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A GPS-based approach to measure the environmental impact of construction-related HGV traffic on city level

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ABSTRACT

Construction logistics (CL) is assumed to represent 20-35% of total urban freight traffic and account for a significant share of environmental nuisances. However, methodologies used so far make abstraction of travelled vehicle-kilometres (vkm), hence inadequately determining the true environmental impact of off-site CL activities. In turn, the lack of baseline assessments renders the development of sector-specific transport policies difficult. In Belgium, the use of On-Board Units shows promising results to answer this research gap. This paper presents a methodological approach to derive CL vkm on vehicle and trip level, based on algorithmic (R) and geospatial (GIS) analyses of GPS data from all HGV driving in or through the territory of Belgium, which serves as input to conduct a city-wide environmental impact assessment in terms of external costs. The proposed methodology was deployed on 66 large construction sites in the Brussels-Capital Region (BCR) active between 2020-2022, during the month of September 2021. Subsequently, results were translated to monetary terms to capture the generated environmental and mobility impacts. With its 968,041.96 monthly driven vkm, CL represents 26.40% of total HGV traffic in the BCR. This share generates €45,631.85 of external costs per workday, totaling €1,003,900.61 per month. Particular attention is paid to local air pollution (NO_x, PM) and global emitted pollutants (GHG; CO_2-eq.) which account for €55,123.07 and €80,409.95 per month of damage costs, respectively. To mitigate these damage costs and meet environmental goals, governments should pay increasing attention to urban construction transport by stimulating CL setups or developing emission-free public procurement procedures. The results of this study can serve as baseline for future policy recommendations and scenario evaluations.

1. Introduction

Mainly driven by a strong urbanization trend, urban centres are progressively focusing on the construction of new buildings and the renovation of older ones (PRDD, 2018; United Nations, 2015, 2018). Cities benefit from construction on the long-haul, as there is a positive correlation between construction works and the urban economic uptake (Janné, 2020). However, construction logistics (CL) activities are also the source of significant environmental nuisances during the construction works, which are often overlooked (CIVIC, 2017; van Lier and Macharis, 2016). Logistics activities are key in urban construction (Lundesjö, 2015), as the large and immobile buildings and the ephemeral nature and location of a construction site (Ekeskär and Rudberg, 2016) calls for significant amounts of transports to and from the site to guarantee timely resource deliveries (Josephson and Lindén, 2013). Current studies estimate that off-site construction logistics (CL) represent 20-35% of all urban freight traffic (UFT) in the EU (Brussels Mobility, 2008, 2016; Transport for London, and OPDC, 2018). Therefore, freight transport policy enforcement strategies are being developed, often on the demand of municipalities and developers to monitor mobility and accessibility (Goldman and Gorham, 2006), However, while authorities call for action with regards to CL-related air pollution, climate change, congestion and traffic safety (Brusselaers et al., 2021), a major issue is the lack of baseline impact measurements for policy recommendations (Brusselaers et al., 2021; Finnveden and Åkerman, 2014). In fact, impact estimations have so far often been conducted using techniques including traffic counts, surveys, camera technologies or data from Construction Logistics Setups (CLS). These rely on the number of vehicles used and/or the transported volume, which are inadequate transport indicators. Because these are not based on vehicle- or tonne-kilometres, very little is known with regards to the actual share or environmental impact of construction transport in UFT, rendering the

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development of sector-specific transport policies difficult. In Belgium, the use of On-Board Units (OBU) has shown promising results to answer this research gap. These GPS-based trackers are mandatory for all vehicles above 3.5t driving in or through the territory of Belgium, hence forming a very robust transport dataset from which precise vehicle-kilometres can be derived on vehicle and trip level (Adam et al., 2021; Brusselaers and Mommens, 2021; Buroni et al., 2018; ViaPass, 2021; Wang et al., 2016).

This paper presents a research design divided in two methodological steps. First, construction-related vehicles are derived from an exhaustive set of heavy goods vehicle (HGV) traffic. Because of the physically substantial surface use in urban areas, the immobile location of the site and the time-sensitive nature of the construction works (Ekeskär and Rudberg, 2016), the transport destination points are always known. Consequently, it is possible to trace the entire route followed by the vehicle delivering to the construction site. The identification of construction-related traffic was done by means of algorithmic analysis of OBU data in an R environment (Crawley, 2012; Pourghasemi and Gokceoglu, 2019). The extracted origin-destination matrices on vehicle and day level were then analyzed in a GIS-environment (Esri, 2022) to associate vehicle-kilometres to each transport movement based on GPS points with a temporal interval of 30 seconds. The developed algorithms were validated on a pilot construction site over a one-year period and then deployed on a next to exhaustive set of 66 large construction sites in the Brussels-Capital Region (BCR) active between 2020-2022, during the entire month of September 2021. Its results serve as input to, secondly, measure the total driven vehicle-kilometres of urban CL, its fleet composition, and a city-wide environmental impact assessment. In the case of transport, environmental damage costs such as air pollution, are economically referred to as external costs (Petruccelli, 2015; van Essen et al., 2019), as these are not borne by the polluter him- or herself (Bickel et al., 2005; Delgado and Gonzalez, 2018; Weinreich et al., 2000). The nuisances were translated to monetary terms to capture the generated economic external costs (van Essen et al., 2019) and the mobility impacts for the BCR, which can serve as baseline for the development of CL transport policies.

2. Literature review

The literature review aims to presents the state-of-the-art and is divided in four sections, covering (1) the importance of CL and its complex organizational nature, (2) currently used data collection techniques along with their advantages and disadvantages, (3) an overview of the main impact measurements in CL conducted and their robustness, finally (4) focusing on the use of OBU data in transport policy.

2.1. Importance of CL

Cities are putting increased significance on new construction projects and renovation of existing ones. This is mainly attributable to the rapid urbanization grade (United Nations, 2015, 2018). From a socioeconomic standpoint, the construction sector accounts for 9.7% of the EU27's GDP, employing 12.7 million people in over 3.1 million businesses (FIEC, 2020). These figures also translate in the CL sector. As suppliers and subcontractors procure 60-80% of the building materials and services required for the gross work (Scholman, 1997), the sector is highly and inherently reliant on logistics activities (Lundesjö, 2015). Current studies estimate that CL represents 20 to 35% of all UFT in the EU (Brussels Mobility, 2008, 2016; Ploos van Amstel and Quak, 2017; Transport for London, and OPDC, 2018) or 20-30% of transported tonnages (Dablanc, 2009; Löfgren, 2010). While construction is positively correlated with attractive, economically growing cities in the long-run and upon completion of sites (Janné, 2020), the environmental damage costs incurred due to logistics activities during the duration of construction cannot be neglected (van Lier and Macharis, 2016). The case-specific nature of building projects, which are physically large, uniquely positioned at the site of production and rely on ephemeral multi-organizational movements, further adds to the complexity of transport movements (Ekeskär and Rudberg, 2016; Josephson and Lindén, 2013; Koskela, 1992). This is especially of importance in urban areas, as construction transport generates impacts that exceed the geographical boundaries of the construction site itself (Fredriksson et al., 2021a; Fredriksson and Huge-brodin, 2022; Ghanem et al., 2018). CL may be rendered more effective and sustainable by optimizing planning, consolidation, and cooperation (Janné et al., 2021), both from an economic and environmental perspective (Fredriksson et al., 2021b; Josephson and Lindén, 2013; Nolz, 2021; Sveriges Byggindustrier, 2010). Overall, sustainable regional planning necessitates a deeper understanding of these externalities associated with material transportation (Finnveden and Åkerman, 2014; Rodrigue, 2020), which are currently lacking in the CL sector. With regards to CL solutions, especially air pollution, climate change, congestion and traffic safety are high on the political and mobility agenda in the BCR (Brusselaers et al., 2021). However, the latter study also concludes that there is a lack of evidence-based quantifications related to (urban) CL, which highlights the need for a baseline impact measurement for policy recommendations (Brusselaers et al., 2021; Finnveden and Åkerman, 2014).

2.2. CL data collection techniques

The main techniques used thus far to assess the impact of CL include: (1) traffic counts, (2) surveys, (3) camera technologies and/or (4) data from Construction Logistics Setups (CLS) such as checkpoints or construction consolidation centres (CCCs). To estimate CL transport flows, most often traffic counts are used (Brussels Mobility, 2008, 2016; Transport for London and OPDC, 2018). For the City of Brussels, analyses with pneumatic readers were conducted on main road axes, allowing for rudimentary vehicle differentiation based on axles spacing. This method does however lead to large inaccuracies as coaches can be counted as trucks, or small vans as cars. Estimations on the differentiation between freight transport sectors were based on visual vehicle identification (either physically or using video techniques), thus making abstraction on the actual vehicle use, cargo type and third-party suppliers (Strale et al., 2015). Camera technologies such as Automatic-Number Plate Recognition are confronted with the same geographical limitations as traffic counts but can be augmented by means of data mining techniques (Hadavi et al., 2020). The issue could partially be remedied by coupling traffic counts with surveys (Mommens and Macharis, 2014; Transport for London, 2017; Transport for London, and OPDC, 2018). The main advantage is that vehicle- or tonne-kilometres can then be derived from respondents' origin-destination and transported volume input. The main (and often decisive) hurdle is the time-intensive nature of this method and the respondents' willingness to participate (Verzosa et al., 2021). Another possibility is to collect digital transport data, often associated to a construction site or project as part of CLS such as checkpoints (Ekeskär and Rudberg, 2016; Sundquist et al., 2018) or CCC (Guerlain et al., 2019; Janné and Fredriksson, 2019; Lundesjö, 2015). These solutions often collect data by means of planning tools and/or gate sensors or camera technology, and often are on the demand of municipalities and developers to monitor mobility and accessibility (Goldman and Gorham, 2006).

