

# Counterfactual Reasoning Using Bayesian Networks for Environmental Policy Analysis

A Case Study of Woodland Caribou in Northern Canada







## Directed Acyclic Graphs

DAGs are "acyclic" in that they contain no directed cycles: one cannot trace a sequence of arcs in the direction of the arrows and arrive whence one started.

"The future cannot directly or indirectly cause the past."

Apparent counterexamples ('schooling and wages cause each other') are usually resolved by redrawing the DAG with a finer temporal articulation.

No "simultaneity."

(There's theory for cyclical graphs, too, see Pearl 2009.)

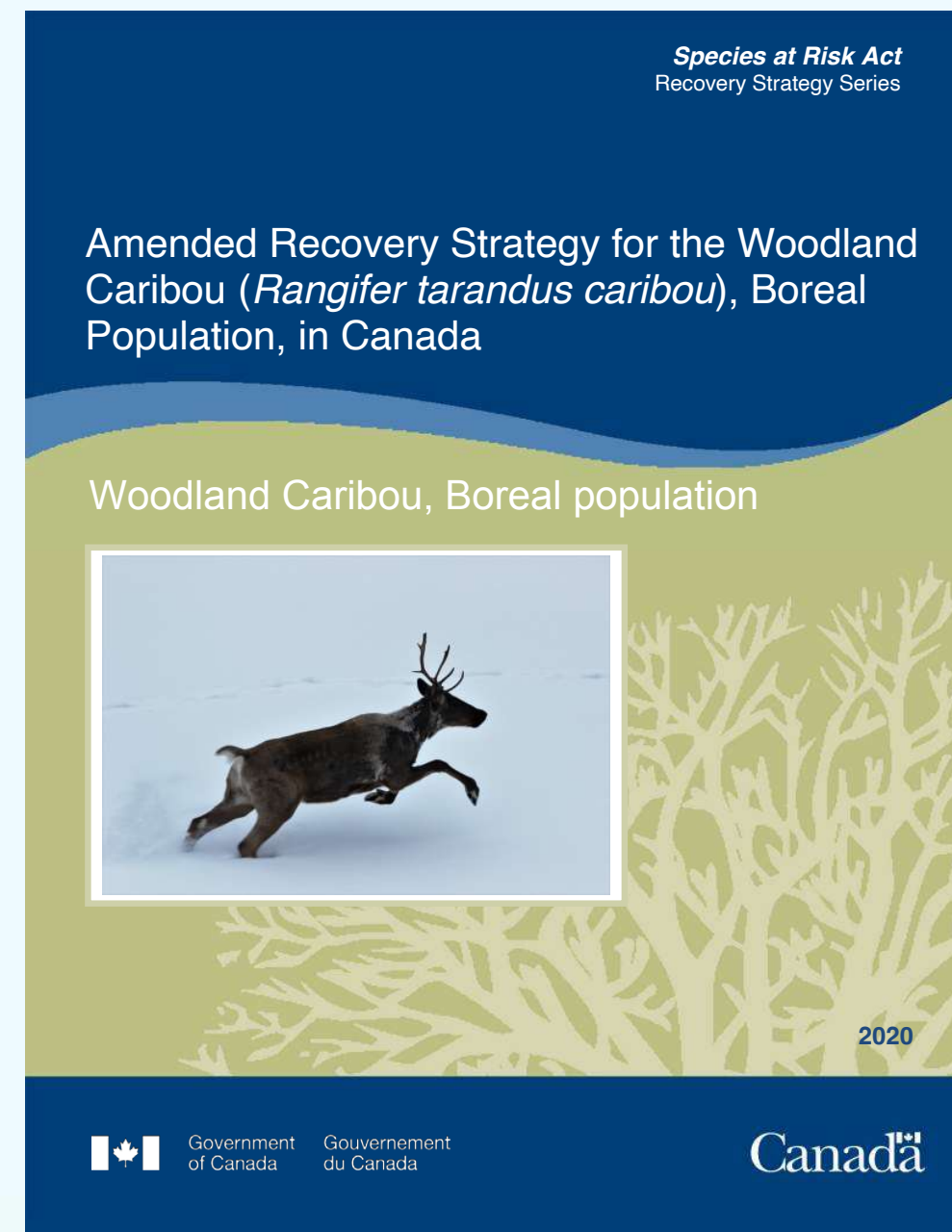
## Direct Effect Estimation

We will assume now that all the graphs we are using are Causal Bayesian Networks

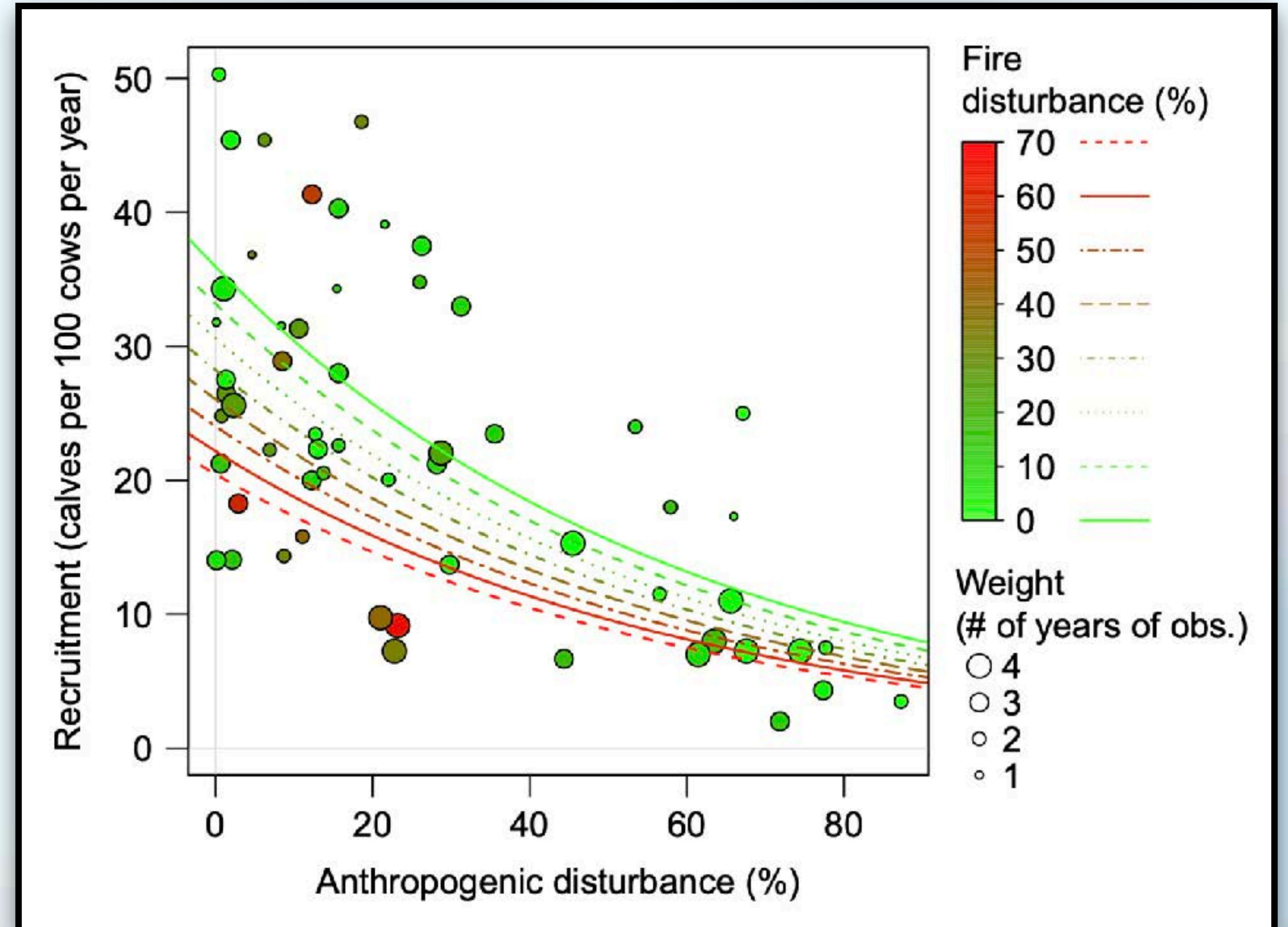
In order to estimate the Direct Effect of X on Y, the descendants of Y should not be controlled.

*Z* should be set as **Non Confounder**.





“Restoration of disturbed habitat to a minimum 65% undisturbed habitat will be necessary.”



Johnson, C.A., Sutherland, G.D., Neave, E., Leblond, M., Kirby, P., Superbie, C., McLoughlin, P.D., 2020. Science to inform policy: Linking population dynamics to habitat for a threatened species in Canada. *J Appl Ecol* 57, 1314–1327. <https://doi.org/10.1111/1365-2664.13637>





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Perspective

## A causal modelling approach to informing woodland caribou conservation policy from observational studies

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### ABSTRACT

As global conservation actions become more urgent, informed decision-making requires robust analyses of the costs and benefits of policy options, based on available evidence. Recovery planning for threatened or endangered species must assume a cause-and-effect relationship between proposed management interventions and population responses. However, a significant portion of current knowledge about threatened or endangered species is derived