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Incorporating Climate Change Predictions in Ecological Risk Assessment: A Bayesian Network Relative Risk Model for Chinook Salmon in the Skagit River Watershed

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By

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Abstract

Climate change is expected to have widespread impacts on future ecosystem services in the Puget Sound and around the world. It is important that climate change be included in ecological risk assessment so that changing climate variables and potential interactive effects with chemical stressors can be taken into account. In this research, I focused on the question of how water temperature changes generated by climate change interact with organophosphate pesticide toxicity to affect Chinook salmon (*Oncorhynchus tshawytscha*) population size in the Skagit River, WA. To answer this question, I conducted an ecological risk assessment using the Bayesian network relative risk model (BN-RRM). It is a quantitative, probability-based approach that calculates complex relationships between ecological variables in a cause-and-effect framework to provide estimates of risk to valued receptors (endpoints). I used region and season specific measurement data for water temperature, dissolved oxygen, chlorpyrifos concentration, and diazinon concentration as the model input. Climate predictions were based on model output between the years 2071 and 2100 from an ensemble of global climate models (GCMs) selected from the Fifth Coupled Model Intercomparison Project (CMIP5). The probability of Chinook salmon population decline, before climate change predictions were taken into account, ranged between 77.1% and 64.0% depending on region and season. I found climate change caused changes in water temperature influenced risk in different ways depending on the region and season. The probability of Chinook population decline increased by up to 4.2% in different regions and seasons. I used sensitivity analysis of the BN-RRM to analyze which stressors had the most influence on Chinook salmon population size. I found that the environmental stressors of water temperature and dissolved oxygen had the most influence, which suggests habitat remediation may be an effective strategy for addressing risk to Chinook salmon in the Skagit River. This research demonstrates that climate change scenarios can be

successfully incorporated into ecological risk assessment using the BN-RRM. This approach can be easily adapted to other watersheds and allows for the inclusion of additional stressors and/or endpoints.

Acknowledgements

Toxicology data from published, peer-reviewed studies were provided by Cathy Laetz and David Baldwin from the National Oceanic and Atmospheric Administration (NOAA) Fisheries. Environmental data were provided by the Washington State Department of Ecology through the Environmental Information Management Database website. Climate model output were provided by the United States Geological Survey through the Geo Data Portal website. Chelsea Mitchell from Washington State University performed the population modeling used in this research. Lacey Rose Lackey assisted with this project as an intern at the Institute of Environmental Toxicology and Chemistry, performing GIS and toxicological analysis. April Markiewicz from the Institute of Environmental Toxicology and Chemistry provided scientific guidance and assistance with this project. Valerie Chu and Megan Harris, former graduate students at the Institute of Environmental Toxicology and Chemistry, provided guidance with constructing Bayesian networks.

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I acknowledge the World Climate Research Program's Working Group on Coupled Modelling, which is responsible for CMIP, and we thank the climate modeling groups (Table 13) for producing and making available their model output. For CMIP the U.S. Department of Energy's Program for Climate Model Diagnosis and Intercomparison provides coordinating support and led development of software infrastructure in partnership with the Global Organization for Earth System Science Portals.

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Acronyms and Abbreviations

AChE	Acetylcholinesterase
BN	Bayesian Network
BN-RRM	Bayesian Network Relative Risk Model
CPT	Conditional Probability Table
CMIP5	Coupled Model Intercomparison Project Five
DO	Dissolved Oxygen
EC50	50% Effect Concentration
ESLOC	Endangered Species Level of Concern
ESU	Evolutionary Significant Unit
GCM	Global Climate Model
NOAA	National Oceanic and Atmospheric Administration
OP	Organophosphate Pesticide
PSP	Puget Sound Partnership
RCP	Representative Climate Pathway
TU	Toxic Units
USEPA	United States Environmental Protection Agency
USGS	United States Geological Survey
WADOE	Washington State Department of Ecology
WADOE EIM	Washington State Department of Ecology Environmental Information Management Database
WRIA	Water Resource Inventory Area

1. Introduction

My research incorporated climate change caused variations in water temperature into the Bayesian network relative risk model (BN-RRM) to assess risk to Chinook salmon (*Oncorhynchus tshawytscha*) in the Skagit River Watershed. I adapted the BN-RRM from current research on ecological risk assessment of Chinook salmon in multiple watersheds in Washington State (Landis et al. 2020) to focus on the Skagit River Watershed, using sub-basin specific data to incorporate spatial and temporal variability within the watershed. I compared relative risk from multiple stressors: water temperature under different climate scenarios, dissolved oxygen, and two organophosphate pesticides: diazinon and chlorpyrifos.

Landis et al. (2013) outlined an approach to incorporating climate change into ecological risk assessment following seven guiding principles that I followed in my research:

1. Consider the importance of climate change related factors in the context of a particular ecological risk assessment.
2. Use ecosystem services as the assessment endpoints.
3. Climate change can influence end points in both positive and negative ways.
4. Using a multiple stressor approach is necessary to take into account the complex ecological context.
5. Use a cause and effect conceptual model to take into account management decisions and use appropriate spatial and temporal scales to represent direct and indirect climate change effects.
6. Determine sources of uncertainty and address them quantitatively when possible.
7. Use adaptive management for adapting to changing ecological conditions and ecosystem services.

1.1 Ecological Risk Assessment

Ecological risk assessment is a science for characterizing risk to endpoints from a variety of stressors (Landis and Wiegers 2005). Ecological risk assessment is also a tool to facilitate the process of environmental resource management and decision-making. As such it is important that endpoints with ecological, social, and economic relevance are chosen.

1.2 The Bayesian Network Relative Risk Model (BN-RRM)

The relative risk model (RRM) with the later inclusion of Bayesian networks (BN-RRM) was developed as a quantitative method to carry out risk assessment that can incorporate multiple stressors and endpoints on a regional scale (Landis and Wiegers 1997, 2005; Ayre and Landis 2012). Sources of stressors are linked to impacts (endpoints) through a cause and effect framework (Figure 1). The BN-RRM has been successfully implemented in several ecological risk assessments for the purposes of assessing risks to habitats and resources from wildfire, grazing, forest management practices, and insects (Ayre and Landis 2012), evaluating low impact development remediation effects to Coho salmon prespawn mortality (Hines and Landis 2014), assessing risk from whirling disease to cutthroat trout populations (Ayre et al. 2014), assessing risk from nonindigenous species (Herring et al. 2015), assessing risk from climate change stressors (Gaasland-Tatro 2016, Landis et al. 2017a), evaluating remediation options for mercury contamination (Johns et al. 2017), integrating ecological and human health risk assessment (Harris et al. 2017) and assessing risk to estuary water quality using eukaryote environmental DNA as a measure of benthic community structure (Graham et al. 2019).

The incorporation of Bayesian networks into the relative risk model (BN-RRM) provided many advantages to ecological risk assessment (Ayre and Landis 2012). Bayesian networks are acyclic models that relate ecological variables in a cause and effect framework based on probabilistic calculations generated from conditional probability tables (CPTs; Marcot et al. 2007). The probability of effects to endpoints with associated uncertainty are calculated based on input from a variety of data sources. Different types of data such as toxicological, spatial, and temporal can be integrated into a Bayesian network as they are all related by conditional probabilities (Barton et al. 2012). Sensitivity analysis can determine which stressors have the most influence on which endpoints (Ayre and Landis 2012, Marcot 2012). Bayesian networks are gaining popularity in risk assessment and modeling ecological systems (Keshtkar et al. 2013; MacDonald et al. 2105; Franco et al. 2016; O'Brien et al. 2018; Sperotto et al. 2017, 2019).

Figure 1. The relative risk model (RRM), adapted from Landis and Wiegers (1997, 2005). The RRM is a causal pathway linking sources of stressors to impacts. Stressors that are present in a habitat cause effects that impact assessment endpoints.

1.3 Causality and Counterfactuals

Another benefit of using Bayesian networks is the ability test counterfactuals, which are "what if" questions within a causal framework (Balke and Pearl 1994, Bottou et al. 2013). When relationships between variables are understood to be causal within a Bayesian network, the modeler can test counterfactuals by altering the states of the nodes to create hypothetical scenarios and see how those effect the states of the other nodes. This is particularly useful in the context of ecological risk assessment where setting the state of the endpoint nodes to the desired management goals will calculate the hypothetical states of environmental parameters to meet those goals.

1.4 The Skagit River Watershed

I used the Skagit River Watershed as my study area. It is located in northwestern Washington State and partially in British Columbia, Canada. The Skagit River drains into the Salish Sea from an agriculturally important delta region. It contains habitat for many wildlife species including all species of salmon native to Salish Sea including Chinook (*Oncorhynchus tshawytscha*), large wintering populations of bald eagles (*Haliaeetus leucocephalus*) and waterfowl (Lee and Hamlet 2011). The wildlife provides important cultural and economic ecosystem services to residents, tribes, tourists, and businesses (Lee and Hamlet 2011). Habitats and the ecosystem services they provide at the Skagit River were identified as particularly vulnerable to climate change effects such as increased temperature and changing precipitation (Lee and Hamlet 2011). Stakeholders in the Skagit River Watershed include three Native American Tribal governments, three county governments, the Puget Sound Partnership, the Canadian federal government, city governments, businesses, and residents.

Land use is diverse in the Skagit River Watershed. There are federal, state, and county owned forest and conservation lands. The delta region and the Lower Skagit have been heavily developed for agriculture and urban city areas. Extensive agriculture and urban areas in the lower Skagit River Delta contribute pesticides through runoff. Juvenile salmon rearing habitat in the delta region is also under threat by the rapid agricultural and urban development in recent history (Beamer et al. 2005a, 2005b).

Changes in precipitation due to climate change within the Skagit River Watershed and in the wider Pacific Northwest is projected to cause relatively wetter winters and drier summers (Lee and Hamlet 2011). Glacier meltwater is an important source of water to maintain stream flow during the summer months but flows are decreasing along with decreasing glaciation in the Skagit River watershed (Lee and Hamlet 2011, Riedel and Larrabee 2016).

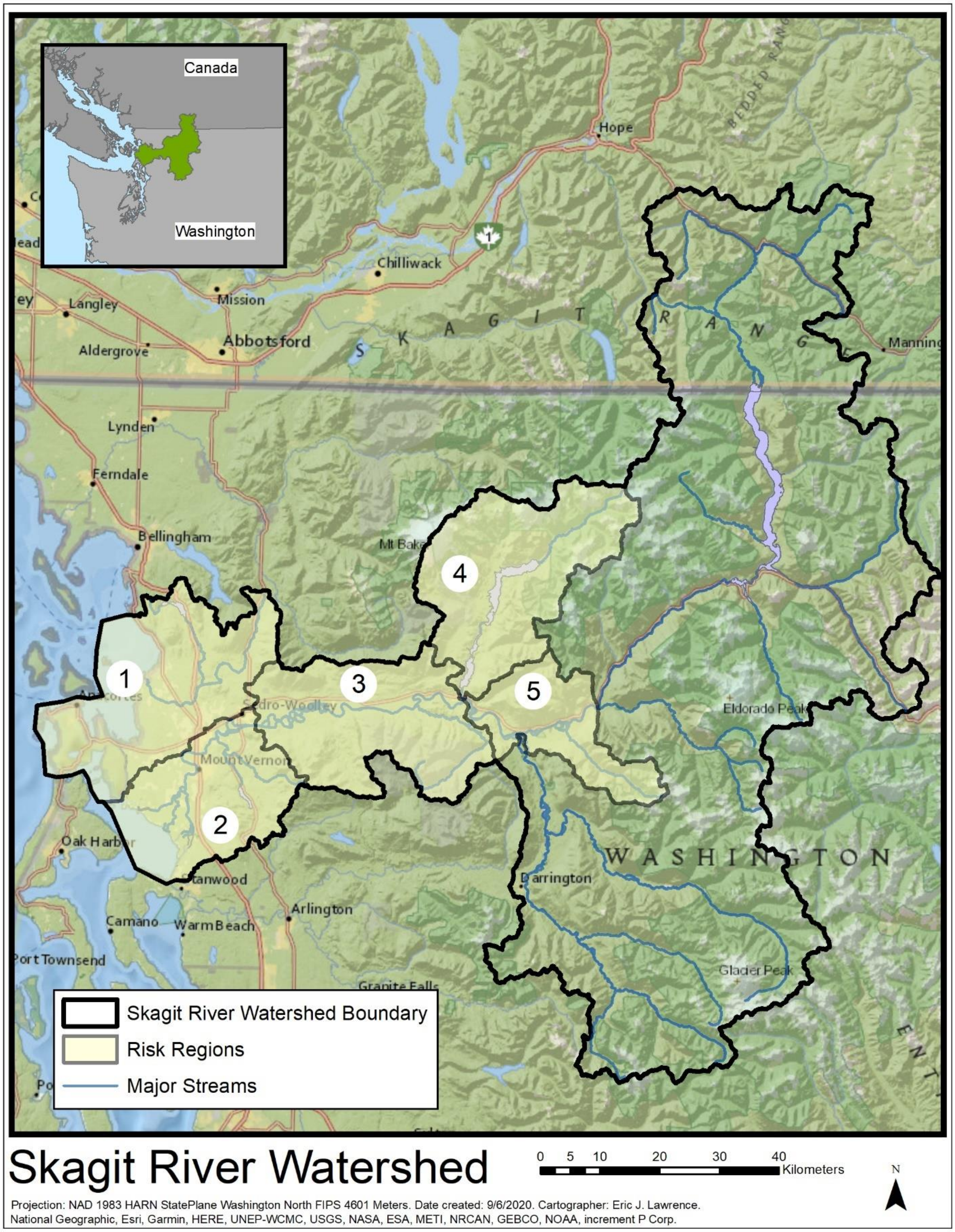

Figure 2. The Skagit River Watershed with risk regions.

1.5 Climate Change

Climate change affects endpoints relevant to ecological risk assessment directly or indirectly on broad temporal and spatial scales. Researchers have called for more research on interactions between climate change caused stressors and chemical stressors and incorporation of those effects into ecological risk assessment (Noyes et al. 2009; Landis et al. 2013; Moe et al. 2013; Sperotto et al. 2017, 2019). Effects from climate change can alter the toxicity of chemical stressors in the environment (Hooper et al. 2013). Similarly, stress from chemical contaminants can make species more sensitive to changes in climate (Hooper et al. 2013). Therefore, it is important that climate change be included in ecological risk assessment so that changing climate variables and potential interaction effects with chemical stressors can be taken into account and better inform environmental resource management.

Climate change is a “wicked problem”, meaning that the complexity of the issue, including the vast spatial and temporal scales and difficulty defining the issue prevent any kind of straightforward solution (NRC 2012, Burke et al. 2017). When addressing wicked problems, it is necessary to use a systems-based approach that is iterative and allows for incorporation of new data as they become available and to expand analysis to a multitude of scales (Burke et al. 2017).

1.5.1 Climate Models

In my research I used air temperature projections from climate models from the fifth phase of the Coupled Model Intercomparison Project (CMIP5) which is a set of coordinated climate model experiments utilizing atmosphere-ocean global climate models (GCMs; Taylor et al. 2012). The GCMs use future CO_2 emission scenarios called representative concentration pathways (RCP) to make projections based on potential mitigation scenarios (Taylor et al. 2012). The “high” scenario, RCP 8.5, represents continuing CO_2 emissions at current trends with increasing radiative forcing reaching 8.5 W/m^2 in the year 2100 (Taylor et al. 2012). The

RCP 2.6, RCP 4.5, and RCP 6 scenarios represent future scenarios with CO_2 emissions reduced from current trends.

