EVALUATION OF GREAT LAKES SEA LAMPREY CONTROL BARRIER EFFECTIVENESS UNDER CLIMATE CHANGE

By

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ABSTRACT

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Control of invasive sea lamprey (*Petromyzon marinus*) populations in the Great Lakes is dependent upon migration barriers in suitable tributaries to limit spawning habitat, but these barriers are occasionally overcome by spawning-phase adults, leading to observable larval production upstream of these barriers. Despite this, empirical evidence of escapement events at barriers is rare. Escapement is hypothesized to be influenced by warmer stream temperatures and high discharge, therefore shifting regional patterns of water temperature and hydrological conditions under climate change could lead to less effective barriers and higher larval production. Increased escapement over barriers would negatively affect control efforts by increasing larval habitat and diluting treatment resources across additional reaches. We applied Bayesian belief network models to categorize the probability of observing adult lamprey upstream of terminal barriers across the Great Lakes Basin and understand the influence of climatic, landscape, and hydrological variables on this parameter. Sensitivity analyses were used to assess the relative importance of each variable and indicated that variation in the size of the spawning run in a stream, and the proportion that subsequently reaches a barrier, have the largest effect on both the probability of passing a moderate or high abundance of adult sea lampreys above a barrier. Incorporating future climate projections into the model to evaluate the effect of climate change did not lead to substantial changes in the probability of escapement at each barrier, suggesting that any potential changes in barrier permeability or spawning run size are masked by the large uncertainties in sea lamprey spawning phenology that will require further research to elucidate.

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CHAPTER 1:

INTRODUCTION AND LITERATURE REVIEW

The sea lamprey (*Petromyzon marinus*) is a hematophagous fish species considered invasive in the Great Lakes Basin that has caused significant ecological damage to both native and introduced fishes. These fishes traditionally support enormous recreational, commercial, and indigenous fisheries in the U.S and Canada estimated to be worth $7 billion annually (Great Lakes Fishery Commission 2020). Sea lampreys are thought to have invaded most of the Great Lakes through a series of dispersal events throughout the early twentieth century (Lawrie 1970; Smith and Tibbles 1980). Documented collapses of ecologically and economically important species followed increases in sea lamprey abundance, particularly their preferred host species lake trout (*Salvelinus namaycush*) (Lawrie 1970; Smith and Tibbles 1980). During their parasitic juvenile life stage, individuals will attach themselves to host fish and feed on their blood. After 12 to 18 months juveniles begin moving towards suitable spawning streams, undergoing metamorphosis into their sexually mature adult phase upon entering the streams, and subsequently, reproduce and die (Lawrie 1970; Smith and Tibbles 1980). Larval sea lampreys hatch and burrow into the substrate for 3 to more than 10 years, eventually emerging from the stream bed, metamorphosing into juveniles, and migrating back out into the lake.

Due to coordinated control measures maintained by the Great Lakes Fishery Commission (GLFC), the U.S. Fish and Wildlife Service, and Fisheries and Oceans Canada, sea lamprey populations have been reduced to mere fractions of their former abundance (GLFC 2020; Robinson et al. *in press*). These measures typically include active control measures such as the application of lampricides 3-trifluoromethyl-4-nitrophenol (TFM) and niclosamide to infested tributaries and trapping of spawning adults, as well as passive measures such as low-head barrier dams (Hunn and Youngs 1980; Smith and Tibbles 1980). Stream low-head barriers prevent up-migrating adult sea lampreys from accessing suitable spawning habitat, thereby intentionally fragmenting populations. These barriers play an important role in preventing infestation in streams that are prohibitively difficult to treat and reducing the need for expensive chemical treatments, but also negatively impact aquatic habitat connectivity (Brege et al. 2003; Dodd et al. 2003; Lavis et al. 2003; McLaughlin et al. 2013; Milt et al. 2018; Hume et al. *in press*). These lowermost barriers block over 54,000 km of stream, which represents $16,215,000 in saved chemical control costs. By comparison, the Sea Lamprey Control Program (SLCP) spends on average $12,900,000 to treat less than 3000 km of stream habitat (Hrodey et al. *in review*). Without these barriers, chemical treatment of all sea lamprey producing streams would be cost-prohibitive. Were upstream barriers to be removed in an effort to improve aquatic connectivity, these lowermost barriers would block an even greater amount of habitat and be of greater importance for sea lamprey control.

Sea lamprey control barrier designs come in a variety of forms but generally are based on a low-head, fixed-crest design that attempts to maintain a 45-centimeter crest height throughout the length of the spawning migration. These barriers are a mix of purpose-built barriers and adaptations of previous dams for sea lamprey control. The SLCP has identified 598 barriers in Great Lakes streams that are important for sea lamprey control, of which 87% were non-purpose built and intended for such uses as hydropower generation, flood control, and navigation, and 13% are purpose-built or modified barriers (Hrodey et al. *in review*). Alternative designs, including adjustable-crest, velocity, and electrical barriers have been used in some places with mixed success, and the SLCP relies on the traditional, fixed-crest design for most control effort (Zielinski et al. 2019). These barriers often include a jumping pool or fishway to aid in the passage of migratory fish species and limit the negative consequences of stream impoundment (Lavis et al. 2003). Barriers may be removed intentionally to improve connectivity but are also at risk of unintentional failure, possibly allowing spawning sea lampreys access to upstream habitat (Lavis et al. 2003; Jensen and Jones 2018). As of 2003, sea lamprey control barriers operated with a 90% effectiveness (Lavis et al. 2003). This rate increases to 94% when considering only low-head, fixed-crest barriers (Lavis et al. 2003). Imperfect blockage has been attributed to washouts from floods, inadequate design or modification to existing dams, improper timing of adjustable-crest barriers, and inadequate construction (Brege et al. 2003; Dodd et al. 2003; Lavis et al. 2003; McLaughlin et al. 2013; Milt et al. 2018). Acknowledgment of the spatial and temporal variation in barrier effectiveness has resulted in several hypotheses of the cause of this variation, but these hypotheses have so far been difficult to test empirically (McLaughlin et al. 2003). These hypotheses include differences in vertical drop distance, barrier design, stream thermal conditions and hydrology, and the size and timing of the spawning migration.

Although an estimate of the rate of escapement can be used as the sole metric to evaluate barrier effectiveness, the size of the spawning run and the subsequent larval production are a better indication of the consequences of barrier failure. While understanding variability in the effectiveness of control barriers is essential, quantifying how and where less effective barriers will affect larval production is more important for control efforts. The GLFC has long set a goal of reducing lampricide use by 50% through alternative methods, and the majority of this reduction is made possible through the use of barriers (Brege et al. 2003). This goal relies on two assumptions: that the mean effectiveness of control measures is not changing over time, and that the public's sanctioning of current control measures will not negate future efforts to maintain or increase control effort (Hume et al. *in press*; Gaden et al. 2021). Both of these constraints should not be taken for granted, and improving sea lamprey control resiliency to social and ecological change should be prioritized.

Climate change and Great Lakes fishes

Climate change is predicted to have important effects on Great Lakes fishes through both direct effects on fish habitat quantity and quality, as well indirect interactions with other stressors (Magnuson et al. 1997; Lynch et al. 2010; Cline et al. 2013; Collingsworth et al. 2017). Warming lake water temperatures are predicted to significantly alter the distributions of existing coldwater, coolwater, and warmwater fishes (Lynch et al. 2010; Melles et al. 2015; Collingsworth et al. 2017). In particular, coolwater fishes will likely face decreased thermal habitat in southern regions of Lakes Michigan, Erie, and Ontario, while parts of Lake Superior will become more favorable (Cline et al. 2013; Collingsworth et al. 2017). Increased temperature and precipitation can also further exacerbate existing stressors such as nutrient loading and eutrophication by increasing surface runoff and stratification (Collingsworth et al. 2017). Seasonal decreases in primary production will affect the abundance and distribution of higher trophic levels (Brooks and Zastrow 2002). Invasive species that were previously limited to the lower lakes by water temperature may also find an opportunity to proliferate, including white perch (*Morone americana*), alewife (*Alosa pseudoharengus*), ruffe (*Gymnocephalus cernua*), round goby (*Neogobius melanostomus*), and carp species (Rahel and Olden 2008; Melles et al. 2015; Collingsworth et al. 2017).

Sea lamprey life history is predicted to be altered by both warming water temperatures and the effects of increased precipitation (Cline et al. 2014; Collingsworth et al. 2017). Although the optimal growth rate for parasitic sea lampreys is 15°C, their thermal history is completely dependent upon host choice and host preferred thermal habitat (Cline et al. 2014). Parasite growth has been strongly linked to prey availability and the preferred thermal habitat of their host species, with increasing preferred thermal habitat for host species such as Chinook salmon (*Oncorhynchus tshawytscha*), lake whitefish (*Coregonus clupeaformis*), and lake trout (*Salvelinus namaycush*), leading to larger, more fecund sea lampreys inflicting greater mortality upon host fish (Cline et al. 2014; Hansen et al. 2016; Gambicki and Steinhart 2017). The effectiveness of lampricide application will also decrease with sufficiently high stream temperatures (Scholefield et al. 2008), and streams with extremely high or low flows will likely be less feasible to treat.

Warming temperatures will likely have a large effect on sea lamprey life history across multiple life stages, through both direct effects of more favorable temperatures and the expansion

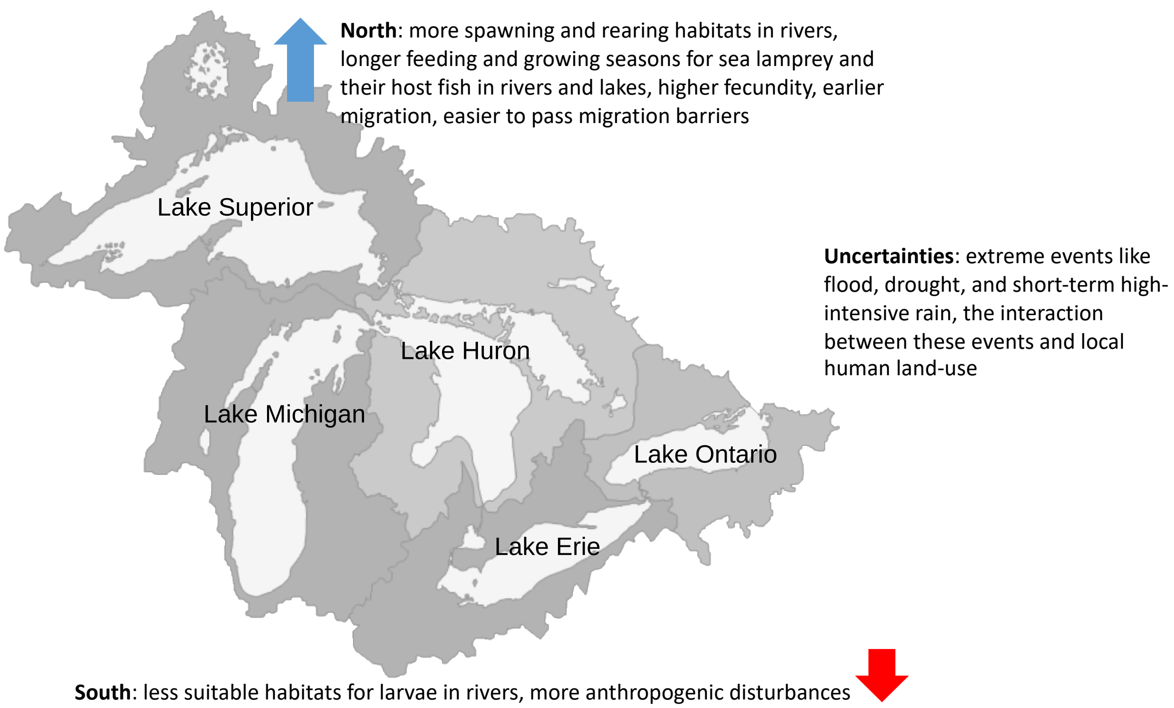


Figure 1. Potential effects of climate change on Great Lakes sea lamprey populations, adapted from Lennox et al. 2020. The blue arrow represents a potential increase in sea lamprey abundance, while the red arrow represents a potential decrease.

of the preferred thermal range of host fish (Figure 1). Previously thermally unfavorable habitat might begin to produce sea lampreys, particularly in the upper Great Lakes, while parts of the lower Great Lakes might become too unfavorable and cease production (Lennox et al. 2020; Hume *in press*). Warming is strongly linked to shorter egg incubation periods (Holmes 1990; Holmes and Lin 1994) as well as altering the duration of the parasitic life stage (Cline et al. 2014). Longer periods of stream temperatures within the preferred thermal niche of larval sea lampreys, 17.8˚C – 21.8˚C, would likely result in faster growth in non-density-limited streams (Holmes and Lin 1994; Lennox et al. 2020), while temperatures outside of that range would likely lead to decreased survival (Dawson and Jones 2009). The upper thermal constraint for survival in sea lampreys is variable and dependent on the life stage, but embryos are the most stenothermic and vulnerable (Beamish 1975; Manion and Hanson 1980; Rodríguez-Muñcoz et al. 2001; Hansen et al. 2016). Metamorphosis of larval sea lampreys is largely a factor of body size, condition, and water temperature, and with a lower thermal threshold of 9˚C – 13˚C and the highest rate of metamorphosis at 21˚C (Holmes and Youson 1994, 1998), warmer streams might allow for increased metamorphosis in smaller, younger individuals. Warming conditions will likely alter the phenology of the sea lamprey life cycle, with earlier warming leading to earlier upstream migrations as spawning events typically only occur once stream temperatures reach 15˚C (Holmes 1990; Jones 2007; Binder et al. 2010; McCann et al. 2018; Lennox et al. 2020). Additionally, warmer temperatures in the upper Great Lakes might elicit a shift in the timing of the sea lamprey life cycle that would more closely mirror that of sea lampreys residing in the lower Great Lakes (McCann et al. 2018).

Previous hydrologic modeling studies predict that flood events in many watersheds of the Great Lakes will be more intense, frequent, and occur earlier in the year as the effects of climate change continue to intensify (Magnuson et al. 1997; Cherkauer and Sinha 2010; Verma et al. 2015; Byun et al. 2019). Greater winter and spring precipitation, predominately rain, may lead to higher flows in many watersheds. Conversely, summer precipitation is predicted to decline, leading to an increased risk of dewatering (Rahel and Olden 2008). High flow events, while unlikely to affect larval lamprey buried in the substrate, would elevate the risk of eggs being washed out of nests and increase egg mortality through predation and decreased chance of settling on suitable habitat (Smith and Marsden 2009), but may contribute to lentic larval populations. In areas where average streamflow might decline during periods of the year, lack of flow might present a problem for larval survival and outmigration (Guo et al. 2017). In total, altered climatic constraints will act in multiple directions across multiple sea lamprey life stages, making the end consequence for the aggregate sea lamprey population difficult to predict.

Climate change and control effectiveness

Physical barriers to sea lamprey upstream migration, both natural and man-made, face an increased risk of failure due to increased precipitation and higher magnitude flood events (Rahel and Olden 2008; Danso-Amoako et al. 2012; Lennox et al. 2020). Higher flows might increase the physical stress on aging or structurally unsound barriers, and higher water levels might allow spawning sea lampreys to overcome barriers during flood events by bringing the vertical drop (difference in height between headwater and tailwater elevation) below 45-centimeters (Lucas et al. 2009; Lennox et al. 2020; Hume et al. *in press*). Human-made barriers beyond their life span or those of a smaller, shallower design might also be at increased risk of failure. Warmer stream temperatures would alter sea lamprey swimming performance and could allow for passage under a wider range of conditions (Castro-Santos et al. 2017). Sea lampreys would likely respond non-linearly to increases in available habitat due to barrier failure, combined with a dilution of lampricide control efforts across a larger treatment area, leading to higher sea lamprey production (Jensen and Jones 2018).

While critical for sea lamprey control, low-head barriers are not without negative consequences to migratory fish passage and stream community health (Dodd et al. 2003; McLaughlin et al. 2011, 2013). While barrier removal or mitigation through a fishway structure can be necessary to improve fish passage, uncertainty in the predicted use of upstream habitat by native migratory species and the consequences for sea lamprey control need to be accounted for. Therefore, it remains essential to correctly categorize the effectiveness of a given barrier at blocking sea lampreys as a part of a larger effort towards prioritizing sea lamprey control barriers for remediation or removal. To accurately allocate limited resources to the most productive streams, the GLFC would benefit from the knowledge of which barriers are at greatest risk of passing sea lampreys and which streams might produce more or fewer larvae than expected under the current assumption of static temperature and flow regimes.

Bayesian belief networks

Bayesian belief networks (BBN) are an increasingly common tool in natural resource management for modeling data-scarce systems and informing complex decisions (Marcot et al. 2001, 2006; McCann et al. 2006; Aguilera et al. 2011; Death et al. 2015; McVittie et al. 2015; Gibson et al. 2017), as is the case for understanding the effects of climate change on barrier effectiveness for sea lamprey control. BBNs are directed acyclic graphs that leverage Bayes' theorem to model causal relationships between important correlates influencing the likelihood of a management target or objective.

In the network, variables are represented as a series of nodes linked through causal relationships (Norsys, 2020). A causal node is referred to as a parent node, with its dependent node referred to as a child node. The structure of the model flows from nodes represented by only marginal distributions, or parent-less nodes, through a flexible hierarchy of causality that terminates in one or more target variables, or child-less nodes. Each link between nodes represents the specific conditional probability distribution governing their relationship. The possible values of each node are represented by a series of states which must take the form of discrete values or a discretized range of continuous values. The joint posterior probabilities of each node are structured through a conditional probability table (CPT), which can be specified through several different methods, including algorithmic learning, statistical models, or expert elicited knowledge. This flexibility in the type and completeness of the data used to build the model has led to the increased usage of BBNs in natural resource management decision-making (Marcot et al. 2001, 2006; McVittie et al. 2015; Kaikkonen et al. 2020). BBNs also allow for transparent representation of variables and their major influences and interactions, incorporation of a wide variety of data types, and estimation of outcomes as probabilities for easy communication of risk. Nodes can be deterministic or stochastic depending on how each conditional probability is structured. Their ability to handle missing data and latent variables is a useful characteristic in addressing uncertainty in barrier effectiveness due to the complexity of the system and scarcity of data appropriate to the spatial and temporal scale of interest. While there are multiple programs built for the graphical construction of BBNs, I chose to use the modeling shell Netica (versions 2.17 or later, Norsys Systems Corp., Vancouver, British Columbia) for its ability to use cases to describe our knowledge of the system as well as native algorithmic learning functionality to build conditional probability distributions from the data.

While BBNs are appropriate tools for certain questions, their usefulness is limited by their lack of capacity to represent feedback loops or continuous variables (Uusitalo 2007). Feedback loops must either be ignored or approximated, and continuous variables must be discretized, resulting in potential information loss. While there are advanced methods of building

BBNs that have addressed these concerns (e.g., dynamic BBNs), I judged these assumptions to be acceptable for the purpose of my research questions. Feedback loops are not important to the proposed explanations for variation in barrier failure and the effects of climate change on sea lampreys, as changes to sea lamprey physiology and phenology do not in turn affect the stream hydrology or climate. The loss of information imposes restrictions on the precision of estimates, but this can be mitigated through informed, ecologically meaningful discretization of each variable.

Research objectives

To address poor understanding of the factors driving variation in barrier effectiveness, especially under changing climatic conditions, I focused on two main questions. First, I aimed to identify the influential factors and uncertainties driving variation in the effectiveness of sea lamprey control barriers and the implications for sea lamprey control. I assessed the relative importance of (1) climatic conditions (2) landscape conditions and (3) the abundance of spawning-phase sea lampreys within a stream in each month. Secondly, I aimed to evaluate how climate change in the Great Lakes Basin might impact the effectiveness of sea lamprey control barriers for future sea lamprey control, hypothesizing that climate change will lead to an increase in the abundance of sea lampreys passing a barrier in regions where the overlap between optimal stream temperatures, heavy precipitation, and sea lamprey spawning activities is greatest.

CHAPTER 2:

METHODS

Overview

I utilized a BBN to evaluate both the variables influencing barrier effectiveness and the potential consequences of climate change across the Great Lakes Basin over time. Multiple BBN structures were developed to account for structural uncertainty in the understanding of known relationships. Two model structures were built with different collections of climatic, landscape, hydrological, physical, and ecological variables associated with lowermost sea lamprey control barriers. The models were parameterized using a combination of algorithmic learning, structural equations, and expert elicitation (Figure 3). Data were obtained from sources with varying comprehensiveness and resolution, which required aggregating and transforming data with statistical models that were then spatially associated with each lowermost barrier. I analyzed the strength and uncertainty of each relationship in the model with the abundance of spawning-phase sea lampreys above a barrier using both sensitivity to findings analysis and one-way sensitivity analysis. Lastly, the posterior probability distribution for the abundance of spawning-phase sea lampreys above each barrier was estimated using historical climate data as well as modeled climate data at four, twenty-year time intervals. Each barrier was then categorized by its probability of a low, moderate, or high abundance of sea lampreys upstream of the structure under each climate projection.

Study area

The data used for this project focused on lowermost sea lamprey control barriers on the U.S side of the Great Lakes Basin. The GLFC provided a list of barriers and metadata, which included 655 structures in total, and comprised of low-head dams, road culverts, hydropower dams, earthen embankments, and waterfalls. Of these, 263 are located in the Lake Erie watershed, 139 are in the Lake Michigan watershed, 94 are in the Lake Ontario watershed, 81 are in the Lake Superior watershed, and 78 are in the Lake Huron watershed. Each barrier was spatially verified using Google Earth Pro (Version 7.3.3; https://www.google.com/earth) to ensure that the coordinates were accurate and could be matched to an associated flowline in the National Hydrography Dataset Plus Version 2 (NHDPlus V2; 1:100,000-scale; http://www.horizon-systems.com/nhdplus). This framework was used to spatially organize and associate barriers with a particular stream reach, local catchment, and network catchment, allowing me to correctly attach spatial variables to each barrier. After removing barriers I was unable to spatially verify, 372 of the 655 barriers were included in this analysis. The spatial distribution of the barriers and the relative proportions of different barrier types, ages, and heights in this subset were similar in proportion to the original list of lowermost barriers (Appendix A). Of these, 127 are in the Lake Erie watershed, 51 are in the Lake Huron watershed, 105 are in the Lake Michigan watershed, 37 are in the Lake Ontario watershed, and 52 are in the Lake Superior watershed (Figure 2).

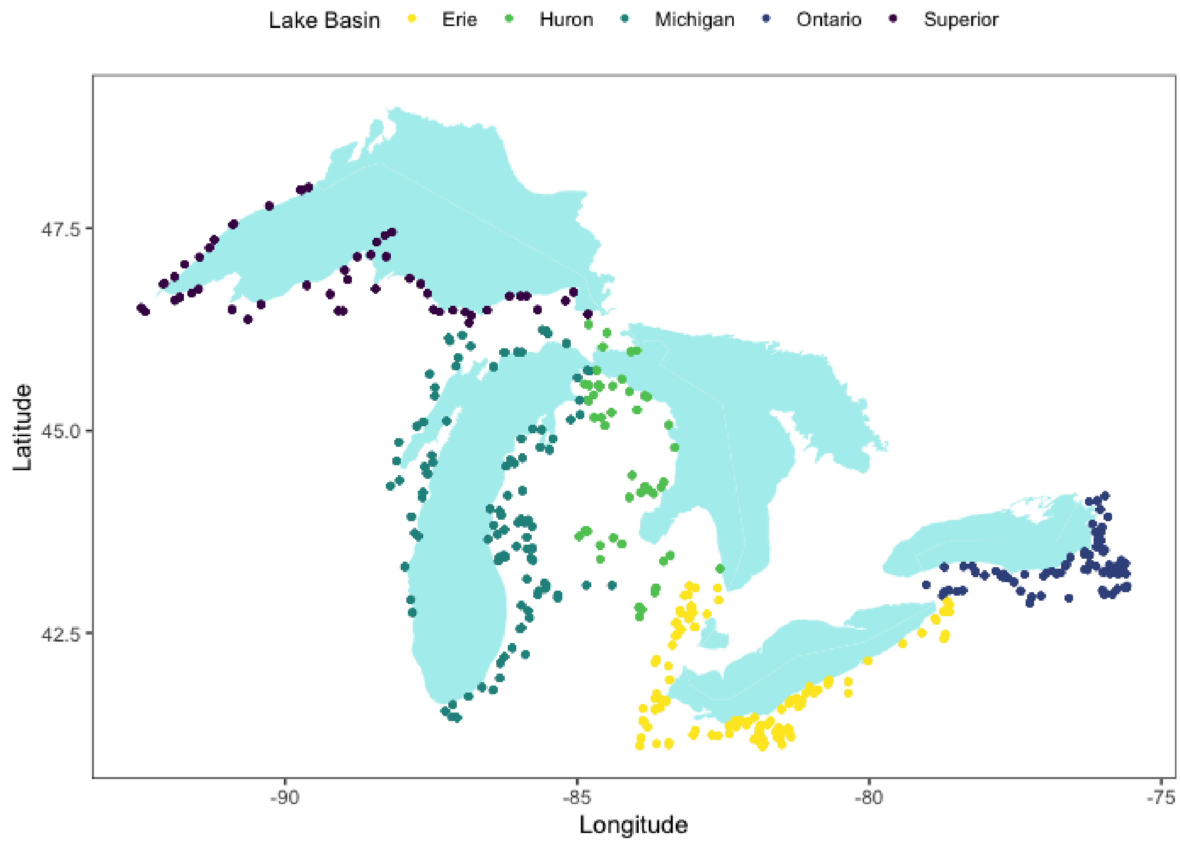


Figure 2. Location of project subset of lowermost sea lamprey control barriers in the Great Lakes Basin, based on data collected and compiled by the GLFC in 2020.

BBN development

I aimed to evaluate the variability in the effectiveness of control barriers through scientists' and managers' current understanding of influential relationships in the system. However, this objective is difficult to address directly because of a lack of data on the passage of spawning-phase sea lampreys over barriers under variable conditions. Instead, I evaluated a set of relationships suspected to be important to the effectiveness of a control barrier and worked backward to obtain an "ecological causal web" that maps all suspected causal variables in this system.

I developed the BBN following the steps outlined in Marcot et al. (2006) and Marcot (2017). Potential responses of sea lampreys to changes in climate were first identified through a thorough literature review and consultation with four subject-matter experts at the GLFC. We discussed important hydrologic and landscape variables and their potential effects on sea lamprey growth, survival, phenology, and habitat while assuming several regional climatic trends that were well-established in the literature (Byun et al. 2019). After this discussion, I built an influence diagram, or "ecological causal web" (Marcot et al. 2006), which linked climate, landscape, and hydrology variables by their identified relationships to each stage of the sea lamprey life cycle. I returned the initial influence diagram for comments and review by the GLFC and adapted the diagram into unparameterized BBNs in Netica. Nodes were organized into node sets describing a category of influence, including climate, hydrology, landscape, physical barrier characteristics, and sea lamprey ecology. The initial BBN structures included relationships affecting sea lampreys at multiple life stages. I refined the scope of the BBN to focus on solely spawning-phase sea lampreys due to a greater body of research regarding important biological thresholds for streamflow and temperature, and the direct effect these have on the success of barriers for control and decisions regarding prioritization.

Efforts to minimize the complexity of the BBNs appreciably improved model tractability (Marcot et al. 2006). Where possible I kept the number of parent nodes of a single child node to three or fewer, which reduced the size and complexity of the associated conditional probability table (CPT). The number of levels in each network was also minimized within the bounds of the process complexity and interactions across spatial scales. Intermediate nodes were generally grouped in a loose hierarchy based on relationship to the target node, and classified by a theme, such as "hydrology" or "climate" (Figures 3-6). This structure allowed for the separation of processes into sub-models to ease comprehension and development, as well as to remove potential probabilistic biases from the asymmetry of the model hierarchy. Continuous variables were discretized by identifying important thresholds in certain processes, or where this was not possible through examining the distribution of available data.

Conditional probabilities were estimated through several methods, based on available data and process complexity. While previous studies have used data from the literature to complete CPTs in a BBN, many CPTs in my BBNs were too complex to be well-suited to this approach. However, my initial literature review did provide system thresholds for bounding discretized states of certain continuous variables as well as several influential variables to include in the network.

Model structures and uncertainty

A single BBN represents a hypothesis about the structure and causality of the modeled system, and the uncertainty around the accuracy of the structure of any individual network necessitated building several candidate networks. Given the general goal of a parsimonious model structure, the BBN with the greatest predictive ability and the fewest number of nodes, links, and states would be the most useful. I built a base model that represented a simplified system with fewer nodes and links (Figures 3, 4), as well as a full model with the complete suite of identified causal variables and corresponding relationships (Figures 5, 6; Appendix B). The nodes in the network fall into several loose groupings that are the same between both network structures, but the included variables are different in each.

In the base model (Figures 3, 4) the left-most level of the network represents parentless nodes, including the lake basin and month which describe the spatial and temporal scales respectively, landscape variables including the network catchment area, cross-sectional bankfull area of the stream reach at a barrier, and the distance from the stream outlet to the barrier, as well as the physical characteristics of the barrier including the slope of the barrier face and the absolute height of the barrier. Air temperature and total precipitation are then influenced by the lake basin and month. Stream temperature is influenced by the month, lake basin, and air temperature nodes, while streamflow is influenced by the network catchment area and total precipitation. The vertical drop is influenced by the streamflow, bankfull area, and absolute barrier height. Stream velocity is influenced by the streamflow and bankfull area, and the physical permeability of a barrier is influenced by the barrier slope, effective height, and stream velocity. The abundance of spawning-phase sea lampreys in a stream is influenced by the lake basin, month, network catchment area, and stream temperature. The proportion of those sea lampreys that migrate upstream to a barrier is influenced by the abundance in the stream, the stream temperature, and the distance upstream to the barrier. The abundance of sea lampreys at the barrier is influenced by the total abundance in the stream and the proportion that migrate upstream to the barrier, and the abundance of sea lampreys to pass a barrier is influenced by the abundance at the barrier and the physical permeability of that barrier.

The full model (Figures 5, 6) was based on the same structure as the base model, with additional nodes and links. Landscape nodes were added that describe the percentage of vegetated cover in the network catchment, the percentage of impervious surface cover in the network catchment, and flowline slope. These variables, along with the total precipitation, influenced the proportion of rainfall that becomes runoff into the stream. The frequency of precipitation was added to influence the streamflow. Lake temperature was added and influenced the average total body length and weight of spawning-phase sea lampreys upon entry into a stream. Total body length influenced the permeability of a barrier, and body weight influenced the proportion of spawning-phase sea lampreys to reach a barrier.

Each model was further divided into three scenarios representing a different understanding of the average vertical drop at the barrier face. This was necessary because of the importance of this variable in determining how permeable a barrier will be to upstream migrating sea lampreys, as well as data scarcity. These scenarios were developed and transformed into a CPT via the same methods used in the structured expert elicitation described below. For each combination of the parent nodes of the effective barrier height, I specified a maximum likely value, minimum likely value, most likely value, and my confidence level that the true value was within the provided bounds, as described in Speirs-Bridge et al. 2010. These values were based on my understanding of the system and the literature. For each model structure, the first scenario (V1) describes a conservative effect of streamflow on the stream water level, the second scenario (V2) describes a moderate effect, and the third scenario (V3) describes a substantial effect. For each increasing state of the node describing the ratio of runoff to rainfall, the confidence level of the effect of streamflow was decreased by 0.1. A stream with a ratio of runoff to rainfall closer to 1 will be more flood-prone than one closer to 0 and would be more likely to exceed the boundaries of the provided range.