from observational studies because experiments that fully meet random and controlled design criteria are largely infeasible or unethical. Large-scale field experiments are becoming more common, yet the greater uncertainty generated by what remain fundamentally observational studies can lead researchers to weak inferences about causal mechanisms, creating debate and confusion among decision-makers, planners and stakeholders. This has been an acute problem facing conservationists and governments as they struggle with the successful recovery of species in decline. In other domains where experimental evidence is difficult to collect, causal modelling has been adopted to identify causal relationships from observational data, based on a set of strong assumptions and identification rules. In Canada, significant and ongoing efforts have had limited success in reversing the population decline of woodland caribou (*Rangifer tarandus caribou*). We examine the scientific framework for woodland caribou recovery efforts through the lens of causal modelling, highlighting feasible steps that could be taken to improve the rigour of causal inferences.

### 1. Introduction

Successful conservation of species and ecosystems requires forecasts of the future benefits of management interventions to ensure sound decision making; however, most assessments rely on retrospective evaluations of observational data that may not generate reliable predictions (Oliver and Roy, 2015; Law et al., 2017). This issue is particularly acute for wide-ranging species on multiple-use landscapes where experimental studies that can fully satisfy random and controlled design criteria are infeasible, and/or where management interventions are associated with significant economic, social or ethical implications. As Druzdel and Simon (1993:4) noted, “the effect of a structural change in a system cannot be induced from a model that does not contain causal information. Having the causality right is crucial for any policy making.”