The climate changed influenced stressor that I used in my model is water temperature. I used regressions to calculate water temperatures based on air temperature GCM projections. There are many other climate change related stressors that were not included in this model. For example, climate change is expected to effect stream flows in the Skagit River which will be an additional stressor and also influence water temperatures (Manuta et al. 2010).

1.6 Ecosystem Services

Ecosystem services are defined by Constanza et al. (1997) as the benefits human populations derive, directly or indirectly, from ecosystem functions. Ecosystem services are an anthropocentric method for assigning value to ecological processes that relate to human health and well-being. As such, they are valuable risk assessment endpoints that link ecological systems to human health and well-being (Harris et al. 2017).

Risk assessment endpoints are selected by local stakeholders and regulators who decide which ecosystem services to prioritize. It is important when selecting endpoints to consider the appropriate level of biological organization from suborganismal to organism, population, and community level or higher (Suter et al. 2005). Any assessment endpoint consists of an entity and an associated attribute (Suter et al. 2005). Confusing entities with attributes can often lead to improper endpoints, especially in the context of whether an endpoint is referring to organismal, population or community level effects (Suter et al. 2005).

1.7 Previous Ecological Risk Assessments Using the BN-RRM

My work builds upon a previous ecological risk assessment using the BN-RRM by Landis et al. (2020) assessing the risk of organophosphate pesticide mixtures to Chinook salmon in the Skagit River along with several other locations in Washington State. My study builds upon that research by incorporating climate projections into the ecological risk assessment framework and dividing the Skagit River Watershed into risk regions to account for spatial variability within the watershed. My work also builds upon the work of Gaasland-Tatro (2016) who successfully incorporated climate change stressors into an ecological risk assessment using the BN-RRM at the South River, Virginia mercury contaminated site.

1.8 Uncertainty in Ecological Risk Assessment

Uncertainty can be broadly categorized into epistemic and linguistic (Regan et al. 2002). Epistemic uncertainty deals with the uncertainty associated with an unknown true value or range of values, which is subcategorized into measurement error, systematic error, model uncertainty, and natural variation (Regan et al. 2002, 2003). Linguistic uncertainty arises from imprecise communication due to vagueness of limited scientific vocabulary, context dependency of language, and other ambiguities related to multiple meanings for certain words (Regan et al. 2002). Some uncertainties are known and others are unknown, with the latter creating difficulties with model uncertainty in particular (Spiegelhalter and Riesch 2011). Therefore, uncertainty is analyzed through quantitative and qualitative methods. Several potential sources of uncertainty arise from cases of misuse or misinterpretation of the Bayesian network model such as unmeasurable node states, using too many parent nodes, not considering confounding variables, not testing model calibration or validation, conflating conditional probabilities with confidence in veracity, and conflating correlation with causation (Marcot 2017).

There is always uncertainty in any model because it is a simplified representation of the real complex system. An important factor that contributes to model uncertainty is the limitations of current knowledge or data. In reality there may be countless factors that contribute risk to a particular endpoint. However, models are useful when there is a specific question to address and at least some basic knowledge of a system. In some cases, even when factors that are known to contribute to a system are included, it may not have large enough of an effect to change the outcome of a model. Sensitivity analysis can be used to detect these factors.

The BN-RRM addresses uncertainty within the model using probability. The uncertainty associated with the variability of input variables is addressed by using monitoring data and model output to generate probability distributions over multiple states of those nodes. Uncertainty associated with the relationships between ecological variables can also be built into the conditional probability tables. The risk that is calculated to the endpoints is also in the form of a probability distribution, which conveys the epistemic uncertainty within those results.

1.9 Study Objectives

The main objectives of this research were as follows:

- Integrate climate change caused stressors into a BN-RRM of the Skagit River Watershed.
- Conduct an ecological risk assessment of the Skagit River Watershed for combined impacts to the ecosystem service, Chinook salmon, from climate change and organophosphate pesticide stressors.
- Characterize relative importance of climate and chemical stressors for different climate scenarios, risk regions, and seasons.
- Develop a tool to serve as part of an adaptive management process for ecological resources in the Skagit River Watershed, and to similar rivers and estuaries.

2. Methods

2.1 Study Area

The study area included the lower Skagit River Watershed and the Samish River Watershed, located in northwestern Washington State (Figure 2). These watersheds combined make up Water Resource Inventory Areas (WRIA) 3 and 4. The Samish River watershed was included in the study area because it comprises a large part of the Skagit valley agricultural and urban center. The study area was divided into five risk regions based on hydrological units from the Watershed Boundary Dataset (USGS 2013). I did not include portions of the upper Skagit River Watershed (WRIA 4) as risk regions due to lack of pesticide and water quality monitoring data.

2.2 Model Construction

My model builds upon the BN-RRM constructed by Landis et al. (2020) assessing risk to Chinook salmon from water temperature, dissolved oxygen, and chlorpyrifos in four watersheds in Washington State. I restructured the water quality stressors input to include multiple climate scenarios and included a second organophosphate pesticide to include mixture toxicology methods. I used region and season specific data as input into the model.

2.2.1 Endpoint

Chinook salmon was the endpoint. The entity is Chinook salmon and the attribute is Chinook population size. Chinook population size includes the egg-to-emergence, juvenile, and adult life stages. Chinook salmon are an important ecosystem service for the people living in the Skagit River Watershed. Chinook salmon contribute to human wellbeing by contributing to commercial, tribal, and recreational fisheries, local economies, culture, and spirituality. Chinook salmon were identified as a vital sign by the Puget Sound Partnership (PSP) as an indicator for the Puget Sound (PSP 2017). The Puget Sound ecologically significant unit (ESU) of Chinook salmon are also listed as a threatened species by the Endangered Species Act (NOAA Fisheries 2020).

There are six identified stocks of Chinook in the Skagit River watershed, all containing stream and ocean-type juvenile life history types (Beamer et al. 2005a, 2005b).

2.2.2 Sources and Stressors

Chlorpyrifos and diazinon were the organophosphate pesticide stressors used to assess toxicological risk. These organophosphate pesticides are used in agricultural and urban systems within the Skagit River Watershed, leading to acute and chronic exposure through runoff to juvenile Chinook salmon rearing the rivers next to agricultural and urban land. Measured concentrations of pesticides specific to risk region and season were used as inputs into the model. These datasets were obtained through the Washington State Department of Ecology Environmental Information Management database (WADOE EIM 2019).

Water quality stressors from Landis et al. (2020), dissolved oxygen and water temperature, were also used in my study. Although water temperature and dissolved oxygen are related variables, I kept them separate in this model to isolate the effects of temperature change. The dissolved oxygen is based on measured concentrations specific to risk region and season.

2.2.3 Climate Change Projections

I adapted methods from Gassland-Tatro (2016) to incorporate water temperature from two different climate scenarios into the BN-RRM. The historical climate scenario is based on observed climate data from 1981 to 2010 (Maurer et al. 2002) and the future climate scenario is based on climate projections from 2071 to 2100.

The future climate scenario used an ensemble of three GCMs from CMIP5 (Table 1). The projections were downscaled using BCCA V2 to a 0.125 degree grid. The RCP 8.5 emission scenario was used to represent CO^2 emissions under current trends.

For both the historical and future climate scenarios, I obtained the model output from the USGS Geo Data Portal website (https://cida.usgs.gov/gdp/, Blodgett et al. 2011). I uploaded a GIS shapefile of the risk regions to the website to obtain weighted means for daily maximum air temperature for each risk region for the selected model output and time range.

Table 1. Global climate models (GCMs) selected from the Fifth Coupled Model Inter-Comparison Project (CMIP5) used for the downscaled climate projections in this study.

Access1.0	Commonwealth Scientific and Industrial Research Organization and Bureau of Meteorology	Australia
CanESM2	Canadian Centre for Climate Modelling and Analysis	Canada
CCSM4	National Center for Atmospheric Research	USA

2.2.4 Habitat

Habitats are the spatial component of the relative risk model. When a stressor or stressors are present in a habitat, it leads to effects in the causal pathway. In this risk assessment the habitat was the Chinook salmon habitat in the Skagit River used for all life stages of Chinook salmon for migration, rearing, and spawning.

2.2.5 Conceptual Model

The conceptual model was based on comparing the climate and toxicity causal pathways within the RRM framework (Figure 3). The blue arrows represent the climate and water quality variables pathway and the orange arrows represent the toxicity pathway. Dissolved oxygen was kept separate from water temperature because dissolved oxygen was based on measured concentrations and water temperature was based on climate model output. The water quality pathway includes effects to all three life stages of Chinook salmon and the Chinook population endpoint. The toxicity pathway describes toxic effects from the OPs chlorpyrifos and diazinon to juvenile Chinook salmon only.

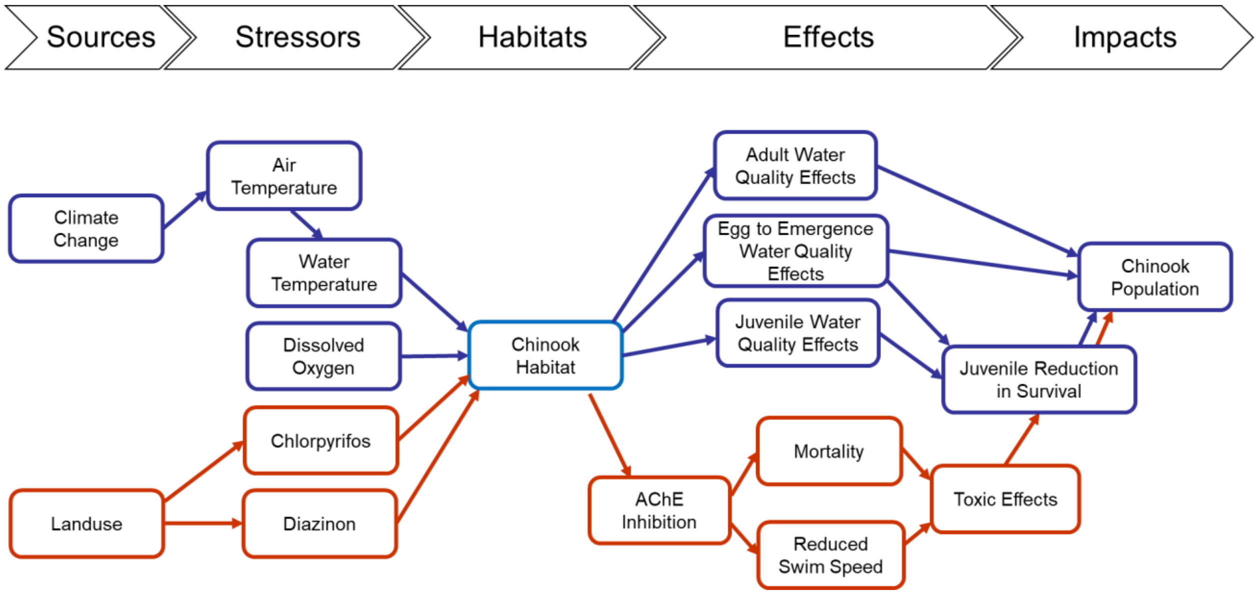

Figure 3. Conceptual model following the relative risk model (RRM) framework showing water quality and toxicity causal pathways. The water quality pathway is in blue and the toxicity pathway is in orange. The toxicity pathway describes effects to juvenile Chinook salmon only and the water quality pathway describes effects to all three life stages of Chinook salmon.

2.2.6 Bayesian Network Construction

I constructed the Bayesian network using Norsys Netica software (Norsys Software Corp. 2017) following the structure of the conceptual model (Figure 3). The boxes from the conceptual model correspond to nodes in the Bayesian network and the causal links were retained (Figure 4). Netica calculates the posterior probabilities of the endpoint node by using probabilistic inference (Spiegelhalter et al. 1993). For a copy of the model viewable with the free version of Norsys Netica (Norsys Software Corp. 2017), see the online Supplementary Materials. For a complete description of each node, see Table S1 in the Supplementary Materials.

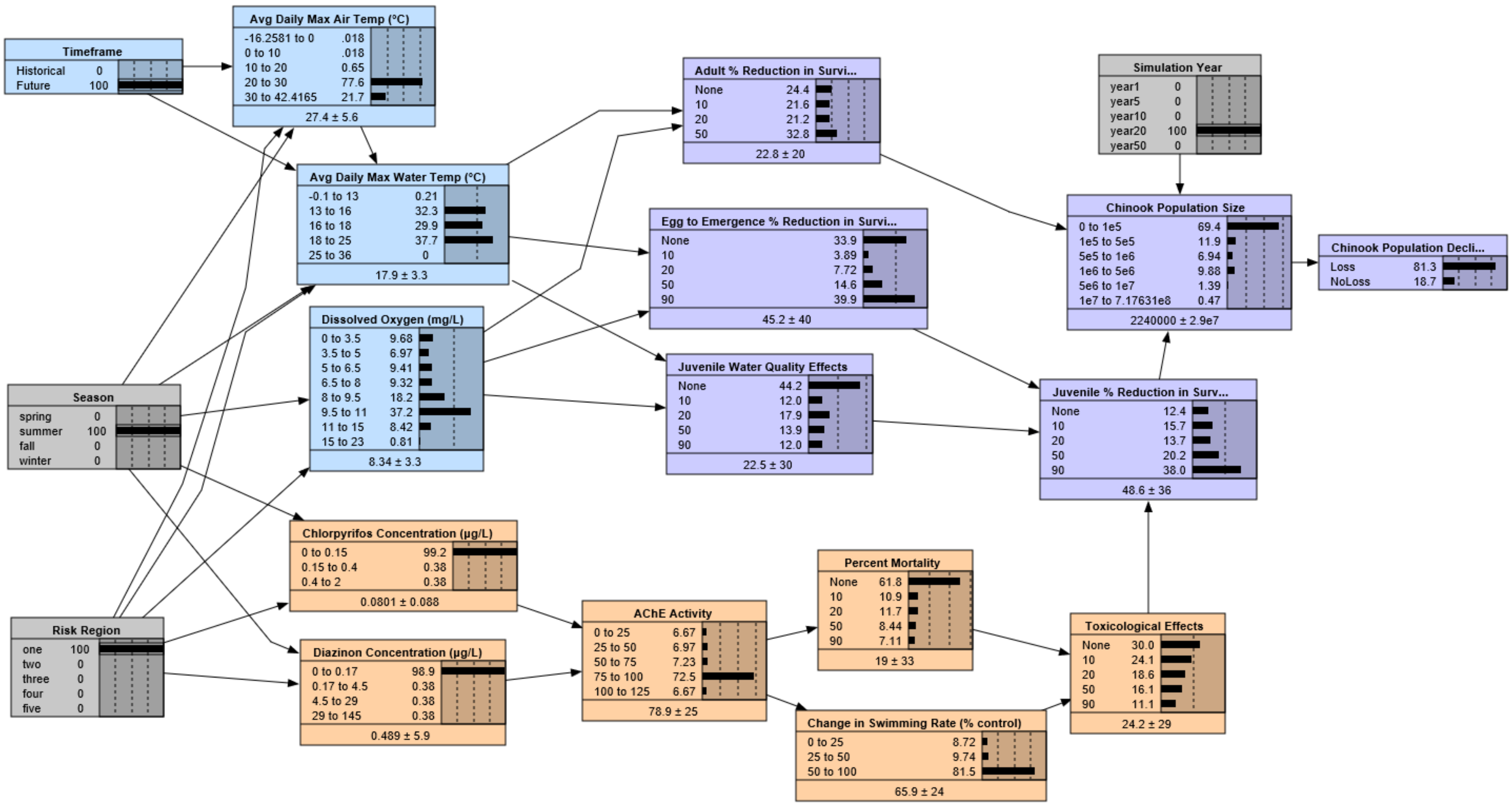

Figure 4. Bayesian network relative risk model set for risk region 1 during the summer and future climate scenario. The water quality nodes are in blue, the toxicity pathway nodes are in orange, and Chinook effects and impact nodes are in purple.