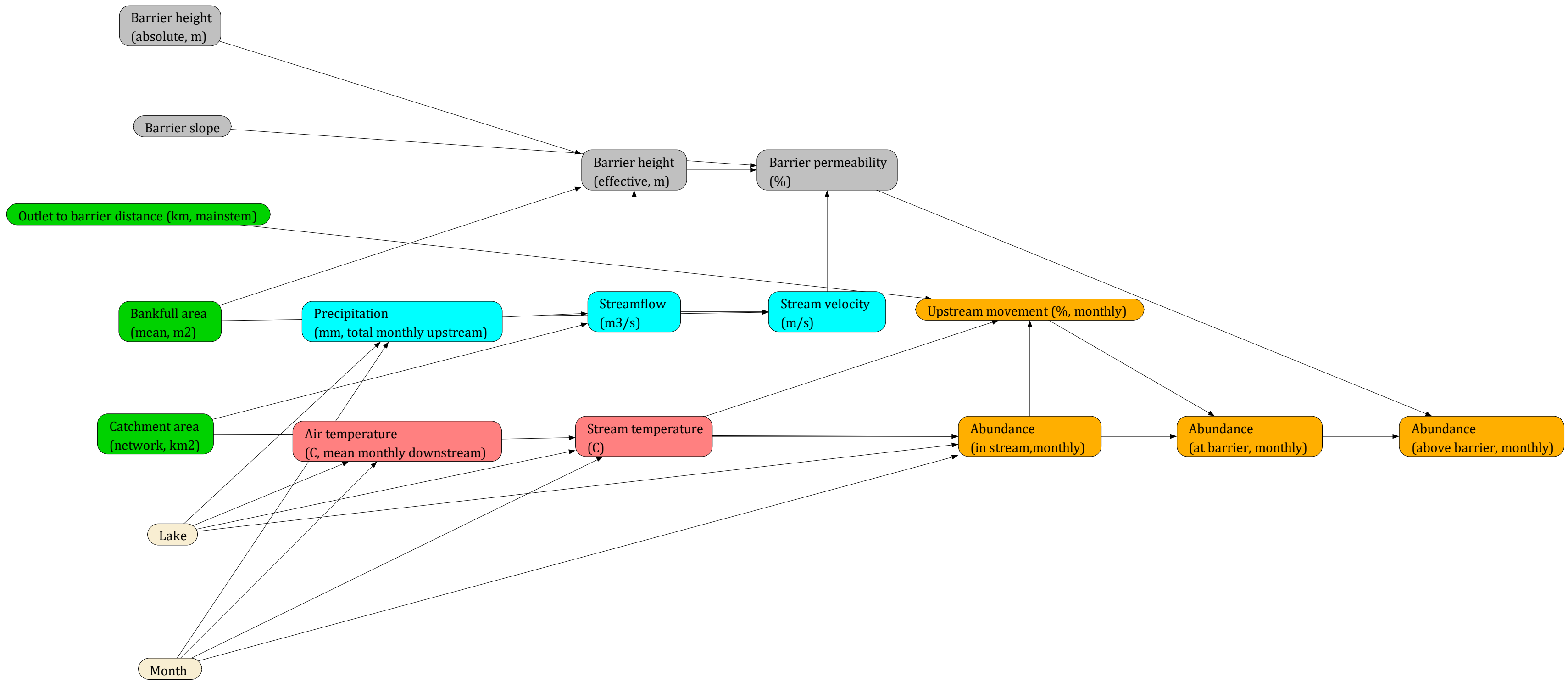


Figure 3. Network structure of the base model showing the variable name and series of linkages between nodes, with the direction of causality following the direction of each arrow. Tan nodes depict the spatial and temporal scales, green nodes depict landscape variables, grey nodes depict variables relating to a barrier's physical characteristics, blue nodes depict precipitation and hydrology, red nodes depict variables relating to temperature, and orange nodes depict variables relating to sea lampreys.

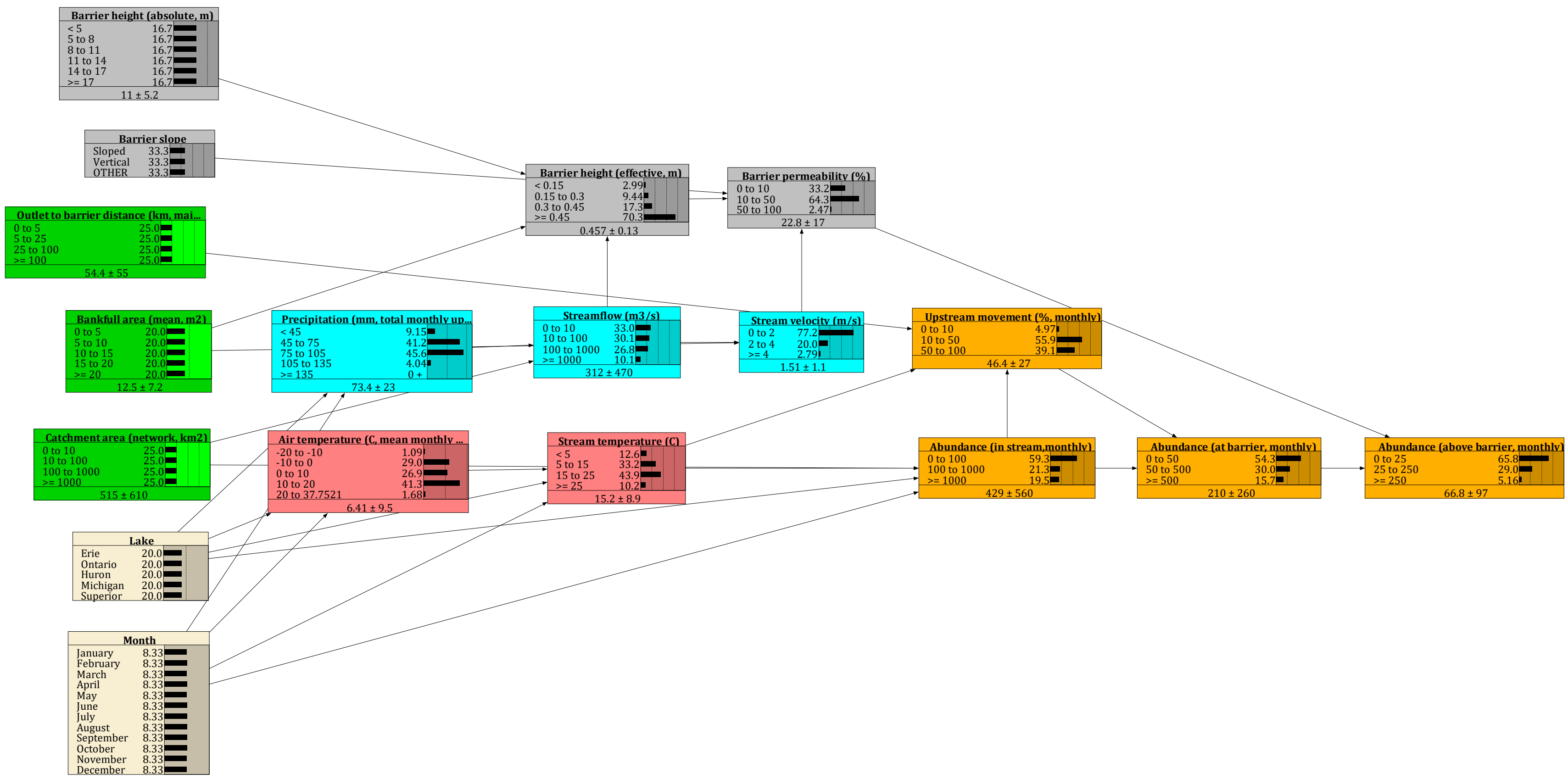


Figure 4. Network structure of the base model V2 with each node state and its naïve belief shown. Naïve beliefs represent understanding given complete uncertainty in the parentless nodes. Tan nodes depict the spatial and temporal scales, green nodes depict landscape variables, grey nodes depict variables relating to a barrier's physical characteristics, blue nodes depict precipitation and hydrology, red nodes depict variables relating to temperature, and orange nodes depict variables relating to sea lampreys.

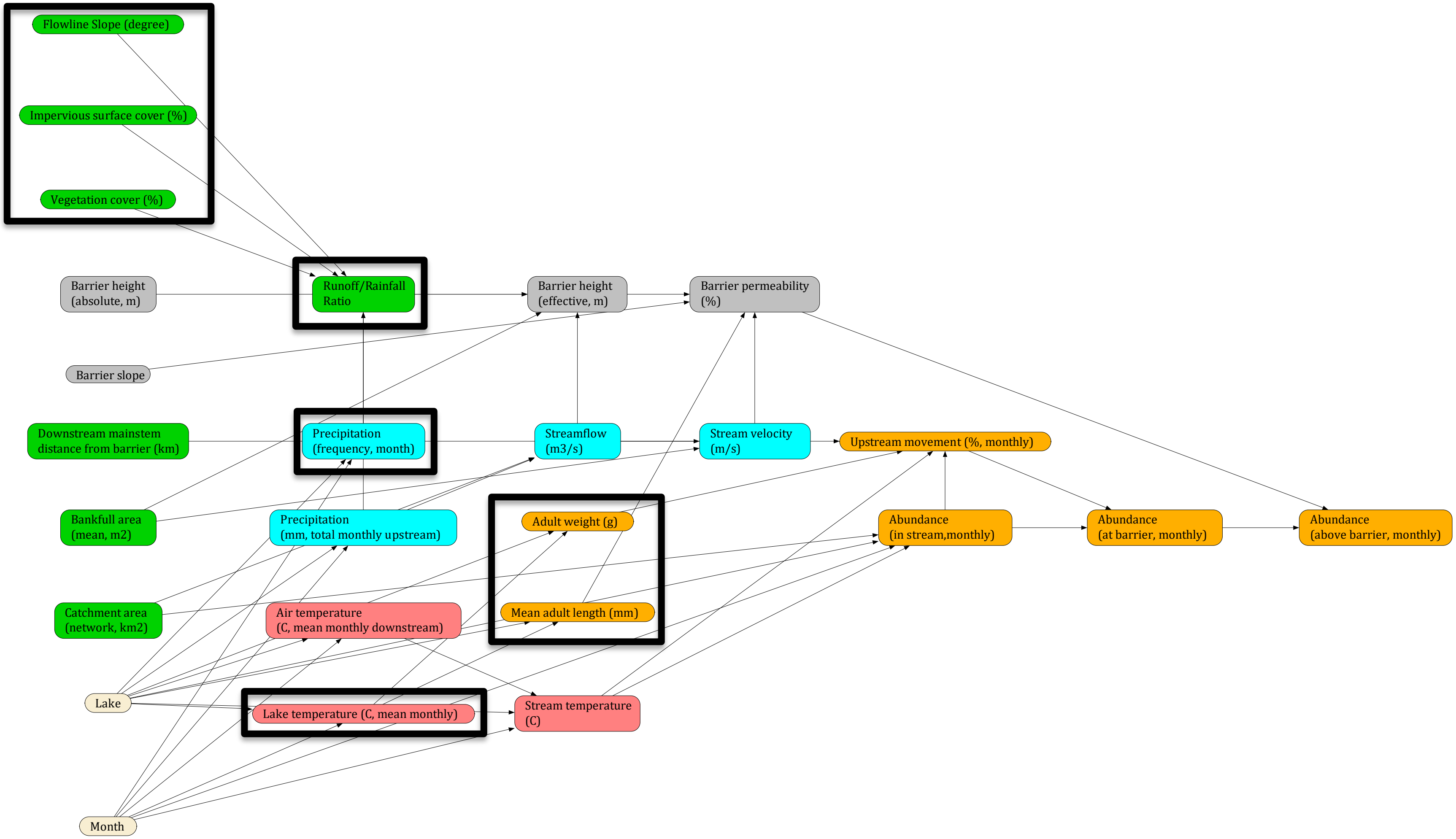


Figure 5. Network structure of the full model showing the variable name and series of linkages between nodes, with the direction of causality following the direction of each arrow. Nodes not present in the base model structure are shown within black boxes. Tan nodes depict the spatial and temporal scales, green nodes depict landscape variables, grey nodes depict variables relating to a barrier's physical characteristics, blue nodes depict precipitation and hydrology, red nodes depict variables relating to temperature, and orange nodes depict variables relating to sea lampreys.

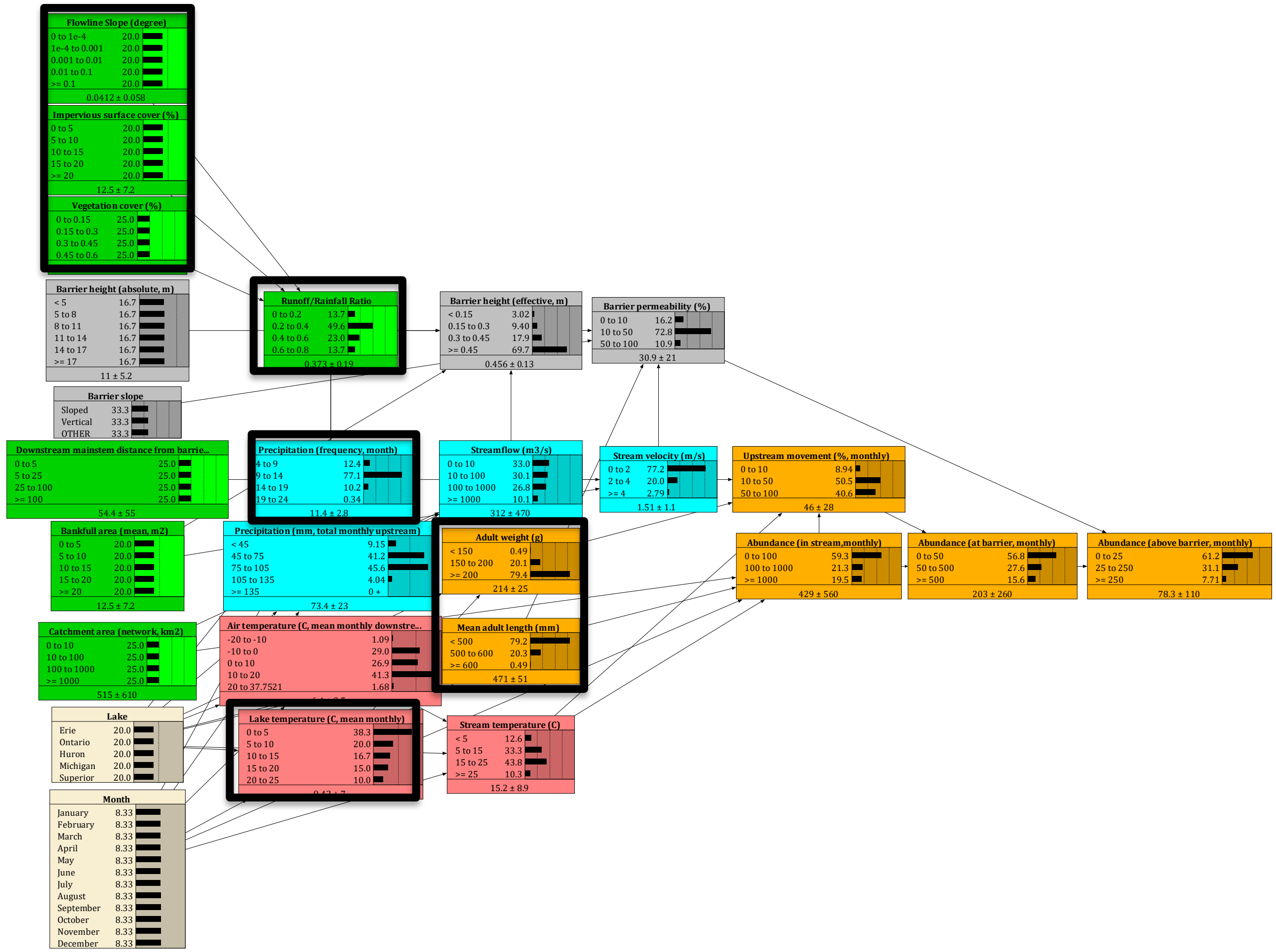


Figure 6. Network structure of the full model V2 with each node state and its naïve belief shown. Naïve beliefs represent understanding given complete uncertainty in the parentless nodes. Nodes not present in the base model structure are shown within black boxes. Tan nodes depict the spatial and temporal scales, green nodes depict landscape variables, grey nodes depict variables relating to a barrier's physical characteristics, blue nodes depict precipitation and hydrology, red nodes depict variables relating to temperature, and orange nodes depict variables relating to sea lampreys.

Data transformation and aggregation

The data used to build the models were obtained from a wide number of sources and represent different spatial and temporal resolutions and extent. Based on the data available, I selected month as the temporal scale and stream reach as the spatial scale for the models. Monthly water temperature in the stream reach was estimated from air temperature data using a simple linear mixed-effect model. Candidate models were compared using AIC (Sakamoto et al. 1986), with the best candidate model including monthly air temperature and month as linear predictors, and the stream reach as a random effect,

$$Y_{ij} = \beta_0 + \beta_1 A_{ij} + \beta_2 M_{ij} + u_j + \varepsilon_{ij},$$

where Y_{ij} represents mean water temperature on day *i* in stream reach *j*, β represents the estimated coefficients, A_{ij} represents the air temperature at day *i* in stream reach *j*, M_{ij} represents the month at day *i* in stream reach *j*, u_j represents the random effect of stream reach *j*, and ε_{ij} represents a normally-distributed error.

The vertical drop from the barrier crest to the height of the tailwater flow was considered an important cause of sea lamprey barrier passage (McLaughlin et al. 2003). Data from 23 level loggers placed at sea lamprey control barriers around the state of Michigan were used to gain an understanding of the frequency of inundation at the barriers but were insufficient to complete the CPT for that node. I created several scenarios to describe the uncertainty around the effect of the vertical drop at the barrier based on my understanding of the literature, conversations with GLFC Barrier Task Force staff, and evaluation of the available data, as described above (*Model structures and uncertainty*). These varied the effect of the mean monthly streamflow and the cross-sectional bankfull area as a fraction of the absolute height of the barrier. In the full model, variables that influence the flood potential, such as the percentage of vegetation and impervious surface cover, modified the confidence level of each scenario. This allowed me to create three different CPTs for the vertical drop for each structure of the model.

I used the methods described in Mullett et al. (2003) to estimate the monthly abundance of adult sea lampreys in each stream and year. This model estimates the abundance of sea lampreys in each stream as a function of stream drainage area, geographic region, larval sea lamprey production potential, the number of years since the last lampricide treatment, and the spawning year to predict the abundance of spawning adults as,

$$ln(S_{ij}) = \beta_0 + \beta_1 \ln(D_i) + \beta_2 R_i + \beta_3 \ln(D_i) R_i + \beta_4 P_i + \beta_5 T_{ij} + Y_j + \varepsilon_{ij},$$

where S_{ij} represents the number of spawning-phase sea lampreys migrating up stream *i* in year *j* (obtained from mark-recapture and trap catch estimates), β represents an estimated coefficient, D_i represents the drainage area, R_i represents the region, P_i represents the production potential, T_{ij} is the number of years since the last treatment, Y_j is the year effect, and ε_{ij} is the normally-distributed error.

The abundance of sea lampreys within any Great Lakes stream is highly variable both throughout the spawning migration and among years. While some streams see spawning-phase sea lampreys annually, others may only see spawning adults every few years (Dawson and Jones 2009). Trap catch data from the SLCP, which describes captures of adults moving upstream on a subset of streams in the Great Lakes Basin, were used to determine monthly relative proportions of spawning-phase sea lampreys present in the stream during the spawning migration. Deployment and collection dates for these traps are relatively standardized across years, and therefore may miss early or late migration spawning-phase sea lampreys. To allocate adults to different months of the year, I used the monthly proportion of trap catch in each month for each stream in each year and the estimated stream population for each stream in each year. This yielded a matrix of monthly abundances of adults in the stream in each year, which was averaged across all years to obtain an average monthly abundance for each stream.

All data about the state of each node in the model for each barrier was aggregated into a series of cases, called a case file. Depending on the specificity available, data about each node for each case were entered as a single value, bounded ranges of possible values, or Gaussian distributions described by a mean and standard deviation. I created the first case file with historical data reflecting current knowledge of conditions at each barrier, and a case file for each of sixteen modeled future climate projections.

Expert elicitation

I used a structured expert elicitation protocol to generate CPTs for two nodes in the Bayesian belief network that were lacking comprehensive empirical information: adult sea lampreys moving upstream and adult sea lampreys passing over a control barrier. My protocol was based on the modified Delphi approach (Kuhnert et al. 2010; Hanea et al. 2017; de Little et al. 2018), but was adapted to an online format.

I first created a question protocol consisting of a series of scenarios for each node I was attempting to inform, with each scenario representing a combination of each state of the parent nodes. The number of combinations was reduced to minimize survey fatigue, and I relied on interpolation to calculate the conditional probabilities of non-elicited scenarios. I organized scenarios into a series of Microsoft Excel spreadsheets, with a written and pictorial description of the scenario (Appendix C). For each scenario, I asked experts to answer according to the four-point method (Speirs-Bridge et al. 2010), reporting a maximum realistic value, a minimum realistic value, a "best-guess" or modal value, and their confidence that the true value was located within the interval provided. After my initial call for experts, five individuals agreed to participate in both questionnaires and discussions, while two agreed to just participate in that regarding upstream movement, and one agreed to just participate in that regarding barrier passage. I created a scenario guide to explain the purpose of my elicitation process, how the questions were to be interpreted and answered, and definitions of the terms used. Each participant received the scenario guide and questionnaires, which they completed individually to reduce cognitive biases due to "group think". I grouped the results of the individual questionnaires by topic and expert and averaged the responses, assuming that each expert's knowledge was equally valid (de Little et al. 2018). These aggregated responses were used to estimate parameters of a beta distribution using the R statistical environment (R Core Team 2020), and the R package 'prevalence' (Devleesschauwer et al. 2014). This allowed me to standardize each expert's provided values to an 80% confidence interval. The aggregate beta density curves for each scenario response were integrated and divided by the range that fell within each discretized state, yielding a table of elicited probabilities (EPT).

As the scenarios included in the questionnaires did not contain each possible combination of parent node states, the non-elicited scenarios were interpolated using the method outlined by Cain (2001). An interpolation factor (IF) was calculated for the number of parent nodes – 1, representing the difference in the state probability when a parent node is transitioned from a more favorable to a less favorable state, as a proportion of the difference between the highest and lowest probability of the target node state across all scenarios. Each IF was calculated as

$$\mathrm{I}F_{x,c_{1:s-1}} = \frac{P_{x,c_{1:s-1}} - min(P_x)}{max(P_x) - min(P_x)},$$

where c is a parent node, s is the number of states of parent node c, P_x is the probability of a child node state x, $\min(P_x)$ is the minimum value of P_x across all elicited scenarios, and $\max(P_x)$

is the maximum value of P_x across all elicited scenarios. The probability of each target node state of a non-elicited scenario was calculated as

$$P_{x,N} = \left[\left(P_{x,E} - min(P_x)\right) * IF\right] + \min(P_x),$$

where E is an elicited scenario, N is the non-elicited scenario containing a single shift in the state of a single parent node to a less favorable state, *x* is a single target node state, and IF is the interpolation factor for the difference in the states of E and N.

Once I obtained a complete CPT for each of the elicited child nodes, I scheduled an online meeting to discuss and evaluate the aggregate and individual responses to the questionnaires. I designed an R Shiny web application to allow participants to explore the raw and processed data, a beta density plot for each scenario, and a plot comparing the range and modal values identified by each participant for each scenario. Individual data were de-identified, and participants were provided a number that corresponded with their responses. The purpose of this meeting was to allow participants to discuss potential differences in their interpretation of the presented scenarios, share their reasoning with the group, and evaluate whether the aggregate distribution was reasonable and acceptable. Where participants felt they either misinterpreted the parameters of the scenario or otherwise felt that their original response was not correct, they were encouraged to submit a revised estimate.

Algorithmic learning

I used the EM algorithm within Netica to learn the structure of CPTs in the BBN using case files, as this algorithm is often faster and more robust to missing data than other options (Chen and Pollino 2012). The historical case file was used, with missing data in each case were represented as complete uncertainty in the corresponding row of the CPT. Algorithmic learning was used to learn the majority of CPTs in the BBN (Figure 3).

Climate scenario projections

I created additional case files using modeled data from future climate projections. Future climate projections included four time horizons: 2021 – 2040, 2041 – 2060, 2061 – 2080, and 2081 – 2100, as well as four shared socio-economic pathways (SSPs) for each time horizon describing the potential emissions trajectory and alternative socio-economic development, from 1–2.5, 2–4.5, 3–7.0, and 5–8.5 (O'Neill et al. 2014). SSP 1 represents the greatest reduction in emissions and largest mitigation strategy, while SSP 5 represents a worst-case scenario where emissions continue to rise unabated, and no mitigation policies are implemented. In total, sixteen future climate projections were used to inform the future case files.

Bayesian belief network analysis

I analyzed each scenario of both model structures using two methods described in Marcot (2012). I used sensitivity to findings analysis to evaluate the degree of uncertainty in the belief about the target node that is explained by other variables. This was performed within the Netica software and measures the mutual information, or reduction in entropy, of the node describing the abundance of sea lampreys above a barrier that is associated with a finding at each variable in the model. I also performed a one-way sensitivity analysis, which measures the degree of influence of each variable in the model on the target node (Marcot 2012; Conroy and Peterson 2013). Each node is varied, one at a time, from its minimum to maximum state, and the variation in the probability of each state of the target node is recorded. One-way sensitivity analysis is important for understanding which variables are driving less than optimal barrier performance, while sensitivity to findings analysis is important for understanding where a lack of understanding around certain variables is limiting certainty in the performance of a barrier.

Barrier analysis

I used the case files describing the state of knowledge about each variable under average climate conditions from 2000 to 2020, and for the sixteen future climate scenarios describing the four twenty-year average climates under each of the four emissions scenarios (Appendix B). Historical conditions were based on precipitation and air temperature monthly averages from 2000 to 2020, while future scenarios used twenty-year monthly precipitation and air temperature averages from downscaled future climate projections estimated from the CMIP6 climate models (Eyring et al. 2016). Projected climate data were spatially associated with the local or network catchment containing each barrier, depending on the scale at which it was relevant. Air temperature values relevant to each barrier were averaged across each local catchment, while precipitation values were averaged across each network catchment. I evaluated each case file using Netica's "Process Case File" tool to obtain the posterior probabilities of each state of the target node. This allowed me to compare each probability of each state of the target node and its change across each climate scenario. Barriers were evaluated based on the proportion of the posterior probability distribution within each state, from the best-case state (0 to 25 sea lampreys passed) to the worst-case state (more than 250 sea lampreys passed). I also created two metrics to classify a high-risk barrier: a conservative metric that included barriers with a greater than 50% mean monthly probability of passing more than 25 sea lampreys, and a stricter metric that included those with a greater than 10% mean monthly probability of passing more than 250 sea lampreys. To account for the uncertainty in the true CPT of the effective barrier height, I averaged the posterior distributions across the three scenarios of each model structure. To do this, I compiled the posterior probability distributions for each barrier in each climate scenario into tables organized by the barrier and climate scenario and averaged across the month to obtain an aggregate posterior probability distribution across each twenty-year period. To account for uncertainty in how future global greenhouse gas emissions will affect the trajectory of climate change, I compared each of the four emissions scenarios and selected a reasonable intermediate scenario based on the observed response, and how each was described in Eyring et al. (2016). To minimize the uncertainty caused by sea lamprey upstream migration across each lake and over time, I created a case file for each climate scenario that fixed the spawning run size in each stream at 500 in each month. This fixed-stream abundance scenario was used to isolate the changes in the physical permeability and rate of upstream passage caused by changes in climatic conditions, which may be a more useful metric for barrier success given current uncertainties.

Peer review

Without data on the abundance of sea lampreys passing each barrier in each month, there are no quantitative methods of estimating the categorization accuracy of each model to determine which model structure is most correct. Therefore, I utilized a combination of the two methods of sensitivity analysis, and an informal peer review process to begin to validate the usefulness of each BBN. I sent reviewers written documentation of the model to help explain both the components of a BBN and the structure and purpose of the specific BBN, a brief video walkthrough that narrated and described the components and structure of the specific BBN, several images of the model, a table containing the posterior beliefs of each barrier at each climate range, and the results of the one-way sensitivity analyses (Appendix D). Reviewers evaluated the model structure, causal relationships, results of the sensitivity analyses, and several lists of barriers for two scenarios to determine if they were valid given the reviewer's understanding of the outlined processes.

CHAPTER 3:

RESULTS OF THE EVALUATION OF VARIABLES INFLUENCING SEA LAMPREY PASSAGE OVER BARRIERS

Expert elicitation

As a whole, participants had higher self-reported confidence about the probability of upstream movement of spawning adults under varying conditions. Participants were noticeably less confident in their understanding of variation in the proportion of spawning adults that would pass over a control barrier under different conditions. This appeared to be from a lack of agreement as to the effect of spawning adult body length on the capacity to successfully pass over a barrier. Participants agreed that more precision required further details on the hydraulic conditions at the barrier, including the depth of tailwater flowing over the barrier face. After discussion, no participants opted to revise and resubmit their responses, and the original responses were used directly to generate the CPTs for upstream movement and barrier permeability (Appendix F).

Model evaluation

Model complexity was measured using the number of nodes, links, and the total number of conditional probabilities, as described in Marcot (2012). The base model was made up of a single network with 18 nodes, 28 links, and contained a total of 5,645 conditional probabilities. The full model was made up of a single network, with 26 nodes, connected by 42 links, and contained a total of 16,218 conditional probabilities. Under complete uncertainty, there was more variation in the posterior distribution of the three scenarios of the base model structure, than those of the full model structure, while the variation among barriers was similar regardless of the model and scenario (Table 1). Averaged across scenarios, the full model structure estimated a

0.2847 probability of passing 25 – 250 sea lampreys and a 0.0588 probability of passing > 250 sea lampreys, while the base model structure estimated a 0.2786 probability of passing 25 – 250 sea lampreys and a 0.0551 probability of passing > 250.

Table 1: Mean and standard deviation of the posterior distribution of each state of upstream passage for each model and scenario across all barriers.

Model and scenario	*P(<25)*	*P(25-250)*	*P(>250)*
Base Model V1	0.6458 (0.2415)	0.2850 (0.1784)	0.0692 (0.0702)
Base Model V2	0.6989 (0.2193)	0.2589 (0.1776)	0.0422 (0.0458)
Base Model V3	0.6541 (0.2226)	0.2920 (0.1772)	0.0539 (0.0502)
Full Model V1	0.6571 (0.22598)	0.2847 (0.1702)	0.0582 (0.0618)
Full Model V2	0.6529 (0.22967)	0.2860 (0.1718)	0.0608 (0.0633)
Full Model V3	0.6589 (0.22396)	0.2837 (0.1688)	0.0575 (0.0616)

Sensitivity to findings

A sensitivity to findings analysis was performed in Netica for each scenario of the base model and full model on the ultimate node representing the abundance of sea lampreys upstream of a barrier (the target node), and comparisons across variants and between models are shown (Table 2). The upper limit for the target node's largest state was unbounded, and an artificial upper limit of 15,000 sea lampreys was used for the analysis. Nodes were ranked by the proportion of entropy reduction observed in the target node given complete certainty about each other node. Nodes with > 1% reduction in entropy were taken to be the main drivers of target node uncertainty, while nodes below 1% were taken to be responsible for only trace amounts of target node uncertainty. Low values of entropy reduction indicate that there is little uncertainty in the values of the described node, or a small influence on the target node, and further knowledge of that node would do little to provide greater target node certainty. For all scenarios of both the base and full model structure, uncertainty in the abundance of sea lampreys in the stream, and the proportion that would successfully reach the barrier, were responsible for > 31% and > 52% of total target node uncertainty respectively. The other main drivers of target node uncertainty, the physical permeability of a barrier, the proportion of successful upstream movement, the size of the network catchment area, the mean monthly streamflow, and the lake basin, were ranked the same among all model and scenario combinations. In the three scenarios of the full model structure, adult length was also responsible for a > 1.6% reduction in entropy. The remaining variables were responsible for < 1% of the entropy reduction, with the five lowest-ranked variables responsible for < 0.001%, suggesting that these variables were less important for accurate categorization of barrier effectiveness.