2.3. Current CL impact assessments and their robustness

Often based on the above-mentioned data collection techniques, cities have attempted to estimate the share of construction-related traffic and its environmental impact. Based on traffic counts in Brussels, construction traffic would represent between 17,5% and 20% in total urban freight traffic (UFT) (Brussels Mobility, 2008, 2016). In London, construction would be responsible for 35% of daytime HGV traffic and cost the city £779,908,000 annually (Transport for London, 2017; Transport for London, and OPDC, 2018). However, these figures are (1) strongly sourced from manual field collection, survey work and/or Delivery Management Systems (DMS), (2) mainly encompass operating costs, (3) often make abstraction of crucial local variables, and (4) consider questionable base values for the estimation of external costs, most notably on climate change, air pollution, infrastructure and accident costs, mainly due to a lack of data(Helman et al., 2013; Transport for London, 2012; UBA, 2012; Watkiss and Downing, 2008). According to studies conducted in the Netherlands, construction projects account for 30-40% of freight traffic (in terms of vehicles) in Amsterdam (Quak et al., 2011). Furthermore, a construction site would be the destination for 3-5 out of every ten lorries (TNO, 2018). The Netherlands' department of transport and logistics analogically shows a 30% share of transported tonnages in a city, in line with observations from Dablanc (2009). According to other estimates in the country, construction accounts for 15 to 20% of trucks and 30-40% of vans in cities (Ploos van Amstel, 2018; Ploos van Amstel and Quak, 2017; Topsector Logistiek, 2017; van Rijn et al., 2020), while 27% of all greenhouse gas emissions in the Netherlands in 2015 (equaling approximately 1Mtonne) would be CL-related (incl. infrastructure, buildings for large companies and material supply) (Quak, 2018). Methodologically, CO2 emissions factors generated by urban logistics in this study were calculated using a top-down analysis based on Eurostat and CBS statistical data, as well as a bottom-up analysis based on data from supply profile studies in the building sector (Otten et al., 2016; Quak, 2018). Here, the high uncertainty in the sector's vehicle share is important to note. In the city of Oslo, transportation is responsible for 61% of greenhouse gas emissions, including both people and freight (City of Oslo, 2016). However, the approximate data (sources) used and the reason of the emissions are still unknown (Climate Agency - City of Oslo, 2019). Construction traffic would account for 20% of overall freight traffic in Sweden in terms of transported weight(Löfgren, 2010). However, no open methodology on how the approximation was achieved is presented.

The main issue with current impact assessments in the sector is the lack of adequate data, which leads to weak results. In the case of transport, environmental damage costs can economically be referred to as external costs (Petruccelli, 2015; van Essen et al., 2019), as these are not borne by the polluter him- or herself (Bickel et al., 2005; Delgado and Gonzalez, 2018; Weinreich et al., 2000). The main external cost categories for (construction) transport are air pollution, greenhouse gas emissions, noise pollution, congestion, accidents, and infrastructure costs. Further details on monetized externalities can be retrieved in transport and externality literature, of which the most recent overview is given by the Handbook of External Costs of Transport (van Essen et al., 2019). To calculate external costs, data on trip and vehicle level is required, as their magnitude is influenced by local variables. These are further explained in the methodology section. To measure the performance of (construction) transport and calculate external costs, vehicle-kilometres or tonne-kilometres need to be used. However, current CL impact assessments so far rely on the number of vehicles used and/or the transported volume, which are inadequate indicators and conclusively, insufficiently robust to determine the sector's environmental impact.

2.4. On-Board Unit data

Policies targeting zero-emission cities (Brussels Mobility, 2020; European Commission, 2020) and the urbanization trend lead to increasing numbers of construction projects (United Nations, 2015, 2018). These push regional authorities to attach more importance to logistics. Therefore, freight transport policy enforcement strategies are being developed, such as On-Board Units (OBU). These GPS-based trackers were implemented in 2016 to introduce a kilometre charge for the use of highways and regional roads across Belgium, as well as the entire inner-city road network in the BCR. Their use is mandatory for all road vehicles with a Maximal Authorized Mass (MAM) of 3,5t or above, driving within or through the territory of Belgium, and is thus applicable both for Belgian as well as foreign vehicles. Excluded from this kilometre charge are machine-vehicles (such as cranes, bulldozers, and lifts) and other types of vehicles such as test drive license plated vehicles and oldtimers. The tariffs of the toll roads are fixed by the regional governments, and are differentiated based on three parameters: (1) the Gross Vehicle Weight (GVW), Gross Combination Weight Rating (GCWR) or Maximal Authorized Mass (MAM); (2) the vehicle's emission standard (EURO norm) and; (3) the type of toll road. As all roads in Belgium are considered toll roads (although most of them are charged at 0 tariff), the OBU are switched on everywhere in Belgium and therefore measure all driven vehicle-kilometers (ViaPass, 2021). Overall, studies thus far reach a consensus on the robustness of OBU data to study vehicle travel patterns. Buroni et al. (2018) present the first preliminary (Belgian) OBU analytics to conduct a freight movement study within the geographical boundaries of the BCR. To this end, a density-based spatial clustering technique was used to detect hot spots in OBU data (Buroni et al., 2018). While the study conducted by Hadavi et al. (2020) focuses on augmenting ANPR data to better understand passenger and freight vehicle movements and stops by detecting parallels and variances, they used OBU data to validate their methodology and results because of its fine spatiotemporal granularity. Adam et al. (2021) propose an exploratory spatial data analysis which reveals the connections between urban hierarchies, transportation infrastructure, company locations or political organizations. While the complete OBU dataset allows for the analyses on overall HGV traffic, it does not include information on the sector the vehicle in which it is operating. Prior studies were therefore mainly aimed at the overall freight transport segment. The most recent study has shown that On-Board Unit data can also be used to conduct macro-level analyses to determine the overall environmental impact of CL within HGV traffic in Belgium (Brusselaers and Mommens, 2021). This study used the simultaneous sector's construction holidays in the month of July (over a 4-year period) to derive the construction-related HGV fleet and its associated driven (differentiated) vehicle-kilometres from total HGV traffic on the national Belgian level. It should however be stressed that this analysis used aggregated data because of the large geographical and temporal scope considered, hence failing to capture detailed information related to its delivery points (and thus its production-attraction) (Brusselaers and Mommens, 2021). Because of the physically substantial surface use in urban areas, the immobile location of the end product (i.e. the building) and the time-sensitive nature of the construction works (Ekeskär and Rudberg, 2016), the material transport destination points are however always known. Consequently, it is therefore possible to trace the entire route followed by the vehicle delivering to the construction site.

Conclusively, this contribution presents a methodological approach to compute CL vehicles from an exhaustive HGV-traffic dataset, based on algorithmic (R) and geospatial (GIS) analyses. Then, this serves as input to measure the actual driven vehicle-kilometres of urban CL, its fleet composition, and a city-wide environmental impact assessment in terms of external costs. These elements are explained in the methodology section.

3. Methodology and materials

This section depicts the methodological pathway which was developed to calculate the magnitude of construction-related traffic and its environmental impact on city-wide level using OBU data. This pathway is represented in Fig. 1. The iterative process comprises (1) the collection of raw On-Board Unit transport data (GPS), (2) the development of a vehicle identification algorithm and its data cleaning, transforming and preprocessing (using R), (3) the analysis of routing and vehicle-kilometre data (using Geographical Information Systems) and (4) the environmental impact assessment, translated into monetary external costs.

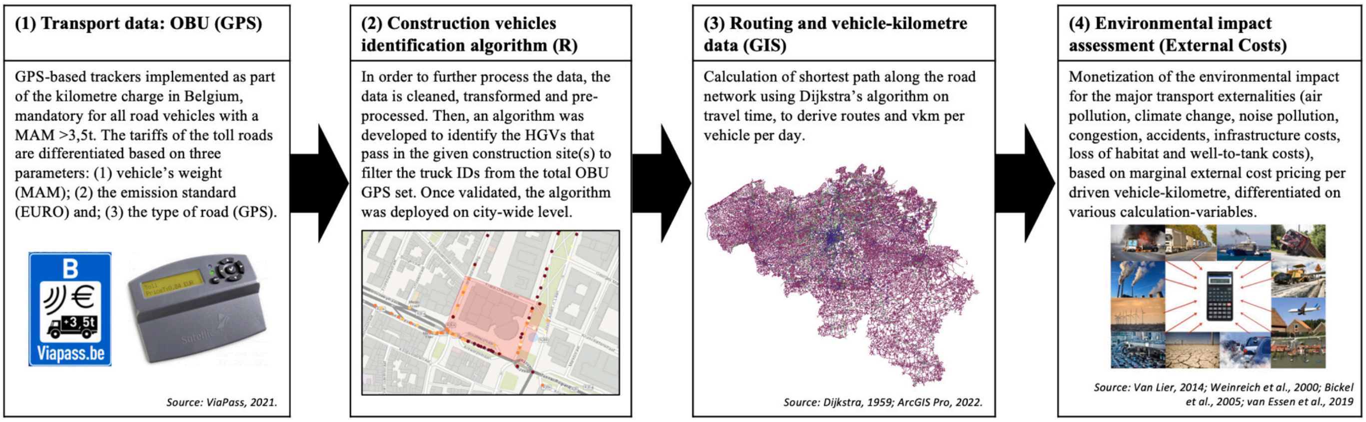

Fig. 1. Methodological pathway.

