# Supporting Landscape-Level Risk Assessment and Decision-Making in Managed Ecosystems Using Novel Modeling Methods

by

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Dissertation submitted in partial fulfillment of
the requirements for the degree of Doctor
of Philosophy in the Department of
Civil and Environmental Engineering in the Graduate School
of Duke University

2022

<u>ABSTRACT</u>

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# Abstract

The process of translating fundamental environmental research into evidence-based policies meant to protect and manage our ecosystems has long fallen short of expectations. Policymakers' desires for straightforward solutions with short-term, certain outcomes are constantly at odds with the nature of uncertainty in environmental research and decision modeling. The current methodologies of bridging the science-policy gap by encouraging researchers to communicate the uncertainties more clearly in their models and relate the results of individual studies to the entirety of complex decision-making frameworks are inadequate. Through this thesis, I explore the role of research within the boundary of science and policy and the ways in which we might increase the translation from research to evidence-based policy. Three different model frameworks employ three methodologies to reach this goal (1) Contextualize model outputs in previously existing policy frameworks; (2) Utilize environmental indicators as model outputs that are known to resonate with policy-makers and the public; and, (3) Collaboratively construct model structures to match to the pre-existing mental models of policy and decisionmakers. By understanding the balance between model complexity, uncertainty, and interpretability researchers can better understand how to integrate across research, social, and political boundaries to effectively inform policy.

## Dedication

This dissertation is dedicated to all the mentors, peers, family, and friends who have over many years shaped me into the researcher, educator, and person that I am today. I would not be here if not for their outpouring of support, guidance, and encouragement. This work would have not been possible without the support and foundation of exploration, curiosity, and determination instilled in me by wonderful parents, Judy and Clarke. Lastly, I must also acknowledge the incredible and unwavering support of my husband, Tom, without whom I could not have completed this thesis.

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# 1. Introduction

The process of translating fundamental environmental research into evidence-based policies meant to protect and manage our ecosystems has long fallen short of expectations (Bradshaw & Borchers, 2000). Policymakers' desires for straightforward solutions with short-term, certain outcomes are constantly at odds with the nature of uncertainty in environmental research and decision modeling. A fundamental lack of understanding of the meaning and impact of uncertainty in research has led to reticence in making swift and decisive changes to policies. This lack of understanding between researchers and policymakers is confounded by a lack of active collaboration between the groups. The framework in which science and policy interact is largely considered to be a simple linear structure as in Figure 1. Once specific policy goals are identified, researchers spur into action to develop the fundamental questions or issues to be addressed to meet those goals. This forms the basis of environmental policy research (Boswell & Smith, 2017).

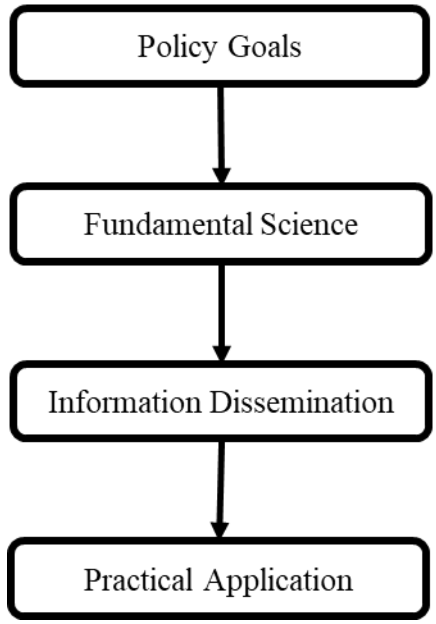


**Figure 1 Representation of the science-policy pipeline.**

**Adapted from Brownell and Roberto (2015)**

This linear structure has largely been proven to be an ineffective method for enacting effective, science-based policy. With limited specific modalities for researchers to disseminate policy recommendations outside of traditional publishing, the onus of communicating these findings has largely been placed on the researchers themselves. In an academic system that incentivizes the publication of fundamental research in high-impact journals over alternative methods of disseminating findings that might have more impact outside of academic settings, few researchers expend valuable time and energy to ponder the most effective ways to describe their findings and the ways in which uncertainty within those findings will impact policy outcomes. Even in a setting where research is effectively communicated to policymakers, without direct discourse between the two groups, there is no guarantee that the researcher has answered the appropriate questions to effectively advise specific policy goals within the constraints of a system and barriers to practical applications (Brownell & Roberto, 2015).

Although communication and collaboration are also at the center of the science-policy gap, the response from environmental scientists has largely been to focus on resolving uncertainty through solving problems using process-based models at finer and finer scales. While essential to the understanding of any system, potential sources of uncertainty, and fine-scale impacts of potential policies, this approach is not the most effective method for informing specific decision-making in a policy context. To directly influence these decisions, simpler models with which non-scientists can engage have a much higher impact (Steger et al., 2021). By engaging policymakers, stakeholders, and researchers in a collaborative process where policy goals are contextualized within the science and vice versa researchers can create models that better inform decision-making. In many ways, it is more effective to embrace uncertainty in the decision-making process. By letting go of the "perfect model" researchers can instead focus on the model that is most applicable to how systems are managed and best represents the decision at hand.

This is not to say that either models representing fundamental knowledge or more simplistic models with stakeholder input are more important to the process of creating evidence-based policy. There is instead a need to for greater differentiation between studies aimed at understanding the detailed dynamics of a system being regulated and studies that contextualize information from multiple research perspectives in a policy decision-making process. Individual attempts to briefly integrate across research and policy in the discussion sections of fundamental research is but a mere half measure (Funtowicz & Ravetz, 1993). There is instead the need to formalize the process of integrating across disciplinary boundaries as well as the boundaries between research, policy, and practice, which has been proposed as an independent field of research (Hoffmann, Deutsch, Klein, & O'Rourke, 2022). In environmental policy, there is need to utilize this framework to analyze and interpret uncertainty holistically and represent it in a way that is transparent to researchers, policymakers, and practitioners by no longer ignoring the social dynamics inherent to the policy-making process.

In this thesis, I explore three environmental models created to inform policy, each with different methods of integration across the boundary between research and policy. For each case study, I analyze the model's representation of uncertainty, its role in the research to policy pipeline, and potential tradeoffs that be made to effectively inform policy. Each case study is independent and unique in its application.

In the first case study and second chapter of this thesis, "Patterns of co-contamination in freshwater and marine fish of the northeastern United States", I use a novel statistical modeling framework to develop a multivariate Bayesian model of current fish tissue co-contamination in the Northeast United States. The goal of the model is to make broad policy recommendations on regional and state levels for fish consumption advisories in lakes, rivers, and coastal waterways. The framing of this work in the context of fish consumption advisories, an already existing policy framework, is the method through which I integrate this work across research-policy boundaries.