Table 2. Results of a sensitivity analysis of the Bayesian belief network models created to predict the effects of climate change on sea lamprey passage above barriers in the Great Lakes. Each column represents either a base (i.e., less complex) or full (i.e., more complex) model framework, and one of three scenarios (V1–V3) of the model that describe uncertainty in the effective barrier height. Sensitivity is measured as the percentage of entropy reduction observed upon a finding at each node. The target node is the abundance of spawning-phase sea lamprey upstream of a barrier.

Node	*Base V1*	*Base V2*	*Base V3*	*Full V1*	*Full V2*	*Full V3*
Abundance at barrier	52.30	52.30	52.30	53.40	53.50	53.20
Abundance in stream	32.10	32.10	32.20	31.90	31.90	31.80
Catchment area	5.24	5.23	5.23	5.20	5.26	5.25
Barrier permeability	6.74	6.69	6.66	5.07	5.02	5.11
Upstream movement	3.36	3.36	3.35	3.03	3.00	3.01
Lake	2.50	2.50	2.50	2.25	2.27	2.27
Streamflow	1.61	1.60	1.59	1.72	1.73	1.73
Adult total length	NA	NA	NA	1.69	1.72	1.70
Month	0.96	0.96	0.96	0.72	0.74	0.73
Barrier slope	0.03	0.05	0.04	0.53	0.50	0.55
Air temperature	0.70	0.97	0.97	0.44	0.46	0.46
Stream temperature	0.96	0.96	0.96	0.42	0.43	0.45
Lake temperature	NA	NA	NA	0.20	0.22	0.22
Precipitation	0.34	0.34	0.34	0.18	0.19	0.19
Vertical drop height	0.70	0.71	0.75	0.15	0.15	0.16
Precipitation frequency	NA	NA	NA	0.10	0.10	0.10
Distance to barrier	0.05	0.05	0.05	0.05	0.06	0.06
Stream velocity	0.05	0.02	0.02	0.03	0.03	0.03
Adult weight	NA	NA	NA	0.00	0.02	0.02
Runoff/Rainfall Ratio	NA	NA	NA	0.01	0.01	0.01
Vegetation cover	NA	NA	NA	0.00	0.00	0.00
Stream bankfull area	0.00	0.00	0.00	0.00	0.00	0.00
Impervious surface cover	NA	NA	NA	0.00	0.00	0.00
Flowline slope	NA	NA	NA	0.00	0.00	0.00
Barrier total height	0.00	0.00	0.00	0.00	0.00	0.00

One-way sensitivity analysis

One-way sensitivity analysis, or sensitivity to parameters analysis, was separately conducted for each of the three scenarios of both the base and full models, and each of the three states of the node representing the abundance of sea lampreys upstream of a barrier. Analysis of the best-case state of the target node (< 25 sea lampreys passed) for each combination of scenario and model ranked the same nodes as being the most influential, while the rank-ordered variables were different when measuring the sensitivity to the worst-case state (> 250 sea lampreys passed).

In the base model V2, the default posterior probability distribution of the target node under complete uncertainty and across all barriers, was estimated to be a 65.8% probability of < 25 sea lampreys passed, a 29.0% probability of 25 – 250 passed, and a 5.2% probability of > 250 passed. In all scenarios, the posterior probability of passing < 25 sea lampreys < 25% given the worst-case state of the abundance present at the barrier and in the stream, while the probability was > 75% given the best-case state of the abundance present at the barrier and in the stream, the physical permeability of the barrier, the proportion of sea lampreys that reach the barrier, the network catchment area, the lake basin, the mean monthly streamflow, and the mean monthly stream temperature (Figure 7). In all scenarios of the base model the posterior probability of > 250 sea lampreys passing above a barrier was nearly 0% given the best-case state of the abundance present at the barrier and in the stream, the physical permeability of the barrier, and the proportion of sea lampreys that reach the barrier, while the probability was greater than 10% only under the worst-case state of the abundance present at the barrier and in the stream, the physical permeability of the barrier, the vertical drop between the barrier crest and the tailwater flow, and the air temperature (Figure 8).

In the full model V2, the default posterior probability distribution under complete uncertainty was estimated to be a 61.2% probability of < 25 sea lampreys passed, a 31.1% probability of 25 – 250 passed, and a 7.7% probability of > 250 passed. In all scenarios, the posterior probability of passing < 25 sea lampreys was < 25% given the worst-case state of the abundance present at the barrier and in the stream, while the probability was > 75% given the best-case state of the abundance present at the barrier and in the stream, the physical permeability of the barrier, the proportion of sea lampreys that reach the barrier, and the network catchment area (Figure 9). In all scenarios, the posterior probability of the worst-case state of the target node was > 20% given the worst-case state of the abundance present at the barrier and in the stream, as well as the physical permeability of the barrier and was nearly 0% given the best-case state of the abundance present at the barrier and in the stream, the physical permeability of the barrier, and the proportion of sea lampreys that reach the barrier (Figure 10).

Peer review

Three reviewers participated in the informal review of the model structure and preliminary results. Each reviewer considered a different facet of the materials they were presented with, and there was little overlap in the content of their feedback. In their review of the model and the results of the one-way sensitivity analysis, Reviewer 1 focused on how the model may be improperly categorizing the risk of flood at each barrier and the lack of model sensitivity to the month, given that many variables in the model could be expected to vary monthly. While Reviewer 1 found it difficult to interpret the results of the table of posterior beliefs for each barrier, this reviewer mentioned the negligible difference among lakes across each climate projection. Reviewer 2 focused on the ecological relevance of the model and preliminary results, and thought the model overall represented a reasonable first attempt at addressing the research questions. This reviewer considered that the monthly time scale of the model is likely blunting the influence of variables relevant over the course of several days. They also mentioned that there is a knowledge gap around the difference between the consequences of passing two adult sea lampreys as opposed to more than 250, but that it is out of the point of current research. Lastly, they identified the larval survey data as a potential validation dataset, and that it would be useful to recategorize the barriers in each case file to match the internal Barrier Task Force designations that are based on the years between inspections. Reviewer 3 considered the model to be redundant in several places, including nodes around air, lake, and stream temperatures, as well as both adult sea lamprey length and weight. They also thought that some important variables were not being included, such as groundwater influence on stream temperature and streamflow influence on upstream movement of adult sea lampreys. They also mentioned that the model only included several proposed explanations for variation in barrier effectiveness and neglected to include variables relating to more fine-scale characteristics of each barrier and their hydraulic conditions. Commenting on the model results, Reviewer 3 acknowledged that they did not have sufficient expertise to evaluate the posterior probabilities for each barrier, but identified a lack of any noticeable variation attributed to each climate projection and a clustering of the posterior beliefs for each barrier into two groupings. The reviewers' concerns were important critiques of the BBNs, but the structural changes and additions to each BBN were largely beyond available time and data. I instead addressed the feedback from each reviewer by incorporating their concerns in the discussion of both the implications and limitations of this work, and suggest them as considerations for future research.

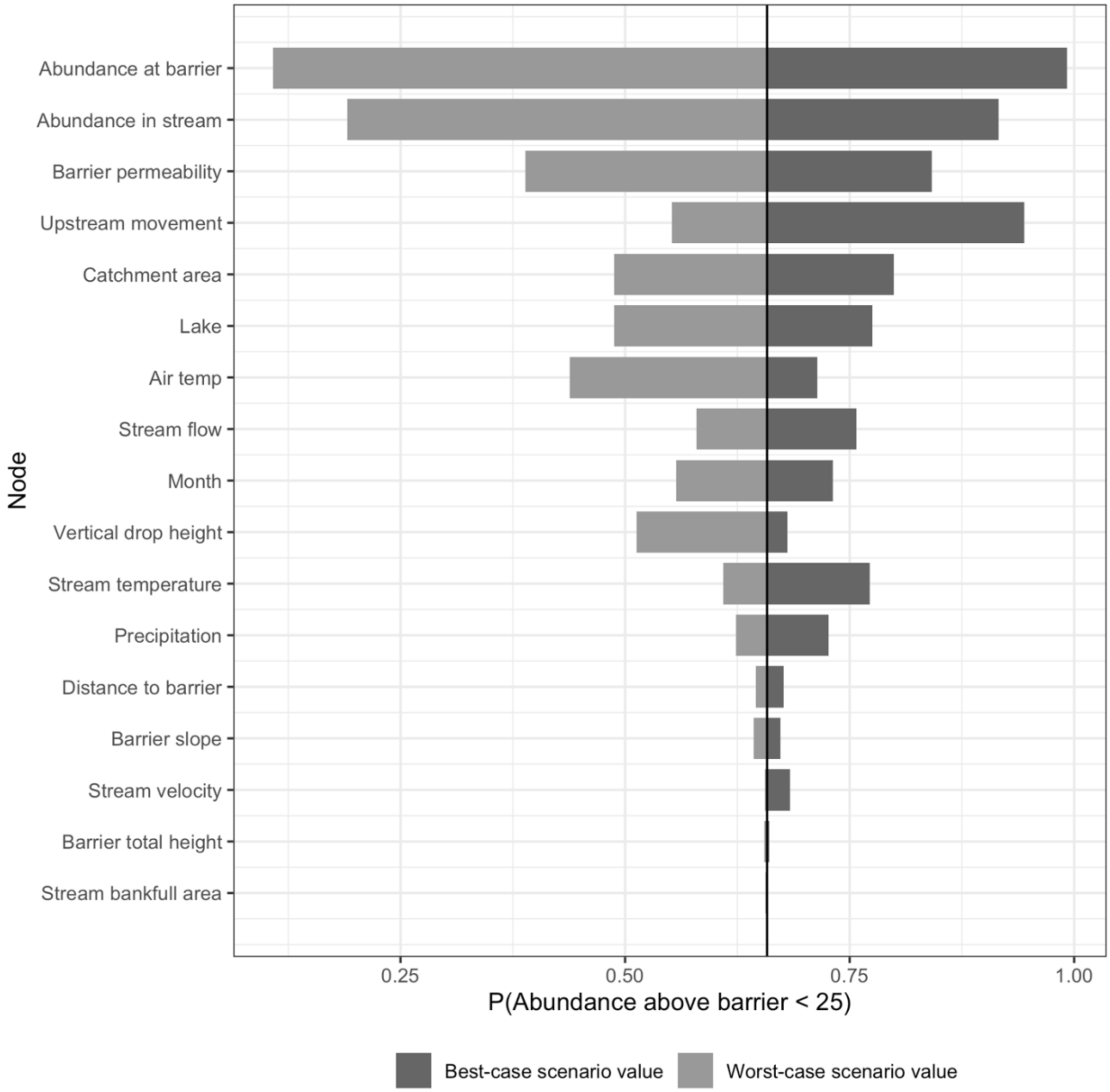


Figure 7. Results of a one-way sensitivity analysis of the base model V2 for the best-case state of abundance of sea lampreys above a barrier. Each node is varied from the worst-case to the best-case state, and the change in the state probability of the target node is recorded. The best-case state of a node is considered that which maximizes the best-case state of the target node, and vice versa.

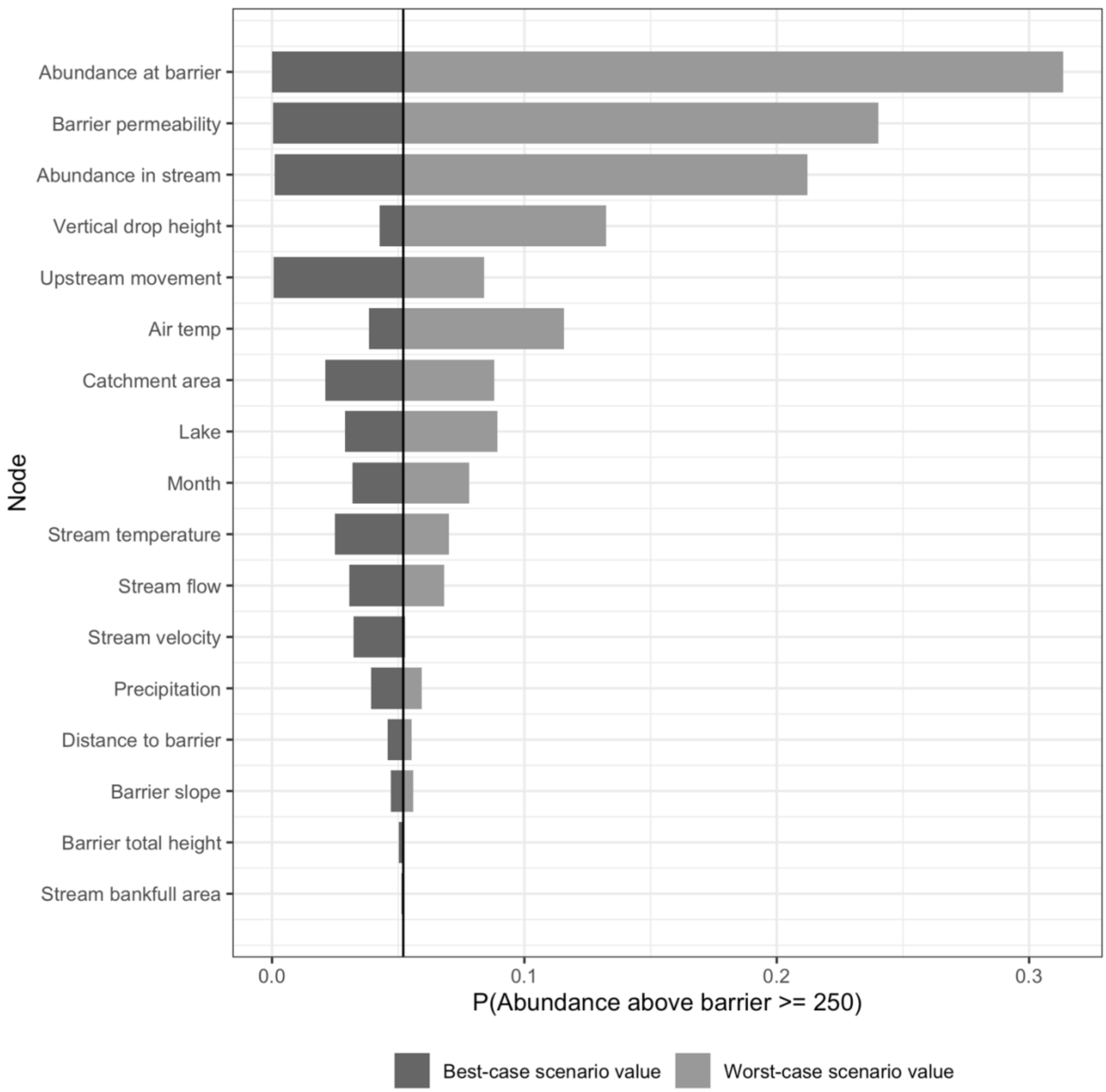


Figure 8. Results of a one-way sensitivity analysis of the base model V2 for the worst-case state of abundance of sea lampreys above a barrier. Each node is varied from the worst-case to the best-case state, and the change in the state probability of the target node is recorded. The best-case state of a node is considered that which minimizes the worst-case state of the target node, and vice versa.

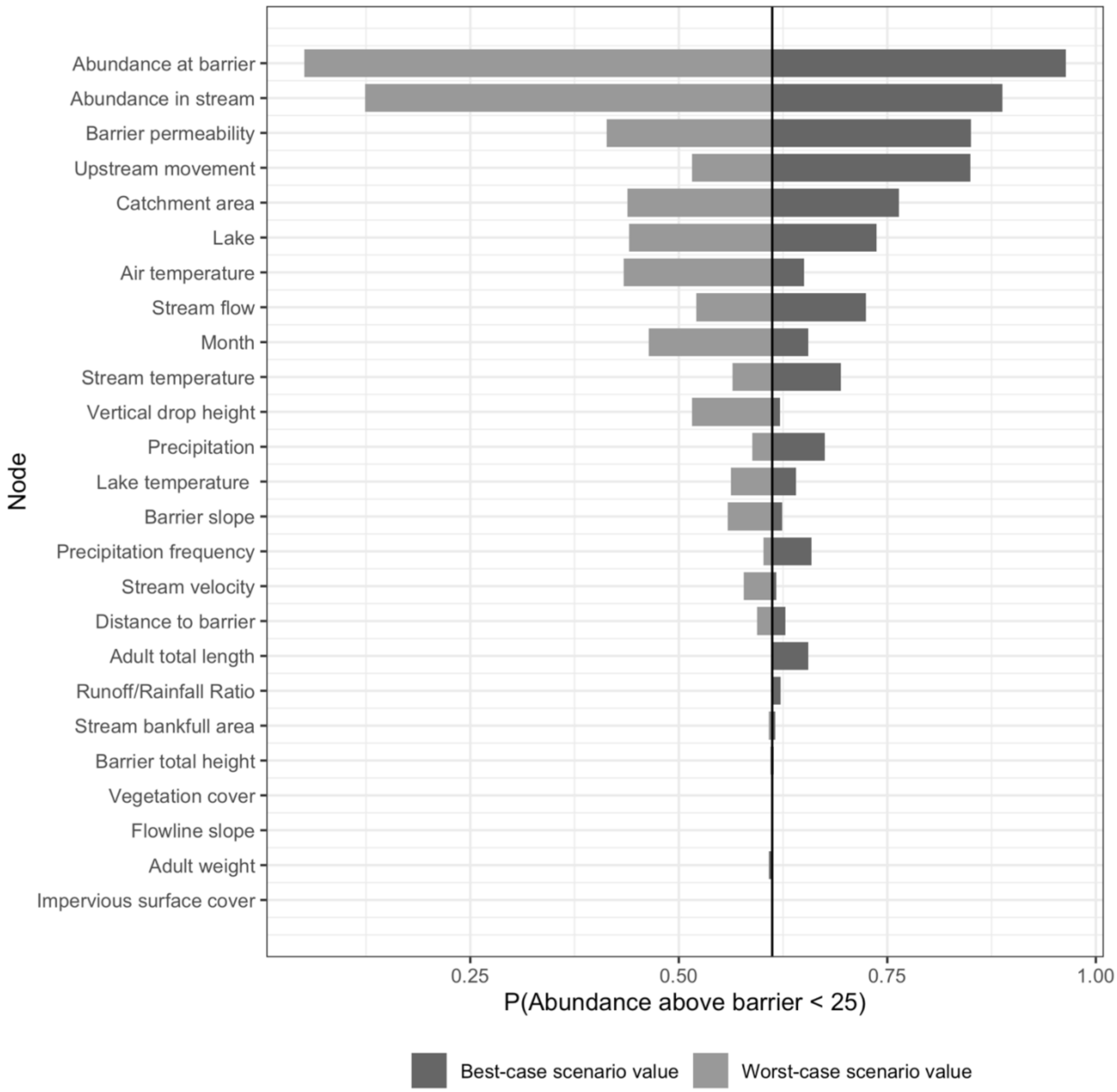


Figure 9. Results of a one-way sensitivity analysis of the full model V2 for the best-case state of abundance of sea lampreys above a barrier. Each node is varied from the worst-case to the best-case state, and the change in the state probability of the target node is recorded. The best-case state of a node is considered that which maximizes the best-case state of the target node, and vice versa.

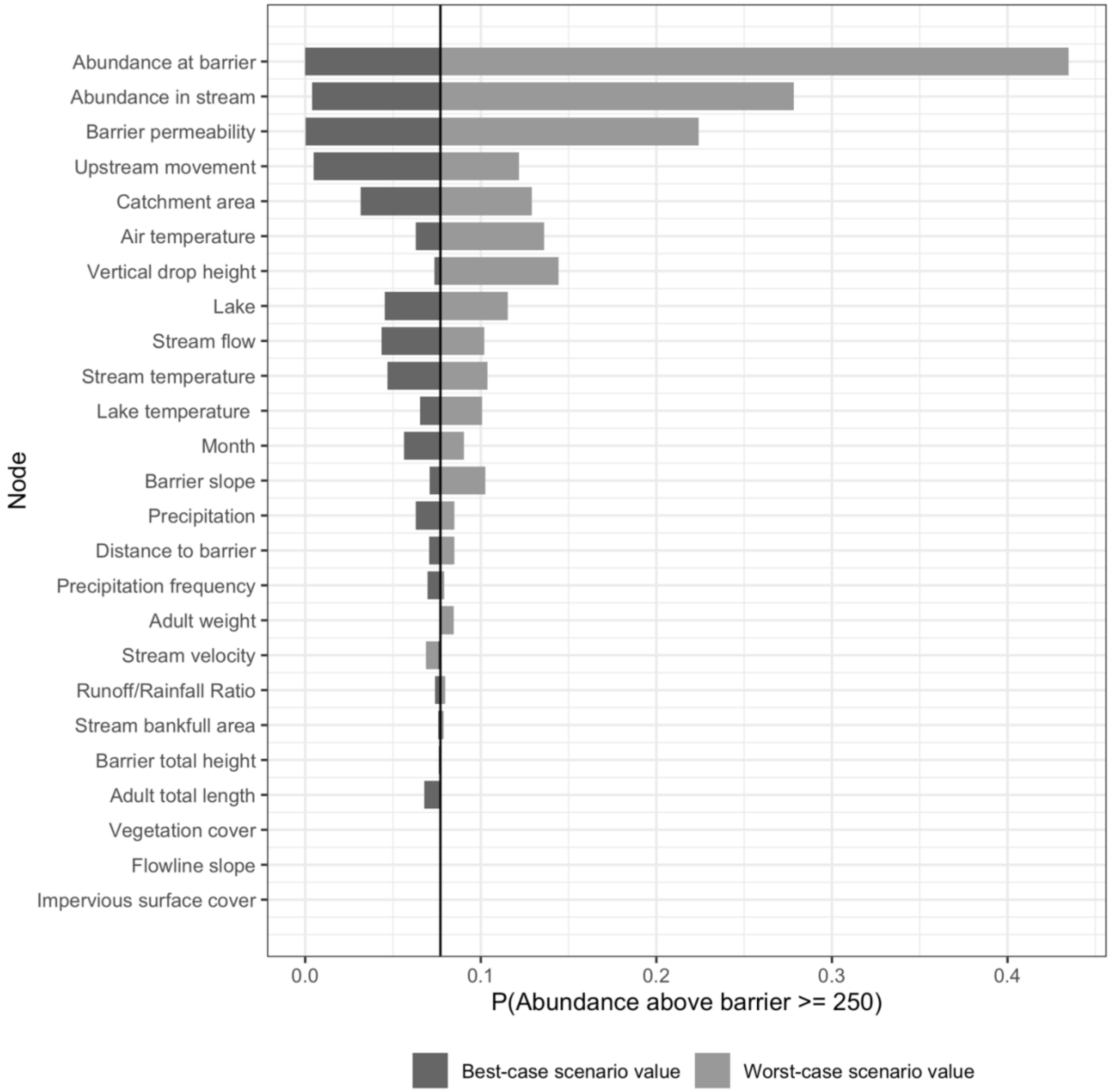


Figure 10. Results of a one-way sensitivity analysis of the full model V2 for the worst-case state of abundance of sea lampreys above a barrier. Each node is varied from the worst-case to the best-case state, and the change in the state probability of the target node is recorded. The best-case state of a node is considered that which minimizes the worst-case state of the target node, and vice versa.

CHAPTER 4:

RESULTS OF THE ASSESSMENT OF SEA LAMPREY BARRIER PASSAGE IN HISTORICAL AND FUTURE CLIMATES

Evaluation of high-risk barriers

Barriers evaluated with the base model did not exhibit large decreases in barrier effectiveness across projected future climates using either measure of high-risk. Using the conservative metric, approximately 13% of barriers in the Lake Michigan and Superior watersheds were considered high-risk under 2000 – 2020 climate conditions, while in the Lake Huron or Ontario watersheds, more than 30% of barriers were included under 2000 – 2020 climate conditions (Table 3; Figure 11). However, when transitioned from historical climate data to the 2021 – 2040 climate projection, far fewer barriers were considered high-risk with almost no change across further climate projections. Using the stricter metric this trend was largely the same, although the proportion of barriers in the Lake Superior watershed increased slightly (Table 4, Figure 12). Data about each node in the future climate case files were much more uncertain, and so this pattern is likely a result of poor categorization of these uncertain nodes under limited data. While the Lake Erie watershed had a high proportion of barriers considered high-risk using both metrics in each set of climate conditions, results from these barriers were considered unreliable due to large uncertainties in spawning migration timing and magnitude.

There was little change in barrier effectiveness over time under the full model, and the proportion of high-risk barriers in each Great Lake watershed was lower than that estimated from the base model. Using the conservative risk metric, fewer than 8% of barriers in the Lake Michigan watershed were included under historical climatic conditions, but this increased to between 10-12% for the remainder of the century (Table 5; Figure 13). More than 25% of barriers in the Lake Huron watershed were included under historical conditions, increasing to 27% for the remainder of the century. Under historical conditions, 27% of the barriers in the Lake Ontario watershed were included, but this decreased to approximately 13% of barriers for the remainder of the century. Approximately 15% of the barriers in the Lake Superior watershed were included under both historical conditions and future climate projections. Almost all barriers in the Lake Erie watershed were included under both historical conditions and future climate projections. Using the strict metric of risk, the Lake Michigan watershed had fewer than 4% of barriers included under both historical conditions and future climate projections. Approximately 18% of barriers in the Lake Huron watershed were included under historical conditions, which increased slightly under each future climate projection. In the Lake Ontario watershed, approximately 13% of barriers were included under both historical conditions and future climate projections. In the Lake Superior watershed, fewer than 8% of barriers were included under historical conditions, which increased to more than 11% for the remainder of the century. In the Lake Erie watershed, approximately 28% of barriers were included under historical conditions, which increased to more than 85% under the projected climates of 2021 – 2040, 2041 – 2060, and 2081 – 2100, then decreased to 70% in 2081 – 2100.

Table 3. Estimated percentage of lowermost barriers within each Great Lake watershed with a greater than 50% mean monthly probability of passing more than 25 sea lampreys across each twenty-year average climate, averaged across the three scenarios of the base model. Each climate projection used the SSP 3-7.0 emissions scenario.

Range of climate data	*Erie (n=127)*	*Michigan (n=105)*	*Huron (n=51)*	*Ontario (n=37)*	*Superior (n=52)*
2000 – 2020	64.57	13.33	31.37	32.43	13.46
2021 – 2040	66.93	10.50	5.88	21.62	3.85
2041 – 2060	73.23	10.50	5.88	21.62	3.85
2061 – 2080	67.72	10.50	5.88	21.62	3.85
2081 – 2100	74.02	10.50	5.88	18.92	3.85

Table 4. Estimated percentage of lowermost barriers within each Great Lake watershed with a greater than 10% mean monthly probability of passing more than 250 sea lampreys across each twenty-year average climate, averaged across the three scenarios of the base model. Each climate projection used the SSP 3-7.0 emissions scenario.

Range of climate data	*Erie (n=127)*	*Michigan (n=105)*	*Huron (n=51)*	*Ontario (n=37)*	*Superior (n=52)*
2000 – 2020	44.88	10.50	17.65	29.73	1.92
2021 – 2040	59.84	10.50	5.88	18.92	3.85
2041 – 2060	62.99	10.50	5.88	18.92	3.85
2061 – 2080	60.63	10.50	5.88	18.92	3.85
2081 – 2100	60.63	10.50	5.88	18.92	3.85

Table 5. Estimated percentage of lowermost barriers within each Great Lake watershed with a less than 50% mean monthly probability of passing more than 25 sea lampreys across each twenty-year average climate, averaged across the three scenarios of the full model. Each climate projection used the SSP 3-7.0 emissions scenario.

Range of climate data	*Erie (n=127)*	*Michigan (n=105)*	*Huron (n=51)*	*Ontario (n=37)*	*Superior (n=52)*
2000 – 2020	99.21	7.62	25.49	27.03	15.38
2021 – 2040	96.85	12.38	27.45	13.51	15.38
2041 – 2060	97.64	11.43	27.45	13.51	15.38
2061 – 2080	96.86	12.38	27.45	13.51	15.38
2081 – 2100	97.64	10.48	27.45	13.51	15.38

Table 6. Estimated percentage of lowermost barriers within each Great Lake watershed with a greater than 10% mean monthly probability of passing more than 250 sea lampreys across each twenty-year average climate, averaged across the three scenarios of the full model. Each climate projection used the SSP 3-7.0 emissions scenario.

Range of climate data	*Erie (n=127)*	*Michigan (n=105)*	*Huron (n=51)*	*Ontario (n=37)*	*Superior (n=52)*
2000 – 2020	27.56	3.81	17.65	13.51	7.69
2021 – 2040	88.98	3.81	19.61	13.51	11.54
2041 – 2060	85.83	3.81	19.61	13.51	11.54
2061 – 2080	88.61	3.81	19.61	13.51	11.54
2081 – 2100	70.08	3.81	19.61	13.51	11.54

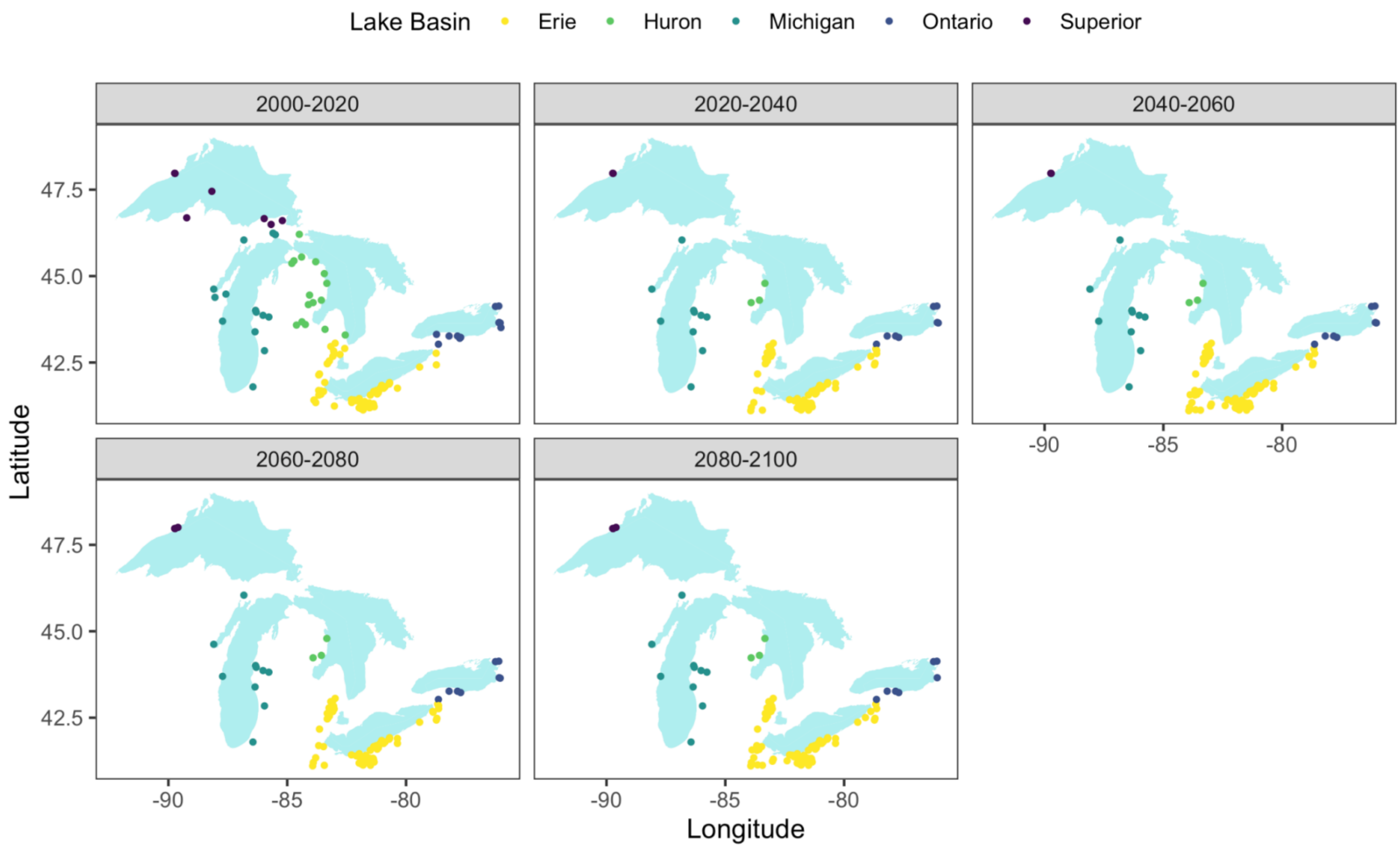


Figure 11. Location of the lowermost barriers within each Great Lake watershed with a greater than 50% mean monthly probability of passing more than 25 sea lampreys across each twenty-year average climate, averaged across the three scenarios of the base model. SSP 3-7.0 was used as the emissions scenario for each future climate projection.