2.2.7 Specification Nodes

In addition to the nodes that correspond to the conceptual model, I used specification nodes to allow the user to select between specific datasets. By setting the discrete states of a combination of specification nodes to 100% probability, the user selects that dataset. The timeframe node allows the user to select between historical and future climate scenarios, the season node allows the user to specify the season, and risk region allows the user to specify the risk region.

The specification nodes in this model select datasets specific to each risk region, season, climate scenario and population model simulation time (Figure 4). Although the population model simulation time specification node is included in the model, I used only the 20 year simulation for all results.

2.2.8 Node Parameterization

Node parameterization within the BN-RRM follows a three-step process (Harris et al. 2017). First, I set the nodes into quantified discrete states. This is based on information relevant to the scientific question being asked. The average daily maximum water temperature and dissolved oxygen nodes were discretized into states based on freshwater regulatory criteria for optimal salmonid conditions (WAC 2011a, 2011b; Table 2). The organophosphate pesticide concentration nodes were discretized into states based on regulatory criteria, such as the Endangered Species level of concern (ESLOC, Tuttle 2014), and EC50 values from toxicity testing on Coho salmon (Laetz et al. 2009, Table 2). Second, I entered the known frequency distributions into the parent nodes. I used case-file learning, a machine learning function within Netica (Norsys Software Corp 2017). Third, I constructed CPTs to quantify the causal relationships between nodes.

Table 2 shows the parameterization details for the input nodes. Dissolved oxygen and organophosphate pesticide concentrations are based on actual field measurements at sampling stations specific to risk region and season. For parameterization of all nodes see Table S1 in the Supplementary Materials.

Table 2. Input node parameterization, description, and data sources. Organophosphate pesticide concentration node discretization includes criteria based on USEPA National Aquatic Life Criteria (USEPA 2020), Endangered Species level of concern (ESLOC, Tuttle 2014), and 50% effective concentration (EC50) values from Laetz et al. (2009).

Node	States	Discretization / Justification	Description	Data Sources
Avg Daily Max Air Temp (°C)	-16 to 0 0 to 10 10 to 20 20 to 30 30 to 42	Discretization based on multiples of 10 with extreme values included in the highest and lowest state.	Average daily maximum temperatures in °C from climate model output or historical meteorological data.	Maurer et al. (2002), USGS Geo Data Portal (Blodgett et al. 2011)
Avg Daily Water Temp (°C)	0 to 13 13 to 16 16 to 18 18 to 25 25 to 36	Discretization based on salmon optimal temp ranges for water temperature from table 200 (1)(c) from WAC (2011a).	Average daily maximum water temperature in °C calculated from air temperature using single regression or from direct measurements.	WADOE EIM (2019), Maurer et al. (2002), USGS Geo Data Portal (Blodgett et al. 2011)
Dissolved Oxygen (mg/L)	0 to 3.5 3.5 to 5 5 to 6.5 6.5 to 8 8 to 9.5 9.5 to 11 11 to 15 15 to 20	Discretization based on salmon specific optimal ranges for dissolved oxygen from table 200 (1)(d) from WAC (2011b)	Measured dissolved oxygen concentrations in mg/L.	Tuttle (2014), WSDOE EIM (2019), Laetz et al. (2009)
Chlorpyrifos concentration (µg/L)	0 to 0.15 0.15 to 0.4 0.4 to 2	0.15 is the ESLOC (Tuttle 2014) 0.4 is the 0.2 EC50 (Laetz et al. 2009) 2 is the EC50 (Laetz et al. 2009)	Measured chlorpyrifos concentrations.	Tuttle (2014), WADOE EIM (2019), Laetz et al. (2009)
Diazinon concentration (µg/L)	0 to 0.17 0.17 to 4.5 4.5 to 29 29 to 145	0.17 is the EPA Criteria (USEPA 2020) 4.5 is the ESLOC (Tuttle 2014) 29 is the 0.2 EC50 (Laetz et al. 2009) 145 is the EC50 (Laetz et al. 2009)	Measured diazinon concentrations.	Tuttle (2014), USEPA (2020), WADOE EIM (2019), Laetz et al. (2009)

2.2.9 Relating Air to Water Temperatures

Because model output from the climate models were in air temperature, I used a regression to predict water temperature from air temperature. The temperature measurements were from three WSDOE monitoring stations in the lower Skagit River Watershed located in risk regions 1 - 3. At each location air temperature and water temperature are continuously and simultaneously measured and recorded every 30 minutes excluding during the spring and winter at the monitoring station in risk region 3. I created a regression and prediction intervals for those datasets using the "drc" package in R statistical software (Ritz et al. 2015) for each sampling station and season, excluding spring and winter for risk regions 3 - 5. I calculated CPTs using the prediction intervals and discretization intervals for air and water temperature as inputs using R statistical software. I created the CPTs for risk regions 4 and 5 using the dataset for risk region 3 as that was the only sampling station located upstream of risk regions 1 and 2 that had continuous air and water temperature monitoring. I used the regressions to construct the CPTs to predict water temperatures from both historical and future air temperatures. See Supplementary Materials (Section S5) for regression models.

2.2.10 Toxicity Pathway

The toxicity data used to construct the CPTs for the AChE Activity, Percent Mortality, and Change in Swimming Rate (% control) nodes were from a series of experiments on Coho salmon by NOAA fisheries (Sandahl et al. 2005; Laetz et al. 2009, 2013, 2014). I used the "drc" package in R statistical software to fit log-logistic models to the concentration-response data (Ritz et al. 2015). The log-logistic models were used to construct the CPTs with the "equation to table" function within Norsys Netica. For the AChE Activity node, a "toxic units" approach was used to relate the mixture of chlorpyrifos and diazinon concentrations to AChE inhibition. The EC50s calculated from the single chemical exposures were used to calculate the toxic units for chlorpyrifos and diazinon. I converted the concentrations from the binary mixture toxicity test for chlorpyrifos + diazinon into toxic units and generated the log-logistic model for the mixture using summed toxic units as the concentration. I altered the log-logistic equation used to construct the AChE Activity CPT to convert the output from the pesticide concentration nodes into toxic units. The CPTs for Percent Mortality and Change in Swimming Rate (% control) nodes were constructed using log-logistic models generated from toxicology data relating AChE activity to mortality and swim speed. See Supplemental Material (Section S4) for more detail.

2.2.11 The Baldwin-Mitchell Model (BMM)

The Chinook population endpoint node was constructed using the Baldwin-Mitchell Model (Baldwin et al 2009, Mitchell et al. 2020). The BMM is a Leslie matrix population model developed by Baldwin et al. (2009) and modified by Mitchell et al. (2020) for stream-type Chinook salmon in the Yakima watershed. The model used a 500,000 starting population with 1, 5, 10, 20, and 50 year simulations.

2.3 Risk Calculation

The Puget Sound Partnership set a management goal of no net loss of Chinook salmon population (PSP 2017). Therefore, I calculated risk as the probability of Chinook salmon population decline. I calculated risk by summing the population probabilities for states below 500,000 within the Chinook population node for each combination of risk region, season, and timeframe. The 500,000 starting population represents the entire age range of salmon. Only 1,382 of the initial 500,000 starting population are three to five year old spawners.

2.4 Sensitivity Analysis

The sensitivity analysis determines which inputs were most important for influencing the states of the endpoint node. Because the input nodes are comprised of discrete states, I measured sensitivity using entropy reduction calculations (also known as mutual information) within Netica (Woodberry et al. 2004, Pollino et al. 2007, Marcot 2012, Norsys Software Corp 2017). Mutual information is a measurement of how much information two variables share, or how knowledge of one variable reduces the uncertainty of another variable.

I analyzed the sensitivity to the Chinook population endpoint node for each combination of risk region, season, and timeframe. To characterize the relative importance of the different inputs of water temperature, dissolved oxygen, and pesticides, I focused on sensitivity for the water temperature, dissolved oxygen, and toxicological effects nodes.

2.5 Counterfactual Analysis

I performed the counterfactual analysis using Norsys Netica software (Norsys Software Corp. 2017). I used the counterfactual analysis to answer the following question: what are the management goals for input variables to reach the Chinook salmon population size management goal of no net loss? By setting the state of the endpoint node to the desired management goal for Chinook Population Size, Netica calculates the node distributions for the rest of the Bayesian network to achieve that state. To perform the counterfactual analysis, I set the Chinook Population Size node to 100% probability of 500,000 to 1,000,000 population size for each combination of risk region and season and recorded the resulting node distributions for the input nodes: Avg Daily Water Temperature, Dissolved Oxygen, Chlorpyrifos Concentration, and Diazinon Concentration.

2.6 Uncertainty Analysis

I quantified and documented uncertainty in this study based on the classifications and descriptions from Regan et al. (2002, 2003). I divided sources of uncertainty into epistemic uncertainty, model uncertainty, and linguistic uncertainty. Epistemic uncertainty represents the quantifiable uncertainty arising from measurement error, systematic error, natural variation, and inherent randomness within input data. Model uncertainty pertains to the uncertainties associated with model limitations and assumptions. I addressed these quantitatively when possible or qualitatively by documenting assumptions and limitations of the models used in this study. I addressed linguistic uncertainty by documenting potential sources of confusion and using clear and consistent language.

3. Results

3.1 Understanding the Model Output

The endpoint node is Chinook Population Size. Selecting the combination of timeframe, season, and risk region yields a Chinook salmon population distribution representing the probability of Chinook salmon population size given those conditions. The risk for each combination of timeframe, season, and risk region is the probability of Chinook population decline. I used the 20 year population model simulation time for all results.

3.2 Risk by Climate Scenario

Table 3 shows the risk calculated as probability of Chinook salmon population decline for each combination of risk region, season, and climate scenario as well as the change in risk for each due to future climate scenarios. Risk regions 1 and 2 during the summer had the highest increase in risk due to climate change. The other combinations that had a notable increase in risk due to climate change were risk region 1 during the spring and risk region 2 during the fall. There was no change in risk during the winter for risk regions 1 and 2. Risk in risk regions 3 - 5 had a slight decrease.

Due to the lack of simultaneous air and water temperature monitoring data during the spring and winter for risk regions 3 – 5 I was unable to predict water temperatures for those regions and future risk was excluded for those scenarios.

Table 3. Percent probability of Chinook population decline from 500,000 starting population by risk region, season, and climate scenario and increase in risk due to climate change by risk region and season. The future risk for winter and spring in risk regions 3 – 5 are excluded due to lack of temperature sampling data.

Risk Region	Season	Historical Risk	Future Risk	Increase in Risk Due to Climate Change
1	summer	77.1	81.3	4.2
	fall	69.5	70.2	0.7
	winter	67.1	67.1	0.0
	spring	70.1	72.7	2.6
2	summer	76.3	79.8	3.5
	fall	70.8	72.5	1.7
	winter	65.9	65.9	0.0
	spring	67.1	67.4	0.3
3	summer	64.0	63.7	-0.3
	fall	64.6	64.4	-0.2
	winter	65.2		
	spring	64.6		
4	summer	64.3	63.9	-0.4
	fall	64.6	64.5	-0.1
	winter	66.5		
	spring	65.6		
5	summer	64.2	63.9	-0.3
	fall	64.6	64.4	-0.2
	winter	66.5		
	spring	65.6		

3.3 Sensitivity Analysis

I used entropy reduction calculations to determine the importance of the ecological parameters water temperature, dissolved oxygen, and toxicological effects in influencing risk to Chinook salmon population. Figure 5 shows the results of the sensitivity analysis for Risk Region 1. The relative importance of nodes, represented by entropy reduction, changed based on the season, climate scenario, and risk region. See Supplemental Materials for sensitivity analysis results for all risk regions.

Changes in sensitivity due to climate change are represented by the change in entropy reduction between historical and future climate scenarios (Figure 5). The relative importance of water temperature increased in the summer, fall, and spring (Figure 5). During the summer, dissolved oxygen was the most important influence in the historical climate scenario, but water temperature became the most important influence during the future climate scenario (Figure 5). During the winter, there was no change in sensitivity due to climate change and water temperature had no influence on results (Figure 5).

The Toxic Effects node is an intermediate summary node but was included in the sensitivity analysis to demonstrate the effect of uncertainty within the toxicity pathway. Diazinon and chlorpyrifos had little to no entropy reduction in each scenario, however the Toxic Effects node had an important effect on results (Figure 5). This is because the uncertainty within the AChE Activity, Percent Mortality, Change in Swimming Rate, and Toxic Effects nodes is propagated through the toxic effects pathway resulting in a wide probability distribution in the Toxic Effects node.

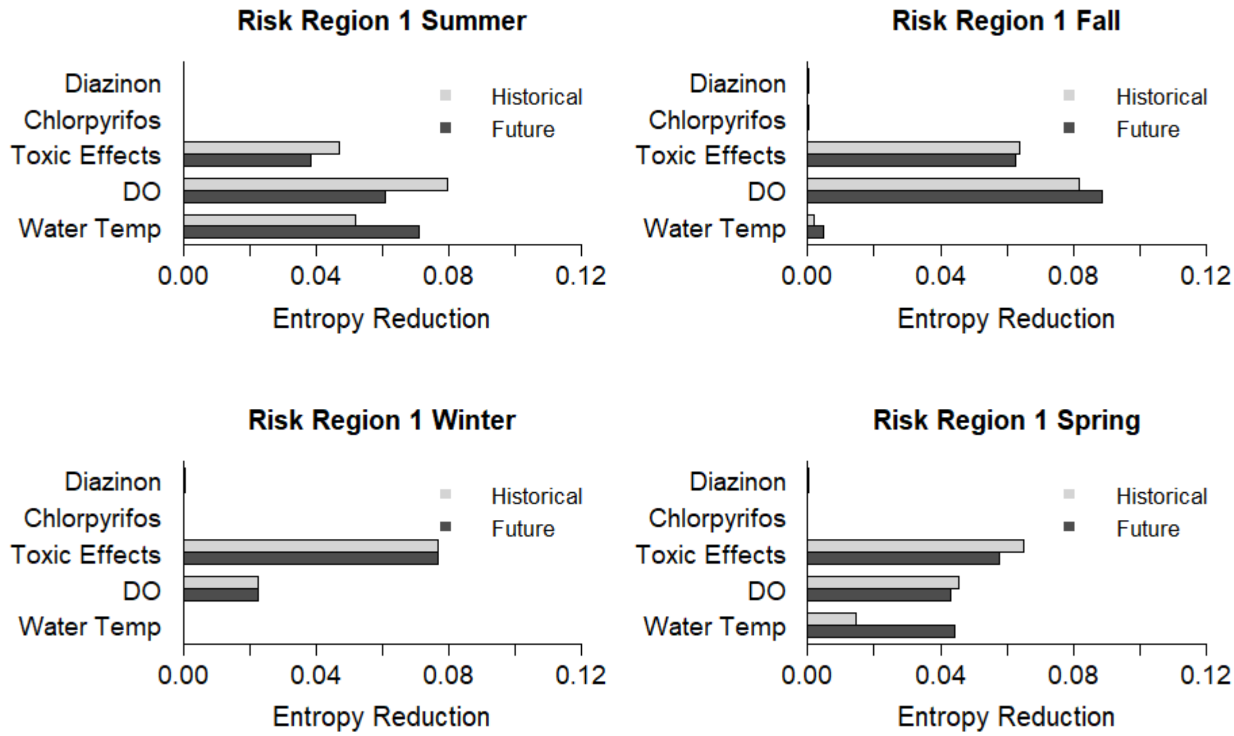

Figure 5. Entropy analysis results for risk region 1 comparing the relative importance of the nodes diazinon, chlorpyrifos, toxic effects, dissolved oxygen (DO), and daily average water temperature (Water Temp) in historical and future scenarios. See supplemental materials for entropy analysis results for each risk region.

