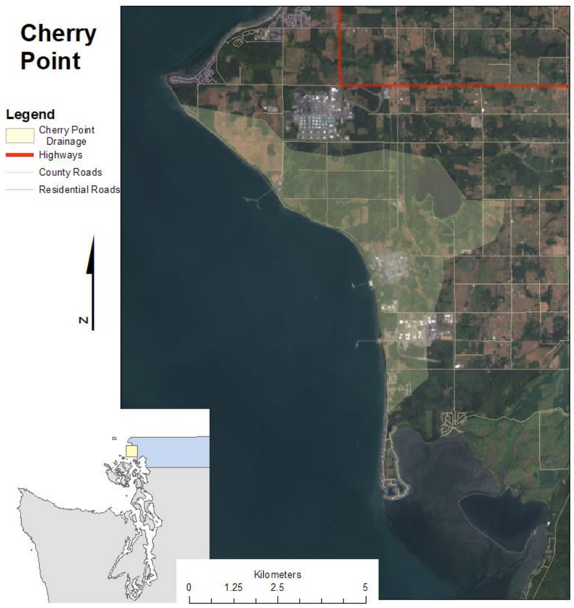
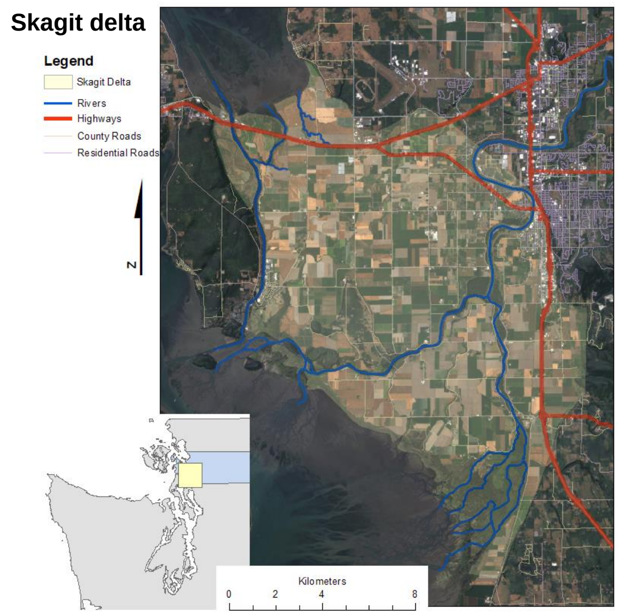
Incorporating Climate Change into the Prediction of Risk to Coho Salmon, Pacific Herring, Estuarine Wetlands, and Agricultural Land in the Puget Sound





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NOTE ON NETICA SOFTWARE

This research used the computer software program Netica™ (Norsys Software Corp. 2014) to construct the Bayesian Networks, calculate relative risks, and evaluate the risk results. A free, limited version of this software is available at https://www.norsys.com/netica.html and can be used to read the models presented. We recommend taking the introductory tutorial at https://www.norsys.com/tutorials/netica/nt_toc_A.htm prior to examining the models.

LIST OF ACRONYMS AND ABBREVIATIONS

BN	Bayesian Networks or Bayes Nets
BN-RRM	Bayesian Network Relative Risk Model
CM	Conceptual Model
CP	Cherry Point
CPTs	Conditional probability tables
EDCs	Endocrine disrupting chemicals
GCC	Global climate change
PAHs	Polycyclic Aromatic Hydrocarbons
PBDEs	Polybrominated diphenyl ethers
PCBs	Polychlorinated Biphenyls
PSM	Pre-spawn mortality
PSP	Puget Sound Partnership
RRM	Relative Risk Model

RISK TERMINOLOGY

The risk assessment terminology used in this report is consistent with the U.S. EPA's framework for ecological risk assessment (U.S. EPA, 1992) and the work of Suter (1993). Additional terminology was derived from peer-review scientific literature, with citations provided at the end of the definitions.

Adaptive Management: An iterative process of "learning by doing," where managers learn about current management practices through monitoring data and use the new knowledge to improve the next set of management decisions (Holling 1978, Nyberg et al. 2006).

Assessment Endpoint: An aspect of the natural system that is of value to society or the local community, as well as important to the ecology of the system.

Bayesian Networks: Bayesian networks (Bayes Nets or BNs) are directed acyclic graphs that links sources of stressors, habitats and endpoints through a web of nodes using conditional probability to estimate the likely outcome (McCann et al. 2006).

Bayesian network relative risk model (BN-RRM): A relative risk model where the linkages between the conceptual models are described by using a Bayesian network (also called a Bayes Net). (See Ayre and Landis 2012).

Conceptual Model: Diagrammatic description of the interactions stressors have with ecological components and their associated endpoints.

Effect: A change in the state or dynamics of an organism or other components of the ecological system resulting from exposure to a stressor. An indirect effect occurs when the initial effect results in additional stressors or effects to any component of the system.

Exposure: In the formulation of the relative risk model it is the colocation of a stressor with a receptor in a geographic area or habitat.

Habitat: The type of environment in which the receptors are found. Receptors may live exclusively within a single habitat or may move between and use several habitats.

Stressor: Anything that is physical, chemical, or biological in nature which causes an effect to an organism or system. Initial stressors may result in secondary stressors, as in the case of excess nutrient input (initial stressor) causing mortality due to microbial activity and a decrease in oxygen (secondary stressor).

Receptor: The organism or group of organisms that have the potential to be affected by a stressor.

Relative Risk Model: A cause and effect modeling approach used to calculate risk to endpoints due to multiple stressors entering a number of habitats and having an effect on the endpoint(s) (See Landis and Wiegers 1997 and 2005).

Response: The effect on the receptor as a result of exposure to a stressor.

Risk: The probability, actual or relative, of an unwanted effect on a receptor judged by society to be important (Hines and Landis 2014).

Source: An anthropogenic input or activity that releases or creates a stressor in the environment. The characteristics of a stressor may be influenced by the type of source.

Uncertainty: There are two types of uncertainty we can address in ecological studies: epistemic and linguistic uncertainty (Regan et al. 2002). Uncertainty addressed in this report is mainly epistemic uncertainty.

> *Epistemic uncertainty*: This includes uncertainty of the knowledge of the state of a system. This could be limitations from measurement devices or uncertainty due to scarce data, extrapolation, and variability in spatial and temporal scales.
>
> *Linguistic uncertainty*: This is the uncertainty due to the language and vocabulary used in scientific writing. This vocabulary can be very technical and context dependent. At times it can also be ambiguous and vague.

EXECUTIVE SUMMARY

We constructed a risk assessment model to assist the Puget Sound Partnership (PSP) with management and monitoring priorities of the Puget Sound. We used the Bayesian network relative risk model (BN-RRM) approach to probabilistically determine risk from multiple stressors to multiple endpoints with established significance to the PSP.

Specifically, we used the BN-RRM to probabilistically determine risk to four select endpoints (Pacific herring, coho salmon, estuarine wetlands, and agricultural land; chosen because of their importance as identified by the PSP) from chemical stressors (PCBs, PBDEs, DDTs, and surface water runoff from commercial lands) and climate stressors (flooding, sea level rise, storm surge, and water temperature) in two locations within the Puget Sound (Skagit River delta and the Cherry Point reach).

We have created a dynamic tool that lends itself well to adaptive management of the Puget Sound, specifically due to the ability to:

- Repopulate with new or updated information to maintain relevance and applicability
- Add additional stressors as new information is obtained or needs of the user change
- Include different habitats within the same framework
- Examine additional endpoints, as needs and interest dictate
- Determine data gaps to highlight research priorities

Our work resulted in four main findings, which are further expanded in the body of the text:

1) GCC stressors can be incorporated into a risk assessment in the same manner as any other stressor
2) A risk assessment model can be developed that includes multiple endpoints
3) More data is needed to make predictions of risk to selected endpoints (Pacific herring, coho salmon, and loss of agricultural land)
4) The BN-RRM can be used as a tool to aid in making management decisions and highlighting research priorities

INTRODUCTION

Background

The Puget Sound Partnership (PSP) is the agency responsible for leading the collaborative effort "to restore and protect Puget Sound" and works "to develop and implement the priority actions needed to accelerate recovery" (Hamel 2015). As such, they have developed numerous Vital Signs to prioritize and assess the recovery efforts (Hamel 2015).

Regional risk assessment and the relative risk model (RRM)

Hunsaker et al. (1990) described the need for landscape scale approaches during the early formulations of ecological risk assessment. That need was the impetus for the development of the relative risk model (RRM). The RRM has now been used at multiple locations and for marine, freshwater and terrestrial environments (Landis and Wiegers 2007).