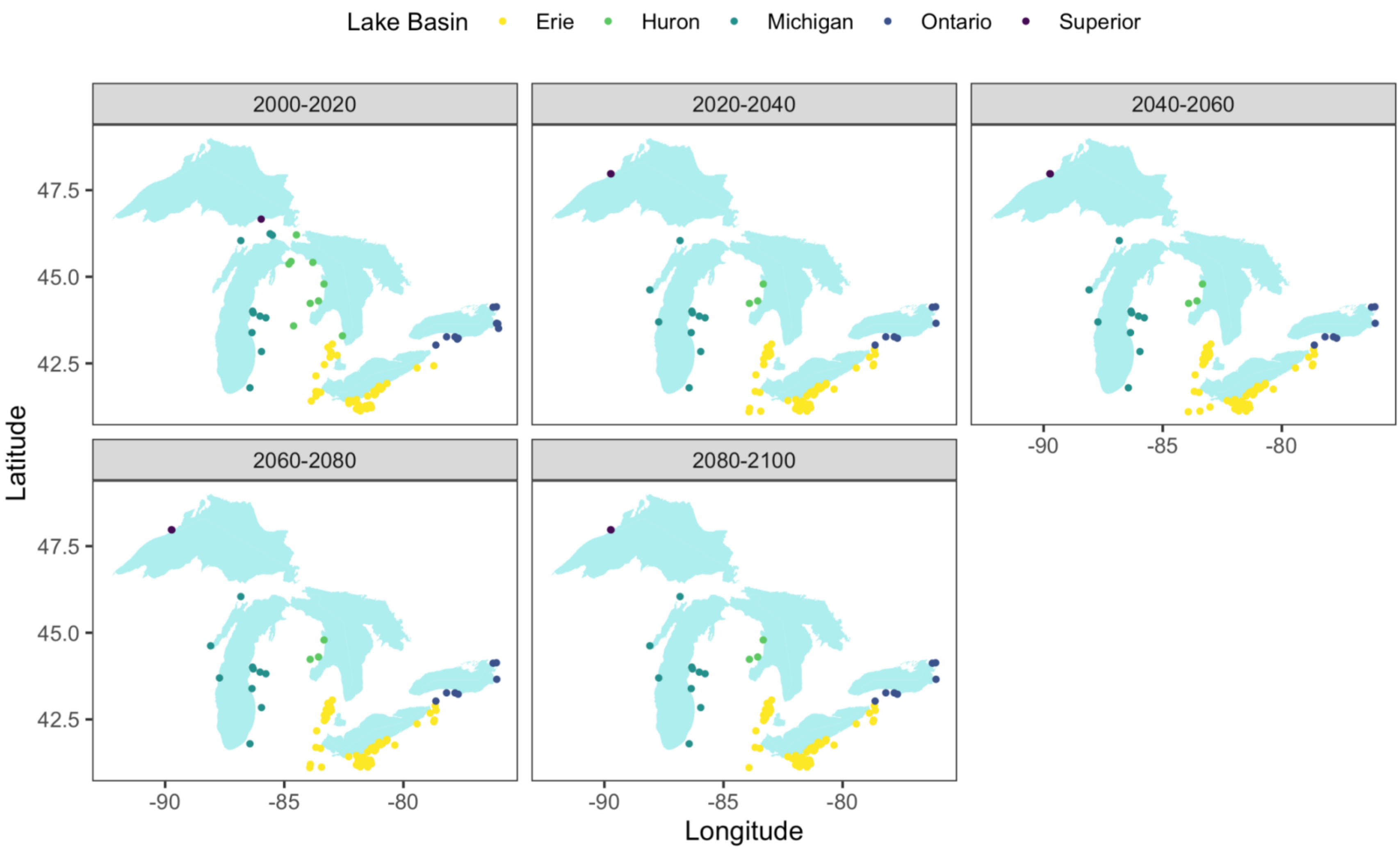


Figure 12. Location of the lowermost barriers within each Great Lake watershed with a greater than 10% mean monthly probability of passing more than 250 sea lampreys across each twenty-year average climate, averaged across the three scenarios of the base model. SSP 3-7.0 was used as the emissions scenario for each future climate projection.

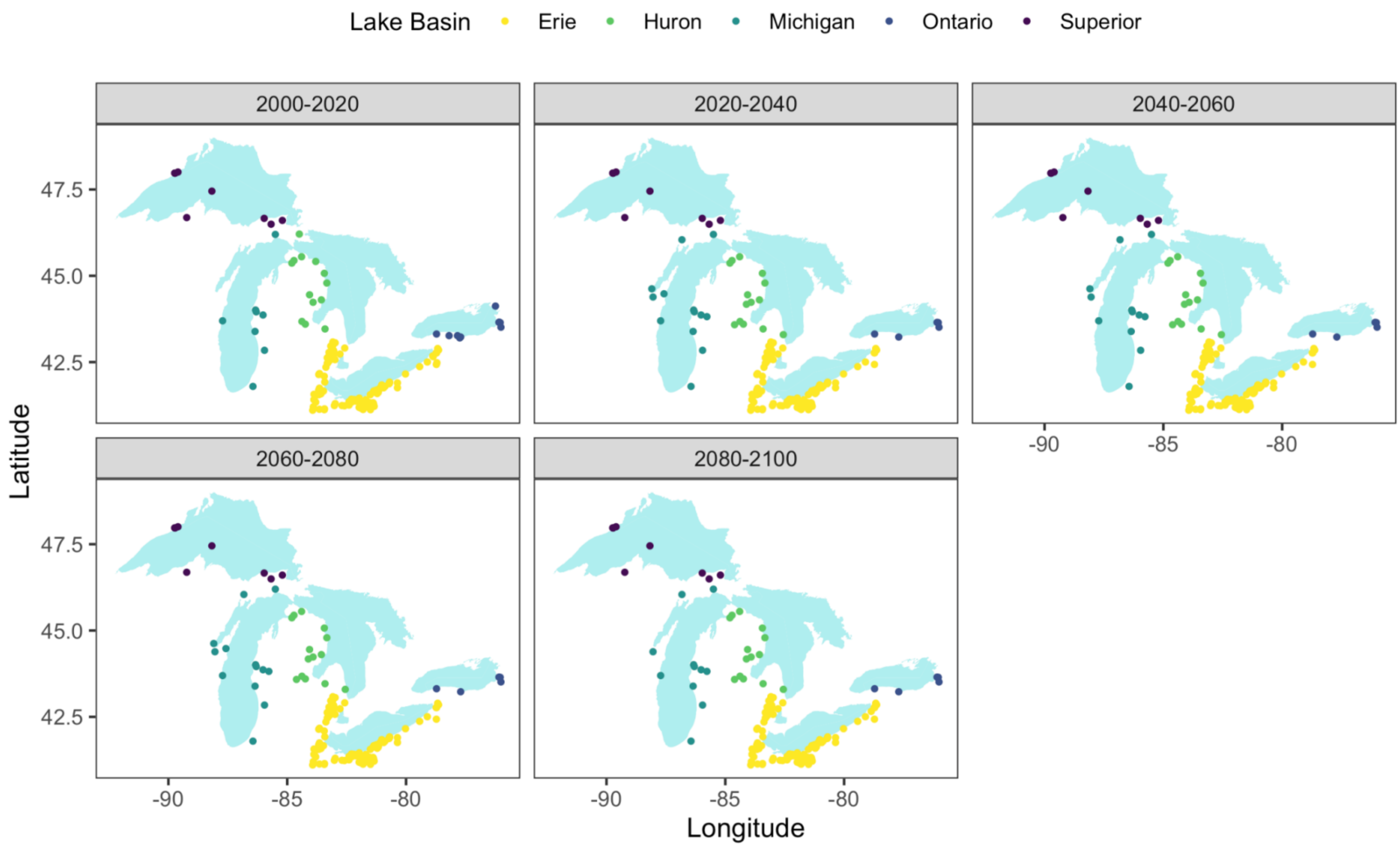


Figure 13. Location of the lowermost barriers within each Great Lake watershed with a greater than 50% mean monthly probability of passing more than 25 sea lampreys across each twenty-year average climate, averaged across the three scenarios of the full model. SSP 3-7.0 was used as the emissions scenario for each future climate projection.

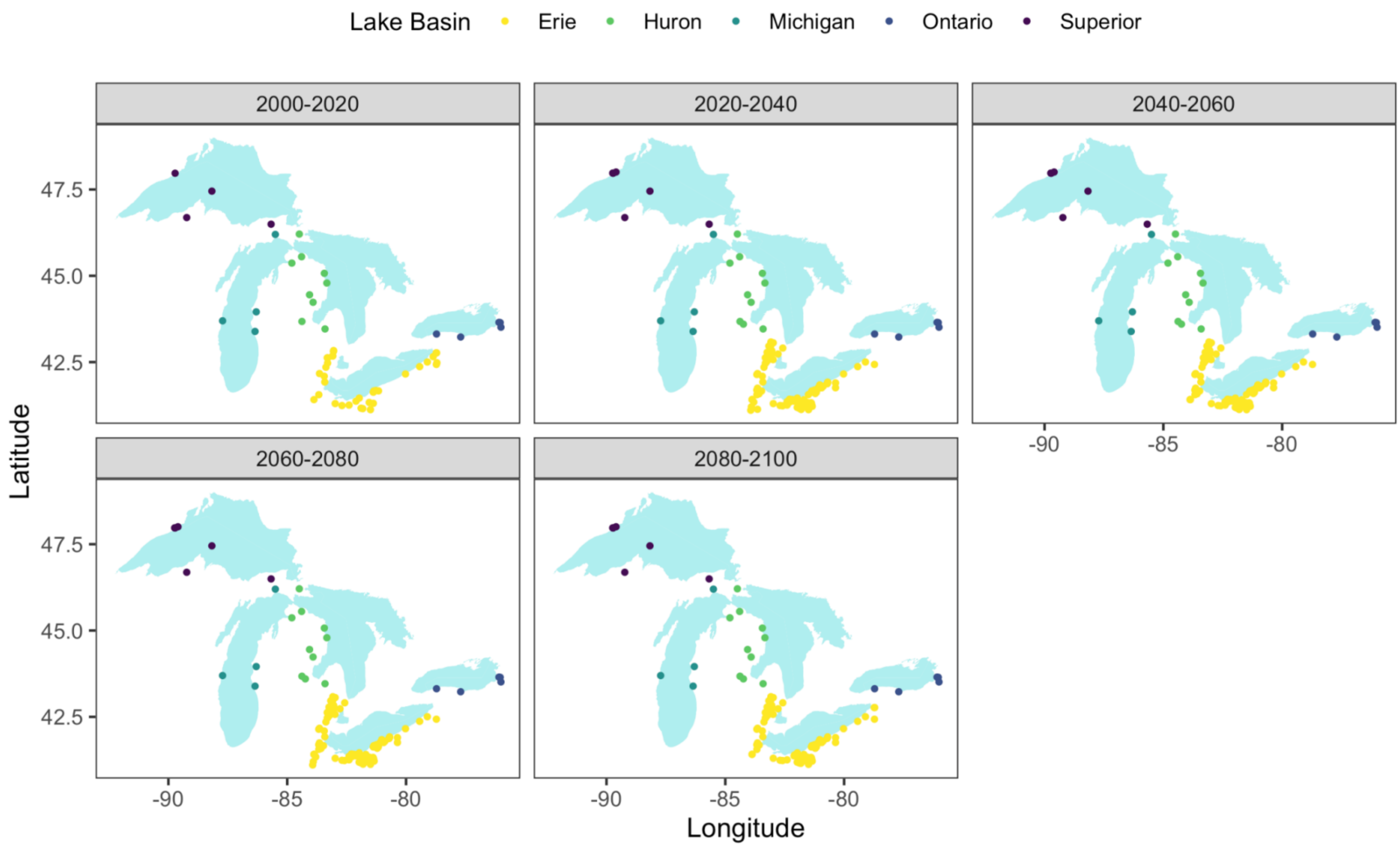


Figure 14. Location of the lowermost barriers within each Great Lake watershed with a greater than 10% mean monthly probability of passing more than 250 sea lampreys across each twenty-year average climate, averaged across the three scenarios of the full model. SSP 3-7.0 was used as the emissions scenario for each future climate projection.

Comparisons across climate projections

Both model structures resulted in variation among months of the spawning migration that appeared to greatly surpass variation among climate projections (Figures 15, 16). The base model resulted in little variation in the posterior probability distributions among months other than May and June (Figure 15), which represent the peak months of sea lamprey spawning activity. This peak was larger for barriers in the Lake Huron and Lake Ontario watersheds. In the Lake Ontario watershed, the probability of passing > 25 sea lampreys was > 50% in May, surpassing the probability of passing < 25 sea lampreys, and in the Lake Huron watershed, the probability of passing > 25 sea lampreys was almost equally as likely as passing < 25. For both lakes, the probability of passing > 25 sea lampreys decreased in all future climate projections. In the Lake Superior and Lake Michigan watersheds, while the months with the highest probability of passing > 25 and > 250 still appeared to track the months of peak spawning activity, this effect appeared weaker than for barriers in the Lake Huron or Lake Ontario watersheds. For barriers in the Lake Erie watershed, uncertainty in migration timing and magnitude left the model unable to effectively categorize the state of abundance upstream of a barrier, and the probability of each state had very little variation across climate projections. Overall, the base model did not characterize any substantial variation among months, or among climate projections, for barriers in any of the Great Lakes watersheds.

The full model resulted in much more noticeable variation among lakes and months of the spawning season (Figure 16). The probability of < 25 sea lampreys passing was lowest in May for the watersheds of Lakes Ontario, Michigan, and Huron, and in June in the Lake Superior watershed. In May, when the spawning migration is typically at its peak, the probability of 25 – 250 sea lampreys passing above barriers in the watersheds of Lakes Ontario and Huron was greater than the probability of < 25. This was particularly true for Lake Ontario barriers, where the probability of passing > 250 sea lampreys was nearly 20%. A secondary peak was observed in the probabilities of both 25 – 250 and > 250 sea lampreys passing in August in the 2081 – 2100 projection for barriers in the Lake Ontario watershed. In most scenarios, the probabilities of passing 25 – 250 or > 250 sea lampreys were consistent among months in the Lake Michigan watershed, except for a small peak in August of the probability of passing 25 – 250 sea lampreys in the 2081 – 2100 projection, and those in the Lake Superior watershed had > 30% probability of passing 25 – 250 sea lampreys in both May and June. For barriers in the Lake Erie watershed, uncertainty in migration timing and magnitude left the model unable to effectively categorize the state of abundance upstream of a barrier, and the probability of each state varied little across climate projections. Excepting barriers in the Lake Ontario and Lake Michigan watersheds, the full model described considerable variation among months and among each Great Lake watershed, but little variation due to climate change. Where variation among climate projections existed, it was in the form of a secondary peak in the probability of passing 25 – 250 and > 250 sea lampreys in August, and only in the 2081 – 2100 climate projections.

For both model structures, varying the emissions scenario of each climate projection had little effect on the probability of each target node state of both model structures, even in the 2081 – 2100 climate projection where any difference between the effects of each emissions scenario would be the greatest (Figures 17, 18). SSP 1 and SSP 2 in both model structures showed very little change. The probability of passing 25 – 250 sea lampreys increased in August for barriers in the Lake Ontario and Lake Michigan watersheds under SSP 3, while the probabilities of passing 25 – 250 and > 250 sea lampreys increased in August in all Great Lake watersheds under SSP 5.

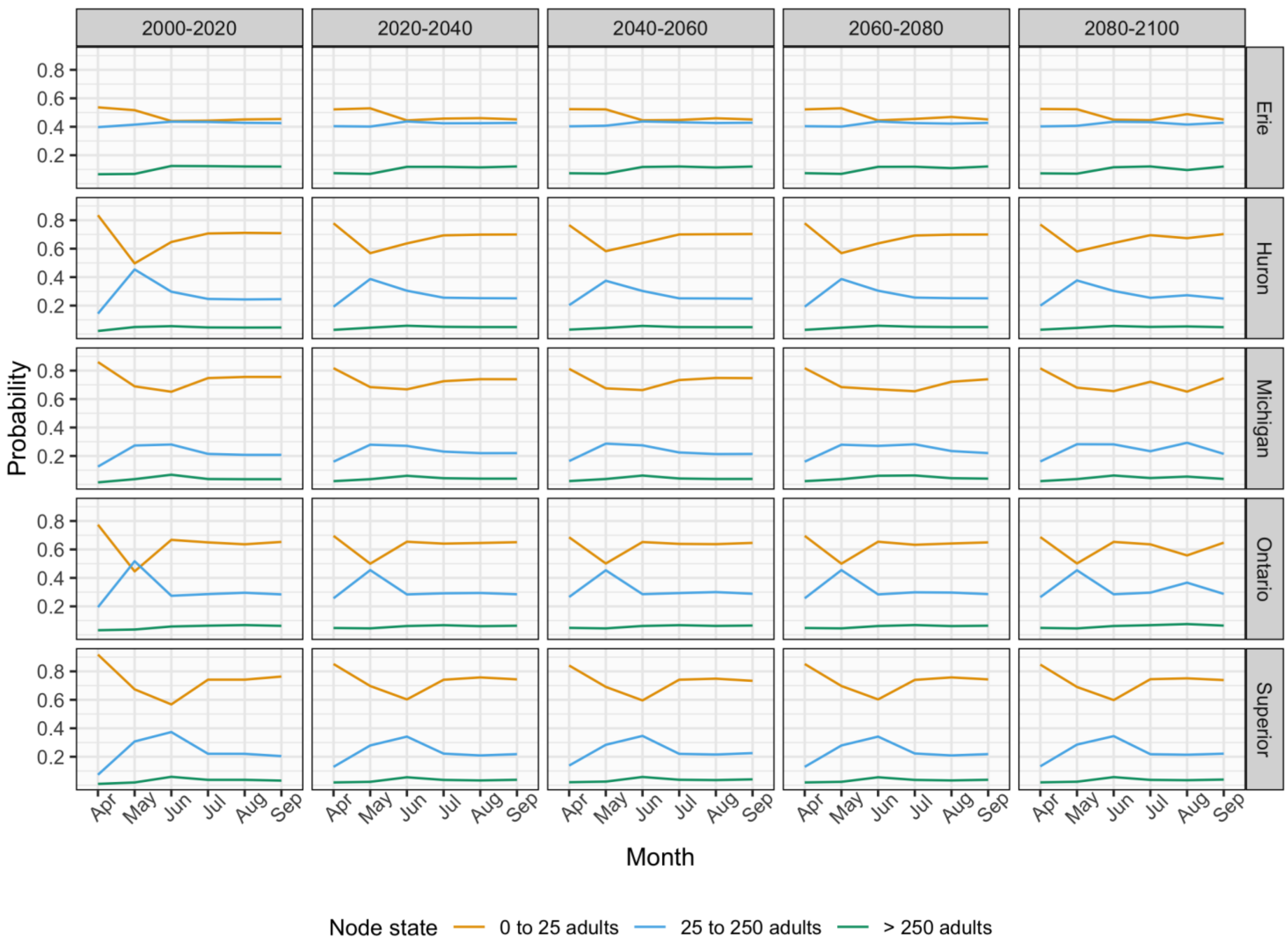


Figure 15. Estimated probability of each state of the abundance of sea lampreys upstream of a barrier across the months of the spawning season for barriers in each Great Lake watershed across each twenty-year climate average, averaged across the three scenarios of the base model. SSP 3-7.0 was used as the emissions scenario for each future climate projection.

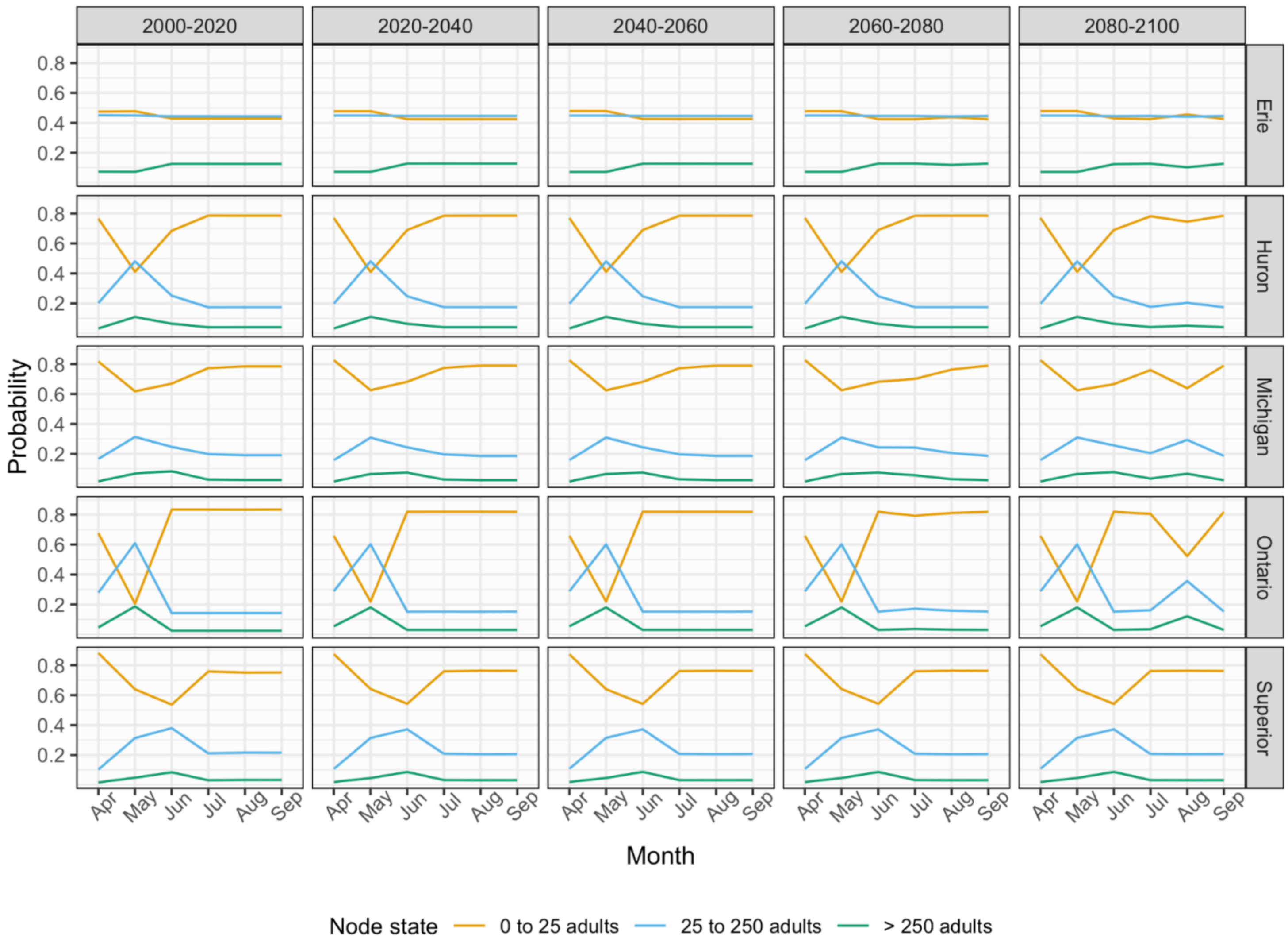


Figure 16. Estimated probability of each state of the abundance of sea lampreys upstream of a barrier across the months of the spawning season for barriers in each Great Lake watershed across each twenty-year climate average, averaged across the three scenarios of the full model. SSP 3-7.0 was used as the emissions scenario for each future climate projection.

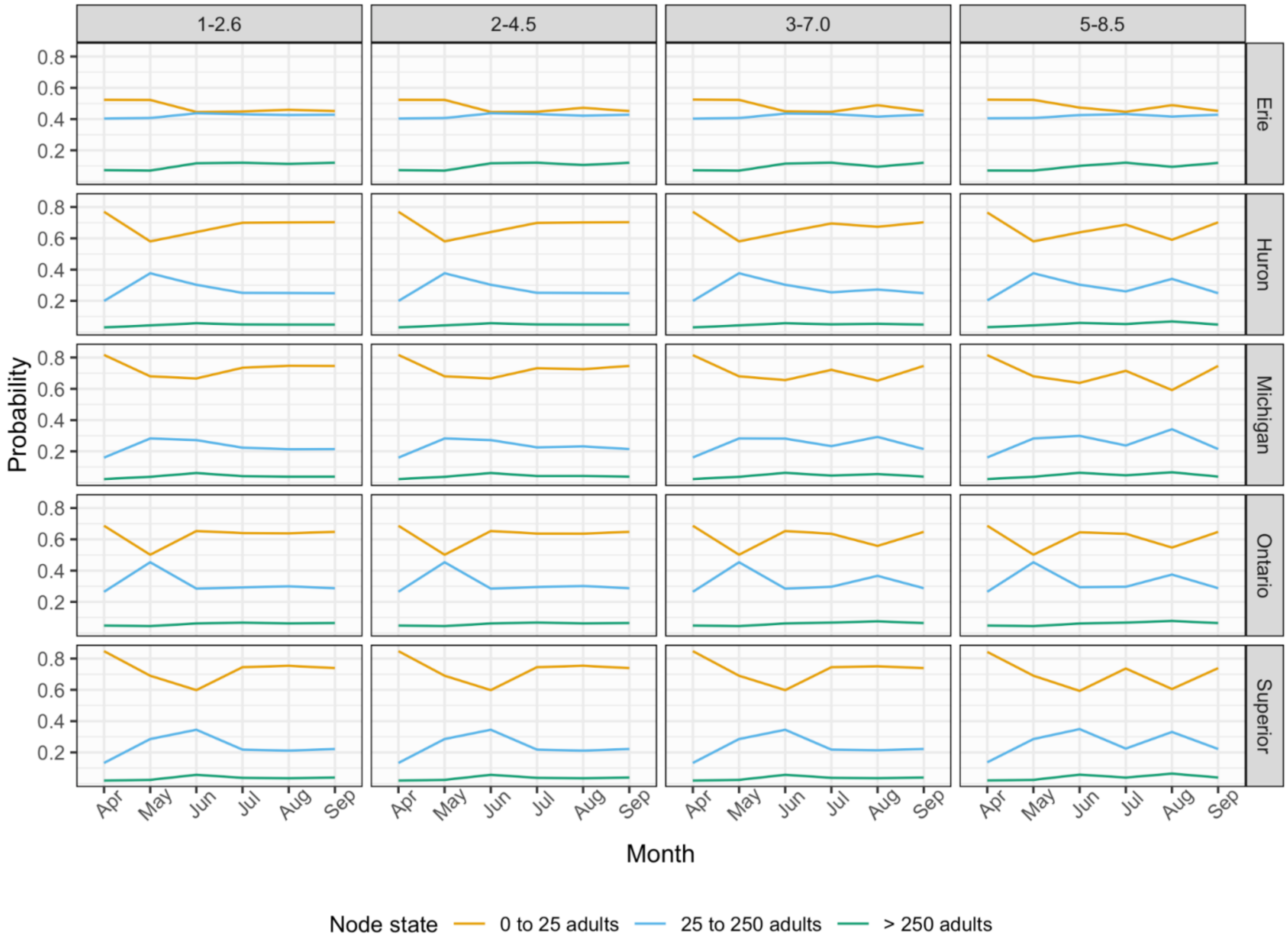


Figure 17. Estimated probability of each state of the abundance of sea lampreys upstream of a barrier across the months of the spawning season for barriers in each Great Lake watershed across each emissions scenario (SSP) for the projected climate of 2081 – 2100, averaged across the three scenarios of the base model.

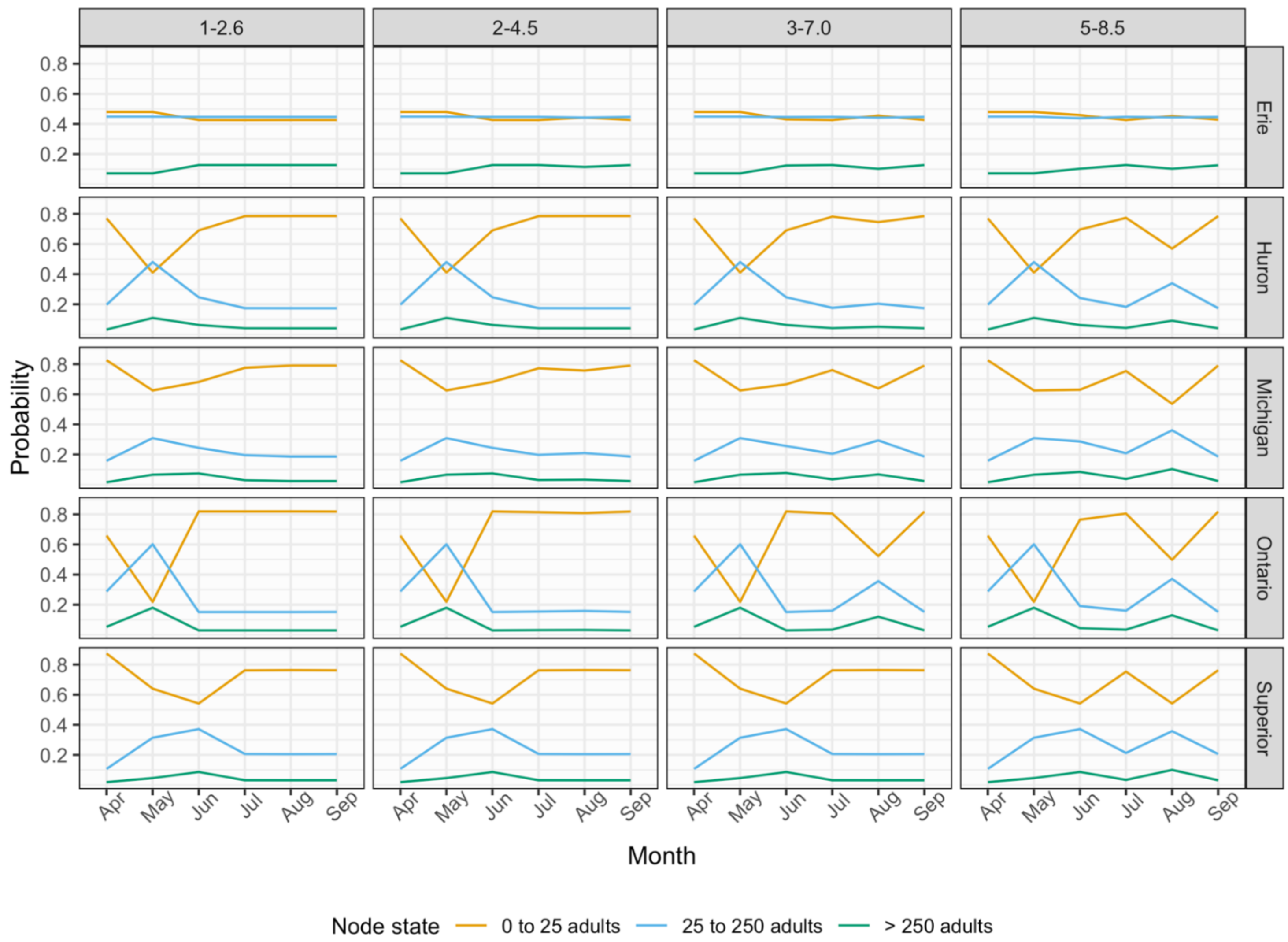


Figure 18. Estimated probability of each state of the abundance of sea lampreys upstream of a barrier across the months of the spawning season for barriers in each Great Lake watershed across each emissions scenario (SSP) for the projected climate of 2081 – 2100, averaged across the three scenarios of the full model.

