential trigger for respiratory issues, particularly for those already experiencing respiratory problems. Likewise, studies investigating total UFP exposure (not specifically from aviation) indicate that children with pre-existing respiratory conditions might be more susceptible to the negative effects of short-term UFP exposure as reflected by increased inflammatory markers in their airways and potentially lower lung function (Da Costa E Oliveira et al., 2019; Li et al., 2019).

Cognitive health – Current evidence *suggests* a link between UFP exposure and adverse effects on the neurological system. The long-term study by Janssen et al. (2022) also investigated the effects of UFP exposure near Schiphol Airport on the neurological system (N. Janssen et al., 2022). This research found *no clear link* between long-term UFP exposure from aviation and *increased mortality from neurological disorders (Parkinson, Alzheimer or dementia) and increased medication use for Parkinson's disease*. The results regarding *dementia* were more complex as medication use for dementia showed a potential association with UFP exposure. However, the study observed an unexpected inverse association with mortality from dementia. If UFP exposure truly increased dementia risk, one would expect higher mortality rates as well. This inconsistency requires further investigation to clarify the relationship. Moreover, the Schiphol study also found *no link* between UFP exposure and *perceived health and severe psychological stress or the use of antidepressiva*. A recent study identified a positive association between prenatal UFP air traffic exposure (measured as $PM_{0.1}$ mass concentration) and autism spectrum disorder diagnosis in children residing in California (Carter et al., 2023). Notably, the link remained after accounting for total UFP and $PM_{2.5}$ but weakened when adjusted for noise exposure. This suggests that airport noise during pregnancy might be a contributing factor alongside UFP. While research on UFP from air traffic and its effects on the neurological system is progressing, studies investigating the link between UFP exposure to UFP in general (all sources) and neurodegenerative disorders are currently lacking (for long-term UFP exposure) or inconclusive (for short-term UFP exposure).

Birth outcomes – While research is still developing, recent research *suggests* a potential association between long-term exposure to UFP and certain *birth outcomes*. This association appears to be particularly relevant for UFP originating from air traffic emissions. The long-term study around Schiphol Airport (N. Janssen et al., 2022) found a *possible link* with negative birth outcomes such as *preterm birth* and *small for gestational age*. They also report a *probable link* with *congenital anomalies*, and *no link* with low birth weight and the Apgar-score. While these associations were not statistically significant in the main analyses, some sensitivity analyses yielded positive results. In contrast, a study by Wing et al. (2020) examining the impact of UFP exposure near Los Angeles International Airport reported a statistically significant association with preterm birth, even after accounting for the influence of other pollutants like NO_2 and noise (Wing et al., 2020). Interestingly, UFP levels around Los Angeles were significantly higher compared to Schiphol Airport. However, when adjusted for this difference in concentration, the estimated effects on birth outcomes appeared to be similar in both locations. Several additional studies have explored the connection between general UFP exposure, not solely from air traffic, and birth outcomes. These studies present mixed results. A study in Toronto identified a potential link between prenatal UFP exposure and specific congenital heart defects (Lavigne et al., 2020). Additionally, research conducted in California reported associations between UFP exposure and increased risk of lower birth weight and preterm birth (O. Laurent et al., 2014, 2016a, 2016b). It's important to note that the association with preterm birth was only statistically significant in specific subgroups within these California studies. A recent study found a potential link between prenatal UFP exposure and preterm birth, but it did not account for the influence of other co-pollutants. Furthermore, another California study investigating the association between UFP exposure and preterm birth in different ethnic groups yielded inconclusive results (Riddell et al., 2022).

Total mortality – There are currently *no indications* to link long-term UFP exposure from air traffic with *overall mortality* (deaths from all natural causes). The long-term study around Schiphol Airport found *no clear association* between UFP exposure related to air traffic and *total mortality* (N. Janssen et al., 2022). Inconsistent evidence is present for the current research on general UFP exposure. An earlier cohort study in California reported no link between overall UFP exposure and total mortality (Ostro et al., 2015). However, it did identify a potential association with deaths specifically from ischemic heart disease. It is important to note that this analysis did not control for the influence of co-pollutants. Two more recent studies offer contrasting findings. A large US national study found a positive association between UFP exposure and both total mortality and cancer mortality (Pond et al., 2022). The association with mortality from cardiopulmonary disease was less consistent in this study. A Dutch study reported positive associations with UFP exposure linked to natural mortality and specifically, mortality from lung cancer (Bouma et al., 2023). The latter two studies hold particular significance because they found that the associations between UFP exposure and mortality remained statistically significant even after adjusting for other pollutants like $PM_{2.5}$ and NO_2 which strengthens the overall evidence base and *suggest* a link between UFP (in general) and total mortality.

Cancer – The long-term effects of UFP exposure from air traffic on cancer risk are still being explored, but there is currently *inadequate* evidence for a connection between both. The multi-year research program around Schiphol Airport did not find conclusive evidence (N. Janssen et al., 2022), but a new study sheds some light on this complex issue. A recent study by Wu et al. (2021) investigated the link between UFP air traffic exposure and cancer in different ethnic groups residing near Los Angeles International Airport (Wu et al., 2021). Intriguingly, they found a positive association with malignant brain cancer, but only in the subgroup of African Americans. This subgroup was also exposed to the highest levels of UFP. Notably, the study did not observe a link with meningioma, another type of brain tumour. It is important to note that this study involved a very small sample size (n=38), demanding further investigation with larger populations. A previous study explored the connection between exposure to total UFP (primarily from road traffic) and cancer and found a significant association with brain tumours (Weichenthal et al., 2020). Other studies did not find consistent links with lung or breast cancer. However, associations have been observed with prostate cancer and childhood cancers, although these findings may be coincidental and require further exploration.

1.2 Standard air pollutants

Here, we consider the quality of evidence relating standard air pollution exposure to health outcomes which were prioritized to inform the formulation of the updated air quality guidelines published in 2021 by the WHO (WHO, 2021). Organizations such as the EPA and the WHO provide extensive and comprehensive information on these effects. Although airport emissions might differ from other sources in terms of pollutant mix, chemical composition or particle size (especially for PM), the health effects of each pollutant remain the same. In other words, assuming identical pollutants (with no variations in characteristics), the same mass of a pollutant emitted from an airport will have the same health consequences as the same amount released from another source (or another airport).

Given the difficulty in achieving “high” quality evidence on the GRADE scale for environmental exposures (especially for noise), WHO used in its 2018 noise recommendations evidence of moderate quality as the basis for setting “strong” recommendations, which “can be adopted as policy in most situations” (WHO Regional Office for Europe, 2018). Below we give an overview of the health outcomes with a harmful effect and their quality of evidence (GRADE scoring) for aviation noise and air pollution.

The following health outcomes were prioritized to inform the formulation of the updated air quality guidelines published in 2021 by the WHO (WHO, 2021):

- All-cause (non-accidental) mortality;
- Cause-specific mortality, as per the International Statistical Classification of Disease and Related Health Problems, 10th edition (ICD-10): cardiovascular (ICD-10 codes I00-I99), lung cancer (ICD-10 codes C30-C39) and respiratory (ICD-10 codes J00-J99);
- Emergency room visits and hospital admissions related to asthma (ICD-10 code J45);
- Emergency room visits and hospital admissions related to IHD (ICD-10 codes I20-I25; ultimately restricted to myocardial infarction (ICD-10 codes I21-I22).

Appendix II Table 1: Summary of quality of evidence for health outcomes related to air pollution exposure.

Pollutant	Outcome	Quality of evidence	REF
Short-term			
	All-cause mortality		
PM_{10}		High	(Orellano et al., 2020)
$PM_{2.5}$		High	(Orellano et al., 2020)
NO_2 (24h)		High	(Orellano et al., 2020)
NO_2 (1h)		Moderate	(Orellano et al., 2020)
O_3		High	(Orellano et al., 2020)
SO_2 (24h)		High	(Orellano et al., 2021)
SO_2 (1h)		Low	(Orellano et al., 2021)
	Cardiovascular mortality		
PM_{10}		High	(Orellano et al., 2020)
$PM_{2.5}$		High	(Orellano et al., 2020)
	Respiratory mortality		
PM_{10}		High	(Orellano et al., 2020)
$PM_{2.5}$		High	(Orellano et al., 2020)
SO_2 (24h)		Moderate	(Orellano et al., 2021)
SO_2 (1h)		High	(Orellano et al., 2021)
	Cerebrovascular mortality		
PM_{10}		High	(Orellano et al., 2020)
$PM_{2.5}$		High	(Orellano et al., 2020)

Pollutant	Outcome	Quality of evidence	REF
	Emergency department visits and hospital admissions due to asthma		
O_3 (8h or 24h)		High	(Zheng et al., 2021)
O_3 (1h)		Moderate	(Zheng et al., 2021)
NO_2 (24h)		High	(Zheng et al., 2021)
NO_2 (1h)		Low	(Zheng et al., 2021)
SO_2 (24h)		Moderate	(Zheng et al., 2021)
SO_2 (1h)		Moderate	(Zheng et al., 2021)
	Emergency department visits and hospital admissions due to myocardial infarction		
CO		Moderate	(Lee et al., 2020)
Long-term			
	All-cause mortality		
PM_{10}		High	(Chen & Hoek, 2020)
$PM_{2.5}$		High	(Chen & Hoek, 2020)
NO_2		Moderate	(Huangfu & Atkinson, 2020)
O_3 (annual)		Low	(Huangfu & Atkinson, 2020)
O_3 (peak)		Moderate	(Huangfu & Atkinson, 2020)
	Respiratory disease mortality		
PM_{10}		High	(Chen & Hoek, 2020)
$PM_{2.5}$		Moderate	(Chen & Hoek, 2020)
NO_2		Moderate	(Huangfu & Atkinson, 2020)
O_3 (annual)		Low	(Huangfu & Atkinson, 2020)
O_3 (peak)		Low	(Huangfu & Atkinson, 2020)
	COPD mortality		
PM_{10}		Moderate	(Chen & Hoek, 2020)
$PM_{2.5}$		High	(Chen & Hoek, 2020)
NO_2		High	(Huangfu & Atkinson, 2020)
	Acute lower respiratory illness mortality		
$PM_{2.5}$		High	(Chen & Hoek, 2020)
NO_2		Moderate	(Huangfu & Atkinson, 2020)
	Lung cancer mortality		
PM_{10}		High	(Chen & Hoek, 2020)
$PM_{2.5}$		High	(Chen & Hoek, 2020)
	Circulatory disease mortality		
PM_{10}		Moderate	(Chen & Hoek, 2020)
$PM_{2.5}$		High	(Chen & Hoek, 2020)
	Ischemic heart disease mortality		
PM_{10}		Moderate	(Chen & Hoek, 2020)
$PM_{2.5}$		High	(Chen & Hoek, 2020)
	Stroke mortality		
PM_{10}		Low	(Chen & Hoek, 2020)
$PM_{2.5}$		High	(Chen & Hoek, 2020)

IHD: ischemic heart disease, COPD: chronic obstructive pulmonary disease, ALRI: acute lower respiratory illness, EDV: emergency department visit, HA: hospital admission

1.2.1 Cardiovascular outcomes

CO – Even brief exposures to CO can disrupt one's heart rate due to reduced oxygen in the blood (Warburton et al., 2019). For people with underlying heart disease, exposures can worsen symptoms and trigger irregular heartbeat, which increases the risk of cardiac-related death. The long-term effects of CO exposure on cardiovascular health are less clear. While some studies have investigated links between CO and heart attacks or strokes, more research is needed to draw definitive conclusions.

NO_2 – Studies suggest that exposure to NO_2 can affect cardiovascular health, both in the short-term and long-term. Short-term exposure may worsen existing heart problems, potentially increasing the risk of heart attacks and death from cardiac-related complications. Long-term exposure may contribute to the development of heart disease, which in turn could increase the risk of heart attacks and cardiac-related death.

O_3 – Evidence suggests that both short- and long-term exposure to O_3 may be linked to cardiovascular problems, although the evidence is not always consistent. Some studies have found associations between short-term O_3 exposure and impaired heart function, changes in heart rate variability, inflammation and oxidative stress. In addition, some evidence suggests a connection between long-term ozone exposure and increased blood pressure, hypertension and cardiovascular mortality. However, there is currently limited evidence for a direct link between ozone exposure and specific cardiovascular events such as heart disease, heart attack, heart failure or stroke.

PM_{10} – Coarse PM exposure can affect cardiovascular health, both in the short- and long-term. High levels of coarse PM for several days can slightly raise blood pressure in healthy people. For those with underlying cardiovascular disease, it can worsen symptoms like chest pain or shortness of breath, increase the risk of blood clots or heart attacks and even lead to death in the days following higher PM_{10} exposure. Long-term exposure over several years may contribute to a higher risk of developing heart disease, stroke and pulmonary embolism.

$PM_{2.5}$ – Exposure to fine PM is strongly linked to increased risk of cardiovascular and cerebrovascular problems, both in the short- and long-term. People with existing heart disease or high blood pressure are more susceptible to heart attacks, strokes and even deaths in the days following exposure to higher $PM_{2.5}$ levels. Even health individuals can experience temporary increases in blood pressure and heart rate variability after short-term exposure to elevated fine PM levels. Chronic exposure to even moderate levels of $PM_{2.5}$ can significantly increase the risk for developing heart disease and hypertension. This may lead to more heart attacks, strokes and cardiac-related deaths. People with underlying heart conditions are especially vulnerable to the harmful effects of $PM_{2.5.}$

SO_2 – The link between short-term SO_2 exposure and cardiovascular problems remains unclear. While some studies suggest a possibility of worsened heart disease, heart failure, heart attack risk and cardiac death following exposure, the evidence is inconclusive and other factors might be contributing. More research is needed to confirm these observations following short-term SO_2 exposure. Similarly, the long-term effects of SO_2 exposure on cardiovascular health are inconclusive. Some studies suggest a potential link to an increased risk of heart disease, heart attack, stroke and cardiac death. However, the evidence has been inconsistent and further evidence is crucial to understand any potential long-term impacts.

Appendix II Table 2: Cardiovascular health outcomes resulting from air pollution exposure, from (Johnson et al., 2020).

Cardiovascular health outcomes		
Pollutant	**Short-term exposure**	**Long-term exposure**
CO	Likely causal	Inadequate evidence
NO_2	Suggestive evidence	Suggestive evidence
O_3	Suggestive evidence	Suggestive evidence
$PM_{2.5}$	Causal	Causal
SO_2	Inadequate evidence	Inadequate evidence

1.2.2 Metabolic outcomes

NO_2 – Limited research exists on short-term NO_2 exposure and metabolism. However, studies suggest a potential link between long-term exposure and increased risk of metabolic problems, such as insulin resistance and type 2 diabetes.

O_3 – Studies suggest a possible link between short-term ozone exposure and changes in metabolism, such as increased blood sugar and insulin levels. The evidence for long-term ozone exposure is less conclusive and suggests a link with diabetes-related deaths.

PM_{10} – Studies suggest that long-term PM_{10} exposure may be linked to an increased risk of developing metabolic disorders, such as type 2 diabetes. Exposure over several years might result in higher chances of experiencing issues like elevated blood glucose levels and insulin resistance.

$PM_{2.5}$ – Evidence suggests a potential link between exposure to fine PM and an increased risk of metabolic problems, both in the short- and long-term. People with existing diabetes or metabolic conditions may experience worsened symptoms and require hospitalization following days with higher $PM_{2.5}$ levels. In addition, short-term exposure may lead to increased blood sugar and insulin levels even in healthy individuals. Long-term exposure to moderate levels of $PM_{2.5}$ over several years may result in a higher risk of developing metabolic syndrome and type 2 diabetes which can lead to higher rates of deaths related to metabolism and diabetes.

Appendix II Table 3: Metabolic health outcomes resulting from air pollution exposure, from (Johnson et al., 2020).

Metabolic health outcomes		
Pollutant	**Short-term exposure**	**Long-term exposure**
NO_2	Inadequate evidence	Suggestive evidence
O_3	Likely causal	Suggestive evidence
PM_{10}	NA	Suggestive evidence
$PM_{2.5}$	Suggestive evidence	Suggestive evidence

1.2.3 Respiratory outcomes

CO – Evidence suggests that short-term CO exposure may lead to respiratory effects. Exposure may worsen symptoms of asthma and COPD in affected populations. Exposure may have small impacts on lung function in the general population. Current evidence is inadequate for long-term CO exposure effects on respiratory functioning. Only a few studies examined CO's impact on allergy and asthma development and severity and alternative explanations were not ruled out when some impact on lung functioning was observed.

NO_2 – NO_2 exposure can harm the respiratory system, with both short-term and long-term effects. Short-term NO_2 exposure worsens asthma symptoms and can trigger attacks. Exposure may also contribute to respiratory symptoms and increase susceptibility to infections in healthy individuals. Exposure may worsen symptoms for people with allergies or COPD. In addition, short-term exposure increases the risk of death from respiratory problems for those with existing conditions. On the other hand, long-term NO_2 exposure likely increases the risk of developing asthma and may contribute to chronic respiratory problems.

O_3 – There is strong evidence that short-term exposure to O_3 can trigger respiratory problems. Multiple studies show a decline in lung function, even in healthy young adults, after short-term ozone exposure. In addition, short-term exposure can make people more susceptible to respiratory infections and worsen symptoms for those with existing conditions like asthma, COPD and allergies. This can lead to increased hospitalization and even death, especially for those with underlying respiratory problems. Long-term O_3 exposure forms also a concern for respiratory health, although the evidence is developing. Long-term exposure may be linked to the development of asthma in children and a worsening of symptoms in both children and adults with existing asthma. It might also increase susceptibility to respiratory infections and the development of allergies and COPD. While some studies suggest a link between long-term exposure and respiratory deaths, the evidence is currently inconsistent.

PM_{10} – While large coarse PM particles mostly get trapped in the upper airways (nose and throat), some can reach your lungs. This can cause irritation and lead to respiratory problems, especially for people with asthma. In this regard, short-term PM exposure to high levels of coarse PM has been linked to more asthma attacks. The evidence is less conclusive on whether coarse PM exacerbates COPD symptoms directly. However, it may increase susceptibility to respiratory infections. This can be particularly dangerous for people with existing respiratory illnesses, who may be more likely to experience breathing difficulties or even death on days with high PM_{10} levels. While some studies suggest a possible link between long-term PM_{10} exposure and respiratory problems, the evidence is currently inadequate to be conclusive. Exposure over several years has been suggested to lead to reduced lung function, asthma development, and susceptibility to respiratory infections among children. However, other factors could also contribute to these health problems.

$PM_{2.5}$ – While the 2009 and 2019 ISAs conclude that $PM_{2.5}$ *likely* causes respiratory effects, many experts agree that the evidence is compelling and points towards a causal relationship between $PM_{2.5}$ exposure and respiratory outcomes, both in the short- and long-term. Fine PM can irritate the lungs and worsen existing respiratory problems. During days of higher $PM_{2.5}$ levels people with asthma are more likely to experience attacks and people with COPD or allergies may have worsened symptoms. Those with underlying respiratory illnesses are at higher risk of breathing difficulties or even death. Long-term effects from moderate $PM_{2.5}$ exposure over years include increased risk of respiratory infections and higher rates of respiratory-related death. Moreover, long-term exposure to moderate levels of fine PM can increase children's risk of developing asthma or hinder their lung development.

SO_2 – Short-term exposure to SO_2 is known to harm the respiratory system. The strongest evidence is for asthma exacerbation. Short-term exposure can also decrease lung function in people with underlying respiratory problems, potentially increasing their risk of death from respiratory issues. Long-term SO_2 exposure may also contribute to respiratory problems, although the evidence is still developing. Long-term exposure might be linked to the development of asthma in children, worsen asthma severity in all ages and increased susceptibility to allergies, respiratory infection and even respiratory-related death.

Appendix II Table 4: Respiratory health outcomes resulting from air pollution exposure, from (Johnson et al., 2020).

Respiratory health outcomes		
Pollutant	**Short-term exposure**	**Long-term exposure**
CO	Suggestive evidence	Inadequate evidence
NO_2	Causal	Likely causal
O_3	Causal	Likely causal
PM_{10}	Suggestive evidence	Inadequate evidence
$PM_{2.5}$	Causal	Causal
SO_2	Causal	Suggestive evidence

1.2.4 Cognitive outcomes

CO – Studies suggest that short-term CO exposure may trigger inflammation in the brain, potentially leading to an increase in depression symptoms. Moreover, there is evidence suggesting a link between long-term CO exposure and an increased risk of developing Parkinson's disease and dementia.

NO_2 – While the link between short-term NO_2 exposure and nervous system effects remain unclear, some studies suggest a potential connection. A few studies have linked short-term exposure to brain inflammation, which might be associated with depression symptoms. On the other hand, there is growing evidence for long-term NO_2 exposure impacting the nervous system. Some evidence suggests a potential association between prenatal NO_2 exposure and an increased risk of autism spectrum disorder in children. Longer-term NO_2 exposure might in turn be linked to dementia, Parkinson's disease and cognitive decline.

O_3 – Evidence suggests potential impacts of both short- and long-term ozone exposure on the nervous system. Some evidence suggests a possible link between short-term exposure and increased depressive symptoms. Stronger evidence exists for the potential effects of long-term O_3 exposure on cognitive function. However, the evidence is still limited regarding the link to depression, neurodegenerative diseases (e.g., Alzheimer's) or autism spectrum disorder.

PM_{10} – The impact of short-term PM_{10} exposure on the central nervous system remains unclear due to inadequate evidence. While a single study suggests that exposure may trigger a stress response and increase stress-related chemicals in the brain, more research is required to confirm this finding. Concerning long-term PM_{10} exposure, studies suggest a possible connection with increased rates of anxiety, depression and cognitive decline in adults.

$PM_{2.5}$ – Long-term exposure to fine PM likely causes nervous system problems, particularly in older adults. Studies suggest a possible link between long-term $PM_{2.5}$ exposure and higher rates of dementia and cognitive decline among elderly. There is also some evidence suggesting short-term $PM_{2.5}$ exposure may affect the nervous system. People with Parkinson's disease may experience worsened symptoms on days with higher $PM_{2.5}$ levels. Moreover, short-term $PM_{2.5}$ exposure might trigger a stress response, leading to elevated cortisol levels in some individuals.

SO_2 – The potential effects of SO_2 exposure on the nervous system are unclear. While a few studies suggest a possible link between SO_2 exposure and depression symptoms, the evidence is very limited. More research is needed to determine if a connection exists.

Appendix II Table 5: Cognitive health outcomes resulting from air pollution exposure, from (Johnson et al., 2020).

Cognitive health outcomes		
Pollutant	**Short-term exposure**	**Long-term exposure**
CO	Suggestive evidence	Suggestive evidence
NO_2	Inadequate evidence	Suggestive evidence
O_3	Suggestive evidence	Suggestive evidence
PM_{10}	Inadequate evidence	Suggestive evidence
$PM_{2.5}$	Suggestive evidence	Likely causal
SO_2	Inadequate evidence	Inadequate evidence

1.2.5 Birth and reproductive outcomes

CO – Evidence suggests that long-term exposure to CO may lead to lead to effects on pregnancy and birth outcomes. This potential risk includes: (i) increased chances of low birth weight and premature birth, (ii) higher risk of stillbirth and heart defects in newborns and (iii) greater likelihood of infant mortality. Prenatal exposure to CO during pregnancy might also be linked to development of autism spectrum disorder as well as increased risk of gestational diabetes.

NO_2 – Some evidence suggests that NO_2 exposure during early pregnancy might slightly increase the risk of gestational diabetes. The link between long-term NO_2 exposure and fertility or reproduction is unclear. While some limited studies suggest a possible impact on sperm count and quality due to inflammation and oxidative stress, the findings are inconclusive, and more research is needed.

O_3 – Some studies suggest that gestational exposure to ozone during the first and second trimesters of pregnancy might be linked to lower birth weight and preterm birth. However, other factors could be contributing to these outcomes and further research is necessary to confirm a direct link with O_3 exposure. Moreover, limited evidence suggests a possible connection between long-term ozone exposure and sperm quality. Likewise, other factors might also be at play.

PM_{10} – Studies suggest that coarse PM exposure during pregnancy may be linked to birth outcomes. There is evidence suggesting an association between PM_{10} exposure and increased risk of preterm birth and lower birth weight. However, other factors might also contribute to these outcomes. There is limited and inconclusive evidence for effects on preeclampsia and some birth defects. A few studies suggest a possible link between PM_{10} exposure and infant death from respiratory problems, but further investigation is necessary. Currently, there is not enough evidence to determine a clear link between PM_{10} exposure and effects on reproduction and fertility. While some hypothesize a possible connection to infertility, endometriosis and reduced birth rates, only a few studies have investigated these outcomes.

$PM_{2.5}$ – Gestational exposure to $PM_{2.5}$ is a growing concern for pregnant people as it may be linked to various birth complications. Studies suggest an association between long-term fine PM exposure and (i) increased rates of preeclampsia and gestational diabetes, (ii) lower birth weight and preterm birth, (iii) some birth defects and (iv) higher occurrences of foetal death, stillbirth and infant death. While some limited studies suggest potential effects of $PM_{2.5}$ exposure on sperm, eggs, ovulation and erectile dysfunction, more research is needed to conform a clear link with fertility problems.

SO_2 – The link between SO_2 exposure and pregnancy and birth outcomes remains unclear. Some studies suggest a possible association with an increased risk of preterm birth, but major uncertainties remain. Limited evidence exists for potential impacts on birth weight, gestational diabetes, pregnancy loss, birth defects and infant death. However, these findings are inconsistent and other factors might be contributing demanding for further research. Similarly, the potential effects of SO_2 exposure on reproduction and fertility are inconclusive. A few studies hint at a possible connection with sperm quality and reduced conception rates. However, major uncertainties remain, and more research is crucial to understand these potential links.

Appendix II Table 6: Birth and reproductive health outcomes resulting from air pollution exposure, from (Johnson et al., 2020).

	Birth outcomes	Reproductive health outcomes
Pollutant	**Long-term exposure**	
CO	Suggestive evidence	NA
NO_2	Suggestive evidence	Inadequate evidence
O_3	Suggestive evidence	Suggestive evidence
PM_{10}	Suggestive evidence	Inadequate evidence
$PM_{2.5}$	Likely causal	Suggestive evidence
SO_2	Inadequate evidence	Inadequate evidence

1.2.6 Cancer and general health outcomes

NO_2 – Evidence suggests a possible link between long-term NO_2 exposure and lung cancer. Other cancers (i.e., brain, breast, cervical, prostate, bladder and leukaemia) may also be associated with exposure, but the evidence is very limited at this time.

O_3 – The link between long-term ozone exposure and cancer risk remains unclear. While some studies suggest ozone exposure can cause DNA damage, a known risk factor for cancer, more research is required to understand the long-term consequences to human health. In addition, a few studies have explored a possible connection with lung cancer, but the populations studied were not representative of the general population, limiting their applicability. Currently, there is no evidence suggesting an association between long-term O_3 exposure and other types of cancer.

PM_{10} – Some studies have shown higher rates of lung cancer in areas with higher levels of PM_{10}. Limited evidence from two studies suggests a possible association between higher PM_{10} exposure and breast and liver cancers. Some animal studies show that PM_{10} exposure may alter brain gene expression and potentially lead to brain tumour formation, but further investigation is needed to confirm this in humans.

$PM_{2.5}$ – Studies suggest a possible link between long-term exposure to $PM_{2.5}$ and an increased risk of lung cancer. Populations exposed to moderate levels of $PM_{2.5}$ over several years have higher rates of lung cancer and lung cancer-related deaths. The evidence for other cancers is limited. While research suggests $PM_{2.5}$ might decrease survival rates for some existing cancers, more investigation is needed to confirm this.

SO_2 – The link between SO_2 exposure and cancer risk remains unclear. While a few studies suggest a possible connection to lung cancer and an increased risk of death among people with existing bladder cancer, the overall evidence is inconsistent. More research is needed to address these inconsistencies.

Appendix II Table 7: Cancer outcomes resulting from air pollution exposure, from (Johnson et al., 2020).

Cancer	
Pollutant	**Long-term exposure**
NO_2	Suggestive evidence
O_3	Inadequate evidence
PM_{10}	Suggestive evidence
$PM_{2.5}$	Likely causal
SO_2	Inadequate evidence

1.3 Hazardous air pollutants (HAP)

Table 5 (main text) highlights the potential health effects of HAPs. The listed health effects are based on reviews by EPA, WHO and the Centres for Disease Control and Prevention (CDC), along with other systematic reviews of ambient HAP exposures. The current understanding of health risks from airport-related HAP exposure comes primarily from controlled animal studies and occupational studies. Formaldehyde has the largest evidence base. Extensive research, including epidemiological studies have been conducted on its health effects. However, a major knowledge gap remains as we did not find significant studies examining the health impacts of chronic, low-level HAP exposure on communities living near airports. This lack of data makes it difficult to definitively link HAP exposure to specific health problems and to inform causal judgements as were described for the other air pollutants.

The Environmental Protection Agency (EPA) and World Health Organization (WHO) classify hazardous air pollutants (HAPs) based on the strength of scientific evidence linking them to cancer. In some cases, the WHO has a stricter classification than the EPA. Among HAPs, formaldehyde is the most concerning for cancer risk. Chronic exposure to outdoor formaldehyde is linked to over half of nationwide cancer cases attributed to outdoor HAPs (A. Laurent & Hauschild, 2014; Scheffe et al., 2016). Acetaldehyde, benzene, naphthalene, and 1,3-butadiene are also significant cancer risks. While evidence for crotonaldehyde, isopropyl benzene, 1-methylnaphthalene and 2-methylnaphthalene causing cancer is limited, they remain a serious health concern. While carcinogenicity is a major concern, it is important to understand the various adverse effects HAPs can have on different organ systems. These effects (e.g., respiratory problems, cardiovascular issues) can significantly impact quality of life and contribute to a variety of health problems, even if the evidence for cancer is less conclusive.

1.3.1 Acetaldehyde

Acetaldehyde is mainly used as in intermediate in the synthesis of other chemicals. It is ubiquitous in the environment and may be produced in the body from the breakdown of alcohol (i.e., ethanol). Acute health effects of acetaldehyde include irritation of the eyes, skin and respiratory tract which can cause symptoms like burning, redness and difficulty breathing. Chronic exposure to acetaldehyde, often through heavy alcohol consumption, can lead to health problems like those seen in alcoholism. While evidence from human studies is limited, acetaldehyde is classified as a **probable human carcinogen** by the EPA and WHO (US EPA, n.d.). This classification is primarily based on animal studies showing nasal tumours in rats and laryngeal tumours in hamsters. The RfC for acetaldehyde is 0.009 milligrams per cubic meter and is based on the degeneration of olfactory epithelium in rats. In addition, acetaldehyde associated with the consumption of alcoholic beverages was evaluated by the WHO IARC as carcinogenic to humans based on sufficient epidemiological evidence showing that humans who are deficient in the oxidation of acetaldehyde to acetate have a substantially increased risk for the development of alcohol-related cancers, in particular cancers of the oesophagus and the upper aerodigestive tract.

1.3.2 Acrolein

Acrolein is primarily used as an intermediate in the synthesis of acrylic acid and as a biocide. It may be formed from the breakdown of certain pollutants in outdoor air or the burning of organic matter including tobacco, or fuels such as gasoline or oil. It is toxic to humans following inhalation, and oral or dermal exposures. Acute (short-term) inhalation exposure may result in upper respiratory tract irritation and congestion. No information is available on its reproductive, developmental, or carcinogenic effects in humans, and the existing animal cancer data are considered inadequate by the EPA to decide that acrolein is carcinogenic to humans. The WHO on the other hand classifies acrolein as **a probable human carcinogen** (IARC, 2021). The rationale for this evaluation is based on (i) sufficient evidence of cancer in experimental animals (increased incidence of either malignant neoplasms or of an appropriate combination of benign and malignant neoplasms in two species) and (ii) strong mechanistic evidence as acrolein exhibits multiple key characteristics of carcinogens (e.g., genotoxic, alters DNA repair, immunosuppressive, etc.) (Marques et al., 2021).

1.3.3 Benzene

Benzene is a chemical found in the air from various sources like coal and oil burning, gas stations and car exhaust. Acute inhalation exposure of humans to benzene can irritate the eyes, skin and respiratory system. At high concentrations, it can also cause dizziness, drowsiness, headaches and even unconsciousness. Chronic exposure to benzene, particularly in occupational settings, has been linked to various blood disorders. This includes a decrease in red blood cell count and a serious condition called aplastic anaemia, which affects bone marrow function. Reproductive effects have been reported for women exposed by inhalation to high levels, and adverse effects on the developing foetus have been observed in animal tests. Increased incidence of leukaemia has been observed in humans occupationally exposed to benzene. EPA and WHO have classified benzene as a **known human carcinogen** for all routes of exposure. The RfC for benzene is 0.03 milligrams per cubic meter based on haematological effects in humans.

1.3.4 1,3-Butadiene

1,3-Butadiene is a gas used in the production of various products like rubber, plastics and resins. It is primarily released into our environment through car exhaust and tobacco smoke. Although 1,3-butadiene breaks down quickly in the atmosphere, it is usually found in ambient air at low levels in urban and suburban areas. Both the US EPA and WHO classify 1,3-butadiene as a human carcinogen based on the combined weight of evidence from various studies (IARC, 2008; US EPA, n.d.). Evidence supporting this classification includes:

- Occupational studies of US workers exposed to 1,3-butadiene (inhalation of either the monomer or polymer) show an increased risk of cancers affecting the blood and lymphatic system (i.e., lymphohematopoietic cancers). Notably, there’s a clear dose-response relationship for leukaemia in workers exposed to the polymer form;
- Animal studies on mice and rats exposed to 1,3-butadiene by inhalation provide convincing evidence that it causes tumours at various sites in their bodies. Animal studies indicate that 1,3-butadiene can cause various reproductive and developmental problems in mice. No human data is currently available for these effects. Based on the most sensitive effect observed, namely ovarian atrophy in female mice, a safe chronic exposure level (RfC) of 0.002 milligrams per cubic meter was calculated to minimize non-cancer health risks. In addition, animal studies suggest females might be more susceptible to cancer from 1,3-butadiene exposure. However, data is limited to draw definitive conclusions about sensitive subpopulations within the human population;
- Numerous studies demonstrate that both animals and humans metabolize 1,3-butadiene into chemicals that damage genetic material. These genotoxic metabolites, including monoepoxide, diepoxide and epoxydiol, are strongly believed to be responsible for the carcinogenic effects of 1,3-butadiene, although the exact mechanisms remain under investigation.

Short-term effects of inhalation of 1,3-butadiene in humans include irritation of the eyes and respiratory system while long-term effects include an increased risk of heart disease and leukaemia.

1.3.5 Crotonaldehyde

Crotonaldehyde or 2-butenal is a reactive aldehyde with a high production volume which is widely used for synthesizing chemical agents used in various industries (e.g., pharmaceuticals, rubber, chemicals, food, etc.). In addition, crotonaldehyde is also found in tobacco smoke and overheated cooking oils. Crotonaldehyde is classified as **possibly carcinogenic to humans** by the EPA and WHO based on strong mechanistic evidence. Research using human primary cell lines and various experimental systems indicates that crotonaldehyde exhibits several key characteristics of carcinogens. These include (i) an electrophilic nature by which it can readily react with cellular components, (ii) genotoxicity, (iii) induction of oxidative stress and (iv) promotion of chronic inflammation. While concerning, evidence from animal experiments on carcinogenicity is limited. Moreover, there is currently no data on whether crotonaldehyde directly causes cancer in humans (Marques et al., 2021). Accordingly, there is no health advisory value or reference value available but an indicative threshold value (based on 'lowest concentration of interest') of 5 µg/m^3 is set forward (*Agreed EU-LCI Values (December 2022)*, n.d.).