Caribou and reindeer (*Rangifer tarandus*) are in general decline throughout their global range, despite ongoing conservation efforts (Vors and Boyce, 2009; Gunn, 2016). Woodland caribou (*R. tarandus*

*caribou*) are legally classified as *Threatened* throughout most of Canada, but subpopulations continue to decline, fragment, and disappear, particularly along the southern extent of their range (Environment Canada, 2014; Environment and Climate Change Canada, 2020). While caribou ecology varies among regions, the primary cause of decline is considered to be apparent competition (Holt, 1977; DeCesare et al., 2009), whereby abundant “primary” prey species such as moose (*Alces alces*), white-tailed deer (*Odocoileus virginianus*), and elk (*Cervus canadensis*) support increased predator populations (primarily wolves, *Canis lupus*, but also cougars, *Puma concolor*, coyotes, *Canis latrans*, and bears, *Ursus spp.*), which consequently prey on caribou. Because caribou have a lower reproductive potential than the primary prey, these species fare better and appear to out-compete declining caribou. Because anthropogenic landscape change and wildfire are argued to be causing the increase in primary prey, the mechanism has been described as “habitat-mediated” apparent competition (Frenette et al., 2020; Neufeld et al., 2021).

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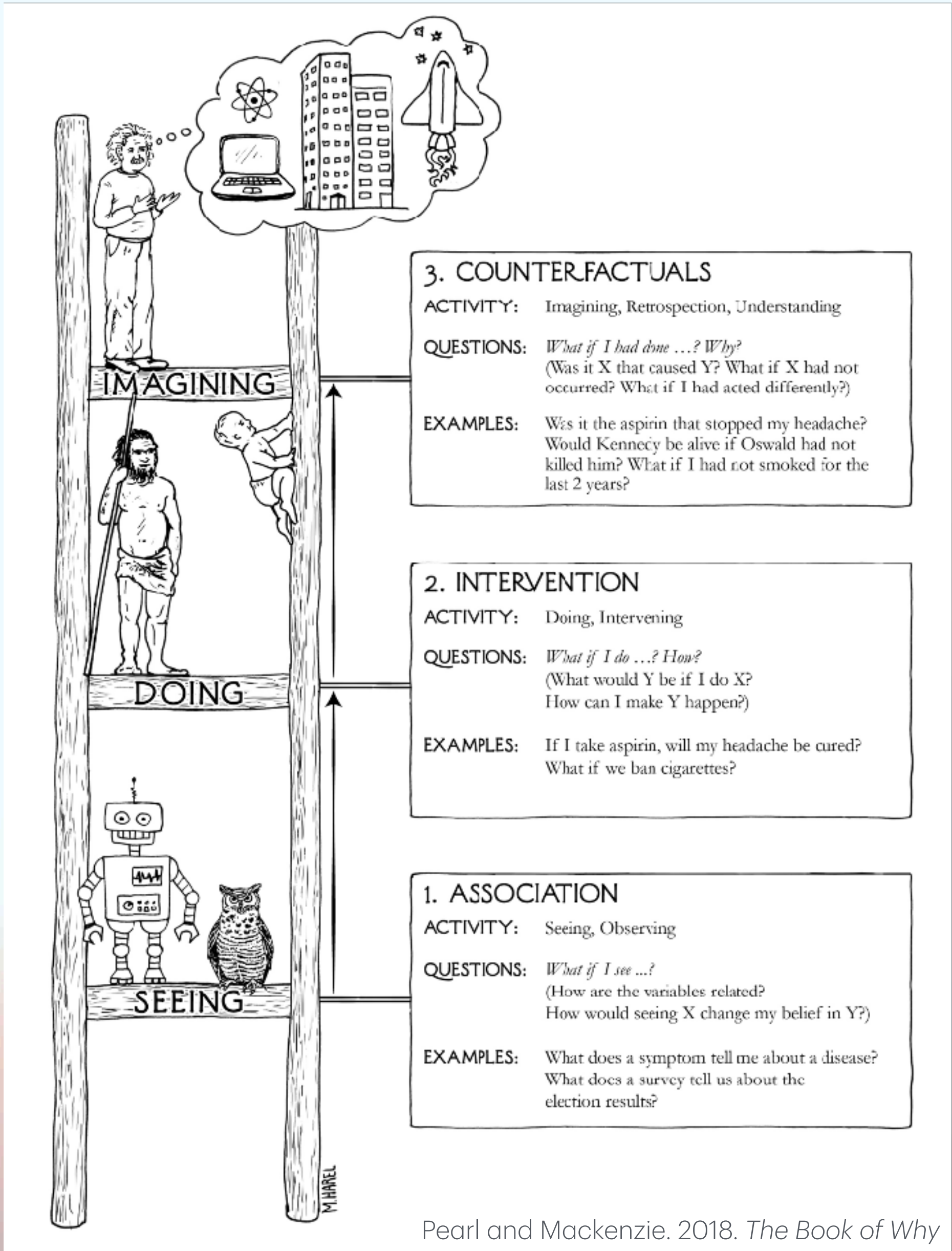
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Pearl and Mackenzie. 2018. *The Book of Why*



“Policy analysis is an exercise in counterfactual reasoning” Pearl (2009)

**Policy option:** if you have a headache, take an aspirin

**1. “If I have a headache, will taking an aspirin cause it to go away?”**

What is the effect (headache goes away) of a cause (taking an aspirin)?