The second case and third chapter of this thesis, "Predicting the effects of climate and land use change on water quality in the river systems of New Hampshire and Vermont", is part of a larger body of work aimed at valuing the ecosystem services provided by small stream systems through valuation workshops and surveys. I use the Random Forest machine learning approach to model the effect of land use, water quality, and hydrological patterns on the presence of species of the orders Ephemeroptera, Plecoptera, and Tricoptera (EPT). These orders are particularly sensitive to poor water quality and hydrological disturbances, making them a good indicator of overall river health. The results of stakeholder workshops in the Great Bay area of New Hampshire were used to determine the extent to which the presence of EPT resonates with the public as an indicator of overall water quality. I explore whether the consideration of public values and interpretation of model outputs increase the applicability of the results of this study for both the public and policy makers.

For the fourth chapter and final case study in this thesis, "Improving intra-agency decision-making for prescribed fire in the Ocala National Forest through the elicitation of a Bayesian Belief Network", I conducted a structured elicitation of a Bayesian belief network to model the decision-making framework for prescribed burning in the Ocala National Forest (ONF). This work is part of a larger initiative to develop decision-support models focused on promoting shared stewardship and the optimization of decision-making in the face of potentially conflicting management goals. Through this case study, I explore the benefits of co-production of knowledge between researchers and environmental managers in an iterative context to develop a model structure that both represents the dynamics of a system and the decision-making framework.

# 2. Patterns of Co-contamination in Freshwater and Marine Fish of the Northeastern United States

This chapter has been submitted for review as *Patterns of co-contamination in freshwater and marine fish of the northeastern United States* to Environmental Modeling & Assessment. The manuscript has been reformatted for this dissertation. Lead author, Kimberly Bourne, completed the statistical analysis presented and was responsible for the drafting of the manuscript. Amanda Curtis aided in the identification of the dataset used and data collected for the trophic level of fish. Jonathan Chipman was responsible for retrieving land use data associated with the National Coastal Assessment data. Celia Chen provided expertise on the dynamics of contaminants within aquatic systems and food chains. Mark Borsuk provided expertise in statistical modeling and interpretation of model results. Mark Borsuk, Celia Chen, and Amanda Curtis assisted with editing and revising the manuscript.

## 2.1 Introduction

Human activities involving the use of chemicals and fossil fuels in industrial, residential, and agricultural settings have led to the presence of contaminants throughout the natural environment (Chase et al., 2001; Driscoll et al., 2007; Phillips et al., 2010). Persistent, bioaccumulative and toxic substances (PBTs) continue to pose human health risk despite efforts to ban their use or curb their emissions (Leanne L Stahl, Snyder, Olsen, & Pitt, 2009). Of particular concern are mercury and organic compounds including pesticides, fungicides, industrial chemicals, and their metabolites. The concentrations of these environmental contaminants are particularly high in the northeastern U.S. due to dense urbanization, a history of agriculture, and proximity to coal fired power plants (Chen, Stemberger, Kamman, Mayes, & Folt, 2005).

The primary route of human exposure to PBTs is through the consumption of fish (Dorea, 2006). These substances bioaccumulate in food chains (Opperhuizen, Wijbenga, & Hutzinger, 1984; Petersen & Kristensen, 1998), leading to concentrations in fish tissue that can cause a variety of health problems, especially to vulnerable populations such as children, the elderly, pregnant women, and their unborn children (Dórea, 2008). The northeastern U.S. has one of the highest consumption rates of fish in the country, so its residents are particularly at risk of contaminant exposure via fish tissue (USEPA, 2014).

In the U.S., the health risks posed by contaminated fish are managed using consumption advisories in the form of recommended meal restrictions. However, advisories vary from state to state in how they are calculated and the number of contaminants included. In a comparative analysis of state consumption advisories across the US, it was found that about a third of states based advisories on a single contaminant either statewide or for each waterbody. Almost half of states include advisories based on multiple contaminants but offer no explanation as to how this advice is developed (Scherer, Tsuchiya, Younglove, Burbacher, & Faustman, 2008). There is evidence that many of the common contaminants included in these advisories have additive or synergistic health effects when consumed simultaneously, but many chemical mixtures have yet to be tested. The toxicity of chemical mixtures is therefore a critical area of health research (Carpenter et al., 1998; Monosson, 2005; Spurgeon et al., 2010; Yang, Hong, & Boorman, 1989), and the CDC has an ongoing effort to build a database of interaction profiles under the Agency for Toxic Substances and Disease Registry (ASTDR, 2018). As the nature of most interactions is currently unknown, the EPA recommends that, as a precaution, additivity should be assumed for carcinogens and contaminants with similar mechanisms of toxicity (USEPA, 2000).

Even if the health impacts of chemical mixtures were to be well-characterized, a separate but related question is, "What are the particular mixtures to which various populations are being exposed?" Answering this question requires analysis of the covariance of contaminants in fish tissue and the dependence of this covariance on local watershed and waterbody conditions. Most studies of fish tissue concentrations to date have only considered contaminants individually or in small groups (De Vault, Hesselberg, Rodgers, & Feist, 1996; Gewurtz et al., 2008; Nicklisch, Bonito, Sandin, & Hamdoun, 2017; Nowell et al., 2013; Leanne L Stahl et al., 2009). However, because we expect many contaminants to have common sources and similar environmental fate and transport mechanisms. A complete assessment of health risk should consider many contaminants simultaneously and with an increased focus on measuring many contaminants at once, the data required to do such an assessment is more available than ever (Gandhi, Drouillard, Arhonditsis, Gewurtz, & Bhavsar, 2017).

In this paper, we apply a novel, multivariate Bayesian modeling method to analyze publicly available fish tissue data from the EPA to address the following three questions: 1) How do measured PBT concentrations in fish tissue covary across different waterbodies and how does this covariance differ between lakes, rivers, and coastal zones? 2) How much of the observed PBT covariance can be explained by models that account for local watershed and waterbody factors? 3) What are the practical implications of PBT covariance that cannot be addressed by models and therefore remains a component of model predictive uncertainty?

## 2.2 Methods

### 2.2.1 Data Description

Our analysis employed three datasets that are publicly available from the U.S. EPA: the Environmental Monitoring and Assessment Program (EMAP) Northeast Lakes data (1991-1994), the National Rivers and Streams Assessment (NRSA) data (2008-2009), and the National Coastal Assessment (NCA) northeast region data (2000-2006) (USEPA, 1999, 2010, 2016b). The sample sites included in this study are mapped in Figure 2. Measured PBTs are listed in Table 1, and fish, waterbody, and watershed variables are listed in Table 2. Most data come from the original datasets, however land use characteristics were derived from the National Land Cover Database (NLCD) for the years 2000 for the EMAP data and 2006 for the NRSA data. A combination of the 2000 and 2006 NLCD data was used for NCA based on which year was closest in time to the fish tissue samples. Because watersheds of the NCA coastal locations are not well-defined, land use characteristics were derived from any land area within 200 km of the point at which the fish tissue samples were collected. Fish species trophic levels were determined through literature review (see Appendix A for details).