1.3.6 Ethylbenzene

Ethylbenzene is mainly used in the manufacture of styrene. Acute (short-term) exposure to ethylbenzene in humans results in respiratory effects, such as throat irritation and chest constriction, irritation of the eyes, and neurological effects such as dizziness. Chronic (long-term) exposure to ethylbenzene by inhalation in humans has shown conflicting results regarding its effects on the blood. Animal studies have reported effects on the blood, liver, and kidneys from chronic inhalation exposure to ethylbenzene. Limited information is available on the carcinogenic effects of ethylbenzene in humans. In a study by the National Toxicology Program (NTP), exposure to ethylbenzene by inhalation resulted in an increased incidence of kidney and testicular tumours in rats, and lung and liver tumours in mice. EPA has classified ethylbenzene as not classifiable as to human carcinogenicity. WHO on the contrary classified it as a **possible human carcinogen** as it induces tumours in rats and mice, but neither the relevance of these tumours to humans nor their mechanism of induction is clear (Henderson et al., 2007).

1.3.7 Formaldehyde

Formaldehyde is a widely used chemical, primarily found in resins for wood products and as a building block for other chemicals. Exposure to formaldehyde may occur by breathing contaminated indoor air, tobacco smoke or ambient urban air. Both acute and chronic inhalation exposure to formaldehyde can irritate the respiratory system, eyes, nose and throat. When chronically inhaled, formaldehyde can cause inflammation, oxidative stress and genotoxicity possible leading to cancer. While evidence is limited, human studies have shown cancers in the nose and throat, but there is also evidence for leukaemia and possibly lung cancer. In addition, animal studies have reported an increased incidence of nasal squamous cell cancer following exposure to formaldehyde through inhalation (IARC, 2004, 2006). While the EPA considers formaldehyde as a **probable human carcinogen**, the National Academy of Sciences has agreed with the WHO and formally concluded that inhaled formaldehyde is **a known human carcinogen** (National Academies of Sciences, Engineering, and Medicine, 2014).

1.3.8 Isopropyl benzene

Isopropyl benzene (or cumene) is a colourless liquid with low water solubility which is used as an intermediate to produce phenol, acetone and in smaller amounts as a solvent or additive in aviation fuels. Acute inhalation exposure to isopropyl benzene may cause headaches, dizziness, drowsiness, lack of coordination and unconsciousness (in high doses). Isopropyl benzene irritates the skin and eyes and acts as a central nervous system depressant. There is limited data on the long-term effects of isopropyl benzene exposure in humans. Animal studies suggest potential damage to the liver, kidneys and adrenal glands. The impact of isopropyl benzene on human cancer is unclear. It is concluded by the EPA that the carcinogenic potential of isopropyl benzene cannot be determined because no adequate data, such as well-conducted long-term animal studies or reliable human epidemiological studies, are available for any assessment (IARC, 2013). On the other hand, the WHO concludes there is sufficient evidence in experimental animals for the carcinogenicity of isopropyl benzene and evaluates that it is **possibly carcinogenic to humans**.

1.3.9 Methanol

Methanol is released to the environment during industrial uses and naturally from volcanic gases, vegetation, and microbes. Exposure may occur from ambient air and during the use of solvents. Acute (short-term) or chronic (long-term) exposure of humans to methanol by inhalation or ingestion may result in blurred vision, headache, dizziness, and nausea. No information is available on the reproductive, developmental, or carcinogenic effects of methanol in humans. Birth defects have been observed in the offspring of rats and mice exposed to methanol by inhalation. EPA has not assessed methanol with respect to carcinogenicity under the IRIS program and it has been assigned a low priority by the WHO IARC Monographs program 2020-2024 (IARC, 2019b).

1.3.10 Naphthalene

Exposure to **naphthalene**, **1-methylnaphthalene**, or **2-methylnaphthalene** happens mostly from breathing air contaminated from the burning of wood, tobacco or fossil fuels, industrial discharges, or moth repellents. High levels of naphthalene can damage red blood cells, potentially leading to anaemia. Naphthalene is a chemical used in various products; it is a white solid that evaporates easily. It is found in mothballs and is produced during burning of coal, tobacco and wood. Exposure to naphthalene can occur through inhalation, ingestion or skin contact. Short-term effects include haemolytic anaemia, liver and nervous system damage. Cataracts have also been reported in workers with high exposure by inhalation and ingestion to naphthalene. In addition, chronic exposure of workers and rodents to naphthalene has been reported to cause cataracts and damage to the retina. Infants born to mothers who used mothballs during pregnancy may develop haemolytic anaemia. While there is currently not enough evidence to definitively link naphthalene exposure to cancer in humans, the data is inconclusive. Due to this uncertainty, the EPA and WHO classify **naphthalene** as a **possible human carcinogen**. The RfC of 0.003 milligrams per cubic meter for naphthalene was based on nasal effects in mice while the RfD for naphthalene of 0.02 milligrams per kilogram body weight per day based on decreased body weight in male rats.

1-Methylnaphthalene and 2-methylnaphthalene are naphthalene-related compounds. 1-Methylnaphthalene is a clear liquid and 2-methylnaphthalene is a solid. They are used to make dyes, resins and vitamin K (2-methylnapthalene). No data are available on the potential toxicity in exposed humans via the oral route. However, animal studies suggest that the lungs are a primary target for harm after long-term oral exposure to 2-methyl naphthalene and chronic dermal exposure to methylnaphthalene mixtures. These studies observed pulmonary alveolar proteinosis, characterized by a buildup of protein and fatty material in the pulmonary alveoli. Since a similar lung condition of unknown aetiology exists in humans, it is anticipated that humans exposed to 2-methyl naphthalene may also develop pulmonary alveolar proteinosis. Symptoms include shortness of breath and cough, but not necessarily breathing problems. The effects of chronic inhalation of 1-methylnapthalene or 2-methylnaphthalene have not been studies in humans or animals. To date, the available data are inadequate to determine if 1-methylnapthalene or 2-methylnaphthalene causes cancer in humans. One animal study showed an increased number of lung tumours in male mice exposed through diet, but the relevance to humans and the reasons for this increase are unclear. No other animal studies have been conducted. Results from short-term genotoxicity tests provide no supporting evidence for the carcinogenicity of 1-methylnapthalene or 2-methylnaphthalene. As such, the **available evidence** of **1-methylnapthalene** or **2-methylnaphthalene is limited and insufficient to determine** that 1-methylnapthalene or 2-methylnaphthalene is **carcinogenic to humans**. The RfD of 0.004 milligram per kilogram per day is based on pulmonary alveolar proteinosis in mice exposed to 2-methylnaphthalene in the diet for 81 weeks.

1.3.11 Xylenes

Commercial or mixed **xylene (m-xylene, p-xylene, o-xylene)** usually contains about 40-65% m-xylene and up to 20% each of o-xylene and p-xylene and ethylbenzene. Xylenes are released into the atmosphere as fugitive emissions from industrial sources, from auto exhaust and through volatilization from their use as solvents. Acute (short-term) inhalation exposure to mixed xylenes in humans results in irritation of the eyes, nose, and throat, gastrointestinal effects, eye irritation, and neurological effects. Chronic (long-term) inhalation exposure of humans to mixed xylenes results primarily in central nervous system (CNS) effects, such as headache, dizziness, fatigue, tremors, and incoordination. In addition, respiratory, cardiovascular and kidney effects have also been reported. EPA and WHO both classify mixed xylenes as **not classifiable as to human carcinogenicity** (IARC, 1999b).

1.3.12 Phenol

Exposure to **phenol** may occur from the use of some medicinal products (including throat lozenges and ointments). Phenol is highly irritating to the skin, eyes and mucous membranes in humans after acute (short-term) inhalation or dermal exposures. Phenol is considered to be quite toxic to humans via oral exposure. Anorexia, progressive weight loss, diarrhoea, vertigo, salivation, a dark coloration of the urine, and blood and liver effects have been reported in chronically (long-term) exposed humans. Animal studies have reported reduced foetal body weights, growth retardation and abnormal development in the offspring of animals exposed to phenol by the oral route. EPA and WHO both have classified phenol **not classifiable as human carcinogenic** (IARC, 1999a).

1.3.13 Propionaldehyde

Propionaldehyde is used in the manufacture of plastics, in the synthesis of rubber chemicals, and as a disinfectant and preservative. Limited information is available on the health effects of propionaldehyde. No information is available on the acute (short-term), chronic (long-term), reproductive, developmental or carcinogenic effects of propionaldehyde in humans. Animal studies have reported that exposure to high levels of propionaldehyde, via inhalation, results in anaesthesia and liver damage, and intraperitoneal exposure results in increased blood pressure. EPA and WHO have **not classified propionaldehyde for carcinogenicity**.

1.3.14 Styrene

Styrene is primarily used in the production of polystyrene plastics and resins. Acute (short-term) exposure to styrene in humans results in mucous membrane and eye irritation, and gastrointestinal effects. Chronic (long-term) exposure to styrene in humans results in (i) effects on the central nervous system (CNS), such as headache, fatigue, weakness and depression, (ii) CSN dysfunction, (iii) hearing loss and (iv) peripheral neuropathy. Human studies are inconclusive on the reproductive and developmental effects of styrene; several studies did not report an increase in developmental effects in women who worked in the plastics industry, while an increased frequency of spontaneous abortions and decreased frequency of births were reported in another study. Several epidemiologic studies suggest there may be an association between styrene exposure and an increased risk of leukaemia and lymphoma. However, the evidence is inconclusive due to confounding factors. EPA has not given a formal carcinogen classification to styrene. The WHO (IARC) classifies styrene as **probably carcinogenic to humans**. This is based on (i) limited evidence in humans where positive associations have been observed between exposure to styrene and lymphohematopoietic malignancies and (ii) sufficient evidence in experimental animals (IARC, 2019a).

1.3.15 Toluene

Toluene is added to gasoline, used to produce benzene, and used as a solvent. Exposure to toluene may occur from breathing ambient or indoor air affected by such sources. The central nervous system (CNS) is the primary target organ for toluene toxicity in both humans and animals for acute (short-term) and chronic (long-term) exposures. CNS dysfunction and narcosis have been frequently observed in humans acutely exposed to elevated airborne levels of toluene; symptoms include fatigue, sleepiness, headaches and nausea. CNS depression has been reported to occur in chronic abusers exposed to high levels of toluene. Chronic inhalation exposure of humans to toluene also causes irritation of the upper respiratory tract and eyes, sore throat, dizziness and headache. Human studies have reported developmental effects, such as CNS dysfunction, attention deficits, and minor craniofacial and limb anomalies, in the children of pregnant women exposed to high levels of toluene or mixed solvents by inhalation. EPA and WHO have concluded that that there is **inadequate information to assess the carcinogenic potential** of toluene.

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Report Work Package 2

Modelling and measurements of environmental stressors around airports

Aims and objectives of Work Package 2

The primary objective of this work package is to offer a concise description of existing models and measurement campaigns for stressors that have been identified in the literature review concerning risk-outcome pairs and their strength of evidence in Work Package (WP) 1. Additionally, it aims to conduct a gap analysis to identify knowledge gaps in modelling and measuring stressors around airports.

For stressors that are already addressed around the Brussels Airport with state-of-the-art modelling and monitoring networks, our focus will primarily be on existing work specific to Brussels Airport. For these stressors, only a succinct overview of relevant studies at other airports will be provided when necessary. Conversely, for stressors with identified modelling and measurement gaps at Brussels Airport, we will also offer a brief review of studies conducted at other airports. This approach will serve as a source of inspiration for replicating or adapting studies at the Brussels Airport.

This analysis encompasses the four categories of stressors outlined in the first work package: **noise**, **standard air pollutants** (NO_2, PM_{10}, $PM_{2.5}$, BC, Pb, benzo(a)pyrene), emerging pollutants (ultrafine particles '**UFP**') and Hazardous Air Pollutants (**HAPs**) (i.e., relevant substances of very high concern cfr. Flemish and Dutch framework, and substances classified as hazardous under the Clean Air Act by the U.S. Environmental Protection Agency (EPA).

The subsequent sections will present the findings per stressor, distinguishing between existing modelling and measurement efforts and conducting a gap analysis for each specific stressor. We will conclude with a summary of the most significant knowledge gaps identified, providing a foundational basis for planning future studies.

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List of acronyms

1 Noise

1.1 Existing modelling

1.1.1 Brussels airport

Modelling the noise pollution from airplanes has been the subject of several official reports. The European Union (EU) Environmental Noise Directive[1] (Directive 2002/49/EC) has mandated member states to model noise around airports since 2002, utilizing strategic noise mapping that includes the indicators L_{den} and L_{night}. The noise maps are constructed post ante, utilizing detailed information on flight movements and the aircraft fleet of the last year. Annually, contours are calculated on behalf of Brussels Airport Company (BAC) and reported to the competent authorities[2]. The reported maps include:

- L_{den} noise contours of 55, 60, 65, 70 and 75 A-weighted decibels (dB(A)) to represent the sound exposure over a 24-hour period. To obtain these maps, the mean noise level over an average 24-hour period in the year is calculated. There is no further distinction between days with low and high noise pollution for this statistic.
- L_{day} noise contours of 55, 60, 65, 70 and 75 dB(A) for depicting daytime noise exposure, with the day period defined from 7:00 to 19:00. To obtain these maps, the mean noise level over an average day period in the year is calculated. There is no further distinction between days with low and high noise pollution for this statistic.
- $L_{evening}$ noise contours of 50, 55, 60, 65, 70 and 75 dB(A) for illustrating evening noise exposure, with the evening period defined from 19:00 to 23:00. To obtain these maps, the mean noise level over an average evening period in the year is calculated. There is no further distinction between days with low and high noise pollution for this statistic.
- L_{night} noise contours of 45, 50, 55, 60, 65 and 70 dB(A) for a depiction of nighttime noise, with the night defined from 23:00 to 7:00. To obtain these maps, the mean noise level over an average night period in the year is calculated. There is no further distinction between days with low and high noise pollution for this statistic.
- Frequency contours[3] for 70 dB(A) and 60 dB(A). These frequency contours report the regions in which the noise level thresholds are exceeded during a fixed number of times during an average day of the year. In detail, the following contours are composed:
    - Frequency contours for 70 dB(A) during the day period (07:00 to 23:00) with frequencies of 5x, 10x, 20x, 50x and 100x.
    - Frequency contours for 70 dB(A) during the night period (23:00 to 07:00) with frequencies of 1x, 5x, 10x, 20x and 50x.
    - Frequency contours for 60 dB(A) during the day period (07:00 to 23:00) with frequencies of 50x, 100x, 150x and 200x.

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[1] This regulation has also been incorporated into the VLAREM regulations since 2005, specifying the computational method to be used for noise contour calculation.

[2] The L_{den}, L_{day}, $L_{evening}$ and L_{night} contours are publicly only provided with a 5dB resolution, but in recent years they have been constructed as will with a 1dB interval. Only polygon information is available, but these datasets can easily be converted in GeoTIFF maps.

[3] While there is no legal obligation under VLAREM to include these maps, they are required by the current permit of BAC.

    - Frequency contours for 60 dB(A) during the night period (23:00 to 07:00) with frequencies of 10x, 15x, 20x and 30x

Between 1996 and 2014, the Acoustics and Thermal Physics laboratory of KU Leuven calculated these contours. From 2015 to 2020, the WAVES research group at Ghent University took over this task. Starting from 2021, the calculations have been performed by To70.

The L_{den} and L_{night} contours of the strategic noise mapping are also utilized to estimate the annual number of Highly Annoyed (HA) and Highly Sleep Disturbed (HSD) individuals related to airplane noise. This calculation is based on the dose-response curves provided in VLAREM (Flemish Regulations on Environmental Permitting), which are, in turn, based on a synthesis of various noise nuisance studies around several European and American airports (EU, 2002). However, it is important to note that this relationship does not align with the most recent dose-response curve provided by the WHO in 2018 (WHO, 2018), which is also the one stipulated in the recent amendment to the EU guidelines (EU, 2020).

Apart from the annual strategic maps, within the framework of the Environmental Impact Assessment EIA, in Dutch: milieueffectenrapport or MER, additional maps for 2019 have been composed by To70. The following parameters have been considered:

- L_{den} noise contours of 45, 50, 55, 60, 65, 70 and 75 dB(A) to represent the sound exposure over a 24-hour period
- L_{night} noise contours of 40, 45, 50, 55, 60, 65 and 70 dB(A) for a depiction of nighttime noise
- Frequency contours for 70 dB(A) and 60 dB(A):
    - Frequency contours for 70 dB(A) during the day period (07:00 to 23:00) with frequencies of 5x, 10x, 20x, 50x and 100x.
    - Frequency contours for 70 dB(A) during the evening period (19:00 to 23:00) with frequencies of 1x, 5x, 10x, 20x and 50x.
    - Frequency contours for 70 dB(A) during the night period (23:00 to 07:00) with frequencies of 1x, 5x, 10x, 20x and 50x.
    - Frequency contours for 60 dB(A) during the day period (07:00 to 23:00) with frequencies of 50x, 100x, 150x and 200x.
    - Frequency contours for 60 dB(A) during the evening period (19:00 to 23:00) with frequencies of 1x, 5x, 10x, 20x and 50x.
    - Frequency contours for 60 dB(A) during the night period (23:00 to 07:00) with frequencies of 10x, 15x, 20x and 30x

The methodology of the MER study aligns with the one applied for the strategic noise maps over the last two years (2021 and 2022). However, in the health impact computation within the MER, the WHO impact functions from 2018 have been utilized. Since these impact functions employ a lower cut-off value, the lowest noise impact displayed on the noise maps for the MER also utilizes a lower cut-off value for L_{den} and L_{night} (45dB for L_{den} and 40dB for L_{night}, in contrast to 55 and 45 dB respectively for L_{den} and L_{night} in the strategic maps). The domain of the noise maps is also determined by this lowest contour, and the spatial extent is thus slightly different for the maps composed within the scope of the MER and within the scope of the annual assessment. The spatial extent for both maps is visualized in *Figure 1*.

Figure 1: Domain of the noise model in the MER (left) and the 2019 annual strategic maps The dark black region indicates all locations where both L_{den} and L_{night} are above the lower threshold considered in the maps, whereas the grey region indicates all locations where only L_{den} is above the threshold. Note that in strategic mapping, higher thresholds have been considered, resulting in a domain much smaller than that of the maps in the MER.

In the most recent maps (MER + 2021 and 2022), the maps have been composed in accordance with the VLAREM environmental legislation, which mandates the use of ECAC Doc. 29, 3rd edition (2005) or a later edition. More in detail, the noise contours have been calculated using the Echo noise calculation model, developed by AerLabs. Echo is designed according to the specifications of ECAC Doc. 29, 4th edition (2016) and the software thus meets the conditions outlined in VLAREM and the European Environmental Noise Directive 2002/49/EC. The model chain applied is therefore a state-of-the-art model chain.

The model begins by calculating the noise impact of each individual aircraft, considering several flight parameters (such as flight path, type of aircraft and engine, estimated load, etc). The outcomes from all individual flights are subsequently combined to obtain frequency contours and long-term averages. The resulting noise maps for the standard indicators (L_{den} and L_{night}) have been validated through measurements taken in the vicinity of Brussels Airport (To70, 2023). However, it should be noted that validations have not specifically concentrated on statistics that might delve into the underlying input parameters of the noise modelling. For instance, it would be interesting to conduct additional validation campaigns focusing on moments with overflights of specific aircraft or engine types or take-off weights, specific wind conditions or specific hours of the day (To70, 2024).

Because the methodology starts from individual flights, it is theoretically possible to also generate additional peak noise statistics focusing on various times of the day or shorter time intervals, should research suggest a stronger causal connection of these indicators with health impacts than the current statistics. However, it should be emphasized that the uncertainty associated with individual flight tracks is quite substantial, and the high-quality end product is achieved due to the statistical principle of large numbers (To70, 2024). Therefore, one should always prioritize statistics that average multiple moments in time, rather than concentrating on the noise from individual events (e.g., a single landing or departing plane). As a result, time series at the scale of seconds, minutes or even hours should currently not be considered. This also implies that the model results cannot readily be used to compute dynamic exposure with a high temporal resolution.

Within the MER, also the noise impact of other sources related to the airport has been modelled, including off-road machinery, engine testing, taxiing of aircraft and road transport. It should finally be noted that all noise maps provide results solely for outdoor noise. Indoor noise has not been modelled, and the effect of building insulation has not been considered. Therefore, the noise maps cannot be used to calculate indoor noise levels in the houses in the vicinity of the airport.

1.1.2 Other airports

Due to the existence of European legislation, noise maps are composed for all major airports in the European Union. Since the legislation stipulates the methods that should be employed, specifically the Common Noise Assessment Methods in Europe (CNOSSOS-EU) methodology, all the maps are modelled using a common methodology. Therefore, we will not provide more details on the noise maps for other airports, as a detailed study of these does not offer us new knowledge that could be applied to Brussels Airport.

1.2 Existing monitoring at Brussels Airport

Several measurement stations from the official noise monitoring network of the Flanders Environment Agency (in Dutch: Vlaamse Milieumaatschappij or VMM) and Brussels Environment are situated around the Brussels Airport. In total, there are 10 permanent stations in Flanders (https://www.omgeving.vlaanderen.be/nl/geluidsmeetnet-cijfers-en-rapporten) and 13 stations in Brussels (https://leefmilieu.brussels/burgers/onze-acties/projecten-en-resultaten/geluidsmeetnet). Given the extensive network in proximity to the airport and considering that the stations are placed both in locations with high and low noise exposure, we conclude that the measurement network around the airport is a state-of-the-art system, which is in line with the requirements of the EU Environmental Noise Directive (Directive 2002/49/EC).

Large monitoring campaigns focusing on dynamic or indoor exposure are currently lacking. To our knowledge, there has been only a single preparatory study focusing on indoor noise levels, conducted within the scope of a PIO project of the Flemish Government. The study primarily focused on determining a protocol, which has been tested using a limited sample of 17 adolescents (Dekoninck et al., 2023a). This study is described in detail in WP1.

1.3 Knowledge gaps related to noise

In general, it can be concluded that a state-of-the-art model chain has already been established for assessing noise due to landing and departing airplanes at Brussels Airport. Furthermore, there is an extensive measurement network, with multiple sampling points located in the vicinity of the airport. However, there are still some remaining knowledge gaps, most of which are related to the monitoring of dynamic exposure. The following points have been identified:

- Most exposure studies have currently focused on a static impact, either using ambient modelled levels or measurements at people's home addresses. Consequently, there is limited information on the dynamic exposure of residents around airports, which would account for both indoor and outdoor noise levels at their home addresses and at work/school. Preparatory studies have focused on establishing a protocol (Dekoninck et al., 2023) and a list of devices (Van Elsen & De Fonseca, 2020) suitable for these dynamic measurements. The protocol has been evaluated with a small group of test subjects (17 adolescents), but a large-scale study has not yet been conducted. It is important to note that standard dose-response curves for significant annoyance and sleep disturbance cannot be applied in conjunction with dynamic noise exposure results, as these curves have been developed using ambient noise levels and implicitly contain the effects of dynamic exposure levels. Therefore, the collection of dynamic noise levels should be accompanied by a determination of health effects.

- The model chain could be further validated through detailed validation campaigns focusing on specific input parameters. For instance, it would be beneficial to conduct additional validation campaigns concentrating on moments with overflights of particular aircraft or engine types, take-off weights, specific wind conditions or particular hours of the day.
- The uncertainty in the modelled noise levels is currently significant when focusing on a sub-hourly time resolution. Since the model chain benefits from averaging over multiple flights and hours, reducing this uncertainty on a sub-hourly basis within the model chain itself is challenging. However, if the model results are combined with measurements for the specific time step—a process commonly referred to as data assimilation—the hourly profiles of the noise model output could be improved. Such a model chain combining noise modelling with measurement will be especially important if a focus on higher temporal resolution is desired, for example, when the focus on peak noise impacts becomes more important. Note that in WP 1, a higher focus on peak noise has been identified as one of the important open research questions.

2 Standard air pollutants

Within this chapter, we refer to standard air pollutants as nitrogen dioxide (NO_2), particulate matter with an aerodynamic diameter of 10 micrometres or less (PM_{10}), particulate matter with an aerodynamic diameter of 2.5 micrometres or less ($PM_{2.5}$), black carbon (BC), lead (Pb) and benzo[a]pyrene (BaP). Some other pollutants, such as ozone (O_3), sulphur dioxide (SO_2) and ammonia (NH_3), also fall under this category, but there are no significant increases in their concentrations around airports, and thus they are not discussed.

2.1 Existing modelling

2.1.1 Brussels airport

Air concentration maps for 2019 for the surroundings of Brussels Airport Zaventem have been generated as part of the environmental assessment study (MER) associated with the new permit for Brussels Airport (Antea Group, 2023). Within this study, a state-of-the-art model chain was employed. This model chain integrates an emission model specifically developed for Brussels Airport, incorporating detailed activity data on flights and taxiing combined with emission factors for various air pollutants based on the EMEP/EEA guidebook (EEA, 2023). The emissions calculated are then used as input for a Gaussian dispersion model, ATMO-Street, which has undergone extensive validation in numerous contexts within Flanders and other European countries (Hooyberghs et al., 2022). Note that this model meets the benchmark set by the EU Commission's FAIRMODE Model Quality Objective, which means that it can be used in policy support. The model domain encompasses a region extending from 15 to 20 km around the airport (see *Figure 2*), with the most significant expansion towards the north-east, attributable to the prevailing south-western winds. Further details on the emission and dispersion modelling processes are included in the reports annexed to the MER (Hooyberghs et al., 2023; Pauwels et al., 2023).

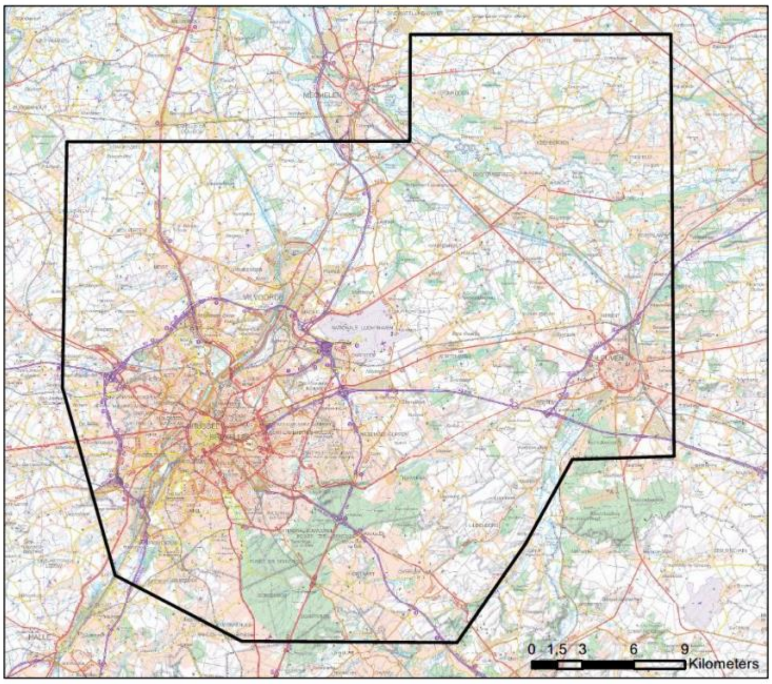

Figure 2: Domain of the air quality model in the MER. Source: MER report (Antea Group, 2023).

Within the MER, annual mean air pollutant maps for total nitrogen dioxide (NO_2), particulate matter ($PM_{2.5}$ and PM_{10}) and black carbon[4] (BC) concentrations have been created, along with exceedance maps for daily mean PM_{10} and hourly mean NO_2 concentrations. Additionally, the study examined the impact of the airport system, encompassing[5] road traffic, flights and off-road activities, with specific maps highlighting the impact attributed solely to the airport. Note that all the annual statistics have been generated starting using a model with an a priori hourly time resolution. Consequently, one could also consider hourly time series or other statistics that start from hourly data. As with the noise modelling, the uncertainty on the maps increases if the time resolution is increased, therefore the uncertainty on hourly maps is much larger than the uncertainty on annual mean maps. The underlying reason for this is very similar to that of noise modelling, as the model chain greatly benefits from averaging over multiple flights of a similar engine and airplane type. Indeed, emissions might vary strongly from flight to flight, even if the exact same engine and airplane type are used. However, by averaging over a large number of flights, the mean statistics incorporated into the emission factors should be retrieved.

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[4] Note that in the MER the maps for EC (elemental carbon) have been modelled, but this pollutant is closely linked to black carbon (BC).

[5] Road traffic here refers to the impact of the airport on all road traffic in the study domain, including traffic to and from the airport and the industrial areas around the airport. It also includes all traffic movements in the domain that are not related to the airport (e.g., long-distance traffic, traffic movements within the domain but not related to the airport). It is very important to consider the total traffic load, as in the absence of the airport, there would be significantly more other traffic on the roads in the vicinity of the airport (e.g., the Brussels Ring), which would occupy the freed space on the already congested roads. For this reason, the airport's impact on the total traffic in the domain of the MER is limited to a few roads (e.g., A102).

In the MER, model results were merged with population data to estimate population exposure. However, a direct translation to health impact was not performed, though it can be readily calculated using the standard methodology that relies on the most recent concentration-response functions provided by the World Health Organization (WHO). This approach aligns with the Environmental Health Impact Simulation (E-HIS) tool used by the Department of Health but utilizes updated concentration-response functions. Utilizing this methodology, the annual increase in the number of deaths in the domain of the MER attributable to NO_2 exposure related to emissions from the airport is estimated to be lower than 5, and the annual increase in the number of deaths attributable to particulate matter ($PM_{2.5}$) exposure is estimated to be lower than 1. According to life expectancy curves from the EHIS tool, this translates to an increase in the number of years of life lost with approximately 65 and 15 for NO_2 and PM exposure, respectively[6]. It is crucial to note that these figures are significantly smaller than the total health impact within the MER domain from exposure to overall pollution caused by emissions from all sectors, both inside and outside the domain. Specifically, there are approximately 300 deaths annually related to NO_2 exposure and approximately 950 deaths attributable to $PM_{2.5}$ exposure within the domain, leading to over 4,600 and 14,200 years of life lost, respectively. Hence, the impact of the airport (on health outcomes related to standard air pollutants) can be described as limited. A comprehensive application of the EHIS tool could also estimate morbidity effects, but given the limited impact observed on premature deaths, the impact on morbidity, especially for PM, is expected to be limited.

A notable omission in the model chain used in the MER is the consideration of the impact of secondary pollution. Currently, only the impact of primary pollution has been considered, which contains the ground-level impact due to direct emissions of particulate matter (PM) and nitrogen dioxide. However, the impact of secondary PM, which is formed by chemical reactions of other pollutants (mainly NO_x, NH_3 and SO_x), has not been addressed. The formation of this secondary pollution occurs on a continental scale because the chemical reactions require time, during which the pollutants are dispersed over hundreds to thousands of kilometres. On this continental scale, additional pollution associated with the Landing and Takeoff (LTO) emissions at Brussels Airport will thus also result in additional attributable mortality. Given that this blanket of secondary pollution spreads over a large geographic scale, affecting millions of inhabitants, the absolute numbers of these effects could be larger than those due to primary emissions. It is, however, crucial to emphasize the non-local impact of secondary pollution. While all mortality attributable to primary pollution occurs within the immediate vicinity of the airport (at most 5 km away), the impact of secondary pollution unfolds on a continental scale (Lefebvre, 2018a). This raises the question of whether the study of secondary pollution's impact is relevant within the current analysis, which primarily concentrates on the immediate vicinity of the airport. Note, finally, that the Department of Environment is currently investigating the feasibility of a tool to model the impact of secondary pollution related to industrial and other localized sources in Flanders. However, this methodology is not yet ready for use in general cases. Consequently, the health impact of secondary pollution ($PM_{2.5}$) related to airport activities cannot be quantified, though is expected to be rather small on a local scale (the immediate vicinity of the airport).

Within the Stargate H2020 project, the model chain has moreover been utilized in a source contribution mode. In this mode, emissions from various airport-related sectors contributing to total

[6] It is further important to note that these figures cannot be directly summed due to the lack of correction for overlap between particulate matter and NO_2 in the dose-response functions.

pollution—including landing, take-off, taxi operations, Auxiliary Power Units (APU), Ground Power Units (GPU), ground heating installations and off-road emissions from non-aviation vehicles—are sequentially input into the model chain. This approach allows for the determination of each sector's contribution with a spatial breakdown. The results of this additional model chain will be detailed in a forthcoming report of the Stargate H2020 project, which is currently in preparation.

Finally, there are no maps available for other standard air pollutants in the vicinity of the airport, typically because the emissions are estimated to be minimal (e.g., for lead, which, as detailed in the MER, is not present in jet fuel (Antea Group, 2023)) or due to the absence of emission factors in the official EMEP/EEA guidebooks applied in the model chain (e.g., for Benzo[a]pyrene (BaP)). Note that the emissions of BaP for the sector aviation are also not estimated in the official Flemish emission inventory compiled by VMM and that BaP emissions and concentrations at airports have been the subject of only a few studies (Riley et al., 2021a). For instance, in 2005, a measurement campaign at Los Angeles International Airport (LAX) compared BaP levels at the blast fence and at a background location (Zhu et al., 2011). It was observed that BaP levels were higher at the background location than at the airport itself, which suggests that airport-related emissions might not be the predominant source of BaP in nearby areas.

2.1.2 Other airports

Air quality modelling has been conducted at several airports around the world to study the health effects related to airport emissions using distinct types of modelling techniques. These can be broadly categorized in order of increasing spatial resolution in chemical transport models (CTM), Gaussian dispersion models (such as Eulerian and Lagrangian models) and computational fluid dynamics (CFD) models. In the next paragraphs, we discuss the distinct options in more detail. In the appendix (see section 6), we also provide an overview of notable studies, but many other studies have been unpublished (Janicke, 2023a).

2.1.2.1 Chemical transport models

Chemical Transport Models (CTMs) are grid-based models, meaning that emissions are aggregated within a grid cell and concentrations are only calculated as an average of that grid cell (Holmes & Morawska, 2006; Woody et al., 2016). Moreover, aircraft LTO emissions are instantaneously diluted into the ground-level grid cell containing the airport. Studies demonstrated that this leads to an overestimation of pollutant concentrations and therefore CTMs have been modified to include emissions at various height levels (Lawal et al., 2022; Woody et al., 2016). An advantage of CTMs is the possibility to incorporate detailed aerosol dynamics and this was found to introduce a substantial increase of 12-40% in the modelled $PM_{2.5}$ concentration when the formation of secondary organic aerosols from the oxidation of semi-volatile and intermediate volatility organic compounds emitted from aircraft was included (Woody et al., 2016). On the other hand, they are less suitable to model pollutant concentrations in a local environment, where concentrations and pollutant dynamics are highly influenced by local changes to the wind field and emissions. An often-used CTM to model the dispersion of emissions related to airport activities (including LTO and non-LTO activities) is the Community Multiscale Air Quality (CMAQ) model with a grid cell size down to 4 x 4 km² (Arunachalam et al., 2011; Lawal et al., 2022; Woody et al., 2016).