**2. “My headache went away; is it because I took an aspirin?”**

What is the cause (taking an aspirin?) of the effect (headache goes away)?



**Counterfactual:** If I hadn't taken the aspirin, would my headache not have gone away?



# Necessary and Sufficient Causation

- **Necessary causation:** probability that an outcome would not have occurred in the absence of an event (given that they both did occur)
- **Sufficient causation:** probability that an outcome would have occurred in the presence of an event (given that they both did not occur)
- **Necessary and sufficient causation:** probability that the outcome would have occurred in the presence of the event and would not have occurred in its absence



# From Rung 2 to Rung 3

Interventions  $\rightarrow$  Counterfactuals



Exogenous and monotonic



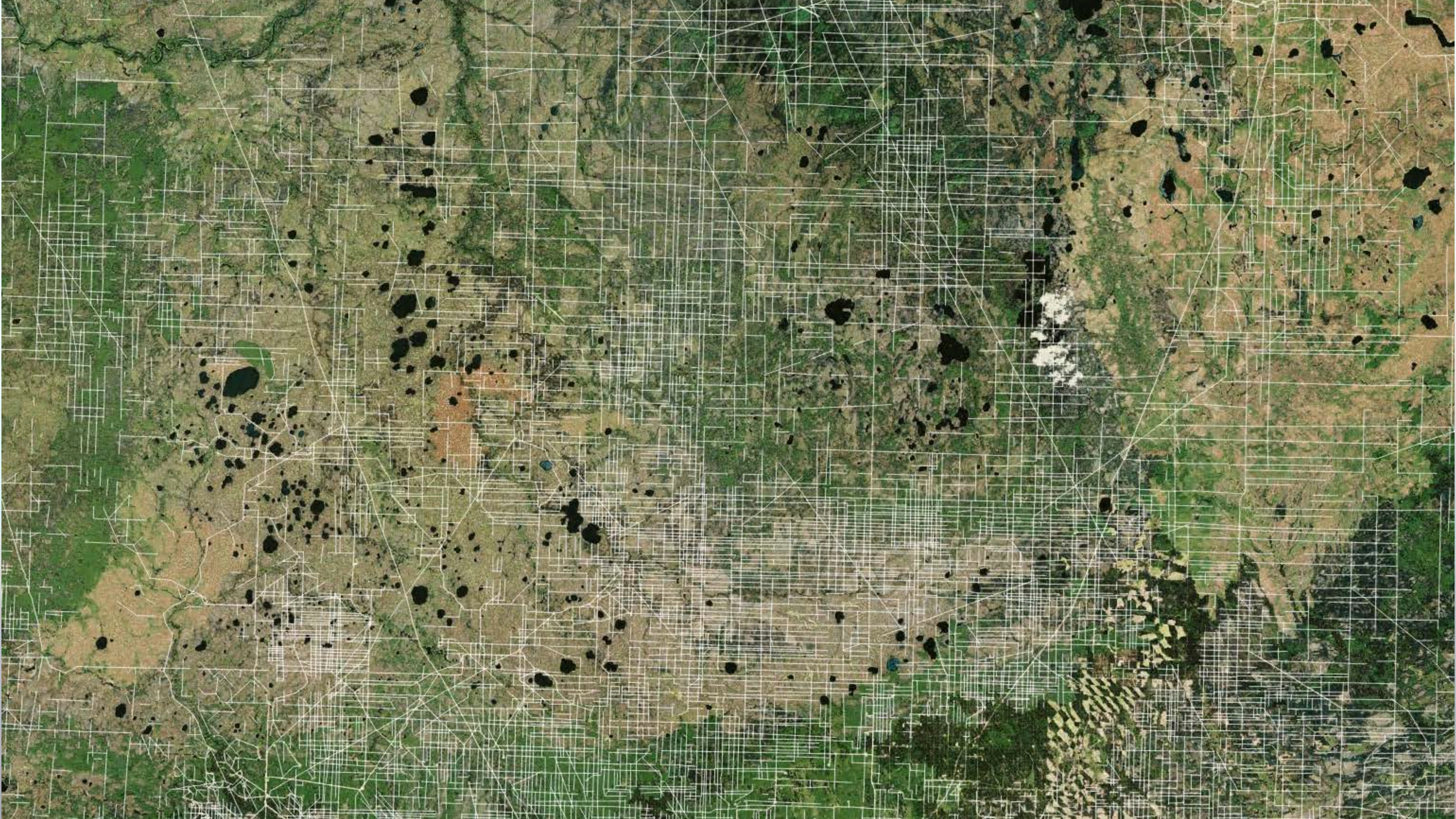
# Causal Effects from Observational Data

- **Observations → Interventions → Counterfactuals** increases the information required about a system and/or the assumptions that need to be made
- Using Bayesian causal networks for counterfactual reasoning with observational data assumes an exogenous exposure and a monotonic effect