The basis of the RRM is a conceptual framework that identifies sources of stressors, stressors, effects of stressors on receptors and the resulting impacts on endpoints at a regional scale (Figure 1). The RRM uses spatially distinct risk regions to organize the information into cause and effect pathways. Ranking schemes are employed to combine variables with different units. Relative risk scores are calculated for assessment endpoints and can be compared across risk regions (spatial gradients) and between endpoints. Assessments using the RRM have been completed for a variety of stressors and combinations of stressors including contaminants, disease, environmental parameters, and non-indigenous species (Walker et al. 2001, Moraes et al. 2002, Hayes and Landis 2004, Colnar and Landis 2007, Anderson and Landis 2012, Ayre and Landis 2012, Bartolo et al. 2012, Hines and Landis 2014, Ayre et al. 2014).

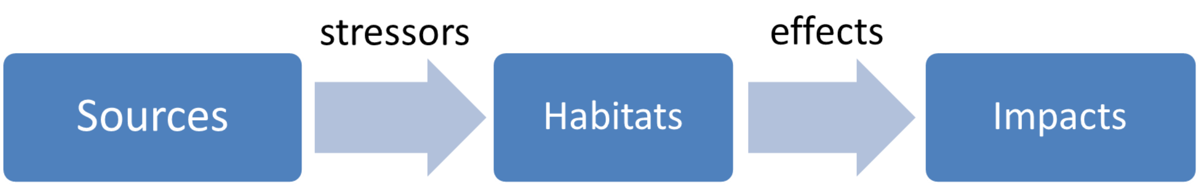

Figure 1. Relative Risk Model (RRM) framework, as described in Landis and Wiegers (1997)

Bayesian network relative risk model (BN-RRM) approach

Bayesian networks link cause and effect relationships through a web of nodes using conditional probability to estimate the likely outcome (McCann et al. 2006). As summarized by Tighe et al. (2013), a BN contains the following components:

Node: A variable that can be divided into a number of states.

State: Conditions of the variable often depicted as numerical ranges or ranks.

Parent or Input Node: A node that provides information to another node.

Child or Conditional Node: The node that receives information from a parent node.

Link: A graphical representation of the causal pathway between parent node(s) and child node(s).

Conditional Probability Table (CPT): This table describes the conditional probabilities between the occurrence of states in the parent nodes and the resulting probabilities of states in the child nodes.

Ayre and Landis (2012) demonstrated how BNs could be used in conjunction with the RRM for forest management. The causal framework of the RRM can be directly translated into the tiered node structure of a BN (Ayre and Landis 2012, Hines and Landis 2014). The application of BNs to evaluate management scenarios and to set management guidelines was immediately apparent. Since 2012, the integrated Bayesian network relative risk model (BN-RRM) has been used for a variety of assessments. Ayre et al. (2014) used the BN-RRM to estimate risk due to whirling disease in cutthroat trout in the Southwestern United States. Hines and Landis (2014) and Herring et al. (2015) applied the BN-RRM to the management of a large watershed and a marine reserve, respectively.

Risk assessment and climate change

There have been numerous calls to consider the implications of global climate change (GCC) in the context of environmental toxicology and risk assessment (Hooper et al. 2013, Landis et al. 2013, Moe et al. 2013, etc.). GCC is projected to be the source of multiple stressors, including but not limited to increased temperatures, increases in extreme temperature and precipitation events, and rising sea levels, which have the potential to affect the sites and species being managed. Including these potential stressors in an examination of risk is therefore imperative for creating the best management of systems.

The incorporation of climate change stressors in the BN-RRM framework has been effectively demonstrated by Gaasland-Tatro (2016) which incorporated the predictions from sets of climate change models to estimate the change in risk to a contaminated site near Waynesboro, Virginia. It was possible to estimate the change in risk due to habitat changes and mercury contamination to several of the regulatory endpoints for the site.

Risk and uncertainty

Throughout this document are references to risk and the associated uncertainty. A brief description of these terms and their meanings are described herein.

In this document, risk is defined as the probability, actual or relative, of an unwanted effect on a receptor judged by society to be important. In the case of the BN-RRM, the risk is the likelihood of one of three states or risk ranks (low, medium and high).

Our treatment of uncertainty is based on Regan et al. (2002) in which there are two types of uncertainty, epistemic and linguistic. Epistemic uncertainty generally addresses the findings under consideration from a study or a model. Classic examples of epistemic uncertainty include the shape of an exposure-effect curve, cause-effect relationships in a conceptual model, and inherent variation in sampling results. Linguistic uncertainty pertains to language as in determining the actual representation of terms like species diversity, ecosystem health, endpoint, or estimated impacts. The use of distributions in this study applies to epistemic uncertainty. Epistemic uncertainty includes measurement error, systematic error, natural variation, inherent randomness, model uncertainty, and subjective judgment.

- **Measurement error** is the uncertainty attributed to random variation existing in equipment and other measurement tools and in the operator. This uncertainty can be reduced but not eliminated.
- **Systematic error** is the bias built into the measurement tool and the sampling method. This bias does not represent a random event, but rather a consistent difference between the actual and calculated values as the sample size increases. This type of uncertainty can be reduced.
- **Natural variation** occurs in dynamic systems that change over time and space in a manner that is difficult to predict. As a result of these changes, natural variation is not considered as classic epistemic uncertainty. However, the precise nature of these changes is extraordinarily difficult to measure, and thus the actual value remains unknown. It is important to understand that natural variation is a deterministic process, but measurement and systematic error apply in the estimation of this property.
- **Inherent randomness**, or stochastic uncertainty, is when the system under consideration cannot be reduced to a deterministic equation. Many aspects of ecological systems are best described by distributions that assume stochastic functions (Wu and Loucks 1995). It is unlikely that this source of uncertainty can be eliminated although the probabilities can be better described.
- **Model uncertainty** stems from the inherent simplification that exists in any representation of reality. Regan et al. (2002) focused on computational and mathematical models; however, laboratory tests, microcosms, and field-scale mesocosms are all physical models of reality and extrapolation to a field site can be problematic. Extrapolation of a result from a laboratory experiment, another field site, or even from a portion of the study site is also subject to model uncertainty. The assumption is that the laboratory or study area is an appropriate analog or model for the system under investigation.
- **Subjective judgment** is the source of uncertainty that stems from data evaluation, especially with uncommon data findings and substantial opportunity for measurement error. In these cases, the parameter values often are determined by experts' subjective estimates of the parameter or the probability of an event. A large literature base now exists for issues associated with the extraction of survey information (O'Hagan et al. 2006).

Linguistic uncertainty is more difficult to describe using distributions. However this type of uncertainty can be minimized by using explicit definitions. In this document we have a glossary that defines the terminology as it is used in the BN-RRM and in the remainder of this paper. As often as possible we use the definitions for thresholds as established by the PSP.

Adaptive management

Ecological managers often implement one or more management options without the direct integration of a quantitative risk assessment and evaluation of management alternatives. Throughout the decision-making process a manager should consider multiple stressors, as well as stressor interactions and the resulting effects.

Decision-making for a contaminated site requires managers to connect the results of a risk assessment with the selection of a management strategy, though there is rarely quantitative integration of these two components. At contaminated sites there is a focus on the stressor of regulatory interest, however at most sites multiple stressors exist. The selection of one or more management options requires managers to make trade-offs between ecological risk, cost, effectiveness, and public opinion (Kiker et al. 2008).

Adaptive management is an iterative process of "learning by doing," where managers learn about the consequence of current management practices through monitoring data and using the new knowledge to improve the next set of management decisions (Holling 1978, Nyberg et al. 2006). It has been proposed that Bayesian networks could easily be incorporated into an adaptive management process although only a few examples exist (Howes et al. 2010, Shenton et al. 2011, Ayre et al. 2014, Hines and Landis 2014). By incorporating one or more management options into the BNs, managers can evaluate changes in risk and unintended consequences. Management strategies are often implemented with consideration of spatial variability, so it makes sense that the evaluation of management options would take into account regional variation in risk as well.

The BN-RRM can be adapted to an adaptive management process. In addition to integrating management into the BN-RRM, risk can be calculated for multiple scenarios by selecting a risk state in one or more nodes that then changes the risk distribution outcome (Ayre et al. 2014). The BNs can also be used to calculate the initial conditions necessary for a desired risk outcome. This is essentially a "back-calculation" where a risk state in the endpoint node is selected and the conditions required to meet the risk level are calculated (Ayre and Landis 2012).