Fixed-abundance scenario

With the number of spawning-phase sea lampreys in the stream fixed at 500 throughout the year, variation in the abundance upstream of a barrier is solely a factor of the physical permeability of a barrier, and the proportion of sea lampreys in the stream that reach the barrier. With 500 spawners present, the target node can be interpreted as the proportion that would pass the barrier, with the states of the target node interpreted as 0 – 5% passed, 5 – 50% passed, and 50 – 100% passed. The base model showed remarkably little variation among barriers of each Great Lake watershed and over each set of climatic conditions (Figures 19, 20). For nearly every scenario, there was a single transition in May to a decreased probability of less than 5% passage, and an increased probability of passing both 5 – 50% and more than 50% of sea lampreys (Figure 19). The full model characterized noticeable differences among barriers of each Great Lake watershed, but relatively little variation across climatic conditions (Figure 20). While barriers in the watersheds of Lakes Erie, Michigan, and Superior had an increased probability of greater than 50% passage from June onwards, barriers in the watersheds of Lakes Huron and Ontario had an increased probability of less than 5% passage from June onwards. For the Lake Ontario watershed in particular, the results suggest that barriers are very likely to be passed during April and May, but much less likely to be passed afterward. In the 2081 – 2100 climate projection, barriers in this watershed had a large increase in the probability of between 5 – 50% passage in August.

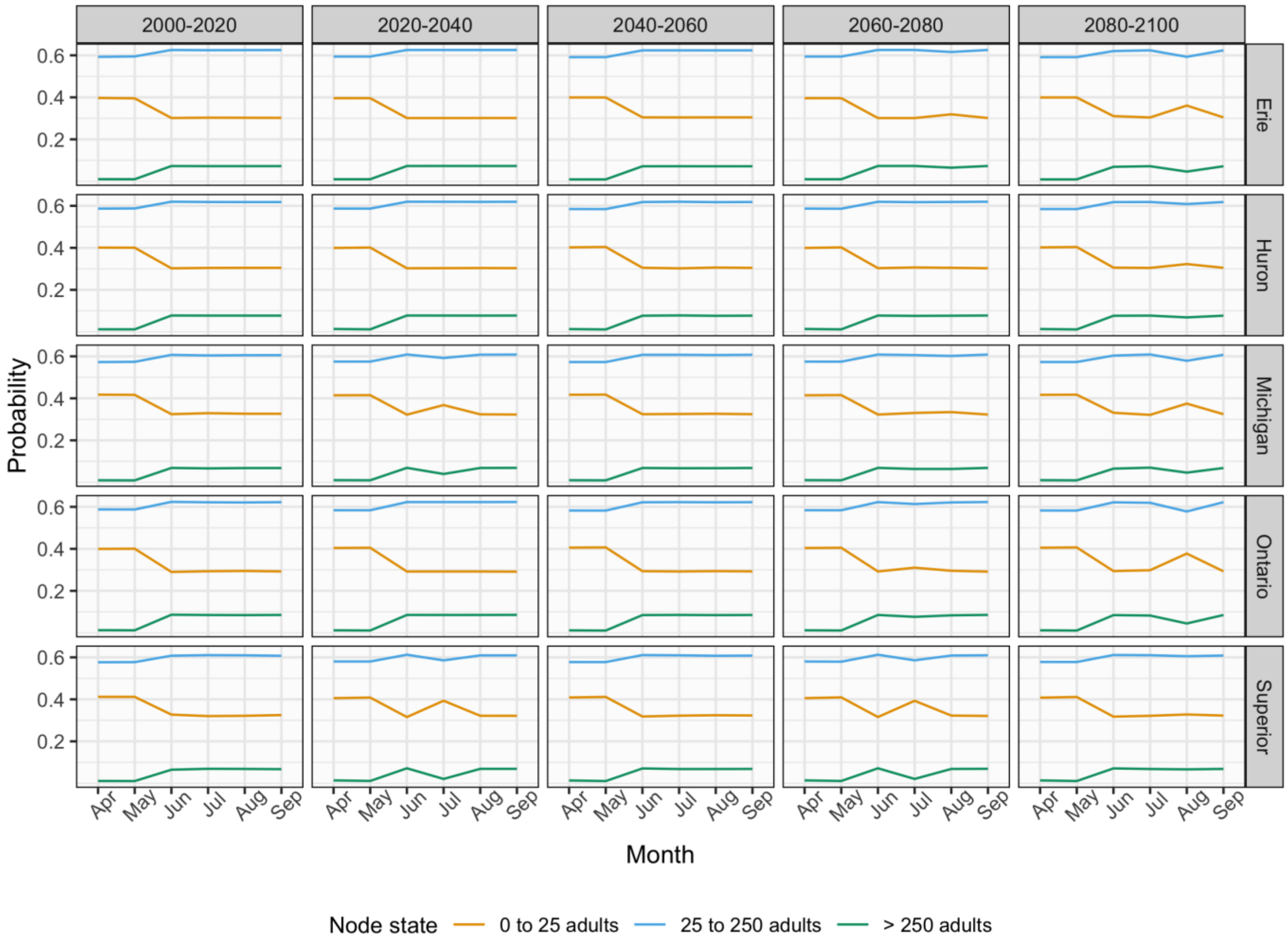


Figure 19. Base model V2 estimated probabilities of each state of the abundance of sea lampreys upstream of a barrier across the months of the spawning season for barriers in each Great Lake watershed across each twenty-year climate average, given a fixed abundance of 500 spawning-phase sea lampreys in the stream. SSP 3-7.0 was used as the emissions scenario for each future climate projection.

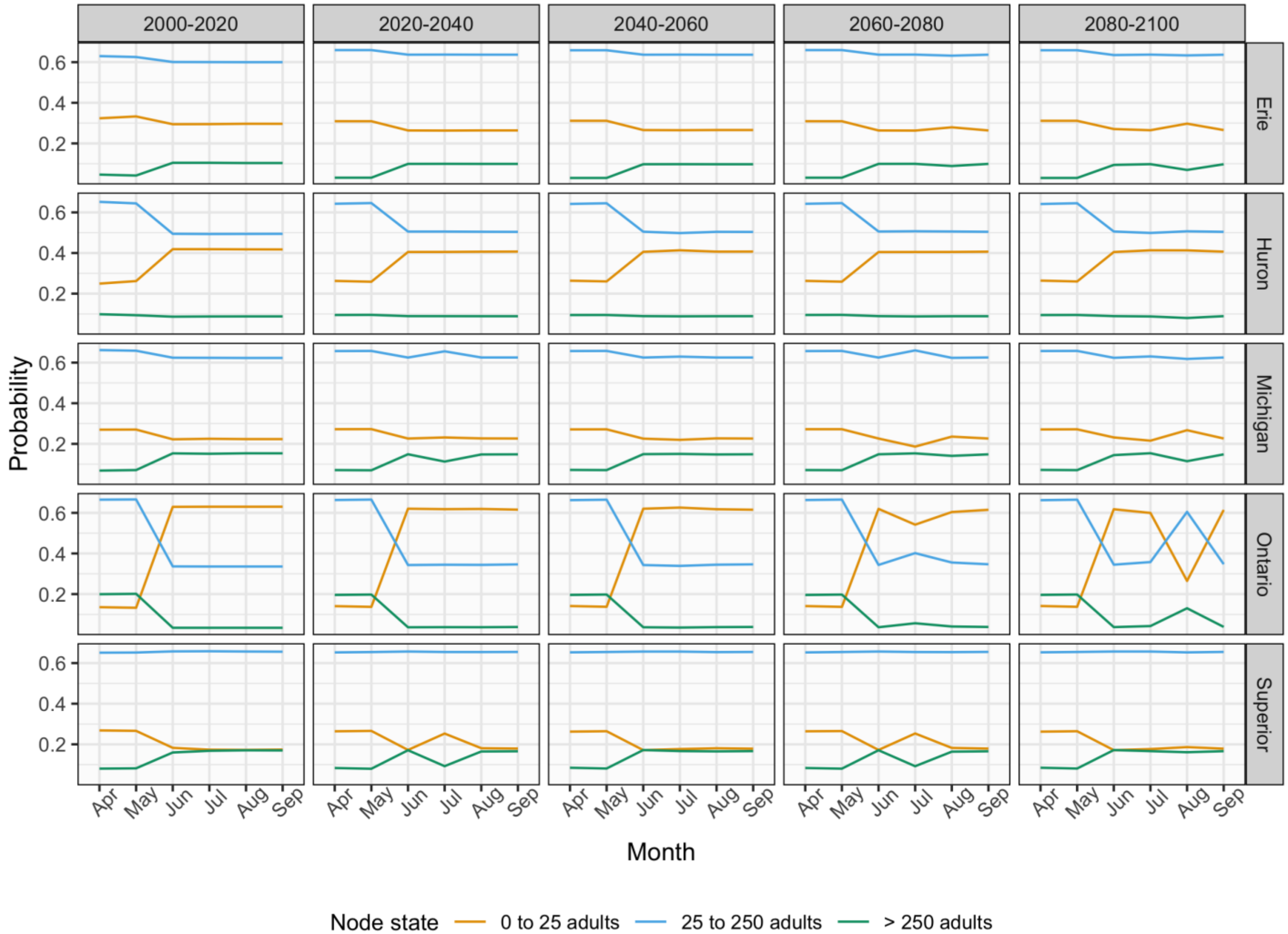


Figure 20. Full model V2 estimated probabilities of each state of the abundance of sea lampreys upstream of a barrier across the months of the spawning season for barriers in each Great Lake watershed across each twenty-year climate average, given a fixed abundance of 500 spawning-phase sea lampreys in the stream. SSP 3-7.0 was used as the emissions scenario for each future climate projection.

CHAPTER 5:

DISCUSSION

This project sought to understand the drivers of variation in the failure of barriers to perfectly block upstream migrating sea lampreys, and the degree to which climate change may affect these variables. I hypothesized that climate, landscape, hydrology, physiology, and phenology would all be influential in categorizing this variation and that where the sea lamprey spawning run overlaps with warming stream temperatures and higher streamflows, the probability of passage would increase. The results of this project suggest that the abundance of spawning-phase sea lampreys in a stream, and the resulting proportion that arrive at the barrier, are both the most critical drivers of the abundance of sea lampreys passing a barrier and the most important sources of uncertainty in evaluating the effectiveness of individual barriers. The effect of these two variables outweighed other variables, including the permeability of a barrier given reductions in the vertical drop at the barrier face. Landscape variables, including those assumed to influence the probability of a flood, were less important drivers; however, the strength of these relationships is uncertain. The watersheds of Lakes Ontario and Huron had the highest proportion of high-risk barriers under each risk metric, but the risk of passage at barriers in each other Great Lake watershed remained largely uncertain. The probability of passing a greater number of sea lampreys increased in all watersheds during the months of peak spawning migration, which may indicate that the consequences for control would be more severe in streams that experience an increase in an earlier or larger spawning run. Varying climatic conditions at each time scale did not strongly affect the risk of passage at barriers in most projections, except for an increased probability of passing a greater number of sea lampreys in August in the 2081 – 2100 climate projection. While these results do not suggest that climate change has a strong influence on barrier passage, knowledge of the spatial and temporal variation is ultimately still useful for sea lamprey control. This work represents a framework for understanding the effects of climate change on sea lampreys and control barriers that can be improved upon given new knowledge and used to inform decisions regarding barrier prioritization and the allocation of sea lamprey control effort.

With no empirical data for quantitative testing of the accuracy of each model structure, I was unable to determine which structure was best able to accurately categorize sea lamprey passage over barriers. The base model structure was able to evaluate the sensitivity of the target node to important causal variables in the network, and the additional variables included in the full model structure did not have a strong influence on the categorization of sea lamprey passage of a barrier. As several of the additional variables included in the full model were intended to categorize the potential for flooding at each barrier, the lack of sensitivity to these variables was unexpected. Potentially, the spatial scale of the model may not have been adequate to capture the influence of the landscape on the potential for flooding, and the monthly time scale of the model likely resulted in important variation being averaged out. Additionally, as there is certainly variation in the propensity of a stream to flood, either the effect of these variables is not being captured adequately by the model or there are aspects of flood potential that were not included. The additional variables included in the full model may also be important for categorizing sea lamprey passage of a barrier, however without the data to complete a robust CPT they are adding very little to the current uncertainty structure. Among the three scenarios of each model structure, the sensitivity to findings analysis indicated that the variance explained by each variable was not affected by uncertainty in the vertical drop height. This was counter to my expectations given the large differences between the CPTs representing each scenario, given the evident differences in the permeability of a barrier under flood conditions as opposed to one with a 45-centimeter vertical drop. This finding could be the result of an inappropriate method used to quantify the three scenarios of the vertical drop, or that the discretization thresholds used to describe barrier permeability are obscuring this influence. Additional data will be necessary to generate a robust CPT and improve model performance.

While the influence of the spawning run size and timing in each stream was dominant, precipitation, stream temperature, the absolute and effective height of the barrier crest, and all landscape descriptors, had a small influence on the number of sea lampreys passed. There are several potential explanations for this given my initial hypothesis of the importance of climatic and landscape variables to barrier effectiveness. First, these variables are relatively certain at the scale of the model, with landscape variables not subject to any change over time and climatic variables included as twenty-year monthly averages. This would lead to high categorization accuracy and little marginal uncertainty. Their influence on the total abundance upstream of a barrier is also likely minimized due to the outsize influence of other variables, particularly those that are highly correlated, and the structure of the model and the data available did not allow us to precisely estimate the effect of these variables on the spawning run size or monthly distribution. Given the current understanding of the effect of temperature and streamflow on sea lamprey spawning, this result is counter to expectation (Binder et al. 2010). Greater certainty about the influence of climatic variables on sea lamprey passage of barriers could be gained with data to precisely categorize the relationship between climatic variables and the monthly distribution of the spawning run. Lastly, while a reduction of the vertical drop at a barrier and variation in the spawning run were modeled as the primary explanations for variation in barrier passage, alternative hypotheses were not modeled. Variables relating to the hydraulic conditions approaching the barrier face, or the presence of native lampreys in streams, were not included and may be responsible for additional unexplained variation that could be influenced by climatic variables (McLaughlin et al. 2003).

While BBNs have been shown to make accurate predictions with scarce data and high uncertainty (Death et al. 2015; Kaikkonen et al. 2020), there were several CPTs with uninformed rows which may have substantially decreased the categorization accuracy of the corresponding nodes. The lack of available data describing the abundance of sea lampreys within a stream in each month of the spawning season is likely a critical uncertainty in the model. Much of the uncertainty about sea lamprey spawning run size and timing appears to come from a lack of knowledge about spawning effort under unfavorable conditions, such as extreme flows or water temperatures at the limit of their physiological capability. As sea lampreys are highly unlikely to spawn in these conditions, traps are not deployed, and no data are collected (McCann et al. 2018). This issue is especially apparent for barriers in the Lake Erie watershed, where sea lamprey production and trapping effort are both low (Mullett et al. 2003). For barriers in the Lake Erie watershed, the model was unable to distinguish differences among months due to this uncertainty, leading to a higher estimated probability of passing sea lampreys than is likely given the low productivity of Lake Erie tributaries.

I observed few substantial changes in the permeability of barriers or the number of sea lampreys passed across each climate projection, my results suggest that unforeseen changes in sea lamprey spawning migration are still a potential problem for maintaining adequate control pressure with barriers and that better prediction of the consequences of climate change on sea lampreys are currently limited by lack of knowledge and available data. While further stream monitoring efforts are necessary to better understand the relationship between climate and sea lamprey phenology and physiology, several studies have begun to predict how sea lampreys might respond to climate change in the Great Lakes (Rahel and Olden 2008; Cline et al. 2014; McCann et al. 2018; Lennox et al. 2020). Current climate models predict warming stream conditions and higher precipitation in the winter and spring in more northern Great Lakes tributaries, and warmer summers in southern tributaries, with a higher risk of dewatering (Cherkauer and Sinha 2010; Byun et al. 2019). Previous work on spawning-phase sea lamprey stream entry and rate of upstream movement (Binder and McDonald 2008; Binder et al. 2010; McCann et al. 2018) suggests that some sea lampreys enter streams as soon as the stream temperature reaches 4˚C with stream entry peaking at 12˚C, whereas trap catches peak at approximately 15˚C. Increased discharge was also correlated with increased spawning activity (McCann et al. 2018), and could also alter the concentration of larval pheromone (Brant et al. 2015; Lennox et al. 2020). Although water temperature is known to be an important predictor of the initiation of the sea lamprey spawning migration, it is still thought to be of secondary importance compared to the concentration of larval pheromone in the water column (Binder and McDonald 2008; Binder et al. 2010; Brant et al. 2015). Future additions to the model could include the effect of changing stream temperature and streamflow on the dispersal and concentration of larval pheromone. Streams experiencing earlier snowmelt-driven runoff, shorter iced-over periods, and higher streamflow could also see earlier stream entry and an increase in the proportion of spawning-phase sea lampreys migrating upstream in tributaries (Lennox et al. 2020). Furthermore, any increase in the number of days with optimal water temperatures for spawning activity could also increase the window of opportunity for barrier passage. An increased density of adults at the barrier might also increase motivation to pass barriers to alleviate habitat limitations. Uncertainty in spawning migration timing may also negatively affect seasonal barrier and trap deployment, further decreasing both control and assessment effectiveness. Additionally, warming conditions may shift the distribution of suitable spawning habitat northward into previously unsuitable streams, and away from previously productive streams. Where streams are becoming prohibitively warm, it is unlikely that upstream migrants will travel far upstream, as spawning activity has been shown to decrease steeply at temperatures above 15˚C, with activity ceasing above 20˚C (Binder and McDonald 2008; Binder et al. 2010).

Another limitation of our approach is the granularity of available data versus the scale at which a barrier passage event might occur. Although the model was developed to evaluate events on a monthly time step, based on climatic and hydrological data resolution, migration events of sea lampreys likely occur over several days (Castro-Santos et al. 2017). Future research should focus on modeling individual processes, with particular focus on the relevant scale of direct effects and indirect interactions with sea lamprey life history. For example, higher streamflow will alter the water level of the stream, the concentration of larval pheromone in the water column, the water velocity in which spawning-phase sea lampreys must swim against, and the substrate composition that affects both spawning and larval habitat, all of which are likely influential at different spatial and temporal scales (Lennox et al. 2020). The modular structure of BBNs lends itself to providing a probabilistic framework for other sub-models, such as individual or cohort-scale models that could precisely estimate upstream movement or barrier passage, which could substantially improve our ability to evaluate the effectiveness of barriers.

Water temperature data for each stream reach containing a barrier were relatively sparse, with the most comprehensive data coming from the USGS Water Data for the Nation (U.S. Geological Survey 2016), but these data were often not located in or close to the reaches of interest. Water temperature data were also available at barriers with traps incorporated, but while usable did not have sufficient spatial extent for my purposes, representing only a small fraction of the total barriers and biased towards streams in the state of Michigan. More complete data, both historical and modeled projections, would strengthen the relationship between changes in climate and potential shifts in sea lamprey phenology and range. The use of level logger data describing the water level at several control barriers was limited by the length of time since deployment, as well as the majority of the level loggers being placed on barriers in the northern Lower Peninsula of Michigan. Lastly, the lack of empirical data to quantify the abundance of sea lamprey adults above a barrier limits quantitative validation efforts such as *k*-fold or leave-one-out cross-validation. While larval surveys are periodically conducted in stream reaches upstream of a barrier, this data only supports that escapement occurred, and does not inform the number of spawning-phase sea lampreys passed, nor the conditions under which it occurred (McLaughlin et al. 2003). Recent research has shown the power of genetic analysis to estimate the potential number of sea lampreys that spawned a cohort (Sard et al. 2020). Further research to understand the hydrological and hydraulic conditions that lead to passage, as well as how increasing passage of spawning-phase adults is related to observable larval production, would be worthwhile.

The posterior probability of each state of upstream passage did not vary as much as I expected, given the variation in spawning run size, stream conditions, and differences in climate. Across all barriers, the average change in monthly precipitation across climate projections was between -3.90 mm and 7.35 mm (SD=2.01), while for monthly minimum temperature it was between 0.80ºC and 2.78ºC (SD=0.28), and for monthly maximum temperature it was between 0.79ºC and 1.64ºC (SD=0.19), but this variation was not present in the posterior probability of each state. There were substantial differences between the estimates of the two model structures, and the full model structure estimated more variation among each Great Lake watershed and month than the base model structure. Given the similarity of both the data included in the construction of the model and the similarity of both sensitivity analyses, this was unexpected. Despite the small percentage of uncertainty on the target node attributed to the variables that were added to the base model structure, they appear to have a substantial influence on barrier passage. This is likely due to how the additional nodes and linkages reduced the uncertainty in nodes that, in turn, have a strong effect on barrier passage. Comparisons across Great Lake watersheds indicated that the Lake Huron and Ontario watersheds contain the highest proportion of high-risk barriers, regardless of climate or the risk metric used. Results from the base model show a noticeable transition from 2000 – 2020 to 2021 – 2040, followed by little change across further climate projections. This does not appear to have an ecological explanation and could indicate that the base model is not accurately estimating barrier passage.

Results from the full model show little change in the proportion of high-risk barriers over time. Comparing across each month of the spawning run, there was little change in the distribution given future climate projections. Although there was a substantial decrease in barrier effectiveness in August in the 2081 – 2100 climate projection, this would be unlikely to affect control efforts as it is after the majority of adult sea lampreys have spawned. If the spawning migration does shift earlier in the year due to warming streams, less effective barriers in August would likely be of even less importance as spawning activity and success would be very low. Although there are relatively few barriers in the Lake Superior watershed, those barriers had a high probability of passing > 250 sea lampreys in June, which is often the peak of the spawning migration in that watershed. If spawning activity increases in more northern streams, such as those in the watersheds of Lakes Superior and Huron, then this could be of consequence for controlling sea lamprey populations in those lakes. When evaluating barriers in streams that would be conducive to sea lamprey spawning based on hydraulic conditions and bottom substrate, but are not currently or regularly producing larvae, efforts should be taken to gauge the stream's suitability for sea lamprey spawning under warmer spring water temperatures.

Differences in the spawning run size in tributaries across the Great Lakes Basin have been previously proposed as a driver of variation in observed larval production upstream of barriers (McLaughlin et al. 2003), which is likely to be influenced by climatic variables. However, we were unable to address several hypotheses (McLaughlin et al. 2003), including the method of attaching a barrier to the streambank, hydraulic characteristics such as water turbidity, and the presence and effect of native lamprey, for which comprehensive data were not available. Therefore, future research should attempt to address each hypothesis when exploring variation in barrier effectiveness. Further data collection should focus on the variables that were found to contribute large amounts of uncertainty to the classification of the risk of passage at each barrier, as well as influence the number of sea lampreys passed, for a greater understanding of both the effectiveness of a barrier and the consequences of passage. Furthermore, while two spawning-phase sea lampreys are sufficient to infest a stream, little is known about the success of spawning after passage. While warming temperatures and more flood-prone streams could drive more sea lampreys to attempt passage, this likely comes at an energetic cost that could negatively affect spawning success (Castro-Santos et al. 2017), particularly if temperatures rose above the optimum for either spawning or egg development. In prioritizing barriers for remediation or removal, combining this body of work with separate models to estimate projected shifts in suitable sea lamprey spawning habitat due to climate change would be useful for predicting barriers that might become more or less essential to the SLCP in the future. Understanding how these climatic changes affect sea lamprey reproductive success, directly and indirectly, is needed to maintain sufficient biological control of the species.

There is little evidence to suggest that the basic structural design of the low-head barrier is flawed (McLaughlin et al. 2003, 2007; Lavis et al. 2003), and these structures have been remarkably successful at preventing passage. However, small reductions in barrier effectiveness, or increases in either the size of the spawning run or the proportion that arrive at a barrier, could result in a greater number of sea lampreys overcoming the structure. A small number of spawning-phase adults can potentially infest a stream given sufficient larval habitat, and the failure of a single, significant control barrier has been shown to lead to a non-linear increase in lake-wide abundance (Jensen and Jones 2018). The potential for even marginal reductions in barrier effectiveness should be a concern, and further research into the number of spawning-phase adults needed to infest a stream could be used to set stream-specific thresholds for control success. Although this study focused on the effectiveness of barriers at preventing invasive sea lampreys from accessing upstream spawning habitat, a similar approach could also be used for assessing and improving passage of migratory fish species over human-made and natural barriers, including anadromous sea lampreys, a species of conservation concern in their native range (Wilkes et al. 2018). This work provides a framework for the creation of a decision-support tool to aid decision-making under multiple uncertainties, whether in the Great Lakes Basin for barrier prioritization and sea lamprey control, or elsewhere for migratory fish conservation.

APPENDICES

APPENDIX A:

SUMMARY TABLE OF LOWERMOST BARRIER TYPES

Table 7: Lowermost barriers by type and Great Lake watershed before and after subsetting the GLFC list of barriers.

Lake Name	*Barrier Type*	*Pre-subset*	*Post-subset*
Erie	Channel	2	0
Erie	Culvert	21	9
Erie	Earthen embankment	32	8
Erie	Hydropower	1	0
Erie	Low head sloped concrete (<8ft)	10	8
Erie	Low head steel sheetpile (<8ft)	3	3
Erie	Low head vertical concrete (<8ft)	12	9
Erie	Other	16	5
Erie	Seasonal (lift gate)	2	2
Erie	Seasonal (stoplog)	1	0
Erie	Sloped concrete non-hydropower (>8 ft)	21	16
Erie	Standpipe	91	38
Erie	Vertical concrete non-hydropower (>8 ft)	15	11
Erie	Waterfall	3	1
Erie	Unknown	33	15
Huron	Culvert	19	10
Huron	Earthen embankment	3	1
Huron	Hydropower	6	5
Huron	Low head sloped concrete (<8ft)	6	5
Huron	Low head steel sheetpile (<8ft)	1	0
Huron	Low head vertical concrete (<8ft)	10	8
Huron	Low head vertical concrete (<8ft)/electrical	1	1
Huron	Other	1	1
Huron	Seasonal (lift gate)	3	3
Huron	Seasonal (stoplog)	1	1
Huron	Sloped concrete non-hydropower (>8 ft)	3	2
Huron	Standpipe	10	5
Huron	Vertical concrete non-hydropower (>8 ft)	6	4
Huron	Unknown	8	5
Michigan	Culvert	6	5
Michigan	Earthen embankment	3	2
Michigan	Hydropower	16	12
Michigan	Low head sloped concrete (<8ft)	6	5

Table 7 (cont'd)

Lake Name	*Barrier Type*	*Pre-subset*	*Post-subset*
Michigan	Low head steel sheetpile (<8ft)	7	5
Michigan	Low head vertical concrete (<8ft)	38	30
Michigan	Other	4	2
Michigan	Sloped concrete non-hydropower (>8 ft)	9	7
Michigan	Standpipe	23	14
Michigan	Steel sheetpile non-hydropower (>8ft)	3	3
Michigan	Vertical concrete non-hydropower (>8 ft)	21	18
Michigan	Unknown	3	2
Ontario	Culvert	6	3
Ontario	Earthen embankment	1	1
Ontario	Hydropower	4	4
Ontario	Low head sloped concrete (<8ft)	6	3
Ontario	Low head steel sheetpile (<8ft)	2	0
Ontario	Low head vertical concrete (<8ft)	21	7
Ontario	Seasonal (lift gate)	2	0
Ontario	Seasonal (stoplog)	1	1
Ontario	Sloped concrete non-hydropower (>8 ft)	6	3
Ontario	Standpipe	11	4
Ontario	Steel sheetpile non-hydropower (>8ft)	1	0
Ontario	Vertical concrete non-hydropower (>8 ft)	18	6
Ontario	Waterfall	8	4
Ontario	Unknown	7	1
Superior	Culvert	3	2
Superior	Earthen embankment	1	0
Superior	Hydropower	6	3
Superior	Low head steel sheetpile (<8ft)	1	1
Superior	Low head vertical concrete (<8ft)	22	16
Superior	Other	3	2
Superior	Seasonal (stoplog)	1	0
Superior	Sloped concrete non-hydropower (>8 ft)	1	1
Superior	Standpipe	9	2
Superior	Vertical concrete non-hydropower (>8 ft)	4	4
Superior	Waterfall	24	20
Superior	Unknown	6	1

APPENDIX B:

DATA SOURCES

Table 8. Full list and description of nodes used between both model structures of the BBN, and source of the data.

Node name	*Node description*	*Unit*	*Spatial scale*	*Temporal scale*	*Source of data*	*Method used to populate CPT*
Lake	Describes watershed	NA	Lake	NA	NA	NA
Month	Describes month	NA	NA	Monthly	NA	NA
Catchment area	Total drainage area of the upstream network catchment	m^2	Network catchment	NA	NHDplus V2	NA
Bankfull area	Mean cross-sectional area of the reach containing the control barrier	m^2	Reach	NA	NHDplus V2.1	NA
Downstream mainstem distance	The distance of the mainstem of the stream, or shortest traveled distance between the barrier and the stream outlet	km	Outlet to barrier	NA	NHDplus V2 High Definition	NA
Barrier type	Describes the angle of the barrier face	NA	Barrier	NA	GLFC list of lowermost barriers	NA
Barrier height (absolute)	The total height of the barrier, not accounting for water level	m	Barrier	NA	GLFC list of lowermost barriers	NA
Vegetation cover	The percentage of vegetated land cover (forested, wetland, grassland, scrub, etc.) of the network catchment that drains to the reach containing the barrier	%	Network catchment	NA	NHDplus V2 modified	NA
Impervious surface cover	The percentage of impervious surface cover (asphalt, concrete, etc.) of the	%	Network catchment	NA	NHDplus V2 modified	NA

	network catchment that drains to the reach containing the barrier					
Flowline slope	The average slope of the network catchment that drains to the reach containing the barrier	degree	Network catchment	NA	NHDplus V2 modified	NA
Lake temperature	The average monthly lake water temperature	C	Lake	Monthly	NOAA GLERL	EM algorithm
Air temperature	The average monthly air temperature	C	Local catchment	Monthly	WorldClim V2.1, 5m	EM algorithm
Precipitation	The average monthly precipitation	mm	Network catchment	Monthly	WorldClim V2.1, 5m	EM algorithm
Precipitation frequency	The average number of rainy days (>1cm) per month	days	Network catchment	Monthly	NHDplus V2.1	EM algorithm
Rainfall/runoff ratio	The average monthly runoff divided by the average monthly precipitation of the network catchment that drains to the reach containing the barrier.	NA	Network catchment	Monthly	NHDplus V2.1	EM algorithm
Mean adult weight	The average annual weight at capture of adult sea lampreys	g	Lake	Annual	SLCP trap catch data	EM algorithm
Mean adult length	The average annual length at capture of adult sea lampreys	mm	Lake	Annual	SLCP trap catch data	EM algorithm
Stream temperature	The average monthly water temperature of the reach containing a barrier	C	Reach	Monthly	Estimated from air temperature	EM algorithm
Streamflow	The average monthly streamflow at the reach containing a barrier	m^3/s	Reach	Monthly	USGS Enhanced Runoff Method (EROM)	EM algorithm
Barrier height (effective drop)	The average vertical drop of the barrier, or the distance between the barrier crest and the water level	m	Barrier	Monthly	Level loggers at control barriers, scenarios	Multiple scenarios
Stream velocity	The average monthly water velocity at the reach containing a barrier	m/s	Reach	Monthly	USGS Enhanced	EM algorithm

					Runoff Method (EROM)	
Barrier permeability	The proportion of spawning-phase sea lampreys able to overcome a barrier in each month	%	Barrier	Monthly	Expert knowledge	Expert knowledge
Upstream movement	The proportion of spawning-phase sea lampreys able to reach a barrier in each month	%	Outlet to barrier	Monthly	Expert knowledge	Expert knowledge
Abundance (in stream)	The number of spawning-phase sea lampreys present throughout the stream in each month	#	Outlet to barrier	Monthly	Calculated from stream abundance model estimates and trap catch data	EM algorithm
Abundance (at barrier)	The number of spawning-phase sea lampreys that are present at the barrier and available to pass in each month	#	Barrier	Monthly	NA	Abundance (in stream) x Upstream movement %
Abundance (above barrier)	The number of spawning-phase sea lampreys that escaped and are present above a barrier in each month	#	Barrier	Monthly	NA	Abundance (at barrier) x Barrier permeability %

APPENDIX C:

EXPERT ELICITATION MATERIAL

Instructions

Begin Questionnaire

Adult sea lamprey abundance at a terminal barrier

We are asking your expert opinion of how the proportion of upstream-migrating adult sea lamprey at a barrier, out of the total abundance of adults in the stream, would vary under different conditions. This will be used to provide prior probabilities for use in a Bayesian Belief Network looking at several effects that climate change will have on sea lamprey and their control in the Great Lakes region.