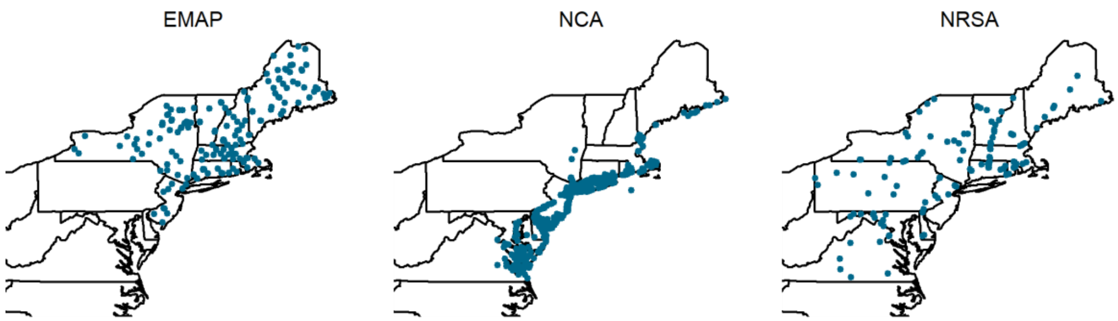


**Figure 2 Spatial representation of the sample locations included in this study.**

### 2.2.2 Data Analysis

Data were analyzed using the R package GJAM (Clark, Nemergut, Seyednasrollah, Turner, & Zhang, 2017). This package is designed to model multivariate response variables that can be both discrete and continuously valued. Importantly for our purpose, all response variables representing PBT concentrations can be modeled simultaneously, with explicit representation of their covariance structure. Also importantly, GJAM appropriately handles data which are variously censored, a common trait of fish tissue measurements that may fall below method detection limits (MDLs) that differ by contaminant. GJAM treats values reported to be below the MDL as being unknown on the interval between zero and the MDL, then simulates these values from a latent scale derived from the truncated distribution of measured values above the MDL. This approach avoids biases that are incurred when censored values are replaced by zeros, the MDL, or any other specific value (Antweiler & Taylor, 2008; Helsel, 1990; Shumway, Azari, & Kayhanian, 2002).

Our GJAM model structure is depicted graphically in Figure 3. In this model, the measured (possibly censored and transformed) concentrations $Y_{ik}$ of contaminant *k* in fish tissue sample *I* are assumed to be the manifestation of the true (uncensored) concentrations $W_{ik}$, with mean $\mu_{ik}$ (each modeled as a linear function of *j* measured environmental and fish attribute predictors $X_{ij}$ and parameters $B_{jk}$) and model error described by a common multivariate distribution with variance-covariance matrix $\Sigma_{kk}$. Thus, the covariance of predicted mean concentrations $\mu_{ik}$ represents the portion of the overall contaminant covariance that is explainable by differences in environmental and fish attributes, while the matrix $\Sigma_{kk}$ represents the portion of the covariance that cannot be explained by these factors, and is based on the joint distribution of model residuals. This remaining covariation should not be ignored, but rather explicitly considered in waterbody assessments, as it represents the residual risk of simultaneous exposure to multiple contaminants.

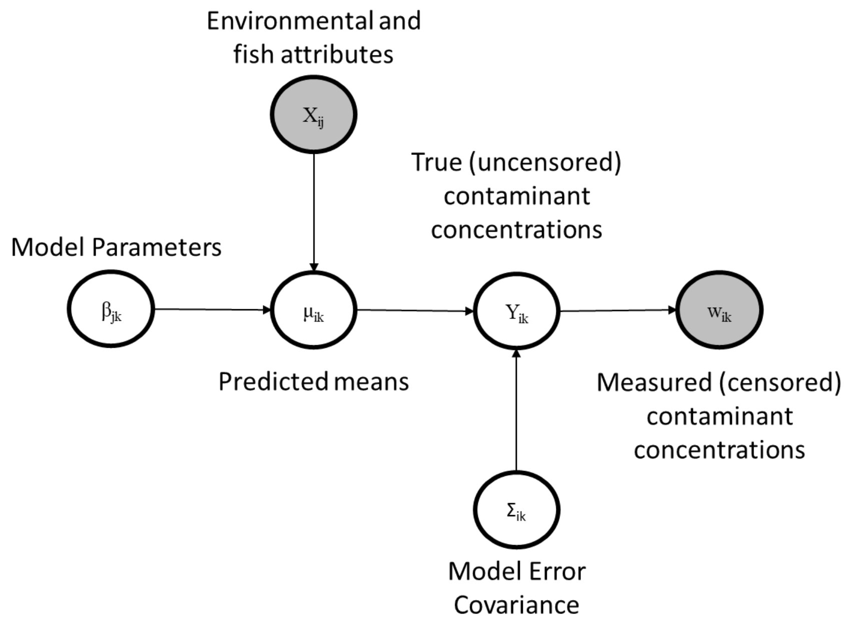


**Figure 3 Graphical representation of our GJAM model structure.**

**Shaded nodes represent observed variables, others are unobserved. Subscript i represents individual fish tissue samples, k represents the various contaminants, and j represents environmental and fish**

GJAM employs a Bayesian approach to model fitting. Parameter and variance-covariance estimates are represented by the posterior distribution $P[B, \Sigma|X, Y]$, which is derived from Bayes theorem as the product of a likelihood function of the fish tissue concentration measurements, $P[Y|X, B, \Sigma]$, and a joint prior distribution of the parameters and model error variance-covariance matrix, $P[B, \Sigma]$,:

$$P[B,\Sigma|X,Y] = \frac{P[Y|X,B,\Sigma] \times P[B,\Sigma]}{\iint P[Y|X,B,\Sigma] \times P[B,\Sigma]dBd\Sigma} \quad (1)$$

We used a multivariate normal likelihood function, after a square-root transformation of concentration measurements to counter skewness and maintain strictly positive values. To minimize the influence of the prior, we used a widely dispersed multivariate normal distribution on the parameters with mean of zero and a Jeffrey's prior on the variances and covariances.

We simulated the posterior distribution using Gibbs sampling, a version of Markov Chain Monte Carlo (MCMC) simulation implemented in GJAM. This allows for estimation of missing and censored values, which were a common occurrence in our data. At each iteration of the Gibbs sampler, missing and censored data are replaced by inferred values derived from that iteration's posterior parameter estimates.