2.1.2.2 Gaussian dispersion models

If results at scales finer than the CTM grid are desired, e.g., if the focus is on the exposure of the population in the immediate vicinity of airports, Gaussian dispersion or CFD models should be used. Gaussian dispersion models are based on a Gaussian distribution of the plume in vertical and horizontal directions under steady-state conditions. There are two types of Gaussian dispersion models: Eulerian and Lagrangian (Lefebvre, 2018b). An Eulerian model describes the concentration of pollutants within a fixed spatial frame of reference. This approach treats the plume as static during a single time step, simplifying the analysis. In contrast, Lagrangian models describe the dispersion of pollutants by tracking the movement of fluid parcels or particles as they move with the wind, allowing the plume to evolve dynamically during a single time step. Eulerian models are generally preferred for larger-scale, steady-state scenarios due to their relative simplicity and lower computational demands. Conversely, Lagrangian models are better suited for smaller scales or scenarios where the flow field is highly irregular, e.g., in locations with rapidly changing wind fields such as mountainous areas or locations where the wind field is modified by the buildings, and the temporal dynamics of dispersion are critical (De Visscher, 2013). Specifically, for modelling around airports, the choice between Eulerian or Lagrangian models depends on the desired time scale and spatial extent (De Visscher, 2013; Janicke, 2023a). To model concentrations on airport premises, a Lagrangian model is usually more appropriate, although it requires detailed meteorological data to produce reliable results. Additionally, for studies requiring time resolutions of seconds, a Lagrangian model might be preferable, though simulating an entire year can be challenging. If the interest is only in concentrations around the airport and a somewhat longer timescale (half hours or longer), an Eulerian model might be more suitable due to shorter simulation times (Janicke, 2023a).

Examples of **Eulerian models** include VITO's IFDM model described above, US EPA's regulatory model AERMOD (Cimorelli et al., 2005) and ADMS-Airport (CERC, 2020). These models regard each step of the LTO cycle, which is included in the model as line sources at different heights in IFDM, as volume sources in AERMOD or as a combination of source types in ADMS.

An overview of existing research that uses AERMOD can be found in Pandey et al. (2023). Validation of AERMOD has been performed for Pb (Carr et al., 2011) and SO_2 (Pandey et al., 2023), both pollutants that mainly stem from the burning of aircraft fuel. Carr et al. (2011) performed measurements at the ends of the runway and at two residential locations 100 and 175 m from the runway. They showed that the 24-hour mean difference between model and measurements was about 40% in winter and 20% in summer. The absolute fractional bias was between 0.29 (winter) and 0.07 (summer), indicating that the model overpredicted the Pb concentration. An overestimation was remarkable in the early evening, because at that time the stable boundary layer was not yet fully developed and the meteorological model that is implemented in AERMOD (named AERNET) underestimated the mixing height during this transition period. Pandey et al (2023) focused on the influence of including specific plume dynamics for aircraft engine exhaust on modelled ground-level SO_2 concentrations. The outcome of AERMOD without and with adjusted plume dynamics was compared with measurements at two locations both 1.5 km downwind of a runway. The model without adjusted plume dynamics overestimated measured concentrations at low wind speeds, while including plume rise made modelled concentrations insensitive to wind speed. This is consistent with the expectation: at lower wind speed, buoyant plume rise will be greater and, as a result, ground concentrations will be lower. On the other hand, when wind speed increases, the plume is brought to the ground and the concentration increases to a maximum after which it decreases. Traffic sources do not have buoyant plumes and exhibit the opposite behaviour, namely a decrease in concentration at ground level with increasing wind speed. This difference has already been used to quantify the contribution of aircraft to NO_x concentrations at and around London Heathrow (Carslaw et al., 2006).

The ADMS-Airport model has a detailed representation of an aircraft's emissions for each LTO phase: take-off and landing as a series of line sources, climb-out and approach as volume sources and taxi as line and surface sources. The series of line sources are associated with the various engines of an aircraft and involve constant acceleration. In addition, effects of buoyancy and momentum of the jet engines are defined. A sensitivity study showed that the buoyancy suppression at the end of the take-off roll did not appear to be very significant, but the enhanced plume rise resulting from modelling the exhausts converging within a few wingspans of the jet exit was more significant. A comparison of ADMS-Airport with NO_x measurements 200 m from the start of the roll on the runway showed an overall good agreement of the concentration pattern, but an overestimation at low wind speeds (Carruthers et al., 2007).

A well-established **Lagrangian model** is the LASPORT model, which is a specific development of the LASAT Lagrangian model (Janicke & Janicke, 2009). This model has been utilized for studies at various airports across Europe, including Frankfurt (Lorentz et al., 2019), Zurich (ZurichAirport, 2013a) and Madrid Barajas (Janicke, 2023a). For many airports, the results have either not been publicly disclosed or not been published in English (Janicke, 2023a). Another study investigated a Lagrangian particle model to study the impact of meteorological conditions on the air quality near an airport (Pecorari et al., 2016).

To conclude, Eularian and Lagrangian models are effective for average annual concentrations analyses and function well under moderate to high wind conditions, particularly in stable or neutral atmospheric boundary layers. Moreover, they can account for a wide array of atmospheric phenomena including the dispersion of various compounds and effects of plume rise. On the other hand, they do not provide accurate results for low wind conditions in complex environments.

2.1.2.3 CFD models

CFD models overcome the issues of Gaussian dispersion models by directly simulating the influence of complex topography, obstructions and recirculation due to buildings and transient meteorological or emission variability, however at a much higher computational cost (Holmes & Morawska, 2006; Sarrat et al., 2017). This high computational cost makes it up to now not possible to simulate an entire year, rather one day or specific meteorological conditions can be studied in detail. For example, Sarrat et al. (2017) simulated NO_x concentrations for one day at an airport by coupling the CFD model IESTA, simulating the aircraft trajectories and engines emissions, and a mesoscale model, simulating the atmospheric dispersion at 10 m horizontal resolution. With this modelling chain, detailed concentration maps could be obtained at the airport (e.g., at terminals) allowing to detect high concentration areas. Another study looked at a mock airport to study the impact of the wind environment around airport buildings and the impact of atmospheric stability on NO_x dispersion (Ghedhaïfi et al., 2022). Again, areas with high concentrations were identified and this information is valuable to unveil major sources. This was also the topic of a study on the air quality at Copenhagen Airport with an emphasis on the apron in relation to the working environment (Ellermann et al., 2012). To this end, the authors used the CFD model MISKAM (5 x 5 m resolution) coupled with a local scale model to obtain the background. They provided a validation with NO_x and $PM_{2.5}$ measurements near a gate. The model overestimated both pollutants, however it was less pronounced for $PM_{2.5}$ since its background concentration was higher than for NO_x. The plausible causes were too high emissions by the emission inventory and an incorrect representation of the initial dispersion of emissions.

In sum, using CFD models is beneficial when highly detailed concentration gradients close to the sources are required, such as when assessing the health of passengers or workers. For exposure studies focusing on larger domains (e.g., residential areas near the airport), the benefits of using CFD models are often outweighed by the negatives. These include increased uncertainty if input parameters are not well-known, plus significantly slower simulation times.

2.1.2.4 Summary

As an overall conclusion, we note that various model chains have been used to study the concentrations of standard pollutants in the neighborhoods of airports. These models vary in their setup details and the specific aspects they can account for. However, no single model can cover all aspects, as models incorporating more details often operate too slowly to study a large area effectively.

When comparing the model chain used at Zaventem with those employed at other locations to study population exposure in the vicinity of airports, it is clear that the model chain utilized at Zaventem is state-of-the-art and aligns with the model chains used at other airports.

2.2 Existing measurements

Several measurement stations from the official telemetric system of VMM and Brussels Environment are situated within the area considered in the air quality modelling chain of the Environmental Impact Report (MER), see *Figure 3*. The station closest to the airport is located in Steenokkerzeel (SZ05), situated at the sewage treatment plant in the Sterckxstraat. This station is positioned in alignment with runway 07L/25R, downwind of the source under prevailing wind directions. At this location, the concentrations of nitrogen oxides (both NO and NO_2), black carbon (BC) and particulate matter ($PM_{2.5}$ and PM_{10}) are continuously monitored[7]. A comprehensive list and parameters for the other stations can be obtained through the IRCELINE (www.irceline.be), VMM (https://www.vmm.be/data/evaluatie-luchtkwaliteit) or Brussels Environment (https://luchtkwaliteit.brussels/) websites. Given the extensive network in proximity to the airport and considering the Steenokkerzeel station is very close to the main runway, we conclude that the measurement network around the airport is a state-of-the-art system, which is in line with the requirements of the EU Ambient Air Quality Directive (Directive 2008/50/EC, and Commission Implementing Decision of 12 December 2011 laying down rules for Directives 2004/107/EC and 2008/50/EC).

It is, finally, important to note that these measurements capture the total concentration, encompassing contributions from the airport, other significant nearby sources (e.g., road traffic) and the regional background concentration. Differentiating between these contributions is only possible when the results are integrated into a model chain.

[7] Note that this station is active since January 14th, 2021, and that is replaces the station SZ01, which was located on the terrain of the airport, also in alignment with the runway 07L/25R.

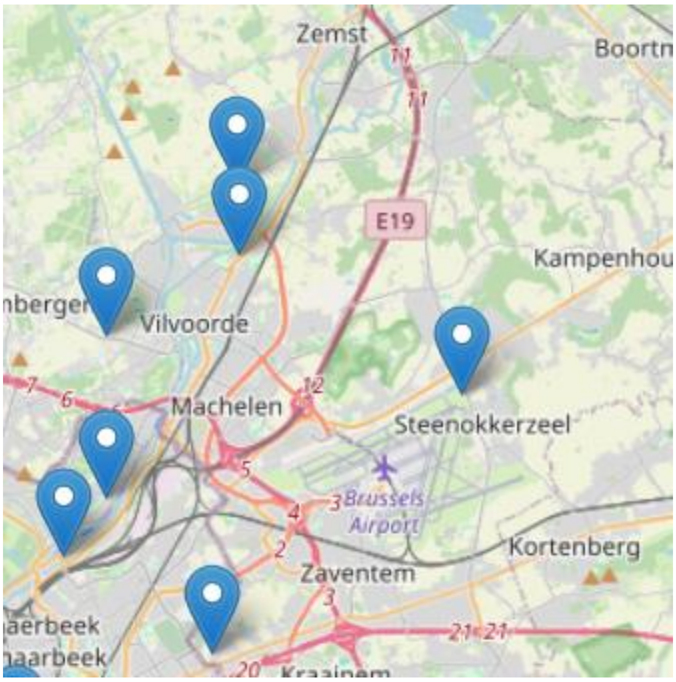

Figure 3: Telemetric measurement stations in the vicinity of Brussels Airport (source: www.irceline.be). Note that the location in Steenokkerzeel still refers to the old location of station SZ01, and not the new station SZ05. The exact location of the new station is described in the text.

2.3 Knowledge gaps related to standard air pollutants

Considering the comprehensive modelling chain and the extensive measurement network deployed around the Brussels airport, alongside the negligible concentrations attributed to the airport's emissions of standard air pollutants, we conclude that further enhancements in both modelling and measurement techniques are unlikely to significantly improve our understanding of the health impacts associated with standard air pollutants from the airport. Nevertheless, some knowledge gaps have been identified:

- The current model chain has exclusively been applied to the year 2019, resulting in detailed maps only for that year. Consequently, it is not feasible to deduce exposure over multiple years, which could be a necessary input for conducting a detailed epidemiological study, especially for chronic diseases, which are related to long term exposure. However, given that all input data is available, it is theoretically feasible to produce air quality maps for additional years.
- The omission of secondary particulate matter in the standard model chain. It is important to note that the health impact of this secondary pollution usually does not manifest near the airport but at the continental scale. Consequently, it falls outside the scope of the current study.

Finally, notwithstanding that standard air pollutants arising form airport sources are likely to contribute only to a limited extend to exposure and health risks, it is advised to take them into account as co-exposures when investigating e.g., the associations between UFP and health.

3 Ultrafine particles (UFPs)

Airports represent a significant source of air pollutants, especially aerosols and ultrafine particles (UFPs) (Artous et al., 2024a). UFPs are a subset of particles with an aerodynamic diameter less than or equal to 0.1 µm (100 nm) (WHO, 2021). In terms of mass, they represent a small fraction of airport-emitted aerosols; however, they represent most emissions when expressed as particle numbers[8] (Artous et al 2024).

A formal standard for ultrafine particles is currently lacking. Due to technical constraints, measurements incorporate a lower limit on the particle diameter. Although the WHO has set forward a good practice (lower limit of 10 nm (WHO, 2021)), presently, there is no universally adopted standard for this lower limit, leading to variability in the lower limit used across different studies. Because particles with finer diameters are especially abundant in emissions related to airplanes (Austin et al., 2021a; Owen et al., 2022a; Stacey, 2019a), the varying lower cut-off value becomes particularly significant when studying UFPs around airports. Consequently, great care is required when comparing the results of different studies.

In its proposal for a new ambient air quality directive, the European Commission aims to address this inconsistency. A provisional political agreement was reached on the revised Ambient Air Quality Directive between the European Parliament and the Council on February 20, 2024 (EU, 2024). The proposed directive defines, in line with the good practice of the WHO, 'ultrafine particles' (UFP) as "particles with a diameter of less than or equal to 100 nm, where UFP are measured as the particle number concentrations per cubic centimetre (cm^3) for a size range with a lower limit of 10 nm with no restriction on the upper limit". Upon the enactment of the updated directive, this guideline will establish a European standard for the lower cut-off diameter of UFPs.

3.1 Existing modelling

3.1.1 Brussels airport

3.1.1.1 ATMO-Street model chain

The concentrations of UFP related to air traffic emissions are mapped using a model chain that has been developed by VITO on behalf of VMM (for 2016) (Lefebvre et al., 2019a) and later refined within the European research project Stargate. The model chain has also been used in the MER to model the annual mean UFP concentrations in 2019 related to air traffic (covering the full LTO cycle) (Antea Group, 2023; Hooyberghs et al., 2023).

The model used is the ATMO-Street model chain, which is also employed to model standard air pollutants in the MER. The model chain begins with detailed activity data on flights and taxiing. For each flight movement, the fuel use is determined using the EMEP/EEA guidebook. In a second step, this fuel use is converted into particle emissions, using emission factors per unit of fuel used. These particle emissions are then put into a Gaussian dispersion model to determine the pollutant concentrations at all locations within the specified domain. The model provides concentrations at an hourly resolution for the designated domain (see *Figure 2*), which are typically processed to obtain annual mean pollution maps. More details on the model chain are provided in the reports of the

[8] Note that, because particles with diameters smaller than 100 nm dominate particle numbers, in practice, UFPs are typically measured without an upper limit on the size of the mass.

studies mentioned above (Hooyberghs et al., 2023; Lefebvre et al., 2019a). As for the standard air pollutants, the model chain has also been utilized in a source contribution mode, thereby providing information on the dominant polluting sectors. The results of this source contribution exercise are, however, unpublished at the moment.

3.1.1.2 Modelling uncertainty for long-term averages

Modelling of UFPs, however, comes with significant uncertainty. Within the report underlying the modelling used in the MER, a dedicated section on the uncertainty of UFP modelling has been added (Hooyberghs et al., 2023). The following paragraph reflects the content of this discussion in the MER report.

The main uncertainty related to the modelled UFP concentrations is caused by the uncertainty on the aircraft emissions. These emissions are calculated by combining the amount of fuel used by the airplanes with a ratio that specifies the particles emissions per unit of fuel used. However, the uncertainty on the latter factor is very high. Typically, the literature shows factors encompassing several orders of magnitude, ranging from 10^{15} to more than 10^{16} particles per kilogram of fuel used. Within the framework of the European research project Stargate[9], a detailed validation was also conducted using UFP measurements from 2018 and 2019. The results of this validation demonstrate that the measurements can only be explained if emission factors at the upper end of the range from the literature are used. There are several underlying causes for the great uncertainty in UFP emissions. Firstly, there is no standard lower limit concerning the particle size to be included. Consequently, different studies and measurement campaigns use different definitions for this minimum particle size. Since UFP emissions from aviation are dominated by a very large number of very small particles, this has a significant effect on the uncertainty of the emissions and concentrations (Shirmohammadi et al., 2017; Stacey, 2019a).

Another cause concerns the processes that occur after the particles are emitted into the atmosphere (Austin et al., 2021a; Owen et al., 2022a)[10]. Most of these processes occur in the first seconds to minutes after the warm emission jet leaves the exhaust of the airplane. During the cooling of the jet, various physical processes occur (condensation, nucleation, coagulation, etc.), which significantly alter both the number of particles and the particle size distribution. The exact nature of these reactions is not fully known, but it is already evident that their specifics depend on many external circumstances, such as meteorological conditions including relative humidity and wind speed. To describe these effects, a distinction between "engine non-volatile particles" (the emitted particles) and "volatile particles" (the particles generated by processes in the atmosphere) is made. On the other hand, dispersion modelling with the ATMO-Street model uses a time resolution of one hour, and thus the physical processes during the cooling of the jet are not included in the dispersion modelling. It is therefore implicitly assumed that the emissions used in the modelling are the sum of the "non-volatile" and "volatile" particles, but this is not always in accordance with the emission factors provided in the literature. It is therefore not surprising that the validation produces better results when emission factors at the upper end of the range from the literature are used.

[9] https://www.greendealstargate.eu/, financed within the scope of the EU Green Deal project.

[10] This section is only a brief introduction to the topic. For a more detailed review, we refer to the references provided in the text, and the references therein.

Finally[11], within the current model chain, the emission factor that describes the number of particles emitted per unit of fuel use is kept constant for all phases of the Landing and Take-Off (LTO) cycle. However, this assumption has been shown to be overly simplistic by recent findings. Studies have observed a significant difference in the number of particles emitted during landing and taxiing compared to take-off (Janicke, 2023b). During take-off, fuel combustion is much more complete because the engine operates at full power, resulting in relatively fewer particles being emitted. In contrast, during taxiing and landing, the engine operates at a lower thrust setting, leading to less complete combustion. Therefore, particle emissions tend to be higher during these phases, and the diameter of the particles tends to be smaller.

In summary, we conclude that the emissions and concentrations for UFP can only be determined approximately and that the absolute concentrations can only be considered accurate to the order of magnitude. On the other hand, despite the many uncertainties, the current model chain does capture the spatial gradient of the UFP concentrations around the airport, as demonstrated by a validation using measurements from 2016 (Lefebvre et al., 2019a), on the one hand, and 2018 and 2019, on the other hand (Ysebaert et al., 2024). Therefore, the model chain can be used to accurately calculate the spatial gradients of long-term population exposure around Zaventem Airport. Within the Stargate project, VITO is also planning to further validate the model chain for UFPs, using measurement campaigns from 2022. This validation campaign will specifically focus on exploring the differences between the various phases of the LTO cycle. By combining the model results with the measurements, better estimates for the emission factors of UFPs around Brussels Airport will be developed, which will also lead to an improved concentration map.

3.1.1.3 Modelling uncertainty for short-term averages

The uncertainty in the model results becomes even larger when focusing on short-term averages. Given the hourly temporal resolution of the model chain, only results averaged over hourly or longer time scales can be used.

For both the 2016 measurement campaign and the 2018 and 2019 campaign (Lefebvre et al., 2019a; Ysebaert et al., 2024), the results at brief time scales have also been validated. At a daily resolution, a decent agreement between measured and modelled results can be observed. However, the correlation between the measurements and the model results diminishes greatly if sub-daily results are considered. Therefore, the model chain can currently only be effectively used at temporal resolutions starting from daily means.

The underlying reason for this is very similar to that of noise modelling. Due to the way in which emissions are modelled, the model chain greatly benefits from averaging over multiple flights of a similar engine and airplane type. Indeed, emissions might vary strongly from flight to flight, even if the exact same engine and airplane type are used. This variation could be due to several reasons, amongst other different settings of the motor or flaps, in-flight corrections to the flight path or meteorological conditions that lead to a different formation process of volatile particles. However, by averaging over a large number of flights, the mean statistics incorporated into the fuel use factors and the emissions factors should be retrieved. In this way, the modelling greatly benefits from the law of large numbers, but of course, a significantly longer time scale is required to achieve reliable results.

[11] This paragraph is based on the results of the Aviator project, https://aviatorproject.eu/, and benefited from personal communication with Ulf Janicke. Note that many of the outcomes of the project are confidential and are therefore not publicly available.

3.1.2 Other airports

The same modelling techniques used for standard air pollutants are applied to map UFP concentrations near airports. We thus refer to the corresponding sector for a general description of the type of models that are being applied around airports. The appendix (see section 6) provides an overview of some studies dealing with modelling of UFP at several airports. Note that most of the studies focusing on UFP are using Gaussian dispersion modelling (either a Gaussian or a Lagrangian model) or a CFD model. Given the complexities of the chemical reactions in the engine exhaust jet, and the limited spatial extent with elevated UFP concentrations, running a CTM for UFP emissions related to air transport emissions is difficult.

The main difference between modelling UFP and other air pollutants lies in the emission factors for UFP, which are more uncertain compared to those for standard air pollutants, as explained above for the model chain at Brussels Airport. As a result, the concentrations of UFP also come with larger uncertainties. In comparison with the modelling performed at Brussels Airport, studies have used the emission factors for UFP (with a lower diameter of 7 nm) derived from a field study performed under real-world conditions at Brisbane Airport (Brisbane, Australia) for each phase of the LTO, except for climbing and approaching aircrafts (Mazaheri et al., 2009).

In general, background concentrations are not available for UFP, as rural or urban background monitoring locations are often missing. A method used in the literature to determine the background concentration of UFP uses UFP measurements when the wind blows from a direction opposite to the direction where the airport is located (Keuken et al., 2015a; Voogt et al., 2023). This background is then subtracted from UFP concentrations measured with winds coming from the airport. Another difficulty comes from the uncertainty related to UFP emissions from road traffic, which must be included if the roads are within the model domain. However, official databases such as COPERT or HBEFA only contain emission factors for non-volatile UFP, while it is known that most UFP is volatile as already highlighted in this document (Keuken et al., 2015a; Lefebvre et al., 2019b). Lefebvre et al. (2019) therefore rescaled road traffic emissions from an official database (HBEFA) based on measurements, to take the volatile fraction into account. Voogt et al. (2023) in turn used NO_x as a proxy for UFP from road traffic, assuming a linear relationship between NOx concentration contributions from traffic and UFP contributions from traffic. This concentration is also subtracted from the measured UFP concentration to obtain the UFP concentration due to airport activities only.

Many of the studies focusing on modelling of UFP concentrations around airports thus identify the same knowledge gaps that have been identified in modelling UFP concentrations at Brussels airport (uncertainty in emission estimates, difficulties in modelling peaks in time series with a high temporal resolution), and that have been identified in studies focusing on monitoring of UFPs at airports (difficulties in estimating the chemical reactions in the exhaust plume, larger need for characterization of particle sizes).

3.1.3 Summary

In sum, we conclude that ultrafine particles have been modelled at various airports using mostly Gaussian dispersion models. However, all these model chains come with a large uncertainty, which is much greater than for standard air pollutants. Typically, an uncertainty factor of ten on the total concentrations is not uncommon. Therefore, data assimilation with measurements might be used to reduce the uncertainties in the absolute concentrations.

The model deployed at Brussels Airport is a new a state-of-the-art model chain, which is in line with the techniques used at other airports. The model chain has been applied for 2019 and can be used to assess concentrations on a daily or longer time resolution.

3.2 Existing measurement campaigns

3.2.1 UFP monitoring near Brussels airport

UFP monitoring near Brussels airport is conducted by the VMM at one site in Steenokkerzeel. Additionally, several measurement campaigns have been conducted in this area over the last decade.

3.2.1.1 Continuous UFP monitoring site of VMM

Currently, there is only one permanent continuous measurement station measuring the UFP concentrations in the vicinity of the airport, located at Steenokkerzeel. The AQM station SZ05 (*Figure 4)* from VMM is equipped with instrumentation for UFP monitoring (SMPS 3938, water-based CPC, 10-800 nm particles, 5-min scans). The UFP measurements were started on 17/06/2022 and are running continuously.

Figure 4: Location and photo of SZ05 AQM station from VMM.

3.2.1.2 Temporary UFP monitoring campaigns

Over the last decade, VITO has been commissioned to conduct several monitoring campaigns for UFP in the Brussels Airport region (*Figure 5*). The duration of the campaigns was two to three months, sometimes split in a winter and summer part.

Figure 5: Overview of monitoring sites from temporary monitoring campaigns.

In the **2015 campaign**, four monitoring stations were located on a transect aligned with a busy runway (25R/07L) at varying distances from the runways (*Figure 6*). Three of the measurement locations are characterized as urban background stations, whereas one location is a rural station. The monitoring was done during a two-month period, i.e., October and November 2015. At the time of this campaign, standard air pollutants were monitored at a nearby AQM station from VMM (SZ02).

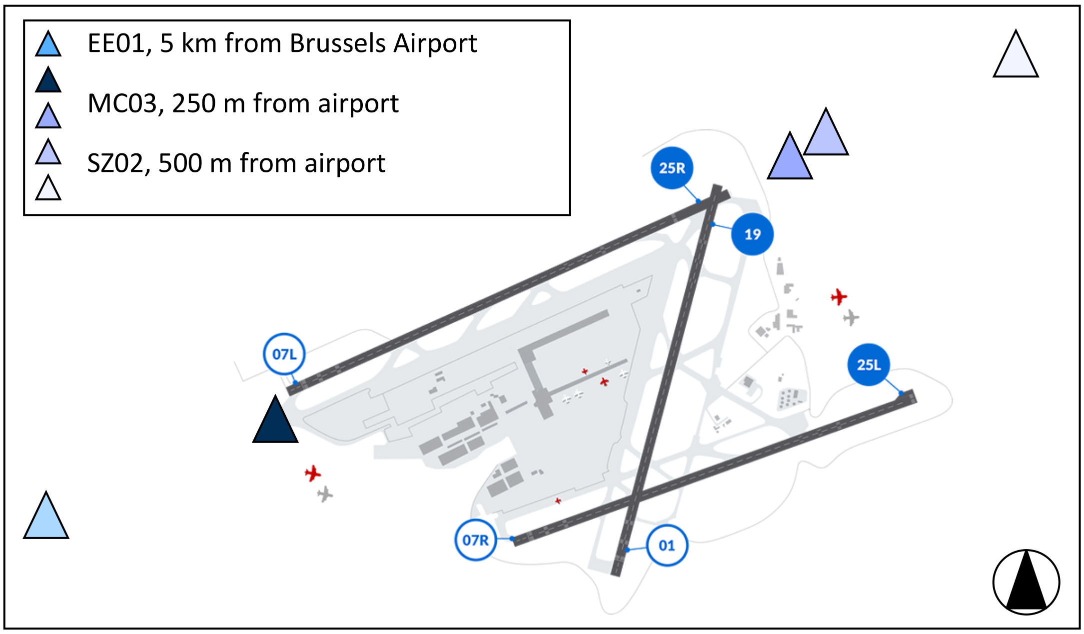

Figure 6: Overview of monitoring sites from the 2015 monitoring campaign.

UFP measurements were made with scanning mobility particle sizers (SMPS) at a 5-min time resolution. Particle number concentrations (PNC) were calculated for 7 size classes:

- 10 – 20 nm
- 20 – 30 nm
- 30 – 50 nm
- 50 – 70 nm
- 70 – 100 nm
- 100 – 200 nm
- 200 – 294 nm.

A full text report (2016/MRG/R/0493) is available in a report in Dutch (Peters et al., 2016).

For the **2018-2019 campaign**, total PNC were measured with water and butanol-based condensation particle counters (CPCs) at a 10-sec time resolution. The measurements were made at 8 sites with different distance and orientation to the airport (*Figure 7*). Two sites were monitored continuously, three sites were first included in the monitoring network near 25R and shifted to the 25L network after some time. The monitoring was split up into a summer and winter campaign. The results of this study are available in a Dutch report (Peters et al., 2019).

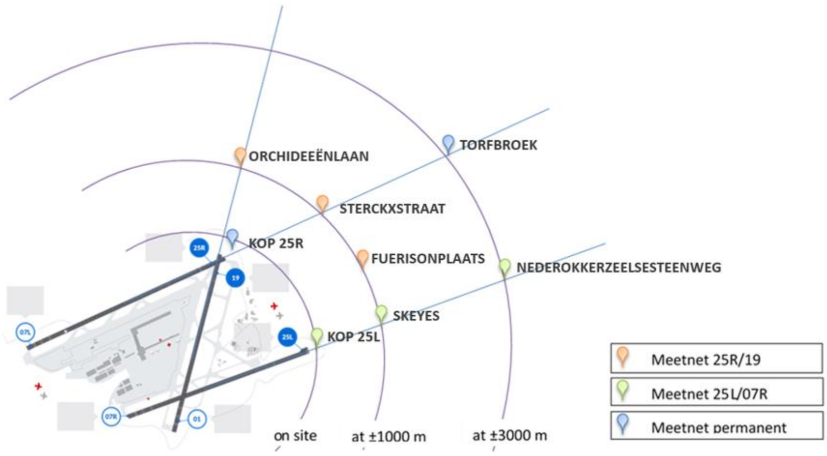

Figure 7: Overview of the monitoring locations from the 2018-2019 study.

The monitoring **campaign of 2022** was performed within the Stargate project of the EU Green Deal (https://www.greendealstargate.eu/). UFP monitoring (total PNC) was performed at four different sites near the airport (*Figure 7*) over a two-month period. Additionally, dedicated measurements at specific sites were done with portable monitors (P-Trak and minidisk) for a shorter period (hours). In this study, a short exploratory campaign with mobile measurements was conducted. Results are indicative. Mobile measurements refer to air quality measurements that are made while moving around, e.g., on foot, by bike, car or other. One of the reasons why mobile measurements are made in air quality research is to obtain a better image of the spatial distribution of pollutants compared to fixed monitoring from a limited number of sites. However, the interpretation of mobile measurements is not straightforward, especially not for highly dynamic environments and pollutants (such as UFP at the airport region). Mobile measurements of UFP were made from a bicycle while travelling an 8 km track at a speed of ca. 10 km/h. The same route was repeated in sequential runs (3, two bicycles) on

28/06/2022 8:40 until 10:50 and repeated once more on 29/08/2022 13h. A report of the campaign of 2022 is provided in a deliverable of the Stargate project but is not publicly available yet.

3.2.2 UFP monitoring at other airports

There is already a significant body of research studies focusing on the UFP concentrations around airports. A systematic literature review of recent research on the impacts of commercial airport emissions on air quality in close proximity to airports was conducted by Riley et al. (Riley et al., 2021b).We have used this review paper as starting point and additional literature was found using reference database searches in PubMed, Web of Science and Google Scholar for the period 2018-2024. The focus of this systematic review was impacts of commercial airports dominated by jet aircraft activity; thus, studies that focused on ground service equipment or piston engine activity were excluded.

The analysis of existing research is described below and subdivided into the following sections: spatial extent, size distribution, chemical characterization, operating modes, fleet, correlation to other pollutants, outdoor and indoor relationship and gaps.

3.2.2.1 Spatial extent and role of geography

As a significant source of UFP, aircraft engine emissions can cause increases in ground-level particle number concentrations (PNC) over large areas downwind of airports (Chung et al., 2023; Gerling & Weber, 2023; Hudda et al., 2020; Lammers et al., 2020; Lopes et al., 2019; Riley et al., 2021c; Seidler et al., 2024; Stacey, 2019b; Stacey et al., 2020, 2021a, 2023a). The spatial extent and magnitude of the impact from UFP varies depending on factors including wind direction and speed (Lopes et al., 2019a), runway use pattern, flight activity and fleet mixes. This can encompass large populations in cities where airports are located close to the urban residential area where the PNC was found to be elevated 7 km downwind of Schiphol Airport Amsterdam (Keuken et al., 2015b) and Berlin Airport (Gerling & Weber, 2023), about 17 km from Logan International Airport Boston (Chung et al., 2023), until 1.2 km from Lisbon airport (Lopes et al., 2019a), until at least 3 km downwind of Mohammad Ali International Airport. Elevated UFP concentrations up to 300,000 particles/cm^3, with the same lower particle diameter of 10 nm, could be measured up to 2.7 kilometres away from Stuttgart Airport (Samad et al., 2022).

Trebs et al. found an UFP concentration that was 5 to 10 times higher when air masses from the Findel Airport in Luxembourg arrived at the measurement site, compared to situations when air from forest or urban background sectors had the highest contribution (Trebs et al., 2023). In addition to the increase in concentration described above, Trebs et al. (2023) found that UFP (nucleation and Aitken mode particles) were reduced substantially during the day near Findel Airport Luxemburg, although flight movements were highest during that time. An effect that the authors attribute to temporal dynamics of the mixing layer. Findel is located at a slightly elevated flat plateau, which is exposed to efficient near-surface turbulence, reducing daytime pollutant and UFP concentrations. Therefore, it is concluded that the airport siting and geographical surroundings could influence UFP spatial distribution substantially.

3.2.2.2 Size

Jet engine tests revealed that the finest particles, less than 30 nm in diameter, are associated with low thrust settings. Larger particles, in the range 30–90 nm, are associated with thrust settings from 35% and higher. In practice, this means that the smallest particles are associated with the airplane modes during which the engine is running at a lower engine mode, resulting in less complete fuel combustion. Consequently, the smallest particles are observed during landing and taxiing, whereas the larger particles are emitted during take-off. NC follows a similar trend in thrust settings. A number of studies have shown that engine design (and fuel burned, in an alternative fuel experiment) is critical to the concentrations and sizes of particles created (Stacey, 2019b). Largest PNC emissions are thus also associated with landing and taxiing.

In ambient setting, i.e., in an external environment, aircraft emissions are dominated by extremely fine particles, 10–20 nm in size (Keuken et al., 2015b; Lammers et al., 2020; Samad et al., 2022; Stacey, 2019c). This contrasts with rural and urban background locations at tens of kilometres from airports, where particles are typically significantly larger (with peaks between 60 and 100nm). The airport-related particle size distribution (PSD) profile is also different to traditional road traffic, which has peak PSD from 30 to 50 nm. Note that the similar behaviour has been observed by VMM when comparing the measurements at Steenokkerzeel with those at an urban background location in Borgerhout[12].

New particle formation (NPF, sub-10 nm) was studied nearby Paphos airport Cyprus using a newly developed DMA-train (Brilke et al., 2020). The airport was found to be a large emission source for nucleation mode particles. Size distribution of airport emission plumes showed a mean mode diameter of 12.6 nm which is in conformity with the studies described above. Strong particle dynamics on relatively short timescales were revealed in the sub-10 nm size range, and early growth events were characterized. The clear appearance of a new mode followed by growth of the particles below 10 nm was found to be interrupted abruptly by changes in the meteorological conditions.

Yin et al (2023) studied the particle size distribution from take-off and landing and found that aircraft landing had the greatest effect on the 6–17 nm particle size range, with an increase in PNC of about 3.27 times. Aircraft take-offs had the largest effect on the 29–57 nm particle size range, increasing the PNC by a factor of about 35.4.

3.2.2.3 Chemical characterization

The vast majority of non-volatile particles from aircraft exists as carbon particles, soot or organic carbon. At low thrust settings, organic carbon particles are more common. Speciation of the exhaust components has not quantitatively succeeded in identifying key tracers unique to aircraft activity (Stacey, 2019c). The majority of the total particle numbers comprises of volatile and semi-volatile particles, condensing and nucleating as the engine exhausts cool and mix exposing the general public downwind of the airport (Stacey et al., 2023a). Ungeheuer et al. (2021) studied the identification and source attribution of organic compounds in UFPs near Frankfurt International Airport. The analysis of the individual pattern of ester molecules and the comparison to jet oil standards revealed the presence of two different oil base stocks that emerge in the UFPs. Jetoil vapours reach gas-phase supersaturation in cooling emission plumes leading to rapid nucleation and formation of UFPs in the range of ~10–20 nm (Ungeheuer et al., 2022).

Chemical analyses of collected particles and online monitoring techniques (mass concentration by the β-ray in-situ detection method, heavy metal elements by X-ray fluorescence and atmospheric water-soluble ion online analyser for detecting water-soluble ions, mainly OC and EC) were used to study the chemical composition of particles at Tianjin Binhai International Airport China (Yin et al 2023). The concentrations of Si, OC, Ca, Al, Fe, Ca^{2+}, EC and Mg^{2+} were considered as prominent species in airport emissions. Additionally, metallic elements including K, Zn, Ti, Mn and Cu can also be considered as tracers in characterizing particulate emissions from civil airports.