3.1. Transport data: On-Board Units (OBU)

The OBU data was sourced directly and in real-time from Viapass, the supervisory and coordinating government organization for the kilometer charge in Belgium. It contains data from Satellic, accredited as a service provider for OBU in Belgium. This provider holds the vast majority of OBU in Belgium for the time frame considered and can be considered as nearly exhaustive (ViaPass, 2021). Data was collected directly and in real-time during a one-year period between October 1st, 2020 and September 30th, 2021. The raw data was collected on the servers of the Vrije Universiteit Brussel and represents approximately 500 megabytes (Mb) of data per day of activity. The data collected through the OBUs is differentiated based on different variables needed to calculate the road price for a variety of road and vehicle types. It includes the vehicle's geometry (extracted via a unique identifier with GPS points per 30" intervals), the vehicle type (the transport mode and capacity), its emission standard (EURO norm) and the time of day (ViaPass, 2021). The OBU database retrieves the data from the Viapass server, which records the information of each trajectory sent by the trackers. One piece of data represents one trajectory, that records: "ID", "X", "Y", "TIMESTAMP", "VELOCITY", "DIRECTION', "COUNTRYCODE", "EUROVALUE", "MIM": Where "ID" represents the unique track that sends the information to the server and which is used as pseudo-ID of each HGV (renewed every 24h); "X", "Y" records the two-dimensional space coordinates, where "Y" is the latitude, "X" is the longitude; "TIMESTAMP" is a sequence of characters or encoded information identifying when this data is generated; "VELOCITY" the speed at which the vehicle is driving; "DIRECTION" the azimuth (orientation) of the vehicle; "COUNTRYCODE" the country in which the vehicle is registered; and "EUROVALUE" the numerical values associated to the emission standard of the vehicle. Analyzing OBU data can improve the understanding of freight movements, and is shown to be robust dataset to study vehicle travel patterns and their associated vehicle-kilometres (Adam et al., 2021; Buroni et al., 2018; Hadavi et al., 2020; Zhao et al., 2011), which includes all off-site construction transport (including transportation of on-site machinery such as cranes and bulldozers) using HGVs (Brusselaers and Mommens, 2021). Additional calculation-variables can further enhance the impact assessment, which are covered in Section 3.4.

3.2. From raw OBU data to construction-related HGV identification

The raw data saved in the database cannot be directly used, and therefore requires cleaning, transforming and preprocessing (Adam et al., 2021). For example, the "X", "Y" values of the collected data are two cardinal values that cannot be directly used in GIS; each piece of data just records the discrete information, i.e., it records the monetary data at the "TIMESTAMP", but the continuous information of the HGVs are required. Therefore, the OBU data is imported in an R environment (Crawley, 2012), as (1) it plays an important role in data analysis, mining and visualization, and as such in spatial analysis, and (2) over 130 spatial-related packages were reached (Pourghasemi and Gokceoglu, 2019). Two algorithms are developed for identifying the construction-related HGVs, the flow chart that illustrates the process of algorithms is presented in Fig. 2. First, the raw data process is presented in Section 3.2.1. Then, the decision and filtering process is depicted in Section 3.2.2.

3.2.1. Raw data processing algorithm

This step aims to process the original OBU data making it executable for the later identification algorithm. Several studies proposed different raw data processing approaches for OBU data. Adam et al. (2021) and Hadavi et al. (2020) both first identify the sequence of trajectories for each individual HGV into the separate datasets as trip per day. Then the individual trips are split into segments. Adam et al. apply this approach to identify the stop mode of the trucks, i.e., the engine shut-down. They can then identify the trips of the HGVs during a full day to calculate the Euclidean distance of the trips. Hadavi et al. apply this approach to improve the efficiency of the map-matching algorithm(Yang and Gidofalvi, 2018). In this paper, we decide not to split the one-day trips of HGVs into multiple segments, as the stop mode is an important criterion to identify the linkage between the specific truck and its construction site (delivery point). The detailed explanation is given in the Section 3.2.3. The pseudocode for the raw data processing is given in Algorithm 1 which can be retrieved in the Annex 1 along with its descriptive text. The objective of this algorithm is to convert the discrete trajectory data from different HGVs into separate datasets that records the complete routes for each HGV.

3.2.2. HGV's identification algorithm

Once the data has been rendered readable, an algorithm to identify construction-related HGVs was built. In this step, the HGVs that work in the target construction site(s) are identified. The pseudocode for the HGVs identification is given in Algorithm 2 as part of the Annex 2, along with its descriptive text. For one HGV route, if one trajectory is shown in one construction site, the HGV will be seen as at least "pass by" the construction site. The "pass by" HGVs are then checked to see if they "work for" the construction site. Different methods exist to determine a stop, such as a running engine (Joubert and Axhausen, 2011), a constant communication or ping with the OBU (Cich et al., 2016), driver-provided surveys (Schönfelder et al., 2002), a combination of velocity and distance (Zanjani et al., 2015), the combination of raw GPS points with Points Of Interests (POI) (Alvares et al., 2007), the combination of a temporal criterion with a spatial attribute of the stop (Gingerich et al.,

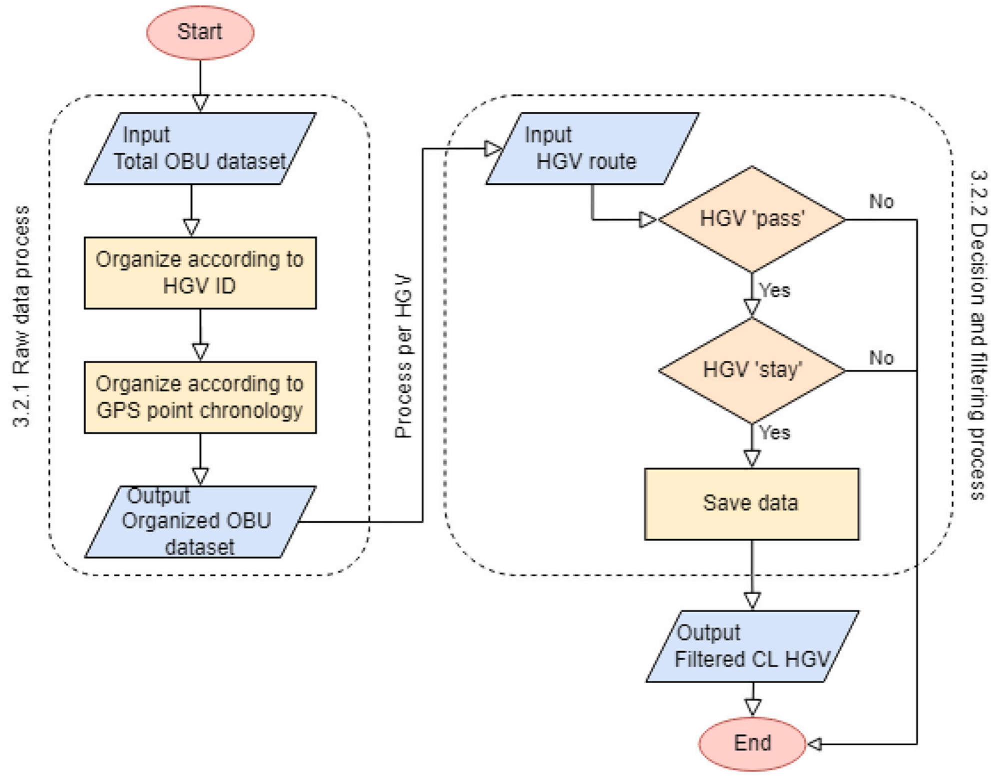

Fig. 2. Flowchart of developed algorithms.

2016), heuristic modelling (Demissie and Kattan, 2022), or simple temporal criteria without specific consensus ranging from 2-20min (Hess et al., 2015; Li et al., 2008; Rasmussen et al., 2015; Xiao et al., 2016). Given the locations of the delivery stop candidates in construction are known and immobile (i.e., the geographic boundaries of the sites) but not the time of passage of the HGV, it was opted to follow the example of Alvares et al. (2007), in combination of a defined construction-specific minimal stop duration criterion. If the stay time of the HGV is more than 10 minutes, i.e., 600 seconds, this HGV is identified as working for the construction site, which is based unloading times of concrete deliveries (Weiszer et al., 2020) which is faster than material deliveries. This duration is short enough to justify a stop (such as loading and/or unloading) and sufficiently large to exclude unwanted stops such as traffic lights, small GPS distortions and congestion (Adam et al., 2021). After applying the algorithm, all the HGVs that delivered at the construction site per day are identified.