Each of the three EPA datasets was analyzed separately using the variables available. Environmental predictor variables (Table 2) included those used in previous analyses of individual contaminants (Nicklisch et al., 2017; Shanley et al., 2012; Leanne L. Stahl et al., 2014; Sunderland, Krabbenhoft, Moreau, Strode, & Landing, 2009). Fish length, trophic level, lipid content, and species were used to control for fish characteristics, except for EMAP which does not include fish length and NRSA which does not include lipid concentration. Further, in the NRSA and NCA datasets, trophic level and species are redundant, so only species data were considered. Species data is included as a categorical variable in the model with GJAM selecting the species with the most data points as the reference species. Contaminants included all PBTs reported by each dataset (Table 1), with efforts to achieve consistency when possible. For example, not all datasets report specific PCB congeners, so we considered only total PCBs. Contaminant properties (e.g., octanol-water partition coefficient) were not considered explicitly, as their effects are presumed to be captured by the estimated model parameters. If only one observation existed for a species in a dataset, that observation was removed. Our analysis thus employed 222 (EMAP), 1001 (NRSA), and 118 (NCA) fish tissue samples across 158, 679, and 118 locations, respectively.

**Table 1 PBTs considered by data source.**

| EMAP | NRSA | NCA |
|---|---|---|
| 2,4'-DDE | Alpha Chlordane | 2,4'-DDE |
| 2,4'-DDD | Cis-Nonachlor | 2,4'-DDT |
| 2,4'-DDT | Dieldrin | 4,4'-DDD |
| 4,4'-DDD | Endosulfan II | 4,4'-DDE |
| Aldrin | Endrin | 4,4'-DDT |
| Alpha Chlordane | Endrin Ketone | 2,6'-Dimethylnaphthalene |
| Cis-Nonachlor | Gamma Chlordane | Acenaphthylene |
| Dieldrin | Heptachlor | Anthracene |
| Gamma Chlordane | Heptachlorepoxide | Benzo(b)fluoranthene |
| Hexachlorobenzene | Mercury | Biphenyl |
| Mercury | Oxychlordane | Chrysene |
| Oxychlordane | Total PCBs | Fluoranthene |
| Total PCBs | Total PFCs | Mercury |
| Trans-Nonachlor | Trans-Nonachlor | Methylnaphthalene |
| | | Naphthalene |
| | | Total PCBs |
| | | Pyrene |
| | | Trans-Nonachlor |

**Table 2 Fish, waterbody, and watershed variables considered by data source. (See Appendix A for definitions and units.)**

| EMAP | NRSA | NCA |
|---|---|---|
| Estimated Trophic Level | Fish Length | Chlorophyll a |
| Species | Species | Total Nitrogen |
| Lipids | Percent Ephemeroptera | Sediment Toxicity |
| Total Zooplankton Abundance | Total Nitrogen | Abundance of Tolerant Benthic Organisms |
| Alkalinity | pH | Abundance of Sensitive Benthic Organisms |
| DOC | DOC | Tissue Type |
| Chlorophyll a | Watershed Area | Percent Agriculture |
| Percent Human Disturbance | Percent Agriculture | Percent Forest |
| Percent Mining | Percent Urban | Percent Impervious |
| Percent Urban | Percent Shrub Grass | Percent Urban |
| Watershed Area | Percent Wetland | Percent Wetlands |
| Percent Agriculture | Percent Impervious | Latitude |
| Latitude | Barrier Disturbances | Longitude |
| Longitude | Riparian Vegetation | Lipids |
| | Longitude | Length |
| | Latitude | Species |

### 2.2.3 Model Selection

We present results for the model of each dataset that includes the combination of environmental predictor variables leading to the minimal value of the deviance information criterion (DIC). The DIC is a measure of goodness of fit, penalizing for model complexity (Gelman, Hwang, & Vehtari, 2014; Spiegelhalter, Best, Carlin, & Van Der Linde, 2014). Unlike other criteria such as the Akaike Information Criterion (AIC), the DIC is easily calculated from MCMC samples. We explored the space of possible models using a two-way stepwise algorithm, initiated with a minimal model including only tissue type and species as predictors, and proceeding to alternatingly add and remove additional predictors to reduce the DIC value.

## 2.3 Results

Covariation among contaminants is presented for each dataset in the form of three normalized variance-covariance matrices of (square-root transformed) fish tissue concentrations representing, respectively: (a) variation in the original measured data, (b) variation attributable to modeled factors, and (c) variation left unexplained by modeled factors. Normalization involved dividing each entry of each variance-covariance matrix by the product of standard deviations of the measured values of the two respective contaminants. Thus, in matrix (a) all diagonal elements equal one and off-diagonal elements represent the correlations between measured contaminant values. In matrix (b), the (off-)diagonal elements represent the normalized (co-) variance explained by the model (equivalent to model $R^2$ values in the case of the diagonal elements). The elements of matrix (c), therefore, represent the (co-)variance not explained by the model.

Parameter estimates for each data set are presented as matrices of the normalized sensitivity of (square-root transformed) fish tissue contaminant concentrations to each fish attribute and environmental predictor variable contained in the final model. Sensitivity values were calculated by multiplying each mean model parameter estimate by the average of its corresponding predictor variable and dividing by the average of the corresponding (square-root transformed) contaminant concentration. To better compare these values across all predictor-contaminant combinations, they are displayed as the signed quantiles across all sensitivity values, and thus range from -1 to 1.

### 2.3.1 EMAP Lakes Data

The covariance structure of the EMAP data (Figure 4, matrix a) reveals that in the tissues of lake fish, mercury is negatively correlated with all other PBTs, which are positively correlated with one another. A linear model accounting for environmental and fish attributes can explain a moderate proportion of the variance in individual contaminants, with $R^2$ values ranging from 0.29 to 0.72 (diagonal elements in matrix b, with specific values given in Appendix B), and a similar proportion of the covariance among contaminants (ratio of the off-diagonal elements in matrix a to those in Figure 4, matrix b) including the negative correlations between mercury and other contaminants. Overall, the chlordanes and related chemicals are predicted most accurately, both individually and in concert, while aldrin, mercury, hexachlorobenzene, and DDT and its breakdown products, as well as their covariances, are predicted least well. A moderate amount of (co-)variance remains unexplained (Figure 4, matrix c), as well as a mild negative covariance between hexachlorobenzene and both aldrin and oxychlordane that was induced by the model's slight overestimate of the covariance between these contaminants.