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[12] See https://www.vmm.be/lucht/fijn-stof/concentratie-ultrafijn-stof,

Elementary analyses of sampled particles at two French airports showed that the chemical composition was linked to the particle size and offered some clues to make a link between metallic tracer elements and the sources of emission. Thus, the elementary analyses showed that the nanometric fraction of the aircraft emissions was mainly due to combustion with a majority presence of carbon/oxygen. The metallic elements that can be used as emission tracers occurred mainly at the micrometric scale. The elements identified as potential tracers of aircraft emissions were titanium, zinc and possibly bromine (Artous et al., 2024b).

3.2.2.4 Sensors

For UFP, some studies are conducted using the Partector 2 sensor for PNC and PSD measurements. For example, at Zurich Airport, the Partector 2 was used to assess the UFP concentrations at different sites. Other measurement campaigns with the Partector 2 were conducted in Zurich and Germany (Asbach et al., 2024; Edebeli et al., 2023).

3.2.2.5 Fleet

Measurements during larger aircraft departing from the runway recorded higher measurements of nucleation particles and NO_x compared to smaller aircraft but emissions of BC, UVPM and NO_2 appear to be more dependent upon the age of the engine design, rather than the size of the aircraft (Stacey et al., 2021b, 2023b). Measurements from individual aircraft show that, although larger aircraft emit significantly more particles per second, the total particle number emission rates per passenger carried are lower compared to smaller aircraft.

3.2.2.6 Correlation other pollutants

Correlation of UFP nucleation particles with NO_x and BC was found during the study at Heathrow airport (Stacey et al 2021). PNC coincided with the periods of highest noise co-exposures at Logan airport Boston (Hudda et al., 2020). Noise and UFP correlations around Gatwick airport were moderate to low suggesting, but the correlations were affected by meteorological factors, which need to be considered in studies of short-term associations between aircraft noise and health (Tremper et al., 2022).

3.2.2.7 Source apportionment

The ability to distinguish between aircraft and other sources of UFPs (e.g., traffic), was studied by Austin et al. (2021) using a mobile measurement platform (Austin et al., 2021b). They showed that roadway traffic consisted of relatively larger UFP sizes and high BC concentrations, while UFP from aircraft sources consisted of relatively smaller UFP sizes and lower BC concentrations. These differences can help distinguish between the spatial impact of roadway traffic and aircraft UFP emissions using a combination of mobile monitoring and standard statistical methods.

Characterization of PNC, the median particle size (dmn50), and the metallic composition of medium-haul area and engine aerosols at two French airports revealed that on the one hand, aircraft engine emissions led to the highest emissions (linked to the engine speed) of UFPs, up to 10^7 p/cm^3, and a median particle size of less than 20 nm. On the other hand, the engines of the various vehicles used on the apron have their own specific emissions (linked to the generation and fuel used), but overall, these emissions are lower (10^4–10^6 p/cm^3), with a higher dmn50 from 20 to 100 nm (Artous et al., 2024b).

Seidler et al (2024) investigated UFPs in close proximity to an airport to disentangle their impact on local air quality from other urban sources. The study analysed the spatial and temporal variations of UFPs and wind data for two residential areas adjacent to Munich Airport for the period of 1 year. UFP concentration roses were derived showing an increase in PNC and a shift of the modal maximum towards smaller mobility diameters became evident for wind directions, including those approaching from the airport. A significant seasonal and diurnal variability of UFPs and wind became evident. The influencing factors were likely other urban local UFP sources, an increased surface roughness due to green vegetation and the atmospheric boundary layer development.

3.2.2.8 Gaps

Several knowledge gaps have been identified concerning the monitoring of UFP around airports:

- Indoor infiltration: Quantify the impact of housing stock characteristics (age, architectural style, and degree of sound insulation) on infiltration. Studying a greater range of behaviours that impact infiltration and indoor air quality (e.g., air conditioner use, in-home filtration and ceiling fans) could help to identify practices that reduce indoor exposures. Measure additional pollutants indoors (e.g., NO_2 and BC) to determine whether other pollutants infiltrate to the same extent as PNC (Hudda et al 2020).
- Source contribution: More research is needed linking particle size distributions to specific airport activities (i.e., take-off and landing), but also including taxi (Riley et al., 2021b; Stacey, 2019d).
- Spatial extent of the plumes: While particle size distribution changes with increasing distance from the airport, transformational behaviour of particles as they are transported downwind of the exhaust needs further study (Riley et al., 2021b; Stacey, 2019d). Due to limitations of stationary measurements, Samad et al (2022) recommends that mobile platform measurements be made to better understand the spatial distribution of aircraft plumes (Samad et al., 2022). This is also confirmed by the work from Austin et al. (Austin et al., 2021b).
- Chemical characterization: Studies of the chemical composition of particles may shed light on the relative contributions from landings, take-offs, idling and taxiing at this scale and may also provide insights into mitigating these impacts (Hudda et al 2020).
- Chemical reactions in the exhaust plume: The emissions and evolution of volatile particles (vPM) in the aircraft exhaust plume should be better estimated (Owen et al., 2022b). vPM condense and agglomerate in the exhaust plume or at a later stage in the ambient atmosphere and, due to their evolution in the aircraft exhaust plume, are more difficult to quantify, measure and assess. However, together with nvPM, vPM contributes to total measured ambient concentrations of particulate matter (the ambient measurements do not usually distinguish between them) which are compared with current local air quality health guidelines.
- Long-term measurement campaigns: Long-term studies should be conducted to capture variation in ambient concentrations (years and seasons) (Riley et al 2021). Droge et al. demonstrated that a large commercial airport (Frankfurt) has the potential to lead to a high PNC even in a distant residential area (7 km) (Dröge et al., 2024). Due to the high PNCs, the diameter of the most abundant particles and strong concentration fluctuations, long-term measurements are essential for a realistic exposure analysis.
- Include all meteorological situations: Exposure monitoring campaigns should be designed to include adequate coverage of the times of day (and times of high flight activity) with specific meteorological conditions of concern, especially wind direction (Hudda et al 2020).

3.3 Knowledge gaps related to UFP

During the literature review, several knowledge gaps and options to improve our knowledge regarding the UFP pollution around airports and Brussels Airport specifically have been identified.

3.3.1 Gap analysis for UFP emissions and concentrations around airports

Further research is needed to accurately estimate total emissions and particle size distributions of specific airport activities such as take-offs, landings and taxiing. Currently, these emissions are only roughly estimated, associated with the complex chemical processes occurring in the engine exhaust jet, which result in a considerable proportion of volatile particles. The evolution of these volatile particles in aircraft exhaust plumes is poorly understood, yet it is crucial for assessing the overall UFP concentrations. Moreover, the behaviour of both volatile and non-volatile particles as they travel downwind from the airport remains a vital area of study. Monitoring the chemical composition of particles could enhance our understanding of all these complex processes. Additionally, not much is known about the impact of future aviation fuels, including sustainable aviation fuels (SAFs). This limitation has been highlighted during the Aviator project, emphasizing the need for comprehensive research into the environmental impacts and emission characteristics of alternative aviation fuels (Aviator Project, 2023; Janicke, 2023b).

In all cases, long-term studies are essential to capture the variability in ambient concentrations across different seasons and years, offering a more realistic assessment of exposure.

3.3.2 Gap analysis for UFP pollution around Brussels Airport

Specifically for the pollution around Brussels airport, knowledge gaps are mainly related to the need for additional permanent measurement stations and improvements in modelling, particularly for short-term model results. More in detail, the following insights have been compiled:

- Currently, there is only one permanent continuous measurement station measuring the UFP concentrations in the vicinity of the airport, located at Steenokkerzeel. During the measurement campaigns described above, which focused on time scales of several months, significant spatial variation in the concentrations has been observed, both on short and longer time scales. Therefore, monitoring of UFP concentrations around the airport would greatly benefit from the addition of extra continuous measurement stations, preferably in multiple wind directions from the airport. This approach would enable a better understanding of the spatial pattern of the pollution and facilitate a clearer distinction between the contributions of the airport and other sources (for example, by comparing the results from downwind and upwind locations). Moreover, there is currently no rural background station measuring UFP concentrations in Belgium. The addition of such a station would be beneficial to establish an absolute baseline for rural background UFP values.
- Only a very limited number of dynamic pollution measurements have been conducted. To get a better indication of personal exposure, and especially to understand the difference between dynamic and static exposure on a population level, additional dynamic measurements should be conducted. This is especially important for UFP, given the large spatial gradients observed in the vicinity of the airport. Note that there are currently already trustworthy "low-cost mobile devices" devices on the market, but that the cost, while low in comparison with the cost of stationary more accurate instruments, is still quite high, at several thousands of euros per device[13].
- The current model chain can only be used at the time scale of daily means or longer averages. Moreover, the uncertainties increase as the temporal resolution increases, hence even the daily results come with substantial uncertainty. Due to the significant variation in the emissions of non-volatile particles from flight to flight, along with the great variation in the formation of volatile particles, it is nearly impossible to accurately estimate the emissions of individual flights, and thus also the concentrations at shorter time scales. A way forward might be to combine the model chain with measurements in a so-called data assimilation step. Note that, for such a process to

[13] Roughly speaking, a low-cost mobile device costs around EUR 10,000, while a stationary, more accurate instrument costs about four times more. These estimates do not include the personnel costs to operate the devices.

work effectively, at least several measurement locations should monitor the UFP concentration at the temporal resolution desired in the model chain. Preferably, these measurement stations are located such that they are spread around the airport in all wind directions, ensuring that always a downwind sensor can model the background concentration with only minor impact from the airport.

- The current model chain has exclusively been applied to the year 2019, resulting in detailed maps with a resolution of tens of meters only for that year. Within the scope of the Stargate project, also maps for 2022 will be composed, but other years are currently not considered. Consequently, it is not feasible to deduce exposure over multiple years, which could be a necessary input for conducting a detailed epidemiological study. However, given that all input data is available, it is theoretically feasible to produce UFP concentration maps for additional years (before 2019) .

4 Hazardous air pollutants (HAPs)

In recent studies, concerns have emerged regarding certain chemical substances potentially hazardous to human health. The Netherlands has compiled a list of these substances, known as "Zeer Zorgwekkende Stoffen" (ZZS), and a similar list is being composed in Flanders (Department of Environment and Department of Health; the latter focusing on ZZS with human relevance). Given the extensive nature of these lists (the Flemish list includes over 2,400 substances), an initial step involves overlaying the Flemish list with one identifying substance found in aircraft emissions to the air. To ensure comprehensiveness, this comparison extends to substances classified as hazardous under the Clean Air Act by the U.S. Environmental Protection Agency (EPA) (this resulted in a few additional compounds)

In a subsequent phase, the focus narrows to pollutants from this refined list to determine their incorporation into air quality modelling. By comparing modelling results with health-based guidance values (referred to as "Gezondheidskundige advieswaarde, GAW"), the number of substances requiring further analysis is reduced. This streamlined list undergoes additional scrutiny through a literature review, examining whether these substances have been analysed through modelling or measurements at international airports. The culmination of this process is the formulation of a set of recommendations concerning Hazardous Air Pollutants (HAPs).

4.1 Determination of HAPs

As detailed in the EMEP/EEA Inventory Guidebook on aircraft air pollutant emissions (EEA, 2023), only a limited number of studies have focused on the chemical specification of exhaust gases from aircraft turbines. Specifically, for the Landing and Take-Off (LTO) phase, the U.S. Environmental Protection Agency (EPA) has documented a profile of Volatile Organic Compounds (VOCs) emitted by aircraft equipped with turbofan, turbojet and turboprop engines (Knighton et al., 2009; US EPA, 2009). In total, the EPA study has identified over 75 substances, drawing on a combination of specification studies by Spicer (Spicer et al., 1994) in the 1980s and 1990s and the more recent Aircraft Particle Emissions eXperiment (APEX) initiated by NASA and supported by a wide range of governmental institutes in the U.S (Lobo et al., 2007; Onasch et al., 2006; Wey, 2004; Wey & Anderson, 2006). The complete list of these substances and their mass fraction relative to the total hydrocarbon emissions are provided in the EMEP/EEA Guidebook. It is important to note that these specifications were established under specific conditions with low thrust settings (below 30% thrust), chosen because at higher thrust ratios, engine combustion efficiency increases, reducing hydrocarbon emissions to very low or undetectable levels. Given that hydrocarbon emissions are predominantly from low thrust phases of the LTO cycle, changes in emission profiles at higher thrust settings are expected to have minimal impact on net HAPs loading. Nevertheless, there is a significant degree of uncertainty associated with the net emissions, and they should be interpreted with caution. When analyzing the results, emphasis should be placed on the emissions' order of magnitude rather than on precise values, due to the potential variability in emission profiles across different operational conditions. Moreover, this study focuses exclusively on current jet fuels, leaving a gap in knowledge regarding potential future fuels, such as Sustainable Aviation Fuels (SAFs). Aircraft emissions included in above mentioned sources capture emissions from exhaust engines and thus do not capture emissions from jet fuels that can be jettisoned from aircraft for safety reasons. Data on quantities for these processes are not available. Such discharges are made at a high altitude, away from areas of populations and the majority of the fuel will be vaporized (Concawe, 2009).

We have performed a cross-referencing of the list of chemical substances observed in jet engine plumes with the list of Zeer Zorgwekkende Stoffen (ZZS) (De Brouwere et al., 2023), which is being compiled on behalf of the Department of Health in Flanders. Through this process, we identified nine substances that appear on both lists:

- 1,3-butadiene
- 1-methyl naphthalene
- 2-methylnaphthalene
- Acetaldehyde / ethanal
- Benzene
- Crotonaldehyde
- Formaldehyde
- Isopropyl benzene / cumene
- Naphthalene

Note that, in comparison with earlier compilations within the scope of the MER (Milieu Effect Rapport) for Brussels Airport and studies for Schiphol Airport, two additional substances, cumene and ethanal, have been added. Aside from these additions, the list remains consistent with those previously utilized.

To mitigate the impact of using a specific list of Hazardous Air Pollutants (HAPs), we also conducted an overlap analysis between the list of substances detected in the emission jet and the list of substances designated as hazardous under the US EPA Clean Air Act. This approach led to the identification of an additional 9 substances:

- Acrolein
- Ethylbenzene
- Methanol
- m-xylene and p- xylene
- o-xylene
- phenol
- propionaldehyde
- styrene
- toluene

Consequently, a total of 18 substances have been recognized as present in the exhaust plumes of jet airplanes and marked as potentially hazardous to human health. In the subsequent section of this chapter, we will first determine which of these substances are already incorporated into air quality model chains and whether the remaining substances can be integrated into the existing models with minor adjustments. By comparing these model outputs (modelled concentrations at locations with relevance for residential exposure) with health-based guidance values (for chronic inhalation exposure) we can perform a first, indicative health risk assessment and narrow down the list of substances for further consideration.

4.2 Existing modelling

4.2.1 Brussels airport

Air concentration maps for the vicinity of Zaventem Airport are derived within the environmental assessment study (MER) related to the new permit for Brussels Airport (Antea Group, 2023). Within the air pollution discipline, the emissions and concentrations of benzene and naphthalene were modelled using the ATMO-Street model chain, whereas the other HAPs have not been considered. The selection of these pollutants was influenced by the list of HAPs identified in the requirements for the environmental impact report and their chemical stability. Given that the model chain operates with a time resolution of an hour, it was decided to include only those substances that are chemically stable over this period.

However, it is feasible to account for all the HAPs within the model chain by assuming they remain chemically inert over an hourly timescale. Should this assumption not hold, the model would overestimate the concentrations, since it operates under the premise that the chemicals do not undergo any reactions, contrary to what may occur in reality. It is also important to note that, in theory, the ATMO-Street model chain could be adapted to consider a substance's limited lifespan by incorporating exponential decay over time into the model. Nonetheless, such modifications would necessitate substantial model development, and the resulting concentrations would only be lower. We therefore neglect the chemical interactions for the moment, and hence provide a worst-case estimate for the concentrations of all HAPs.

Since the emissions of all HAPs are quantified relative to the total emissions, and since, in the context of this analysis chemical reactions are not considered, the concentrations of all HAPs can be straightforwardly calculated by rescaling the concentration maps for a specific HAP. In this instance, we use the air pollutant map for naphthalene from the MER as a base. For any given HAP, we adjust the map according to the ratio of the HAP's emission fraction to that of naphthalene's emission fraction. Concentrations are then determined at two key locations: one where the highest concentrations are recorded (on the airport near the apron, affecting only airport facility workers and not the general public), and another at the residential location experiencing the highest concentrations (in Steenokkerzeel along the extension of runway 07L/25R). The concentrations at both sites for all HAPs identified previously are listed in Table 1.

Besides concentration data, the table also includes health-based guidance values e for the substances for chronic exposure (inhalation). Whenever possible, the health advisory value (Gezondheidsadvieswaarde, GAW) utilized in Flanders has been applied. In instances where GAWs were not available, the gaps were filled with official values from the United States (US EPA Integrated Risk Information System), Germany (UBA Indoor Air Limit Values), the European level (EU CLI) and France (ANSES) (more details on selection process: see WP 1 report). A comparison of health-based guidance values with the maximum exposure and concentration levels reveals that for nearly all HAPs, the concentrations are significantly lower—more than an order of magnitude—than the health-based guidance values. Consequently, it is highly unlikely that individuals living in proximity to the airport will experience adverse health effects from these substances. The sole exception is benzene, where the maximum value on the tarmac exceeds the GAW, and the maximum exposure reaches 80% of the GAW. However, it is important to note that for benzene, the GAW is substantially lower than the limit value for air pollution stated in the Ambient Air Quality Directive (AAQD) (5 µg/m³) and its proposed revision (3.4 µg/m³) (EU, 2024).

It is critical to acknowledge the uncertainties inherent in this analysis. While there is some uncertainty associated with emission and dispersion modelling, the greatest uncertainty lies in the estimation of emission factors, as detailed previously. Despite these uncertainties, given the significant disparity between the health-based guidance values and maximum exposure for most substances, it is unlikely that the overall conclusion—that negative health impacts from the airport due to these substances are very improbable—will change. The exception is benzene, where the narrow gap between maximum exposure and health limit values means that uncertainties regarding emission factors could potentially alter the final conclusions. Corroborating the modelling results with additional data, such as those obtained from an in-situ measurement campaign, would be beneficial to reduce the uncertainties in the model chain.

4.2.2 Other airports

Although many studies have focused on determining the total VOC and hydrocarbon emissions and concentrations in the vicinity of airports, few have explored the modelling of individual HAPs (Vennam et al., 2015). An exception is a study on the T.F. Green Airport (PVD), a medium-sized airport in Providence, Rhode Island, USA. They focused on formaldehyde, acetaldehyde, acrolein, 1,3-butadiene, benzene, toluene, xylene and naphthalene. To estimate the emissions of the HAPs, the study used a methodology similar to that employed for Brussels Airport, with minor differences (approximately 1%) in the actual emission factors for individual HAPs. The modelled emissions were then integrated into a chemical transport model (CMAQ) with a coarse resolution of 4x4 km, incorporating estimates of general background concentrations. The concentrations attributable to the airport were minor, with less than 15% of total concentrations linked to airport emissions for most HAPs, except for acrolein, which accounted for 19-28% of the total in the grid cell comprising the airport. Notably, the observed concentrations were significantly lower than those at Brussels Airport. The study also included a brief validation exercise, concluding that there is substantial uncertainty in the model results. This uncertainty is attributed to the model's coarse resolution and the sparse distribution of measurement stations near the airport. It was observed that both acrolein and formaldehyde showed the largest underestimation, similarly at measurement locations close to and further from the airport, suggesting that the underestimation is likely related to the background concentration (arising from other sources).

Table 1: Modelled concentrations for the HAPs identified in the current document. The table provides the maximal concentration in the domain, the maximal exposure (by overlaying the concentration map with the population map) and the health advisory value.

Substance	CAS	Maximal annual mean concentration (µg/m³)	Maximal annual mean exposure (µg/m³)	Health-based guidance value (chronic exposure)* (µg/m³)
1,3-butadiene	106-99-0	0.374	0.031	2
1-methyl naphthalene	90-12-0	0.055	0.005	14
2-methyl naphthalene	91-57-6	0.046	0.004	14
acetaldehyde	75-07-0	0.948	0.079	160
acrolein	107-02-8	0.543	0.045	0.8
benzene	71-43-2	0.373	0.031	0.038
crotonaldehyde	4170-30-3	0.229	0.019	5
ethylbenzene	100-41-4	0.039	0.003	260
formaldehyde	50-00-0	2.730	0.228	100
isopropyl benzene	98-82-8	0.001	0.000	400
methanol	67-56-1	0.400	0.033	2000
m-xylene and p- xylene	108-38-3 / 106-42-3	0.063	0.005	217
naphthalene	91-20-3	0.120	0.010	3
o-xylene	95-47-6	0.037	0.003	217
phenol	108-95-2	0.161	0.013	20
propionaldehyde	123-38-6	0.161	0.013	8
styrene	100-42-5	0.069	0.006	260
toluene	108-88-3	0.142	0.012	5000

*Source of health-based guidance value: see Table 5 in WP 1.

4.3 Measurement campaigns at other airports

To our knowledge, no detailed measurement campaigns specifically targeting the HAPs discussed in the previous sections have been conducted around Brussels Airport. However, several studies have been conducted to measure both general hydrocarbons and specific HAPs near other airports. Comparisons between these studies are challenging, as they often employ slightly different assumptions and target various substances. Generally, the concentrations of most substances around airports align with those measured at nearby urban background locations, suggesting that the airport's contribution to local pollution levels is not significant.

In the following paragraphs, we provide an overview of measurement campaigns that targeted total hydrocarbons and campaigns that measured specific HAPs. We specifically focus on studies that measured concentrations outside the actual airport grounds-, as this is the primary concern of the current document.

4.3.1 Overview of campaigns

- A measurement campaign was conducted around the military airfield of Leeuwarden during Operation Frisian Flag, focusing on the concentrations of various substances (Tromp & Esveld, 2024). The conclusions from this campaign indicate that no discernible influence of air traffic could be detected on the concentrations of organic substances such as mineral oil (oil mist), volatile organic compounds (VOCs), BTEX (benzene, toluene, ethylbenzene and xylene), other aromatic components, polycyclic aromatic hydrocarbons (16-EPA-PAH) and carbonyl compounds. The concentration levels of all these substances are low and comparable to regional background values in the Netherlands.
- The concentration of polycyclic aromatic hydrocarbons (PAHs) bound to PM was studied around the runways at Barajas International Airport (Madrid, Spain) (Rodríguez-Maroto et al., 2024). The highest concentration of PM measured was 31 µg m^{-3}, while the concentration of total PAH was 3 ng m^{-3}, both comparable to those recorded in a semi-urban area of Madrid. The PAHs showed a similar profile to the particle size distribution, with a maximum in the 0.27–0.54 µm size range, being preferentially found in the submicron size fractions (84%) and UFP (15–20%). The ratio PAH(m)/PM(m) was more than twice as high in the colder months. The greater PAH concentrations in the cold campaign corresponded to compounds with higher molecular weight. This could be due to the additional contribution of other external sources, such as thermal and related combustion processes.
- Other measurement campaigns focused on hydrocarbon concentration at LAX. Westerdahl et al. (Westerdahl et al., 2008) observed particle-phase polycyclic aromatic hydrocarbon (PM-PAH) concentrations two orders of magnitude higher at downwind locations compared to upwind locations, although aircraft-dominated areas showed lower PM-PAH than vehicular traffic areas. PM-PAH values observed at the site 500 m downwind of landings were only slightly elevated above the coastal background.
- Benzene and toluene have been measured around an Italian airport in Rome (Ciampino Airport) to assess the long-term spatial variability of these pollutants (Stafoggia et al., 2016). They reported that the presence of the airport was not associated with an increased presence of benzene or toluene.
- In a buffer of 1000 m around Mehrabad International Airport (Tehran) the annual median benzene and total BTEX concentrations were compared with the rest of the city-wide sites (Amini et al., 2017). The annual mean benzene and total BTEX concentrations at these 10 sites were 7.8 mg/m^3 and 57.3 mg/m^3, respectively, while they were 7.9 mg/m^3 and 58.7 mg/m^3 at the city-wide sites, suggesting that airports do not affect BTEX concentrations within 1 km.

- Comparable results were found by Jung et al. (Jung et al., 2011) using passive samplers to determine the average concentrations of benzene, toluene, ethylbenzene, m-, p- and o-xylene concentrations at the airport runways, respectively 0.84, 3.21, 0.30, 0.99 and 0.34 µg/m^3. However, the average neighbourhood concentrations were not significantly different to those measured at the airport runways and were higher than the out-of-neighbourhood location.
- VOCs measurements were also performed at Beijing airport (Yang et al., 2018). In this study, 53 VOCs were detected at the airport, including 28 alkanes, 9 alkenes, 15 aromatics and acetylene. The average VOC concentration in the airport was 65.51–95.84 µg/m^3. The most abundant species in the airport was toluene (7.03–16.65 µg/m^3), followed by benzene, ethane, isopentane, ethane, acetylene and n-butane.

4.4 Measurement methods

As highlighted in the previous sections, substantiating the modelling of the HAPs with measurements is essential to validate the modelling results and further assess the impact of these pollutants around airports. The Appendix of this report (see *Section 6*) provides an overview of the sampling techniques available for the HAPs identified previously. The general conclusion is that, for most of the HAPs of interest, measurement methods are available. For some compounds, it might be challenging to find a measurement method with appropriate sampling volume to assess concentrations at or below health-based guidance values.

4.5 Knowledge gaps regarding HAPs

The following knowledge gaps have been identified during the literature review and gap analysis:

- There is a need for additional experiments on the chemical specification of plumes from jet engines. The existing results are derived from studies conducted in the 1990s and the early 2000s, and all the results are originating from a relatively limited number of studies.
- There is a need for measurement campaigns to validate the modelling results and reduce the uncertainties related to the emission factors. The emphasis should be on benzene, as this is the substance for which population exposure is closest to the health-based guidance values but conducting measurements for the other HAPs identified previously could also be beneficial. It is, however, important to acknowledge that such measurements will capture total concentrations, which combine the contribution of the airport with background levels attributable to various sources. Distinguishing between these contributions poses significant challenges, particularly when the airport's impact is as minimal as modelling predictions suggest. Moreover, it might be challenging to find a measurement method with appropriate sampling volume to assess levels below or around health-based guidance value, with acrolein, benzene and methanol as most critical substances.
- The air pollutant model chains utilized at Brussels Airport (i.e., ATMO-Street) currently do not account for a substance's limited lifespan. However, this could be achieved by incorporating exponential decay over time into the model. Given that the concentrations of the most unstable HAPs are well below the health impact limit values, it is observed that this modification is probably not crucial when calculating the health impact of the airport.
- Not much is known about the impact of future aviation fuels, including sustainable aviation fuels (SAFs). This limitation has been highlighted during the Aviator project, emphasizing the need for comprehensive research into the environmental impacts and emission characteristics of alternative aviation fuels (Aviator Project, 2023). The exploration of SAFs is crucial for the aviation industry's transition towards more sustainable operations, yet the specific emission profiles and environmental implications of these fuels remain under-examined.

5 Items that might be relevant for WP4

The following items should be considered when compiling a research plan:

- Model limitations
    - For many environmental stressors, modelling data is only available specific periods.
        - Standard air pollutants: only 2019
        - UFP: 2015 (partially), 2018 (partially), 2019 and 2022
        - ZZS: only annual mean for 2019
        - Noise: all recent years (but at the moment only the parameters mentioned in the section on noise modelling)
    - Modelling data is only available for outdoor situations. No indoor levels have been studied for any of the stressors.
    - All knowledge is based on current-day operations. There are large research gaps related to future fuels and technologies.
- Model uncertainty for long-term modelling
    - Limited for noise and standard pollutants
    - Large uncertainty for HAPs, as no validation has occurred, and the modelling is based on a few specific emission measurement campaigns. Measurements needed to back-up the modelling (but it might be difficult to distinguish between contribution of airport and other sources). Focus depends on the perspective (from health: benzene)
    - Model results for UFP come with a significant uncertainty, due to uncertainty in the emission factors and the knowledge gaps regarding the complex chemical processes associated with engine exhaust jets (see discussion in the specific section). Data assimilation might improve the results, but multiple permanent monitoring locations required
- Model uncertainty for short-term modelling
    - Modelling with a high time resolution comes with a large uncertainty (for all stressors). Data assimilation might improve the results (especially for UFP), but some uncertainty will remain when sub-daily results are considered. See detailed discussions in the relevant sections.
- Static monitoring data is available for some longer periods, but this is spatially disaggregated data (only snapshots at specific locations)
    - Standard pollutants:
        - Continuous monitoring during all recent years (but only at standard monitoring stations)
    - UFP:
        - Continuous monitoring at VMM station Steenokkerzeel since 17/06/2022
        - Campaigns at various locations in 2015, 2018/2019 and 2022
    - Noise
        - Continuous monitoring at standard locations
- Dynamic monitoring data is currently lacking for all stressors (apart from a small prototype study for noise exposure)
- Regarding the spatial scale, the modelling results indicate that
    - The influence of the airport on standard air pollutants is limited to an area with a radius of 7km. Determined based on a contribution > 0.6 ug/m3 (3% of GAW) for NO_2, which is the most important pollutant. The plume is mostly in the direction of Kampenhout (NE of airport) but is rather spatially isotropic.
    - The influence of the airport of noise spans a very wide area, ranging from Ternat to Aarschot (WE) and from Muizen to Hoeilaart (NS) (see figures in text). The contours are

highly anisotropic, and therefore any spatial division of the study domain should not solely be based on the distance to the airport, but also on the actual noise levels.

- It is difficult to estimate the spatial extent for UFP, as no limit values exist, but in a domain with a radius of 7km around the airport the concentrations fall below 10.000 part/cm3 (annual mean).

6 Appendix: overview of modelling studies for air pollution

Table 2: Overview of important studies using air quality modelling to assess the pollutant concentrations near airports.

Authors	Pollutants	Location	Model type	Model
Carruthers et al. (2007)	NO_x	Heathrow (UK)	Eulerian	ADMS
Mazaheri et al. (2009)	UFP, $PM_{2.5}$, NO_x	Brisbane airport (AU)	Eulerian	AERMOD
Carr et al. (2011)	Pb	Santa Monica Airport (US)	Eulerian	AERMOD
Arunachalam et al. (2011)	$PM_{2.5}$	3 airports (US)	CTM	CMAQ
Ellermann et al. (2012)	NO_x, SO_2, $PM_{2.5}$, BC, PH, VOC	Copenhagen (DK)	CTM	MISKAM
Keuken et al. (2015)	PNC, BC	Schiphol Airport (NL)	Eulerian	SRM3
Pecorari et al. (2016)	NO_x, HC, CO	Marco Polo Airport (IT)	Eulerian	SPRAY5
Woody et al. (2016)	SOA, VOC	99 airports in US	CTM	CMAQ
Sarrat et al. (2017)	NO_x, SO_2, VOC, CO, CO_2	Regional airport (FR)	CFD	IESTA
Kuzu (2018)	NO_x, CO, HC	Atatürk International Airport (TR)	Eulerian	AERMOD
Lorentz et al. (2019)	UFP	Frankfurt (DE)	Lagrangian	LASPORT
Bo et al. (2019)	NO_x, CO, HC, VOC, SO_2, PM_{10}, $PM_{2.5}$, BC	217 airports in China	CFD	CAMx
Lefebvre et al. (2019)	UFP	Brussels Airport (BE)	Eulerian	IFDM
Makridis et al. (2019)	NO_x, CO, HC, VOC, SO_2, PM_{10}, $PM_{2.5}$, BC	Chania Airport (GR)	Eulerian	AERMOD
Ghedhaïfi et al. (2022)	NO_x	Mock airport representative of medium size airports (ICAO)	CFD	CEDRE
Lawal et al. (2022)	O_3, UFP, $PM_{2.5}$, NO_2	Atlanta Hartsfield–Jackson Airport (US)	CTM	CMAQ
Bajgai et al. (2023)	NO_x, CO, HC, VOC, SO_2, PM_{10}, $PM_{2.5}$, BC	Tribhuvan International Airport (NP)	Eulerian + CTM	AERMOD + WRF
Pandey et al. (2023)	SO_2	Los Angeles International Airport (US)	Eulerian	AERMOD
Voogt et al. (2023)	UFP	Schiphol Airport (NL)	Eulerian	STACKS+
Zurich Airport (yearly reporting)	NO_2, PM, UFP	Zurich Airport (CH)	Lagrangian	LASPORT

7 Appendix: Measurement techniques for HAPs

In general, three types of sampling techniques exist. Online sampling is performed when a measurement instrument directly samples the air and produces (semi-)directly concentrations of interest. Offline sampling is performed with a sorbent tube (or whole air canister) to sample the air, followed by an analysis afterwards in the laboratory. The sample is either active with a sampling pump or passive where compounds are collected through molecular diffusion. All three techniques are applicable to the HAPs listed in Table 1. Whole air sampling using canisters is left out of the scope as it is not suitable for long term air sampling.

7.1 Online Sampling

Online sampling can be divided into component-specific and non-specific methods. The first type of technique contains Total VOC analysers or sensor boxes. Concentrations obtained are totals and do not give compound-specific information. The advantage of these techniques is foremost that they result in time-resolved concentration profiles. More compound-specific information can be obtained by using mini-gas chromatographs (GCs) (Vallecillos et al., 2024) . An online (mini)-GC completes a measurement in a relative brief time (e.g., 6 minutes). The use of a chromatographic column enables compound-specific measurements, on the condition of a relatively clear sample matrix. As the actual detector is a non-specific instrument (typically Flame ionization detector or photoionization detector), interferences from unknown compounds are possible.

A gas mass spectrometer is capable of making compound-specific measurements (except for some isomers). Possible instruments that have been used to measure ambient air are PTR-MS, SIFT-MS and ion mobility spectroscopy. Possible instruments that have been used to measure ambient air are PTR-MS (Blake et al., 2009), SIFT-MS (Smith & Spanel, 2005) and ion mobility spectroscopy (Pozzi et al., 2006).

Online sampling is normally adequate for all compounds that are present in the gas-phase (up to the smallest PAHs). Heavier compounds that are solid at ambient room temperature, or adsorb to PM, cannot be measured using online sample techniques. Typically, TVOC FID analysers only measure ppm levels. Low ppb levels should be measured easily with online gas mass spectrometers or mini-GCs.

7.2 Offline sampling of adsorbents (passive or active)

Available measurement techniques for the HAPs from Table 1 are discussed alphabetically for each class of compounds.

7.2.1 Aldehydes

Many measurement techniques are available (Salthammer, 2023). One of the most used techniques uses DNPH (2,4-Dinitrophenylhydrazine) to derivatize the sampled aldehydes to form a stable complex that is analysed by liquid chromatography. Both active and passive sampling are possible. For active sampling, Sep-Pack DNPH-Silica cartridges (Waters Corp., Milford, MA, USA) are one of the most used cartridges. Detection limits between 0.12 µg/m³ (formaldehyde) and 0.7 µg/m³ (acrolein) with a sample volume of 1 litre are reported (García et al., 2022). A possible brand of passive samplers is Radiello (Ninyà et al., 2022). The samplers are exposed between 7 days and two weeks, depending on the expected concentration. The detection limits reported in this paper range from 6 µg/m³ (formaldehyde) to 19 µg/m³ (propionaldehyde) while the manufacturer's application note species a detection limit ≤ 0.3 µg/m³ for these compounds. Acrolein is known to be unstable, even as a DNPH derivative (Destaillats et al., 2002). Therefore, more specific methods for the determination of acrolein are developed using either thermal desorption (Schieweck et al., 2021) or derivatisation by PFBHA (Cahill, 2014).