The method we are using is the 4-step interval elicitation procedure (Speirs-Bridge et al. 2010, de Little et al. 2018).

This questionnaire contains a series scenarios based on adult sea lamprey **abundance in the stream**, **stream temperature**, **weight**, and the **distance from the stream mouth to the barrier**. These are described both in writing and with a picture depicting the given scenario. Scenarios can be navigated through using the yellow buttons at the top of each page.

For this process, please provide a value for the **proportion of adult sea lamprey** in the stream that would reach the first barrier in a stream over the course of a month, ie. P(Abundance_barrier | Abundance_stream, StreamTemp, Distance, Weight). Each scenario will represent different variations of the aforementioned variables. To reduce fatigue, there are fewer scenarios presented than potential combinations in the data, and we will rely on interpolation of aggregated responses to fill in the remaining combinations of states. At the bottom of the form will be a box for your **rationale**, which will be used to determine whether different lines of reasoning led to differences in responses.

For each scenario, please provide:
The **lowest proportion** of adults that you would realistically expect to reach the barrier
The **highest proportion** of adults that you would realistically expect to reach the barrier
Your **best guess of the proportion** of adults that you would realistically expect to reach the barrier
Your **confidence (50-100%)** that the interval you have provided, from lowest to highest, contains the actual proportion of adults that would reach the barrier

<u>Variable Description/Explanation</u>

Adult abundance in stream
The abundance of adult sea lamprey in a stream each month is broken up into three discretized states, **less than 100, 100 to 1000 adults**, and **greater than 1000 adults.**

Water temperature
There is evidence that upstream movement by adult sea lamprey is influenced by relative temperature changes. States of this variable are divided into **less than 5°C, 5 - 15°C, 15 - 25°C, greater than 25°C.**

Stream length from mouth to barrier
Barriers that are further upstream from the mouth of the river are assumed to be more difficult for adult lamprey to reach due to limited energy reserves. States of this variable are divided into **less than 5 km, 5 – 25 km, greater than 25 km**

Weight
Total upstream movement is thought to be largely a factor of limited energy reserves and weight at entry. We have discretized adult sea lamprey body size into **50g bins.**

Previous Scenario

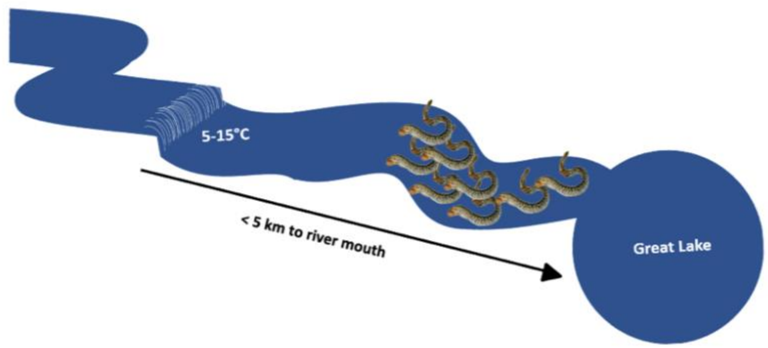
Scenario 1

Next Scenario

Imagine a sea lamprey blocking barrier in a tributary to one of the Great Lakes. Over the course of a single month...

1. The mean abundance of adult sea lamprey in this stream is **greater than 1000 adults**
2. The stream temperature is between **5 - 15°C**
3. The barrier is **less than 5 km** from the stream mouth

Please provide your responses in the table below. For variable descriptions, refer to the list on the **Instructions** sheet.



	Adult weight: **100-150g**	Adult weight: **150-200g**	Adult weight: **200-250g**
What is the **lowest proportion** of adults you would expect to reach the barrier?			
What is the **highest proportion** of adults you would expect to reach the barrier?			
What is your **best guess** of the **true proportion** of adults that would reach the barrier?			
How **confident (50-100%)** are you that the true value is within your given interval?			

Please provide your rationale for your answer here:

Figure 21. Scenario 1 of expert elicitation questionnaire about spawning-phase sea lamprey upstream migration.

Previous Scenario

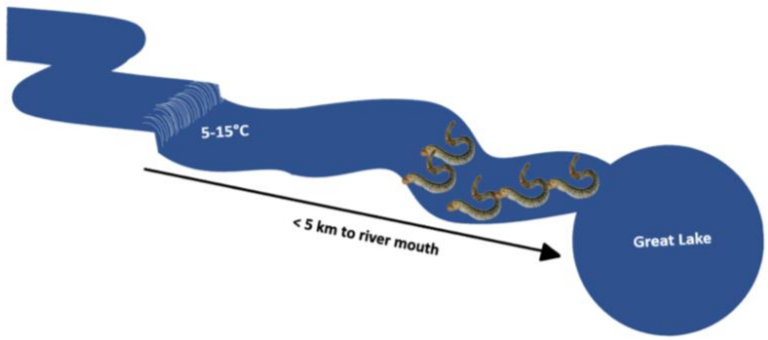
Scenario 2

Next Scenario

Imagine a sea lamprey blocking barrier in a tributary to one of the Great Lakes. Over the course of a single month...

1. The mean abundance of adult sea lamprey in this stream is **100 - 1000 adults**
2. The stream temperature is between **5 - 15°C**
3. The barrier is **less than 5 km** from the stream mouth

Please provide your responses in the table below. For variable descriptions, refer to the list on the **Instructions** sheet.



	Adult weight: **100-150g**	Adult weight: **150-200g**	Adult weight: **200-250g**
What is the **lowest proportion** of adults you would expect to reach the barrier?			
What is the **highest proportion** of adults you would expect to reach the barrier?			
What is your **best guess** of the **true proportion** of adults that would reach the barrier?			
How **confident (50-100%)** are you that the true value is within your given interval?			

Please provide your rationale for your answer here:

Figure 22. Scenario 2 of expert elicitation questionnaire about spawning-phase sea lamprey upstream migration.

Previous Scenario

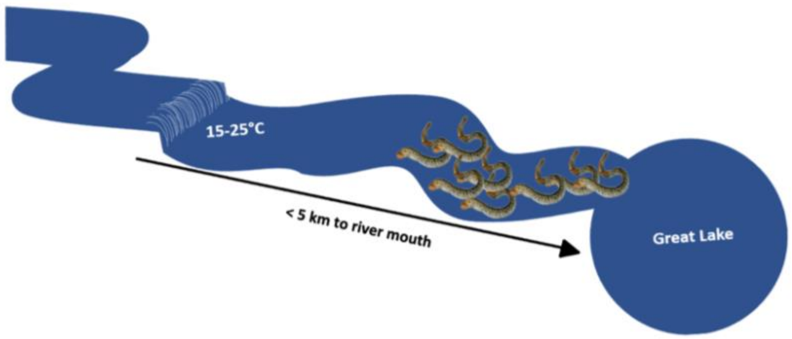
Scenario 3

Next Scenario

Imagine a sea lamprey blocking barrier in a tributary to one of the Great Lakes. Over the course of a single month...

1. The mean abundance of adult sea lamprey in this stream is **greater than 1000 adults**
2. The stream temperature is between **15 - 25°C**
3. The barrier is **less than 5 km** from the stream mouth

Please provide your responses in the table below. For variable descriptions, refer to the list on the **Instructions** sheet.



	Adult weight: **100-150g**	Adult weight: **150-200g**	Adult weight: **200-250g**
What is the **lowest proportion** of adults you would expect to reach the barrier?			
What is the **highest proportion** of adults you would expect to reach the barrier?			
What is your **best guess** of the **true proportion** of adults that would reach the barrier?			
How **confident (50-100%)** are you that the true value is within your given interval?			

Please provide your rationale for your answer here:

Figure 23. Scenario 3 of expert elicitation questionnaire about spawning-phase sea lamprey upstream migration.

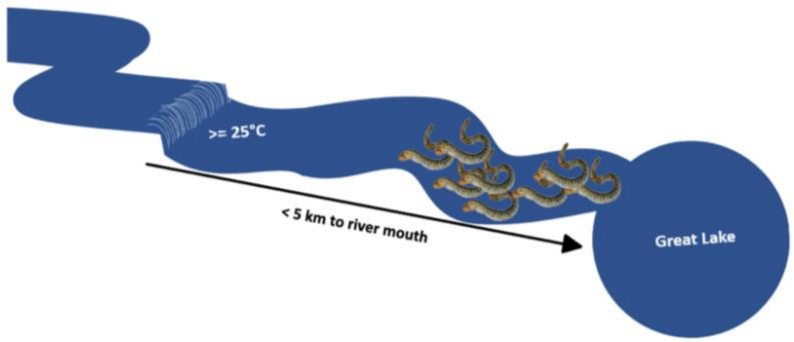
Previous Scenario

Scenario 4

Next Scenario

Imagine a sea lamprey blocking barrier in a tributary to one of the Great Lakes. Over the course of a single month...

1. The mean abundance of adult sea lamprey in this stream is **greater than 1000 adults**
2. The stream temperature is between **greater than 25°C**
3. The barrier is **less than 5 km** from the stream mouth



	Adult weight: **100-150g**	Adult weight: **150-200g**	Adult weight: **200-250g**
What is the **lowest proportion** of adults you would expect to reach the barrier?			
What is the **highest proportion** of adults you would expect to reach the barrier?			
What is your **best guess** of the **true proportion** of adults that would reach the barrier?			
How **confident (50-100%)** are you that the true value is within your given interval?			

Please provide your rationale for your answer here:

Figure 24. Scenario 4 of expert elicitation questionnaire about spawning-phase sea lamprey upstream migration.

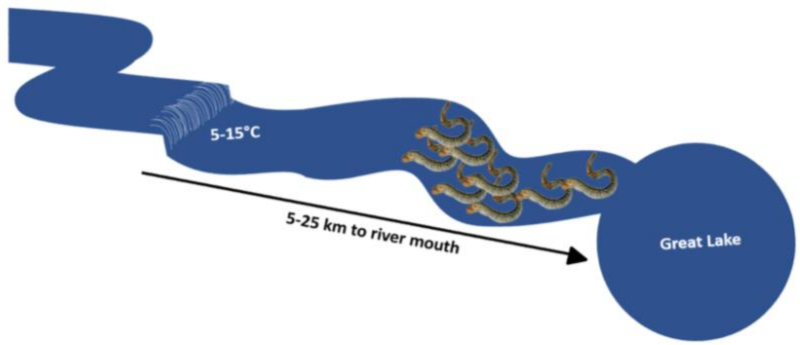
Previous Scenario **Next Scenario**

Scenario 5

Imagine a sea lamprey blocking barrier in a tributary to one of the Great Lakes. Over the course of a single month...

1. The mean abundance of adult sea lamprey in this stream is **greater than 1000 adults**
2. The stream temperature is between **5 - 15°C**
3. The barrier is **between 5 and 25 km** from the stream mouth

Please provide your responses in the table below. For variable descriptions, refer to the list on the **Instructions** sheet.



	Adult weight: **100-150g**	Adult weight: **150-200g**	Adult weight: **200-250g**
What is the **lowest proportion** of adults you would expect to reach the barrier?			
What is the **highest proportion** of adults you would expect to reach the barrier?			
What is your **best guess** of the **true proportion** of adults that would reach the barrier?			
How **confident (50-100%)** are you that the true value is within your given interval?			

Please provide your rationale for your answer here:

Figure 25. Scenario 5 of expert elicitation questionnaire about spawning-phase sea lamprey upstream migration.

Previous Scenario

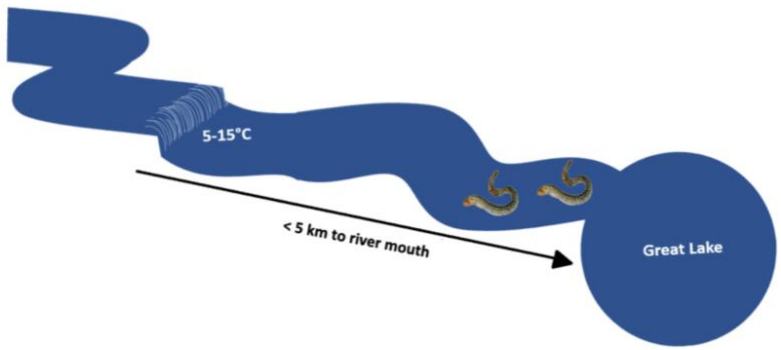
Scenario 6

Next Scenario

Imagine a sea lamprey blocking barrier in a tributary to one of the Great Lakes. Over the course of a single month...

1. The mean abundance of adult sea lamprey in this stream is **less than 100 adults**
2. The stream temperature is between **5 - 15°C**
3. The barrier is **less than 5 km** from the stream mouth

Please provide your responses in the table below. For variable descriptions, refer to the list on the **Instructions** sheet.



	Adult weight: **100-150g**	Adult weight: **150-200g**	Adult weight: **200-250g**
What is the **lowest proportion** of adults you would expect to reach the barrier?			
What is the **highest proportion** of adults you would expect to reach the barrier?			
What is your **best guess** of the **true proportion** of adults that would reach the barrier?			
How **confident (50-100%)** are you that the true value is within your given interval?			

Please provide your rationale for your answer here:

Figure 26. Scenario 6 of expert elicitation questionnaire about spawning-phase sea lamprey upstream migration.

Previous Scenario

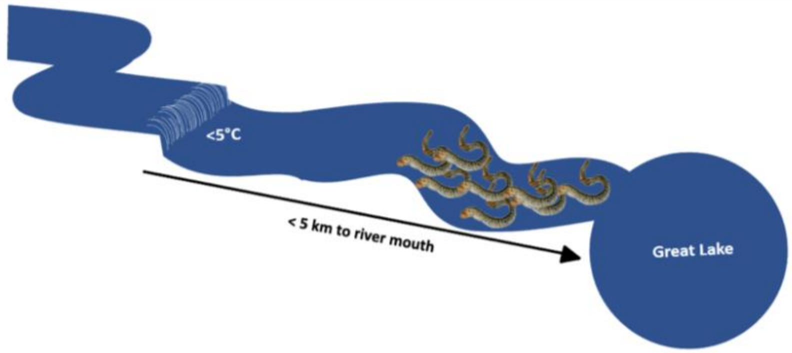
Scenario 7

Next Scenario

Imagine a sea lamprey blocking barrier in a tributary to one of the Great Lakes. Over the course of a single month...

1. The mean abundance of adult sea lamprey in this stream is **greater than 1000 adults**
2. The stream temperature is between **less than 5°C**
3. The barrier is **less than 5 km** from the stream mouth

Please provide your responses in the table below. For variable descriptions, refer to the list on the **Instructions** sheet.



	Adult weight: **100-150g**	Adult weight: **150-200g**	Adult weight: **200-250g**
What is the **lowest proportion** of adults you would expect to reach the barrier?			
What is the **highest proportion** of adults you would expect to reach the barrier?			
What is your **best guess** of the **true proportion** of adults that would reach the barrier?			
How **confident (50-100%)** are you that the true value is within your given interval?			

Please provide your rationale for your answer here:

Figure 27. Scenario 7 of expert elicitation questionnaire about spawning-phase sea lamprey upstream migration.

Previous Scenario

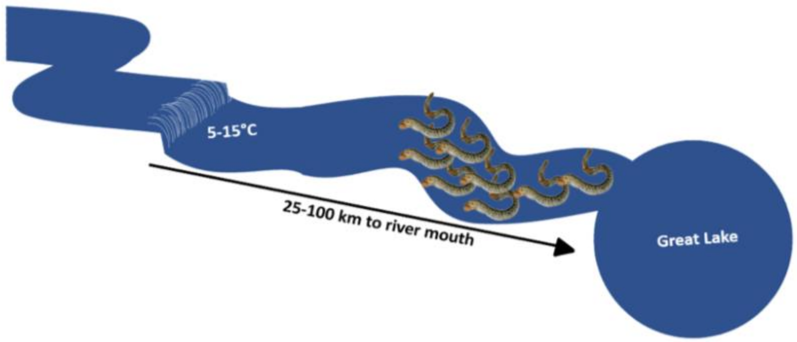
Scenario 8

Next Scenario

Imagine a sea lamprey blocking barrier in a tributary to one of the Great Lakes. Over the course of a single month...

1. The mean abundance of adult sea lamprey in this stream is **greater than 1000 adults**
2. The stream temperature is between **5 - 15°C**
3. The barrier is **between 25 and 100 km** from the stream mouth

Please provide your responses in the table below. For variable descriptions, refer to the list on the **Instructions** sheet.



	Adult weight: **100-150g**	Adult weight: **150-200g**	Adult weight: **200-250g**
What is the **lowest proportion** of adults you would expect to reach the barrier?			
What is the **highest proportion** of adults you would expect to reach the barrier?			
What is your **best guess** of the **true proportion** of adults that would reach the barrier?			
How **confident (50-100%)** are you that the true value is within your given interval?			

Please provide your rationale for your answer here:

Figure 28. Scenario 8 of expert elicitation questionnaire about spawning-phase sea lamprey upstream migration.

Previous Scenario

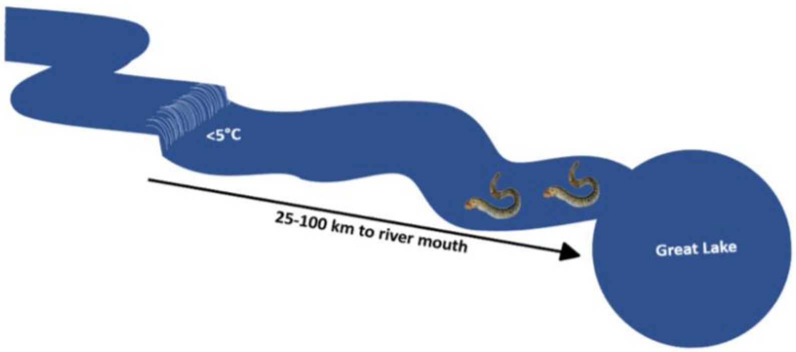
Scenario 9

Next Scenario

Imagine a sea lamprey blocking barrier in a tributary to one of the Great Lakes. Over the course of a single month...

1. The mean abundance of adult sea lamprey in this stream is **less than 100 adults**
2. The stream temperature is between **less than 5°C**
3. The barrier is **between 25 and 100 km** from the stream mouth

Please provide your responses in the table below. For variable descriptions, refer to the list on the **Instructions** sheet.



	Adult weight: **100-150g**	Adult weight: **150-200g**	Adult weight: **200-250g**
What is the **lowest proportion** of adults you would expect to reach the barrier?			
What is the **highest proportion** of adults you would expect to reach the barrier?			
What is your **best guess** of the **true proportion** of adults that would reach the barrier?			
How **confident (50-100%)** are you that the true value is within your given interval?			

Please provide your rationale for your answer here:

Figure 29. Scenario 9 of expert elicitation questionnaire about spawning-phase sea lamprey upstream migration.

Instructions

Begin Questionnaire

Adult sea lamprey rate of passage over barriers

We are asking your expert opinion of how the rate of passage for upstream-migrating adult sea lamprey over a barrier would vary under different conditions. This will be used to provide prior probabilities for use in a Bayesian Belief Network looking at several effects that climate change will have on sea lamprey and their control in the Great Lakes region.

The method we are using is the 4-step interval elicitation procedure (Speirs-Bridge et al. 2010, de Little et al. 2018).

This questionnaire contains a series of scenarios based on hypothetical barriers of varying **slopes, minimum effective heights,** and **mean water velocities,** with adult sea lamprey of a range of **total lengths**. These are described both in writing and with a picture depicting the given scenario. Scenarios can be navigated through using the yellow buttons at the top of each page.

For this process, please provide a value for the **proportion of spawning adults** that would successfully pass the barrier over the course of a month, ie. P(Passage | Type, Height, Water Velocity, Total Length). Each scenario will represent different conditions at the barrier, and three different length categories of adult sea lamprey. To reduce fatigue, there are fewer scenarios presented than potential combinations in the data, and we will rely on interpolation of aggregated responses to fill in the remaining combinations of states. At the bottom of the form will be a box for your **rationale**, which will be used to determine whether different lines of reasoning led to differences in responses.

For each size class of sea lamprey in a scenario, please provide:

The **lowest proportion** of adult sea lamprey that you would realistically expect to pass the barrier
The **highest proportion** of adult sea lamprey that you would realistically expect to pass the barrier
Your **best guess of the true proportion** of adult sea lamprey that would pass the barrier
Your **confidence (50-100%)** that the interval you have provided, from lowest to highest, contains the actual proportion of adult sea lamprey that would pass upstream

<u>Variable Description/Explanation</u>

Barrier Slope
The classification of barriers is based on the GLFC list of barriers, but has been summarized for simplicity. We are defining a barrier as all **fixed-crest dams** that regularly prevent sea lamprey passage, including but not limited to, hydropower dams, earthen embankments, and low-head dams. Barriers are divided by incline, with **sloped-face barriers** including those with inclines between 30-60 degrees and **vertical-face barriers** with a 90 degree face.

Minimum Effective Barrier Height
The minimum distance between the crest of a barrier and the water level at peak flow is a metric of how much of an obstacle the barrier would be for up-migrating sea lamprey. In these scenarios, consider the presented distance to describe the **minimum height of the barrier at peak flow.** Effective heights are discretized into **15 cm bins**

Adult Total Length
Fish swimming performance has been shown to be highly correlated with body length. We have discretized mean adult total length into **100 mm size ranges**.

Water Velocity
While high flow events will decrease the effective height of a barrier, they will also increase the water velocity and potentially make it more challenging for adult lamprey to pass. Water velocities have been discretized into **2 m/s bins**.

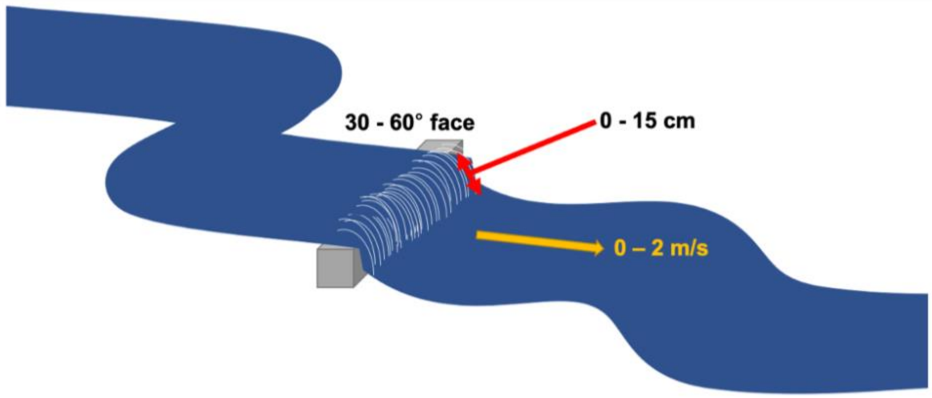
Previous Scenario

Scenario 1

Next Scenario

Imagine a sea lamprey blocking barrier in a tributary to one of the Great Lakes...

1. It is a **sloped-face dam** with an effective height of **0 - 15 cm**
2. The mean water velocity at the barrier is **0 - 2 m/s.**



	Adult length: **400-500mm**	Adult length: **500-600mm**	Adult length: **600-700mm**
What is the **lowest proportion** of adult sea lamprey, that would realistically pass?			
What is the **highest proportion** of adult sea lamprey that would realistically pass?			
What is your **best guess** of the true proportion of adult sea lamprey that would pass?			
How **confident (50-100%)** are you that the true value is within your given interval?			

Please provide your rationale for your answer here:

Figure 30. Scenario 1 of expert elicitation questionnaire about spawning-phase sea lamprey passage over control barriers.

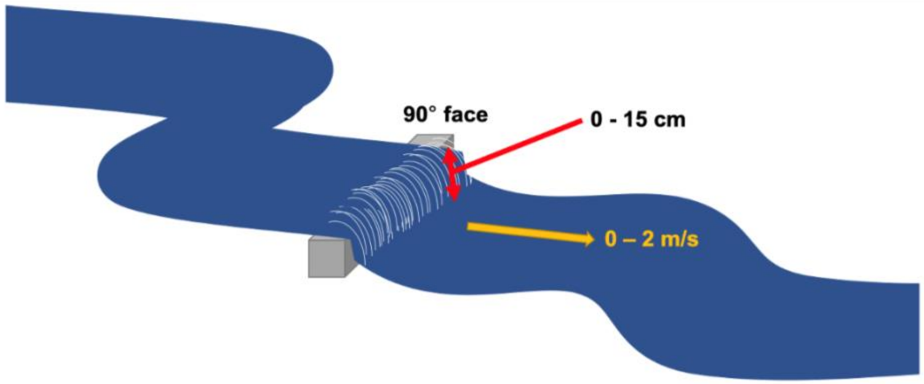
Previous Scenario

Scenario 2

Next Scenario

Imagine a sea lamprey blocking barrier in a tributary to one of the Great Lakes...

1. It is a **vertical-face dam** with an effective height of **0 - 15 cm.**
2. The mean water velocity at the barrier is **0 - 2 m/s.**



	Adult length: **400-500mm**	Adult length: **500-600mm**	Adult length: **600-700mm**
What is the **lowest proportion** of adult sea lamprey, that would realistically pass?			
What is the **highest proportion** of adult sea lamprey that would realistically pass?			
What is your **best guess** of the true proportion of adult sea lamprey that would pass?			
How **confident (50-100%)** are you that the true value is within your given interval?			

Please provide your rationale for your answer here:

Figure 31. Scenario 2 of expert elicitation questionnaire about spawning-phase sea lamprey passage over control barriers.

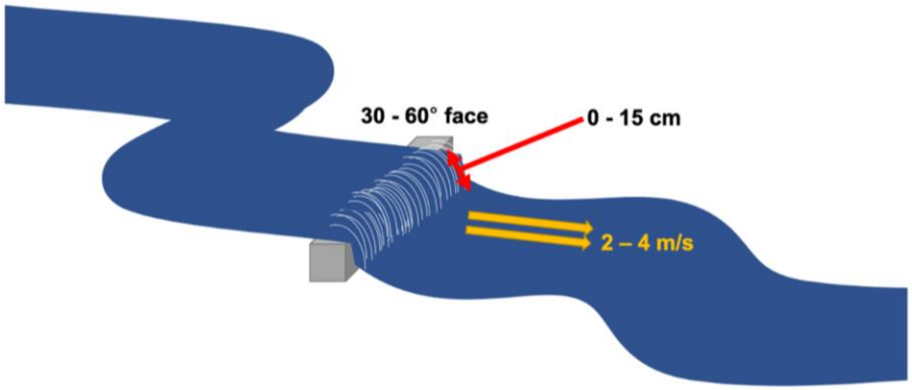
Previous Scenario

Scenario 3

Next Scenario

Imagine a sea lamprey blocking barrier in a tributary to one of the Great Lakes...

1. It is a **sloped-face dam** with an effective height of **0 - 15 cm.**
2. The mean water velocity at the barrier is **2 - 4 m/s.**



	Adult length: **400-500mm**	Adult length: **500-600mm**	Adult length: **600-700mm**
What is the **lowest proportion** of adult sea lamprey, that would realistically pass?			
What is the **highest proportion** of adult sea lamprey that would realistically pass?			
What is your **best guess** of the true proportion of adult sea lamprey that would pass?			
How **confident (50-100%)** are you that the true value is within your given interval?			

Please provide your rationale for your answer here:

Figure 32. Scenario 3 of expert elicitation questionnaire about spawning-phase sea lamprey passage over control barriers.

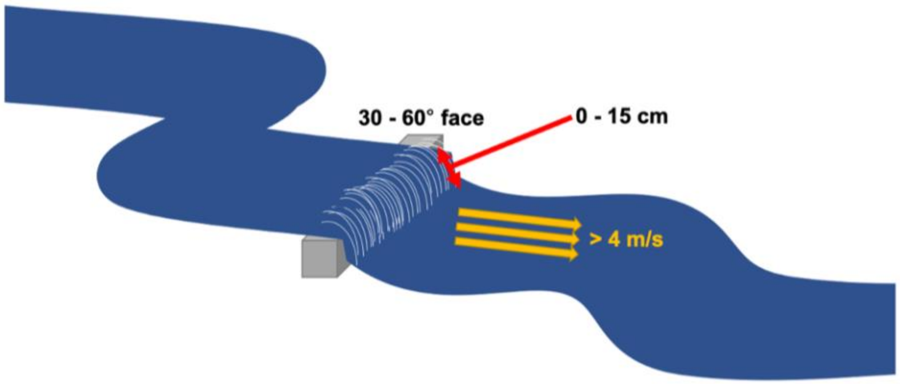
Previous Scenario

Scenario 4

Next Scenario

Imagine a sea lamprey blocking barrier in a tributary to one of the Great Lakes...

1. It is a **sloped-face dam** with an effective height of **0 - 15 cm.**
2. The mean water velocity at the barrier is **> 4 m/s.**



	Adult length: **400-500mm**	Adult length: **500-600mm**	Adult length: **600-700mm**
What is the **lowest proportion** of adult sea lamprey, that would realistically pass?			
What is the **highest proportion** of adult sea lamprey that would realistically pass?			
What is your **best guess** of the true proportion of adult sea lamprey that would pass?			
How **confident (50-100%)** are you that the true value is within your given interval?			

Please provide your rationale for your answer here:

Figure 33. Scenario 4 of expert elicitation questionnaire about spawning-phase sea lamprey passage over control barriers.

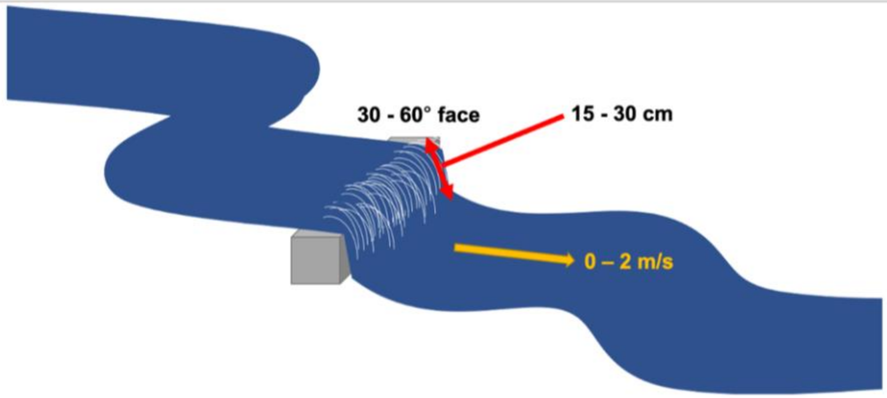
Previous Scenario

Scenario 5

Next Scenario

Imagine a sea lamprey blocking barrier in a tributary to one of the Great Lakes...