3.4 Counterfactual Analysis

I conducted a counterfactual analysis to determine potential management goals for input variables to reach the Chinook salmon population size management goal of no net loss. Table 4 shows the input node distributions under historical and future climate scenarios and calculated management goals for historical and future management goals for Risk Region 1 during the summer. Management goals changed between the historical and future climate scenarios for water temperature and dissolved oxygen (Table 4).

Table 4. Comparison of historical and future input node distributions with historical and future management goals in Risk Region 1 during the summer. The management goals were calculated using a counterfactual analysis, setting the Chinook Population Size node to 100% probability of 500,000 to 1,000,000 population size. See supplemental materials for counterfactual analysis results for each season and risk region.

Node	Node States	Historical	Historical Management Goal	Future	Future Management Goal
Avg Daily Max Water Temp	-0.1 to 13	9.58	12.2	0.21	0.31
	12 to 16	41.4	48.0	32.3	44.2
	16 to 18	29.2	32.7	29.9	39.7
	18 to 25	19.8	7.01	37.7	15.8
	25 to 36	0	0	0	0
Dissolved Oxygen	0 to 3.5	9.68	1.72	9.68	1.94
	3.5 to 5	6.97	2.38	6.97	2.40
	5 to 6.5	9.41	5.43	9.41	5.29
	6.5 to 8	9.32	6.73	9.32	6.49
	8 to 9.5	18.2	23.3	18.2	23.3
	9.5 to 11	37.2	48.5	37.2	48.7
	11 to 15	8.42	10.8	8.42	10.8
	15 to 23	0.81	1.06	0.81	1.07
Chlorpyrifos Concentration	0 to 0.15	99.2	99.3	99.2	99.3
	0.15 to 0.4	0.38	0.38	0.38	0.38
	0.4 to 2	0.38	0.37	0.38	0.37
Diazinon Concentration	0 to 0.17	98.9	98.9	98.9	98.9
	0.17 to 4.5	0.38	0.38	0.38	0.38
	4.5 to 29	0.38	0.37	0.38	0.37
	29 to 145	0.38	0.35	0.38	0.35

3.5 Uncertainty Analysis

I used the classifications and descriptions of uncertainty from Regan et al. (2002, 2003) in my uncertainty analysis.

3.5.1 Epistemic Uncertainty

I quantified the epistemic uncertainty arising from measurement error, systematic error, natural variation, and inherent randomness within the sampling data and climate model output by including the entire frequency distribution generated by the case file learning of the input. This uncertainty within the input node was propagated through the Bayesian network through probabilistic inference. The probability distribution of the endpoint node represents this uncertainty within the model output.

I addressed natural variation due to regional scale spatial variation by dividing the study area into risk regions. I used sampling data specific to each region for dissolved oxygen, pesticide concentrations, and simultaneous air and water temperature measurements used for the temperature regressions. Similarly, temporal variation was addressed at a seasonal scale for those datasets.

3.5.2 Model Uncertainty

Due to lack of data, I used the same temperature regression to predict water temperature for risk regions 3 – 5 for summer and fall and was unable to predict water temperatures for winter and spring. Also due to lack sampling data for pesticides in risk regions 4 and 5, I averaged the pesticide concentrations for the risk regions 1 – 3 to construct the CPTs for risk regions 4 and 5. These are both examples of uncertainty due to data limitations in the study area.

There are several types of uncertainty in multi-model climate projections including sample uncertainties, model uncertainty, initial condition uncertainty, and projection uncertainty (Knutti and Sedlacek 2012). Downscaled climate projections also accumulate additional uncertainty with choices made in bias-correction and through the spatial downscaling process (Brekke et al. 2013). I addressed uncertainty for climate modeling by including the model output for three GCMs over a 30-year range. All of the model output was used to populate the air temperature nodes, thereby representing the full spectrum of model output. I accounted for uncertainty in using regressions to predict the water temperature by using prediction intervals to construct the CPTs.

I addressed the uncertainty represented in the toxicity pathway by using the 95% confidence intervals for the entire dose-response model to construct the CPTs. There is additional uncertainty in this pathway due to using Coho salmon as a surrogate species for Chinook salmon.

There is uncertainty associated with the population model due to its construction based on a generalized model of the Puget Sound region rather than using parameters specific to the Skagit River (Baldwin et al. 2009, Mitchell et al. 2020). For example, the model was based on ocean-type salmon but Chinook in the Skagit River have both ocean and stream-type life histories.

There is also sampling uncertainty associated with using data from static sampling stations located within each of the risk regions and making the assumption that water temperature, dissolved oxygen, and pesticide concentration data from those sampling stations represent the variation within the entire risk region. It is likely that the true variation within these parameters is greater throughout the entire risk region than at the one sampling station.

3.5.3 Linguistic uncertainty

The PSP management goal of no net loss for Chinook salmon is a source of linguistic uncertainty in the results of this ecological risk assessment (PSP 2017). The full distribution of the Chinook population endpoint node is not fully utilized by this management goal. This can be addressed by asking more specific management questions that allow for the utilization of the full results. This also allows for more specific questions to be address using counterfactuals.

Another potential source of linguistic uncertainty is the use of a 500,000 starting population in the population model. This number seems very high but the majority of this number are fry and only a small percentage of this population are adults that will return to spawn.

4. Discussion

I characterized risk to Chinook salmon population from climate change, dissolved oxygen, and organophosphate pesticide stressors and characterized the relative importance of those stressors under different climate scenarios taking into account spatial variability across risk regions and temporal variability across seasons. I also used a counterfactual analysis to calculate potential management goals for ecological variables. This model can serve as a tool within an adaptive management framework for ecological resources in the Skagit River Watershed that can be adapted to other watersheds.

There are many uncertainties in this model. It is not meant to be a comprehensive risk assessment of the Skagit River Watershed but primarily to demonstrate the use of the BN-RRM as an effective tool for ecological risk assessment that can incorporate climate change stressors, characterize the relative importance of multiple stressors, quantify or otherwise address uncertainty, and fit into an adaptive management framework.

4.1 The Influence of Climate Induced Changes in Water Temperature on Risk

The overall change in risk due to climate change induced changes in water temperature was small. This might be due to the already high risk that Chinook are facing even before changes to water temperature were taken into account. The most notable increases in risk were during summer in risk regions 1 and 2 (Table 3). This is because the change in risk was entirely based on increased water temperature and salmon prefer colder water. The results of the sensitivity analysis also support this, showing that for the seasons and regions with colder temperatures, water temperature has little to no importance for determining risk and toxic effects becomes relatively more important.

4.2 Other Climate Change Factors

It is important to keep in mind that this model was limited to the influence of only water temperature as a climate change stressor. Other factors like changes in precipitation and stream flow were not taken into account which can affect salmon habitat and alter the fate and behavior of pesticides in the environment (Noyes et al. 2009). Changes in flow may also be an important factor in influencing climate change induced changes in water temperature.

Also, the interaction effects between temperature and pesticides are not incorporated into this model. In this model they are separate pathways but there are interactions that can influence risk. For example, increased temperature can increase the toxicity of pesticides and alter uptake and elimination (Noyes et al. 2009).

4.3 Counterfactual Analysis

In this study I used a counterfactual analysis to calculate potential management goals for environmental variables. This is an important benefit of using a Bayesian network based on cause-and-effect pathways. This is also important for adaptive management. The calculated management goals can be easily updated with new information as it is added to the model.

4.4 Incorporating Climate Change in Ecological Risk Assessment

I followed the principles laid out in Landis et al. (2013) for incorporating climate change in ecological risk assessment. In this and future ecological risk assessments, changing conditions due to climate change need to be addressed to better estimate risk.

4.4.1 Ecosystem Services

The assessment endpoint was expressed as a quantified ecosystem service, Chinook salmon population size. Ecosystem services tie directly into environmental management goals and decision making. Because of the direct and indirect effects from climate change, having clearly defined and quantified ecosystem services allow climate change to be linked clearly to climate change effects in the BN-RRM.

4.4.2 Positive and Negative Effects from Climate Change

This study demonstrated that changes due to climate change can have both positive and negative effects on risk. In this case the positive and negative effects were due to variation in region and season. Salmonids prefer colder water temperatures and are therefore vulnerable to increases in water temperature due to climate change but there are other fish species that prefer warmer temperatures that might benefit from the same conditions.

4.4.3 Using the BN-RRM to Incorporate Climate Change in Ecological Risk Assessment

It is necessary to take in to account multiple stressors and causality when addressing climate change in ecological risk assessment. Climate change affects many ecological parameters directly and indirectly. The BN-RRM allows us to incorporate our knowledge about how these parameters interact and cause effects into a powerful ecological risk assessment model. Because Bayesian networks are probabilistic and can represent causality, we can use counterfactuals to predict management goals for parameters related to climate change. The BN-RRM also allows for the inclusion of multiple climate scenarios, remediation options, and spatial and temporal variation.

4.4.4 Uncertainty in Addressing Climate Change

Incorporating climate change in ecological risk assessment presents real challenges in terms of uncertainty. All climate change projections have associated uncertainty and assumptions. I addressed this uncertainty by bounding the projections with prediction intervals and documenting the assumptions built into the climate models that I used. Continuing to evaluate and document uncertainty as part of an adaptive management process is key to incorporating climate change into ecological risk assessment so that risk estimates become more accurate with improvements in climate models and knowledge of how climate change affects risk.

4.4.5 Adaptive Management

Adaptive management puts ecological risk assessment into the context of an iterative process for natural resource management and mitigation strategies for identified risks (Landis et al. 2017b). Ecological risk assessment using the BN-RRM identifies relative risk to various endpoints, identifies which stressors are most important in influencing that risk, and uses counterfactuals to calculate management goals for ecological variables. This information can be valuable to environmental decision-makers on what stressors to prioritize with mitigation efforts and what the goals of those mitigation efforts should be. The BN-RRM allows for the inclusion of new data as they become available, providing new information to decision makers on progress of mitigation efforts as well as changing environmental factors. This iterative approach to ecological risk assessment and management is critical for addressing climate change because of the uncertainty associated with climate change projections and unforeseen effects.

4.5 Next Steps

Ecological risk assessment models are built to answer specific questions about ecological systems. Depending on the question being asked this model can be modified in many ways for future research and use in adaptive management. Bringing in additional stressors relevant to managing Chinook salmon populations would potentially address model uncertainty around the accuracy of risk estimations. Additional climate change stressors that can affect Chinook populations include changes in stream flow and sea-level rise.

Recent efforts in Chinook recovery are focused on habitat restoration (Beamer et al. 2005a, 2005b, Beechie et al. 2010, NIFC 2016). The results my study showing the higher relative importance of environmental variables over current pesticide concentrations agrees with this approach. As demonstrated by Hines and Landis (2014), mitigation scenarios can be incorporated into the BN-RRM. To incorporate habitat restoration into this model, quantitative relationships between habitat and chinook population effects need to be developed. Alternatively, expert elicitation can be used to set a starting point. In this way habitat restoration projects and their impact on risk to Chinook populations can be included.

Chinook population is an ecosystem service that influences human health and well-being. The PSP identified several vital signs related to human health and well-being that can serve as risk assessment endpoints such as economic vitality and cultural well-being (Stiles et al. 2015). Donatuto et al. (2016) also developed indigenous community health indicators that can be used as endpoints specifically for tribal communities. Establishing quantitative relationships between Chinook population and human health and these endpoints is critical for their use in this BN-RRM.

This BN-RRM can be easily adapted to other watersheds. The monitoring datasets for organophosphate pesticides, dissolved oxygen, and water temperature are available for watersheds across the Puget Sound. The Shared Strategy Development Committee (SSDC 2007) running the Puget Sound salmon recovery plan currently have Chinook salmon recovery chapters for several watersheds in the Puget Sound including the Nooksack, Stillaguamish, Snohomish, Nisqually, and Green/Duwamish.

The climate change projections can also be easily adapted for other watersheds by following the steps in this study with GIS shapefiles of risk regions in other watersheds. In any ecological risk assessment using the BN-RRM that includes parameters susceptible to climate change, climate change scenarios can be included by following the methods in this study to estimate risk and prepare our environmental decision makers for ongoing climate change effects.

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Supplemental Materials

S1. Node Discretization, Description, and Data Sources

Table S1. Discretization, description, and data sources for each node. Organophosphate pesticide concentration node discretization includes criteria based on USEPA National Aquatic Life Criteria (USEPA 2020), Endangered Species level of concern (ESLOC, Tuttle 2014), and 50% effective concentration (EC50) values from Laetz et al. (2009). This model builds on the BN-RRM used in Landis et al. (2020).

Node	States	Discretization / Justification	Description	Data Sources
Avg Daily Max Air Temp (°C)	-16 to 0 0 to 10 10 to 20 20 to 30 30 to 42	Discretization based on multiples of 10 with extreme values included in the highest and lowest state.	Average daily maximum temperatures in °C from climate model output or historical meteorological data.	Maurer et al. (2002), USGS Geo Data Portal (Blodgett et al. 2011)
Avg Daily Water Temp (°C)	0 to 13 13 to 16 16 to 18 18 to 25 25 to 36	Discretization based on salmon optimal temp ranges for water temperature from table 200 (1)(c) from WAC (2011a).	Average daily maximum water temperature in °C calculated from air temperature using single regression or from direct measurements.	WADOE EIM (2019), Maurer et al. (2002), USGS Geo Data Portal (Blodgett et al. 2011)
Dissolved Oxygen (mg/L)	0 to 3.5 3.5 to 5 5 to 6.5 6.5 to 8 8 to 9.5 9.5 to 11 11 to 15 15 to 20	Discretization based on salmon specific optimal ranges for dissolved oxygen from table 200 (1)(d) from WAC (2011b)	Measured dissolved oxygen concentrations in mg/L.	Tuttle (2014), WSDOE EIM (2019), Laetz et al. (2009)
Chlorpyrifos Concentration (µg/L)	0 to 0.15 0.15 to 0.4 0.4 to 2	0.15 is the ESLOC (Tuttle 2014) 0.4 is the 0.2 EC50 (Laetz et al. 2009) 2 is the EC50 (Laetz et al. 2009)	Measured chlorpyrifos concentrations.	Tuttle (2014), WADOE EIM (2019), Laetz et al. (2009)
Diazinon Concentration (µg/L)	0 to 0.17 0.17 to 4.5 4.5 to 29 29 to 145	0.17 is the EPA Criteria (USEPA 2020) 4.5 is the ESLOC (Tuttle 2014) 29 is the 0.2 EC50 (Laetz et al. 2009) 145 is the EC50 (Laetz et al. 2009)	Measured diazinon concentrations.	Tuttle (2014), USEPA (2020), WADOE EIM (2019), Laetz et al. (2009)

Table S1. Continued.