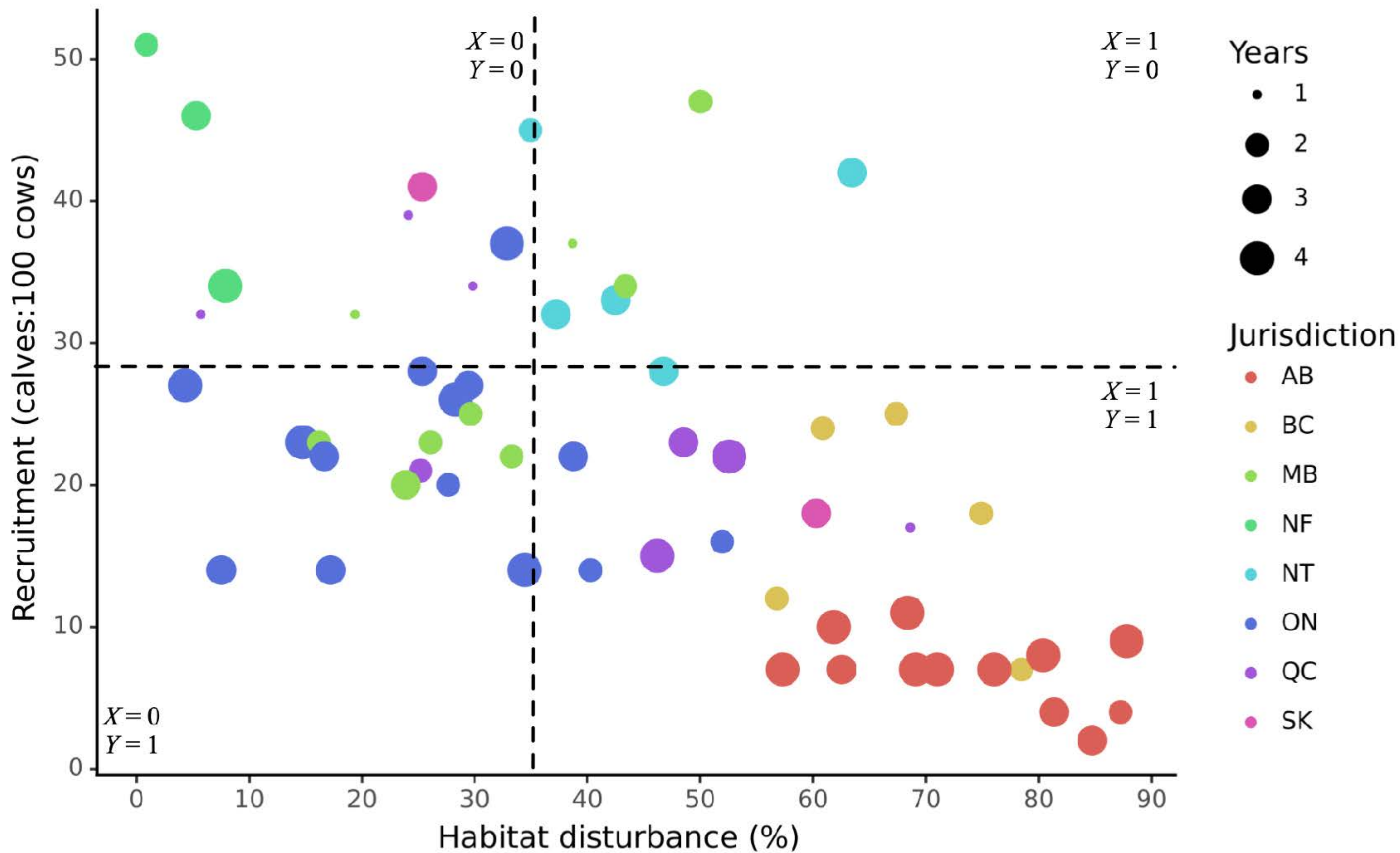














# Implied Causal Model



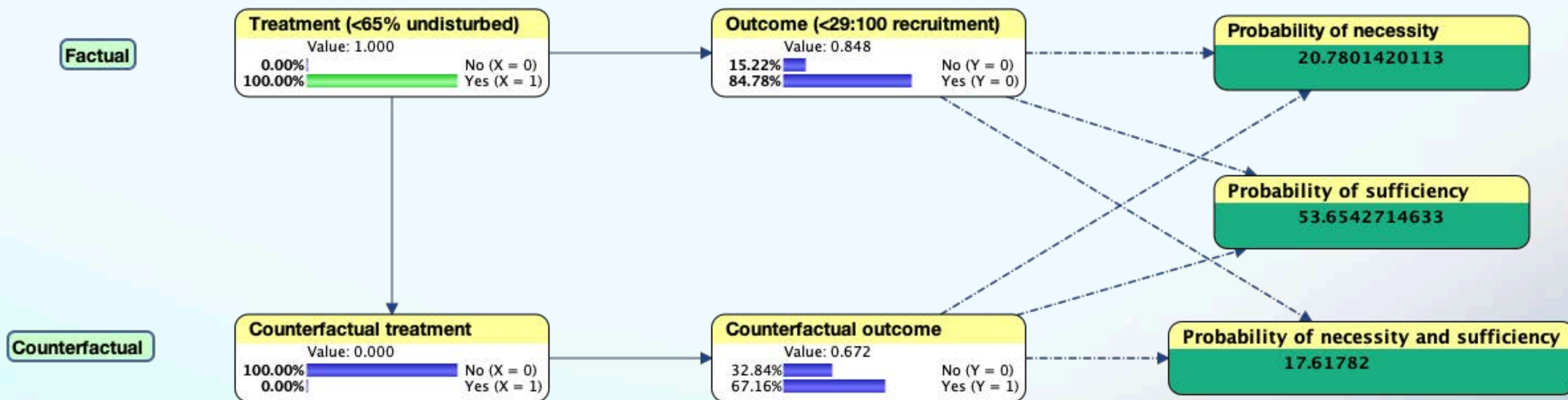
Factual:  $p_1 = P(Y = 1|X = 1)$

Counterfactual:  $p_0 = P(Y = 1|X = 0)$

$$PN = \max \left\{ 1 - \frac{p_0}{p_1}, 0 \right\} \quad PS = \max \left\{ 1 - \frac{1 - p_1}{1 - p_0}, 0 \right\} \quad PNS = \max \{ p_1 - p_0, 0 \}$$

Assuming exposure is exogenous and has a monotonic effect







A warmer climate generates larger and more frequent fires, resulting in more young forest