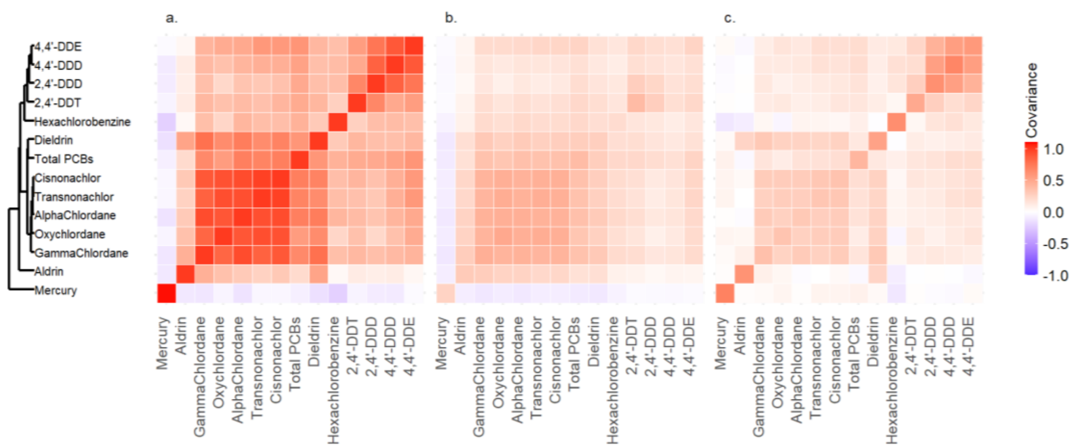


**Figure 4 Heat maps of normalized variance-covariance matrices of (square-root transformed) fish tissue contaminant concentrations from the EMAP data.**

**Each graph corresponds to: (a) measured data variation, (b) model-predicted variation, and (c) unexplained variation. Contaminants are ordered based on a hierarchal cluster analysis of original fish tissue concentrations shown on the left-hand side of the figure.**

The model best accounting for the variances and covariances among fish tissue contaminants in the EMAP data is one that includes, in addition to trophic level, lipid content, and fish species, the environmental variables percent agriculture, alkalinity, latitude, urban land, and zooplankton abundance (Figure 5). Significant parameters in this model indicate that the measured contaminants generally increase with greater trophic level and lipid content and, relative to yellow perch, are generally greater in lake trout and white perch and lower in Allegheny pearl dace, blue gill, brown bulkhead, and chain pickerel, with a few exceptions. Both lake trout and white perch have higher concentrations of all contaminants. Contaminant concentrations are generally lower at sites from higher latitudes, except for aldrin and mercury which are higher. Greater levels of urban land and zooplankton abundance are each generally associated with higher contaminant concentrations. Fish tissue concentrations are generally most sensitive to trophic level, species, and latitude.

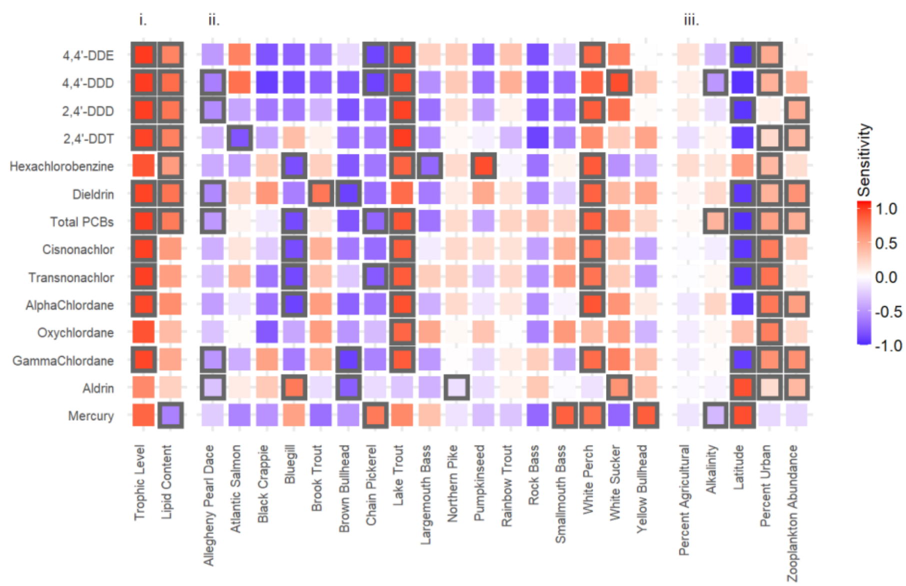


**Figure 5 Heat map of the sensitivity of fish tissue contaminant concentrations from the EMAP dataset.**

**The predictors are separated into (i) fish attribute, (ii) species, and (iii) environmental variable categories. Solid cell borders indicate parameters with a 95% Bayesian posterior credible interval that does not contain 0. Species effects are shown with reference to Yellow Perch.**

### 2.3.2 NRSA River Data

The NRSA data (Figure 6, matrix a) reveal that mercury, heptachlor, and total PFC concentrations negatively covary with most other PBTs in the tissue of fish from rivers and streams, and that these other PBTs positively covary with each other. Only a fraction of this covariance structure was captured in the modeled mean concentrations (Figure 6, matrix b) with proportions of explained co-variance ranging from zero to 0.59. Endosulfan II was predicted especially poorly, as the model only captured 16% of the variation in this contaminant, and a comparably low proportion of its covariance with other contaminants. Mercury, heptachlorepoxide, the nonachlors, the chlordanes, and their covariances were predicted reasonably well, with $R^2$ values all above 0.3. A substantial amount of variance and covariance in the NRSA data remains unattributable to modeled factors (Figure 6, matrix c).

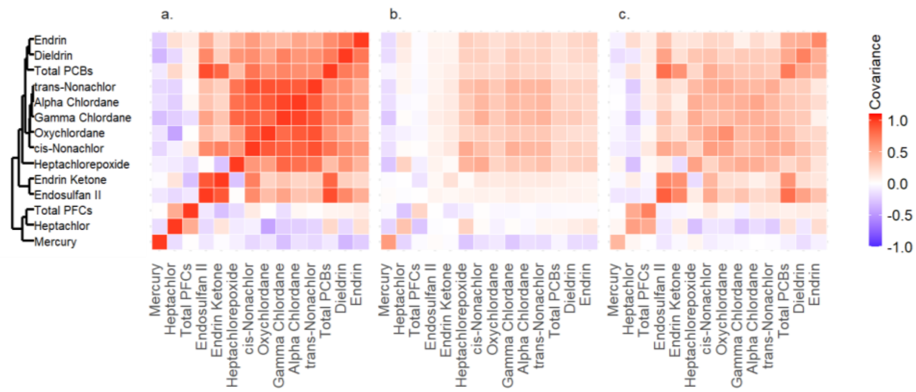


**Figure 6 Heat maps of normalized variance-covariance matrices of (square-root transformed) fish tissue contaminant concentrations from the NRSA data.**

**Each graph corresponds to: (a) measured data variation, (b) model-predicted variation, and (c) unexplained variation. Contaminants are ordered based on a hierarchal cluster analysis of original fish tissue concentrations shown on the left-hand side of the figure.**

The model best accounting for the variances and covariances of fish tissue contaminants in the NRSA data is one that includes, in addition to lipid content, total length, and species, the environmental variables: riparian vegetation, instream dissolved organic carbon (DOC) and pH (Figure 7). Riparian vegetation is a positive and significant predictor for total PFCs but a significant negative predictor for heptachlor. DOC is a significant positive predictor for mercury, total PFCs, endrin ketone, and heptachlorepoxide. For nearly all contaminants, pH is a significant and positive predictor of fish tissue contaminant concentration. Heptachlor and mercury generally show quite different relationships across species (relative to smallmouth bass) than the other contaminants.