Node	States	Discretization / Justification	Description	Data Sources
AChE Activity	0 to 25 25 to 50 50 to 75 75 to 100 100 to 125	Discretization based on multiples of 25.	Change in AchE activity relative to control due to OP toxicity.	Landis et al. (2020), Laetz et al. (2009, 2013)
Percent Morality	None 10 20 50 90	Discretization based on mortality percentages as input to population modeling.	Percent mortality due to AChE inhibition.	Landis et al. (2020), Laetz et al. (2009)
Change in Swimming Rate (% control)	0 to 25 25 to 50 50 to 100	Discretization adapted from Chu (2018) to fit range from dose-response model	Percent change in swimming speed relative to control due to AChE inhibition from OP exposure.	Laetz et al. (2009, 2013), Sandal et al. (2005), Tierney et al. (2007)
Toxicological Effects	None 10 20 50 90	Discretization based on mortality percentages as input to population modeling.	Summary node combining effects from mortality and swimming speed nodes.	Landis et al. (2020), Coppage et al. (1975), Duangsawaski (1977), Laetz et al. (2009)
Juvenile Water Quality Effects	None 10 20 50 90	Discretization based on mortality percentages as input to population modeling.	Percent mortality to juvenile salmonids due to effects from water temperature and dissolved oxygen.	Landis et al. (2020), Brett (1952), Carter (2005, 2008), Geist et al. (2006), Warren et al. (1973)

Table S1. Continued.

Node	States	Discretization / Justification	Description	Data Sources
Juvenile % Reduction in Survival	None 10 20 50 90	Discretization based on mortality percentages as input to population modeling.	Percent mortality for juvenile salmonids due to combined OP toxicity and water quality effects.	Brett (1952), Carter (2005), Landis et al. (2020), Coppage et al. (1075), Duangsawasdi (1997), Geist et al. (2006), Jager (2011), Laetz et al. (2009), McCullough (1999), Richter and Kolmes (2005), Warren et al. (1973).
Egg to Emergence % Reduction in Survival	None 10 20 50 90	Discretization based on mortality percentages as input to population modeling.	Percent mortality for egg and larval salmonids due to effects from water temperature and dissolved oxygen.	Carter (2005, 2008), Landis et al. (2020) Geist et al. (2006), Jager (2011), McCullogh (1999), McCullough et al. (2001), Richter and Kolmes (2005)
Adult % Reduction in Survival	None 10 20 50 90	Discretization based on mortality percentages as input to population modeling.	Percent mortality for adult salmonids due to effects from water temperature and dissolved oxygen.	Landis et al. (2020), Jager (2011), McCullough (1999), McCullough et al. (2001), Peery (2010), Richter and Kolmes (2005)
Chinook Population Size	0 to 1e5 1e5 to 5e5 5e5 to 1e6 1e6 to 5e6 5e6 to 1e7 1e7 to 7.2e8	Discretization based on population modeling output.	Chinook total population based on RAMAS GIS 6.0 software population modeling.	Applied Biomathematics (2017), Mitchell (2020)

Table S1. Continued.

Node	States	Discretization / Justification	Description	Data Sources
Simulation Year	year1 year5 year10 year20 year50	One year simulation Five year simulation Ten year simulation Twenty year simulation Fifty year simulation	Selects population model duration.	Applied Biomathematics (2017), Mitchell (2020)
Chinook Population Decline	Loss NoLoss	Decline in Chinook population No decline in Chinook population	Probability of Chinook population decline from starting model population.	Chinook Population Size Node

S2. Complete probability distributions for Chinook Population Size Node.

Table S2. Chinook Population Size node probability distributions for each scenario.

Timeframe	Season	Risk Region	0 to 1e5	1e5 to 5e5	5e5 to 1e6	1e6 to 5e6	5e6 to 1e7	1e7 to 7.2e8
Historical	Spring	1	54.5	15.5	10.5	16.6	2.3	0.6
		2	51.3	15.8	11.2	18.5	2.6	0.6
		3	47.8	16.8	11.9	20.2	2.8	0.7
		4	49.2	16.4	11.6	19.4	2.8	0.7
		5	49.2	16.4	11.6	19.4	2.8	0.7
	Summer	1	64.0	13.2	8.2	12.4	1.7	0.5
		2	62.9	13.4	8.4	12.9	1.8	0.5
		3	47.6	16.4	11.9	20.5	3.0	0.7
		4	47.9	16.4	11.8	20.3	2.9	0.7
		5	47.8	16.4	11.8	20.4	2.9	0.7
	Fall	1	55.0	14.6	10.2	17.2	2.5	0.6
		2	56.4	14.4	9.9	16.4	2.4	0.6
		3	48.0	16.6	11.9	20.0	2.9	0.7
		4	48.0	16.6	11.9	20.0	2.8	0.7
		5	48.0	16.6	11.9	20.0	2.8	0.7
	Winter	1	50.9	16.2	11.3	18.4	2.6	0.6
		2	49.5	16.4	11.5	19.2	2.7	0.7
		3	48.5	16.7	11.8	19.6	2.8	0.7
		4	50.2	16.2	11.3	18.9	2.7	0.6
		5	50.2	16.2	11.3	18.9	2.7	0.6
Future	Spring	1	58.1	14.7	9.6	15.0	2.1	0.6
		2	51.6	15.8	11.1	18.3	5.6	0.6
		3	64.6	12.8	8.1	12.2	1.7	0.5
		4	64.9	12.7	8.0	12.2	1.7	0.5
		5	64.9	12.7	8.0	12.2	1.7	0.5
	Summer	1	69.4	11.9	6.9	9.9	1.4	0.5
		2	67.4	12.4	7.4	10.8	1.5	0.5
		3	47.4	16.3	11.9	20.7	3.0	0.7
		4	47.7	16.2	11.8	20.6	3.0	0.7
		5	47.7	16.2	11.8	20.6	3.0	0.7
	Fall	1	55.7	14.6	10.0	16.7	2.4	0.6
		2	58.3	14.2	9.5	15.3	2.2	0.6
		3	47.8	16.5	11.9	20.2	2.9	0.7
		4	47.9	16.6	11.9	20.1	2.9	0.7
		5	47.9	16.6	11.9	20.2	2.9	0.7
	Winter	1	50.9	16.2	11.3	18.4	2.6	0.6
		2	49.5	16.4	11.5	19.2	2.7	0.7
		3	65.1	12.7	8.0	12.0	1.7	0.5
		4	65.5	12.6	7.9	11.9	1.7	0.5
		5	65.5	12.6	7.9	11.9	1.7	0.5

S3. Complete Entropy Analysis Results.

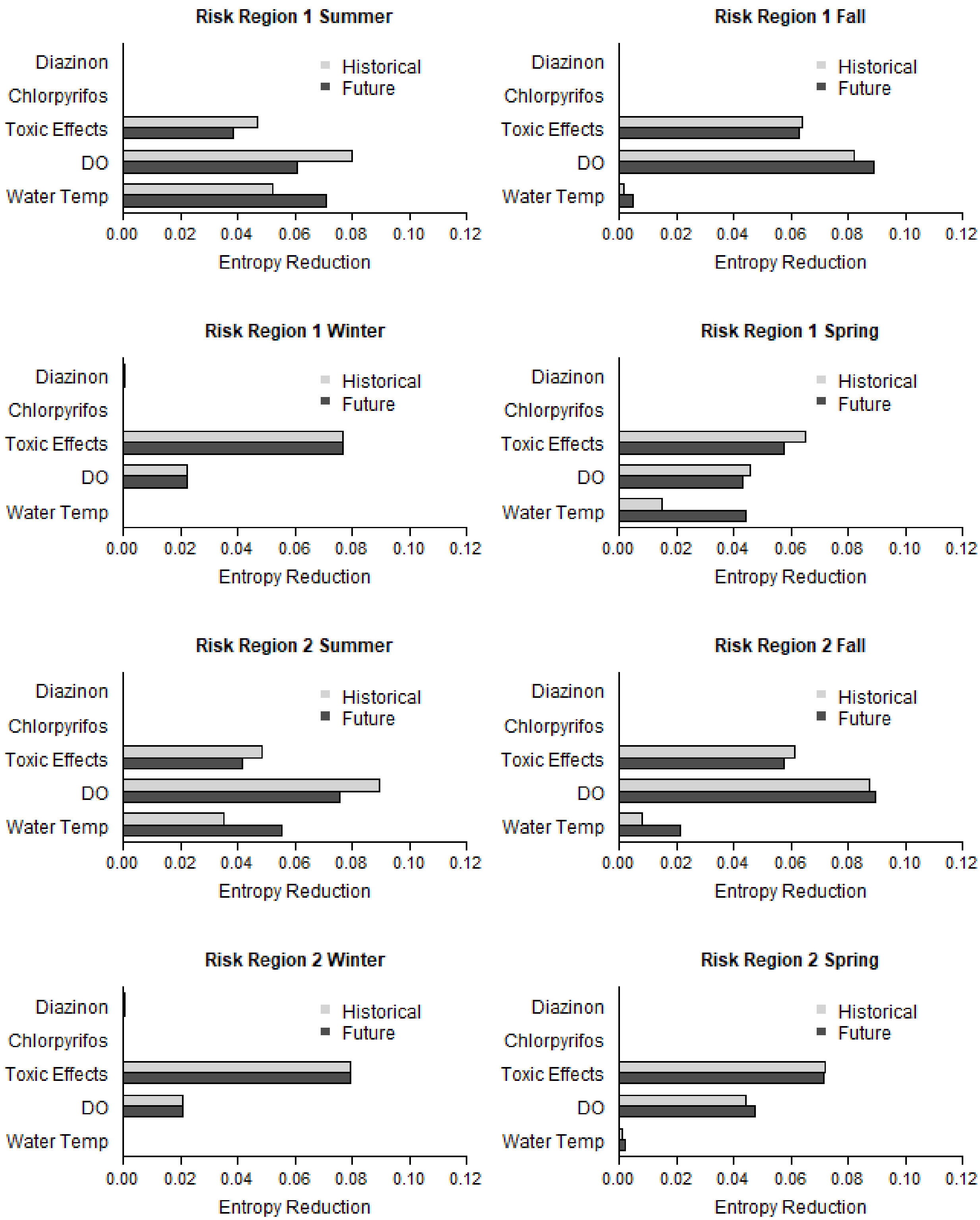

Figure S1. Entropy analysis results for risk regions 1 and 2.

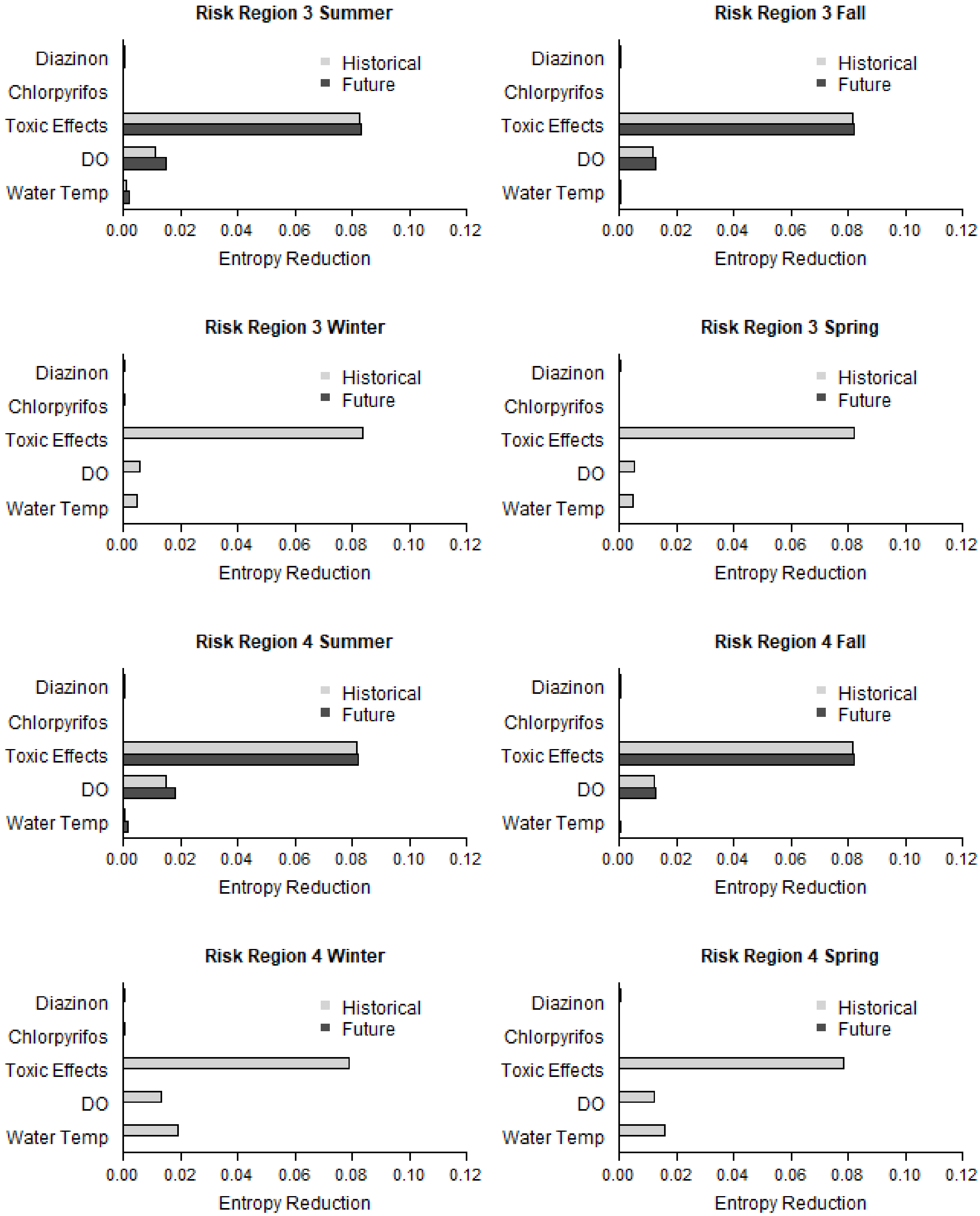

Figure S2. Entropy analysis results for risk regions 3 and 4.