Research objectives

The objective of this work is to use the Bayesian network relative risk model (BN-RRM) to demonstrate the usefulness of applying this framework and an adaptive management approach to managing for multiple stressors, including those from GCC, to multiple endpoints in the Puget Sound. To do so, we built a BN-RRM to address in a probabilistic manner the changes to two biotic and two abiotic important endpoints for the Puget Sound: 1) Pacific herring populations, 2) coho salmon populations, 3) estuarine wetlands, and 4) agricultural land inundation from sources of climatic and chemical stress.

Summary of main findings

Our work resulted in four main findings, which are further expanded in the body of the text:

1) GCC stressors can be incorporated into a risk assessment in the same manner as other "traditional" stressors
2) A risk assessment model can be developed that includes multiple endpoints
3) More data is needed to make predictions of risk to selected endpoints (Pacific herring, coho salmon, estuarine wetlands, and agricultural land)
4) The BN-RRM can be used as a tool to aid in making management decisions and highlighting data gaps and research priorities

METHODS

Selection of endpoints

Endpoints were chosen based on select PSP Targets for 2020 (Hamel 2015). Endpoints include both the entity (ex. Pacific herring population as a Vital Sign for a PSP goal) and its attributes (ex. abundance, reflecting the adopted indicator and, if applicable, target for the Vital Sign), as shown in Table 1. Endpoints chosen were: 1) Pacific herring populations, 2) coho salmon populations, 3) estuarine wetlands, and 4) agricultural land.

Pacific herring

Pacific herring are a forage fish species in the Puget Sound, vital to the marine food web. However, since the 1970s, there have been massive declines in Cherry Point Pacific herring populations (Landis et al. 2004). Because of this, the biomass of spawning Pacific herring has been identified as a PSP indicator. This work focused on Pacific herring because of previous work done by the IET and affiliates (ex. Landis et al. 2004, Landis and Bryant 2010).

Coho salmon

Salmon are an important part of the marine food web, as well as being of cultural and economic importance to residents of the Puget Sound area. Although PSP has specifically named Chinook salmon in their Vital Sign, indicator, and target, PSP's interest is in all species of salmon, including coho, which is designated as a species of concern within the Puget Sound/Strait of Georgia Evolutionarily Significant Unit (ESU).

Estuarine wetlands

Estuarine wetlands provide important habitat for salmon, migratory birds, and other species by providing a unique location for spawning, rearing, and feeding. However, much of these estuarine wetlands have been lost or degraded due to agricultural development, forestry activities, or the diking, dredging, and ditching of streams (Beechie et al. 2001).

Agricultural land

Land available for agricultural operations is a critical factor in the vitality of agriculture as a resource-based industry in the Puget Sound region. Many of the region's lands best suited for agricultural production are low elevation areas that were converted from wetlands by draining floodplain and river mouth deltas.

Table 1. Entity-attribute combinations for the four endpoints selected (Hamel 2015).

Endpoint	Entity	Attributes
Pacific herring, Coho salmon	Water quality	In Pacific herring and salmon, concentrations of PCBs and PBDEs below adverse effects thresholds
		In Pacific herring and salmon, concentrations of PCBs and other bioaccumulative toxics below human-health screening levels
	Species and food web	Stop the overall decline and start seeing improvements in wild Chinook salmon abundance in two to four populations in each biogeographic region.
		Increase the overall amount of spawning herring throughout Puget Sound to 19,380 tons; Increase Cherry Point to 5,000 tons
Agricultural land	Economic vitality	Regional economic activity from agriculture (one of six categories of resource-based industry)
		Employment from agriculture (one of six categories of resource-based industry)
Estuarine wetlands	Protect and restore habitat	7,380 quality acres of estuarine wetlands are restored basin-wide, which is 20 percent of total estimated restoration need.
		By 2020, all Chinook salmon natal river deltas meet 10-year salmon recovery goals (or 10 percent of restoration need as proxy for river deltas lacking quantitative acreage goals in salmon recovery plans).

Selection of regions

This project focused on two specific areas within the Puget Sound that are important to the endpoints selected, 1) Cherry Point, and 2) the Skagit River delta.

Cherry Point

The Cherry Point nearshore area (Figure 2) has been shown to be an important area for Pacific herring. Specially, it is utilized by the Cherry Point stock of Pacific herring for spawning in the spring, between early April-early June, when eggs are deposited in the intertidal and shallow subtidal eelgrass and marine algae (WDFW 2017).

The Cherry Point stock of Pacific herring has been identified as a distinct stock with a specific target. Because of this, and the and the information obtained from previous studies done by IET and affiliates (ex. Landis et al. 2004, Landis and Bryant 2010), this research is focused on Cherry Point as a specific study area.

Within the Cherry Point area lies urban development, two refineries, an aluminum smelter, and three deep-water shipping piers, all in close proximity to the Cherry Point Aquatic Reserve, an area originally designated for protection of the Pacific herring spawning habit (Landis et al. 2004).

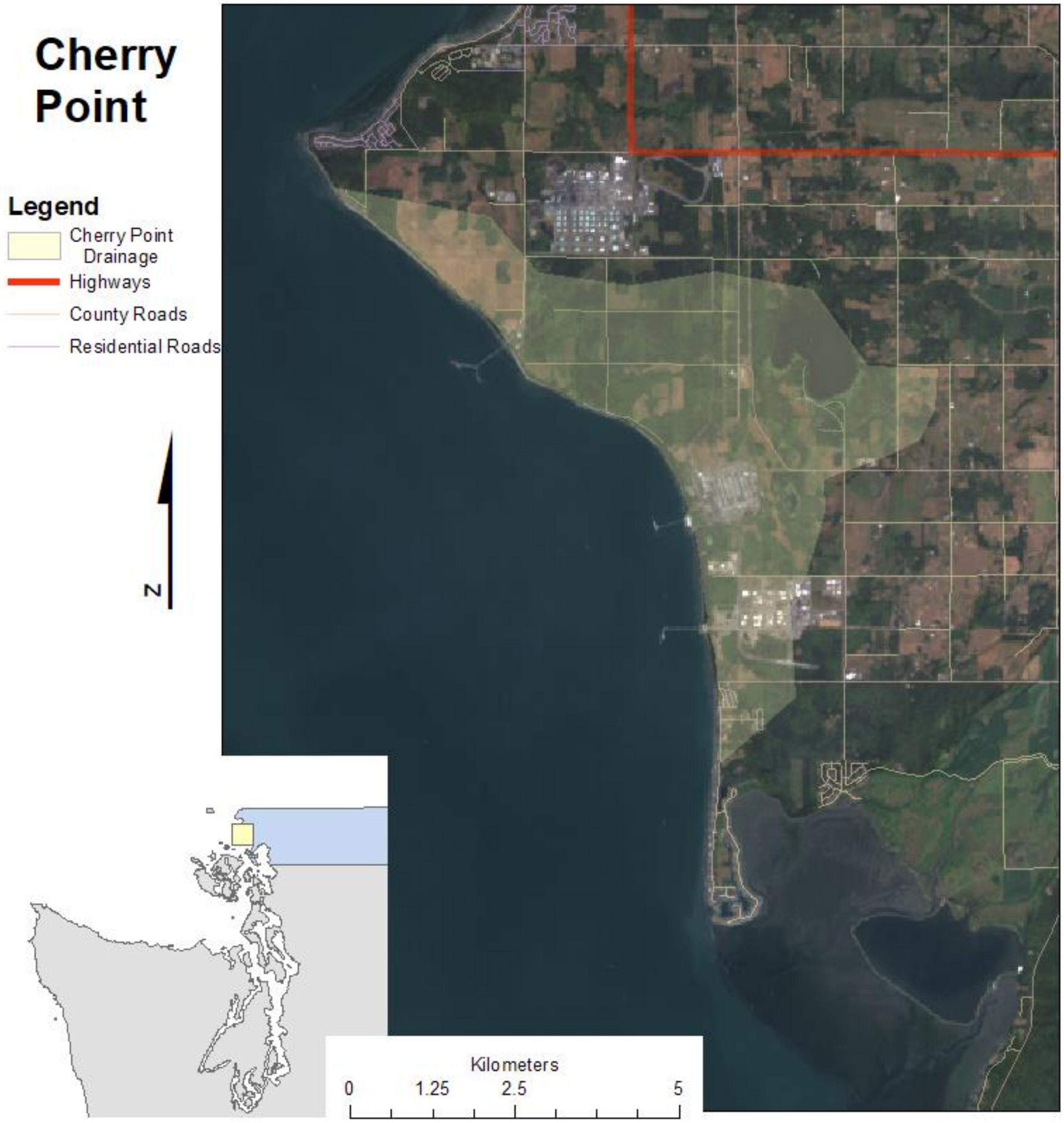

Figure 2. Map of Cherry Point

Skagit River delta

The Skagit River delta is an area that has been studied at length and identified as an important location for salmon and agricultural land. The estuarine wetlands of the Skagit River delta provide transitional habitat for juvenile salmonids in between their time in freshwater and saltwater (Greene and Beamer 2012) as well as being identified as providing important habitat for other wildlife populations (Rybczyk et al. 2016).