3.2.3. Explanation of the data processing pathway

Fig. 3 shows the part of trajectories HGVs entering and leaving one construction site, illustrating the considered delivery period. The time duration between two trajectories is saved in the second trajectory of the two, so that the duration time of every trajectory is compared by the

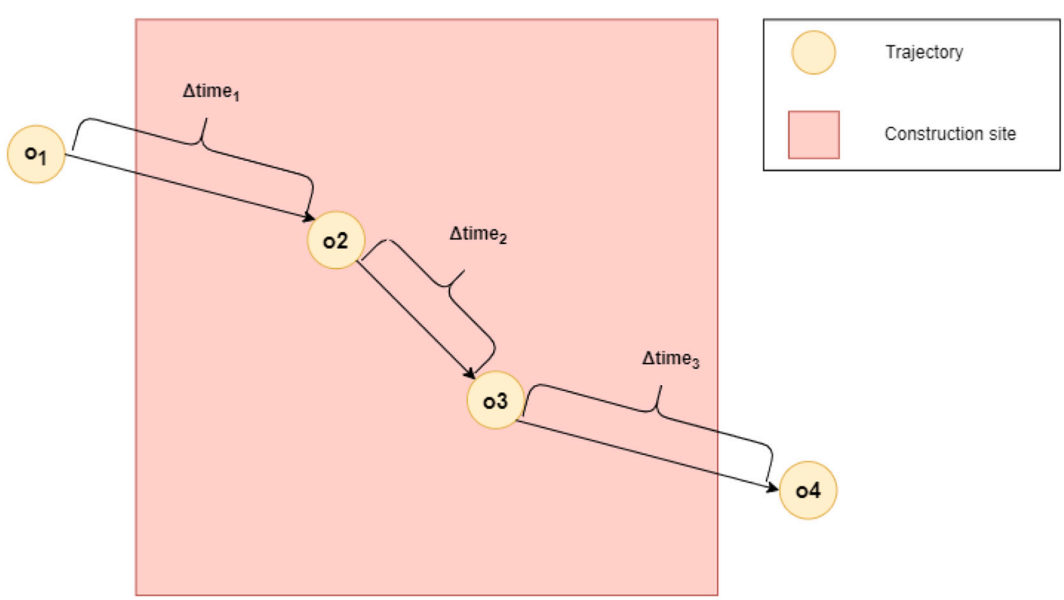

Fig. 3. Illustration of the calculation of the duration between trajectories.

previous trajectory, for example, $\Delta time_1$ will be saved in o_2.

If Algorithm 2 is applied in the situation of Fig. 3, $\Delta time_1$, $\Delta time_2$ and $\Delta time_3$ are considered as "timestay", i.e. the duration of the HGV is present within the boundaries of the construction site. $\Delta time_2$ is considered in "timestay", as the two trajectories o_2 and o_3 are in the construction site. However, the situation of $\Delta time_1$ and $\Delta time_3$ are more complicated. $\Delta time_1$ reflects the time duration between o_1 and o_2, which is saved in o_2, while $\Delta time_3$ are the time duration between o_3 and o_4 is saved in o_4. For $\Delta time_1$ and $\Delta time_3$, there are trajectories o_1 and o_4 which fall outside of the construction site's boundaries. Yet, they are also considered as "timestay" as these time durations include the HGV entrance and exit of the construction site. This is attributable to the mechanism of the OBU data: normally, the OBU will send the information to the server every 30 seconds. However, the OBU is switched off and thus stops transmitting location data when the truck's engine is shut off. Data transmission is resumed when the engine is turned on again. This situation will happen at least once in $\Delta time_1$, $\Delta time_2$ or $\Delta time_3$ as illustrated in Fig. 3. The HGV is shut off in one of these three durations (during unloading), and after the server received the next trajectory, it means the HGV is ready to leave the site. This causes a significant time interval through one of these three durations, and a regular time interval through the other two, i.e., 30 seconds. As observed in the collected data, most often the engine shut-off happened in $\Delta time_1$ or $\Delta time_3$, i.e., the trajectories marked as entering or leaving the construction site. After a thorough experiment, around 86% of the trajectories entering or leaving the construction sites take more than 30 seconds, which increases the probability that the HGVs are shut off and unloaded when they enter or leave the construction site. As a means not to neglect any one of the situations mentioned above, all three time durations will be taken into consideration as "timestay". This can be achieved by aggregating all the trajectories in which "inarea" is true or "change" is -1. Following the developed algorithms, it is possible to distinguish the idling time in the total on-site stop duration. Specifically, the duration can be recognized as the duration between fixed 30 seconds interval GPS pings (when both the engine and OBU are switched on) which are continuously received when the HGV is on-site (taken as proxy for idling state). When the time interval between two GPS pings exceeds 30 seconds, the OBU (and engine) must have been turned off between these two time stamps. As a consequence, the maximal theoretical time one HGV's engine is on when it is on-site, is given by:

$$t_{idling}(s) = (n+1) \times 29$$

where n is the number of the fixed 30 seconds intervals of the HGV, i.e., the trajectories recorded on-site before/after the HGV's engine is shut down. The theoretical idling time before engine off of one HGV trajectory is 29 seconds, otherwise the OBU would send another GPS ping. After testing the one-month OBU data, the ratio of (maximal theoretical) idling time compared to the total HGV stop duration on-site equals 1,64%, i.e., the time HGVs spend on-site, with a switched-on engine. On average, a typical HGV delivering to site has its engine turned on for 112

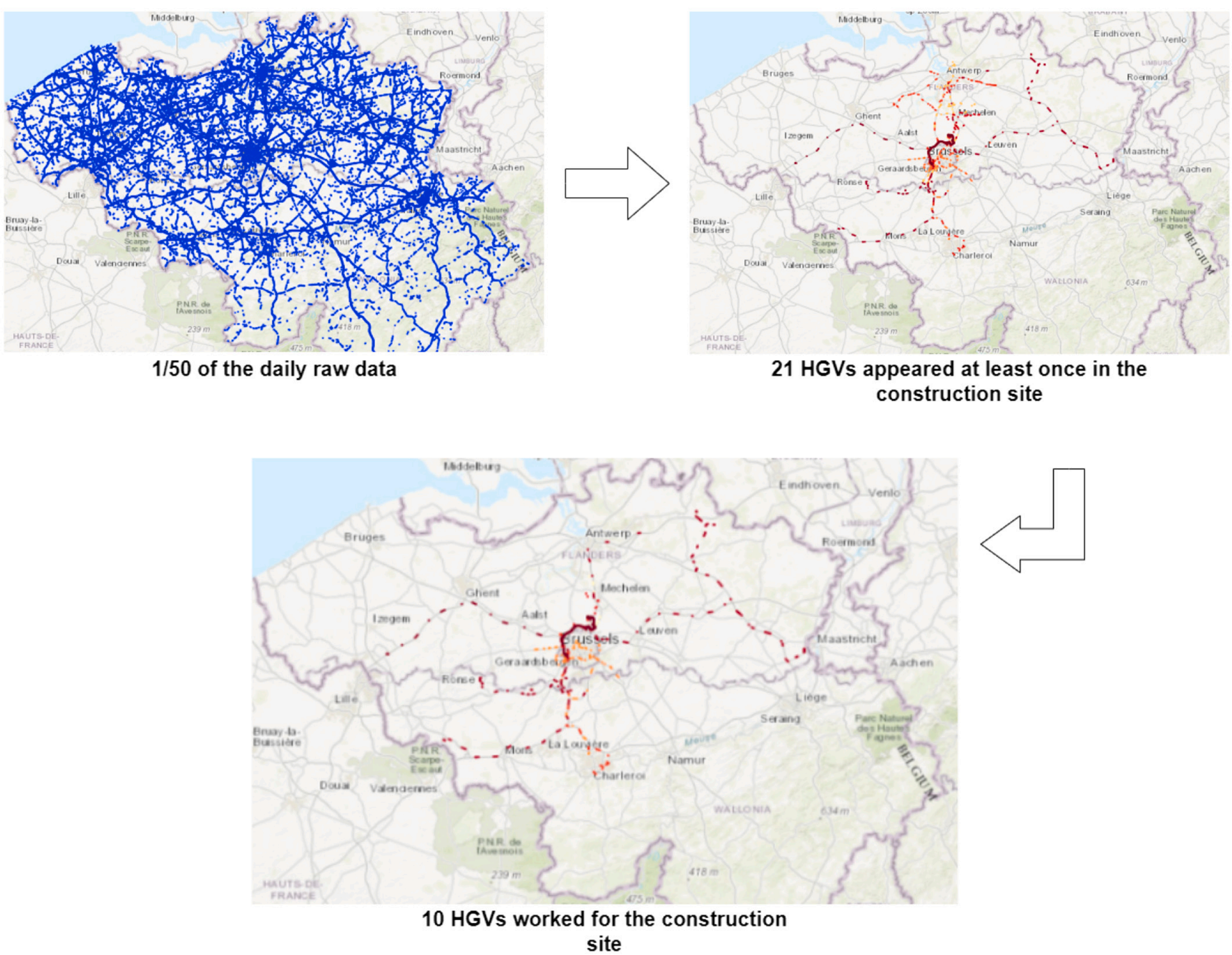

Fig. 4. Visualization of the algorithm processing.

seconds (1,88 minutes). This means that the engine is turned off for the remaining 98,36% of the on-site time. It was therefore opted not to include this impact, especially in light of the off-site focus of this paper.