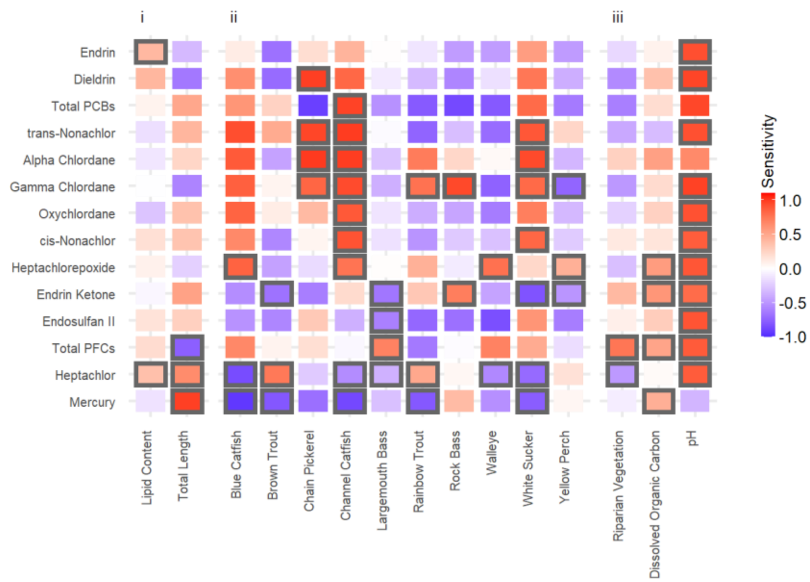


**Figure 7 Heat map of the sensitivity of fish tissue contaminant concentrations from the NRSA dataset.**

**The predictors are separated into (i) fish attribute, (ii) species, and (iii) environmental predictor variables. Solid cell borders indicate parameters with a 95% Bayesian posterior credible interval that does not contain 0. Species effects are shown with reference to Smallmouth Bass.**

### 2.3.3 NCA Data

In coastal waterways, all contaminants positively covary (Figure 8, matrix a). This dataset is limited, however, in that many contaminants were not measured concurrently. DDT and related metabolites covary particularly strongly with each other and with transnonachlor, with normalized covariance (correlation) values close to 1. While the best fitting model yields $R^2$ values for 4,4-DDT,4,4-DDD, 4,4-DDE, total PCBs, and transnonachlor from 0.43 to 0.66, most others are quite low. Additionally, only small portion of the observed covariance among contaminants is reproduced by the model (Figure 8, matrix b), with the vast majority remaining unexplained (Figure 8, matrix c).

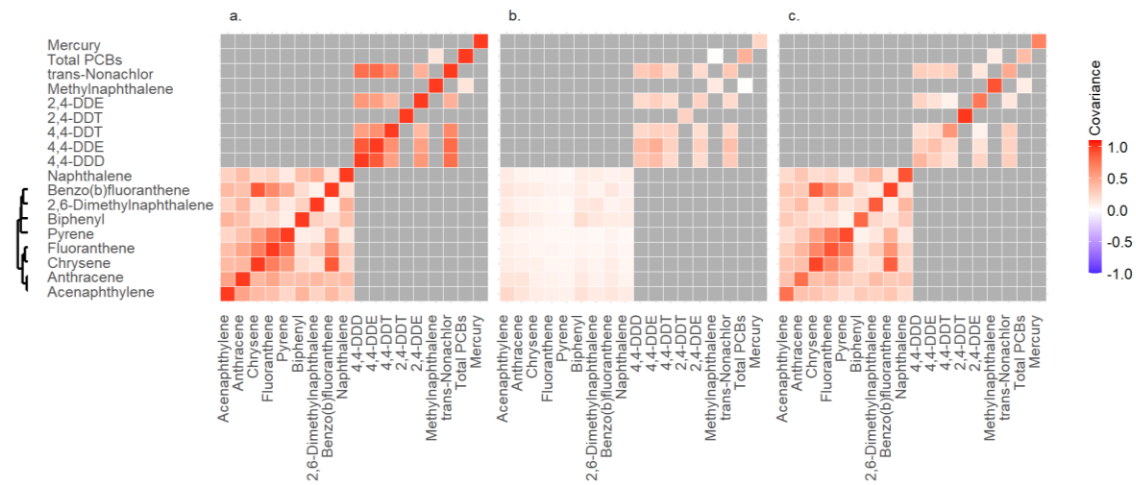


**Figure 8 Heat maps of normalized variance-covariance matrices of (square-root transformed) fish tissue contaminant concentrations from the NCA data.**

**Each graph corresponds to: (a) measured data variation, (b) model-predicted variation, and (c) unexplained variation. Contaminants are ordered based on a hierarchal cluster analysis of original fish tissue concentrations shown on the left-hand side of the figure.**

For the NCA data, the best fitting model (Figure 9) includes the fish characteristics: tissue type (offal generally lower than filet and whole fish generally greater), lipid content (weak positive and negative relations with contaminant concentration), fish length (positive when significantly different from zero), and species (mixed sign and significance, but perch and catfish species notably positive). Significant environmental variables include: the percentages of agricultural, forested, and urban land, as well as the total nitrogen concentration, all of mixed sign and significance depending on the contaminant. Comparisons between species show channel catfish and white perch having relatively high concentrations of all contaminants in their tissues.