The largest land use in the Skagit River delta is agricultural lands, a large source of economic development in the area. The delta also provides hydropower and other water resources (Rybczyk et al. 2016).

For this study, the Skagit River delta is defined as the area in between and including the North and South Skagit Rivers and the extending intertidal areas, as shown in Figure 3.

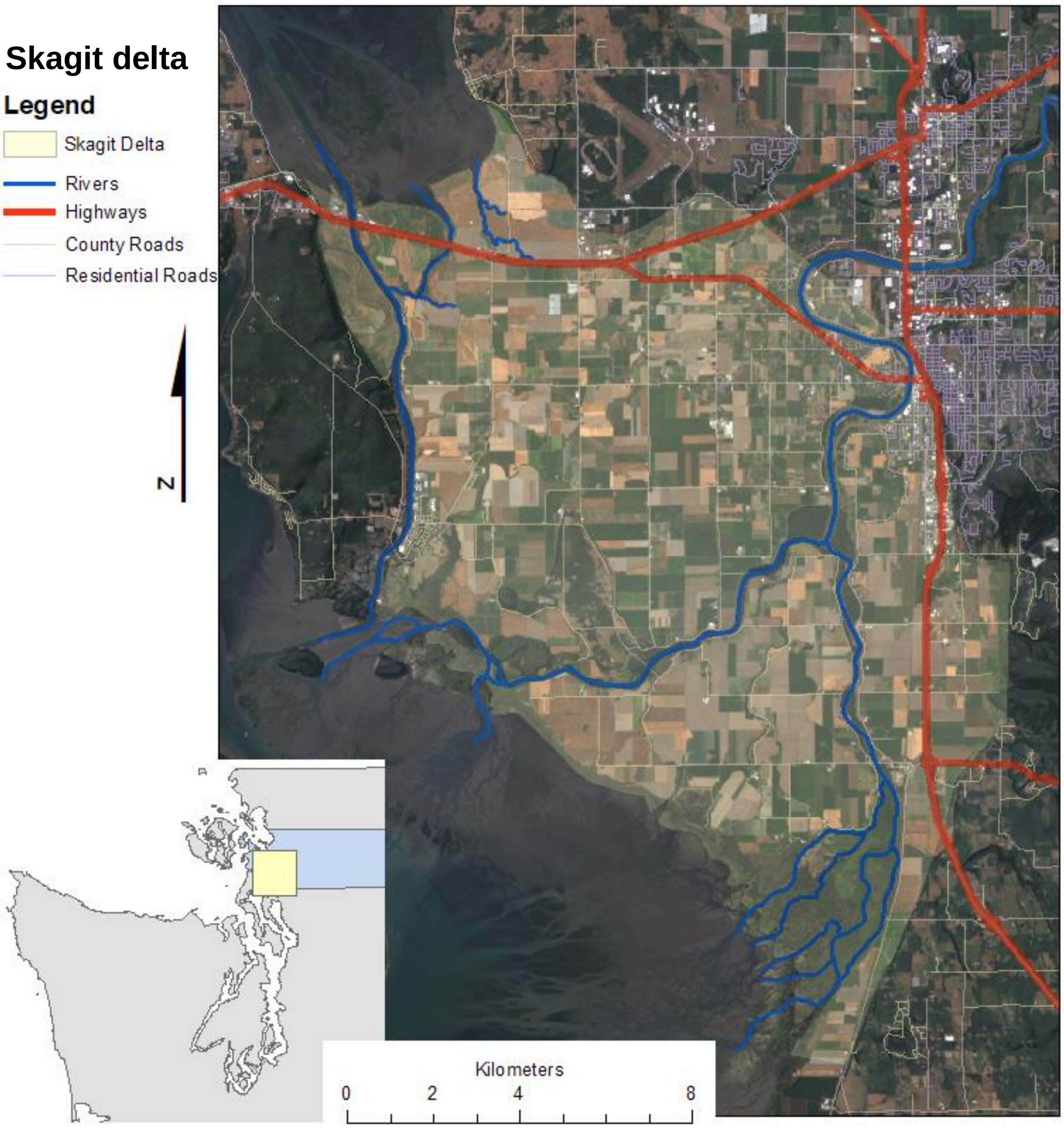

Figure 3. Map of Skagit River delta

Conceptual model (CM) design

The CM was constructed as the foundation for which to build the BN and was designed to show the relationships between sources of stressors and their impacts in an organized and linear way. It was derived from site-specific data, peer-reviewed literature, and expert opinion. Figure 4 shows the basic CM.

The first step in the building of the CM began with identification of potential stressors to the chosen endpoints using expert opinion with a prior knowledge of the systems as well as an extensive literature search. This resulted in a unique set of stressors to each target endpoint (Table 2). These stressors were categorized into three categories based on a similar cause and effect pathway: 1) chemical stressors, 2) climate stressors, and 3) habitat stressors.

Stressors to Pacific herring

Cherry Point herring have seen a massive decline in populations since the 1970’s (Landis et al. 2004) that has been attributed to a number of factors, including harvesting, habitat changes, climate change (GCC and Pacific Decadal Oscillation [PDO]), and contaminants (Landis et al. 2004). This research uses three of those factors as stressors: habitat changes, climate change, and contaminants.

Because Cherry Point Pacific herring deposit eggs on the nearshore intertidal region, impacted nearshore intertidal areas are expected to decrease herring populations (WDFW 2017). Cherry Point Pacific herring survival rates have been shown to be decreased at temperatures exceeding 12 ˚C, with almost complete mortality above 18 ˚C (Dinnel et al. 2011, Marshall 2012). These temperatures also decrease hatch rate to a lesser degree (Marshall 2012). Thus, climate change (in the form of increased water temperatures) is expected to influence Pacific herring populations. Contaminant exposure is a known stressor pathway to aquatic organisms and a potential source of risk to populations.

Stressors to coho salmon

Loss of estuarine wetlands has been identified as a limiting factor to salmon recovery in the Skagit basin (Beamer et al. 2005). However, there is little data on how these factors are related quantitatively. Magnusson and Hilborn (2003) showed no significant relationship between the percent of estuary in natural condition and coho salmon survival. David et al. (2016) showed no relationship between wetland area lost and the salmon instantaneous ration or the energy ration. The effects of exposure to contaminants to coho were described in two main pathways: 1) pre-spawn mortality (PSM), and 2) direct chemical toxicity. Coho salmon have been shown to exhibit PSM (death preceded by gaping, swimming in circles, and loss of equilibrium), most likely from exposure to a currently undefined chemical contaminant mixture from run-off to urban streams (Feist et al. 2011, Spromberg et al. 2011). The amount of PSM has been directly linked to amount of commercial land, with areas of higher percentages of commercial land exhibiting more PSM (Feist et al. 2011). Our model included commercial land as a surrogate for industrialization that may be causing this phenomenon. An important factor for freshwater juvenile coho survival has been identified as water temperatures, with high water temperatures a known stressor (Mantua et al. 2010).

Stressors to estuarine wetlands

Pressures from GCC, namely increased flooding, increased sea level rise, and increased storm surges, are expected to decrease the available estuarine habitat in the Skagit River delta, which have already seen massive decline in recent years (Mauger et al. 2015, Hamman et al. 2016, Rybczyk et al. 2016, Hood et al. 2016). Estuaries are subject to climatic pressures from both the freshwater (ex. river flows) and saltwater (ex. sea level rise, storm surge) sides, making them areas more vulnerable to climate stressors (Hamman et al. 2016).

Stressors to agricultural lands

Because of their proximity within the river delta, agricultural lands within the Skagit River delta are subject to similar stressors as those to estuarine wetlands, as described above.

Table 2. Summary of chemical, ecological, and habitat stressors to Pacific herring, coho salmon, estuarine wetlands, and agricultural land endpoints. Italicized stressors were considered but not used in the risk assessment model due to lack of site-specific data.