7.2.2 1,3-Butadiene

As 1,3-butadiene is a very volatile organic substance, methods applicable for regular VOCs do not necessarily apply to 1,3-butadiene. Activated charcoal is not optimal for sampling due to a lack of sample stability (Sakurai et al., 2013). Either a stabilizer is used, or sorbents such as Carbopack X or Carboxen 1000 that are suitable for thermal desorption (Urupina et al., 2022; Vallecillos et al., 2018). Both active and passive sampling can be applied using thermal desorption cartridges. A commercially available passive sampler for 1,3-butadiene (Radiello 141) species has (?) a limit of quantification of 0.01 µg/m³ with a 7-day sample period. However, it was concluded that 7-day passive sampling is not reliable due to the high rate of back diffusion (Urupina et al., 2022). 24-hour sampling on multi-sorbent thermal desorption tubes should lead to reliable results (Gallego et al., 2018).

7.2.3 Methanol

Methanol is not the most convenient compound to measure in ambient air, certainly at the concentrations listed in Table 1Several techniques exist (Solomon et al., 2005). Chemisorption with nitrogen dioxide in a glass bottle gives a detection limit of 1.2 µg/m³ (Nguyen et al., 2001), alternatively, a sample train consisting of impingers and Anasorb 747 sorbent cartridges was used (Peterson et al., 1995) with a detection limit of 4 mg/m³. In Germany, a method was developed using thermal desorption for sampling emission test chambers (Pech et al., 2013) with an estimated detection limit of 15 µg/m³ but with a problematic influence of humidity. A validated workplace method (NIOSH 2000) was further improved (Muna et al., 2015) to obtain a limit of detection of 20 mg/m³. Up to date, there is no standardised sorbent method available for measuring methanol in ambient air at low µg/m³ concentration levels. Online gas mass spectrometers might be an option, but for now research focus is on method development (Kajos et al., 2015) or breath research (Spanel et al., 2015).

7.2.4 Phenol

When more phenolic compounds need to be measured then only phenol itself, high-volume sampling on glass fibre filters backed with XAD resins is the more appropriate method (Delhomme et al., 2010). In this paper, a sampling period of 4 hours was used to obtain detection limits between 20 pg/m³ - 40 pg/m³. If phenol is the only compound of interest, passive sampling is a possibility using thermal desorption cartridges filled with Tenax TA (Sturaro et al., 2010). With a weekly sampling period, the measurement range was 1.7–17.5 µg/m³.

7.2.5 Total VOC

A wide range of sorbent tubes is available for active sampling of VOCs. One recent paper (Urupina et al., 2023) used thermal desorption tubes with low flow sampling pumps (4 mL/min). With a sampling time up to 1 month, a theoretic limit of quantification of 0.0069 µg/m³ for benzene is possible, low enough to assess a health advisory value of 0.038 µg/m³. However, for long term monitoring of the hazardous air pollutants specified, passive sampling is more often applied. Either samplers for solvent desorption or for thermal desorption are used. Solvent based samplers (f.i Radiello) are typically deployed for two weeks (Cocheo et al., 2009) with a reported detection limit of 0.05 µg/m³ for benzene. Thermally desorbed passive samplers are deployed for one to two weeks. Benzene detection limits of 0.05 µg/m³ (1-week sampling) to 0.01 µg/m³ (2-week sampling) are found in literature (Mason et al., 2011; Vallecillos et al., 2019).

7.2.6 PAH

If only naphthalene is of interest, canister sampling according to EPA-TO15 or regular activated charcoal passive sampling is possible. If other PAHs (typically EPA 16 priority PAH) are to be measured, high volume sampling on polyurethane (PUF) foam is routinely used (Fortune et al., 2010). In this paper, sampling time was 8 - 10 hours with reporting limits from 0.01 to 0.03 µg/m³. However, naphthalene might be underestimated due to the lack of adsorption efficiency of PUF for gas phase compounds. PUF Passive samplers (PUF-PAS) are being developed for measuring symptomatic vitreous opacities in ambient air (Bohlin-Nizzetto et al., 2014) but for now 2 ring PAHs, such as naphthalene, are hard to sample due to their volatility. Last years, thermal desorption methods have been optimised for sampling PAHs in air (Jia et al., 2023). Reported sampling times start from 1 hour up to 168 hours (1 week) with a typical detection limit for naphthalene of about 1 ng/m³.

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Report Work Package 3

Health surveillance by use of secondary data

vito sciensano Provincie Antwerpen

Aims and objectives of Work Package 3

As explained in work package (WP) 1, airport operations create a dual environmental burden, namely air and noise pollution, which have an impact on the health of surrounding communities. Numerous studies have linked these stressors to numerous health conditions, including respiratory and cardiovascular diseases, as well as sleep disturbance and stress. A summary of existent risk-outcome pairs and their strength of evidence in the current literature was already described in WP1. The overall objective of the current chapter is to explore the possibility to quantify the impact of the environmental burden of the airport on the health of the population living in communities nearby Brussels Airport. This would require the use of data on the exposure to environmental stressors (see report WP2), as well as data on the health status of the population exposed to these stressors. More specifically, this chapter focuses on the assessment of health effect associated with air pollution and noise derived by the airport, which would specifically require health, disease and mortality data for the population living in the proximity of the airport.

Considering that health data is recurrently collected in Belgium (even if with different objectives), these outcomes can be (partially) investigated by looking into available data sources. Secondary data analysis represents a considerable advantage in terms of the use of resources and time, as it does not require the collection of new data (contrary to primary data collection). The possible analysis to be conducted using secondary data is highly dependent on the quality and availability of the data. Often these data sources are not "ready-to-use" as they are only publicly available at an aggregated level and with a considerable time delay. Nevertheless, using existing data sources is a meaningful resource for answering our research objectives.

Within WP3, the aim is to reuse available health data to assess the burden attributable to Brussels Airport (Zaventem). Overall, it is desirable to achieve a continuous monitoring of this burden throughout time. Many methodological options are possible which depend on the type of data sources used. We will start giving an overview of these, complemented by their evaluation or continue with the descriptions of the methodological options and their outputs.

The following sections address the following objectives:

1. Provide a summary of relevant exhibiting data sources containing data on health to estimate the impact of Zaventem airport on health;
2. Evaluate their appropriateness for continuous monitoring and surveillance of the past and future impact of the airport on health, taking into consideration the outcomes identified in WP1;
3. Propose different methodological options to estimate the impact of Zaventem airport on health using existing health data sources.

Table of contents

List of acronyms

BCR
Belgian Cancer Registry ______ 5
BHIS
Belgian Health Interview Survey ______ 6
BMI
body mass index ______ 7
CEpiP
Centre d'épidémiologie périnatale ______ 8
COPD
chronic obstructive pulmonary disease ______ 5
DALY
Disability-Adjusted Life Year ______ 20
EPS
Échantillon permanent(e) steekproef ______ 5
GBD
Global Burden of Disease ______ 20
GP
general practioner ______ 7
HDD
Hospital Discharge Data ______ 5
HIA
Health impact assessment ______ 24
ICD
International Statistical Classification of Diseases and Related Health Problems 4
ICPC
International Classification of Primary Care6
IMA
Intermutualistic Agency ______ 4
MCD
Minimum Clinical Data ______ 5
O.N.E.
Office de la Naissance et de l'Enfance ______ 7
PFAS
per-and polyfluoroalkyl substances ______ 9
PM
particulate matter ______ 23
SIR
Standardized Incidence Ratio ______ 17
SLO
Schriftelijk Leefomgevinsonderzoek ______ 8
SMR
Standardized Mortality Ratio ______ 17
SPE
Studiecentrum voor Perinatale Epidemiologie ______ 8
UFP
ultrafine particles ______ 4
WHO
World Health Organization ______ 4
YCG
yearly contact group ______ 7
YLD
Years Lived with Disability ______ 20
YLL
Years of Life Lost ______ 20

1 Overview of available health data sources

A variety of data sources are available in the Belgian context. These differ in terms of type of data collection and aims, e.g., registry versus surveys, and spatial and time representation, e.g., overall Belgian territory versus Flemish region. The selection of the data sources should consider its exhaustiveness in terms of spatial coverage and be sensitive/specific enough to estimate the outcome of interest. To answer the above-mentioned research questions, different data sources will be selected considering the information presented on the health status of the people living in the proximity of the airport.

In the following chapter, the possible use of different data sources is described. Strengths and limitations in answering the research questions are discussed. A particular focus is given to:

1. **Spatial coverage of data source**: is the data collected representing the whole Belgian population or only a sample?
2. **Time span of the data source**: is the data collected repeatedly over time? If yes, is it a registry or a recurrent collection of data? How often?
3. **Geographical resolution** included in the data source: what is the smallest geographical unit for which the data is available for continuous monitoring (e.g., province, municipality, statistical sector, individual level)?
4. **Information regarding relevant health effects** related to airport environmental stressors (mainly noise and ultrafine particles [UFP]) – see *Section 2 Evaluation of health data sources.*

1.1 National Mortality Register

Belgium has a complete and longstanding cause-of-death database that integrates all death certificates in the whole Belgian territory since 1987. The latter are based on the World Health Organization (WHO) International Form of Medical Certificate of Cause of Death and are filled in by a certifying physician that specifies the underlying or external cause of death, possibly complemented with immediate, intermediate and associated causes of death. The completed death certificates are collected by the municipal offices and sent to the regional health authorities which encode the information listed on the death certificates into ICD-10 codes starting from 1998 (before 1998 ICD-9 codes were used). The resulting datasets from these agencies are compiled by Statistics Belgium (Statbel), the national institute of statistics, which is thus responsible for managing the national cause of death database. Completeness of demographic data in the national causes of death database is very high with information on age, sex and place of residence.

The exhaustiveness in terms of spatial coverage of the national mortality registry is very high as it collects data for every death that occurs within the Belgian territory. Information on the place of residence is also available, which could be used to identify the people who are living in the proximity of the airport. In terms of health outcomes, only mortality estimates are available including the cause of death, but no information on other aspects of the health status, e.g., comorbidities, risk factors. It is possible to have the data regarding causes of death at a small geographical resolution (i.e., statistical sector).

1.2 Intermutualistic Agency

The Intermutualistic Agency (IMA) database contains exhaustive and detailed information on the reimbursed healthcare of over 99% of the total population since 2002. IMA is a joint venture of the seven national health insurances that collects and manages all data on healthcare expenditures. It contains three datasets linked to each other: population data (with a limited amount of demographic and socio-economic information), healthcare expenditure data and pharmanet data (detailed information on all prescriptions for reimbursed drugs dispensed in public pharmacies). Data on healthcare expenditure comprises reimbursed total healthcare for every payment modality (i.e., directly paid by the health insurance, patients out-of-pocket and supplements). These expenditures include ambulatory care (over-the-counter pharmaceuticals excluded), hospital care and reimbursed medicines purchased through pharmacies. Available information on hospital care only includes variable costs that depend on the type of treatment. Although healthcare consumption is registered in detail, diagnostic information is not available. A proxy for diagnostic information on a number of chronic health conditions is available in the IMA dataset. These are cardiovascular diseases, thrombosis, chronic obstructive pulmonary disease (COPD), asthma, diabetes, pancreatic insufficiency, psoriasis, Parkinson's, epilepsy, HIV, chronic hepatitis B and C, multiple sclerosis, Alzheimer's, renal insufficiency and thyroidism.

For research purposes, the IMA created the permanent sample (Échantillon permanent(e) steekproef, EPS), i.e., a sample of 1/40 of the IMA data, with an oversampling of 1/20 of the population older than 65 years. A legal framework regulates the modalities for using the EPS to study and monitor healthcare consumption and expenditure in Belgium.

The exhaustiveness in terms of spatial coverage of the IMA dataset is very high as it collects data for every person who has a compulsory health insurance. This is only applicable to the whole IMA dataset, not the EPS. The national registry number could be used to identify the people who live in the proximity of the airport. In terms of health outcomes, only a specific set of chronic diseases can be identified through the IMA dataset (see above). This is because only diseases with a specific care trajectory (inpatient care, outpatient care and medications) can be identified through healthcare reimbursements. The rest of the information available is limited and does not include other aspects of the health status, e.g., comorbidities and risk factors.

1.3 Belgian Cancer Registry

The Belgian Cancer Registry (BCR) is a population-based registry regularly reporting on cancer patterns and trends in incidence and cancer survival from 2004 onwards. It is nationally representative and exhaustive, collecting data from oncological care programs and pathology laboratories (Belgian Cancer Registry, 2020). The recording of data (topography and morphology) is done using the International Classification of Diseases for Oncology third edition (ICD-O-3), which is combined into an ICD-10 classification (International Classification of Diseases tenth edition). BCR is the most appropriate source for estimating the incidence and prevalence of different cancer types, due to its completeness of cancer cases for the whole of Belgium. This also represents the only data source where information on the cancer type is available.

The exhaustiveness in terms of spatial coverage of BCR is very high as it collects data for almost every cancer diagnosis within the Belgian territory. The national registry number could be used to identify the people who live in the proximity of the airport. In terms of health outcomes, these are clearly linked to the occurrence and mortality of cancer. Other aspects of the health status, e.g., comorbidities, risk factors, are not included.

1.4 Hospital Discharge Data

The Hospital Discharge Data (HDD) represents the collection of the records for all hospital stays (general hospitals) in the Minimum Clinical Data (MCD). The information in the MCD includes relevant clinical data (e.g., primary and secondary diagnosis) and demographic characteristics of patients. Records are mainly collected as tools for the measurement of hospital needs for public financing, and evaluation of the effectiveness and quality of hospital care. Primary and secondary diagnoses are mapped using the ICD-10 code classification.

The exhaustiveness in terms of spatial coverage of HDD is very high as it collects data for every hospitalization within the Belgian territory. The national registry number could be used to identify the people who live in the proximity of the airport and were hospitalized, summarized by statistical sector. In terms of health outcomes, hospitalization due to specific diseases can be interpreted as prevalent cases. This is the case for a handful of diseases, i.e., cardiovascular diseases. Other aspects of the health status, e.g., comorbidities, risk factors, are not included.

1.5 Belgian Health Interview Survey

The Belgian Health Interview Survey (BHIS) is a national, cross-sectional household survey conducted by Sciensano collecting information on the health status, lifestyle and medical consumption of a representative sample of the general Belgian population. Information is also collected on a wide range of sociodemographic background characteristics. Participants are selected from the national population register through a multistage stratified sampling procedure including a geographical stratification, households and individuals (Demarest et al., 2013). To date, a BHIS has been organized in 1997, 2001, 2004, 2008, 2013 and 2018. At the time of writing, the BHIS 2023 is being conducted. Each BHIS has a basic sample of 10,000 persons made representative of the total population using weighting factors. These are equal to the inverse of the sampling probability, based on the (known) size of each province-age-household size stratum. Interviews were performed using a face-to-face paper and pencil interview supplemented with a self-administered questionnaire covering more sensitive topics (Demarest et al., 2013). The data collected includes self-reported information on health status and health behaviour and determinants. Socio-demographic information such as age, gender, household educational level and income level is available in the data set.

The exhaustiveness in terms of spatial coverage of BHIS is quite limited, as it is a survey that concerns only a limited sample of people living in Belgium. This means that there is a low probability that a sufficient number of participants to the BHIS lives in the proximity of the airport. In terms of health outcomes, BHIS is a very exhaustive data source as it would allow to identify people suffering from many different diseases and their exposure to risk factors, including environmental stressors, noise and air pollution annoyance.

1.6 Intego

The Intego network is a sentinel registration network for general practices in Flanders. It includes anonymised diagnoses, laboratory results and drug prescriptions from around 55 general practitioners (GPs) (Bartholomeeusen et al., 2005; Intego, n.d.). The network is coordinated by the Academic Centre for General Practice at KU Leuven and covers approximately 2% of the Flemish population. Intego uses International Classification of Primary Care (ICPC) codes for registering diseases.

The exhaustiveness in terms of spatial coverage of Intego is limited, as not all the GPs are included in this dataset. This means that there are regional differences in the coverage rate. In the year 2023, the Intego database contained data of approximately 500,000 patients, hence representing on average 7% of the territory in Flanders. However, there are substantial geographical differences. As an example, we considered 11 municipalities in the proximity of Brussels airport (see further, *Figure* 1 & *Figure 2*). The total coverage in these 11 municipalities is 3.6%. Data per municipality is given in *Table 1*.

Table 1: Coverage of Intego in 11 municipalities in the proximity of Brussels airport.

Municipality	YCG 2023	Citizens	Coverage (%)
Grimbergen	80	39838	0,20%
Vilvoorde	109	47385	0,23%
Machelen	25	16554	0,15%
Zaventem	603	36670	1,64%
Kraainem	44	13906	0,32%
Wezembeek-Oppem	117	14735	0,79%
Steenokkerzeel	107	12673	0,84%
Kortenberg	1970	21156	9,31%
Kampenhout	92	12523	0,73%
Haacht	334	15513	2,15%
Rotselaar	4118	17675	23,30%

Definitions: Yearly contact group (YCG) = number of patients that had at least 1 contact with their general practitioner (GP) in 2023; Citizens = number of citizens living in the municipality on January 1st, 2024 (Source: BelStat); Coverage = YCG/Citizens

In terms of health outcomes, Intego is a very exhaustive data source as it would allow to identify people suffering from many different diseases and their exposure to risk factors, including confounders such as smoking status, body mass index (BMI), etc.

1.7 Belgian Diabetes Registry

The Belgian Diabetes Registry represents a national network of physicians, researchers and their teams, all collaborating in scientific research on diabetes since 1989. The primary task of the Belgian diabetes registry is to collect data from all types of diabetes presenting before age 40 in Belgium with the ultimate goal of improving treatment and finding a cure and effective prevention of the disease. The data source includes information on the diseases from the patients and their relatives, mainly regarding the occurrence of diabetes, its causes and markers, the current treatment and the potential experimental therapies.

Data is collected throughout the overall Belgian territory, which makes it exhaustive in terms of spatial coverage. The information is collected at an individual level, which in theory makes it possible to aggregate the data to the smallest geographical level, i.e., statistical sector. In terms of outcomes, these are limited to diabetes and more specifically diabetes that appeared before the age of 40.

1.8 Kind & Gezin and O.N.E.

Kind & Gezin, an independent organisation within the agency 'Opgroeien' of the Flemish government, offers services and assistance to Flemish-speaking families in Flanders and Brussels. The French-speaking sister organisation is O.N.E., l' Office de la Naissance et de l'Enfance founded and collecting data since 2002. The mission of these organisations is to actively contribute to the well-being of young children and their families through preventive family support. This includes medical screening and follow-up of babies and toddlers at different time points with standardized registration of growth, nutritional status, vaccination, hearing test, eye test, etc. Additionally, a large set of socio-demographic data is registered. The perinatal screening visits reach a large majority of newborns; the coverage rate is above 95%. The database is available for scientific research after the application of an authorization request. Data in principle are available at the individual level, but aggregation might be included in the authorisation.

1.9 SPE and CEpiP Perinatal health

Within Belgium, there are two organizations that collect data on perinatal health starting from the birth and mortality registry. The Studiecentrum voor Perinatale Epidemiologie (SPE) collects and summarizes information for the Flemish region. The Centre d'épidémiologie périnatale (CEpiP) does the same for the Walloon and Brussels regions since 2008. Each year, each organization releases a report with information on the new births, including sociodemographic and medical information about the mothers, indicators related to the pregnancy, the delivery and the birth. The complementarity of the two institutes allows to have a broader picture regarding perinatal health for the overall Belgian territory. For each birth and stillbirth, a statistical bulletin is completed which is then collected by the two organizations and used for their analysis. In theory, the data could be aggregated at different geographical levels. Considering the specificity of the topic, the data source represents a valuable reference of information for outcomes related to neonatal health.

1.10 SLO and Gemeente-stadsmonitor

Considering that annoyance is an important outcome of airport noise, it is also relevant to describe data on annoyance. Since 2001, the Flemish Department of Environment has performed standardized surveys on the experience of nuisance through validated questionnaires. This survey is the 'Schriftelijk Leefomgevinsonderzoek' (SLO) and is a tool to assess the quality of the environment in Flanders with the aim of supporting and evaluating environmental policy programs. Up to now, 5 SLO's have been performed, i.e., in 2001 (SLO_0), 2004 (SLO_1), 2008 (SLO_2), 2013 (SLO_3), 2018 (SLO_4); the next SLO is currently being performed. Each survey includes a representative sample of the Flemish population of about 5.000 participants with an age range from 16 to 61+ years. The survey includes demographic data, descriptive data on the living environment, and data on annoyance from odour, light and noise. With respect to noise, information is obtained on annoyance in general, by sources of noise, nightly awakenings, and personal noise sensitivity (Department Omgeving, 2018). The exhaustiveness in terms of the spatial coverage of SLO is quite limited, as it is a survey that concerns only a limited sample of people living in Flanders. This means that there is a low probability that a sufficient number of participants to the SLO living in the proximity of the airport. However, it is a valuable data source concerning specific endpoints on annoyance and therefore of interest as an inspiration to perform a targeted study in the neighbourhood of the airport (use of validated questions) and a valuable background reference to use as a control group for such a targeted study around the airport.

The 'Gemeente-Stadsmonitor Vlaanderen' is an environmental scanner that maps the broad environment of every Flemish municipality or city. The monitor contains more than 400 environmental and subjective health indicators; a set of around 100 indicators is collected through a three-yearly citizen survey. Data are available per community on a public platform (https://gemeente-stadsmonitor.vlaanderen.be/) and can be used for strategic purposes. In the context of the airport, there is a limited number of indicators of well-being and nuisance. The advantage is that the monitor is available for the whole territory of Flanders. The disadvantage is that indicators are rather global, and the finest geographical level is the community.

Table 2 summarizes the information of each data source with a focus on their spatial representativeness, whether the data source is recurrent and the available information. Almost all the data sources are registries or administrative datasets which continuously collect information about the overall Belgian population. Two exceptions are the BHIS which happens every 5 years and the SLO which happens every 3-5 years. In terms of representativeness of the population of interest (living close to the airport), BHIS, Intego and SLO are data sources that cannot be considered fully representative of that area. In the case of Intego, there have been examples of the expansion of the network to achieve higher representativeness of a specific area, more specifically in a study investigating the effect on the health of per-and polyfluoroalkyl substances (PFAS) in the 5 km zone around 3M (communities of Zwijndrecht, Beveren and Antwerp).

The outcomes collected by the ensemble of data sources are very variable. Most likely more than one source can be used to cover the outcomes of interest (see *Table 3*).

Table 2: Summary of relevant data sources

Name	Description	Recurrent dataset	Representativeness of the target population	Available outcomes
National Mortality Registry	Cause-of-death database that integrates all death certificates in the whole Belgian territory	Yes, registry providing yearly statistics	Yes, whole Belgian population	- Cause of death: day/month of death - Age, sex and place of residence
Intermutualistic agency (IMA)	Information on the reimbursed healthcare of over 99% of people living in Belgium	Yes, administrative dataset providing yearly statistics	Yes, whole Belgian population	- Direct healthcare expenditure and medication consumption (possibility to identify certain diseases) - Age, sex, reimbursement status and place of residence
Belgian Cancer Registry (BCR)	National registry on cancer patterns and trends in incidence and cancer survival	Yes, registry providing yearly statistics	Yes, whole Belgian population	- Cancer incidence, survival (by type) - Age, sex and place of residence
Hospital Discharge Data (HDD)	Collection of the records for all hospital stays (general hospitals) in the minimum clinical data (MCD).	Yes, administrative dataset providing yearly statistics	Yes, whole Belgian population	- Number and length of hospitalization by cause - Age, sex and place of residence
Belgian health interview survey (BHIS)	National, cross-sectional household survey collecting information on the health status, lifestyle and medical consumption	No, survey conducted every five years	Yes, sample at national level – representative for Flanders	- Self-reported occurrence of diseases, and lifestyle (including annoyance) - Many different socioeconomic variables
Intego	Registration network for general practices in Flanders	Yes, registry providing yearly statistics	No, sample of the Flemish and Brussels region – not representative	- Diagnoses, laboratory results and drug prescriptions - Age, sex and place of residence
Belgian Diabetes Register	Recording diagnoses from diabetic patients	Yes, registry providing yearly statistics	Yes, whole Belgian population	- Diabetes diagnosis and tests - Age, sex and place of residence

Name	Description	Recurrent dataset	Representativeness of the target population	Available outcomes
Kind & Gezin and O.N.E.	Recording data on young children and their families by providing services in the field of prevention	Yes, registry providing yearly statistics	Yes, whole Flemish-speaking population (including Brussels region) via K&G plus French-speaking population (Brussels region) via O.N.E.	- Death at birth, eye test, hearing test, cot death, gestational age, breast or bottle feeding with parameters for duration of breastfeeding, biometrics (weight, height, head circumference), vaccination, child health, postpartum depression, referrals
SPE and CEPIP perinatal health	Recording data on obstetric and maternal health	Yes, registry providing yearly statistics	Yes, whole Belgian population	- Maternal data (parity, sociodemographic and clinical information of the mother, date of birth, height and weight), pregnancy (onset of pregnancy, complications during pregnancy, duration), delivery (position of child, induction, epidural analgesia, date, time and manner of delivery), and child (gestational age, weight, length, head circumference, complications)
Schriftelijk Leefomgevings-onderzoek (SLO)	Flemish, cross-sectional household survey collecting information on nuisance	No, every 3-5 years	Yes, representative sample for Flanders	- Noise annoyance (general + specific, e.g., air traffic, car traffic, train traffic, …), nightly annoyance, awakenings, subjective sensitivity
Gemeente- en stadsmonitor	Flemish platform with indicators per community	Diverse set of indicators	Yes, all Flemish communities	- Annoyance and satisfaction about the living environment, happiness, subjective health indicators.

2 Evaluation of health data sources

The data sources selected based on their spatial coverage, geographical resolution and repetition over time are presented in *Table 3* together with the outcomes of interest for the projects, derived from the work undertaken in WP1. *Table 3* identifies which outcomes are available in each data source.

In general, cancers and birth outcomes are the ones for which the selection of the data source was straightforward. Outcomes like cardiovascular health or respiratory health can be identified using the medication consumption of the patients and/or their hospitalization for these causes. Some question marks are placed in the table for which IMA could be used for identifying the related outcomes but the sensitivity of the use of medication for the identification of these outcomes has not been validated (i.e., sleep disturbance and depression). A clear gap in data is visible regarding sleep-related outcomes, cognitive health and annoyance. These could be collected for this project (see WP4).

Table 3: Presence of selected outcomes in data sources of interest

Outcome	Stressor	Level of evidence - UFP	Level of evidence - noise	Data sources								
				National Mortality Registry	IMA	BCR	HDD	Belgian Diabetes Registry	Kind en Gezin	Neonatal registries	Intego	BHIS
Cardiovascular health	UFP	Suggestive			x		x				x	x
Arterial stiffness	UFP/noise		Low									
Cortisol levels	UFP/noise		Very low									
Heart rate	UFP/noise		Very low								x	
Hypertension incidence	UFP/noise		Low		?						x	
Ischemic heart disease incidence	UFP/noise		Low				x (prevalence)				x	
Asymptomatic heart damage	UFP/noise		Very low								x	
Stroke incidence	UFP/noise		Moderate				x (prevalence)				x	
Mortality	UFP/noise			x								
Metabolic health	UFP	Inadequate						x				
Diabetes	UFP/Noise		Low		x			x			x	x
Obesity	UFP/Noise		Very low					?			x	x
Sleep-related outcomes	Noise				?							

Outcome	Stressor	Level of evidence - UFP	Level of evidence - noise	Data sources								
				National Mortality Registry	IMA	BCR	HDD	Belgian Diabetes Registry	Kind en Gezin	Neonatal registries	Intego	BHIS
Physiologically measured awakenings in adults	Noise		Moderate									
Self-reported sleep quality and sleep coping behaviours	Noise		Very low									
Self-reported awakenings	Noise		Very low									
Self-reported sleep disturbance in adults	Noise		Very low / moderate									
Respiratory health	UFP	Suggestive			x (Asthma)		x (hospitalization)				x	x
Cognitive health	UFP	Suggestive										
Assessment of student distraction	Noise		Very low									
Impairment assessed through SATs	Noise		Moderate									
Reading and oral comprehension	Noise		Moderate									
Short- and long-term (episodic) memory	Noise		Moderate									
Birth outcomes	UFP	Suggestive							x	x		

Outcome	**Stressor**	**Level of evidence - UFP**	**Level of evidence - noise**	**Data sources**								
				National Mortality Registry	IMA	BCR	HDD	Belgian Diabetes Registry	Kind en Gezin	Neonatal registries	Intego	BHIS
Congenital malformation	Noise		Very low						x	x		
Low birth weight	Noise		Very low						x	x		
Preterm birth	Noise		Very low						x	x		
Cancer	UFP	Inadequate			x	x						
Incidence of breast cancer	Noise		Low			x					x	x
Annoyance	Noise											
Depression	Noise		Low		?							x
Hyperactivity	Noise		Low									x
Well-being	Noise		Very low									x
Total mortality	UFP	Suggestive		x								

UFP: Ultrafine particles, IMA: intermutualistic agency, BCR: Belgian Cancer Registry, HDD: hospital discharge data

Another important aspect to consider when working with data at a small geographical level is the accessibility to the data. It is worth noticing that for almost all data sources it is possible to access individual level data via specific data requests. Nevertheless, this is in contrast with the general aim of continuous monitoring and surveillance that needs continuously updated data. That is why we propose to use data at the statistical sector which is small enough for the purposes of this study. Nevertheless, this still represents a considerable amount of detail that is not freely accessible to the public for data privacy reasons. Organizations often provide access to their data via either structural cooperative agreements or ad-hoc applications. The data use in the latter case is tied to the specific objectives presented in the application and access is granted for a limited amount of time (which conflicts with the need for continuous monitoring of the burden).

In terms of structural agreements, the Flemish Department of Health has a structural cooperative agreement with the BCR, Intego, SPE and the mortality registries. Sciensano has an agreement for access to the EPS, but this is considered not sufficiently representative.

3 Analytical methods

The main part of the proposed analysis concerns the monitoring and surveillance of the effects on health for the population living in proximity to Zaventem airport. This requires a repeated and sustained overtime assessment of the health of the population living in the proximity of the airport (see *Section 3.1 Monitoring and surveillance using existing health data*). Additionally, the subsequent part of the planned analysis puts forward different options to explore relevant research objectives in the context of the health effects of airport-related stressors. These should be considered as ad-hoc projects that have a more in-depth analysis, a shorter life span and a precise objective (see *Section 4.2*).

3.1 Monitoring and surveillance using existing health data

Up-to-date information on the health status of the population is key to the monitoring and surveillance of the population's health to highlight the need of public health policies. This evidence is important for decision-making processes to make relevant decisions and set appropriate priorities, policymakers need to be informed about the extent of health problems in the population, the groups that are particularly at risk, and the health trends over time. The disease burden of a population can be described by a variety of indicators. Indeed, population health is a multifactorial phenomenon with many facets and different ways to measure it.

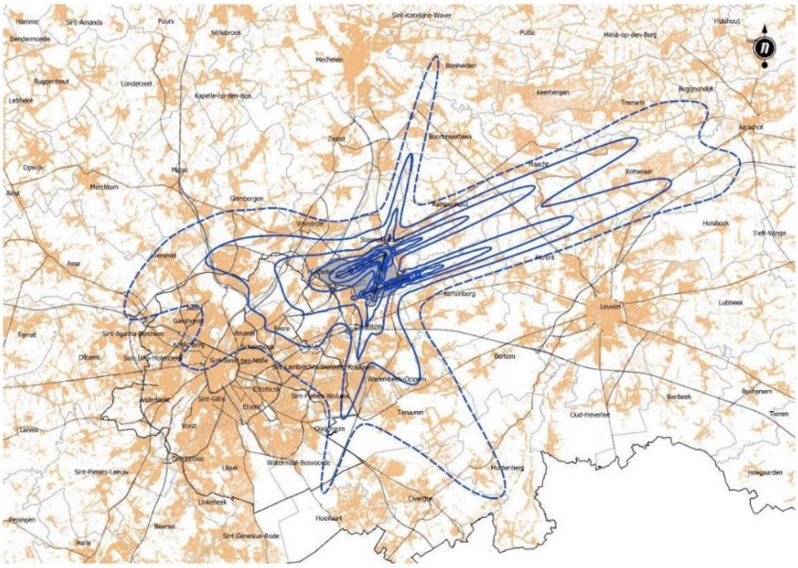
3.1.1 Incidence/prevalence data

Typical indicators of population health are life expectancy, cause-specific mortality rates, numbers of new and existing cases of specific diseases (i.e., incidence and prevalence, respectively) or self-perceived health.

Calculating Standardized Incidence Ratios (SIR) of Standardized Mortality Ratios (SMR) for specific geographical areas allows to compare different areas while considering the population characteristics (age and sex distribution). In order to follow up on the impact of the environmental burden around the airport, a geographical analysis of SIRs/SMRs at one cross-sectional point in time will allow to assess the health impact of the environmental burden at a specific moment. Additionally, by repeating the analysis over time, longitudinal data will allow to follow up possible impact of deterioration/reduction of the environmental burden and evaluate economic trends and/or policy measures that influence the local situation around the airport. A geographical analysis can be performed at various levels. First, it is possible to define one 'impact zone,' based on environmental data for noise and UFP, and to compare SIRs/SMRs in this zone with a control group, i.e., the rest of Flanders/Brussels. Further, within the 'impact zone', a geographical gradient can be studied, hence allowing to assess health outcomes in relation to the source of UFP/noise, which can be defined as a type of dose-response analysis. The geographical gradient for studying environmental impacts should ideally be defined based on the levels of the stressors. For UFP, the mapping can be structured as concentric circles or ellipses, such as 1 km, 3 km, 5 km, etc., because the concentration gradients primarily extend outward in concentric circles, with a bulge towards the northeast due to prevailing wind directions. Conversely, for noise, which typically displays more anisotropic patterns, the gradient can be defined using geographically specific areas, such as groups of statistical sectors. The decision on the zones will also depend on the availability of the health data in the registries (smallest available geographical level) and on the incidence/prevalence of the health endpoint (power of the analysis). Alternatively, both for UFP and noise, an option could be to compare quartiles of exposure where Q1 serves as a reference (see (Wing et al., 2020)).

As an example, *Figure 1* presents noise and UFP maps for the area around Zaventem airport. Based on these exposure patterns, a selection of communities and statistical sectors can be made. Again, as an example, *Figure 2* shows a possible selection of 11 municipalities around Zaventem airport with a display of the statistical sectors (n=332). The final selection should be made by a team of experts and will be a compromise between the desire to select the most detailed geographical pattern on the one hand, and the availability of the specific data sources that are selected, on the other hand.

(a)



(b)

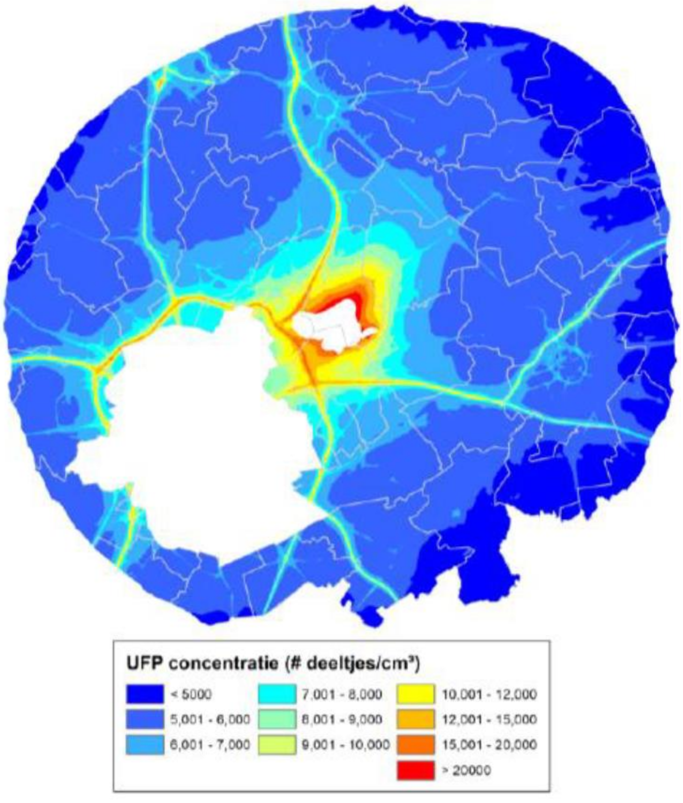


Figure 1: Examples of air traffic noise map (a) and UFP map (b) for the area around Zaventem airport.