3.2.4. Output single-site validation and city-wide analysis

The algorithms were tested with a randomized day's OBU data. Fig. 4 illustrates the algorithm processing in different steps for its validation.

There are 5,097,330 trajectories collected in one day, the first part of Fig. 3 shows the first 10,000 trajectories, which is 1/50 of the daily raw data. Then the algorithm identifies 21 HGVs of which at least one trajectory appears in the construction site. Finally, after running the HGVs identification algorithm, 10 HGVs are identified that are worked for the tested construction site. These algorithms were then tested within the context of a single-site analysis serving as pilot case (Brusselaers et al., 2022). This was validated by cross-matching the OBU data to the construction site logistics planning and bill of materials over the course of 1 year, from November 1st, 2020 to October 31st, 2021. The results on this large construction site over an extended period show that accurate vehicle-kilometres generated by transport movement to and from the site can be measured and analyzed accurately. Consequently, it showed that planning processes can be optimized when compared to the construction site's delivery schedule, and scenario analyses can be simulated to determine more sustainable CL possibilities. In what follows, the methodological approach is deployed on city-wide level.

3.3. Routing and vehicle-kilometre data: Geographical Information System

To determine the number of vehicle-kilometres driven on a city-wide level, large construction sites were considered active in the period between 2020 and 2022, with a minimal built surface of 1,600m^2 (SAU, 2021). This built surface was taken as a lower bound, as large construction sites in the BCR most often deploy HGV for material deliveries to and from the site, rather than Light Commercial Vehicles (<3.5t) (Brusselaers et al., 2022; Dablanc, 2009). Hence, the considered construction sites form the primary target type to use HGV as main mode of transport, which is also in line with the OBU data. The dataset comprises 71 large construction sites within the boundaries of the BCR and within the analysis period, which is considered nearly exhaustive for this type of site (SAU, 2021). These sites are represented in Fig. 5. The average built surface for these considered sites is $\bar{x}$ =42,119m2, resulting in a total construction size of approximately 3,000,000m^2 upon completion. Given the size of the data to process and the geographical scope considered presented in this paper, the analysis comprised transport data from September 1st, 2021 to September 30th, 2021. This month was chosen as it reflects the most complete data, and it is characterized by very few (sector) holidays affecting the construction planning.

Next, a road network, taking into consideration specific freight transport speed limits and road restrictions, was created for the territory of Belgium in ArcGIS Pro 2.8 (Esri, 2022). The GPS points from the OBU dataset were overlayed onto the network. These points, with an interval of 30", were then compiled based on unique truck and day ID. The

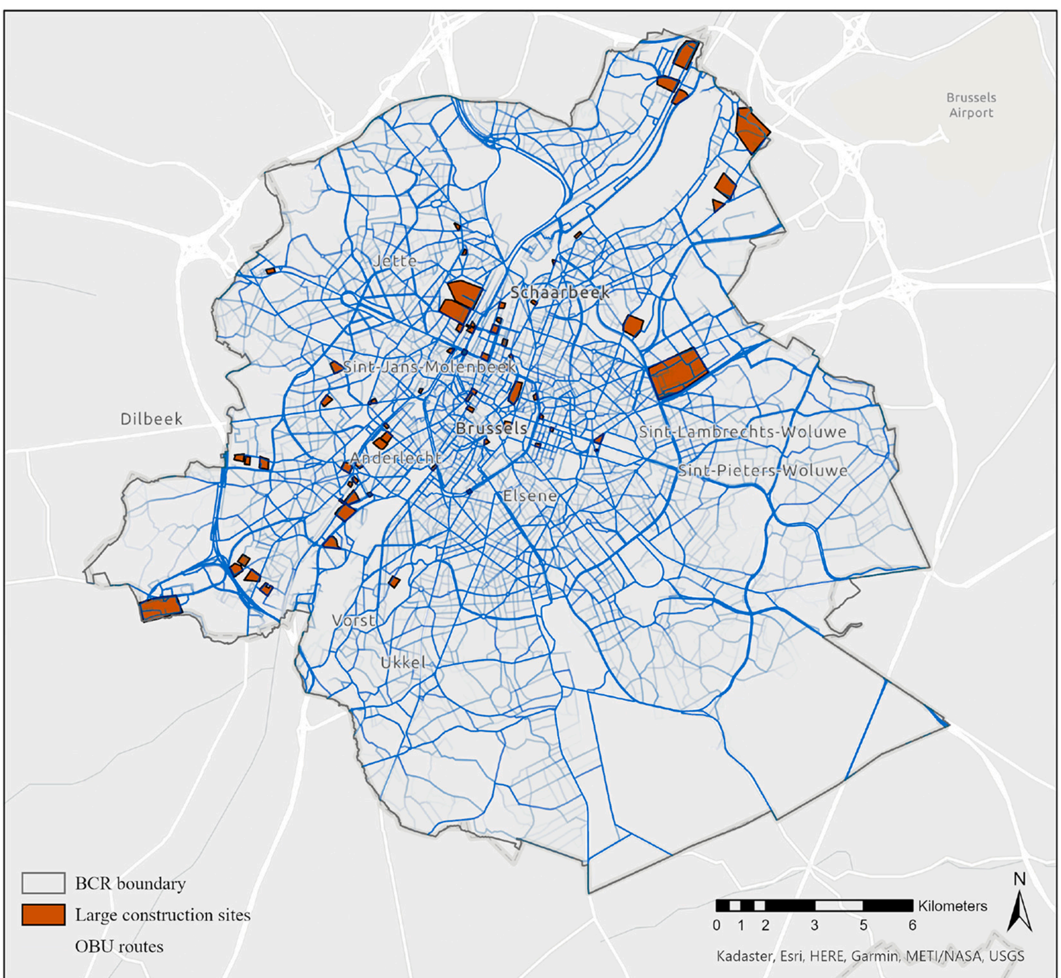

Fig. 5. Considered construction sites in the BCR.

shortest path between points along the network (following chronology of the coordinate points) was calculated following Dijkstra's algorithm on travel time (Dijkstra, 1959). Each intermediate location point was considered as a stop in a milk run (Shen and Stopher, 2014), hence deriving routes between Origin and Destination for each HGV between each point. The road restrictions included the avoidance of carpool roads, express lanes, gates, private roads, truck restricted roads and unpaved roads. Preferred truck roads (and truck impedance) were used were available. To this end, historical and live traffic data is used, but the speed was capped at the posted truck speed limit. This allowed for modelling the time it takes for the trucks to travel along the roads at specific times of the day. As represented by the blue lines in Fig. 4, the created routes were clipped within the boundaries of the BCR. This resulted in a dataset of over 12 million data points, consisting of 692,849 GPS points and 26,468 individual routes covering close to 1,000,000vkm.

Fig. 6 shows a histogram of the number of routes which are linked to each of the 71 considered construction sites. Three sites, i.e. #11, #16 and #57, show no activity during the considered analysis period between the 1st and 30th of September 2021. Consequently, these sites were left out of the analyses. Four construction sites show a significantly larger route volume. Sites #13 and #70 are by far the largest construction sites in terms of built surface, respectively 450,000m^2 and 300,000m^2. The associated delivery counts to these sites are considered reasonable given the amplitude of the required material volume on both sites. However, sites #3 and #6, which are located near eachother, have respectively a built surface of 36,300m^2 and 30,940m^2. Here, the transport counts are likely contaminated by other transport flows in direct vicinity of these construction sites, such as a water management company (with a high volume of container shipments), a postal service and a waste treatment center. Therefore, it was chosen to remove these flows from the analysis. Consequently, 66 large construction sites are considered in the final analysis.

3.4. Environmental impact assessment: external cost calculations (ECC)

CL activities are the source of nuisances during the duration of the construction works which cannot be neglected in the environmental equation. These nuisances are often referred to as externalities which arise when the associated changes in wealth are not included in the market price of its usage (Bickel et al., 2005; Weinreich et al., 2000). Hence, the polluter does not bear the costs of these nuisances, although they are shown to have significant impact on the environment (European Commission, 2018; European Environment Agency, 2021). In the case of transport, the main externalities are air pollution, climate change, noise pollution, congestion, accidents, infrastructure costs, loss of habitat and well-to-tank costs (Petruccelli, 2015; van Essen et al., 2019). The size of external costs of transport is estimated to reach approx. €1,000 billion per year in the EU-28, representing 7% of the region's GDP (European Commission, 2018). However, little attention has been paid to the environmental costs of CL so far(Janné et al., 2021; van Lier and Macharis, 2016). As indicated, current studies so far often do not consider vehicle-kilometres linked to the sector, although this is the most important performance metric in ECC. The system boundary of this paper is clearly defined on the vehicle usage part of off-site construction logistics.