1. It is a **sloped-face dam** with an effective height of **15 - 30 cm**
2. The mean water velocity at the barrier is **0 - 2 m/s.**



	Adult length: **400-500mm**	Adult length: **500-600mm**	Adult length: **600-700mm**
What is the **lowest proportion** of adult sea lamprey, that would realistically pass?			
What is the **highest proportion** of adult sea lamprey that would realistically pass?			
What is your **best guess** of the true proportion of adult sea lamprey that would pass?			
How **confident (50-100%)** are you that the true value is within your given interval?			

Please provide your rationale for your answer here:

Figure 34. Scenario 5 of expert elicitation questionnaire about spawning-phase sea lamprey passage over control barriers.

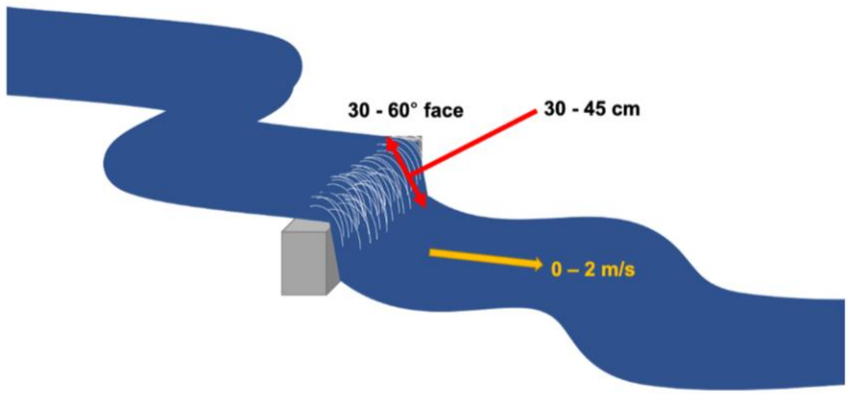
Previous Scenario

Scenario 6

Next Scenario

Imagine a sea lamprey blocking barrier in a tributary to one of the Great Lakes...

1. It is a **sloped-face dam** with an effective height of **30 - 45 cm**
2. The mean water velocity at the barrier is **0 - 2 m/s.**



	Adult length: **400-500mm**	Adult length: **500-600mm**	Adult length: **600-700mm**
What is the **lowest proportion** of adult sea lamprey, that would realistically pass?			
What is the **highest proportion** of adult sea lamprey that would realistically pass?			
What is your **best guess** of the true proportion of adult sea lamprey that would pass?			
How **confident (50-100%)** are you that the true value is within your given interval?			

Please provide your rationale for your answer here:

Figure 35. Scenario 6 of expert elicitation questionnaire about spawning-phase sea lamprey passage over control barriers.

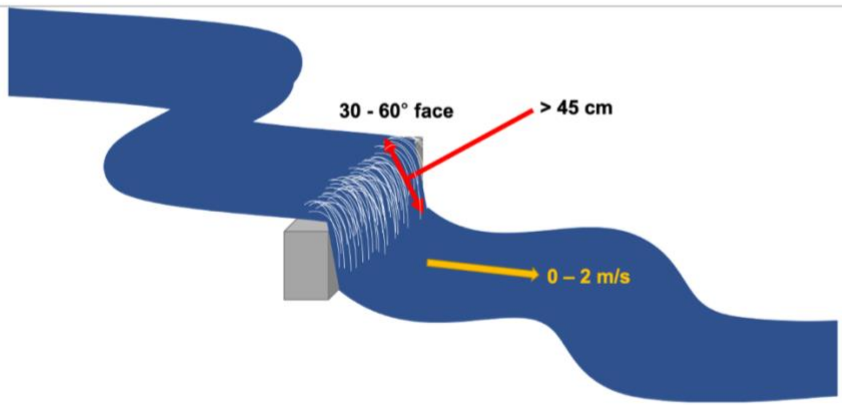
Previous Scenario

Scenario 7

Next Scenario

Imagine a sea lamprey blocking barrier in a tributary to one of the Great Lakes...

1. It is a **sloped-face dam** with an effective height of **> 45 cm.**
2. The mean water velocity at the barrier is **0 - 2 m/s.**



	Adult length: **400-500mm**	Adult length: **500-600mm**	Adult length: **600-700mm**
What is the **lowest proportion** of adult sea lamprey, that would realistically pass?			
What is the **highest proportion** of adult sea lamprey that would realistically pass?			
What is your **best guess** of the true proportion of adult sea lamprey that would pass?			
How **confident (50-100%)** are you that the true value is within your given interval?			

Please provide your rationale for your answer here:

Figure 36. Scenario 7 of expert elicitation questionnaire about spawning-phase sea lamprey passage over control barriers.

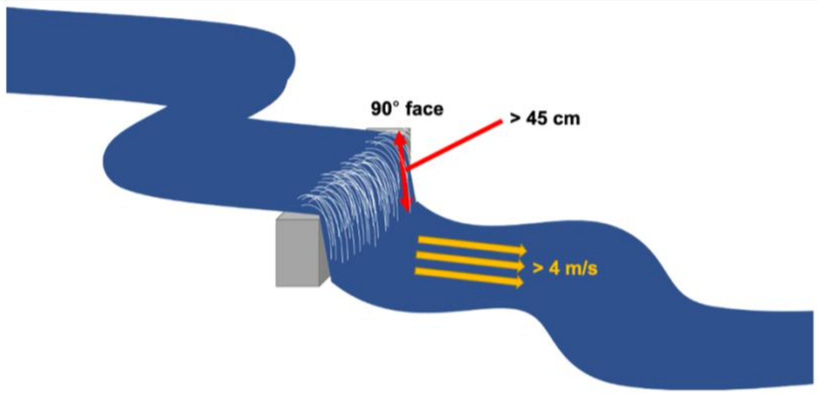
Previous Scenario

Scenario 8

Next Scenario

Imagine a sea lamprey blocking barrier in a tributary to one of the Great Lakes...

1. It is a **vertical-face dam** with an effective height of **> 45 cm.**
2. The mean water velocity at the barrier is **> 4 m/s.**



	Adult length: **400-500mm**	Adult length: **500-600mm**	Adult length: **600-700mm**
What is the **lowest proportion** of adult sea lamprey, that would realistically pass?			
What is the **highest proportion** of adult sea lamprey that would realistically pass?			
What is your **best guess** of the true proportion of adult sea lamprey that would pass?			
How **confident (50-100%)** are you that the true value is within your given interval?			

Please provide your rationale for your answer here:

Figure 37. Scenario 8 of expert elicitation questionnaire about spawning-phase sea lamprey passage over control barriers.

APPENDIX D:

DOCUMENTATION FOR INFORMAL REVIEW OF BAYESIAN BELIEF NETWORK

Documentation for informal review of Bayesian belief network

Project objectives

The main objective of this project is to develop a Bayesian belief network model (BBN) to evaluate the effect of various factors on the effectiveness of a sea lamprey control barrier. As direct monitoring of escapement is difficult, our model instead integrates our knowledge of the factors responsible for escapement, quantifies these relationships, and hopefully results in a fairly accurate representation of the system. Without data on the number of sea lamprey passing each barrier, we cannot quantitatively determine the categorization accuracy of the model. Therefore, as part of our project, we are conducting an expert review of the model and its components to help ensure that model behavior conforms with our best understanding.

Bayesian belief network models

BNs are probabilistic models that graphically represent the conditional independence between variables. This type of model is a directed, acyclic graph, with causation flowing in a single direction, and is incapable of representing feedback loops. In a BN, each variable is shown as a **node**, and each relationship is shown as a **link**. A causal node is referred to as a **parent node**, and each node it influences, a **child node**.

Each node is broken down into a series of discrete **states** that represent the possible outcomes of that node. Continuous variables need to be discretized into “bins” for proper classification. In general, we attempt to keep the number of discretized states of a continuous variable to five or fewer to improve classification accuracy but this can come with a degree of information loss. These states can either be determined by evenly dividing the data into equally sized bins, or based off of important ecological or physical thresholds.

Each node is defined by a **conditional probability table** (CPT) that structures the relationship between the child node and its parent nodes, giving the probability of each state under each combination of states of the parent nodes. These CPTs form the basis of the model and can be completed in a number of ways depending on the complexity of the process and the availability of data. It is important to note that these CPTs directly reflect the spatial and temporal resolution and extent of the data, and thus there can often be missing or highly uncertain values that represent real-world scenarios that are either impossible or infrequent.

In our model, we have a hierarchy of parent nodes that are loosely grouped by the spatial scale at which they are influential. Starting with nodes defining the lake basin and the month, we look at climate, hydrology, landscape, ecology, and physical barrier characteristics and their effect on the state of the abundance of sea lamprey upstream of a barrier. CPTs are completed using several methods, including machine-learning algorithms using a series of cases describing the conditions of each barrier in each month, expert knowledge gathered through a structured elicitation process, and structural equations representing simpler relationships between nodes.

For a video walkthrough of the model function, please refer to the explanation in *modelwalkthrough.mp4*.

Model review

The primary purpose of this review is to evaluate whether the behavior of the model matches experts' best understanding of the factors that influence the effectiveness of a control barrier, and which barriers are likely to be less effective than others over the year. We are using this review as a means to validate model behavior, and to that end we've provided a series of model outputs evaluating both our current best knowledge, and a scenario that attempts to reduce output uncertainty by fixing an important node in the model.

Results are in the form of a table of lowermost barriers and their associated probabilities of the true state of the abundance upstream of the barrier, including 0 to 25, 25 to 250, and > 250 adult sea lamprey. For the first table, these are the mean probabilities of each month of the year, using historical data from 2000 – 2020, and projected climate scenarios from 2020 to 2100, while the second table reports only the results from the projected climate scenarios.

The first table (*barrierranks_fullv2_1.csv*) represents our expectations of the abundance of spawning adults in each stream in each month, while the second table (*barrierranks_fullv2_2.csv*) specifies a scenario in which each stream and each month are identical in their abundance of spawning adults. The latter effectively ignores differences between streams in the total pool of spawning adults available to pass a barrier across the year, and solely look at differences between barriers that can be attributed to the effectiveness of the barrier and the proportion that would move upstream to the barrier. We have also included the results of a one-way sensitivity analysis that was performed, looking at the individual influence of each node in the model on the abundance of sea lamprey that have passed a barrier. There are several aspects we would request you focus your attention on, however more general comments and observations on the model are also welcome.

1. **Does the relative influence of each node make sense? Are there variables you would think to be more or less influential relative to others?**

2. **Does the risk of escapement at various barriers make sense for each scenario? For each table of barrier risk, does the order make sense for each scenario?**

Included files

modelwalkthrough.mp4 – An explanation of the different components of BBNs in general and how they function, as well as a brief walkthrough of our specific model.

nodedescription.csv – A spreadsheet with a description of each node in the model, including units, scale, data sources, and method of populating the CPT *modelstructure_minimized.pdf* – An image of the model structure, minimized to more clearly show the links between nodes

modelstructure.pdf – An image of the model structure, expanded to show the default belief of each node

tornadoplot.png – Tornado plot displaying results of one-way sensitivity analysis in which we evaluate the sensitivity of the probability of a large escapement event (> 250 adults) to the range of potential values for each other node in the network. The plot shows the range of potential probabilities of this escapement event when each node (parameter) shown on the y-axis is varied from its minimum to maximum state.

barrierranks_fullV2_1.csv – A table of the estimated probability of escapement at each terminal (first blocking) barrier from the U.S side of the GL basin and across each modeled climate projection. This is a fairly rough first look, as our categorization accuracy of the abundance of adults in the stream in each month varies depending on the lake and month. Where no data exists (months or lakes where there is no trap catch data, like January in a tributary of Lake Erie), these show perfect uncertainty (a uniform probability of each state of the abundance of passed adults). While this helps us be transparent about where we are missing data, it also inflates the probability of sea lamprey being in a stream outside the months of the spawning run.

barrierranks_fullV2_2.csv – A table of the estimated probability of escapement at each terminal (first blocking) barrier from the U.S side of the GL basin and across each modeled climate projection, but with the abundance of adults within each stream in each month fixed to 500 adults. Essentially, this is a scenario ignoring spatial and monthly differences in the abundance of adults within a stream, focusing just on the permeability of the control barrier and their rate of upstream movement. We anticipate this being a more useful scenario to investigate which barriers are most/least effective at blockage, but it ignores the more relevant question of where are adults passing in numbers likely to lead to significant production.

APPENDIX E:

RESULTS OF EXPERT ELICITATION

Table 9: Conditional Probability Table describing the relationship between barrier permeability and its parent nodes, ordered by the decreasing probability of passing more than 50% of sea lampreys present at the barrier. Rows of the CPT are also labeled with the method used to obtain the values, either directly through the expert's responses, or interpolated from those data.

Type	*Water Velocity*	*Vertical Drop*	*Adult Weight*	*Method*	*pLower*	*pModerate*	*pHigh*
sloped	0 to 2	0 to 15	600 to 700	Elicited	0.00116	0.23676	0.76208
sloped	0 to 2	0 to 15	500 to 600	Elicited	0.00075	0.31240	0.68684
vertical	0 to 2	0 to 15	600 to 700	Elicited	0.00408	0.33370	0.66221
sloped	2 to 4	0 to 15	600 to 700	Elicited	0.00026	0.37273	0.62700
vertical	0 to 2	0 to 15	500 to 600	Elicited	0.00134	0.42951	0.56915
sloped	0 to 2	0 to 15	400 to 500	Elicited	0.00043	0.44580	0.55377
vertical	2 to 4	0 to 15	600 to 700	Interpolated	0.00408	0.45108	0.54484
sloped	2 to 4	0 to 15	500 to 600	Elicited	0.00038	0.56990	0.42972
vertical	0 to 2	0 to 15	400 to 500	Elicited	0.00130	0.59071	0.40799
sloped	0 to 2	15 to 30	600 to 700	Elicited	0.01572	0.59263	0.39165
vertical	2 to 4	0 to 15	500 to 600	Interpolated	0.00134	0.64257	0.35609
vertical	0 to 2	15 to 30	600 to 700	Interpolated	0.01947	0.64020	0.34033
sloped	2 to 4	15 to 30	600 to 700	Interpolated	0.01572	0.66205	0.32223
vertical	2 to 4	15 to 30	600 to 700	Interpolated	0.01947	0.70052	0.28001
sloped	0 to 2	15 to 30	500 to 600	Elicited	0.00851	0.71507	0.27642
sloped	2 to 4	0 to 15	400 to 500	Elicited	0.00074	0.76204	0.23722
vertical	0 to 2	15 to 30	500 to 600	Interpolated	0.00947	0.76147	0.22905
sloped	0 to 2	15 to 30	400 to 500	Elicited	0.00873	0.79838	0.19289
vertical	2 to 4	0 to 15	400 to 500	Interpolated	0.00161	0.82362	0.17477
sloped	2 to 4	15 to 30	500 to 600	Interpolated	0.00851	0.81854	0.17294

vertical	2 to 4	15 to 30	500 to 600	Interpolated	0.00947	0.84722	0.14331
vertical	0 to 2	15 to 30	400 to 500	Interpolated	0.00960	0.84829	0.14211
sloped	0 to 2	30 to 45	600 to 700	Elicited	0.06386	0.82870	0.10744
sloped	2 to 4	15 to 30	400 to 500	Interpolated	0.00904	0.90833	0.08263
vertical	2 to 4	15 to 30	400 to 500	Interpolated	0.00990	0.92922	0.06088
vertical	0 to 2	30 to 45	600 to 700	Interpolated	0.08177	0.87025	0.04798
sloped	2 to 4	30 to 45	600 to 700	Interpolated	0.07827	0.87630	0.04543
vertical	2 to 4	30 to 45	600 to 700	Interpolated	0.08177	0.87875	0.03948
sloped	0 to 2	30 to 45	500 to 600	Elicited	0.07263	0.89626	0.03111
sloped	0 to 2	>45	600 to 700	Elicited	0.15234	0.83448	0.01318
sloped	>4	0 to 15	600 to 700	Elicited	0.07057	0.91677	0.01266
vertical	0 to 2	30 to 45	500 to 600	Interpolated	0.08103	0.90859	0.01038
vertical	>4	0 to 15	600 to 700	Interpolated	0.07410	0.91685	0.00905
sloped	0 to 2	30 to 45	400 to 500	Elicited	0.14049	0.85123	0.00827
sloped	2 to 4	30 to 45	500 to 600	Interpolated	0.08014	0.91202	0.00783
sloped	>4	15 to 30	600 to 700	Interpolated	0.08487	0.90863	0.00650
vertical	2 to 4	30 to 45	500 to 600	Interpolated	0.08103	0.91248	0.00649
sloped	>4	0 to 15	400 to 500	Elicited	0.35494	0.63925	0.00581
vertical	>4	15 to 30	600 to 700	Interpolated	0.08834	0.90701	0.00465
sloped	>4	0 to 15	500 to 600	Elicited	0.15299	0.84364	0.00337
sloped	0 to 2	>45	500 to 600	Elicited	0.19368	0.80409	0.00223
vertical	0 to 2	30 to 45	400 to 500	Interpolated	0.14836	0.84951	0.00212
sloped	>4	15 to 30	400 to 500	Interpolated	0.36026	0.63772	0.00202
vertical	>4	0 to 15	400 to 500	Interpolated	0.35569	0.64247	0.00183
vertical	>4	0 to 15	500 to 600	Interpolated	0.15380	0.84445	0.00175
sloped	>4	15 to 30	500 to 600	Interpolated	0.15981	0.83883	0.00136
sloped	2 to 4	30 to 45	400 to 500	Interpolated	0.14788	0.85088	0.00123
sloped	>4	30 to 45	600 to 700	Interpolated	0.14274	0.85634	0.00092
vertical	2 to 4	30 to 45	400 to 500	Interpolated	0.14863	0.85047	0.00091

vertical	0 to 2	>45	600 to 700	Interpolated	0.22067	0.77850	0.00083
sloped	2 to 4	>45	600 to 700	Interpolated	0.21774	0.78148	0.00079
vertical	>4	15 to 30	500 to 600	Interpolated	0.16061	0.83868	0.00070
sloped	0 to 2	>45	400 to 500	Elicited	0.29314	0.70617	0.00069
vertical	2 to 4	>45	600 to 700	Interpolated	0.22067	0.77865	0.00068
vertical	>4	30 to 45	600 to 700	Interpolated	0.14598	0.85336	0.00066
vertical	>4	15 to 30	400 to 500	Interpolated	0.36101	0.63835	0.00064
sloped	>4	30 to 45	500 to 600	Interpolated	0.21982	0.78012	0.00006
vertical	0 to 2	>45	500 to 600	Interpolated	0.25776	0.74221	0.00003
vertical	>4	30 to 45	500 to 600	Interpolated	0.22056	0.77941	0.00003
sloped	>4	30 to 45	400 to 500	Interpolated	0.44928	0.55069	0.00003
sloped	2 to 4	>45	500 to 600	Interpolated	0.25706	0.74292	0.00003
vertical	2 to 4	>45	500 to 600	Interpolated	0.25776	0.74222	0.00002
sloped	>4	>45	600 to 700	Interpolated	0.27179	0.72820	0.00002
vertical	>4	30 to 45	400 to 500	Interpolated	0.44993	0.55006	0.00001
vertical	0 to 2	>45	400 to 500	Interpolated	0.39722	0.60278	0.00000
sloped	2 to 4	>45	400 to 500	Interpolated	0.39688	0.60312	0.00000
vertical	2 to 4	>45	400 to 500	Interpolated	0.39740	0.60260	0.00000
sloped	>4	>45	500 to 600	Interpolated	0.36802	0.63198	0.00000
sloped	>4	>45	400 to 500	Interpolated	0.60893	0.39107	0.00000
vertical	>4	>45	500 to 600	Elicited	0.94092	0.05908	0.00000
vertical	>4	>45	600 to 700	Elicited	0.94092	0.05908	0.00000
vertical	>4	>45	400 to 500	Elicited	0.98784	0.01216	0.00000

Table 10: Conditional Probability Table describing the relationship between the proportion of sea lampreys that migrate upstream to a barrier and its parent nodes, ordered by the decreasing probability of more than 50% of sea lampreys successfully migrating upstream

to a barrier. Rows of the CPT are also labeled with the method used to obtain the values, either directly through the expert's responses, or interpolated from those data.

Abundance (stream)	*Stream temperature*	*Distance to barrier*	*Adult length*	*Method*	*pLower*	*pModerate*	*pHigh*
>=1000	5 to 15	<5	150 to 200	Elicited	0.00000	0.00623	0.99377
>=1000	5 to 15	<5	100 to 150	Elicited	0.00000	0.00630	0.99370
>=1000	5 to 15	<5	200 to 250	Elicited	0.00000	0.00699	0.99301
>=1000	5 to 15	5 to 25	200 to 250	Elicited	0.00000	0.02982	0.97018
>=1000	5 to 15	5 to 25	150 to 200	Elicited	0.00000	0.03435	0.96565
100 to 1000	5 to 15	<5	200 to 250	Elicited	0.00000	0.03992	0.96008
100 to 1000	5 to 15	<5	150 to 200	Elicited	0.00000	0.04302	0.95698
100 to 1000	5 to 15	<5	100 to 150	Elicited	0.00000	0.04813	0.95187
>=1000	5 to 15	5 to 25	100 to 150	Elicited	0.00000	0.05573	0.94427
100 to 1000	5 to 15	5 to 25	200 to 250	Interpolated	0.00000	0.06199	0.93801
100 to 1000	5 to 15	5 to 25	150 to 200	Interpolated	0.00000	0.07010	0.92990
<100	5 to 15	<5	200 to 250	Elicited	0.00000	0.08096	0.91903
<100	5 to 15	<5	150 to 200	Elicited	0.00000	0.08808	0.91192
100 to 1000	5 to 15	5 to 25	100 to 150	Interpolated	0.06092	0.03456	0.90452
<100	5 to 15	<5	100 to 150	Elicited	0.00000	0.09728	0.90272
<100	5 to 15	5 to 25	200 to 250	Interpolated	0.00000	0.10209	0.89791
<100	5 to 15	5 to 25	150 to 200	Interpolated	0.00000	0.11388	0.88612
<100	5 to 15	5 to 25	100 to 150	Interpolated	0.06092	0.08127	0.85781
>=1000	15 to 25	<5	200 to 250	Elicited	0.00003	0.15423	0.84574
>=1000	15 to 25	<5	150 to 200	Elicited	0.00000	0.16372	0.83628
>=1000	15 to 25	5 to 25	200 to 250	Interpolated	0.00003	0.17368	0.82629
>=1000	5 to 15	25 to 100	200 to 250	Elicited	0.00000	0.18094	0.81906
100 to 1000	15 to 25	<5	200 to 250	Interpolated	0.00003	0.18228	0.81769
>=1000	15 to 25	<5	100 to 150	Elicited	0.00000	0.18581	0.81419
>=1000	15 to 25	5 to 25	150 to 200	Interpolated	0.00000	0.18738	0.81261

100 to 1000	15 to 25	<5	150 to 200	Interpolated	0.00000	0.19468	0.80532
100 to 1000	15 to 25	5 to 25	200 to 250	Interpolated	0.00003	0.20108	0.79889
>=1000	5 to 15	25 to 100	150 to 200	Elicited	0.00000	0.20805	0.79195
<100	15 to 25	<5	200 to 250	Interpolated	0.00003	0.21724	0.78273
100 to 1000	15 to 25	5 to 25	150 to 200	Interpolated	0.00000	0.21747	0.78253
100 to 1000	15 to 25	<5	100 to 150	Interpolated	0.00000	0.22008	0.77992
100 to 1000	5 to 15	25 to 100	200 to 250	Interpolated	0.00000	0.22631	0.77369
>=1000	15 to 25	5 to 25	100 to 150	Interpolated	0.06092	0.16540	0.77369
<100	15 to 25	<5	150 to 200	Interpolated	0.00001	0.23259	0.76740
<100	15 to 25	5 to 25	200 to 250	Interpolated	0.00003	0.23523	0.76474
<100	15 to 25	5 to 25	150 to 200	Interpolated	0.00001	0.25431	0.74569
100 to 1000	15 to 25	5 to 25	100 to 150	Interpolated	0.06092	0.19796	0.74112
100 to 1000	5 to 15	25 to 100	150 to 200	Interpolated	0.00000	0.25895	0.74105
<100	5 to 15	25 to 100	200 to 250	Interpolated	0.00000	0.25938	0.74061
<100	15 to 25	<5	100 to 150	Interpolated	0.00000	0.26035	0.73965
>=1000	5 to 15	25 to 100	100 to 150	Elicited	0.00000	0.28802	0.71198
<100	5 to 15	25 to 100	150 to 200	Interpolated	0.00000	0.29384	0.70616
<100	15 to 25	5 to 25	100 to 150	Interpolated	0.06092	0.23623	0.70285
>=1000	15 to 25	25 to 100	200 to 250	Interpolated	0.00003	0.31843	0.68154
100 to 1000	15 to 25	25 to 100	200 to 250	Interpolated	0.00003	0.34103	0.65894
100 to 1000	5 to 15	25 to 100	100 to 150	Interpolated	0.06092	0.29100	0.64809
>=1000	15 to 25	25 to 100	150 to 200	Interpolated	0.00000	0.35241	0.64759
<100	15 to 25	25 to 100	200 to 250	Interpolated	0.00003	0.36920	0.63077
100 to 1000	15 to 25	25 to 100	150 to 200	Interpolated	0.00000	0.37638	0.62361
<100	5 to 15	25 to 100	100 to 150	Interpolated	0.06092	0.32446	0.61462
<100	15 to 25	25 to 100	150 to 200	Interpolated	0.00001	0.40574	0.59425
>=1000	15 to 25	25 to 100	100 to 150	Interpolated	0.06092	0.38474	0.55434
100 to 1000	15 to 25	25 to 100	100 to 150	Interpolated	0.06092	0.40807	0.53101
<100	15 to 25	25 to 100	100 to 150	Interpolated	0.06092	0.43549	0.50359

>=1000	>=25	<5	100 to 150	Elicited	0.00863	0.90524	0.08614
>=1000	>=25	5 to 25	100 to 150	Interpolated	0.06879	0.84936	0.08185
100 to 1000	>=25	<5	100 to 150	Interpolated	0.00863	0.92377	0.06760
>=1000	>=25	<5	150 to 200	Elicited	0.00742	0.92781	0.06476
100 to 1000	>=25	5 to 25	100 to 150	Interpolated	0.06880	0.86696	0.06424
>=1000	>=25	<5	200 to 250	Elicited	0.00499	0.93085	0.06416
<100	>=25	<5	100 to 150	Interpolated	0.00863	0.92726	0.06411
>=1000	>=25	5 to 25	150 to 200	Interpolated	0.00742	0.92965	0.06293
>=1000	>=25	5 to 25	200 to 250	Interpolated	0.00499	0.93232	0.06268
<100	>=25	5 to 25	100 to 150	Interpolated	0.06880	0.87028	0.06092
>=1000	>=25	25 to 100	100 to 150	Interpolated	0.06879	0.87256	0.05865
100 to 1000	>=25	<5	200 to 250	Interpolated	0.00502	0.94215	0.05283
100 to 1000	>=25	<5	150 to 200	Interpolated	0.00743	0.94009	0.05248
>=1000	>=25	25 to 100	200 to 250	Interpolated	0.00499	0.94330	0.05170
100 to 1000	>=25	5 to 25	200 to 250	Interpolated	0.00502	0.94336	0.05162
100 to 1000	>=25	5 to 25	150 to 200	Interpolated	0.00743	0.94158	0.05100
<100	>=25	<5	200 to 250	Interpolated	0.00503	0.94440	0.05057
>=1000	>=25	25 to 100	150 to 200	Interpolated	0.00742	0.94243	0.05015
<100	>=25	<5	150 to 200	Interpolated	0.00743	0.94256	0.05001
<100	>=25	5 to 25	200 to 250	Interpolated	0.00503	0.94556	0.04941
<100	>=25	5 to 25	150 to 200	Interpolated	0.00743	0.94398	0.04860
100 to 1000	>=25	25 to 100	100 to 150	Interpolated	0.06880	0.88518	0.04603
<100	>=25	25 to 100	100 to 150	Interpolated	0.06880	0.88755	0.04365
100 to 1000	>=25	25 to 100	200 to 250	Interpolated	0.00502	0.95240	0.04257
<100	>=25	25 to 100	200 to 250	Interpolated	0.00503	0.95422	0.04075
100 to 1000	>=25	25 to 100	150 to 200	Interpolated	0.00743	0.95193	0.04064
<100	>=25	25 to 100	150 to 200	Interpolated	0.00743	0.95384	0.03873
>=1000	<5	<5	200 to 250	Elicited	0.16255	0.80993	0.02752
>=1000	<5	5 to 25	200 to 250	Interpolated	0.16255	0.81056	0.02689

>=1000	<5	<5	150 to 200	Elicited	0.17568	0.79998	0.02433
>=1000	<5	5 to 25	150 to 200	Interpolated	0.17568	0.80067	0.02364
>=1000	<5	<5	100 to 150	Elicited	0.19251	0.78512	0.02237
>=1000	<5	25 to 100	200 to 250	Interpolated	0.16255	0.81527	0.02218
>=1000	<5	5 to 25	100 to 150	Interpolated	0.23675	0.74200	0.02126
>=1000	<5	25 to 100	150 to 200	Interpolated	0.17568	0.80547	0.01884
>=1000	<5	25 to 100	100 to 150	Interpolated	0.23675	0.74802	0.01523
100 to 1000	<5	<5	100 to 150	Interpolated	0.19878	0.79970	0.00152
100 to 1000	<5	<5	200 to 250	Interpolated	0.16627	0.83226	0.00146
100 to 1000	<5	5 to 25	100 to 150	Interpolated	0.24247	0.75609	0.00145
<100	<5	<5	100 to 150	Interpolated	0.19878	0.79978	0.00144
100 to 1000	<5	5 to 25	200 to 250	Interpolated	0.16627	0.83230	0.00143
<100	<5	<5	200 to 250	Interpolated	0.16627	0.83232	0.00140
<100	<5	5 to 25	100 to 150	Interpolated	0.24247	0.75616	0.00137
<100	<5	5 to 25	200 to 250	Interpolated	0.16627	0.83236	0.00137
100 to 1000	<5	<5	150 to 200	Interpolated	0.18108	0.81764	0.00129
100 to 1000	<5	5 to 25	150 to 200	Interpolated	0.18108	0.81767	0.00125
<100	<5	<5	150 to 200	Interpolated	0.18108	0.81769	0.00122
<100	<5	5 to 25	150 to 200	Interpolated	0.18108	0.81773	0.00119
100 to 1000	<5	25 to 100	200 to 250	Interpolated	0.16627	0.83255	0.00118
100 to 1000	<5	25 to 100	100 to 150	Interpolated	0.24247	0.75650	0.00104
100 to 1000	<5	25 to 100	150 to 200	Interpolated	0.18108	0.81793	0.00100
<100	<5	25 to 100	200 to 250	Elicited	0.62685	0.37315	0.00000
<100	<5	25 to 100	150 to 200	Elicited	0.64205	0.35795	0.00000
<100	<5	25 to 100	100 to 150	Elicited	0.70297	0.29703	0.00000

APPENDIX F:

RESULTS OF ONE-WAY SENSITIVITY ANALYSIS

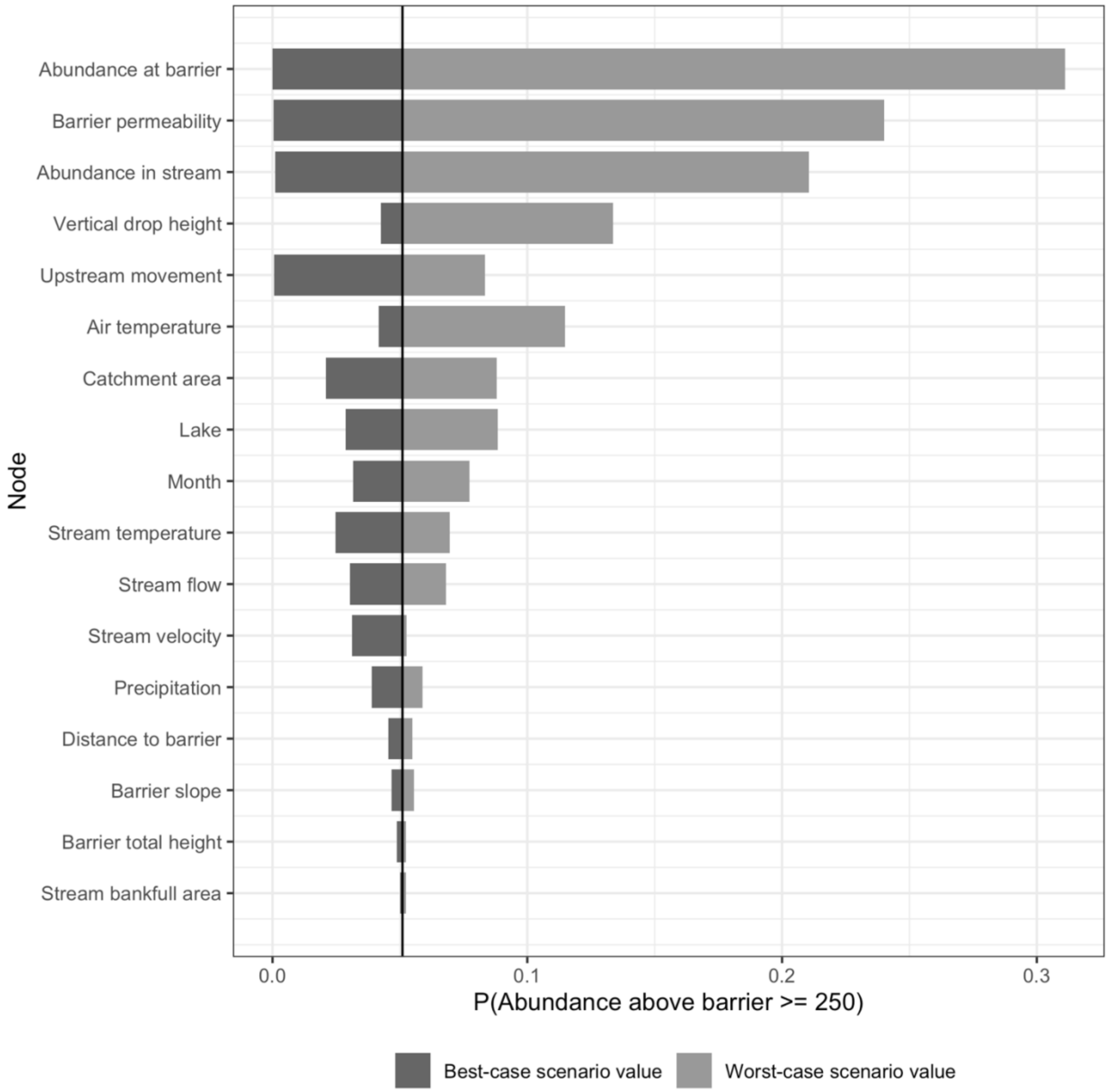


Figure 38. Results of a one-way sensitivity analysis of the base model V1 for the worst-case state of abundance of sea lampreys above a barrier. Each node is varied from the worst-case to the best-case state, and the change in the state probability of the target node is recorded. The best-case state of a node is considered that which minimizes the worst-case state of the target node, and vice versa.