Pacific herring	Coho salmon	Estuarine wetlands	Agricultural lands
Chemical Stressors			
PCBs PBDEs Organochlorine Pesticides *PAHs* *Surface water runoff* *Industrial effluent*	PCBs PBDEs Organochlorine Pesticides *PAHs* Surface water runoff *Industrial effluent*		
Climate Stressors			
Water Temperature	Water Temperature *Stream flow*	Flooding Sea level rise Storm surge *Stream flow*	Flooding Sea level rise Storm surge *Stream flow*
Habitat Stressors			
Loss of spawning habitat	Loss of rearing habitat		

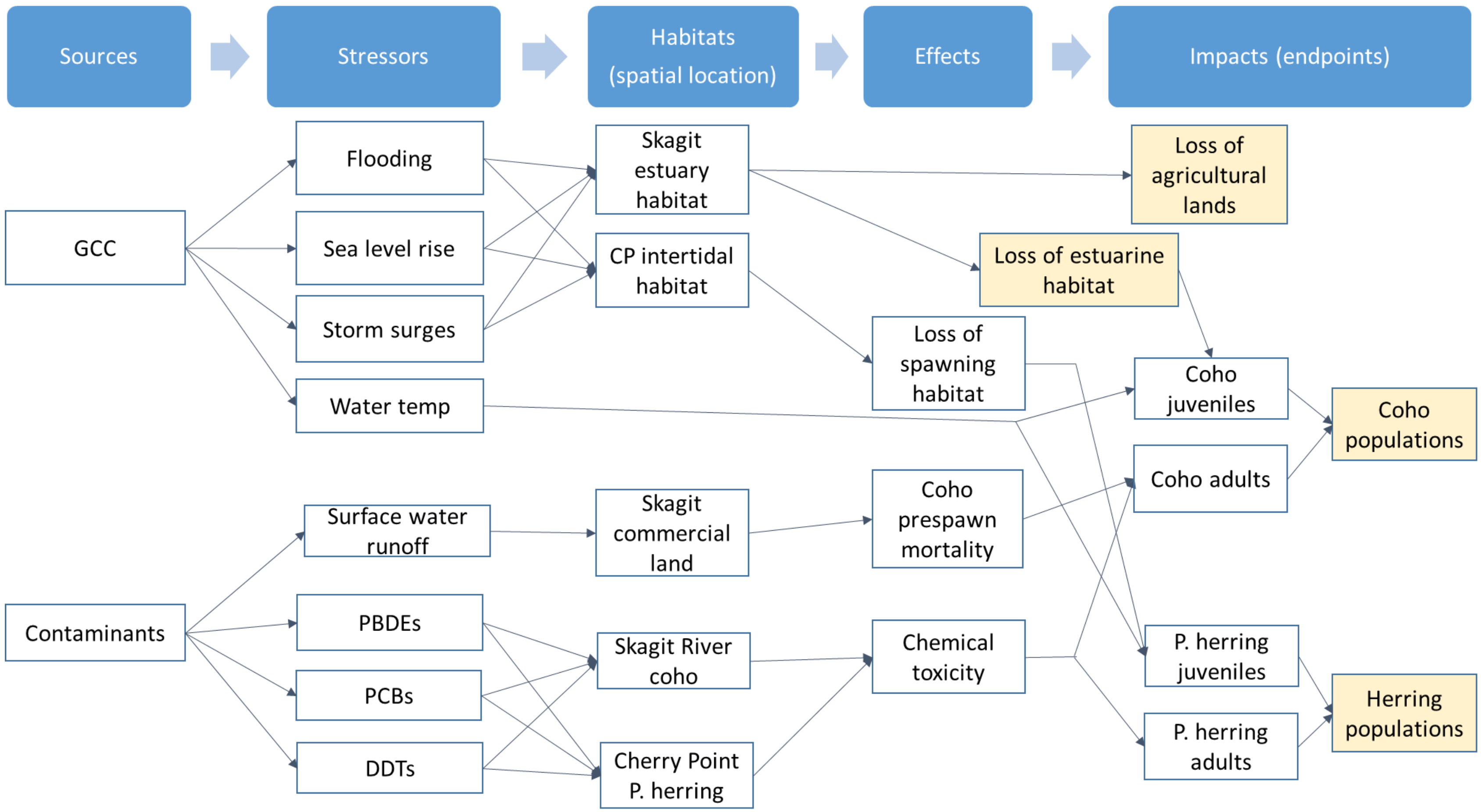

Figure 4. Relative Risk conceptual model (CM) showing sources of stressors, stressors, habitat, and effects to specified endpoints. Highlighted nodes are defined endpoints.

Bayesian network (BN) development

The BN structure was formed directly from the CM, with each node in the BN derived from an individual box in the CM. The endpoints were set as terminal nodes, with the exception of the estuarine wetlands endpoint which was included as an intermediate node because of its impact as a habitat stressor to the biotic endpoints. The links between the nodes represent the causal relationships. The tiered nature and linear flow of the CM was retained in the BN. The BN is shown in Figure 5.

Each node was parameterized with site-specific data or data from peer-reviewed literature and government reports in three steps: 1) discretizing nodes, 2) inputting known frequency distributions, and 3) creating conditional probability tables (CPTs).

Discretizing nodes

Each node is composed of two or more states which represent different scenarios. These states of parent nodes were labeled with the unique identifier. For instance, within the Region node, either the Skagit river delta (Skagit delta) or Cherry Point can be selected to represent different scenarios. The states of child nodes were labeled low, medium, or high to represent values of a parameter that, when all the interactions between the nodes are considered, pose a low, medium, or high risk to the endpoint. The values that corresponded to this ranking scheme were unique to each node and corresponded to either 1) an equal distribution (ex. 0-33%, 33-66%, 66-100%) or 2) node-specific values (ex. corresponding to an established screening level value).

Inputting known frequency distributions

Where site-specific data existed, they were input into the nodes with their known distributions. Where the frequency of occurrence was unknown, an even distribution was input to indicate the current state of knowledge. These can be updated with known distributions when the state of knowledge is increased. In this way, different forms of information can be used to describe complex systems, including when expert opinion suggests a causal connection but no scientific evidence exists to support the cause and effect relationship.

Creating conditional probability tables (CPTs)

For each child node, a conditional probability table (CPT) was compiled to quantify the relationship shown by the link between the nodes. These CPTs were compiled with site-specific data and data from peer-reviewed literature and government reports. Specific data sources are described in the following section.