This study presents the calculations for the major transport externalities and are based on the latest marginal external cost factors available in economic literature to date (van Essen et al., 2019; van Lier, 2014). To quantify external costs, output factors were gathered and organized. These are monetary values (EUR) per vehicle- or tonne-kilometre according to different situations (such as vehicle characteristics, environment, road type and time of day) which can i.a. be retrieved from the Handbook on the External Costs of Transport (van Essen et al., 2019) or STREAM Goederenvervoer 2016 (Otten et al., 2017). Each of these calculation-variables has an impact on the

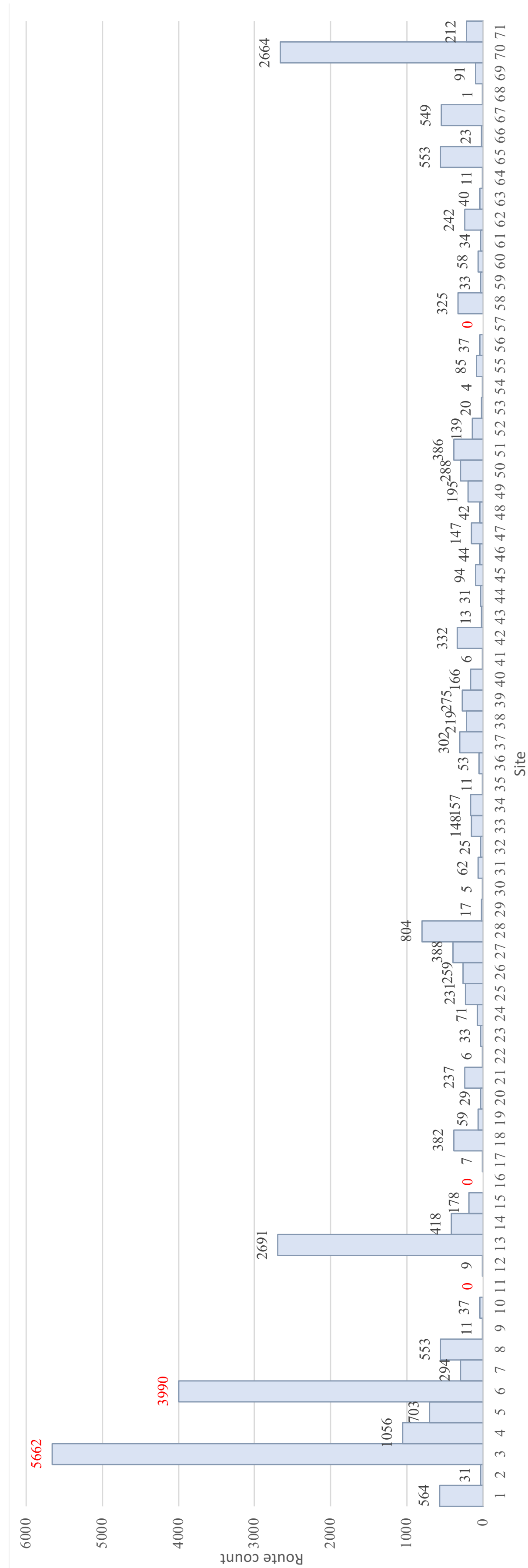

Fig. 6. Histogram of site route count.

magnitude of the considered nuisance, and therefore has an effect on the amplitude of generated external costs. This paper differentiates external costs using output values per vkm on various calculation-variables, which are presented in Table 1. As highlighted in Section 3.1, the CL-related movements are gathered from processed OBU data, which include trip and vehicle information on the geometry, time of day, transport mode, capacity, propulsion type, consumption, and speed. Transport trips before 06:00AM were considered night-time deliveries. From this dataset, the filtering algorithm lists the location points between the Origin and Destination of the vehicle's trajectory (OD-matrix), deriving the travelled vkm and the duration and speed of the trip of vehicle's which delivered to site (GIS). Environment and road types were derived through a geospatial road network analysis. The loading rates, which are not included in the OBU dataset, were based on European load factors from the STICITE study (van Essen et al., 2019). These

Table 1
Data sources and calculation-variables for external cost calculations.

Data category	Data variables	Data source	Explanation
O-D Matrix	Total transport flows (vkm/tkm) given origin and destination points[R]	OBU, GIS	Algorithmic identification of GPS points and GIS network analysis for the calculation of total vkm distance per trip.
	Road type[A]	GIS	GIS network analysis and subdivided in metropolitan and urban/inter-urban share of driven vkm.
	Environment[A]	GIS	
Time of day	Hour of the day (differentiation day/night)[A]	OBU	Transport trips before 06:00AM were considered night-time deliveries. This is variable per trip.
Traffic	Loss of time and traffic situation (thin/dense)[A]	OBU, GIS, A/S	Time and velocity were available through OBU data, processed using GIS network analysis and solidified based on national statistics. It was subdivided in 4 traffic scenarios for ECC: freeflow; over capacity; congested; near capacity.
Vehicle type	Transport mode[R]	OBU	The dataset includes all HGV with a MAM >3.5t.
	Vehicle capacity (size)[R]	OBU	The exact capacity was processed and categorized in the following segments: 3.5t-7.5t; 7.5t-12t; 12t-14t; 14t-20t; 12t-14t; 20t-26t; 26t-28t; 28t-32t; 32t-40t; 40t-50t and 50-60t.
	Vehicle propulsion type[R]	OBU	Available from OBU dataset.
	Vehicle consumption[R]	OBU	The fleet was composed of diesel trucks only. The dataset includes the differentiation per emission standard (EURO 0-6). Enhanced Environmentally-friendly Vehicles are included in EURO 5.
	Vehicle speed[A]	OBU	Available from OBU dataset (cf. traffic).
	Cargo type[A]	N/A	N/A for road transport.
	Loading rate[A]	A/S	Based on EU statistics differentiated on vehicle type and MAM (van Essen et al., 2019).

[R]Minimum data requirement.
[A]If no data is available, these could be based on solid assumptions or derived through geocoding or other calculations.
OBU: Information available from pre-processed On-Board Unit (GPS) dataset.
GIS: Information indirectly available from dataset through calculations (e.g. OD matrix through GPS points linkages, geocoding, routing algorithm, etc.).
A/S: Assumptions/Statistics.
N/A: not applicable for off-site construction logistics data gathering.

were differentiated based on vehicle type and MAM, ranging from 10.996% to 45.714%, depending on the vehicle's size class. The summary of the data sources is presented in Table 1.

Road congestion can be defined in a variety of ways (Grant-Muller and Laird, 2007). Most often, from an external cost perspective, it is defined as the impedance that vehicles impose on the network and on its users, when approaching the maximum capacity of the network (Goodwin, 2004). Time stamps and velocity information were available as part of the OBU dataset per GPS point. However, these data offer information on a particular instant, i.e. on the coordinates collection moment, thus making abstraction of the driving behavior and situation between each 30" interval. It therefore makes it difficult to accurately derive congestion situations, especially in urban environments (Shen and Stopher, 2014). Furthermore, it would not be possible to validate the actual network saturation as the OBU data does not include background information on other network users, such as passenger transport, which would make congestion assumptions prone to unrelated causes (such as driver's parking and small GPS distortions). It is however possible to derive average speeds over an extended length (i.e. trip) as part of the GIS analysis where traffic data was used (Esri, 2022). National statistics on monthly road segment saturation and weekly traffic conditions (Federaal Planbureau, 2017; TomTom, 2021; Vlaams Verkeerscentrum, 2021) solidified the traffic situations which were categorized for ECC analysis in free flow (47.527%), near capacity (14%), congested (29%) and over capacity (9.473%). Flow to network capacity ratios are set to 0.8-1.0 for near capacity, 1.0-1.2 for congested and >1.2 for over capacity (van Essen et al., 2019). Where relevant, figures for Belgium were applied (mainly for congestion and accidents).

4. Results

This section presents the findings of the measured vehicle-kilometres associated to and the impact assessment generated by urban CL in the BCR.

4.1. Production-attraction

Fig. 7 presents the transport attraction generated for each of the considered 66 construction sites in the BCR. Its magnitude (chart size) is determined by the sum of individual routes, i.e. transport deliveries, associated to each site. This allows to pin the attraction of individual transport flows (including vehicle characteristics and calculation-variables shown in Table 1). The map on the left (A) shows the total number of vehicle-kilometres travelled to and from each respective site within the BCR (chart circle size), equated with the share of vkm per EURO-norm. The map on the left (B) presents, in similar fashion, the external costs of air pollution generated per site and per EURO-norm. The combination of both charts highlights that most of the measured vehicle-kilometres are driven with EURO-6 (followed by EURO-5) engines, as shown in Table 2. However, the engendered air pollution external costs are disproportionately distributed, especially between these two emission standards. This is further analyzed in Section 4.2. Overall, 968,041.96vkm are registered associated to CL over the month of analysis; a share of 26.40% of all OBU-registered vehicle-kilometres. Leaving out the weekend days (Saturday-Sunday), 940,977.92vkm are measured for the sector. With 22 working days during the analysis period, this averages 42,771.72vkm per day. As can be seen in Fig. 7, construction logistics not only has an impact in the immediate vicinity of the sites, but on the city as a whole. Further details on congestion costs are given in Section 4.3 and in the discussion section.