(a) L_{night} – 2019 from 40 dB(A) to 70 dB(A). The dashed lines are the 45 dB(A) contour (outer contour), and the next contour is the 50 dB(A). The first full line contour is 55 dB(A) L_{den}, which is important for Vlarem II;

(b) Yearly average of UFP concentrations in the research area of the VITO/VMM study

Online geraadpleegd op 15/05/2024: https://merregister.omgeving.vlaanderen.be/dossier/PR3448) - Ref: 4723913060_mer_brussels_airport_deel_2_effectenanalyse_en_beoordeling.pdf

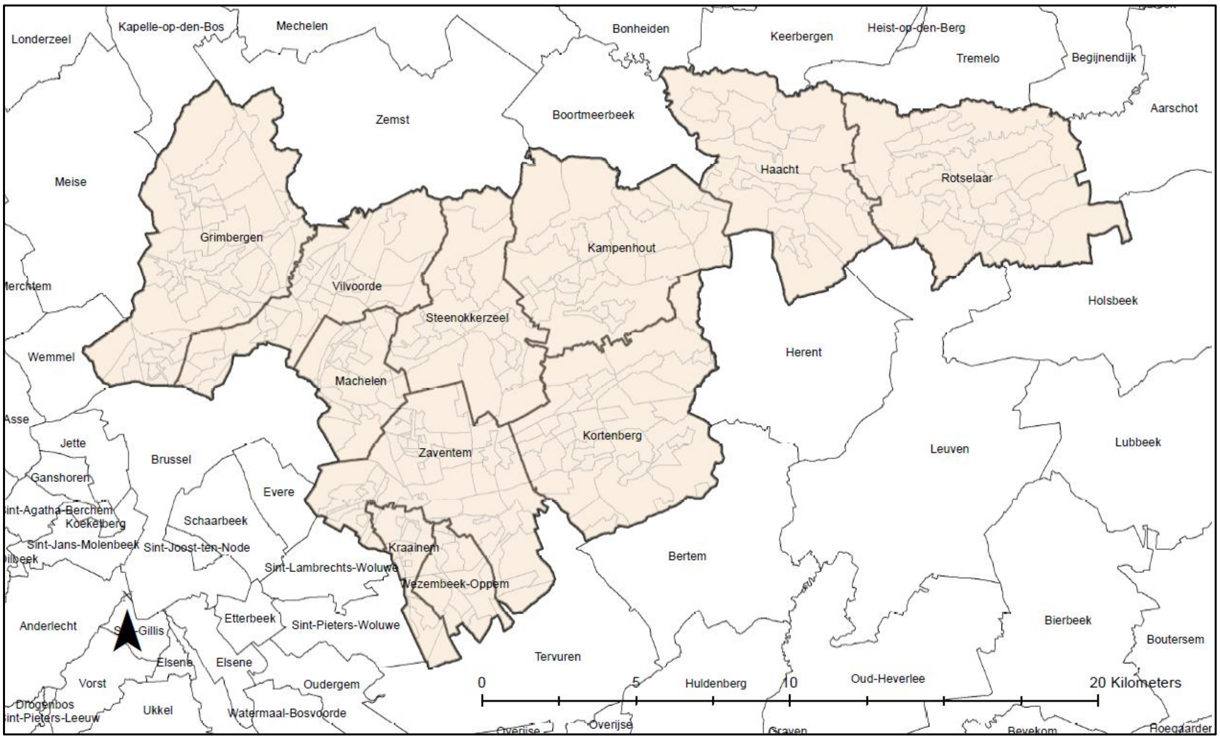


Figure 2: Example of study area around airport Zaventem, based on environmental data.

The use of SIRs or SMRs from health registries as a tool to follow up on local environmental hotspots has several precedents, for example, analysing cancer mortality data concerning asbestos, cancer incidence in relation to PFAS contamination in the area around 3M, or regarding the metal contamination around a gold smelter in Antwerp. The advantage of this technique is that it provides simple data on mortality or disease incidence that is understandable for a layman's public and that areas can be compared straightforwardly. Even though it is considered a rather robust technique, **the association with environmental pollution is indirect** and is based on an appropriate selection of the study area. Further, it does not allow to control for population characteristics such as socio-economic status or lifestyle factors such as smoking, overweight, etc.

Additionally, or as an alternative, to SIRs/SMRs, data from health registries could be used to apply more complex statistical models for disease mapping. Examples of such complex models that are frequently used in small area statistics are Bayesian hierarchical models such as Leroux or BYM2. These analyses are more data- and resource-intensive but are more accurate as they consider data of neighbouring geographical units, and hence introduce a form of smoothing. Further, the models have the advantage that – on condition that the data are available – diverse types of data from different data sources can be included in the same model. Hence, it is possible to adjust for population characteristics (e.g., from Statbel data). Further, if geographical differences are observed, it is also possible to include environmental data in the model to study whether these environmental data can explain the observed differences. As such, the link between environment and health is studied in a more direct way. The presentation of the data can be made user-friendly, e.g., by calculating relative risks. Using these paired data has an added value in comparison to the calculation of SIRs/SMRs that are calculated for predefined zones within a specific exposure range. These techniques are applied in cancer cluster analysis by CDC (CDC, 2024).

3.1.2 Disability-Adjusted Life Years

The above-mentioned indicators highlight only one facet of public health, i.e., either mortality or morbidity. Within the available health indicators, Disability-Adjusted Life Year (DALY) encompasses more than just the presence/absence of specific diseases and conditions, by providing a comprehensive and comparable quantification of the physical and psychosocial health impact of diseases, injuries and risk factors (Devleesschauwer et al., 2014). Driven by the Global Burden of Disease (GBD) projects initiated in the early 1990s (Murray et al., 1996), the DALY has become the key measure for quantifying the burden of disease. DALYs measure the health gap from a life lived in perfect health and quantify this health gap as the number of potentially healthy life years lost due to morbidity, disability and mortality. A disease burden of 100 DALYs per 1000 people-year would thus imply a loss of 100 healthy life years per 1000 people per year. Diseases or risk factors accounting for more DALYs thus have a higher population health impact. DALYs may be calculated for different (sub)populations (e.g., geographical areas), allowing for a more detailed perspective on population health. DALYs are composed of standard expected years of life lost due to premature mortality (YLLs) and years lived with disability (YLDs):

$$DALY = YLL + YLD$$

The YLL component reflects the impact of fatal health outcomes. For each considered cause, YLLs are obtained by multiplying the age-specific number of deaths with the standard expected residual life expectancy at the age of death:

$$YLL = \sum_{i=1}^{a} M_i * RLE_i$$

where $i = 1, \dots, a$ is one of the considered age groups, M_i the age-specific number of deaths due to the outcome, and RLE_i the age-specific residual life expectancy.

The YLD component reflects the impact of non-fatal health outcomes. A prevalence approach can be applied to estimate YLDs for specific diseases:

$$YLD = p * DW$$

where p is the prevalence of the outcome and DW the associated disability weight.

Considering the objectives of this working package, DALY could be calculated using secondary data sources to quantify the disease burden of people living in the proximity of the airport. The mortality component of DALY makes use of the national cause of death dataset which is exhaustive in terms of spatial coverage and causes of death. For the morbidity component instead, there is no single comprehensive data source on the prevalence of non-fatal health outcomes in Belgium, meaning that each outcome needs to be addressed in an ad-hoc way, following the recommendations in the previous chapters. The estimation of DALY should be part of a sustainable system for monitoring the health status of the population living in the proximity of the airport. At the moment, DALY were computed related to aircraft noise for the Zaventem region as a snapshot in time (for the years 2019 and 2032) (Department Zorg, n.d.). These can be systematically updated making us of the methods used in the E-HIS tool for aircraft noise (Department Zorg, n.d.). In addition, the results of the Belgian Burden of Disease study (De Pauw, Robby et al., n.d.) could be used for the regular update of the DALY estimates, by which trends in population health can be monitored over time.

3.1.3 Suggestion for the selection of outcomes and sources

The evaluation of the data sources described in this proposal could be used to prioritize risk-outcome pairs to be included in a continuous monitoring of the burden of Zaventem airport (see *Table 4*). In addition, a number of possible expansions of this objective could be potentially investigated using secondary data. For instance, the investigation of the associations between airport related environmental exposure (noise and UFP) and health outcomes in the airport regions is an important addition to the current literature as these associations have been described around airports in other countries, but not yet investigated in Zaventem airport region. Since every setting is different (exposure, exposure modifiers, population characteristics) it is recommended to investigate this specific for Zaventem airport region (instead of extrapolation/applying D-R functions from other airports to Zaventem region).

Table 4: Suggestion for selection of health outcomes and data sources

Health outcome	Disease	Available data source that meets the requirements (1)
Cardiovascular health	Blood pressure	Intego (2)
	Hypertension	IMA/Farmanet: use of hypertensive medication (3)
	Stroke incidence	Hospital discharge data
	Stroke mortality	Mortality registry
Metabolic health	Diabetes	Intego (2)
	Obesity	Intego (2)
Respiratory health	Asthma	IMA/Farmanet
Sleep	Sleep disturbance	IMA/Farmanet: use of sleep medication (3)
Pregnancy	Congenital anomalies at birth	Perinatal registry
	Low birth weight	Perinatal registry
	Preterm birth	Perinatal registry
Well-being	Depression	IMA/Farmanet: use of anti-depressants (3)
Cancer	Several types of cancers	Belgian Cancer Registry
Mortality	All-cause mortality	Mortality registry

IMA: intermutualistic agency; (1) sufficiently representative for the area around the airport, data collected repeatedly over time, availability of the data at a small geographical level; (2) not yet representative for the area around the airport but there is the possibility to have an oversample if requested; (3) to be checked as to date there is no validation on the specificity of these medications for the condition of interest.

In addition to the above-described criteria for the selection of the sources, research efforts should prioritize outcomes where airport-related stressor exposure is likely to have a significant impact (see WP1).

3.2 Possible expansions of objectives using existing health data

In addition to the necessity of continuously assessing the health burden associated with the airport, many different research questions could be answered using the existing health data sources described above. Here we present a few examples of possible expansions towards different objectives. These are divided considering their data needs.

3.2.1 Data coupling at individual level

As previously mentioned, individual level data is usually made accessible by the data owners following ad-hoc data requests with specific research questions. These requests entail usually lengthy procedures and limited access to data, which is why they are not considered suitable for continuous and sustained overtime monitoring.

As reported in WP1, the association between airport-related stressors and health is often confounded by several factors that are not always considered when deriving associations. Air pollution and noise exposure often show collinearity with other health risk factors like socioeconomic status, stress and adverse lifestyle factors. Causal inference methods have been suggested over the years as reliable to account for possible confounders that might affect the relationship between the risk factor and the outcome (Hernán & Robins, 2006). In particular, the g–computation approach (a model-based direct standardization) can manage continuous risk factors and predict the causal impact of these on the population burden of disease, using cross-sectional data. In particular, environmental data could be coupled with health data at individual level to create a data set that would include the risk factor of interest (i.e. aircraft pollution and noise) and the outcome of interest (e.g. cardiovascular and respiratory diseases), together with any identifiable confounder (e.g. lifestyle factors) (Palazzo et al., 2019). G-computation would be implemented through the use of the counterfactual framework, which posits the existence of unobserved outcomes corresponding to theoretical unobserved exposures in addition to the observed data that are collected. We estimated the marginal mean of Y (disease outcome) that would be observed if A (exposure to risk factor) were set to a = 1 when exposed, a = 0 when unexposed. To obtain this expectation, we perform two mathematical operations. The first is a traditional regression model [$E(Y|A, W)$, where W is a set of confounders], which allows us to predict counterfactual outcomes for each observation under each exposure regimen, by plugging a = 1 and then subsequently a = 0 into the regression fit to obtain a predicted outcome under these two settings. When considering a dichotomous exposure setting, the counterfactual outcomes correspond to Y_1 for exposed and Y_0 for unexposed. The coefficients from each model are then used to predict the values of Y_1 and Y_0 for each observation, leaving their covariates at the observed values but intervening on the value of a as described above. The value of Y_0 is equal to the predicted value of Y when setting the risk factor at a = 0 and, therefore, observations with the same value of W have the same value for Y_0 regardless of their observed risk factor exposure, A. This equality also holds for Y_1 when observations share values of W. The causal difference is then the difference of the above-described predictions $E(Y_1 - Y_0)$. This represents the number of deaths, cases and/or burden that can be causally attributable to the risk factor. Setting the risk factor exposure to various levels can be used to compile continuous risk-outcome associations. The currently available estimates on the association of health outcomes and environmental exposures (so-called dose-response functions) are computed using data from airports that are different from the one of Brussels Zaventem. As previously stated within WP1, noise might be influenced by intervening buildings and geographical features, while air pollution might be dependent on weather conditions like wind speed and direction which are specific to the area where the airport is located. This will sum up to the influence of other key factors, like the socio-economic status of the population in the vicinity of the airport and/or the chemical characterization of the pollution (e.g., PM/UFP represents a mix of many chemical substances which will depend on the fuel, engine, etc). Additionally, investigation into the combined effects of aircraft noise and UFP exposure on human health needs further research and would provide valuable insights for developing effective mitigation strategies around airports.

Health data sources and individual environmental data at home address could be linked at individual level. The health data source should include as much as possible comorbidities and risk factors that could be considered confounders. The Intego database could be an option. The fact that it is not fully covering the area around Brussels Airport, is less relevant to investigate causal relationships in the risk-outcome pairs. The most critical issue is that the exposure range has to be broad enough to study dose-response associations.

3.2.2 Collecting new data

Considering that available secondary data does not cover all the outcomes of interest, we would need to set up specific data collections (e.g., questionnaires, saliva samples, blood samples, blood pressure, etc). We identified specific data gaps in terms of outcomes: wellbeing, annoyance, sleep disturbance (subjective endpoints). See WP4 for more details.

3.2.3 Health impact assessment

Health impact assessment (HIA) can be used to evaluate policies aiming to reduce the burden of airport pollution from two different perspectives: ex-ante and ex-post evaluation. In the first case, HIA is considered as a tool to foresee how realistic and potentially achievable levels of exposure to a risk factor may affect population health. This makes HIA a useful prospective tool for elaborating the potential effect of policies, plans or interventions and supporting evidence-based decision-making. Where the methods above described give a measure of the total attribution of the burden to a specific risk factor, HIA aims to estimate the avoidable burden, meaning the expected reduction of exposure if a policy context is in place. An example of its application in the context of population weight reduction can be found in (Pelgrims et al., 2024). Similarly, to what has been discussed above, g-computation could be used to predict the effect of policy scenarios on the burden attributable to aircraft pollution. Counterfactual levels of aircraft pollution will be created to mimic the effect of the intervention on the exposure to the risk factor. These different counterfactuals are then included in the g-computation formula.

In the context of an ex-post evaluation, researchers can undertake a so-called “adaptation evaluation” (GLISA, n.d.). This is particularly tailored for policies and programs specifically focused on climate change adaptation. It entitles that when an intervention is implemented, a process of continuous collection of information will determine if measures are effective. To ensure the effective and sustainable implementation of regional or local authority’s measures over time, it is important to evaluate the progress of planned activities and to check actual outcomes against their initial objectives. This evaluation will help determine whether an adaptation of the policies is needed to reflect the expectations. Adaptation evaluation considers that the policy or program’s impact, measurable indicators and goals may fluctuate over time as localized impacts unfold. Active and continued engagement of stakeholders is required because all stakeholders playing a role and having responsibility for implementation need to be part of the monitoring and evaluation process (Climate-ADAPT, 2023).

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Report Work Package 4

Proposal for health surveillance and research around Brussels Airport

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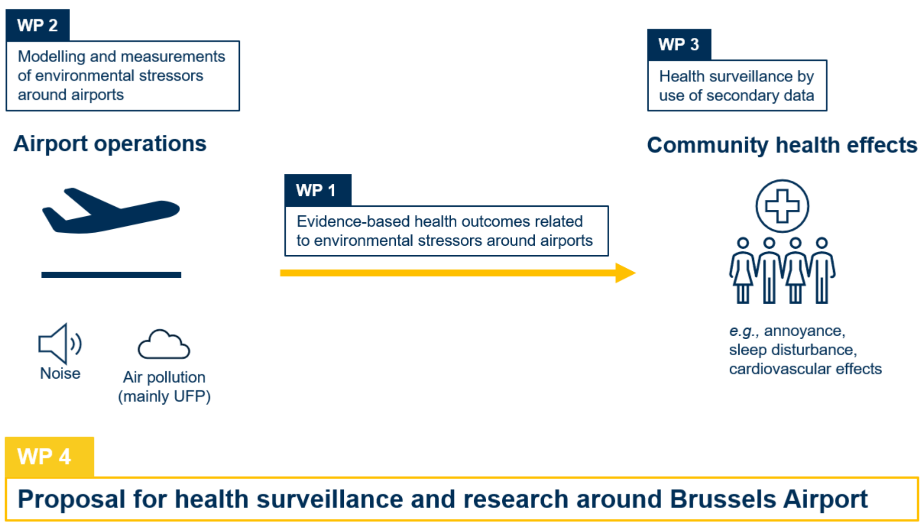
Aims and objectives of Work Package 4

Brussels Airport plays an important role in the region's economy and connectivity. However, concerns exist regarding the environmental impact of the airport's operations on the health of residents living in its vicinity. While research around airports in other countries clearly demonstrates the negative effects of airport proximity on annoyance, sleep quality and overall health, a similar investigation specific to Brussels Airport and its surrounding neighbourhoods has not yet been performed. The current knowledge relies primarily on theoretical impact assessments (Environmental Impact Assessment (EIA, in Dutch: milieueffectenrapport or MER) and the E-HIS study for air traffic noise[1]). However, relying on theoretical calculations and extrapolations from studies conducted at other airports has limitations. Airport operations, local air quality patterns and population demographics can vary significantly, making direct comparisons between airports challenging.

To address this knowledge gap, this work package (WP) proposes a comprehensive approach for health surveillance and research tailored to Brussels Airport. It leverages the findings from three interrelated WPs to support evidence-informed decision-making. WP1 critically reviews existing literature to identify well-established health outcomes associated with environmental stressors typically found around airports, such as noise pollution and air quality (mainly ultrafine particles (UFP)). WP2 delves into the practicalities of measuring and modelling these environmental stressors around Brussels Airport. WP3 explores the potential of existing health registries to conduct health surveillance around the airport. By integrating the knowledge gained from each of these WPs, the project aims to propose a framework for health surveillance and research tailored specifically to the region around Brussels Airport. Important to note is that selection of the specific exposure-outcome pair to investigate and the study approach fall outside the scope of this project. However, this comprehensive approach aims to provide (i) a picture of the current health situation for residents living near the airport and (ii) possibilities for a surveillance program to monitor the health situation in light of the effectiveness of measures outlined in the permit conditions of Brussels Airport. By identifying potential health concerns and engaging with relevant stakeholders, plans can be developed or strengthened to address these concerns and ensure the long-term well-being of the community.



[1] E-HIS geluid luchtverkeer rapport_finaal v24 april 2024.pdf (zorg-en-gezondheid.be)

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1 Considerations regarding set-up of airport-related health research

Airports play an important role in our globalized world, but their operations can come at a cost to the health of nearby communities. Exposure to aircraft noise and air pollution, including UFP, has been linked to a range of health problems (see report WP1), raising **concerns about the well-being of residents living in the vicinity of airports**. Each health outcome might require a different approach for investigation, depending on the research question or policy goal. This WP first explores **opportunities for surveillance** by gaining **insight into site-specific health risks in the region of Brussels Airport** – considering that well-known effects reported around other airports might not directly pertain to the region surrounding Brussels Airport due to differences in the airport settings, population demographics and other factors. Results from the **surveillance programs** could inform future research directions which could involve **dedicated studies** on specific health concerns identified as priorities through surveillance. Such detailed studies can delve deeper into the mechanisms linking airport-related stressors (i.e., aircraft noise and UFP) to health problems observed in the Brussels Airport region. Findings from surveillance and specific research can ultimately inspire policy changes to enhance the protection of public health in the region.

Some pollutant-outcome pairs, such as aircraft noise and sleep disruption or UFP and cardiovascular effects, are **well-established** and could serve as a good starting point for surveillance purposes around the national airport. On the other hand, there are also pollutant-outcome pairs with limited or *low* quality evidence, such as the associations between UFPs and birth outcomes, where further investigation is needed. These pairs may have been less studied due to various reasons, including the complexity of the health outcome, challenges in accurately measuring exposure or the relatively recent emergence of the pollutant as a concern. Investigating these pairs could help fill evidence gaps and provide a more comprehensive understanding of the health impacts of airport-related stressors.

The choice between focusing on well-established or less-studied pollutant-outcome pairs depend on the specific research question or policy goal. An overview of relevant pollutant-outcome pairs and a rationale to prioritize these pairs are discussed below and presented in *Table 1*.

1.1 Selection of health outcomes

Communities residing near airports face a dual environmental burden: noise and air pollution exposure (mainly UFP). Scientific literature has linked these airport-related stressors to negative health outcomes, but the strength of evidence varies for the different health endpoints. Additionally, while some underlying mechanisms are understood, further research is needed for most endpoints.

Surveillance is primarily used to monitor the local situation and track health status in relation to environmental stressors for health endpoints with strong evidence from the literature. For example, surveillance of aircraft noise might involve tracking noise levels and self-reported health issues like sleep disturbances or annoyance in a representative sample of residents. Surveillance programs typically use larger sample sizes and less invasive, cost-effective methods (e.g., questionnaires) to provide a general picture of population health trends. This allows for (i) assessing the severity of the health impact in the local situation, (ii) detecting vulnerable subgroups (e.g., geographically or demographically) and (iii) tracking changes in response to policy measures or environmental burden.

Research studies, on the other hand, aim to improve scientific knowledge to delve deeper into specific cause-and-effect relationships (i.e., exposure-response functions (ERFs)). This can be done by including relevant health endpoints with less robust evidence or by identifying mechanistic pathways in the dose-response chain to strengthen causal evidence. Examples include clinical sleep studies with detailed information on sleep patterns, cardiovascular outcomes and neurological parameters; or mechanistic studies linking biological stress parameters (e.g., cortisol) and cardiovascular parameters (e.g., heart rate variability) to sleep disturbance or subjective stress experience. These studies are typically more expensive, time-consuming and conducted on smaller sample sizes. They allow to monitor the local situation to some extent but as the subgroups are smaller, limiting their usefulness for broad policy support. However, their strength lies in providing a better understanding of the biological pathways linking environmental stressor exposure to health problems, thereby contributing to the scientific evidence base.

1.2 Prioritizing research efforts

It is important to note that there is no single answer as to which of these outcomes is "most important" and for which to seek higher quality evidence of the effect of airport-related stressors, as different outcomes may require distinct research approaches depending on the research question or policy goal. This section explores several approaches for **prioritizing research efforts**. First, stressors with high levels of exposure in airport communities should be prioritized, hence our focus on **aircraft noise** and **UFP**. Next, prioritization of pollutant-health outcome pairs could be based on (i) the **severity** of the health outcome, (ii) the **strength and quality** of the causal relationship and/or (iii) the **number of people affected**. These criteria could be combined into summary measures of population health, such as the Disability-Adjusted Life Year (DALY). As such, the Belgian national burden of disease study provides a platform to quantify and prioritize the burden of airport-related stressors (Pauwels et al., 2023). Other possible priority-setting approaches include prioritizing health outcomes that disproportionately affect **vulnerable populations** like children, pregnant women or those with existing health conditions and/or including **public opinion and concerns** in the prioritization process. Also, important to note is that the research on specific health effects of airport-related stressors (i.e., aircraft noise, UFP, hazardous air pollutants (HAPs)) is still developing, and clear exposure-response relationships (from reports, or meta-reviews meeting Grading of Recommendations Assessment, Development and Evaluation (GRADE) criteria) are not yet readily available for all health outcomes. Additionally, many health outcomes have **complex, multifactorial** causes, making it difficult to isolate the specific contribution of an airport-related stressor from other environmental or lifestyle factors.

The feasibility of assessing both the health outcome and environmental stressors is crucial for effective studies. First, it is important to consider the feasibility and cost of accurately assessing stressor levels around the airport (e.g., air quality monitors, noise level meters or adequate modelling approaches). Second, the cost-effectiveness of health outcome assessment should also be considered. For surveillance purposes, requiring a much larger number of participants than a dedicated research project, one could choose health outcomes that are relatively easy and cost-effective to assess (e.g., self-reported sleep disturbance surveys; low-cost monitors) (also see output WP3).

1.2.1 Prioritizing based on impact

If one would focus on the **severity of the health outcome** and **number of people affected**, one could include pollutant-health outcome pairs with a **well-established contribution** of airport operations to ambient levels of the pollutant and a **high burden of disease**. Airport operations are considered primary contributors to ambient levels of noise and UFP whereas their contribution to standard air pollutants (e.g., $PM_{2.5}$, O_3 and NO_2) or hazardous air pollutants (e.g., benzene, naphthalene) appears relatively modest or undefined, respectively.

Evidence links aircraft noise to sleep disruption, a major risk factor for various chronic illnesses (e.g., cardiovascular disease, diabetes), mental health issues and reduced quality of life. While research on UFPs from aircraft is limited, early indications suggest they might adversely affect the cardiovascular system, potentially increasing cardiovascular disease medication use and mortality (possible link between UFP exposure and deaths due to arrhythmia, see *Appendix II*). The severity of these potential health outcomes is amplified by cardiovascular disease being a leading cause of death globally.

1.2.2 Prioritizing based on the strength and quality of the evidence

The **strength and quality of the causal relationship** could also serve as an important aspect for the selection of specific health outcomes to consider in a research or surveillance programme. Note that the strength of evidence relates to the certainty of the study findings as it reflects the degree of confidence in the conclusions drawn from the research whereas the quality of evidence of a study refers to how well the study was designed, conducted and analyzed often scored by the GRADE scoring system. While *high* quality evidence on the GRADE scale for environmental exposures is difficult to achieve, the WHO recommends using evidence of *moderate* quality as the basis for setting “strong” recommendations, which “can be adopted as policy in most situations”. Therefore, it is reasonable to consider outcomes with a **defined harmful effect** for which there is already *moderate* quality evidence as a priority for setting up **health surveillance or research around Brussels Airport**.

1.2.3 Prioritizing new research areas

On the other hand, **under-researched areas** could also serve as a priority for new research. There is currently no evidence on the effects of aircraft noise on dementia and other neurodegenerative diseases which forms a significant concern considering their high prevalence among older populations. Likewise, diseases like diabetes and hypertension, which are major contributors to population morbidity, currently only have *low* or *very low*-quality evidence linking them to aircraft noise exposure. In addition, current evidence (*very low quality*) suggests the potential impact of airport-related stressors (i.e., aircraft noise or UFP) on birth outcomes (such as low birth weight or prematurity) might be relatively minor compared to other exposures (as is also true for many cardiovascular and metabolic outcomes). However, the long-term health consequences associated with adverse birth outcomes (i.e., Developmental Origins of Health and Disease) warrant further investigation in this area.

1.2.4 Prioritizing mechanisms and early indicators

While studying health outcomes like chronic illnesses and acute disruptions in relation to environmental pressure is crucial, understanding the **intermediate mechanisms** through which airport-related stressors trigger these negative health outcomes offers valuable insights. Some intermediate mechanisms through which airport-related stressors might trigger adverse health outcomes include, among others, the release of stress hormones (like cortisol) and inflammation, impaired sleep and circadian rhythm disruption or increased vulnerability and reduced resilience. Examining **effect biomarkers,** measurable biological indicators reflecting the body’s stress response, can help understand these underlying mechanisms. One important biomarker of effect is cortisol which is a hormone regulated by the endocrine system and that plays a vital role in the body’s stress response. A study by (Baudin et al., 2019) is an exemplary study investigating the potential link between aircraft noise exposure and cortisol levels and rhythms, exploring how noise disrupts the hormonal balance. Other potential mechanisms by which airport-related stressors could lead to ill-health include inflammation and oxidative stress. In this regard, some associations were found between short-term UFP exposure near the airport and markers of inflammation in a small group of healthy adults (Habre et al., 2018). Non-invasive markers are important for population studies in vulnerable populations, such as urinary markers for airway inflammation in children (Nauwelaerts et al., 2023).

Obtaining higher-quality evidence on the relationship between airport-related stressors and (early) effect biomarkers may be more informative, or at least complementary, than focusing solely on downstream disease outcomes. This is because they act as early markers of an effect before the onset of diseases and consequently are often more prevalent. Moreover, early effect biomarkers are reversible and therefore are interesting tools to demonstrate the impact of policy measures.

Sleep disturbance, linked to aircraft noise exposure and annoyance, is a well-established example of a risk factor for various diseases. Additionally, it has a role in physiological stress reactions and is a quality-of-life issue (Bartels et al., 2022; Benz et al., 2022). Sleep disturbance and aircraft noise annoyance also highly correlate with each other and are believed to contribute to an increased risk of cardiovascular disease (Eriksson et al., 2018; Van den Berg et al., 2014). While the causal relationship between annoyance and sleep disturbance remains unclear, i.e., whether aircraft noise annoyance leads to more sleep problems or whether difficulty sleeping makes people more annoyed by noise. The possibility of a **reciprocal relationship** exists. Annoyance could worsen sleep, cause tiredness and reduce one's resources, which in turn could heighten annoyance with noise. On the other hand, if one feels annoyed by aircraft noise this could disturb one's sleep more easily. Exploring such intermediate mechanisms and their impact on various health outcomes can provide a more comprehensive understanding of how airport-related stressors affect health.

1.2.5 Prioritizing based on vulnerability and community concerns

Beyond traditional approaches, several other factors can be considered when prioritizing health outcomes from airport-related stressors, namely **vulnerability and equity** and/or **public input and concerns**. One could prioritize health outcomes that disproportionately affect children as their developing bodies are more susceptible to the negative health effects of these stressors. Moreover, through stakeholder engagement, one can know what topics are most salient for the affected communities.

Considering the **socioeconomic status** (SES) of residents is crucial, as lower-income communities are often disproportionately located near airports due to factors like zoning and land prices. This often means they experience higher levels of noise pollution, air pollution and traffic congestion compared to wealthier neighbourhoods. Even with similar exposure, residents with lower SES might be more vulnerable to health risks. They may have less access to quality healthcare, healthy food options and green spaces, which can mitigate the negative effects of environmental stressors. SES is intertwined with other social determinants of health, such as education, employment opportunities and access to healthy lifestyles. These factors can all influence how individuals respond to environmental stressors like those related to airport operations (i.e., aircraft noise and UFP).

1.2.6 Strategic data collection: balancing efficiency and depth

Understanding the health impact of airport-related stressors requires a **strategic approach to data collection**. Leveraging existing datasets (i.e., secondary data) from government agencies, public health departments or previous research studies is cost-effective as it saves time and resources compared to collecting entirely new data (i.e., primary data). However, data on endpoints of interest (e.g., sleep disturbance, stress biomarkers, etc.) are not readily available or are not collected at a granular level suitable for the study. This is where a targeted collection of primary data comes into play as it allows for collection of data concerning, for example, noise annoyance levels, sleep quality or biomarkers of stress directly from the residents. However, collecting primary data is more expensive and time-consuming than utilizing existing secondary data and may increase the participant burden potentially affecting response rates. In general, secondary data provides context, historical trends and readily available data. On the other hand, primary data offers deeper insights into residents' experiences and health status.

1.3 Possible exposure-health outcome pairs to investigate around Brussels Airport

Table 1 summarizes important exposure-health outcome pairs associated with airport operations and their potential impact in surrounding communities. The table also includes considerations for prioritization research and surveillance efforts based on factors such as the strength of existing evidence, public health significance and the feasibility of objective measurement.

Table 1: Evidence-based surveillance and research options

Pollutant – outcome pair	Measure	Considerations for prioritization
Noise – effects on sleep	Physiologically measured awakenings in adults	- *Moderate quality evidence of a harmful effect* - Public health significance given link of sleep disturbance to range of adverse outcomes - Direct and objective measure of sleep disruption
	Self-reported awakenings in adults	- *Low quality evidence of a harmful effect* - Subjective experience collected via surveys or questionnaires - Practical and cost-effective (suitable for large-scale studies)
	Self-reported sleep disturbance in adults (source specified)	- *Moderate quality evidence of a harmful effect* - Subjective experience collected via surveys or questionnaires - Practical and cost-effective (suitable for large-scale studies)
	Sleep disturbance and/or awakenings in children	- Very limited number of studies - Vulnerability of children (long-term impact on development and academic performance)
Noise – cardiovascular effects	Ischemic heart disease	- *Low quality evidence of a small harmful effect for IHD incidence* - Public health significance: leading cause of mortality - Plausible biological mechanism (increased stress hormone levels and disrupted endothelial function) - Established association (dose-response function) - Distinct clinical endpoint with well-defined diagnostic criteria - Objective measure for CVD (except for self-reports)
	Hypertension	- *Low quality evidence of a harmful effect for hypertension incidence* - Prevalent and significant public health issue contributing to various CVD - Plausible biological mechanism (increased sympathetic nervous system activity and elevated blood pressure) - Feasibility of research (common, smaller sample size and shorter follow-up period) - Objective measure for CVD (except for self-reports) - Additional and recent evidence for the influence nighttime exposure
	Stroke	- *Moderate quality evidence of (i) a small harmful effect for stroke incidence and (ii) no effect for stroke mortality* - High disease burden, leading cause of disability and mortality - Distinct clinical endpoint with well-defined diagnostic criteria - Objective measure for CVD (except for self-reports)
	Arterial stiffness	- *Low quality evidence of a harmful effect* - Early indicator of cardiovascular risk - Intervention possibilities (modifiable risk factor) - Non-invasive measurements (e.g., pulse wave velocity) - Limited evidence available

Pollutant – outcome pair	Measure	Considerations for prioritization
Noise – annoyance	Annoyance	- High prevalence of annoyance - Daily impact on quality of life - Potential as a modifiable risk factor for adverse health outcomes (e.g., CVD, mental health disorders and impaired cognitive function) - Community engagement and advocacy
Noise – cognitive impairment	Reading and oral comprehension, assessed with standardized tests in children	- *Moderate quality evidence of a harmful effect* - Vulnerability of children (critical period of cognitive development and academic achievement)
Noise – adverse birth and pregnancy outcomes	Preterm delivery	- High prevalence of preterm birth and significant contributor to infant morbidity and mortality - Vulnerability of pregnant women and their unborn infants - Limited low quality evidence available but growing insights from new research (also on combined exposure with air pollution)
	Gestational diabetes	- Common and serious public health concern - Vulnerability of pregnant women and their unborn infants - Limited evidence available
Noise – quality of life, well-being and mental health	Interview measures of depression and anxiety	- *Low quality evidence of a harmful effect* - Amongst most prevalent mental health disorders - Vulnerability of individuals with pre-existing mental health conditions, children and elderly - Comprehensive assessment via interview measures - Limited evidence available
	Depression mediated by annoyance	- *Low quality evidence of a harmful effect* - Leading cause of disability - Limited evidence available
Noise – metabolic outcomes	Diabetes	- *Low quality evidence of a harmful effect* - Growing number of studies - Growing prevalence - Comorbidity with CVD - Diagnosis via standardized criteria and diagnostic tests
	Obesity	- *Low quality evidence of a harmful effect* - Limited number of studies - Growing prevalence - Comorbidity with CVD and metabolic syndrome - Feasible measurement (BMI, waist circumference, body fat percentage, etc.)