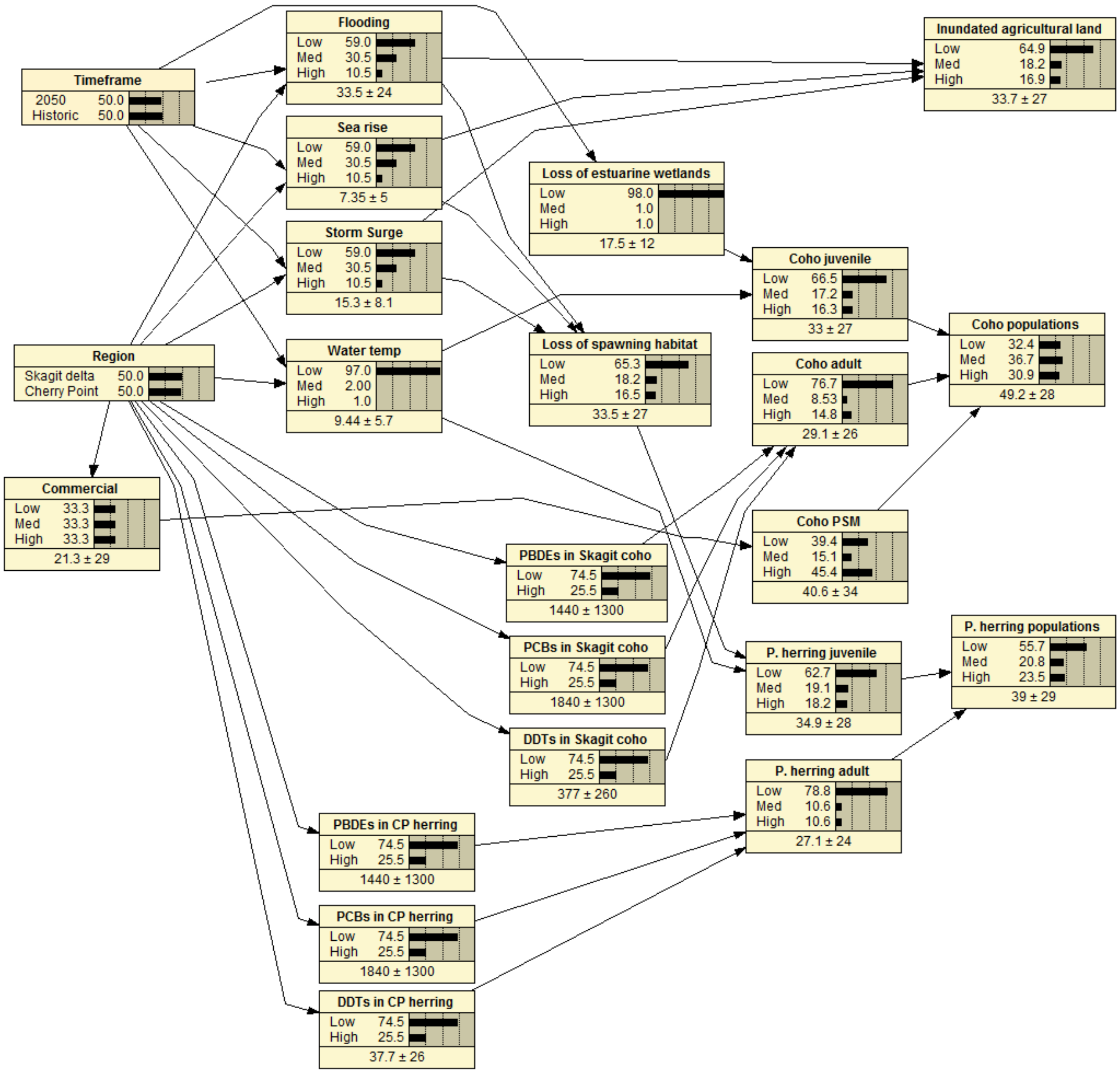

Figure 5. Bayesian network (BN), derived from the CM and RRM framework.

Data to inform the model

Discretizing nodes

Each variable (node) was discretized into states (ranks), following the low, medium, high ranking scheme used in previous risk assessments (Hayes and Landis 2004, Colnar and Landis 2007, Hines and Landis 2014, Herring and Landis 2015). Table 3 describes the breakdown of rankings for each variable.

For example, risk from PCBs to coho is described as low if fish have a concentration <2400 ng/g-lipid and high if >2400 ng/g-lipid, the residue effect threshold determined by Meador et al. (2000) and high if >2400 ng/g-lipid.

Table 3. Justification of node discretization for each parameter.

Node	State	Definition	Reference
Commercial	Low Med High	<2% 2-12% >12%	Connection between commercial land cover and coho pre-spawn mortality (PSM; Feist et al. 2011)
Flooding	Low Med High	4% 42% 86%	Based on projections from Mauger et al. (2015) for moderate emissions (A1B) in 2080s relative to 1970-1999 for 100 year flood event (1% annual probability)
Sea rise	Low Med High	3-5 in 5-15 in 15-22 in	Based on projections from Mauger et al. (2015) for moderate emissions (A1B) in 2050 relative to 2000 for relative sea level rise for the latitude of Seattle, assuming a land uplifting rate of ~0.4±0.6 inch/decade.
Storm surge	Low Med High	5% 22% 34%	Based on projections from Mauger et al. (2015) for high emissions (RCP 8.5) in 2080s relative to 1970-1999 for annual 99th percentile of 24-hour precipitation in western OR and WA (latitudes 40-49N).
Water temp	Low Med High	0-18 ºC 18-25 ºC 25-30 ºC	Critical temp for P. herring is above 18-20 ºC (dnr.wa.gov); Critical temp for coho salmon ~25 C (Geist et al. 2006, McCullough 1999)
Change in rearing habitat	Low Med High	0-33% 33-66% 66-100%	Equal distribution to represent the current state of knowledge
Loss of spawning habitat	Low Med High	0-33% 33-66% 66-100%	Equal distribution to represent the current state of knowledge
PBDEs in coho	Low High	<160 ng/g >160 ng/g	Reference concentration used in PSP Vital Signs (Arkoosh et al. 2010, Hamel et al. 2015)
PCBs in coho	Low High	<2400 ng/g >2400 ng/g	Residue effect threshold used in PSP Vital Signs (Meador et al. 2000, Hamel et al. 2015)
DDTs in coho	Low High	<500 ng/g >500 ng/g	Most reported effects in salmonids associated with whole body tissue tDDT concentrations ≤500 ng/g (Buhler et al. 1969, Beckvar et al. 2005)
PBDEs in herring	Low High	<160 ng/g >160 ng/g	Reference concentration used in PSP Vital Signs (Arkoosh et al. 2010, Hamel et al. 2015)
PCBs in herring	Low High	<2400 ng/g >2400 ng/g	Residue effect threshold used in PSP Vital Signs (Meador et al. 2000, Hamel et al. 2015)
DDTs in herring	Low High	<500 ng/g >500 ng/g	Most reported effects in salmonids associated with whole body tissue tDDT concentrations ≤500 ng/g (Buhler et al. 1969, Beckvar et al. 2005)

Coho PSM	Low Med High	<10% 10-50% >50%	Natural breaks from Feist et al. (2011)
Coho juv. populations	Low Med High	0-33% 33-66% 66-100%	Equal distribution to represent the current state of knowledge
Coho adult populations	Low Med High	0-33% 33-66% 66-100%	Equal distribution to represent the current state of knowledge
Pacific herring juv. populations	Low Med High	0-33% 33-66% 66-100%	Equal distribution to represent the current state of knowledge
Pacific herring adult populations	Low Med High	0-33% 33-66% 66-100%	Equal distribution to represent the current state of knowledge
Inundated agricultural land	Low Med High	0-33% 33-66% 66-100%	Equal distribution to represent the current state of knowledge
Coho populations	Low Med High	0-33% 33-66% 66-100%	Equal distribution to represent the current state of knowledge
Pacific herring populations	Low Med High	0-33% 33-66% 66-100%	Equal distribution to represent the current state of knowledge

Inputting frequencies

Where known frequency distributions for nodes existed, they were input directly into the model. For example, concentrations of contaminants (mean and standard deviations) in Skagit coho and Cherry Point herring were obtained from West et al. (2016) and West et al. (2008). The full list of references for input nodes are listed in Table 4.

Land cover (specifically commercial land cover) was input as an even distribution (the probability of commercial land cover being <2% = the probability of commercial land cover being 2-12% = the probability of commercial land cover being >12%) to describe the uncertainty with this node. A GIS analysis of the area would result in known frequencies which could be input into the model.

Table 4. Input parameters

Input Parameter	Reference
Flooding	Mauger et al. (2015)
Sea rise	Mauger et al. (2015)
Storm surge	Mauger et al. (2015)
Water temp	Mote and Salathe (2010)
Change in estuarine wetland	Jones (2015)
PBDEs in coho	West et al. (2016)
PCBs in coho	West et al. (2016)
DDTs in coho	West et al. (2001)
PBDEs in herring	West et al. (2016)
PCBs in herring	O'Neill and West (2001), West et al. (2008)
DDTs in herring	West et al. (2001), West et al. (2008)

Creating conditional probability tables (CPTs)

Linkages connecting nodes in the BN were based on known cause-effect pathways and were derived directly from the conceptual model. In the BN, each line connecting two or more input nodes to an intermediate node relied on a CPT to quantify the causal relationships and calculate the probability distributions in the intermediate node. The full list of input nodes entering child nodes with associated references used to derive CPTs is included in Table 5.

Table 5. CPT derivations

Node	Input nodes	Reference
Loss of spawning habitat	Flooding Sea rise Storm Surge	
Coho PSM	Commercial	Feist et al. (2011)
Coho juv. populations	Change in rearing habitat Water temp	Magnusson and Hilborm (2003), David et al. (2016) Mantua et al. (2010)
Coho adult populations	PBDEs in coho PCBs in coho DDTs in coho	Arkoosh et al. (2010) Meador et al. (2000) Buhler et al. (1969), Beckvar et al. (2005)
Pacific herring juvenile populations	Loss of spawning habitat Water temp	Shelton et al. (2014) Dinnel et al. (2011), Marshall (2012)
Pacific herring adult populations	PBDEs in herring PCBs in herring DDTs in herring	Arkoosh et al. (2010) Meador et al. (2000) Buhler et al. (1969), Beckvar et al. (2005)
Inundated agricultural land	Flooding Sea rise Storm surge	
Coho populations	Coho juvenile Coho adult Coho PSM	Spromberg and Meador (2004) Spromberg and Meador (2004) Spromberg and Scholz (2011)
Pacific herring populations	P. herring juvenile P. herring adult	

Model evaluation

After completing the BNs and calculating risk, we evaluated the models using a sensitivity analysis and uncertainty analysis. A brief description of both methods follows. Additional information can be found in Pollino et al. (2006) and Marcot (2012).