Logging requires roads and removes older trees, creating young forest

Gas exploration and development creates linear features and removes old forest

1 Young regenerating forests provide abundant forage for moose, deer and elk populations that are expanding northward with warmer temperatures

2 Wolf populations increase with abundant moose, deer and elk

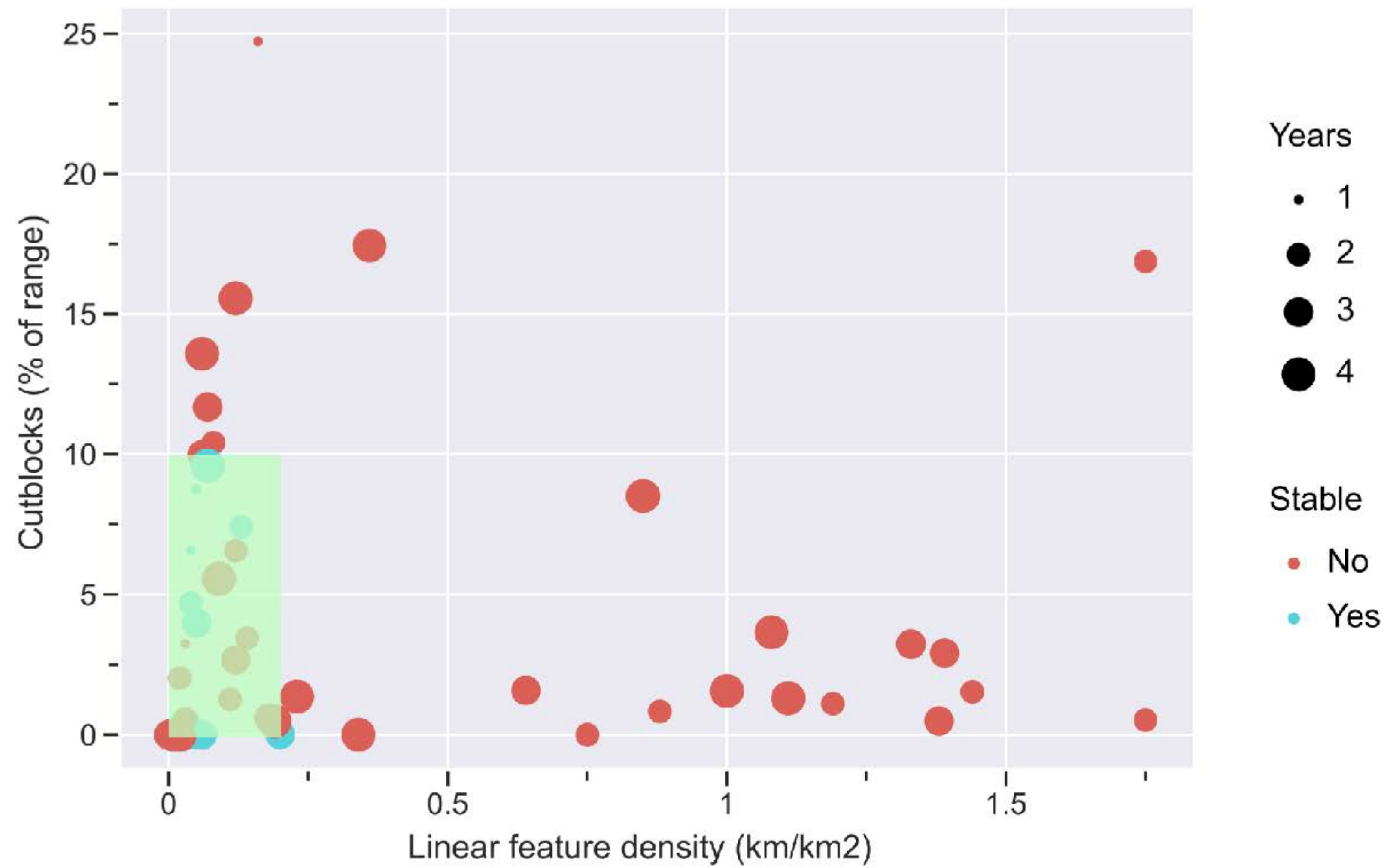
3 Linear features such as seismic lines, pipelines and roads create travel corridors into caribou habitat