Pollutant – outcome pair	Measure	Considerations for prioritization
UFP (long-term) – cardiovascular effects	Increased use of cardiovascular medication	- Prevalence of CVD - UFP as emerging pollutant - Probable association found in long-term study around Schiphol
	Mortality from cardiovascular disease (specifically observed for cardiac arrhythmias)	- Severity of cardiovascular mortality (CVD leading cause of death) - Probable association found in long-term study around Schiphol
UFP (short-term) – intermediate mechanisms	Systemic inflammation	- Linked to chronic diseases - Marker of increased risk of adverse health outcomes - Probable association found in short-term study around LAX
UFP (short-term) – respiratory effects	Exacerbation and medication use for respiratory complaints in children	- Vulnerability of children (developing respiratory systems, higher respiratory rates and increased susceptibility) - Public health significance of respiratory diseases - Possible long-term health implications for respiratory health and lung function in adulthood - Probable association found in short-term study around Schiphol
	Decreased lung function (vulnerable subgroup: asthma)	- Probable association found in short-term study around LAX
UFP (long-term) – birth outcomes	Preterm birth	- Vulnerability of pregnant women and unborn infants - Public health burden of preterm birth and long-term health implications - Probable association found in studies around Schiphol and LAX (also correction co-pollutants)
	Small for gestational age	- Vulnerability of pregnant women and unborn infants - Public health burden of small for gestational age and long-term health implications - Probable association found in short-term study around Schiphol
	Congenital anomalies	- Vulnerability of pregnant women and unborn infants - Public health burden of congenital anomalies and long-term health implications - Probable association found in short-term study around Schiphol

2 Proposals for health research studies around Brussels Airport

This report outlines various research proposals to assess the potential health impacts of Brussels Airport on surrounding communities. The proposed research plans draw on existing international research and insights from preceding WPs, aiming to inform methodologies and target specific environmental stressor and health outcome pairs. Within this project, **we do not make one distinct choice but rather give various options**. The choice of research approach (to be selected in a later phase, ideally via stakeholder consultation) will depend on the specific research question or policy need, as determined through prioritization (discussed above in *Section 1.2 Prioritizing research efforts*).

2.1 Optimizing research strategies: balancing complexity and feasibility

Generally, a **tiered approach** can be taken as shown by the subsections below which have a **varying complexity** in data gathering, analysis and resource (financial, time, expertise) requirements. Study design complexity directly affects the feasible sample size, with less complex studies typically allowing for larger study populations and more intricate designs necessitating smaller, targeted samples due to factors like participant recruitment and data collection intensity. For example, **ecological studies** offer **population-level insight** by analyzing existing (i.e., secondary) aggregated health data (e.g., hospital admissions) from areas with different levels of airport-related noise/pollution levels to identify potential associations between environmental stressors and health outcomes. Due to their reliance on readily available data, they allow larger sample sizes, yet ecological studies are less complex as they can only establish correlations, no individual-level causal relationships. In contrast, **longitudinal cohort studies** have a higher complexity and follow residents over a defined period to monitor health changes in relation to environmental exposures hereby building a stronger understanding of ERFs. Longitudinal cohort studies provide valuable insights into cause-and-effect relationships but require a substantial investment in terms of time, resources and participant recruitment. Consequently, sample sizes are typically smaller compared to other study designs. **Cross-sectional studies** are in between both and involve collection of paired data on health and exposure at a single point in time within a specific population but are not able to establish cause-and-effect relationships.

One could also consider **citizen science projects** as an approach (also see *Section 2.5 Citizen science projects*) where the public is engaged in data collection and environmental health research. Complexity can vary depending on the project's design, ranging from collecting basic noise level data using smartphone apps to self-reported health surveys. Citizen science can serve as a valuable tool for gathering large amounts of preliminary data or providing insights into community experiences. However, poor data quality and lack of standardization might be limitations.

The optimal research tier depends on the specific research question and available resources. A tiered approach might begin with surveillance based on secondary (see *Section 2.3 Surveillance based on secondary data*) or primary (see *Section 2.4.1 Large-scale primary data surveillance*) health data in a cross-sectional set-up to identify potential associations between airport-related stressors and health problems. These findings could then be complemented with objectively measured data from more in-depth surveillance studies (see *Section 2.4.2 In-depth monitoring*). To establish causal links and ERFs, site-specific longitudinal studies would be necessary (see *Section 2.6 Establishing site-specific exposure-response functions*). In turn, citizen science projects can provide valuable complementary data in a cost-effective manner while increasing public engagement (see *Section 2.5 Citizen science projects*).

2.2 Spatial delineation of study area

An important aspect to consider is the **spatial delineation** of the study area which is constrained by (i) the estimated impact and (ii) (in the case of using secondary health data) the availability of health data in the considered study area. As detailed below, based on these two factors, it is not possible to provide a general research domain that is fit for all stressors and all surveillance studies. Rather, the domain will be determined by the specific stressors and the health endpoint being surveilled.

2.2.1 Estimated spatial extent of environmental stressors

2.2.1.1 Spatial extent

The estimated spatial impact of airport-related stressors varies across locations. Analysing the **spatial patterns** of the model results is the best way to obtain an accurate assessment. Modelling results indicate that the impact of each stressor requires a different research domain as the modelled impact varies significantly among them.

The influence of airport operations on noise spans a vast area, from Ternat to Aarschot (west to east) and from Muizen to Hoeilaart (north to south). Because the noise contours are highly **anisotropic**, any spatial division of the study domain should consider actual noise levels, not just distance from the airport. These conclusions are based on modelling conducted for the 2019 Environmental Impact Assessment (EIA, in Dutch: MER), using the maximal area in which the WHO guidelines for L_{night} (40 dB) are exceeded (see *Figure 1*). Note that the contour maps in the figure pertain to the yearly average L_{night}. For investigating certain health outcomes, such as sleep disturbance, **frequency contours or noise metrics for shorter time windows** (seasonal or daily patterns) might be more relevant than yearly average L_{den} and L_{night}. In current monitoring, nighttime is defined as the period between 23:00 and 07:00 for both average and peak indicators. It is worth investigating whether modified indicators of nighttime, e.g., earlier/longer time spans for children sleep at night, changes the observed patterns. However, these noise maps are currently unavailable and should be developed through new modelling exercises.

Finally, it should be noted that these contours might change over time, for instance, if flight routes are modified. Therefore, an analysis of the spatial delineation should always begin with the latest noise impact maps.

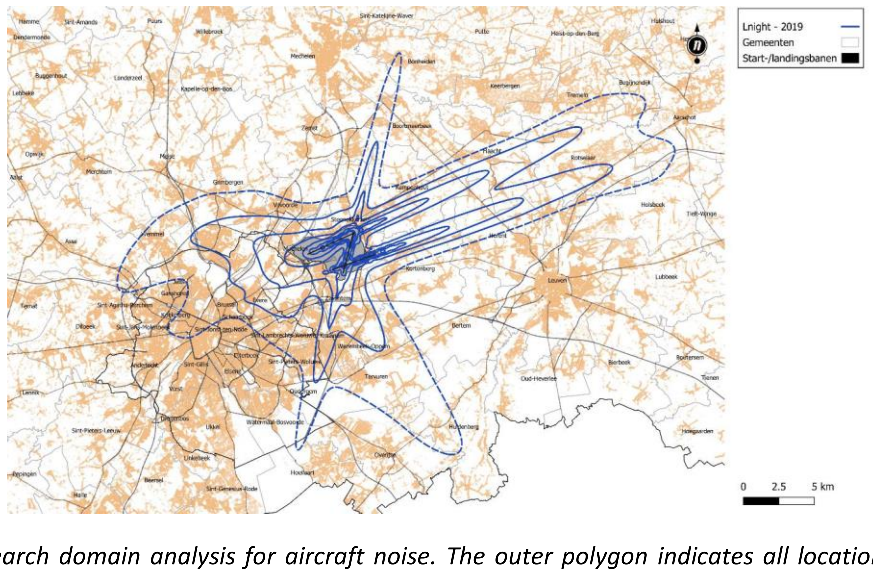

Figure 1: Research domain analysis for aircraft noise. The outer polygon indicates all locations where L_{night} is above the respective WHO guidelines, according to the noise impact modelling from the MER.

For standard air pollutants, the influence of the airport is limited to an area with a radius of 7 km, with the northeastern edge of the runway 07L/25R as the reference point (see *Figure 2*). This domain is determined based on model results from the MER, focusing on locations where the contribution exceeds 0.6 µg/m^3 (3% of the former health advisory value, in Dutch: gezondheidskundige advieswaarde (GAW)) for NO_2, the most significant standard air pollutant. While the pollution plume is predominantly directed towards Kampenhout (northeast of the airport), it is **relatively spatially isotropic**. A spatial division of the study domain could thus be based on the distance to the airport.

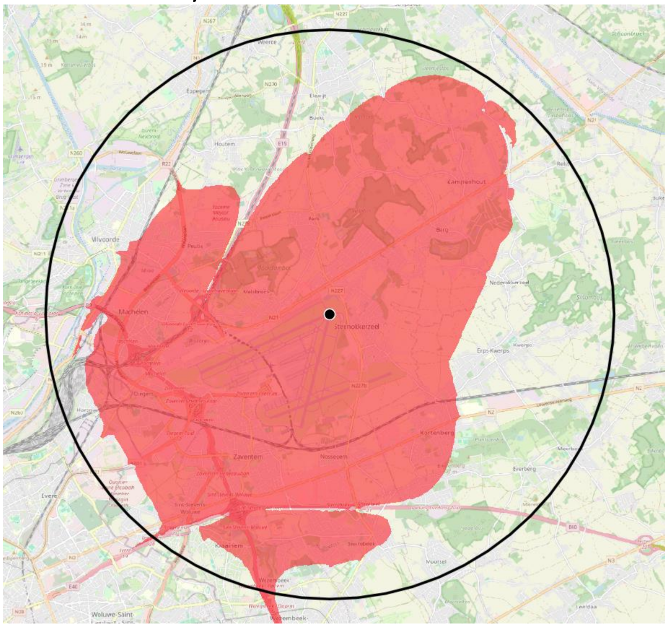

Figure 2: Research domain analysis for standard air pollution (contribution from aircraft to air pollution). The spatial extent of all locations where the contribution of the airport emissions to the NO_2 concentrations exceeds 3% of the GAW (0.6 µg/m^3) is shown in red. The black circle indicates an area with a 7 km radius centered at the northeastern edge of runway 07L/25R (black dot). Source: MER

Estimating the research parameters for studying the impact of ultrafine particles (UFP) is challenging, as **no limit values exist**. However, in a domain with a radius of 5 km centered around the northeastern edge of the 07L/25R runway, annual mean particle numbers due to aircraft fall below[2] 7,000 particles/cm^3 and in a domain with a radius of 7 km, annual mean particle numbers fall below 5,000 particles/cm^3. As for standard air pollutants, while the pollution plume is predominantly directed towards Kampenhout (northeast of the airport), it is relatively spatially **isotropic**. A spatial division of the study domain could thus be based on the **distance to the airport**. One should however also consider the **number of inhabitants** in all contours, especially if uncommon health effects are considered. For instance, if only locations with particle numbers above 10,000 particles/cm^3 are considered, there are only 20,000 inhabitants, which might be too limited to obtain statistically significant results when investigating exposure–health outcome associations.

[2] The WHO considers particle number levels above 10,000 particles/cm^3 as high (based on 24-hour mean concentrations). Urban background levels measured in Borgerhout ranged between 8,000 and 10,000 particles/cm^3 from 2015 to 2020 but rose to over 11,000 particles/cm^3 in 2022 for reasons that remain unknown (see https://www.vmm.be/lucht/fijn-stof/concentratie-ultrafijn-stof). There are no long-term UFP measurements at rural sites in Flanders, making it impossible to estimate rural background values.

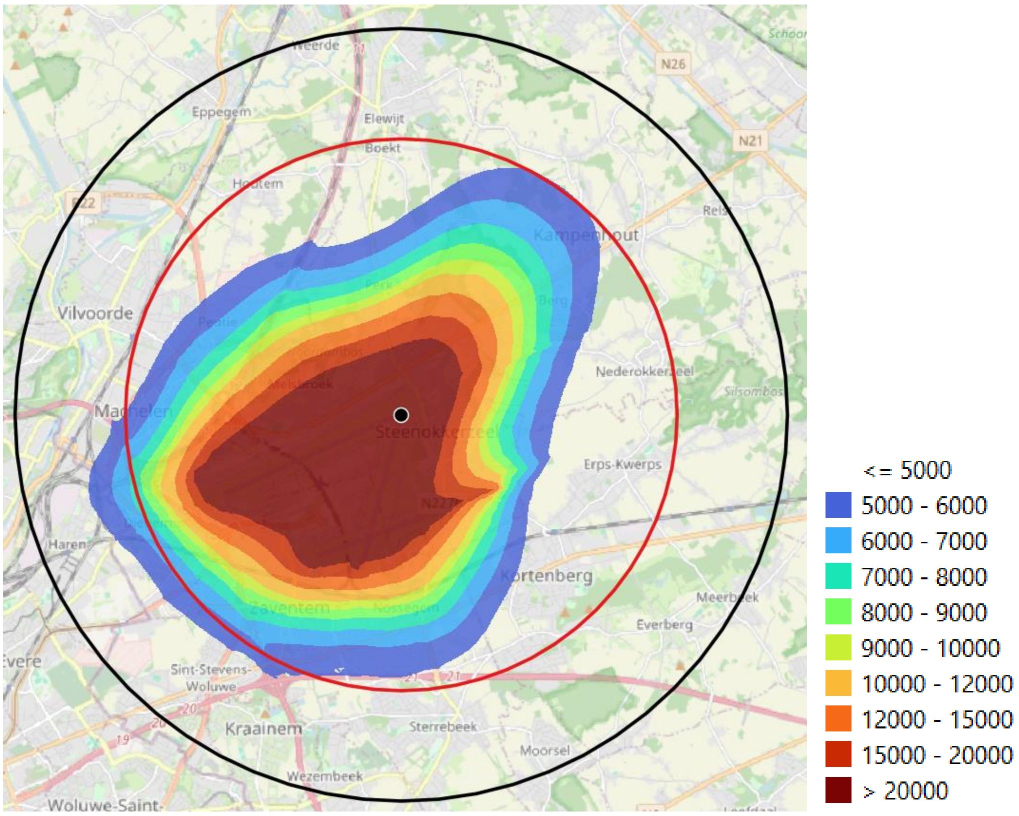

Figure 3: Research domain analysis for UFP. The maps show the UFP concentrations related to the emissions of the airport in (part / cm^3). The black circle indicates an area with a 7 km radius centered at the northeastern edge of runway 07L/25R (black dot), the red circle an area with a 5 km radius. Source: MER.

2.2.1.2 Spatial stratification

In the context of health research around airports, focusing on **spatial stratification** (particularly in relation to SES) is important to understand how exposure to airport-related stressors might impact different communities. Lower-income communities are often situated closer to runways and flight paths due to factors like zoning regulations and land affordability. By analyzing spatial patterns of SES and airport operations, researchers can identify areas with the highest concentrations of airport-related stressors. This allows them to target these communities for health studies and **track potential health disparities**. Within high-exposure zones, residents' vulnerability can vary. Spatial stratification helps to identify social factors that might influence health outcomes. For instance, lower-income residents might have less access to quality housing with poor air filtration, potentially leading to increased UFP inhalation.

Spatial stratification can be applied in airport health research by:

- **Geographical analysis:** Maps of airport operations (e.g., runways, flight paths) can be overlayed with SES data (e.g., Belgian index of multiple deprivation or individual SES indicators such as income levels and housing density) to identify areas with potential for disproportionate exposure.

- **Community selection:** Participants can be recruited from specific neighbourhoods with varying SES and proximity to the airport to understand how these factors interact with UFP and noise exposure.

- **Exposure assessment**: Spatial data can be used alongside exposure data to create a more accurate picture of exposure variations across different communities.

By incorporating spatial stratification, researchers can gain a **more complete understanding** of (i) how airport operations impact health outcomes across different socioeconomic groups and (ii) whether low-income communities experience a greater burden of illness due to combined effects of UFP, noise and social determinants of health. This knowledge can be used to **ensure environmental justice** and protect the health of all residents living near airports, regardless of their socioeconomic background.

2.2.2 Availability of health data

When collecting new health data (i.e., primary data), spatial delineation based on environmental stressors is sufficient. However, when using secondary data, the availability of health data, both the **spatial extent of the research perimeter and the spatial scale of the data** are crucial. The spatial extent (i.e., the size of the domain) should be linked to the statistical significance required. Enough people should live in the research domain to obtain statistical significance. For example, if an endpoint with only a few cases per 10,000 inhabitants is being investigated, a population much larger than 10,000 inhabitants is required. Moreover, if non-exhaustive health datasets are being used, the health dataset should include a large enough sample in that region (e.g., for Intego).

Moreover, the spatial scale of the data should match the spatial scale of the stressors. For instance, statistical sectors may not always be appropriate, especially for noise exposure, as they might include locations with both high and low exposure due to anisotropic maps. Ideally, data should be based on exact locations (patients' address level) to ensure accuracy and relevance to avoid exposure misclassification.

2.3 Surveillance based on secondary data

2.3.1 Relevance of surveillance

To monitor trends in health threats around Brussels Airport, registry-based health data could be used as a basis for an **ecological study**. This information gathered through **population health surveillance**, reveals critical trends in health effects and the associated **disease burden**. With this evidence, policymakers can (i) target interventions by identifying the most at-risk groups and tailor solutions to their specific needs, (ii) set priorities and allocate resources effectively based on the most pressing health issues and (iii) track progress by monitoring the effectiveness of public health policies over time.

2.3.1.1 Secondary data sources for health surveillance

The data sources are routinely collected health, disease and mortality data with high spatial coverage. The basis for the selection of the health endpoints is reported from literature in relation to **noise** and **UFP** (see above *Table 1*). Additionally, the health data should be available at the finest aggregated level possible, preferably at the **statistical sector** level or smaller. Based on the inventory made in WP3, a selection of data sources and health endpoints is presented in *Table 2*. The mortality registry, Belgian cancer registry, database of the Intermutualistic Agency (IMA), hospital discharge data and perinatal registry are exhaustive registers, covering the (semi-)total population in Flanders (and Brussels). Also, these data are accessible for research and have routine procedures to get access to the (aggregated) data. Currently, the use of the Intego database for these purposes has some constraints. Since it is a sentinel database, it does not cover the entire population; it only includes patients from a network of voluntary general practitioner (GP) practices. Therefore, the exhaustiveness is regionally heterogeneous. At the moment, the coverage in the communities around the airport is low to moderate. However, the Intego researchers have experience with hotspot analyses (e.g., in the per- and polyfluoroalkyl substances (PFAS) region around 3M), and are able to recruit extra GP's in a region of interest and hence increase the coverage in this area in the future database. Therefore, Intego is a potentially interesting data source for the future on condition that the Intego management decides to augment the coverage rate in the region around the national airport. From a scientific perspective, this would be a great added value since Intego has the potential to deliver data for clinical endpoints (e.g., blood pressure) or diseases that are not well covered in other databases (e.g., obesity).

Table 2: List of data sources and possible endpoints for an ecological study around Brussels Airport

Data source	Health endpoint*	Indicator
Mortality Registry	All-cause mortality	Standardized mortality ratio
	Cause-specific mortality, e.g., cancer mortality, cardiovascular mortality, stroke mortality	Standardized mortality ratio
Belgian Cancer Registry	Total cancer incidence	Standardized incidence ratio
	Specific cancer incidence, e.g., breast cancer	Standardized incidence ratio
IMA/Farmanet	Hypertension	Frequency use of hypertensive medication
	Sleep disturbance	Frequency use of sleep medication
	Depression	Frequency use of anti-depressants
	Asthma	Asthma prevalence
Hospital discharge data	Total cardiovascular disease, stroke	Standardized morbidity ratio
	Asthma	Standardized morbidity ratio
	Diabetes	Standardized morbidity ratio
Perinatal registry	Low birth weight, preterm birth	Standardized incidence ratio
Intego	Blood pressure	Average values
	Hypertension, diabetes, obesity,	Incidence

* Selected health endpoints based on evidence from research around other airports (see WP 1)

2.3.1.2 Methods for surveillance based on secondary data

In addition to health data, it is also important to inventorize **demographic data** (i.e., age and gender distribution) and the **socio-economic profile** (i.e., education, income, nationality, origin, etc.) to describe the population characteristics per geographical area (e.g., statistical sector). These data can be obtained via Statbel or at the platform of Provincie in Cijfers (https://provincies.incijfers.be/databank). To classify statistical sectors by social deprivation level, the Belgian index of multiple deprivation can be readily applied (https://bimd.sciensano.be). Knowledge on socio-demographic population characteristics is important for a correct interpretation of the health data. Depending on the statistical methods that are used, these variables might be introduced in the statistical analysis as correction factors. Other important confounders such as smoking, body mass index, alcohol intake, physical activity or genetic factors (familial history) would ideally also be included in the model, preferably at an individual level. Apart from the Intego database (with personal information available in the medical records), none of the selected databases will contain these data. This is one of the reasons why it is advisable to invest in an expansion of Intego with recruitment of new GPs in the airport area. Using individual data (cfr. Intego) offers the opportunity to go beyond an ecological study.

Individual data pairing

Individual data, obtained from databases like Intego, provides a granular view of health outcomes but is more complex to obtain and analyze then aggregated data. The achievable sample size varies depending on the database and inclusion criteria. The sample size may be smaller than aggregated data, but the level of detail allows for a deeper understanding of individual health in relation to environmental stressors.

Clustering for targeted analysis

Clustering techniques can identify areas with similar exposure levels to pollutants like noise or UFP. This geographical analysis approach, often used in ecological studies, groups individuals or locations based on exposure, enabling targeted assessment of health outcomes within these clusters. However, it is crucial to evaluate the level of heterogeneity within each statistical sector. If there is significant variation in exposure levels within statistical sectors before using them as clustering units. Exposure assessment with aggregated data typically relies on population-weighted estimates, considering residential addresses of individuals and excluding non-residential establishments.

Analyzing health impacts

Standardized ratios

In order to follow up on the impact of environmental burden around the airport, calculating **Standardized Incidence Ratios** (SIRs) or **Standardized Morbidity/Mortality Ratios** (SMRs) at one point in time (i.e. cross-sectional study) for specific geographical areas will allow comparing the health impact of the environmental burden (mainly noise and UFP) in a population residing in proximity to the airport (i.e., exposed group in impact zone) to a reference population (i.e., the remainder of the population or a control group in rest of Flanders/Brussels). Here, it needs to be considered that the control population is similar to the exposed population in all characteristics other than the proximity to Brussels Airport, in particular with respect to SES, which is a strong confounder of health (see above).

Time trends

Additionally, by repeating the analysis over time, longitudinal data will allow to follow up possible impact of deterioration/reduction of the environmental burden and evaluate economic trends and/or policy measures that influence the local situation around the airport. The follow-up of timelines for health registries should be tailored to the specific health endpoints being examined and the frequency of changes in airport operations. For health effects with shorter **lag times** between exposure and effect and higher prevalence/incidence, (bi-)annual follow-ups may be sufficient. For rare effects with longer lag times, data may require pooling over several years to achieve adequate statistical power.

Geographical gradients

An additional type of geographical analysis involves analyzing SIRs/SMRs values within the impact zone using a **geographical gradient** to assess how health outcomes change as distance from the airport increases. The ideal way to define these zones varies between pollutants. For UFP, concentric circles or ellipses work well (e.g., 1 km, 3 km or 5 km) as UFP spreads outwards with a downwind bulge towards the northeast due to prevailing winds. Conversely, noise patterns are less uniform hence zones might be defined using specific geographical areas like groups of statistical sectors. Moreover, the zone definition will also depend on the availability of the health data in the registries (i.e., the smallest available geographical level) and the incidence/prevalence of the health endpoint. Therefore, power analyses should be performed prior to the actual analysis to select the relevant health outcomes. In this context, it is also important to define the relevant time window. For example, for cancer endpoints which have a long lag time, historical data on environmental factors, is crucial and 5- or 10-year periods are very commonly used. Lag times can vary depending on the specific health effect and the environmental stressor involved. Not all health effects have long lag times. Some respiratory problems, for instance, asthma exacerbation, might manifest more quickly after exposure to air pollution (e.g., $PM_{2.5}$, ozone).

Health data analysis and considerations

Exposure-response functions

Health data from registries can be used to construct ERFs by grouping areas with similar environmental burdens and calculating disease risk per exposure quintile. Again, an important issue is the problem of confounding; socio-demographic data can be used to adjust for the population characteristics at the aggregated level.

Advanced modelling

Additional approaches to explore include more complex models for disease mapping, e.g., Bayesian hierarchical models. Here, register-based health data are used to search for clusters or patterns of disease. In a second step, environmental data (e.g., noise and/or UFP) can be introduced into the model to test whether the environmental burden can explain the disease patterns, thus confirming the existence of an association.

Data availability

The availability of historical datasets on environmental data (mainly modelling) is crucial when studying health outcomes with long lag times (e.g., cancer) or short lag times (e.g., asthma exacerbation). In both cases, it's important to match environmental data with health data from the same period. While recent environmental data is readily available, historical data availability varies (partially for 2015 and 2018; complete for 2019 and 2022 for UFP). Historical noise maps are readily available for a longer period than UFP data, but calculations for historical years might need recalculation to ensure consistency with current methods due to changes in models and threshold values.

Burden of disease monitoring

Based on available health data, the **disease burden** of airport-related stressors might be quantified and monitored on a regular basis. As such, it will become possible to continuously (re)assess priorities, and to assess the impact of policy measures in a comparable and consistent way.

2.3.2 Strengths of surveillance based on secondary data

The use of routinely collected data (i.e., secondary data) from health registries is a cost-effective approach for epidemiological studies, requiring minimal effort and cost for data collection. By combining health data with demographic and environmental data, researchers can gain a comprehensive understanding of the health impacts and disease burden associated with living near Brussels Airport. Standardized health databases, such as the mortality register, perinatal register or cancer register, offer high-quality and quasi-exhaustive data that adhere to international standards. The high quality and consistency of these data allow for repeated analyses over time, enabling the monitoring of time trends and the evaluation of policy actions or interventions on health outcomes and disease burden.

2.3.3 Limitations of surveillance based on secondary data

Secondary health data are considered to be sensitive personal data, and their reuse and are subject to stringent privacy regulations. In Belgium, requesting approval for reuse of health data can be cumbersome, leading researchers to sometimes use aggregated secondary health data, which are less prone to privacy concerns. However, this approach introduces the potential for **ecological fallacy**, where conclusions about individuals are drawn based solely on associations observed at the population level. Ecological study designs, which rely on aggregated data, can only identify associations between environmental factors and health outcomes in a population. They cannot establish causal relationships at the individual level or estimate ERFs.

Secondly, existing health registries might not cover the full spectrum of health concerns relevant to Brussels Airport or ensure enough spatial coverage in the region. For instance, data on sleep disturbance and annoyance, well-established consequences of aircraft noise exposure, are largely absent in the region around the airport.

Lastly, existing registries predominantly capture diagnosed health conditions, potentially underestimating the true public health burden. Individuals may experience health effects from noise or UFP exposure without seeking medical attention, leading to an underestimation of the issue's severity.

2.4 Surveillance based on primary individual data

While existing databases offer a readily available source of secondary data for health surveillance around Brussels Airport, their inherent limitations necessitate the collection of primary data for robust and actionable insights. Collecting paired primary data (on exposure and effect) offers a more comprehensive approach to health surveillance around Brussels Airport. This data would encompass (i) **individual-level exposure data** collected via precise measurements or modelling of airport-related stressors such as noise and UFP, (ii) **granular health data** on aspects such as sleep quality, annoyance levels and both diagnosed and self-reported other relevant health conditions and (iii) data on possible **exposure or effect modifiers** such as socioeconomic status (SES), demographics, lifestyle factors (e.g., smoking, physical activity, etc.) and living conditions (e.g., housing quality, access to green space, etc.). Ideally, the same information is also available for a control group not exposed to airport noise.

By employing detailed individual data collection, researchers can **move beyond mere associations and provide valuable insights into cause-and-effect relationships** between exposure to airport-related stressors and specific health outcomes. This approach facilitates the calculation of accurate health burdens and the development of targeted interventions to safeguard the health of communities surrounding Brussels Airport.

When conducting a large-scale surveillance or in-depth monitoring study, one should take advantage of using primary data to connect exposure to environmental factors with the resulting health outcomes. Accordingly, it is crucial to gather **paired data** on exposure and health outcomes to link specific exposures with specific health effects in the same individual. By prioritizing exposure-outcome pairs with a strong evidence base in existing research (also see *Section 1.2 Prioritizing research efforts*), large-scale surveillance studies can efficiently utilize resources, maximize statistical power and generate valuable information to guide further research and potentially inform public health interventions aimed at improving the well-being of communities. In this regard, long-term exposure to aircraft noise is acknowledged as a growing public health concern and the evidence linking it to several non-auditory health outcomes such as cardiovascular diseases, cognitive dysfunction and sleep disorders (see report WP1), is strong. These adverse effects may arise from the body's unconscious response to noise, a reaction captured by the concept of **noise annoyance**. Noise annoyance serves as an early warning signal for health risks, playing a key role in setting noise exposure limits and creating action plans for noise exposure mitigation. However, only one-third of the variance of noise annoyance is explained by physical noise exposure, the majority is attributable to other, often non-acoustical, aspects such as expectations regarding aircraft noise, noise sensitivity, age and living conditions (Guski et al., 2017). As highlighted in WP3, **there are currently no registries available that include this type of data**.

Given the robust evidence base linking chronic aircraft noise exposure to sleep disruption and its cascading negative health effects (elaborated on in WP1), this WP mainly delves deeper into this association. However, we acknowledge the **importance of considering other potential stressors** (e.g., UFP, HAPs) **and health outcomes** (e.g., cognition, well-being, cardiovascular effects, etc.). The **framework established here could be adapted** to explore these additional research areas as well.

As visualized in *Figure 4* and discussed below, different approaches could be proposed to collect individual paired data for surveillance purposes ranging from large-scale surveillance to in-depth monitoring studies using a combination of self-reported data and standardized measurements to gain a holistic understanding of the issue.

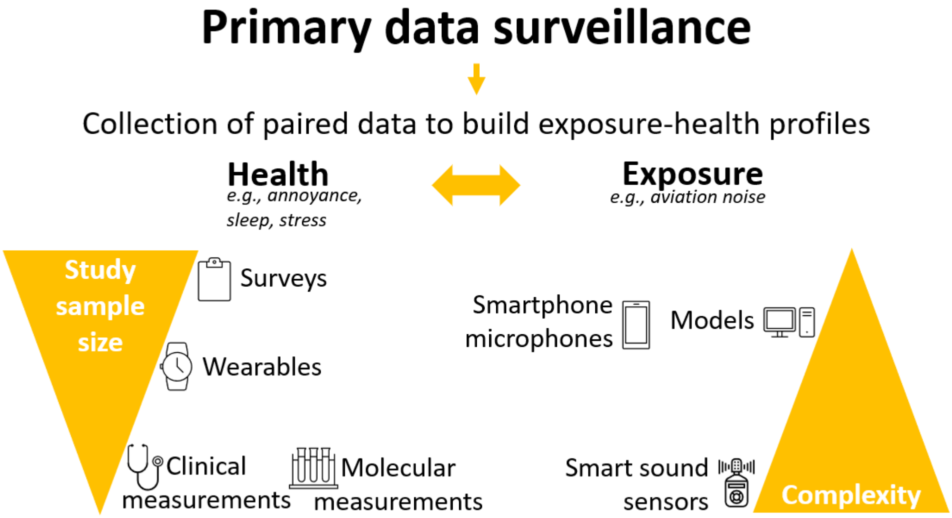

Figure 4: Paired data collection methods for health surveillance. Various methods can be used to collect paired data on both health outcomes and environmental exposures for surveillance purposes. These methods differ in complexity and achievable study sample sizes also depending on resources and feasibility.

When setting up studies collecting primary health data and surveys, one should follow all **required procedures** regarding collecting, storing, sharing and treatment of individual personal data (compliance to the General Data Protection Regulation (GDPR), informed consent, study approval by the ethical commission, etc.).

2.4.1 Large-scale primary data surveillance

As discussed above, assessing the health consequences of airport operations on nearby communities can be done by the collection of paired data on health and exposure in individual residents.

2.4.1.1 Self-reported measures via questionnaires

To assess the impact of noise on sleep disturbance and annoyance around the national airport (i.e., to get better estimates than the theoretically calculated impact), **validated questionnaires** (online, postal or interviewer-led) (also see *Section 2.4.2.1 Intensive data collection by interviewer/field worker*) can be used for large-scale data collection, potentially in a longitudinal design. These questionnaires could collect data on (i) noise annoyance from various sources (incl. aircraft noise), (ii) aspects of quality of life and health (such as those related to sleep and stress) and (iii) background information such as sociodemographic data, effect modifiers (e.g., noise sensitivity) and exposure modifiers (e.g., sound insulation). An example of such an extensive survey is the “Large Sound Survey” (Grote Geluidsbevraging) in the Flemish citizen science project “De Oorzaak” (Universiteit Antwerpen, 2024). It is based on established questionnaires like the ‘Schriftelijk Leefomgevingsonderzoek’ (SLO) to assess general quality of life (Department Omgeving, n.d.), the Epworth Sleepiness Scale for daytime sleepiness (Johns, 1991), the Fatigue Assessment Scale for tiredness (Michielsen et al., 2003), the Perceived Stress Scale to capture stress levels (Cohen et al., 1983) and the Weinstein Noise Sensitivity Scale for individual noise tolerance (Weinstein, 1978). Additionally, from other international airport-related studies, well-established questionnaires are available (for example, see (Dekoninck et al., 2023; Rocha et al., 2019) and WP1). Ideally, the general elements of the survey are aligned with the questions of the Belgian health interview survey, so that study-specific results can easily be compared with the readily available population norms.

A cross-sectional large-scale population survey using these questionnaires can provide valuable insights into:

- **The prevalence and severity of annoyance, sleep disturbance and/or stress**: the survey would estimate the number of residents experiencing noise annoyance and sleep disturbance within the airport community. Additionally, it can assess the severity of these issues through appropriate questions in the survey instrument. Ideally, a control group is also surveyed to allow meaningful interpretations.
- **Noise exposure and reported outcomes:** by correlating reported noise levels (using various noise metrics) with annoyance and sleep disturbance (i.e., establish exposure-response functions), and controlling for relevant confounders, the survey could identify which noise metrics are most strongly associated with these health outcomes. This information is crucial for policymakers to develop targeted interventions.

To gain a more comprehensive understanding, longitudinal or repeated cross-sectional studies can be employed. A longitudinal design entails following the same cohort of residents near Brussels Airport over an extended period (typically several years). An alternative approach to capture changes over time is a repeated cross-sectional design which involves administering the same survey to a different (yet comparable) group of individuals. While it does not track the same individuals, it allows to compare different cohorts and identify population-level shifts in a generally less time-consuming and resource-intensive manner compared to a longitudinal study. The choice between following up on the same group of individuals in time or repeating the same study in a different cohort depends on the specific research question and available resources. If the primary focus is on understanding individual changes and long-term health effects, a longitudinal design is ideal. However, if the goal is to identify trends across a broader group of individuals or conduct more frequent assessments, a repeated cross-sectional design might be more suitable.