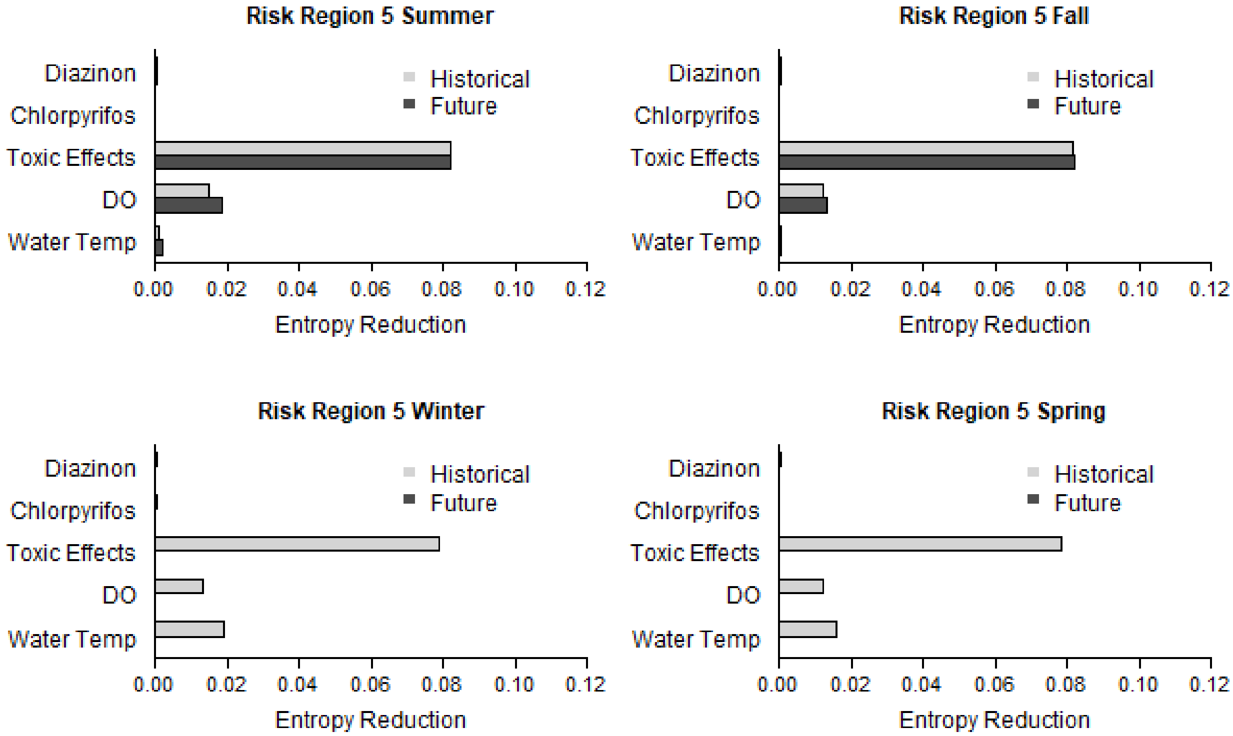

Figure S3. Entropy analysis results for risk region 5.

S4. Toxicity Pathway and Mixture Methods.

I used the drc package in R (Ritz et al. 2015) to construct a model equation for the chlorpyrifos mixture results from Laetz et al. 2013.

Single Chemical Analysis

In order to use the toxic units approach, I needed to calculate the EC50s from the single chemical data. I used the data from Laetz et al. 2009.

EC50s calculated from single chemical analysis:

Diazinon EC50 = 39.55 ug/L

Chlorpyrifos EC50 = 1.99 ug/L

Diazinon Model

I used the drc package in R to construct the Diazinon single chemical model (Figure S4). A log logistic five parameter model was chosen as best fit because it had the lowest residual variance. The parameters are: b: -1.072, c: 100.160, d: 26.859, e: 4.927, f: 6.803.

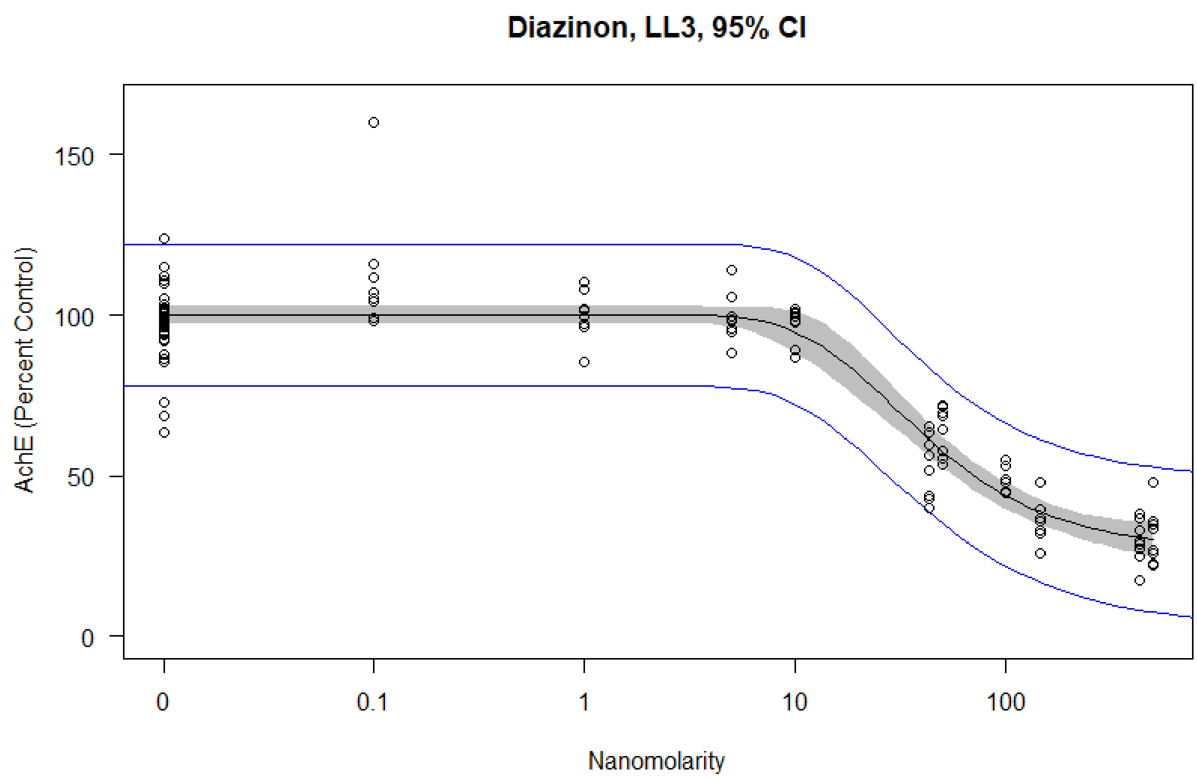

Figure S4. Diazinon single chemical model. Log logistic 5 parameter model. Data from Laetz et al. 2009.

Chlorpyrifos Model

I used the drc package in R to construct the Chlorpyrifos single chemical model (Figure S5). A log-logistic three parameter model was chosen as best fit because it had the lowest residual variance. The parameters are: b: 1.479, d: 100.736, e: 1.990.

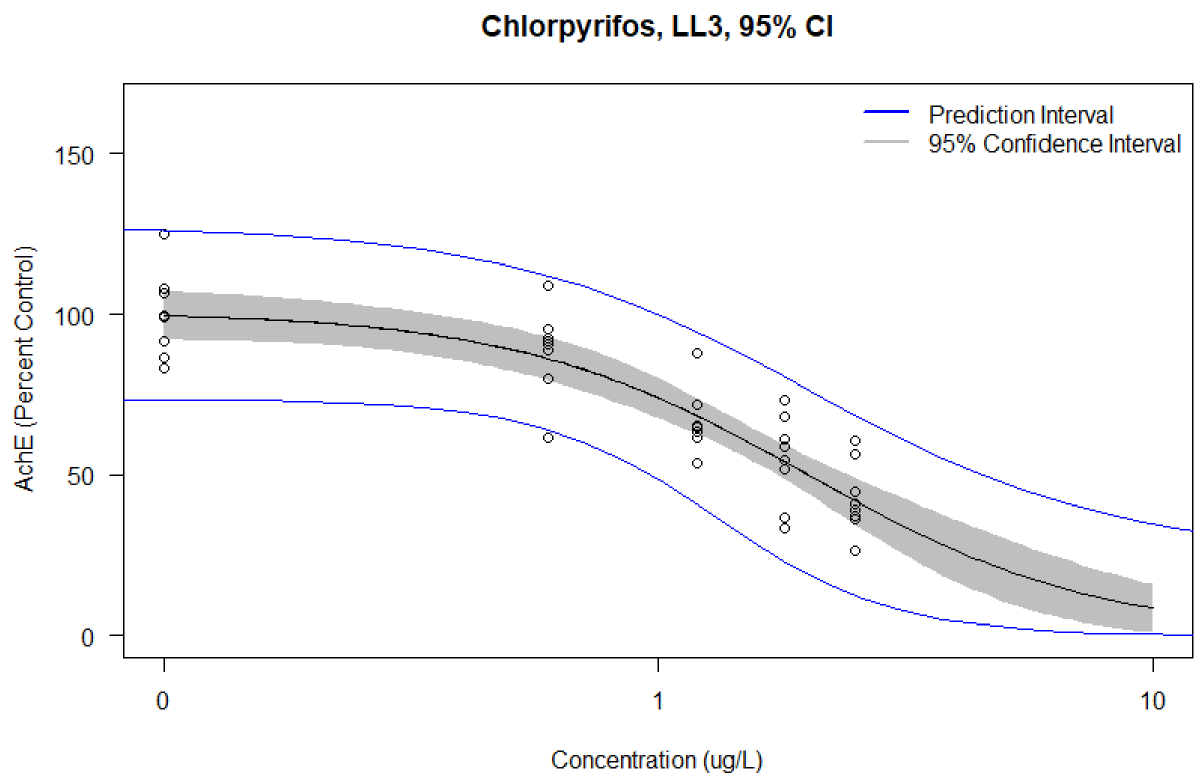

Figure S5. Chlorpyrifos single chemical model. Log-logistic three parameter model. Data from Laetz et al. 2009.

Chlorpyrifos + Diazinon Mixture Model

To convert the concentrations to toxic units, I used the equation:

TU = Measured Concentration of OP X (ug/L) / EC50 value of OP X (ug/L)

I constructed the mixture model using the drc package in R using the sum of toxic units as the concentration and the AChE % Control Inhibition as the response (Figure S6). A log logistic 3 parameter model was selected as best fit based on the log logistic model with the lowest residual variance.

Log Logistic 3 Parameter model from TU data:

AChE % Control = 101.7768/ (1+exp(0.6127 *(((log(Toxic Units)) - log(0.8359)))))

To enter this equation into Netica and use the Equation to Table function, I converted the pesticide concentrations into TU within the equation. The equation I used in Netica is:

ache (chlorpyrifos,diazinon) = 101.7768/ (1+exp(0.6127 *(((log((diazinon/39.552)+(chlorpyrifos/1.99))) - log(0.8359)))))

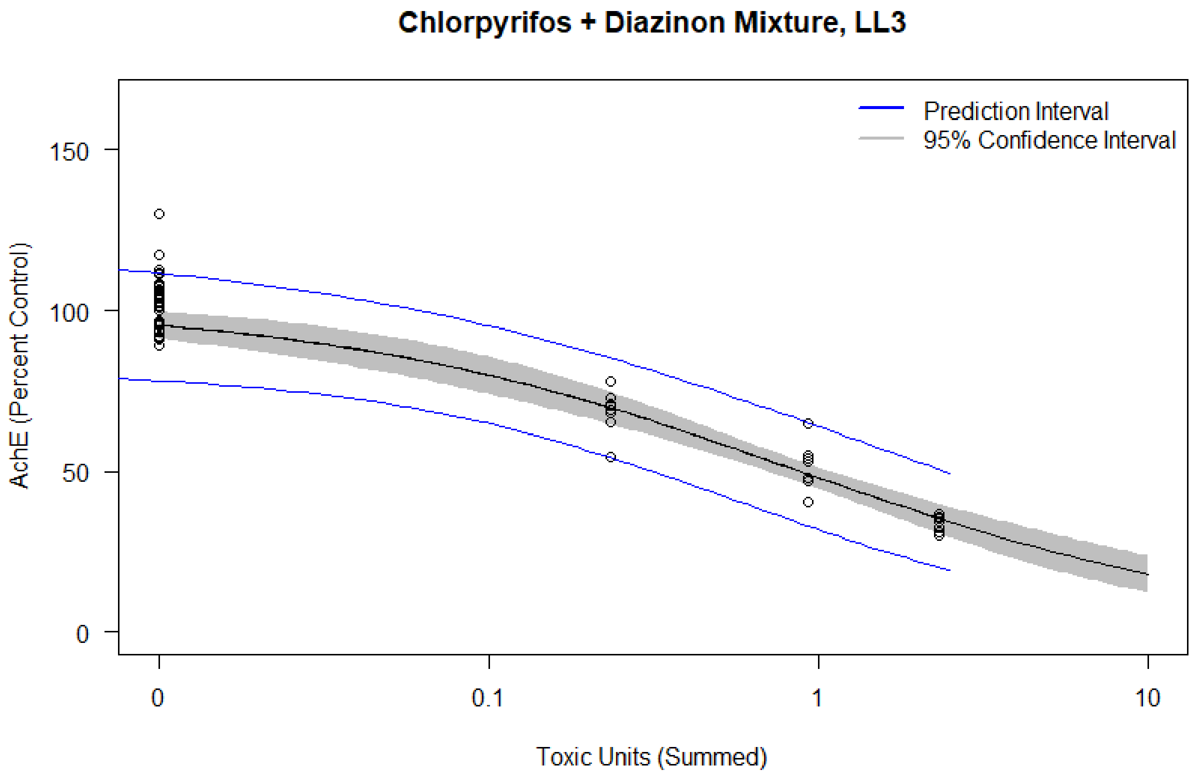

Figure S6. Chlorpyrifos + Diazinon mixture model. Log logistic three parameter model. Data from Laetz et al. (2009, 2013).

Mortality Model

I used the drc package in R to construct the Mortality model (Figure S7). A log-logistic two parameter, binomial type model was chosen as best fit because it had the lowest residual variance. The parameters are: b: 2.523, e: 30.579.

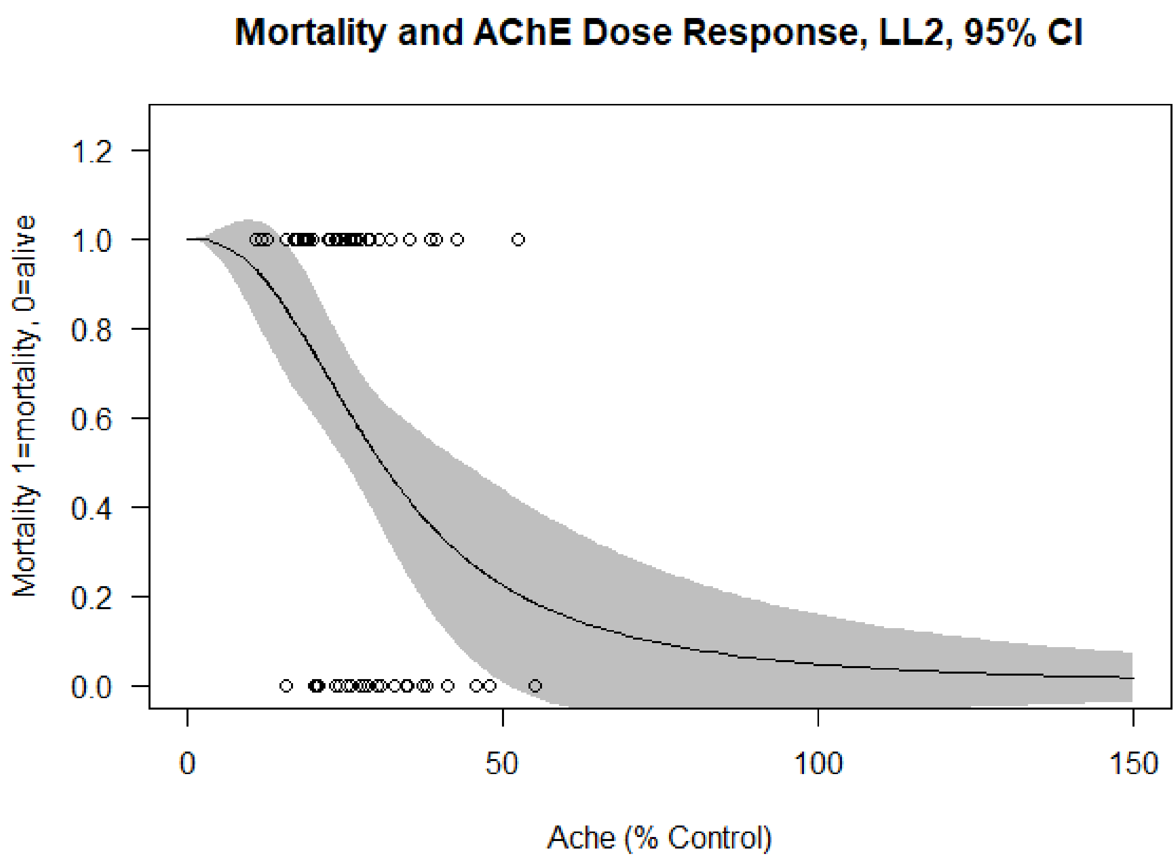

Figure S7. Log-logistic two parameter dose-response model for mortality as a response to acetylcholinesterase (AChE) inhibition with 95% confidence intervals.