4.2. Travelled vehicle-kilometres and CL HGV fleet

Fig. 8 further analyses the relationship between the measured construction-related vehicle-kilometres and its fleet composition, specifically in light of generated air pollution costs. To this end, the total

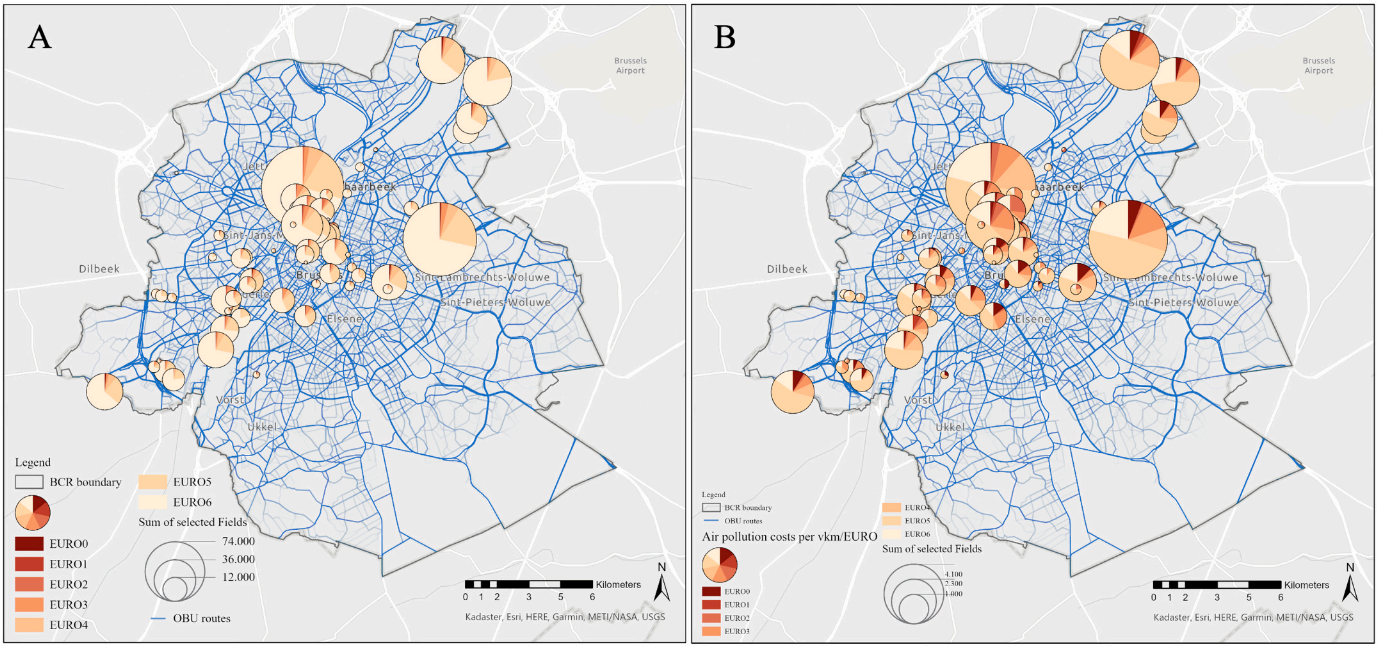

Fig. 7. Transport attraction in number of vehicle-kilometres per construction site, subdivided per (A) total vkm/EURO-norm and (B) external costs of air pollution/EURO-norm.

Table 2
Descriptive table of CL vehicle-kilometres covered in the BCR during Sep-2021, per MAM (t) and emission standard.

MAM (t)	EURO-0	EURO-1	EURO-2	EURO-3	EURO-4	EURO-5	EURO-6	Total
3.5–7.5	438.922	13.555	38.373	1,473.650	5,168.562	14,788.528	17,709.078	**39,630.669**
>7.5–12	1,410.020	30.547	2,141.419	6,662.242	10,390.475	36,432.925	93,529.416	**150,597.043**
>12–14	107.564			80.465	485.466	1,132.019	8,359.447	**10,164.961**
>14–20	699.098	60.708	583.311	2,950.645	6,503.282	24,307.118	89,508.491	**124,612.653**
>20–28	731.068	3.204	973.700	3,495.546	5,773.168	24,739.750	51,825.801	**87,542.237**
>28–34	15.075		78.071	544.548	1,403.741	155,290.293	18,401.805	**175,733.532**
>34–40	115.393			474.116	75.359	2,816.720	5,818.229	**9,299.818**
>40–50	120.835	11.034	1,583.496	4,474.453	10,347.279	53,975.857	224,179.387	**294,692.341**
>50–60	1,251.429	537.236	333.607	3,413.027	4,072.744	17,024.299	49,136.360	**75,768.703**
Total	**4,889.404**	**656.284**	**5,731.977**	**23,568.693**	**44,220.075**	**330,507.511**	**558,468.013**	**968,041.957**

fleet and its vkm was subdivided in MAM classes and EURO-norms. Two major conclusions can be drawn. First, within the urban setting of the BCR, the CL sector is majoritarily reliant on the use of 34-50t truck-trailers, covering over 300,000vkm during the period of analysis during September 2021. This is followed by 28-34t trucks, which are also running on older engines. Related to the latter, the second conclusion is that it is especially this vehicle category, often associated to EURO-5 standards, responsible for close to one third (33.11%) of the burden caused on the surrounding communicity in terms of air pollution. Taking all EURO-5-related vehicle-kilometres into account across all vehicle sizes, this share rises to 66.37%. The impact of HGVs with the strictest emission standard (EURO-6) are still accountable for € 10,656.79, or 12.83% of all air pollution costs.

4.3. External costs

Next, the environmental impact is calculated beyond the costs of air pollution, including climate change, noise, accidents, congestion, infrastructure, well-to-tank and loss of habitat costs, of which the breakdown is presented in Table 3.

The total generated external costs (across categories) associated to large active construction sites in the BCR account for 1,003,900.61 EUR over the month of analysis. With a total of 22 in September 2021, this equals a generated impact of 45,631.85 EUR per workday. The sector would be responsible for over 8,000 tonnes of emitted global pollutants (GHG; CO2-eq.), equaling a damage cost of 80,409.95 EUR per month. The local air pollution costs (NO_x, PM) highlighted in the previous section account for 55,123.07 EUR. Because of the combination of large (and often noisy) truck sizes and the dense urban environment, noise costs represent over 1/5 of total damage costs incurred. The same is true for congestion, although this is traditionally very pronounced in external cost calculations due to the evaluation of cost of time.

5. Discussion

This paper identified a research gap in which very litttle is known with regards to the actual share or environmental impact of CL in UFT. As opposed to prior studies which estimate the share of CL or its environmental impacts using indicators such as number of vehicles used or transported volume, this contribution presents a methodology measuring actual vehicle-kilometres (incl. environment and road types) on vehicle and trip level. This is based on fine-grained GPS data from an dataset containing all HGV movements in or through the territory of Belgium. Results show that 26.40% of all OBU-registered vehicle-kilometres (968,041.96vkm over the course of one month) in the BCR are related to CL movements, i.e. material and machinery delivery to and from large construction sites. Thus far, it was estimated that 20% of UFT was related to CL in the BCR (Brussels Mobility, 2016), including vans. It