2.4.1.2 Non-invasive objective measures with participant involvement

In addition to self-reported data, a large-scale surveillance approach could incorporate **non-invasive self-sampling or data collection**. Clear and detailed instructions are paramount to ensure consistent and reliable sample or data collection by participants at home.

As an example, participants could collect non-invasive samples such as saliva, urine or hair at home following clear instructions for sampling, storing and shipment provided by the research team. After collection, these samples could be analyzed for **biomarkers of effect** (e.g., cortisol levels for chronic stress, club cell secretory protein-16 (CC16) levels for airway inflammation, epigenetic markers on methylation, etc.) or **exposure** (e.g., urinary trans,trans-muconic acid (tt-MA) levels for benzene exposure). Important to note, currently, the specific contribution of airport operations to benzene (and HAPs in general) in communities surrounding Brussels Airport is unknown. Accordingly, before implementing tt-MA as a biomarker of benzene exposure in a large-scale surveillance study, conducting a **pilot study** within a high-exposure group around Brussels Airport and comparing it to a national reference group (Flemish Environment and Health Studies, FLEHS (Schoeters et al., 2017, 2022)) is paramount. Such a pilot study would assess the feasibility and effectiveness of using urinary tt-MA as a biomarker of benzene exposure around the airport and possibly warrant large-scale surveillance. While exposure to benzene arises as primary volatile organic compound (VOC) of concern due to aircraft emissions, additional exposure markers for kerosine-related VOCs could be worth to investigate as well in a pilot study.

There is also a possibility to distribute validated blood pressure devices or wearables (e.g., smartwatches or activity trackers) among participants to monitor **self-assessed** blood pressure readings or sleep patterns and heart rate variability, respectively. Participants could be guided to take self-assessed blood pressure readings at home using validated devices. These readings, along with self-reported stress levels could offer additional insights into potential stress responses associated with aircraft noise exposure. Here, one may explore the possibility of participants taking assisted self-assessed blood pressure readings at a central reference point, such as a nearby pharmacy, which could address concerns about user technique at home. The potential of wearables in citizen science projects also holds in this context of surveillance and is discussed below (see *Section 2.5 Citizen science projects*). Training and clear instructions should be provided to ensure accurate data collection for both self-assessed blood pressure and wearables. The final study design should also consider the potential burden on participants and strive for a balance between data quality and participant feasibility. Also, considering the complexity and the supplementary costs for sampling and measurements, it may be more realistic to perform this sampling in a subgroup of the survey population. This might be a randomized sample (selected at random) or a stratified sample (e.g., based on the geographical distribution or on the outcome of the questionnaire data).

2.4.1.3 Exposure data

In a next step, the above health data could be paired with the participant's noise exposure. The setup of a smart sound sensor network to conduct standardized acoustical measurements at the participant's home location is quite complicated and resource-intensive and hereby limits the achievable sample size. Therefore, it would be more practical to **combine the extensive survey data with modelled residential noise exposure** data as it allows analysis of a larger sample size compared to individual sensor deployment. While not a direct measurement, modelled data provide a valuable tool to assess noise exposure (e.g., at the home address of participants) and this avoids the complexity and resource limitations of deploying a large-scale smart sensor network. To gain a deeper understanding of the impact of noise on sleep, one can delve into the specific characteristics of noise exposure. As highlighted above (see *Section 2.2 Spatial delineation of study area*), it might be useful to extend the classical noise metrics (L_{den} and L_{night}) with frequency contours for nighttime noise as this approach better represents high peaks of noise. Additionally, the current definition of nighttime (23:00 – 07:00) might be worth revising. Sleep patterns vary, and some individuals might be more sensitive to noise during early evening or late morning. Exploring noise metrics for these refined periods could provide valuable insights (such maps can be readily generated). Traditional metrics provide average noise levels, but what about sudden loud events interrupting an otherwise quiet night? The intermittency ratio (IR) quantifies the "eventfulness" of noise by measuring how much a loud event stands out from the background noise. A high IR indicates loud events interrupting an otherwise quiet background, while a low IR suggests higher background noise levels. This metric provides a more nuanced understanding of how disruptive individual flights might be, even if they do not reach a specific threshold. In addition, models could be employed to estimate relevant co-exposure to other stressors such as road or railway traffic noise or classic air pollutants (e.g., NO_2, $PM_{2.5}$) for aircraft noise and UFP, respectively.

An alternative, **straightforward and cost-effective method** to collect noise exposure data might be the use of smartphone microphones which are pre-installed on most participants' devices (also see *Section 2.5 Citizen science projects*). Collection of noise data via personal devices (e.g., smartphone) overcomes the problem that modelled noise levels reflect outdoor noise levels, while acoustic isolation/opening of windows and orientation of rooms can have an impact on the personal noise exposure level. Participants can be instructed to download a dedicated noise monitoring app such as the De Oorzaak application developed in collaboration with Sorama[3] or the AnimApp developed within the ANIMA project (Aviation Noise Impact Management through novel Approaches)[4]. The accuracy of the measurements, the conditions for the use of such apps and data flow of generated data to the researcher team should be investigated.

2.4.1.4 Study population

For large-scale primary data surveillance, ensuring representativeness and validity involves several key strategies. The study population should ideally be limited to adults living in communities near Brussels Airport to maximize the relevance of the findings (see *Section 2.1* for the selection of the research domain). However, careful consideration of **sampling strategies** is required to ensure a **representative and unbiased sample** of the target population.

While **convenience sampling**, which involves recruiting participants who are easily accessible, may seem appealing due to its ease and low cost, it is prone to potential bias due to self-selection. Individuals who volunteer to participate may have stronger opinions or experiences related to airport operations, leading to a possible overrepresentation of certain viewpoints. To mitigate this and ensure a more representative sample, **random sampling** is recommended. Simple random sampling involves randomly selecting participants from the entire population, while stratified random sampling divides the population into subgroups (i.e., strata) based on relevant factors (e.g., distance from the airport, age, gender, SES, etc.). Participants are then randomly selected from each stratum in proportion to their representation in the overall population. This approach ensures that the sample reflects the diversity of the communities and exposure levels around the airport. An important aspect of sampling is the collection of sufficient data across various exposure levels. By intentionally recruiting more participants from under-represented exposure groups (high or low), researchers can achieve statistically relevant results faster. This can be done through stratified sampling, where a minimum

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[3] De Oorzaak | De Oorzaak | Universiteit Antwerpen (uantwerpen.be)

[4] AnimApp (anima-project.eu)

number of participants are strategically selected from each stressor exposure category. Challenges in random sampling include participant recruitment and non-response bias, which occurs when individuals who do not participate in the study differ systematically from those who do. Strategies such as offering incentives, follow-up calls and partnering with community organizations can improve participation rates.

A sample size in the thousands is often ideal for large-scale population survey studies. A one-time cross-sectional survey offers a snapshot of the participant's health at a specific point in time and has a lower participant burden compared to a longitudinal study with repeated surveys at multiple time points in time (e.g., every 1 or 2 years). However, longitudinal studies are better able to capture changes over time in noise exposure and effects, but they increase participant burden and can suffer from higher dropout rates.

By conducting a large-scale population survey, either cross-sectional or longitudinal, one can gain valuable insights into the impact of noise exposure on the airport community. A **multifaceted approach** can encompass (i) self-reported measures of noise annoyance, sleep disturbance and stress levels and (ii) large-scale objective measurements (e.g., blood pressure readings or cortisol levels) that supplement the self-reported data. The obtained results should be communicated to the community and relevant stakeholders to raise awareness and used to inform policy and action plans to improve public health and quality of life for residents.

2.4.2 In-depth monitoring

Assessment of the health consequences of airport operations on surrounding communities hinges on robust data collection strategies. While large-scale surveillance studies (as described in *Section 2.4.1 Large-scale primary data surveillance*) even when complemented with self-collected biological measurements, may lack the granularity required to provide insight into cause-and-effect relationships and underlying mechanisms, in-depth monitoring studies, while providing detailed biological insights, are often limited in scope.

Certain biological measurements, such as self-assessed blood pressure readings or cortisol levels in self-sampled hair or saliva samples, offer distinct advantages for large-scale studies due to their convenience and moderate time commitment, facilitating the inclusion of a larger participant pool and possible integration into a survey. However, while valuable for assessing population-level health concerns, they offer limited insights into the specific mechanisms by which airport-related stressors influence health. In-depth monitoring studies could offer a d**eeper dive into the biological processes** at play. Below we list research approaches to explore how aircraft noise or UFP exposure might be linked to specific health outcomes.

2.4.2.1 Intensive data collection by interviewer/field worker

Large-scale surveillance studies often rely on self-administered questionnaires and self-sampling/assessment methods due to their cost-effectiveness and ability to reach a broad participant pool. However, these approaches have limitations when it comes to in-depth exploration of specific topics and ensuring robust data quality. The inclusion of trained interviewers or field workers would allow to (i) asking follow-up questions for clarification and elaboration, (ii) facilitating informed consent procedures and answering participant questions, (iii) collecting the above samples or measurements using strict protocols to ensure sample integrity or measurement accuracy and (iv) collecting invasive biological samples (e.g., blood) or performing specific clinical measurements (e.g., fractional exhaled nitric oxide measurements, FeNO).

2.4.2.2 Dedicated in-depth studies for mechanistic insights

An in-depth monitoring study allows for **leveraging high-precision technologies** in a smaller participant group to explore specific health outcomes and gain mechanistic insights. Building upon the established link between chronic aircraft noise exposure and sleep disruption (as discussed in WP1), this dedicated in-depth monitoring study proposal aims to delve deeper and explore the underlying mechanisms by which noise disrupts sleep.

2.4.2.2.1 In-depth sleep study

Polysomnography in a sleep lab setting (i.e., laboratory polysomnography) or at the participant's home (i.e., ambulatory polysomnography) is considered the most accurate methodology for obtaining standardized physiological data that can identify changes in sleep stages and awakenings. This sleep monitoring technique records brain waves, the oxygen level in blood, heart rate, breathing and eye and leg movements during sleep. However, it is expensive and time-consuming, and it is an invasive method that requires the attachment of multiple sensors which might be considered uncomfortable and potentially influence sleep patterns hence the observation. Accordingly, this technique is not ideal for a surveillance study.

Alternatively, the use of **actimetry** has been used as a proxy for sleep-wake activity. Within the 'Programma Innovatieve Overheidsopdrachten (PIO)' of the Flemish Government, a validated protocol using actimetry and heart rate monitoring (Bittium Faros) has been developed, offering a **user-friendly and non-invasive** method to assess sleep quality and arousal (Dekoninck et al., 2023). This validated method was shown to be sensitive enough to detect biological responses in young and healthy subjects exposed to rather low noise levels. Accordingly, in studies with a higher noise burden (i.e., impact zone of Brussels Airport) it is expected that the technical setup, proposed post-processing and analysis will enable advanced detection of biological responses to aircraft noise with high accuracy.

The sleep- and/or stress-related health data could be coupled with nighttime noise exposure data collected for each participant using **advanced sound sensors** placed inside and outside the participant's bedroom. This simultaneous in- and outdoor noise monitoring allows for relating and isolating outdoor noise events to indoor disturbances and evaluating noise source type.

2.4.2.2.2 Other exposure-outcome pairs to consider for in-depth studies around Brussels Airport

Aircraft noise – cognition in children

Another critical outcome to consider related to chronic aircraft noise exposure could be potential cognitive effects in children residing near Brussels Airport. Children are particularly vulnerable to the negative effects of chronic noise exposure due to their developing brains and nervous systems. Cognitive impairment, including difficulties with memory, attention and learning has been associated with noise exposure in children (Clark & Paunovic, 2018) .

A possible study approach could leverage the school environment as a central location for data collection on both noise exposure and cognitive function in children. Here, collaboration with school administrators and teachers would be crucial to ensure ethical considerations and smooth implementation. Researchers could administer standardized, age-appropriate neuropsychological tests administered in a controlled environment to assess various cognitive domains, such as memory (e.g., digit span test), attention (e.g., continuous performance test, d2 test of sustained attention) and processing speed (e.g., symbol coding). Additional health data on self-reported sleep quality (questionnaires completed by parents) and socioeconomic factors could provide valuable additional information. Similar to the aircraft noise monitoring in the above sleep study, strategically placed sensors within the school environment could be employed to capture detailed noise data throughout the school day.

By focusing on cognitive function within the school environment, the study can provide valuable insights to inform interventions aimed at protecting children's health and learning abilities.

UFP – inflammatory responses

Regarding the ability of UFPs to penetrate deep into the lungs and their link to various health concerns (e.g., respiratory issues and inflammation), another possibility would be to delve deeper into the relationship between exposure to UFP and inflammatory markers or lung function measurements in residents living near Brussels Airport.

A possible study approach could include the collection of blood samples from participants at designated intervals. These samples could be analysed for various inflammatory markers, such as C-reactive protein (CRP) and interleukin-6 (IL-6), which can indicate the body's response to potential inflammation caused by UFP exposure. In addition, spirometry, a standardized lung function test, could be performed to assess lung capacity (i.e., forced vital capacity) and airflow limitations (i.e., forced expiratory volume in one second) and provide insights into potential UFP-related respiratory impairments. Measuring FeNO can be used to monitor inflammatory changes in the airway.

Modelling approaches discussed in WP2 could be employed to estimate UFP concentrations across the study area. In general, these models consider various factors influencing UFP distribution, such as airport operations (flight patterns, take-off and landing activities), local meteorological conditions (wind speed, direction, temperature) and geographical features (topography, buildings). However, these model chains still come with a large uncertainty (much greater than for standard air pollutants). Therefore, data assimilation with measurements might be used to reduce the uncertainties in the absolute concentrations. Participants could wear portable UFP monitors throughout the day to assess individual UFP exposure. Yet the accuracy of these devices is currently rather limited, and the cost is very high (around EUR 10 000 for one device). Overall, by combining UFP dispersion modelling with personal UFP monitoring, this study design could offer a robust and multifaceted approach to assess UFP exposure for participants. This comprehensive strategy strengthens the investigation into potential health effects associated with chronic UFP exposure near Brussels Airport (e.g., inflammatory responses and lung function).

2.4.2.3 Study population

In-depth monitoring studies, which typically involve smaller, targeted groups of participants, also require careful consideration of representativeness and validity. Partnering with local healthcare providers or community organizations can help identify and recruit eligible participants who meet the study's specific criteria. Additionally, offering compensation for participation and minimizing the burden on participants, such as by providing transportation or scheduling flexibility, can improve recruitment and retention rates.

A **pilot study** with around 20 participants within the impact zone of Brussels Airport could validate the sleep study protocol and identify potential challenges without extensive resource investment. The effect sizes observed in the pilot study could inform the sample size for the main study, which should aim for a larger sample size (hundreds to potentially thousands dependent on measurements) to achieve generalizable results and represent the diversity of the target population. A longitudinal design with repeated measurements is recommended. As discussed above, various recruitment methods, including online platforms, flyers and posters, collaborations with local authorities and community organizations or media outreach, can be used to ensure a diverse and representative sample.

2.5 Citizen science projects

Citizen science projects offer a valuable approach to **engaging the public** in scientific research, particularly in areas where large-scale data collection is needed. In the context of aircraft noise exposure and its impact on aspects of health (e.g., sleep quality, annoyance), citizen science can play a valuable role in gathering comprehensive data and generating insights.

For the surveillance of primary data on sleep parameters (discussed above in *Section 2.4 Surveillance based on primary individual data*), actimetry, often integrated into smartwatches, fitness trackers and dedicated actigraphs, can be used as a **low-cost alternative** to measure human rest-activity cycles. While not as accurate as the approaches above, this method allows for larger sample sizes data collection.

As visualized in *Figure 5*, a **combination of straightforward data collection tools** could be used, such as (i) **wearable devices** (e.g., smartphones, smartwatches) to collect data on heart rate, sleep patterns and physical activity (see e.g., (Buekers et al., 2023) for a comparable combination of wearables), (ii) **noise monitoring apps** to record indoor and outdoor noise levels, allowing participants to self-report noise annoyance and (iii) **questionnaires** to gather detailed information on sleep quality, stress levels, lifestyle factors and demographics.

It is important to use a single type of device (e.g., Apple Watch or Fitbit) for maintaining consistency in data collection. While using a single device type is important in terms of standardization, comparability and data integrity, diversity in the study population is equally critical. A diverse participant pool ensures that study findings apply to a broader population. If the study only includes a specific demographic (e.g., young adults, wealthy people), the results may not generalize well. Moreover, excluding certain groups (e.g., older adults, lower incomes) can perpetuate health disparities.

Citizen science enables large-scale real-world data collection from a diverse range of participants and can be more cost-effective and time-efficient compared to traditional research methods. Moreover, citizen science fosters **public engagement** in scientific research, raising awareness and empowering individuals to contribute to knowledge generation which has been shown to be important in research-related environmental health impacts (Heyes et al., 2022).

However, there are limitations to consider, such as **challenges in data quality and consistency** due to variations in data collection methods, participant compliance and device limitations. It is important to find a balance between capturing temporal trends (frequency of measurements) and minimizing participant burden. Additionally, citizen science projects might be susceptible to selection bias, as participants may be more motivated or aware of the issue being studied, and access to wearable devices might not be evenly distributed across socioeconomic groups. The project design needs to address this by employing alternative data collection methods such as sleep diaries and surveys, to ensure inclusivity and a more representative sample. Targeted outreach efforts should also aim to reach diverse populations and minimize the risk of excluding certain demographics.

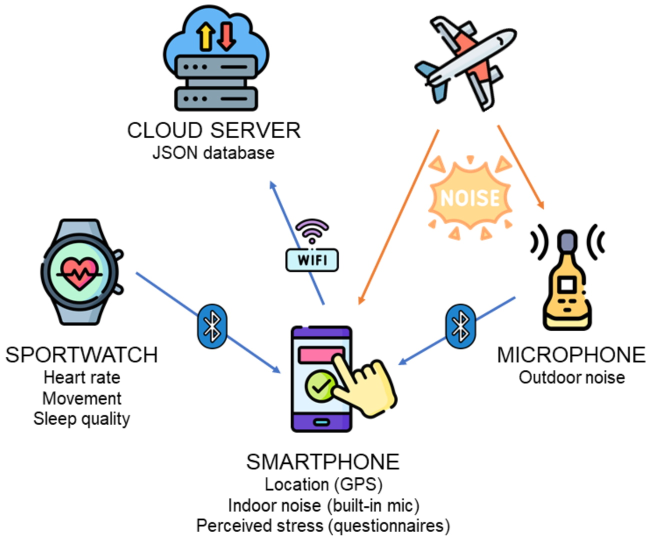

Figure 5: Potential set-up of a citizen-science system for surveillance of the health impacts of aircraft noise.

2.6 Establishing site-specific exposure-response functions

Although ERFs are available from literature for noise, these are often based on populations that can be different from the population living in the proximity of Brussels Airport. Populations can differ in underlying health status, stress levels and co-exposures to other environmental stressors. Therefore, it is recommended to derive **situation-specific ERFs** (WHO Regional Office for Europe, 2018).

The results that would originate from site-specific research as described in *Sections 2.3 - 2.5* could be used to derive site-specific ERFs as discussed in the below paragraphs for secondary and primary data studies.

2.6.1 ERF based on secondary health data, using health and environmental data paired at the level of individuals

For some health effects, ERFs can be derived based on secondary health data (see *Section 2.3 Surveillance based on secondary data*). Data on mortality and morbidity on an individual basis is collected by different institutions in Belgium. Registries contain information on the complete population, such as the mortality registry data (managed by the Belgian statistical office (Statbel)) or the cancer registry (managed by the Stichting Kanker Register) (See WP3 on relevant data sources). When available, these are the preferred data sources for establishing ERFs. When registry data is not available for the specific outcome of interest, data from other health databases (e.g., Intego, hospital discharge data, etc.) and questionnaires can be used. Health databases such as Intego, hospital discharge data, intermutualistic agencies hold valuable information for disease or indicators (e.g., medicine use) linked to noise and UFP. Surveys collect data on health at a given time point, such as the Belgian Health Interview Survey (BHIS), which has taken place every 5 years since 1997. However, since these only cover a subset of the population, survey weights need to be considered to obtain results that are representative for the Belgian population. Survey weights are typically computed using information on sex, age and household data on e.g., education level.

Access to personal data, such as health data, is overseen by the Information Security Committee (In Dutch: informatieveiligheidscomité, IVC), which issues authorizations for the electronic exchange of personal data. As a rule, authorizations are only given for the exchange of **pseudonymized data**, where data on an individual is available, but all data that can lead to the identification of the individual has been removed. This includes names, national registry number, residence address, ...

To link one case (e.g., mortality or cancer diagnosis) to (models estimating) environmental exposure, access to residence information is required. **Data coupling** of historical or current data on individual health cases and environmental exposure needs to be done by a trusted third party, and the data coupling procedure needs to be approved by the IVC, which is a lengthy process. Once the process has been approved, the authorization can cover data coupling of historical, contemporary datasets and can be extended when new datasets become available.

Disposing of individual health data coupled with address-based environmental data allows for testing the effect of a large variety of metrics for environmental stressors, such as UFP maps (when they become available), noise data on peak noise level exceedances or noise levels for specific time slots (for instance 02:00-05:00), in complement to the available L_{night} and L_{den} maps. It would also allow for testing this relationship over a variable period. Depending on the health outcome under consideration, a different exposure window might be relevant. For example, quality of sleep will most probably be influenced by noise levels between 23:00 and 7:00; in the case of asthma exacerbation, the exposure to UFP over hours to days before the exacerbation is most relevant; the outcomes of questionnaires on wellbeing are most often associated with exposures during the weeks prior to the survey; finally, for chronic conditions, an exposure window over years to decades is most appropriate. Residence history, combined with modelled exposures, allow to compute exposure over the most appropriate time interval.

When investigating a rare health effect (e.g., child leukaemia), the incidence recorded over one year can be too small to detect significant results. This can be mitigated by pooling data over several years or decades to obtain sufficient statistical power.

2.6.2 ERF based on primary individual paired health data

Although pre-existing administrative databases and surveys are a valuable source of information, they are not a panacea (see reasons described in *Section 2.4 Surveillance based on primary individual data*). Designated surveys can provide info in exposure responses of the targeted population. Similar statistical methods to derive ERF as for use of secondary individual paired health data can be applied.

2.6.3 Application of ERF functions from the population living in the proximity of Brussels Airport

The ERFs derived from populations living near Brussels Airport (as to be derived see *Sections 2.6.1* and *2.6.2*) can be applied to the entire population in the vicinity of the airport, taking into account differences in environmental pressure (e.g., noise levels) and demographics within the region.

For the ERFs to be accurate and applicable, it is essential that the study population used to derive the ERFs is sufficiently representative of the broader population living near the airport. This means that the study participants should reflect the diversity of the population in terms of age, sex, SES and other relevant factors.

One practical application of these new ERFs is to incorporate them into the E-HIS tool “aircraft noise – health". This tool currently uses literature-based ERFs, which may not accurately reflect the specific situation around Brussels Airport. By upgrading the tool with region-specific ERFs, the estimated number of people affected by sleep disturbance and annoyance due to aircraft noise will be more reliable and tailored to the local context.

2.7 Considerations regarding complexity, sample size, time and cost for different types of health surveillance and research

Understanding the potential health impacts of airport operations on surrounding communities requires a multifaceted approach utilizing various data sources. This section outlines the commonly used data sources in airport health research, considering their complexity, achievable sample size, accuracy, cost and time to collect, along with other interesting factors as also visualized in *Figure 6*.

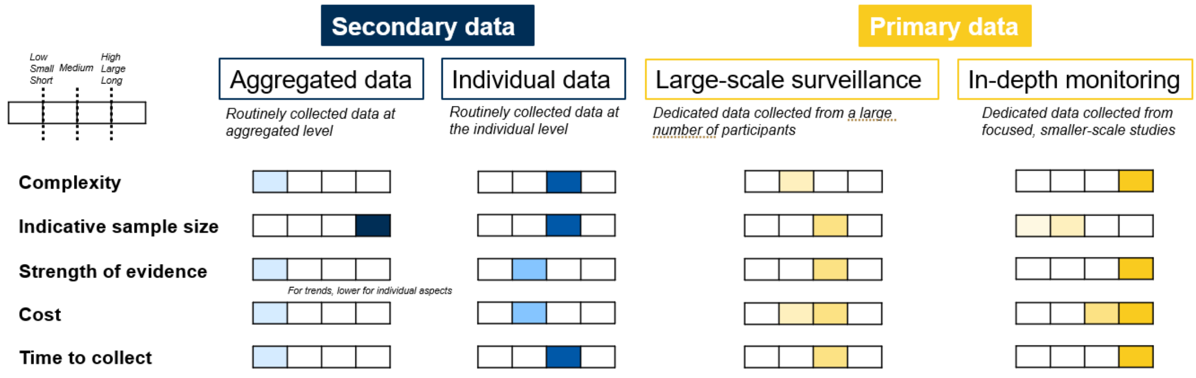

Figure 6: Primary and secondary data sources that could be employed in airport-related health studies.

2.7.1 Secondary data

2.7.1.1 Aggregated data

Complexity: This data is readily available and relatively straightforward to analyze using ecological studies. This type of study analyses existing data at the group level to identify potential relationships between exposures (e.g., aircraft noise) and health outcomes (e.g., cardiovascular disease mortality). Although simple in design, interpreting findings can be challenging due to confounding factors (e.g., SES) that can influence exposure and effect. Most importantly, ecological studies suffer from ecological fallacy, i.e., what happens at an aggregated scale does not necessarily happen at the level of every individual.

Achievable sample size: Ecological studies typically deal with large sample sizes, often encompassing entire populations within defined geographic areas, not individual participants. While a large number of groups might seem like a strength, the analysis is limited to group-level averages. It does not consider individual variations within each group.

Strength of evidence: Can establish ecological associations between exposure and health outcomes at the population level. Not able to explore individual-level factors or causal relationships due to the aggregated nature of data.

Cost and time: A significant advantage of ecological studies is the fact that they are cost-effective and time efficient. These studies rely on readily available data eliminating the need for expensive recruitment, data collection procedures and interventions, making it suitable for initial surveillance or hypothesis generation.

Additional considerations: Data quality and consistency across datasets needs careful evaluation. Limited control over data collection methods and potential biases from the original studies. Can be linked with environmental data using Bayesian models. May include data on demographics (e.g., age, gender), but might lack detailed information on SES or lifestyle.

Exemplar study: Evrard et al. (2015) exemplifies the strengths and weaknesses of ecological studies with secondary data. While it provides valuable insights into a potential link between aircraft noise and cardiovascular disease mortality, its ecological nature limits its ability to establish causality.

2.7.1.2 Individual data

Complexity: Obtaining and analyzing individual-level data is more complex than aggregated data analysis due to potential inconsistencies in data collection methods and variable formats across datasets. Moreover, it requires access to existing databases with individual health information (e.g., Intego) which is often a tedious process.

Achievable sample size: The sample size can vary depending on the database and inclusion criteria. It may be smaller than aggregated data but offers a more granular view of health outcomes for included individuals.

Strength of evidence: Can provide stronger evidence for associations compared to aggregated data analysis due to the ability to control for some individual-level confounding factors. However, causal relationships are still challenging to establish without additional data.

Cost and time: Generally, less expensive than primary data collection studies, but data acquisition costs may apply depending on the source. The costs and time to access and analyze individual data vary depending on access agreements and data security protocols. Data coupling procedures need to be approved by the Information Security Committee which is a lengthy process and limits the feasibility of this data source for rapid assessment.

Additional considerations: Individual data can be linked with detailed demographics, SES, lifestyle (smoking, diet) and even genetic factors. This allows for more robust analyses exploring potential associations between these factors and health outcomes which could be used to establish ERFs. Again, potential biases from the original data collection methods need to be considered.

Exemplar study: The long-term RIVM study around Schiphol airport on UFP exposure exemplifies the strengths of secondary data analysis on an individual level (Janssen et al., 2022) .

2.7.2 Primary data

2.7.2.1 Large-scale surveillance

Complexity: Relatively straightforward to design and implement due to standardized questionnaires and the possibility to complement with self-sampling procedures.

Achievable sample size: In general, the sample size is large and varies depending on the budget, available resources and targeted population. This increases the generalizability of findings to the broader population.

Strength of evidence: Can establish robust associations between exposure and health outcomes due to the large sample size and statistical power. However, these studies often lack detailed information on exposure patterns and mechanisms underlying observed associations.

Cost and time: Surveys are moderately costly and time-consuming. They involve survey design, participant recruitment, data collection and analysis.

Additional considerations: Data quality may be compromised by participant recall bias or errors in self-reported information or self-sampling.

Exemplar study: Hypertension and Exposure to Noise near Airport (HYENA) (Selander et al., 2009) and Discussion on health effects of aircraft noise (DEBATS) (Lefèvre et al., 2017) study are two examples of large-scale European surveillance studies integrating two complementary primary data collection methods. Namely survey research and molecular measurements (i.e., cortisol levels in saliva). The latter was for both studies performed on a subsample of individuals with a high exposure to aircraft noise based on their survey responses and residential noise level estimates.

2.7.2.2 In-depth monitoring

Complexity: Most complex and resource intensive. Requires specialized equipment, trained personnel (e.g., interviewers, field workers) and protocols for sample collection and analysis.

Achievable sample size: Often involves smaller, targeted groups due to intensive data collection procedures, higher costs and potentially higher participant burden. Findings may be more relevant to the specific population but require careful consideration for generalizability.

Strength of evidence: Can provide stronger evidence for causal relationships due to the ability to collect more precise exposure data, control for confounding factors and potentially explore biological mechanisms in depth through objective measurements. However, findings might be less generalizable to the broader population due to the smaller sample sizes.

Cost and time: More expensive due to specialized equipment, trained personnel and potentially longer data collection periods. Data analysis could be more time-consuming due to the complexity of integrating diverse data sources.

Additional considerations: Participant recruitment and retention can be challenging due to the intensive nature of the study design.

Exemplar study: The PIO study presents a strong example of an in-depth noise monitoring study that could be adapted to focus on aircraft noise (Dekoninck et al., 2023). By analyzing personal exposure, health effects, sleep disturbance and noise perception, researchers could gain valuable insights into the overall burden of aircraft noise on resident's health and wellbeing and possible underlying biological mechanisms.

2.8 Recommendations

This report provides an **overview of relevant study approaches and considerations** to set up a health surveillance or research study to assess the health impact and disease burden of Brussels Airport on nearby residents. Each study fits a specific research question and will contribute to a piece of the puzzle to understand the impact of aircraft activities on the health of people living in the neighbourhood. Several considerations (see *Section 1.2*, i.e., impact, strength and quality of evidence, new research areas, understanding mechanism, focus on vulnerability, cost and feasibility, etc.;), can be taken into account when selecting or prioritizing which study to set forward and launch.

These considerations are aimed to provide a framework to help select a study approach in view of the identified research questions and are key to allow flexibility and inform choices for setting up a dedicated health study around Brussels Airport. In addition, beyond selecting the appropriate research design, sequencing those studies in a logical order would improve overall research efficiency and allow to build a strong foundation of knowledge (partly based on suggested prioritizations). Hereto, we propose a **tiered methodological approach** providing a structured framework for investigating the health impacts of Brussels Airport on nearby residents. The optimal tier for a study depends on the specific research question and available resources. For instance, surveillance based on ecological studies with secondary (see *Section 2.3 Surveillance based on secondary data*) or primary (see *Section 2.4.1 Large-scale primary data surveillance*) health data gathered in a cross-sectional set-up could be a good starting point to identify potential associations between airport-related stressors and health problems with existing evidence of a link and/or public health significance. These findings could be complemented with objectively measured data collected in more in-depth surveillance studies (see *Section 2.4.2 In-depth monitoring*). However, site-specific longitudinal studies provide valuable insight into cause-and-effect relationships (see *Section 2.6 Establishing site-specific exposure-response functions*). In turn, citizen science projects can provide valuable complementary, large-scale data in a cost-effective manner and increase public engagement (see *Section 2.5 Citizen science projects*).

As a starting point, we recommend enrolling a **surveillance study** based on **primary data** collection to investigate the potential association between **aircraft noise exposure and sleep disturbances** among residents near Brussels Airport. Standardized questionnaires (readily available from international research around other airports and national studies such as De Oorzaak, PIO, SLO, FLEHS and the Belgian health interview survey) could be employed to collect self-reported data on sleep disturbance, annoyance and quality of life (including stress). An option would be to incorporate self-sampling for cortisol measurements to provide additional insights into potential stress responses associated with aircraft noise exposure. Such a surveillance study offers a valuable starting point for investigation of the potential impact of aircraft noise on sleep and well-being of residents near Brussels Airport. The findings could in turn inform more in-depth research proposals.

In parallel, ecological studies using existing (i.e., secondary) data can be conducted to explore a broader range of associations between aircraft noise and various noise-related health outcomes at the population level. Here it is recommended to focus on established noise-related health outcomes, such as cardiovascular diseases, mental health issues (e.g., anxiety, depression) or metabolic disorders (e.g., diabetes, obesity).

Representative surveillance data, both from primary and secondary health data, in connection with paired environmental data, could furthermore be used to derive site-specific ERFs which in turn would allow to quantify and monitor the burden of disease linked to airport-related stressors, e.g., in terms of various environmental burden of disease indicators (i.e., number of affected people, population attributable fraction, Disability-Adjusted Life Years, etc.).

In a possible next step, an in-depth monitoring study delving deeper into the aircraft noise-sleep relationship employs more rigorous data collection methods to strengthen the evidence base. These studies can involve standardized measurements (e.g., noise monitoring network) alongside questionnaires and biological effect measurements to gain a more comprehensive understanding of exposure patterns and health effects. Within the 'Programma Innovatieve Overheidsopdrachten (PIO)' of the Flemish Government, a methodology was developed to measure nightly indoor and outdoor noise, simultaneously with cardiovascular parameters and accelerometer data, hence assessing the impact of nightly noise exposure on sleep disturbance. This user-friendly and non-invasive yet accurate and validated tool is utmost suited to assess the impact of noise in the population living around the airport.

Lastly, citizen science projects can complement the above studies by providing large-scale, cost-effective data collection while engaging the public.

This report gave the most attention to the investigation of sleep disturbance caused by aircraft noise in communities surrounding Brussels Airport grounded by two considerations. First, a robust body of existing research from various studies demonstrates a clear link between aircraft noise exposure and sleep disturbance. Second, while the detrimental effects of aircraft noise on sleep are well-documented elsewhere, data on this specific aspect in the region of Brussels Airport is currently missing. However, the impact of aircraft noise on other health outcomes (e.g., cognition in schoolchildren, cardiovascular effects, etc.) is also recommended to investigate.

We strongly recommend to also set up research regarding the impact of UFP on health in the vicinity of Brussels Airport. While there are not yet established health advisory values (in Dutch: GAWs) for UFP exposure, there are several reasons to be concerned about UFP exposure in neighbourhoods of Brussels airport: (i) UFP exposure levels reach up to very high levels in some residential areas around Brussels airport, (ii)) UFP originating from other sources (e.g., road traffic) is associated with adverse outcomes (e.g., suggestive evidence for several long-term effects, i.e. cardiovascular, respiratory, cognitive effects, effects on birth outcomes and mortality; suggestive evidence for short-term effects: cardiovascular effects, respiratory and cognitive health) and (iii) epidemiological evidence of health effects from UFP arising mainly from airports is growing (e.g., suggestive evidence between aircraft UFP exposure and cognitive health and birth outcomes). To expedite progress in this critical area, it is advised to establish collaborative research initiatives with established research groups operating around other (international) airports. This collaborative approach would foster knowledge exchange and contribute to aircraft UFP – health research programs and a comprehensive understanding of the relationship between aircraft UFP exposure and human health.

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