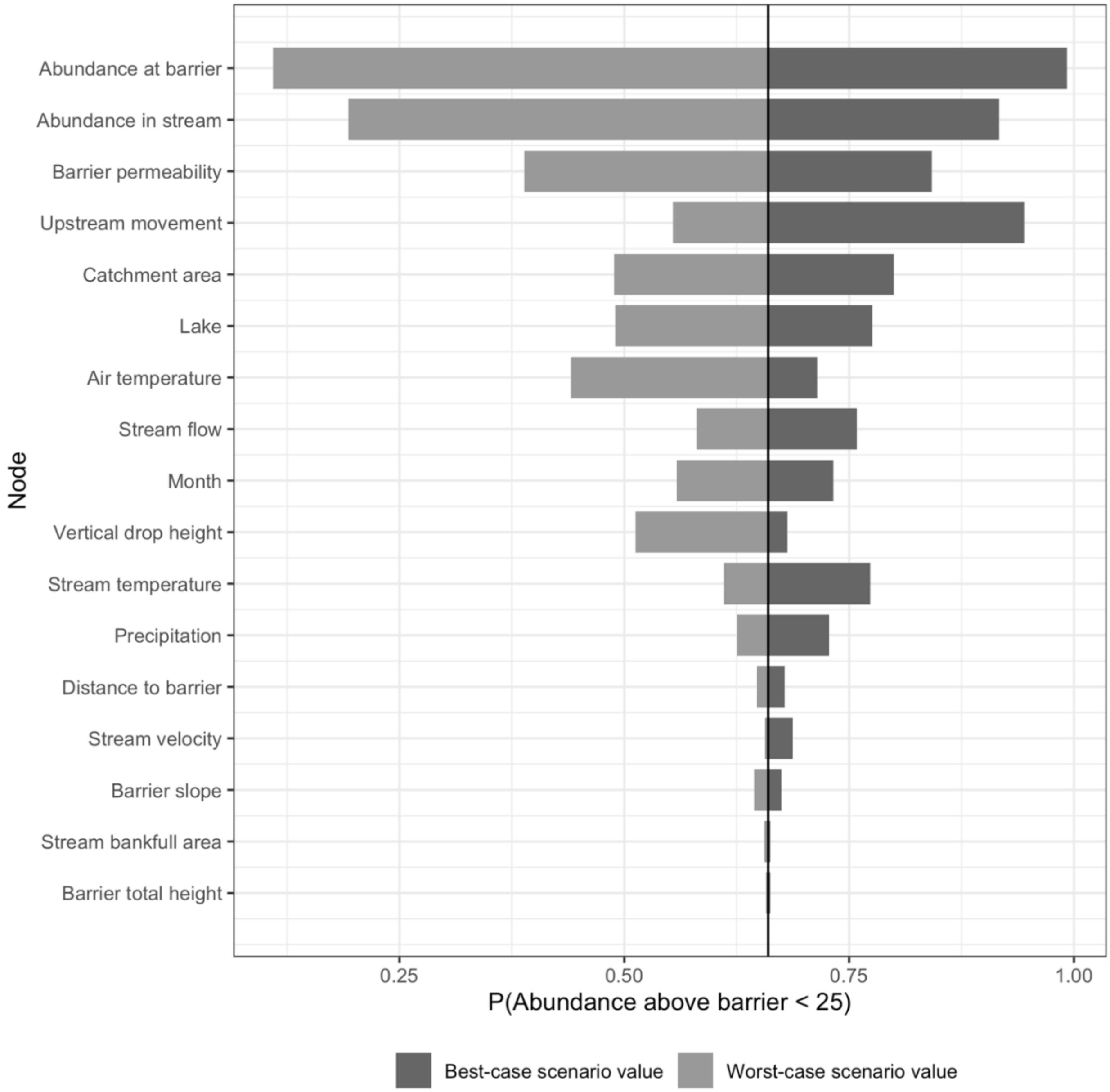


Figure 39. Results of a one-way sensitivity analysis of the base model V1 for the best-case state of abundance of sea lampreys above a barrier. Each node is varied from the worst-case to the best-case state, and the change in the state probability of the target node is recorded. The best-case state of a node is considered that which maximizes the best-case state of the target node, and vice versa.

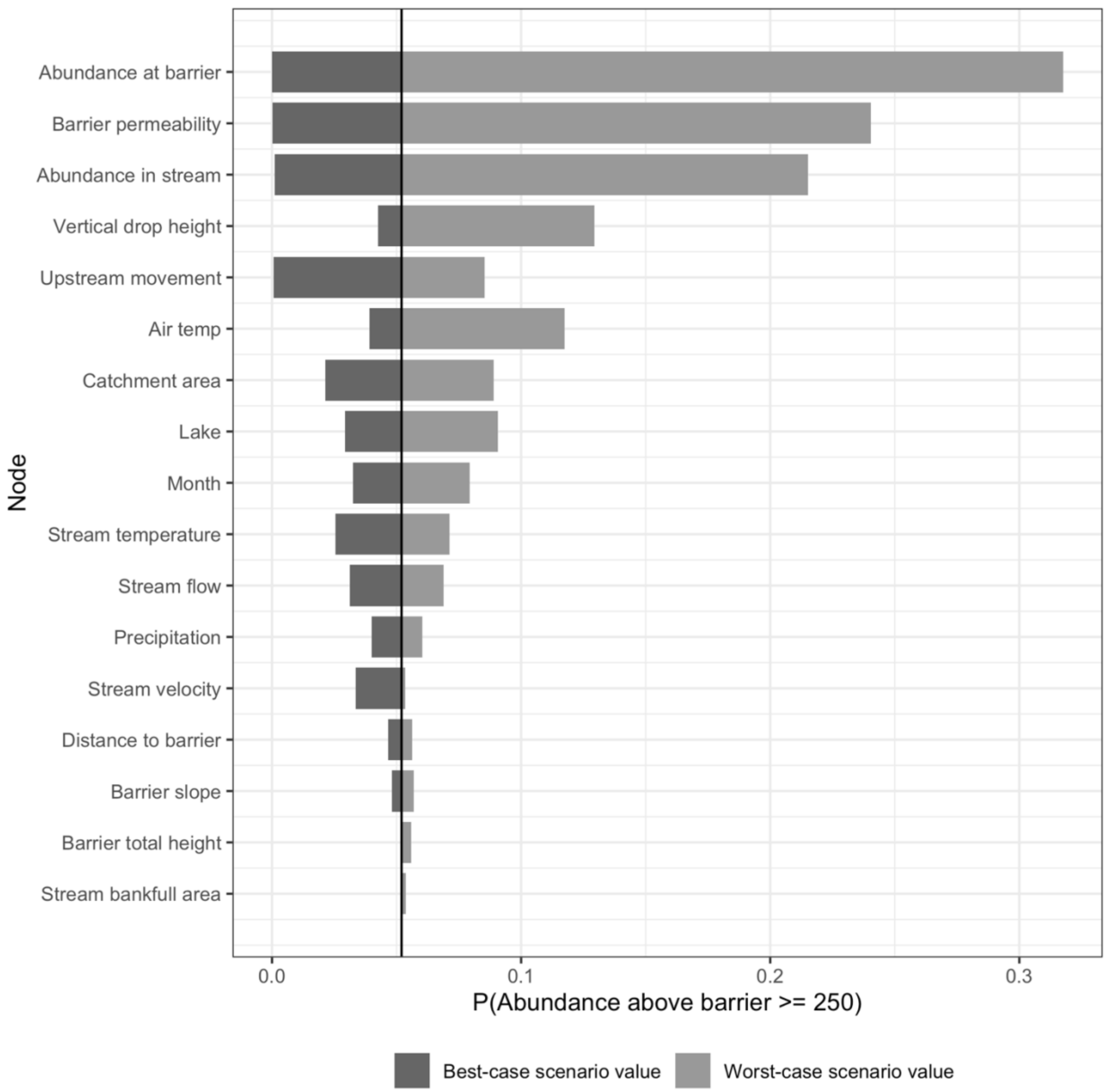


Figure 40. Results of a one-way sensitivity analysis of the base model V3 for the worst-case state of abundance of sea lampreys above a barrier. Each node is varied from the worst-case to the best-case state, and the change in the state probability of the target node is recorded. The best-case state of a node is considered that which minimizes the worst-case state of the target node, and vice versa.

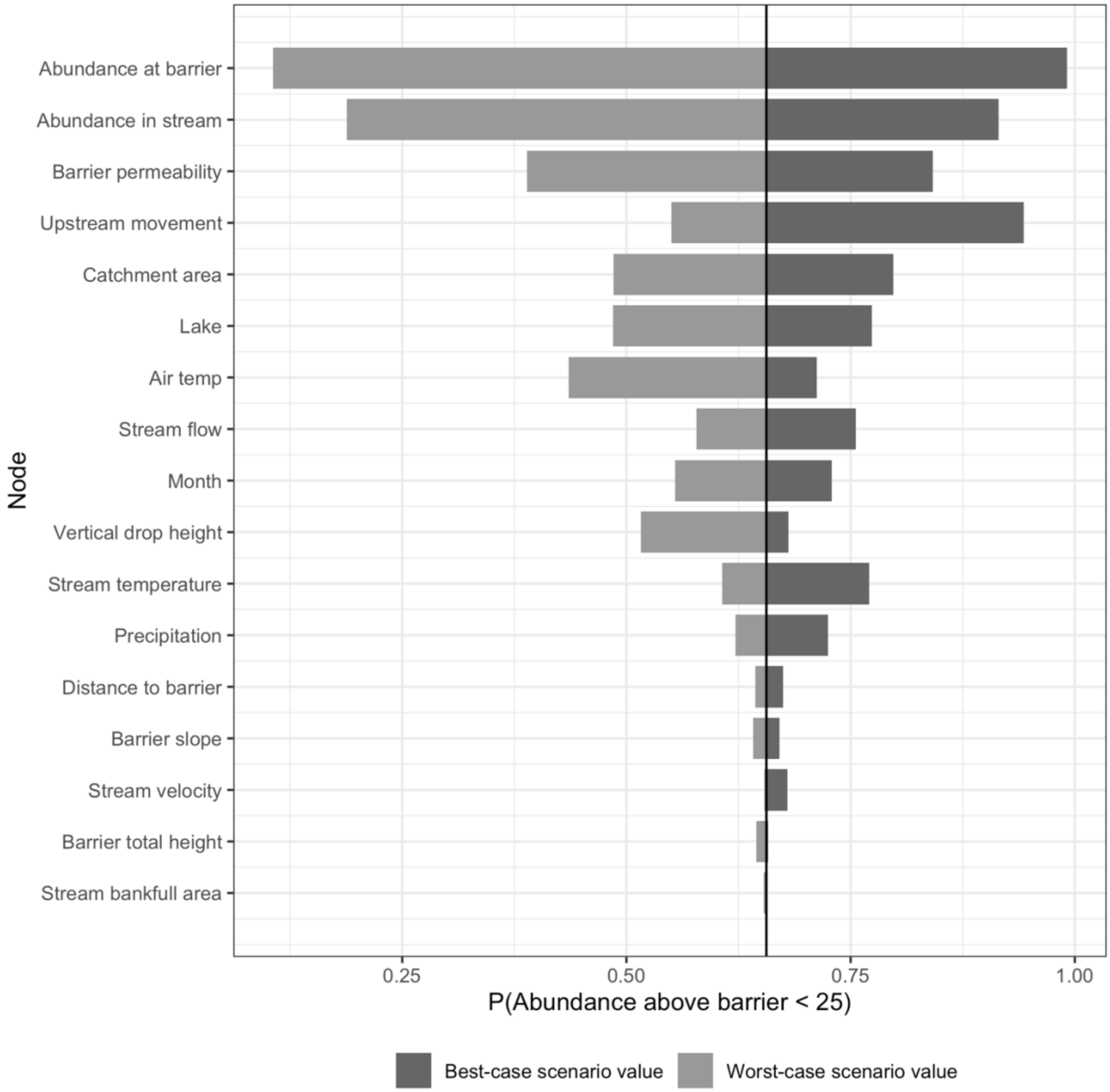


Figure 41. Results of a one-way sensitivity analysis of the base model V3 for the best-case state of abundance of sea lampreys above a barrier. Each node is varied from the worst-case to the best-case state, and the change in the state probability of the target node is recorded. The best-case state of a node is considered that which maximizes the best-case state of the target node, and vice versa.

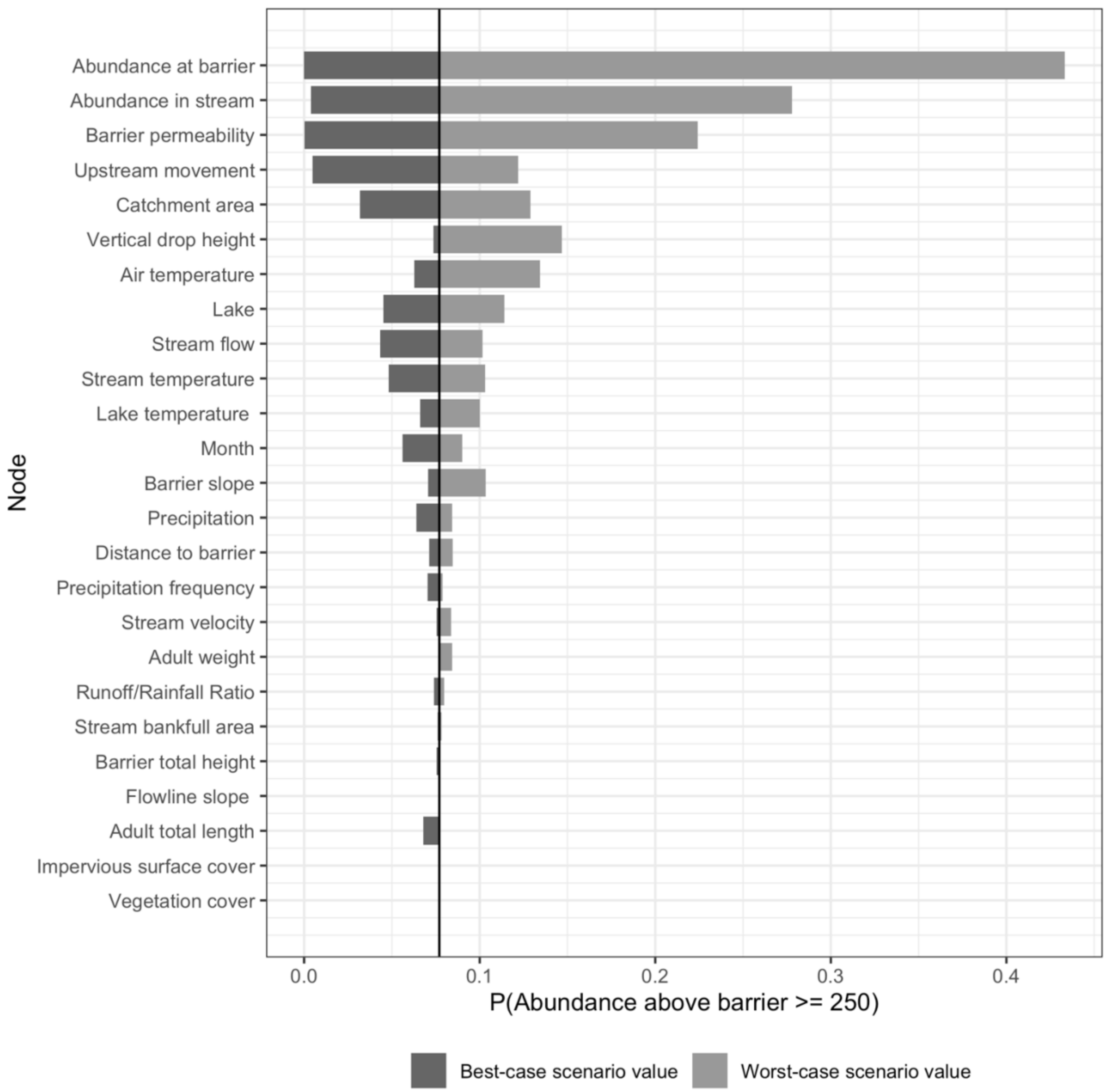


Figure 42. Results of a one-way sensitivity analysis of the full model V1 for the worst-case state of abundance of sea lampreys above a barrier. Each node is varied from the worst-case to the best-case state, and the change in the state probability of the target node is recorded. The best-case state of a node is considered that which minimizes the worst-case state of the target node, and vice versa.

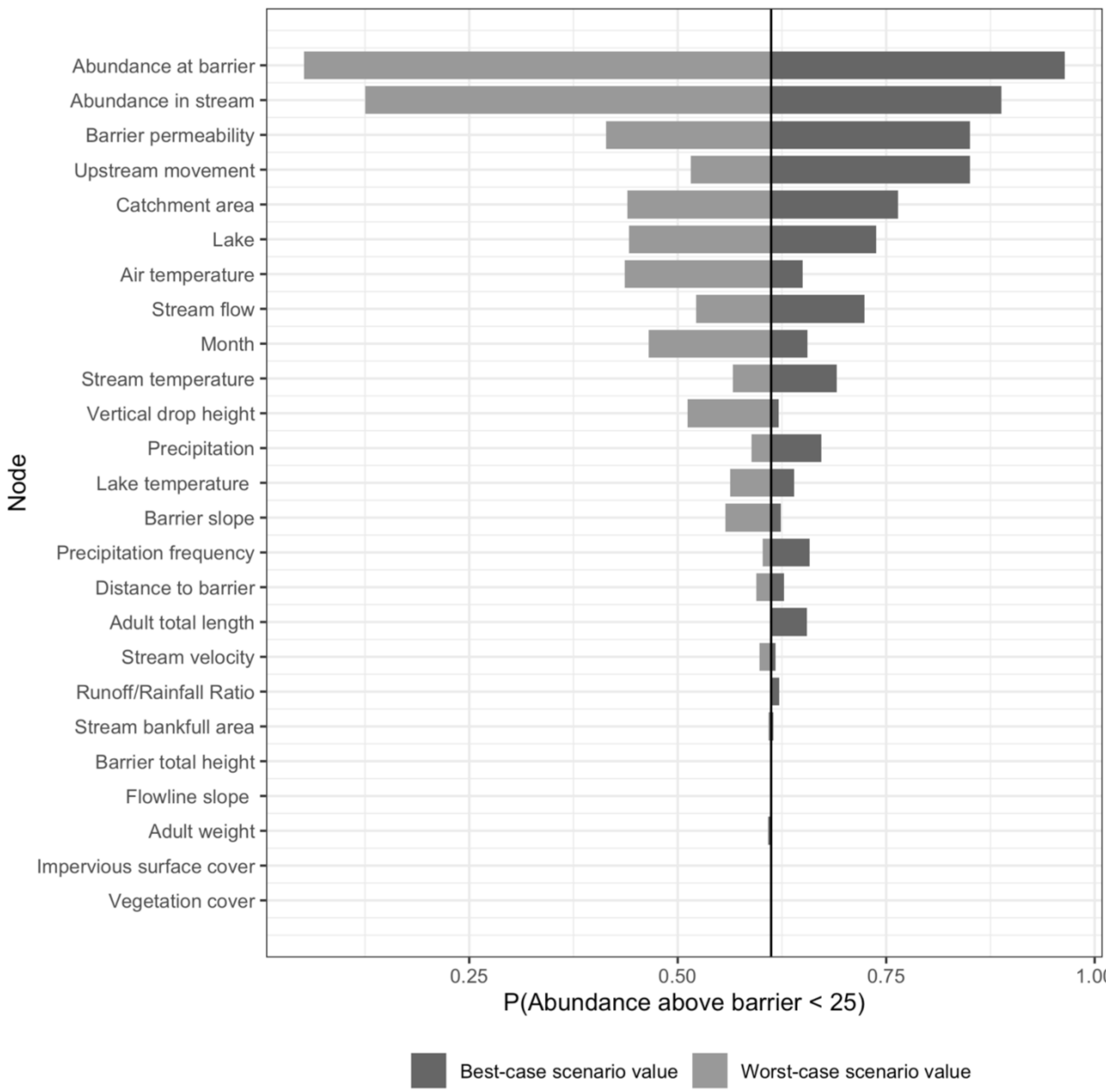


Figure 43. Results of a one-way sensitivity analysis of the full model V1 for the best-case state of abundance of sea lampreys above a barrier. Each node is varied from the worst-case to the best-case state, and the change in the state probability of the target node is recorded. The best-case state of a node is considered that which maximizes the best-case state of the target node, and vice versa.

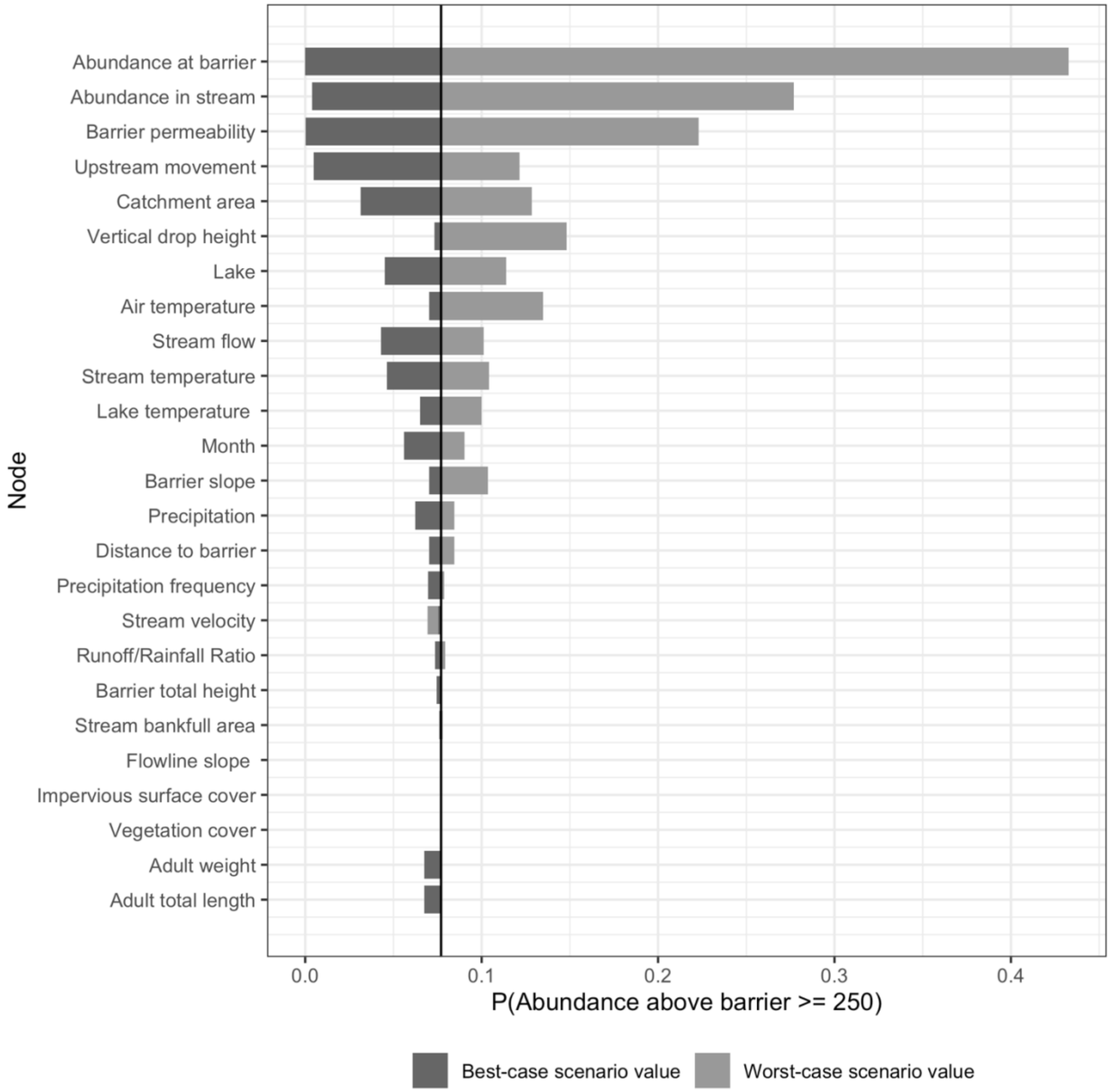


Figure 44. Results of a one-way sensitivity analysis of the full model V3 for the worst-case state of abundance of sea lampreys above a barrier. Each node is varied from the worst-case to the best-case state, and the change in the state probability of the target node is recorded. The best-case state of a node is considered that which minimizes the worst-case state of the target node, and vice versa.

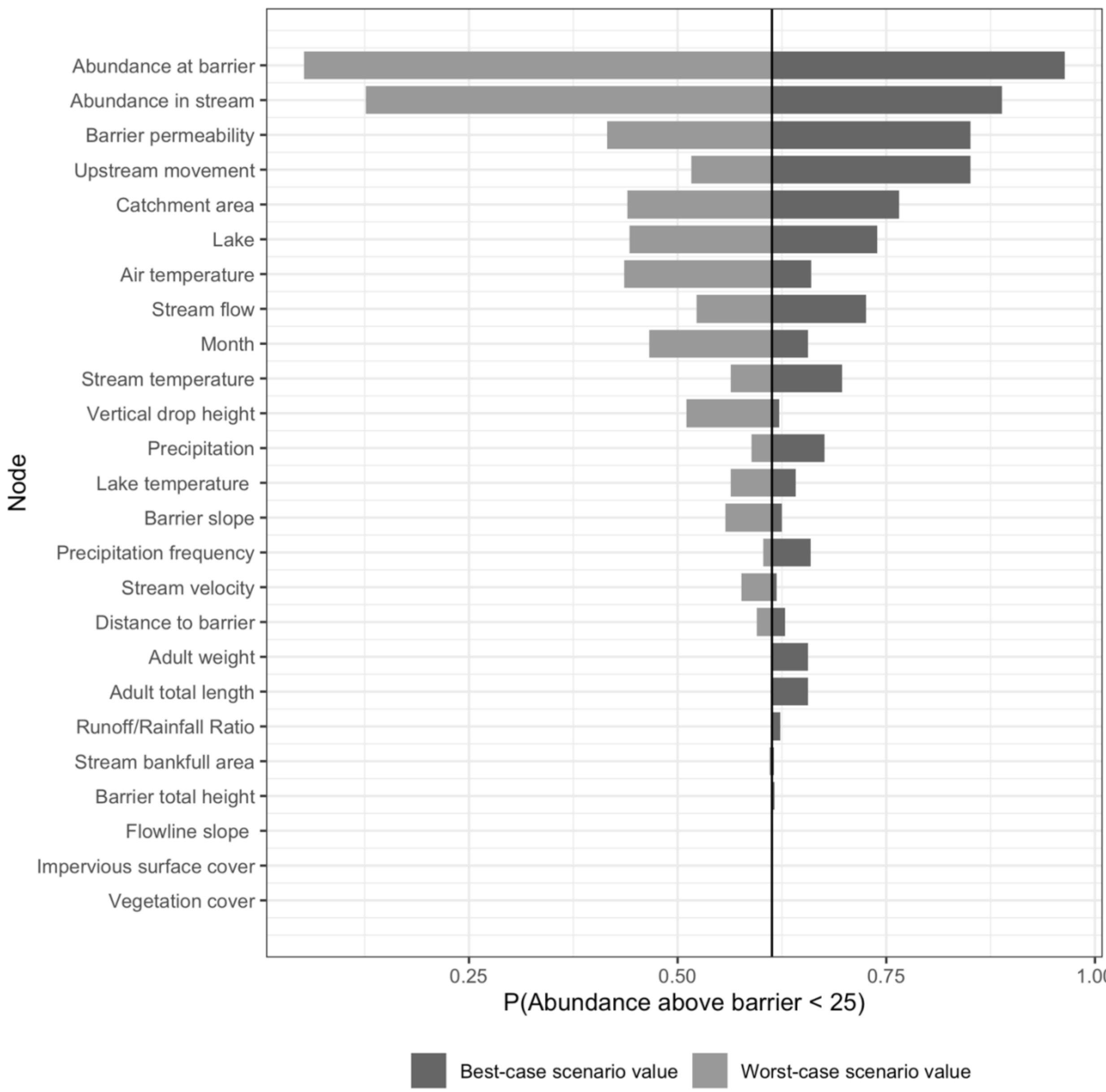


Figure 45. Results of a one-way sensitivity analysis of the full model V1 for the best-case state of abundance of sea lampreys above a barrier. Each node is varied from the worst-case to the best-case state, and the change in the state probability of the target node is recorded. The best-case state of a node is considered that which maximizes the best-case state of the target node, and vice versa.

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