4 Wolves encounter caribou more often and caribou populations decline

Excerpted from the  
**BC BOREAL CARIBOU  
RESEARCH AND EFFECTIVENESS  
MONITORING BOARD  
ANNUAL REPORT 2016**

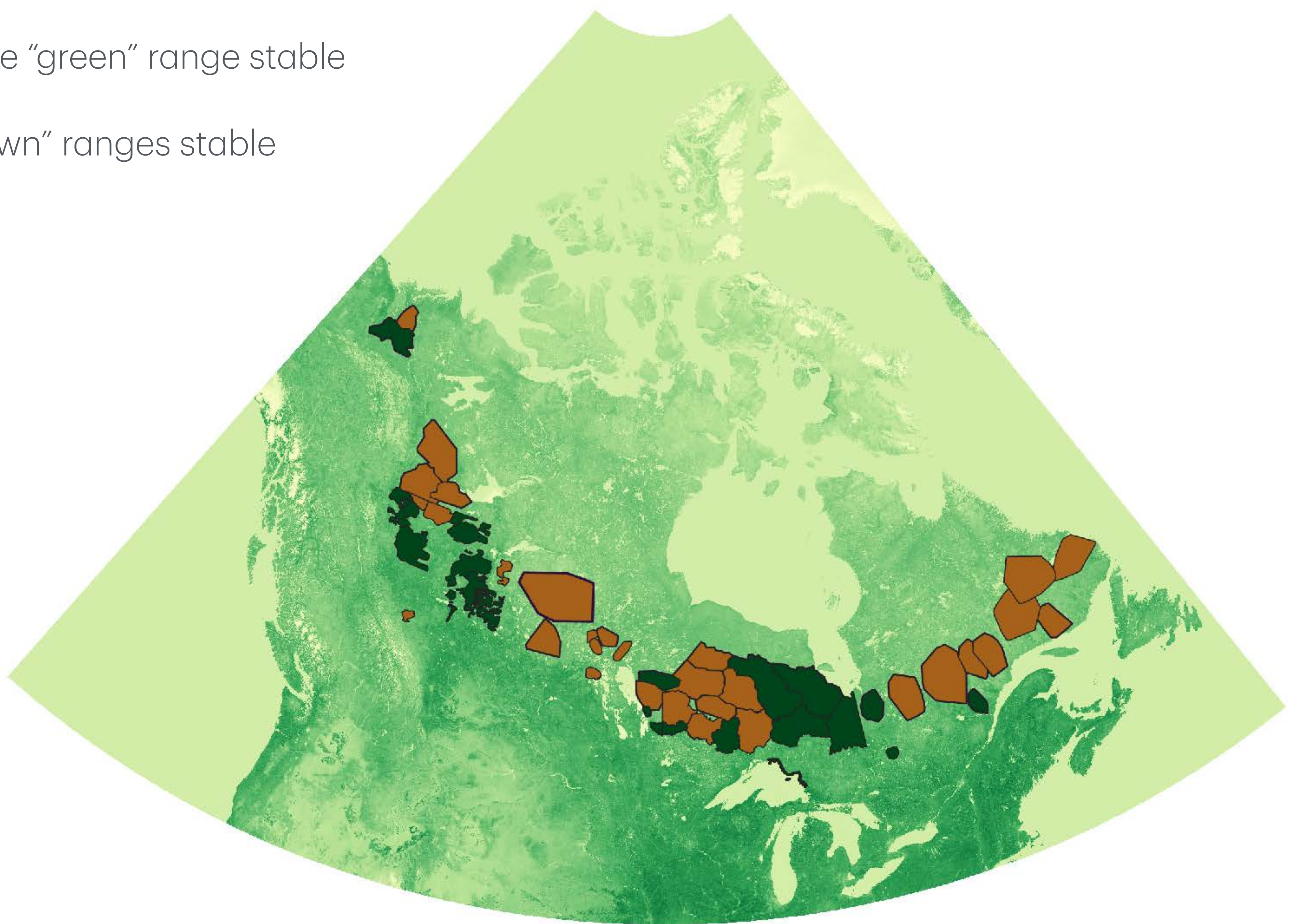
DESIGN: Alaris Design ILLUSTRATION: Soren Henrich