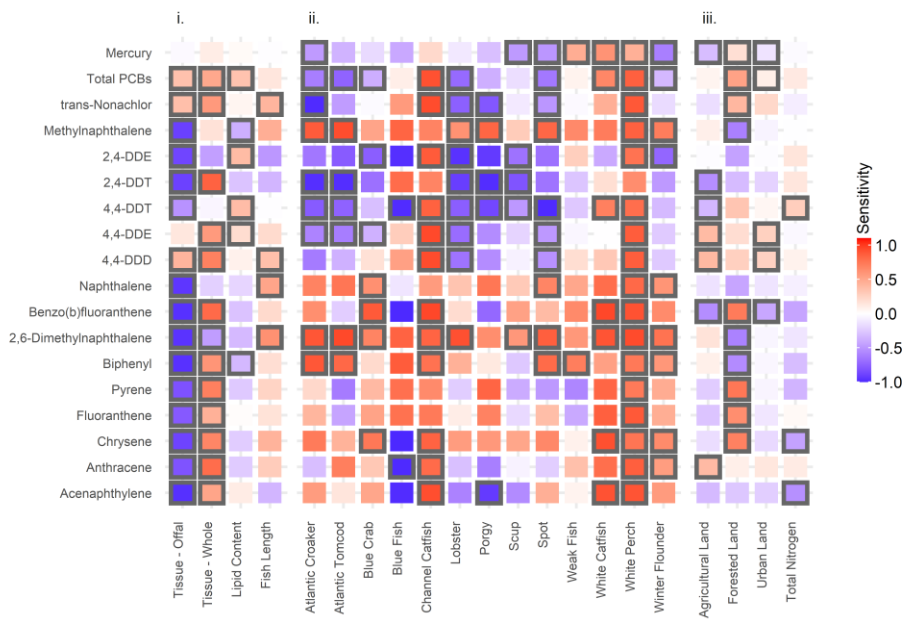


**Figure 9 Heat map of the sensitivity of fish tissue contaminant concentrations from the NCA dataset.**

**The predictors are separated into (i) fish attribute, (ii) species, and (iii) environmental predictor variables. Solid cell borders indicate parameters with a 95% Bayesian posterior credible interval that does not contain 0. Species effects are shown with reference to Summer Flounder, and tissue type effects are shown with respect to filet.**

## 2.4 Discussion

The data on contaminant concentrations in fish tissue show that PBTs generally covary positively across all types of waterbodies, with the exception of mercury against other contaminants in both lakes and rivers, and total PFCs and heptachlor against other contaminants in rivers. In coastal waters, these particular contaminants were not measured concurrently with others. The positive covariance among most contaminants implies that, lacking any more detailed information on fish characteristics or environmental conditions, one should assume that if one contaminant is elevated at a site, most others will be as well. However, in lakes and rivers, mercury is low when other contaminants are high in fish tissue. Gandhi et al. (2017) show empirically that the covariance patterns present in fish tissue data from the Great Lakes imply that the current practice of basing fish consumption advisories on the single most restrictive contaminant is not adequately protective. Gandhi et al. note, however, that both the magnitude and sign of the covariance among contaminants can differ according to location and fish species. They thus call for a more generalizable statistical approach for performing chemical mixture assessments than the simulation-based method they employ. In particular, they call not for multiple single-contaminant models, but rather for single multi-contaminant models such as that employed in the current study.

The performance of our multivariate modelling approach differed across the three data sets. In lakes, the joint distribution of multiple contaminants was captured reasonably well, with $R^2$ values as high as 0.72 and never below 0.29, and similar proportions of covariance among contaminants explained by the model. This is a level of explanatory power that is similar to previously published, single-contaminant models (Chen et al., 2005; Shanley et al., 2012; Visha, Gandhi, Bhavsar, & Arhonditsis, 2015). The model performed less well in rivers, with captured proportions of variances and covariances ranging from 0.16 to 0.59. This may be because riverine fish may occupy a variety of locations over the course of their lifetimes and therefore land use variables are not predictive fish tissue contaminant concentrations. The model of coastal marine systems was able to account for only a small proportion of the variance and covariance among fish tissue contaminant concentrations ($R^2$ values ranging from 0.04 to 0.66, with most in the lower half of this range). This may be because of the wider variety of tissue types, species, and corresponding life cycles of fish included in this data set. Also, as for rivers, fish living in coastal areas are highly mobile and may not spend the majority of their time near the land used to calculate land use percentages. In general across all waterbodies, the contaminants best fit by the models were mercury, total PCBs, DDT and its metabolites, the nonachlors, and oxychlordanes and their covariances.

The majority of the (co-)variation accounted for by the models could be attributed to fish characteristics, such as tissue type, lipid content, length, trophic level, and species. However, watershed land uses and waterbody characteristics were also significant predictors – again in line with the results of single-contaminant modeling (Chen et al., 2005; De Vault et al., 1996; Shanley et al., 2012). In the model of the EMAP lake and river data, for example, lakes with watersheds having more urban land showed consistently higher fish tissue contaminant concentrations (except for mercury). For coastal fish, agricultural and forested land were significant predictors of contaminant concentrations, although the sign of these relationships varied by contaminant.

Water chemistry has been shown to be important in the bioaccumulation of Hg but is less well explored for organic contaminants (Lange, Royals, & Connor, 1993; Miskimmin, Rudd, & Kelly, 1992; Ravichandran, 2004; Shanley et al., 2012). We found that fish tissue mercury concentrations decreased with greater alkalinity in lakes and pH in rivers. This is consistent with the finding that acidity is associated with enhanced mercury methylation and uptake in lower alkalinity and pH systems (Miskimmin et al., 1992). Concentrations of contaminants other than mercury were positively associated with pH levels in rivers. While metal contaminants are more bioavailable at lower pH, there is little research on the relationship of pH with organic contaminant bioavailability. Mercury, PFCs, and some other contaminants were found to be positively associated with DOC in riverine fish from the NRSA dataset. Like pH, the influence of DOC on metal transport and bioavailability are known but not commonly studied for organic contaminants. Mercury concentrations in water are positively related to DOC, but DOC appears to reduce the bioaccumulation of mercury particularly at high DOC ranges (Broadley et al., 2019; Tsui & Finlay, 2011). In the few studies that exist for organic contaminants, the influence of DOC does not show consistent patterns(Akkanen, Penttinen, Haitzer, & Kukkonen, 2001; Bejarano, Decho, & Thomas Chandler, 2005; Gourlay, Tusseau-Vuillemin, Garric, & Mouchel, 2003; Haitzer, Akkanen, Steinberg, & Kukkonen, 2001).

Our intent with this study was to demonstrate a method of modeling multiple contaminants simultaneously, using a Bayesian approach that can account for both missing and censored values (i.e. below detection limit). With such a model, one can assess how much of the covariance present among fish tissue contaminants can be accounted for by similar responses to modeled factors, and how much remains unaccounted for. Because we used a simple linear approach to model many contaminants, in many species, across many aquatic environments, each with particular fish characteristics, water chemistry attributes, and land use variables, our model results may not be as precise or mechanistically interpretable as more focused analyses. Yet, the

$R^2$ values we were able to obtain are comparable to those of previously-published statistical models of single contaminants.

A more novel contribution of this study is our demonstration that, while a multivariate model can explain some of the covariance inherently present among contaminants, the proportion of covariance that remains *unexplained* is at least as large as the proportion of *variance* left unexplained for individual contaminants. This means that the application of multiple single-contaminant models – even those that fully account for predictive uncertainty – misestimate true human health risk. This is because unexplained covariance implies that, even after all modeled factors are taken into account, the likelihood of unusually high (or low) levels of one contaminant at a site are not independent of the likelihood of unusually high (or low) levels of another contaminant. The fact that most contaminants (except mercury and heptachlor in rivers) display unexplained variation with positive covariance means that unexpectedly high levels of multiple contaminants are likely to occur simultaneously, exacerbating human health risk.