Swim Speed Inhibition Model

I used the drc package in R to construct the swim speed inhibition model (Figure S8). A log-logistic three parameter model was chosen as best fit because it had the lowest residual variance. The parameters are: b: -1.8328, d: 88.6685, e: 12.019.

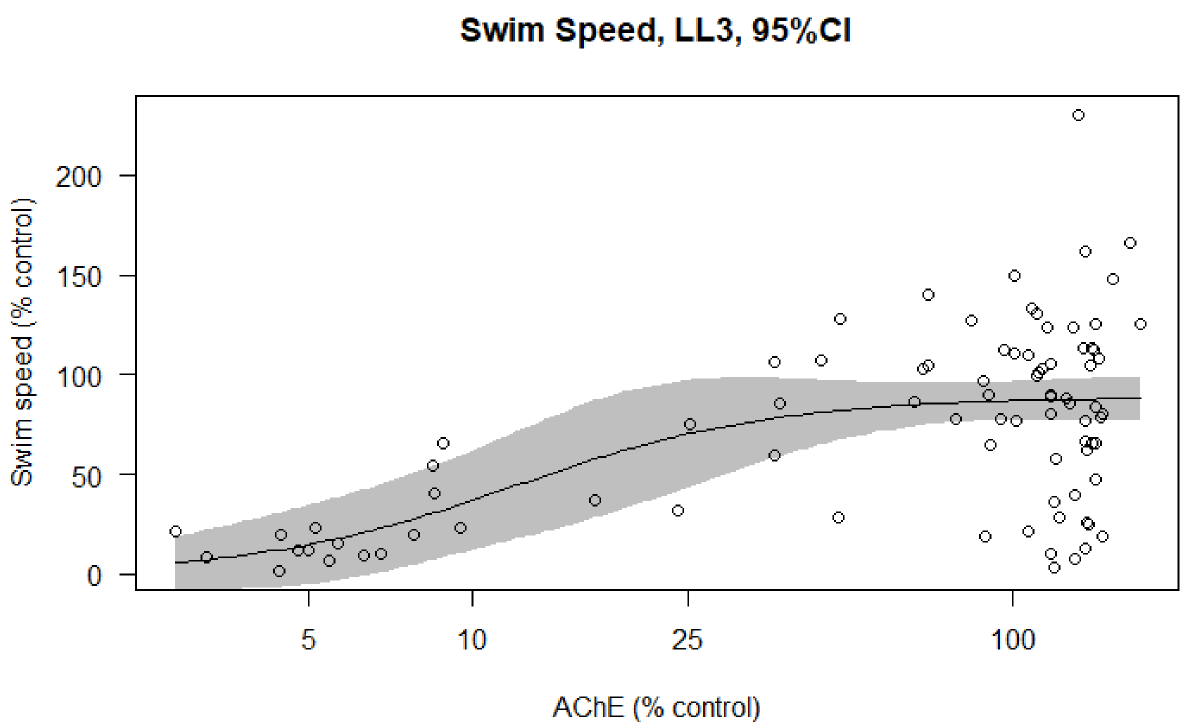

Figure S8. Log-logistic three parameter dose-response model for swim speed inhibition as a response to acetylcholinesterase (AChE) inhibition with 95% confidence intervals.

S5. Air Temperature to Water Temperature Regressions

I used R Statistical Software to create regressions of air temperatures to water temperatures. Figure S9 and Figure S10 show regressions specific to region and season for each region and season where simultaneous air and water temperature data were available. I used the 95% prediction intervals to construct the CPT for the water temperature node. The 95% confidence interval was not an accurate representation of uncertainty due to the large sample sizes.

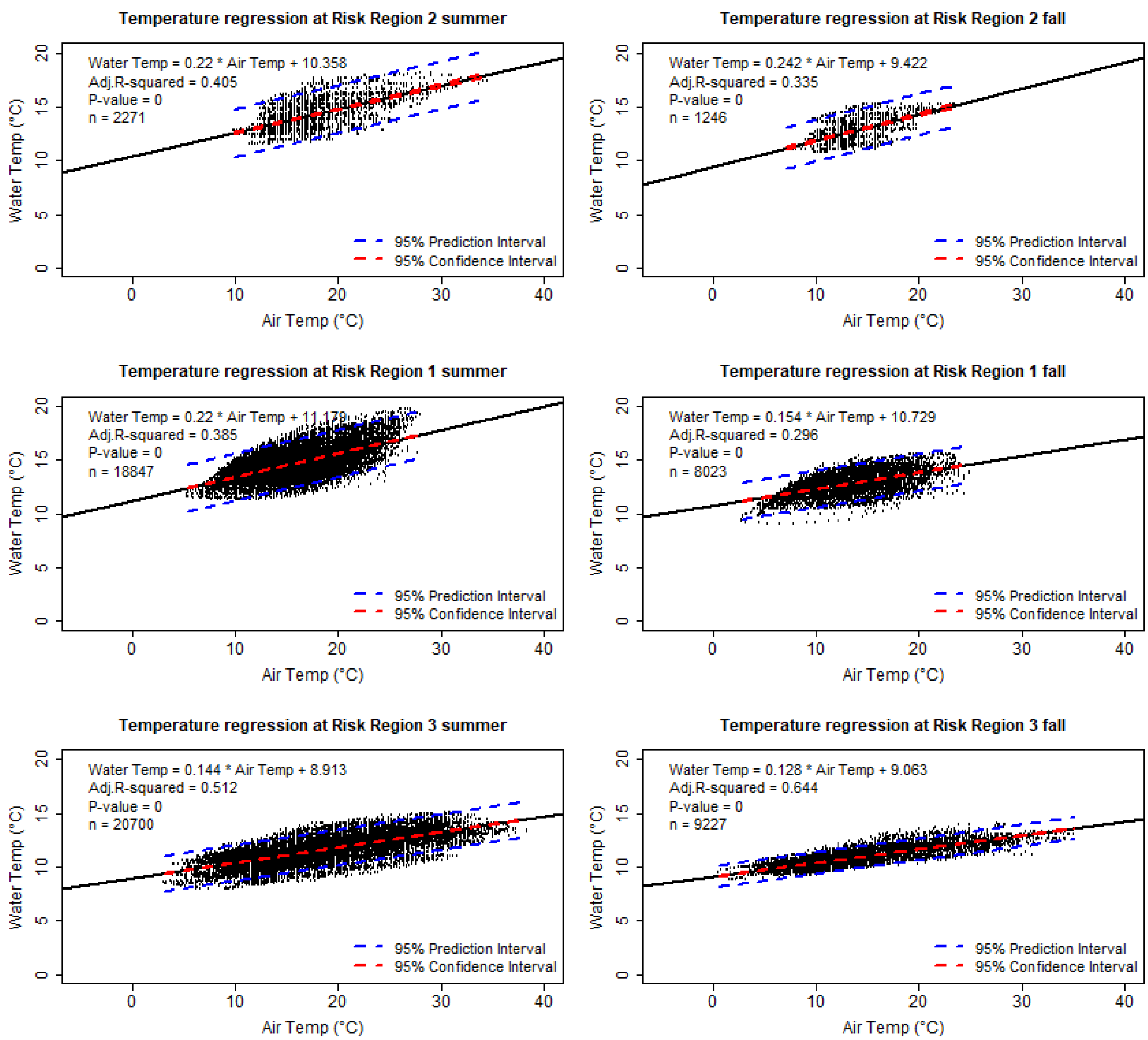

Figure S9. Temperature regressions for summer and fall in risk regions 1 to 3. The linear model equation, adjusted R^2, p-value, and sample size (n) are included in each regression, along with the 95% prediction and confidence intervals.

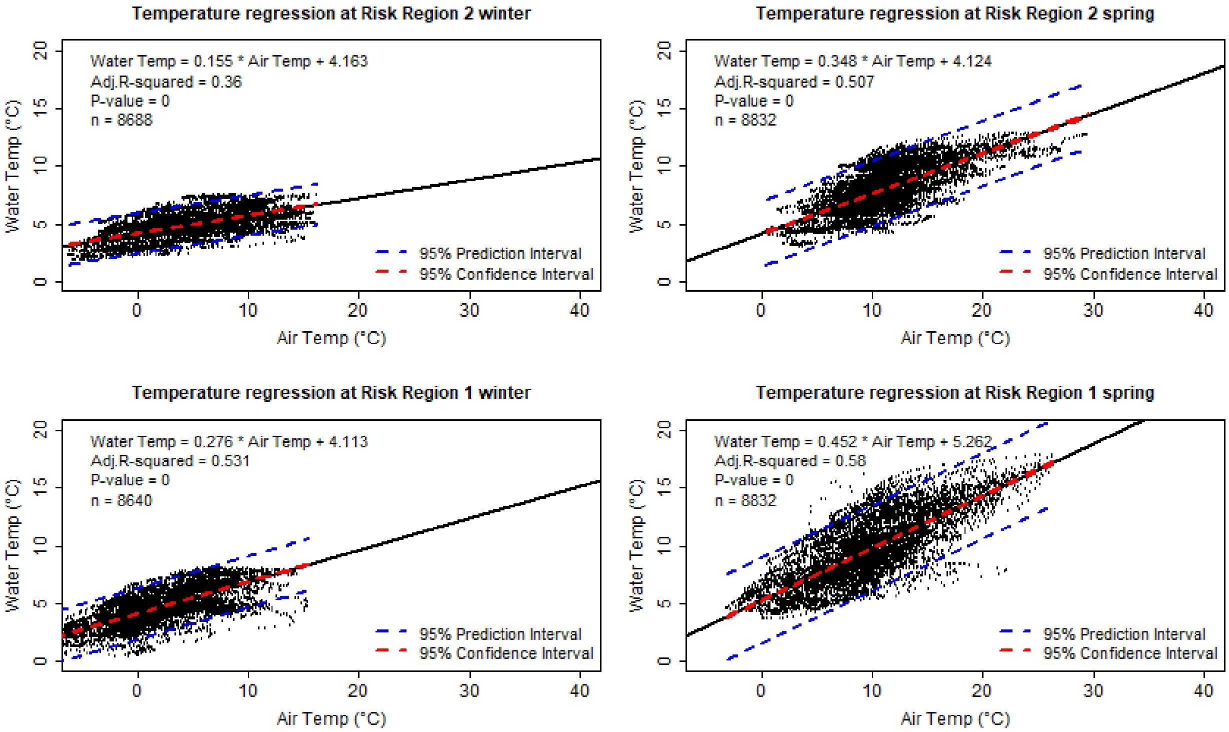

Figure S10. Temperature regressions for winter and spring in risk regions 1 and 2. The linear model equation, adjusted R^2, p-value, and sample size (n) are included in each regression, along with the 95% prediction and confidence intervals.

S6. Sample Location Maps

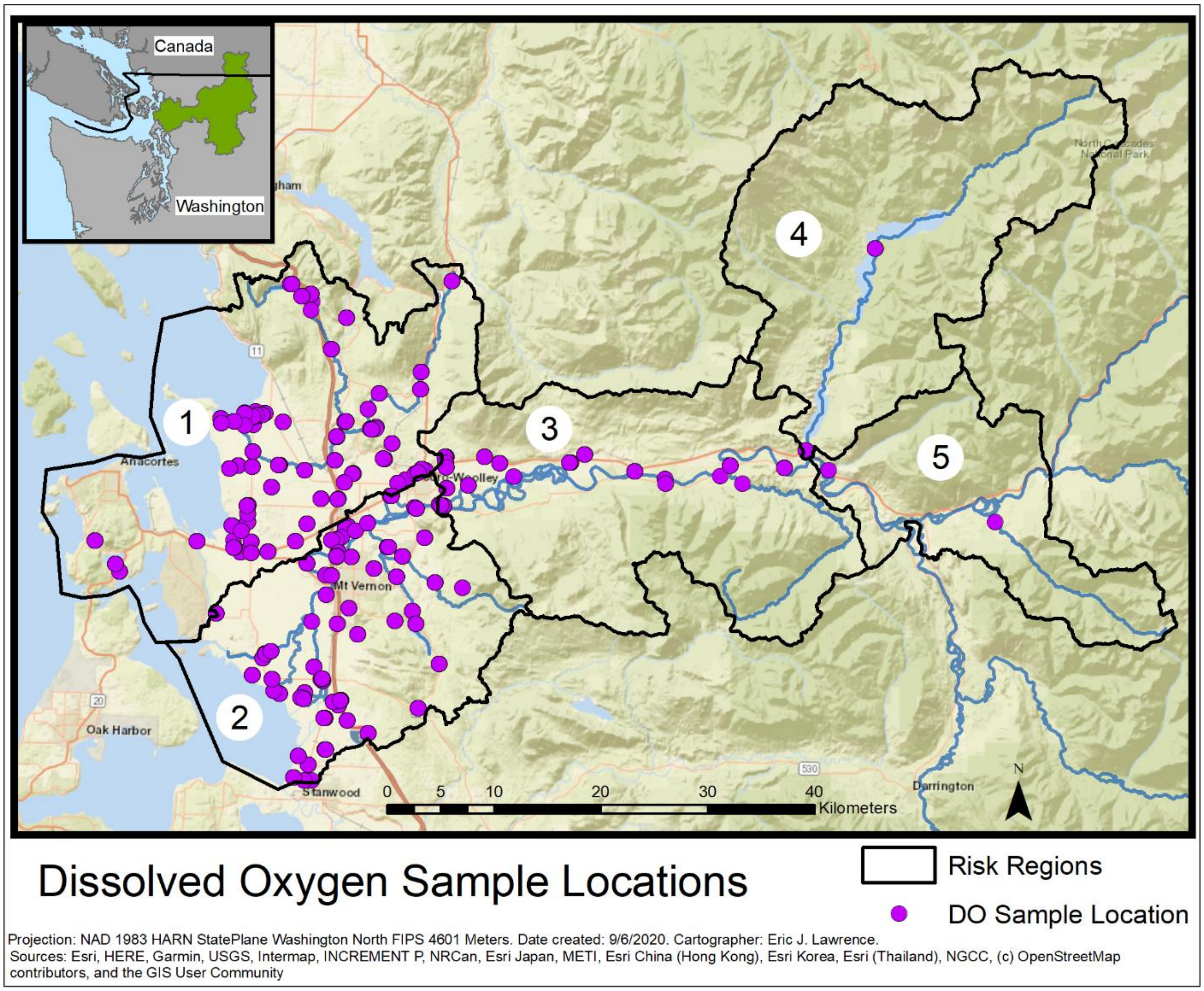

Figure S11. Dissolved oxygen (DO) sample locations within the Skagit River Watershed study area. Data from WADOE EIM (2019).