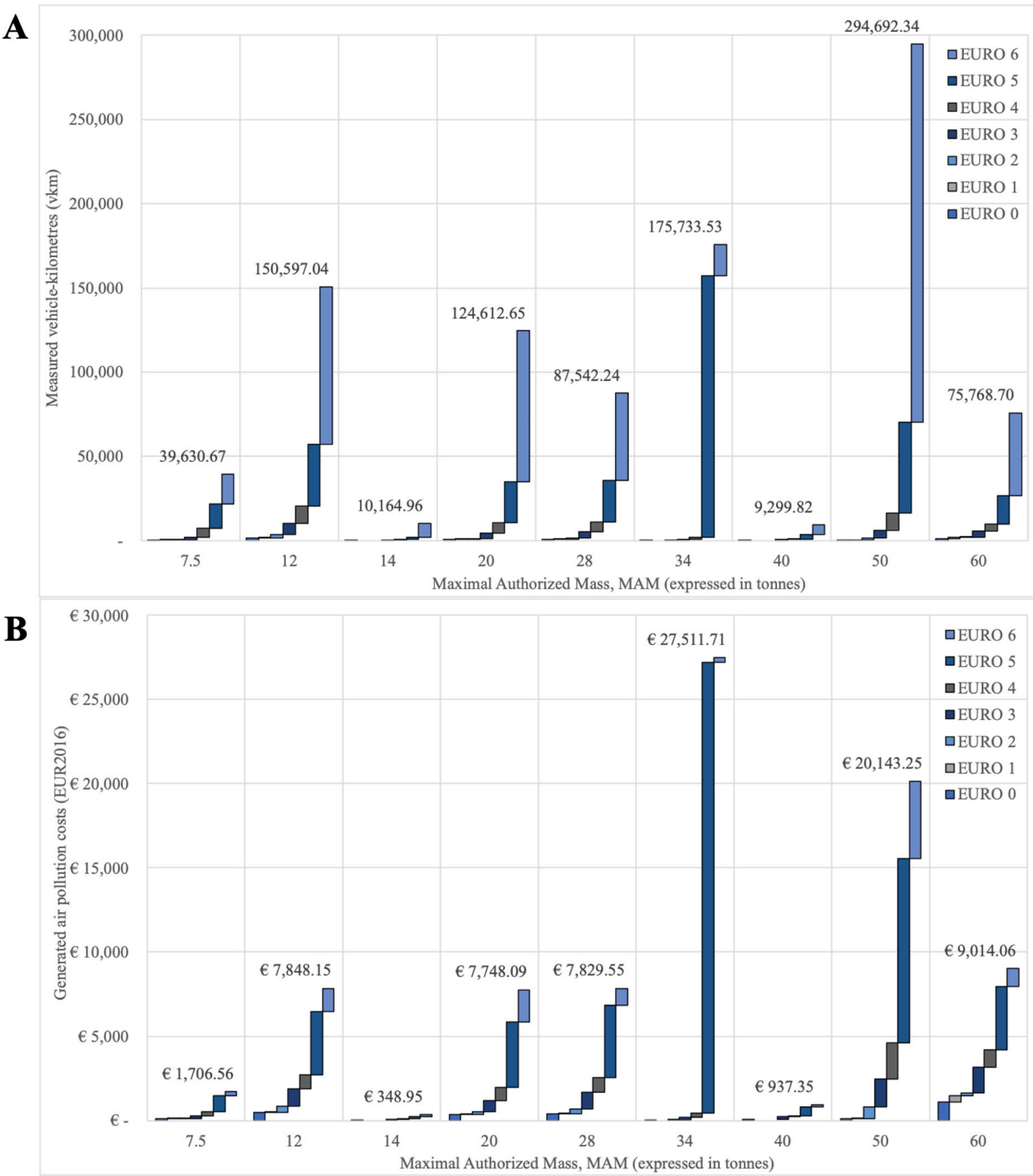

Fig. 8. The link between HGV size class (MAM) and EURO-norm, expressed (A) per measured vehicle-kilometres and (B) in generated external costs of air pollution ($EURO_{2016}$) for the period of analysis.

Table 3
External costs (in EUR_{2016}) generated by HGV construction traffic for the month of September 2021 and per average workday during the same period in the BCR.

ECC	Sep-21	$\bar{x}$ workday (95% CI)	Stdev (σ)	Max	Min
Air pollution	55,123.07	2,505.59 (2349.97-2661.21)	342.92	3089.11	1,667.12
Accidents	14,367.82	653.08 (614.7-691.46)	84.57	770.72	452.59
Climate change	80,409.95	3,655 (3440.18-3869.82)	473.37	4342.90	2,597.12
Congestion	544,513.93	24,750.63 (23296.11-26205.15)	3,205.14	29208.85	17,152.18
Loss of Habitat	15,697.34	713.52 (671.59-755.45)	92.40	842.04	494.47
Infrastructure	61,185.44	2,781.16 (2617.72-2944.6)	360.15	3282.11	1,927.34
Noise	213,876.14	9,721.64 (9164.96-10278.32)	1,226.69	11522.49	6,902.33
Well-to-Tank	18,726.92	851.22 (801.19-901.25)	110.24	1011.43	604.85
Total	**1,003,900.61**	**45,631.85 (42975.51-48288.19)**	**5,853.43**	**53,610.54**	**31,798.00**

has to be noted that this study did not encompass vehicles with a MAM <3.5t, as the focus was on large urban construction sites (Brusselaers et al., 2022; Dablanc, 2009). The presented share is also higher than the 17.58% found across the entire Belgian territory (Brusselaers and Mommens, 2021), indicating that CL generates relatively more vehicle-kilometres in the dense BCR. While daily air pollution costs account for 169,036.29 EUR in Belgium, it equals 45,631.85 EUR per day in the BCR alone, despite its relatively small surface area (162 km^2) but high population density (1.2 million or 10.38% of the population) in Belgium. This concludes that prior estimations for the BCR slightly underestimated the share and impact of CL. While a comparison between (international) assessments is not straightforward due to the lack of vehicle-kilometre data in prior studies, the calculated share using the proposed methodology (vkm) sits in between estimations in The Netherlands (20% of trucks), Sweden (20% of construction vehicles) and London (35% of daytime trucks) (Climate Agency - City of Oslo, 2019; Ploos van Amstel and Quak, 2017; Transport for London, 2017). The proposed methodology should be replicated in other cities or regions to evaluate local differences. From the analyzed transport flows, it becomes evident that construction transport not only has an impact in the immediate vicinity of the sites, but also on the city as a whole, in line with construction impact zones from Fredriksson et al. (2021a). For the BCR, the measured density is highest in immediate vicinity of each site. This is expected, as the location of a site is immobile. Higher than average traffic densities are also measured on the primary road network (R0 and E19 highway infrastructure), as well as along the Canal region. The latter can be explained by the many construction projects along this region and the presence of construction material companies. However, although the impact of construction traffic extends throughout the city, there is no discernable pattern for these transport movements. A reason for this could be that site deliveries are typically characterized by an affluence of different material suppliers, although this could not be concluded from this analysis. When comparing the CL HGV fleet in the BCR with the Belgian one in terms of travelled vehicle-kilometres, similarities are found. Despite approximately half of the trucks running on a EURO 6 engine, older EURO 5 (and to a limited extent also older ones) are still ubiquitous. This can be explained by the fact trucks are not affected by the LEZ restrictions until 2025. However, results show disproportionately distributed air pollution costs, indicating (1) more performant (i.e. less polluting) vehicle technologies are to be used and/or (2) less performant engines should avoid dense population clusters (Mommens et al., 2019).

6. Conclusions, limitations and future research

While urban construction is necessary and desirable (Janné, 2020; PRDD, 2018), its vast and significant logistics activities pose an environmental burden which are currently underresearched (CIVIC, 2017; van Lier and Macharis, 2016). Estimations so far assume the CL sector to represent 20 to 35% of UFT in the EU, but studies so far are insufficiently robust due to a lack of adequate indicators such as vehicle- or tonne-kilometres. This contribution answers this research gap by presenting (1) a methodological approach to derive construction-related vehicles from an exhaustive set of HGV traffic based on algorithmic (R) and geospatial (GIS) analyses using OBU (GPS) data, which served as input to (2) measure the actual driving distance of urban CL, its fleet composition, and a city-wide environmental impact assessment in terms of external costs. The proposed methodological approach enhances traditional methodologies used so far, as this method considers actual vehicle-kilometres driven, environment types and road types, which are linked to (individual) vehicle characteristics. These are calculated based on OBU data which collects information of all HGVs travelling in or through the territory of Belgium. The analysis considers the production-attraction of an exhaustive list of large construction sites in the BCR active between 2020-2022, enabling the computation of the total number of vehicle-kilometres travelled to and from each respective site within the BCR, equated with the vehicles' EURO-norm and engendered external costs. Overall, the sector is responsible for 42,771.72vkm per working day, totalling 968,041.96vkm registered over the entire month of analysis, a share which represents 26.40% of all HGV traffic in the BCR. Results show that engendered air pollution external costs by construction transport in the BCR are disproportionately distributed across emission standards. It shows that the sector is majoritarily reliant on the use of 34-50t truck-trailers, covering over 300,000vkm (31.4% of total vkm from the CL fleet) during the period of analysis. Together with the segment of 28-34t HGV, this share rises to 49.56%. Special attention needs to be paid to less efficient engines running on older emission standards (≤EURO-5), as these are responsible for 87.17% of all air pollution costs. Across all external costs, construction-related HGV traffic generates €45,631.85 of external costs per workday or €1,003,900.61 per month. Particular attention is paid to local air pollution costs (NO_x, PM) and global emitted pollutants (GHG; CO2-eq.) which account for €55,123.07, and €80,409.95 per month of damage costs, respectively. Given the high cost to society, governments should pay increasing attention to the construction transport industry, especially in dense urban centres. To mitigate damage costs and meet environmental goals, a combination of transport policy measures needs to be considered (Finnveden and Åkerman, 2014), such as the implementation of multimodal Construction Consolidation Centres, or the development of emission-free procurement procedures (Venås et al., 2020).

The results of this study can serve as baseline for future policy recommendations, including scenario evaluations to measure the effects across all external cost categories. The identified construction flows can be overlaid with mobility and logistics plans. To this end, further research could measure specific impacts, such as air pollution or noise, following the path of the freight vehicle and considering spatiotemporal population movements (Mommens et al., 2019). Given the generated local air pollution costs, some vulnerable drive-through links or locations could potentially be avoided to lower negative health effects. A limitation of the OBU data is that it fails to capture the loading rate of the vehicle. Consequently, this paper used assumptions for the loading rate based on statistics, differentiated per vehicle type and MAM, as actual HGV's individual loading rates on city- or sector-wide scale is neither collected nor accessible. The focus of this paper is on the off-site CL impact of large urban construction sites: as such, future research could shine a light on (1) the use of off-site road vehicles with a MAM <3.5t by equipping vans with an OBU to capture broader vehicle fleets and potentially smaller construction site types, (2) multimodal off-site solutions or (3) on-site CL impacts.

Author statement

All authors have read and agreed to the published version of the manuscript. The following author contributions follow the Contributor Roles Taxonomy (CRediT).

Author Contributions: Nicolas Brusselaers: Conceptualization, Methodology, Formal Analysis, Data curation, Writing—original draft, Writing—review and editing, Visualization. He Huang: Methodology, Software, Writing—original draft, Writing—review and editing. Cathy Macharis: Writing—review and editing, Supervision, Validation. Koen Mommens: Data curation, Writing—review and editing, Supervision, Validation.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The raw OBU data was made available for the purpose of this study and can be accessed upon approval of the issueing instances.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.eiar.2022.106955.

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