Sensitivity analysis

Sensitivity analysis explains the extent to which the endpoint node is influenced by the values of the input nodes (Pollino et al. 2006, Marcot 2012, Hines and Landis 2014). The sensitivity analysis is used to understand which variables contribute risk to the endpoint (Ayre et al. 2014, Hines and Landis 2014, Landis et al. 2017). The sensitivity analysis results can be used to compare the relative influence of input nodes on the endpoint to evaluate the model structure, interpret the risk results, and provide further information to the risk managers as to the sources of risk to the endpoint. For example, Hines and Landis (2014) used sensitivity analysis to identify variables important for future monitoring efforts or risk management actions.

The sensitivity analysis also measures mutual information between each of the input nodes and the endpoint node (Norsys Software Corp. 2014, Pollino et al. 2006, Woodberry et al. 2004). Mutual information measures how much one random variable tells us about another, i.e., their mutual dependence. A high value of mutual information for an input indicates a greater degree of influence on the endpoint node (Hosack et al. 2008, Marcot 2012). Mutual information is a function of both the findings in the node (probability distributions) and the relationship described in the CPT (Marcot 2012, Norsys Software Corp. 2014).

Uncertainty analysis

We quantitatively and qualitatively assessed the uncertainty in the network and model outputs through several methods. Uncertainty in the model structure was assessed qualitatively through a discussion of input parameters and pathways both included and excluded in the model. In some cases, literature searches identified important stressors where site-specific data or regional equivalent data were not available, which will be discussed later. We described uncertainty in input parameters explicitly in the probability distributions. We applied identical distributions for the risk states when there were no data available for a particular parameter in the risk region.

Uncertainty in the cause and effect pathways resulted in more similar conditional probability distributions in the CPTs. Since there was little site-specific information describing the interactions of parameters, all conditional probability tables were constructed based on information obtained from scientific literature.

RESULTS AND DISCUSSION

Risk projections

Risk to Pacific herring does not change dramatically from present to 2050. This is largely explained by the model construction. Current projections are for water temperatures to increase 1.2 ºC by 2050 which is still below the temperature threshold of 18 ºC that has been shown to cause decreased survival to Cherry Point herring. Additionally, there is a large amount of uncertainty as to the amount of spawning habitat that will be lost due to GCC as well as the effect that this decreased habitat will have on Cherry Point Pacific herring survival. There is some evidence that Pacific herring populations are more limited by habitat quality rather than habitat quantity (Shelton et al. 2014).Because of a lack of data, our model did not include degradation of habitat quality as a stressor and used an equal likelihood of all effects from spawning habitat because of our uncertainty.

Risk to coho salmon is similar to that of Pacific herring, in that we don’t see much change in risk from current to future. The same rationale discussed above holds true here as well. Additionally, we did not include future projections for commercial development (changing risk from PSM) although that could be changed to better understand potential scenarios and associated risk.

Risk to estuarine wetlands was not found to change dramatically from present to 2050, in large part because the total loss of estuarine wetlands is not projected to be substantial in these regions (0-3% [Jones 2015]). Although the amount of total estuarine wetlands is not forecasted to dramatically change, there is large variation in changes to subcategories of estuarine habitat types (tidal flat, brackish marsh, etc.; Jones 2015), which could have an influence on risk.

Risk to agricultural lands dramatically rises in 2050 compared to current (Figure 6). This increase in risk over time is not surprising, as the CPT was developed to display this relationship (ex. increased flooding resulting in increased inundated agricultural land), despite not currently having quantitative data to support this. Our model shows a <2% probability of medium and high risk inundation of agricultural lands (>33%) historically, compared to a 68% probability in 2050 as the result of increased flooding, sea level rise, and storm surge (Figure 6).The selected output from the model is shown in Figure A1.

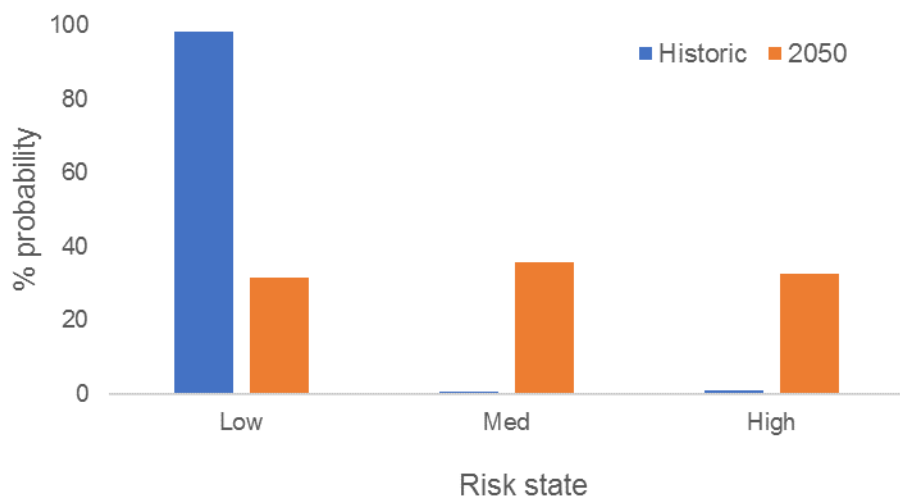

Figure 6. Probability of low, medium, or high risk to agricultural lands in 2050 compared to historic.

Sensitivity analysis

The sensitivity results using mutual information as the measurement are shown in Table 6. Sensitivity of the endpoints nodes of the mode to the upstream nodes was calculated for Current Conditions and for 2050 and compared.

For the Pacific herring, the top three variables were P. herring juvenile, P. herring adult and the Region. In the population models (Landis and Bryant 2010) it is common that these two factors determine both the age structure and population dynamics. The Region is important because the P. herring run is found at Cherry Point. The contaminant loadings were as important as the other three variables. All of the contaminant loadings are below criteria. The sensitivity analysis for Current Conditions and 2050 are identical.

The node Coho Population was sensitive to PSM and Commercial, which is an indicator of impervious surface in the landscape. Commercial is a surrogate for the number of roads in the region and roads are a good indicator of the probability of PSM being observed. The sensitivity analysis was identical for Current Conditions and 2050.

Inundated Agricultural Lands was the node in which the sensitivity results changed from Current Conditions to 2050. The endpoint node is sensitive to the nodes Storm Surge, Sea rise, Loss of spawning habitat and Flooding and in that order for Current Conditions. As expected Storm Surge and Sea Rise are major drivers for both scenarios. For the 2050 scenario Flooding and Loss of Spawning habitat switch positions.

A sensitivity analysis could not be run on the estuarine wetlands endpoint because it was input directly from climate projections.

Table 6. Sensitivity Analysis for the three endpoints for current conditions and in 2050. The only case in which the results were different between current and 2050 projections were for Inundated Agricultural Lands.

Node	Mutual Information	Percent
P. Herring Current Conditions		
P. herring juvenile	0.29058	20.3
P. herring adult	0.29128	20.3
Region	0.05511	3.84
PCBs in CP herring	0.05284	3.68
PBDEs in CP herring	0.05284	3.68
DDTs in CP herring	0.03507	2.44
P. Herring 2050		
P. herring juvenile	0.29058	20.3
P. herring adult	0.29128	20.3
Region	0.05511	3.84
PCBs in CP herring	0.05284	3.68
PBDEs in CP herring	0.05284	3.68
DDTs in CP herring	0.03507	2.44
Coho Population Current Conditions		
Coho PSM	0.08534	5.4
Commercial	0.04863	3.08
Coho Population 2050		
Coho PSM	0.08534	5.4
Commercial	0.04863	3.08
Inundated Agricultural Lands Current Conditions		
Storm Surge	0.02468	17.1
Sea rise	0.02468	17.1
Loss of spawning habitat	0.01913	13.3
Flooding	0.01888	13.1
Inundated Agricultural Lands 2050		
Storm Surge	0.07449	4.71
Sea rise	0.07449	4.71
Flooding	0.07027	4.44
Loss of spawning habitat	0.03654	2.31

Uncertainty analysis

There was a high degree of uncertainty associated with the exact influence that climatic stressors would have on the amount of estuarine wetlands, spawning habitat, and agricultural land. It is expected that these relationships exist (for instance, more sea level rise results in less agricultural land) but there is a current lack of data on the exact relationships. To decrease this uncertainty and increase the confidence in risk projections, more site-specific research on this pathways is needed.