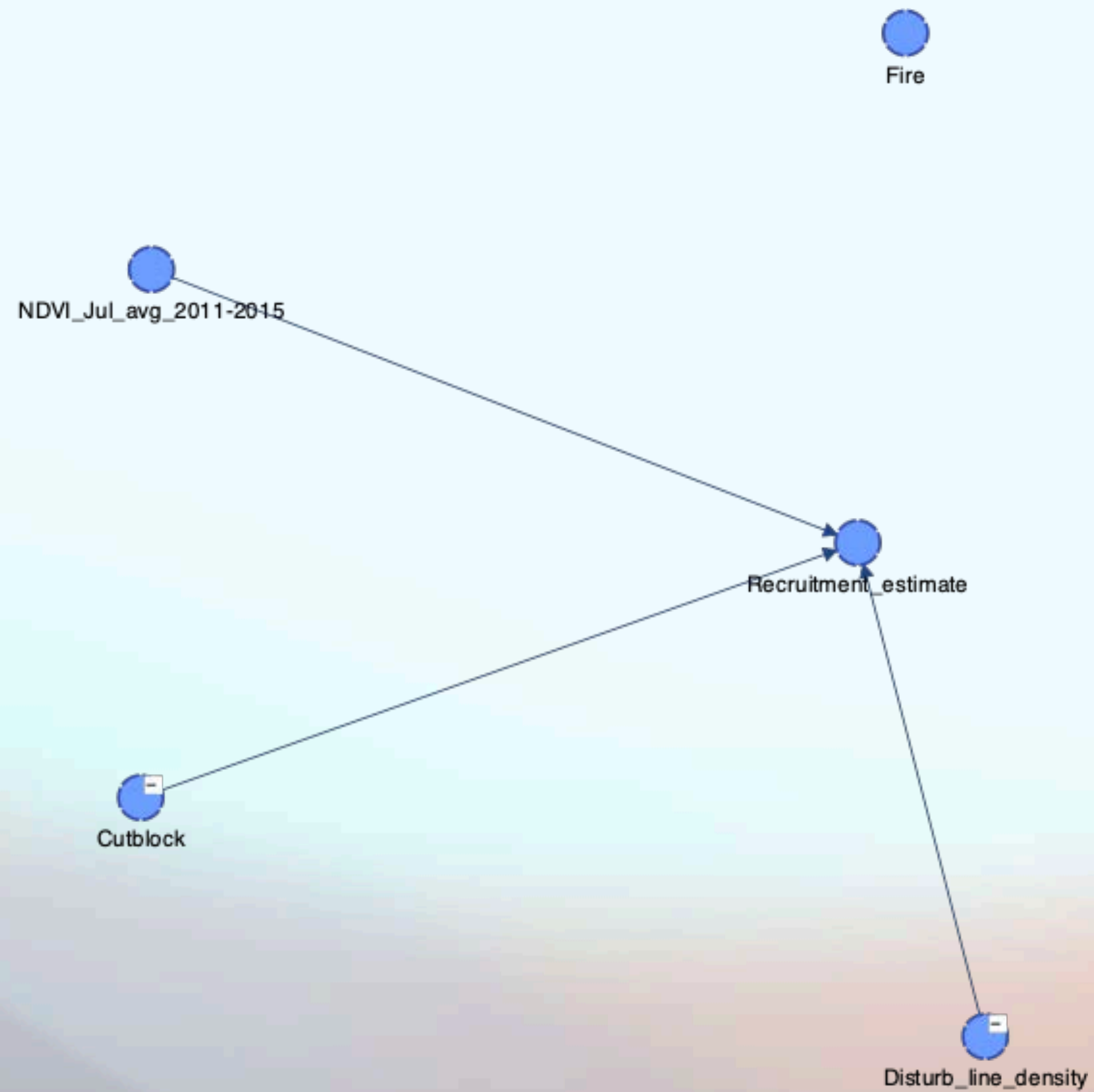
- Only one “green” range stable
- 1/3 “brown” ranges stable











- Assume no unobserved variables
- Set temporal indices
- Learn network
- Delete/reorient edges and relearn, if necessary



Model	Conditioning	Exposure	p <sub>1</sub>	p <sub>0</sub>	PN (%)	PS (%)	PNS (%)
Aggregate disturbance	None	<65% undisturbed	0.8483	0.6722	20.8	53.7	17.6
Separate disturbance	None	Linear >0.02	1.0000	0.7418	25.8	100.0	25.8
		Cutblock >10%	1.0000	0.8030	19.7	100.0	19.7
		Cutblocks >10%, Linear >0.02	1.0000	0.7049	29.5	100.0	29.5
	High EVI	Linear >0.02	1.0000	0.9701	3.0	100.0	3.0
		Cutblock >10%	1.0000	0.9772	2.3	100.0	2.3
		Cutblocks >10%, Linear >0.02	1.0000	0.9659	3.4	100.0	3.4
	Low EVI	Linear >0.02	1.0000	0.5154	48.5	100.0	48.5
		Cutblock >10%	1.0000	0.6307	36.9	100.0	36.9
		Cutblocks >10%, Linear >0.02	1.0000	0.4462	55.4	100.0	55.4



# Implications for Caribou Management

- Current model has low causal attribution → poor restoration outcomes based on average causal effect
- Separating habitat disturbance by pathway and setting different thresholds improves attribution → better restoration results, particularly if targeted in low productivity ranges





## Policymakers

### Necessary Causation

Does an outcome require the action to have occurred?

Researchers, lawyers, advocates

### Sufficient Causation

What action(s) will generate the desired outcome?

Planners, managers

Implement effective actions but avoid those that are unnecessary (and costly)



# Intervention → Counterfactual Analysis

- Important when interventions are costly
- Enables targeted policies: moving from average to individual effects
- Requires additional knowledge and/or assumptions about a system