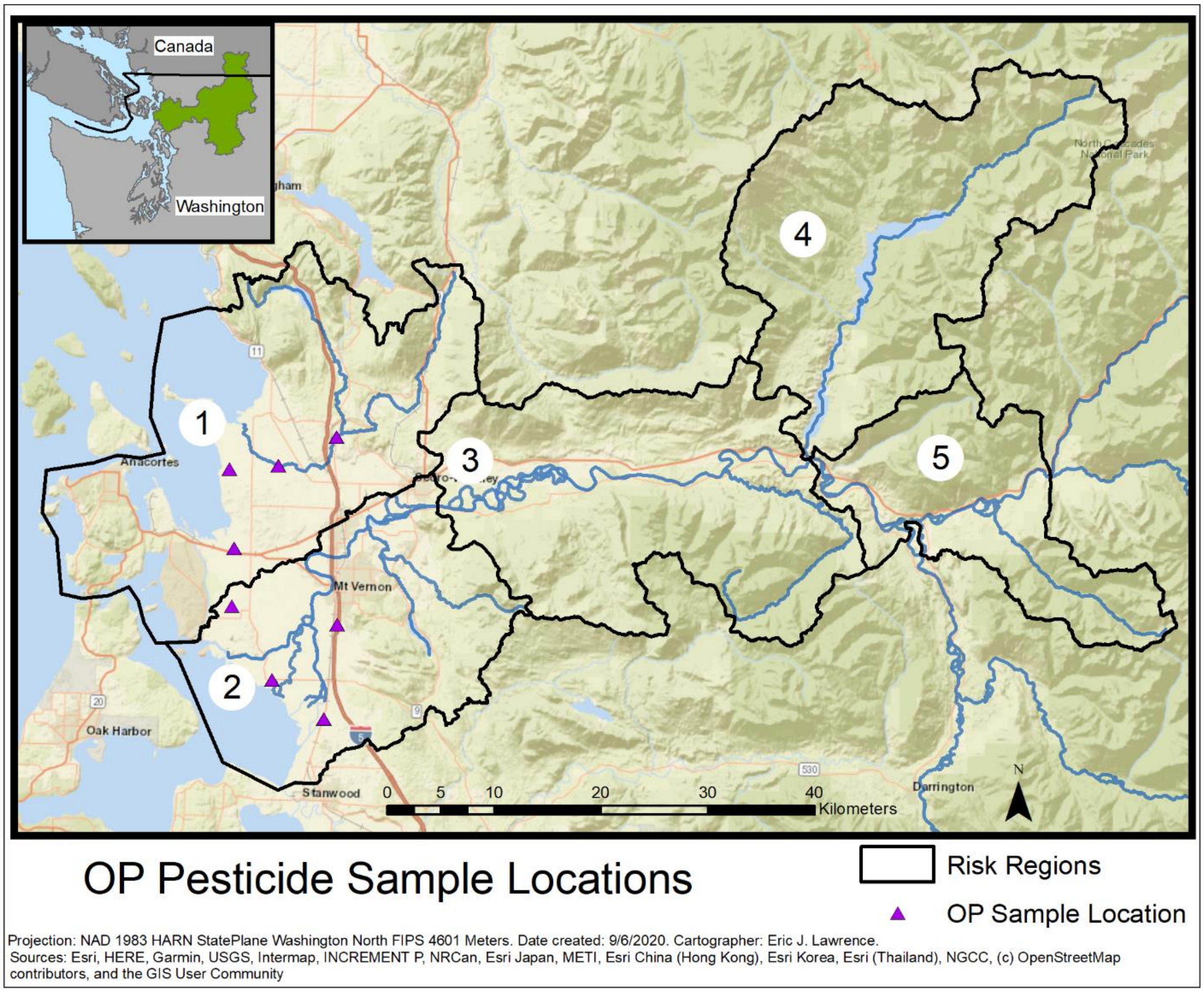

Figure S12. Organophosphate Pesticide (OP) concentration sampling locations within the Skagit River Watershed study area. Data from WADOE (2019).

S7. Air Temperature: Historical and Climate Model Projections

Figures S13 – S15 compare the distributions of average daily maximum air temperature between historical observed climate data and future climate projections by risk region and season. The historical climate scenario is based on observed climate data from 1981 to 2010 (Maurer et al. 2002) and the future climate scenario is based on climate projections from 2071 to 2100. The future climate projections are from an ensemble of GCMs from CMIP5 (Table 1). The RCP 8.5 projections were downscaled using BCCA V2 to a 0.125 degree grid. I obtained the model output from the USGS Geo Data Portal website (https://cida.usgs.gov/gdp/, Blodgett et al. 2011).

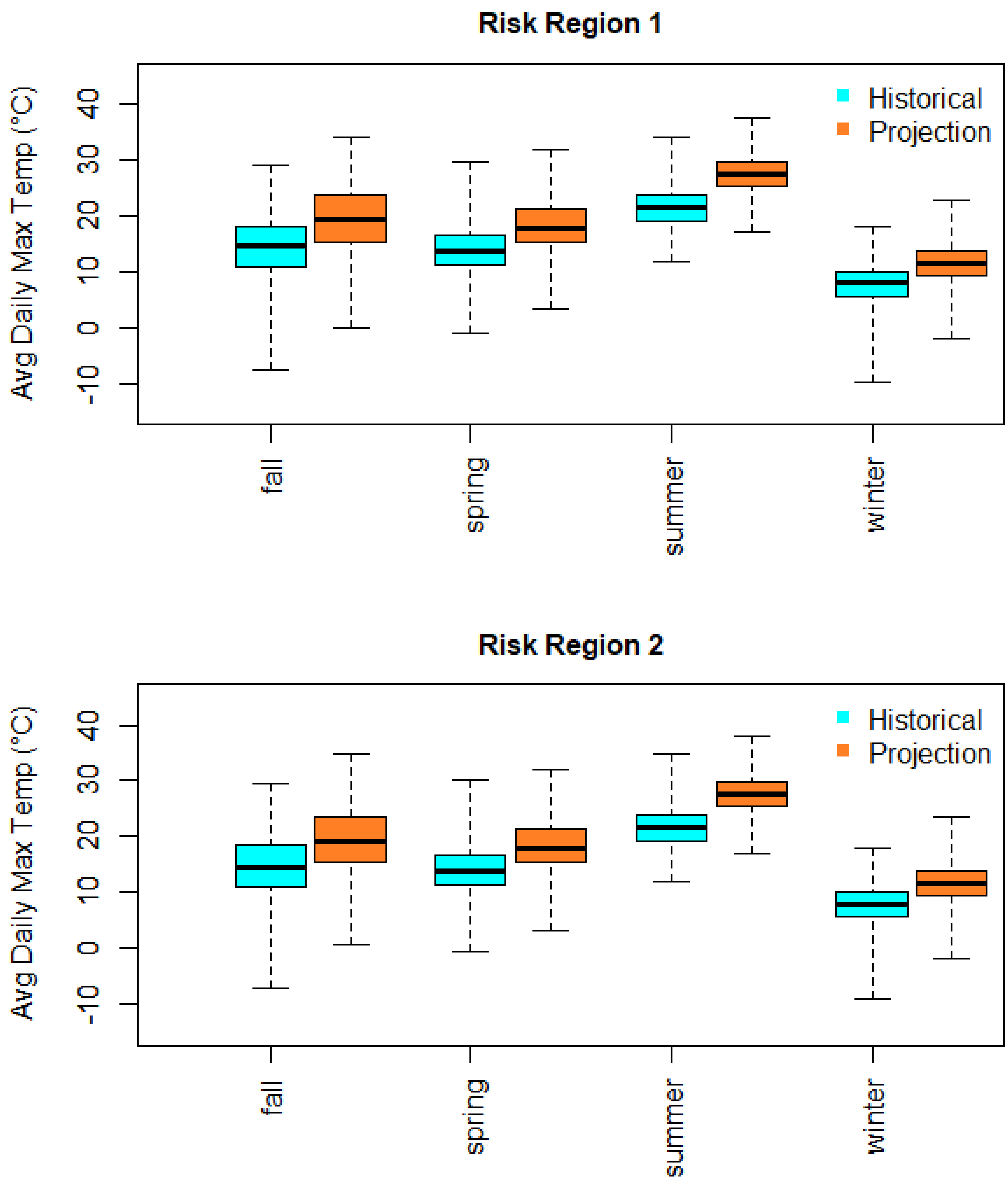

Figure S13. Box and whisker plots comparing measured historical air temperatures with climate projections by season for risk regions 1 and 2. The box shows the median and interquartile range and the whiskers show the min and max values.

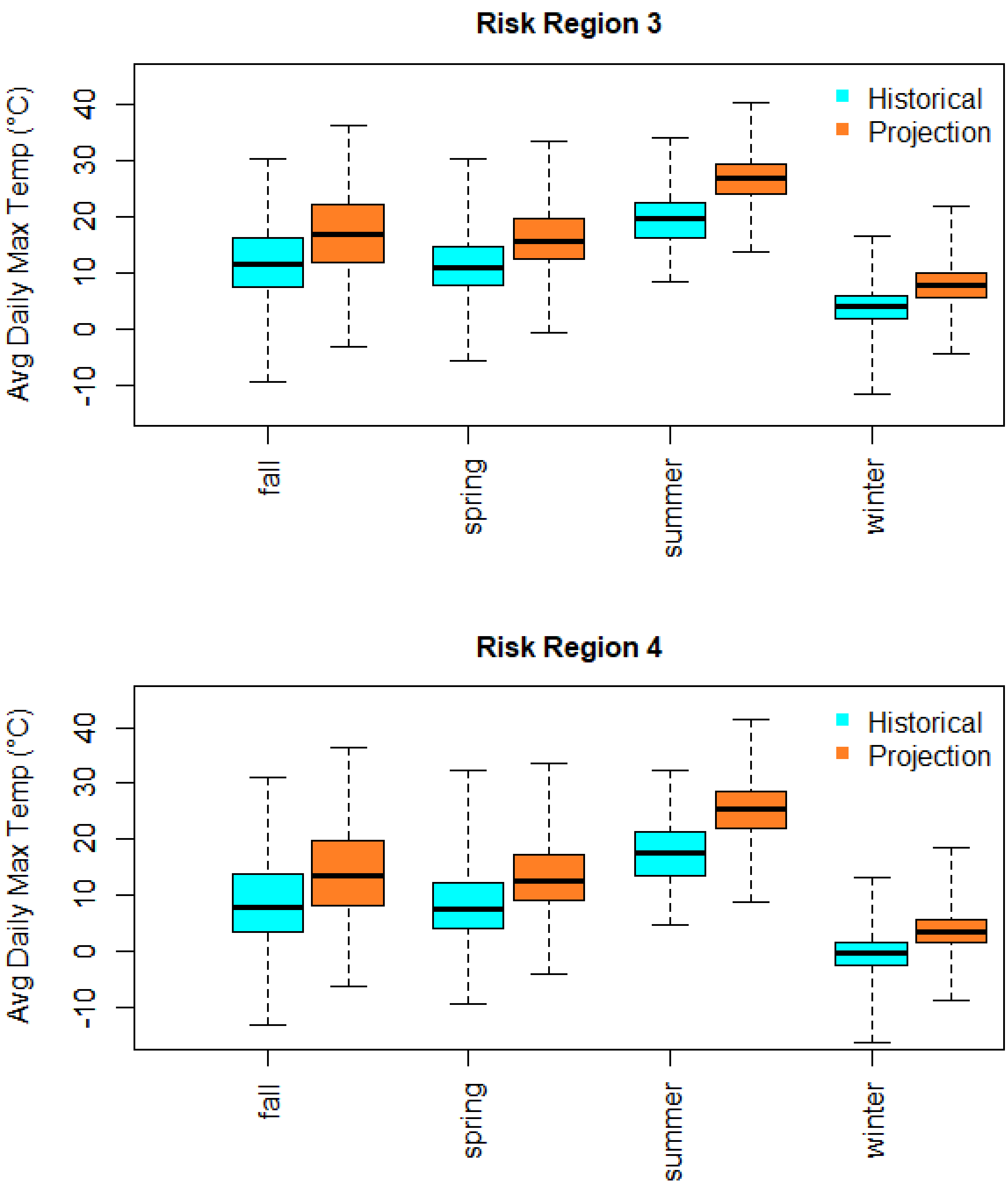

Figure S14. Box and whisker plots comparing measured historical air temperatures with climate projections by season for risk regions 3 and 4. The box shows the median and interquartile range and the whiskers show the min and max values.

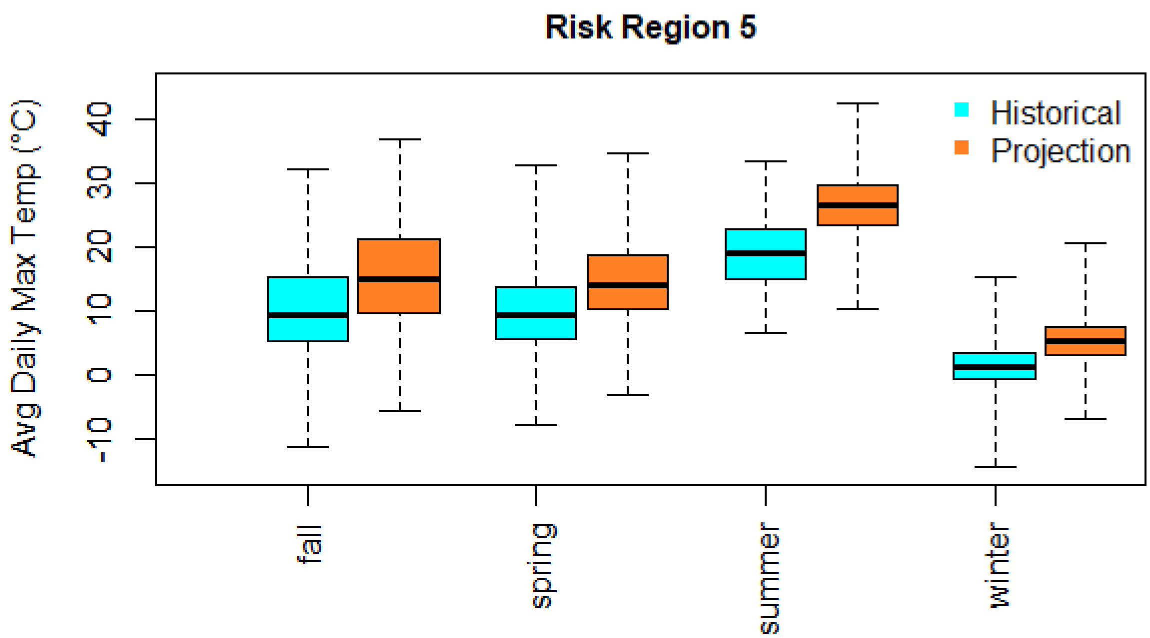

Figure S15. Box and whisker plots comparing measured historical air temperatures with climate projections by season for risk regions 5. The box shows the median and interquartile range and the whiskers show the min and max values.

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