Another source of uncertainty is the relationship between loss of habitat (both rearing and spawning) on biotic endpoints. It has been surmised that loss of estuarine habitat would result in decreased salmon populations (Magnusson and Hilborn 2003, Greene and Beamer 2012) but there is still a large data gap in how much of an influence it plays specifically. In fact, the study by Magnusson and Hilborn (2003) found no significant relationship between the amount of estuarine area or the amount of estuarine area in “natural condition” and coho survival rate.

Without doing a full population modeling analysis, there was large uncertainty associated with the influence to juveniles and adults to the overall population structure, Adding to this pathways would decrease the uncertainty and increase the interpretation of these pathways.

There were several pathways that were excluded from the model because there was too high of uncertainty. It is expected that increased water temperatures will alter chemical toxicity but there are high levels of uncertainty associated with this pathway (Moe et al. 2013, Hooper et al. 2013).

Considerations

Endpoint choice

An examination of different salmonids would have a higher influence from the temperature node, as Chinook and coho are found to be the most resistant of the salmonids to high water temperature (Waldichuk 1993, Aitkin 1998).

A study examining Chinook salmon, rather than coho salmon would likely show an increased effect from chemical contaminants than shown in the present study. Chinook salmon have been shown to have higher concentrations of PCBs than coho and higher than established adverse effects levels (O’Neill et al. 1998, West et al. 2016). Chinook were below the adverse effect level for PBDEs (1600 ng/g lipid [Arkoosh et al. 2010]) in the West et al. (2016) study but above that level in previous studies (ranging from 350 to 2800 ng/g lipid; Sloan et al. 2010).

Different species also have different life histories that result in different exposure times and responses, and associated risks. For instance, Chinook appear to have greater dependence on estuaries than coho (Magnusson and Hilborn 2003). Additionally, there is evidence that pink and chum salmon can spawn in intertidal areas (Meehan and Bjornn 1991, Aitkin 1998). Thus, examination of these species as endpoints would have additional stressors and linkages that would need to be considered.

The use of total estuarine wetlands resulted in a much different interpretation than if a subcategory of estuarine type was chosen because of the large variability in projected responses.

Region choice

Concentrations of PCBs and PBDEs in coho in the Skagit are lower than in other regions (ex. Nisqually and Deschutes; O’Neill et al. 1998, West et al. 2016). Additionally, rates of PSM are lower in the Skagit than more urbanized watersheds. Concentrations of contaminants in Cherry Point herring were found to be lower than those at more urbanized watersheds (O’Neill and West 2001). Thus, a risk analysis of more urbanized watersheds would likely have a heavier influence of the contaminant loading stressors.

The projections of response to GCC stressors are spatially distinct and assessment of risk to estuarine wetlands and/or agricultural lands elsewhere in the Puget Sound would be expected to differ greatly that in this assessment.

Stressor choice

Three individual toxicant stressors (PBDEs, PCBs, and DDTs) were included in this model because of monitoring data in the select regions. Coho salmon and Pacific herring are exposed to numerous other toxicants (lead, mercury, arsenic, endosulfan, etc. [West and O'Neill 2001]) that may also contribute to the contaminant loadings (and resulting risk). Additionally, the effects of mixtures was not included despite being an important consideration that could result in either increased or decreased toxicity (Bliss 1939, Monosson 2005).

Additional climate stressors not included in this model are expected to act as stressors to select endpoints including but not limited to changes in precipitation, stream flow amounts, and timing of peak flows are expected to have influences on both biotic and abiotic endpoints. Including additional stressors would provide a whole complete picture of total risk expected to endpoints if the cause-effect relationship is well understood and documented. However, too many stressors would result in a complex picture with limited interpretability.

NEXT STEPS

Site specific data

There are currently no data on concentrations of chemical stressors not included in the model (PAHs, metals, etc.) in coho or Pacific herring and thus no estimates of effects from those stressors. Including these chemical stressors and others that are expected to contribute to risk, would better describe the actual risk to Pacific herring and coho populations from this stressor pathway.

An extensive analysis of commercial land cover would provide a better description of risk to biotic endpoints from surface water runoff. Including point source locations could also increase knowledge of potential chemical stressors with the additional inclusion of risk regions.

Refined climate projections

As described in the results and discussion section, the current climate projections influenced the results found in this project. By including a fine-resolution spatial component to the climate projections, a better calculation of inundated agricultural land will be possible.

Further work to include more refined projections, specifically for water temperatures specific to the Skagit river delta and Cherry Point reach, would improve the model and decrease associated uncertainty with the temperature nodes.

Additionally, future work may include additional climate change stressors as well as different emission scenarios and timeframes for a more robust understanding of expected effects.

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APPENDIX

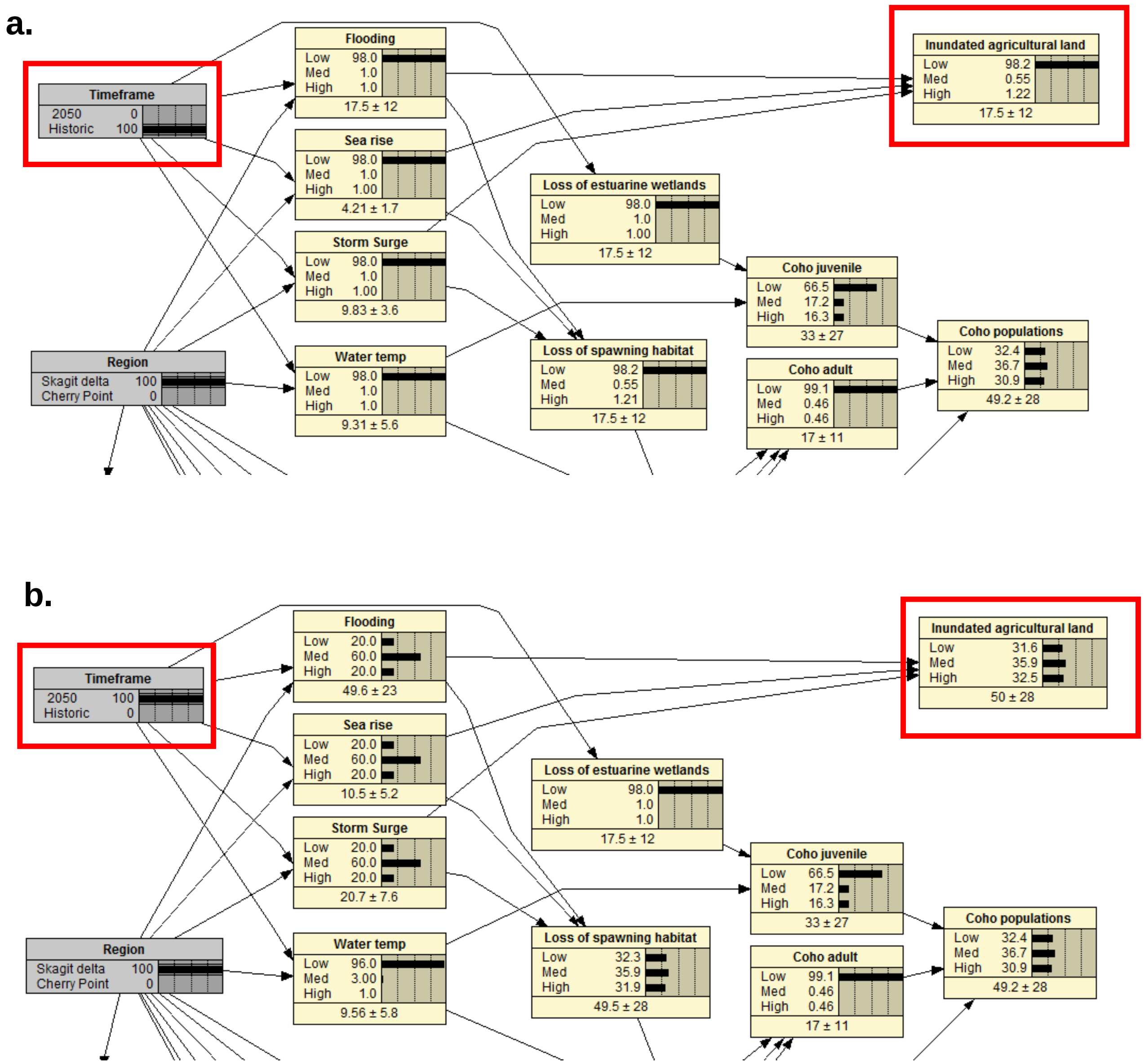

Figure A1. Results of BN for inundation of agricultural land in the Skagit delta for a) historic and b) 2050 projected risk.