It is important to emphasize that this underestimation of health risk that results from ignorance of positive error covariance among contaminants is a systematic bias and not just an overlooked contribution to predictive uncertainty. This is clear from the fact that the variance of the sum of two correlated random variables $X_1$ and $X_2$, for example, is computed as:

$$\sigma^2_{X_1+X_2} = \sigma^2_{X_1} + \sigma^2_{X_2} + 2 \cdot Cov(X_1, X_2) = \sigma^2_{X_1} + \sigma^2_{X_2} + 2 \cdot \rho \cdot \sigma_{X_1} \cdot \sigma_{X_2} \tag{2}$$

where $\sigma^2$ represents variance, *Cov*( ) represents covariance, and $\rho$ represents correlation between $X_1$ and $X_2$. Thus, with positive covariance/correlation between two variables, the variance of the sum is always greater than the sum of the variances. Thus, the probability of high concentrations will be larger than would be calculated by assuming independence between the variables. This result can easily be extended to more than two random variables and to any linear combination of variables, making it applicable to the analysis of contaminants assumed to have additive health effects (USEPA, 2000).

Models can be useful tools for predicting fish tissue contaminant concentrations at unsampled sites or under new conditions as a function of watershed attributes, water quality measures, and fish characteristics. However, model-based estimates of human dietary exposure for the purposes of setting fish consumption advisories need to account for the full distribution of possible contaminant concentrations, not just single point estimates. Several studies have demonstrated the value of a Bayesian approach in this context, as these methods allow for the characterization of both parametric and structural error (Mahmood, Bhavsar, & Arhonditsis, 2013; Visha et al., 2015; Visha, Gandhi, Bhavsar, & Arhonditsis, 2016). This approach has long been advocated in the academic literature (Craig & Moreton, 1986; Visha et al., 2016) and is starting to make its way into fish consumption advisory decisions, at least for individual contaminants (Hope, Lut, Aldrich, & Rubin, 2007). The present study is the logical extension of that approach to multiple contaminants, acknowledging that, if one contaminant happens to be unexpectedly elevated at a site, others are likely to be as well.

While our study demonstrates a moderate ability to predict contaminant concentrations with a multivariate model, much of the covariance among contaminants remains in the residuals. This indicates that the presence and composition of mixtures are relatively unpredictable, even knowing watershed attributes, water quality measures, and fish characteristics. Further analyses might reveal the importance of including additional predictor variables or formulating nonlinear models, and thus more precisely characterize the patterns of suites of contaminants. In the meantime, uncertainty in both single contaminants and their co-occurrence needs to be reflected in fish consumption advisories and in more holistic assessments of risk-risk and risk-benefit tradeoffs (Cohen et al., 2005; Rheinberger & Hammitt, 2012).

# 3. Predicting the Effects of Climate and Land Use Change on Water Quality in the River Systems of New Hampshire and Vermont

This chapter has not yet been published in a journal. Other researchers who worked on this project are Shantar Zuidema, Ryan Calder, Celia Chen, and Mark Borsuk. Kimberly Bourne created the statistical model. Shantar Zuidema provided data from the UNH Water Balance Model and adapted the land cover scenarios for this model. Ryan Calder aided in data collection and model interpretation. Celia Chen aided in the selection of the index of biological integrity and model results. Mark Borsuk aided in model interpretation. Shantar Zuidema, Ryan Calder, and Mark Borsuk aided in the editing and revision of the text.

## 3.1 Introduction

Changing environmental conditions due to increased land development and climate change have the potential to severely impact river systems on a large spatial scale. According to the National Rivers and Streams Assessment, rivers in the US have decreased in quality between the 2004 and 2008-2009 surveys. During this time, the percentage of river length in good biological condition based on macroinvertebrate indices decreased by almost 9% (USEPA, 2016a). These changes are associated with nitrogen and phosphorus concentrations in surface waters as well as stream bed quality (Delpla, Jung, Baures, Clement, & Thomas, 2009; Murdoch, Baron, & Miller, 2000;

Whitehead, Wilby, Battarbee, Kernan, & Wade, 2009). However, these characteristics are often not of direct interest to the public.

The difficulty of this task stems from the complexity of the relationship between the drivers of change, resultant climate and land use changes, and the quality of surface waters (Murdoch et al., 2000; Tu, 2009). Interacting physical, chemical, and biological processes lead to highly variable trends in the way these systems are altered across watersheds. Sparse environmental data have made it difficult to calibrate models to characterize these relationships (Cruise, Limaye, & Al-Abed, 1999; Sliva & Dudley Williams, 2001). This challenge is confounded by the complexity of connecting these attributes to those that people care about – ecosystem services (Goldstein et al., 2012; Polasky, Nelson, Pennington, & Johnson, 2011; Sample, Baber, & Badger, 2016).

One of the ways to characterize the connection between water quality and ecosystem services is through indices that describe the structure of the benthic biological community in stream systems. Indices of biological integrity (IBIs) relate water quality features to outcomes of interest such as biodiversity and health of the food chain. Biological integrity is directly regulated in the Clean Water Act of 1972. It is an essential aspect of our riverine ecosystems and provides valuable insight into the overall quality of our water resources. (Karr, 1991) Previous models show that benthic communities are a function of nutrient concentrations, stream bed quality, and pollutant concentrations (Qian & Miltner, 2015; Reckhow, 2010). These relationships are generally used to understand the way organisms are responding to the quality of a stream. (Bain, Harig, Loucks, Goforth, & Mills, 2000; Barbour, Gerritsen, Snyder, & Stribling, 1999)

The varying level of tolerance to ecological disturbances characteristic to different benthic macroinvertebrates can be leveraged as an indicator of water quality. The orders Ephemeroptera, Plecoptera, and Tricoptera, specifically, are intolerant of poor environmental conditions and are used to indicate good water quality in regulatory frameworks (Barbour et al., 2000; Hale & Heltshe, 2008; Lenat, 1988). The index, EPT, is a count of taxa from these orders present in a stream sample. This index has been recognized as a useful regulatory tool and many states have implemented monitoring programs to measure EPT throughout stream systems (Barbour et al., 1999; Reckhow, 2010).

The combination of the widespread availability of macroinvertebrate population data and the organisms' responsiveness to climate change and other environmental drivers make indices like EPT strong candidates for environmental evaluation on a long-term basis (Boyd & Banzhaf, 2007; Boyd et al., 2015). However, often considered an intermediate service in ecosystem service frameworks, the linkage between macroinvertebrate populations and a final service and its value is uncertain (Johnston, Segerson, Schultz, Besedin, & Ramachandran, 2011; Prather et al., 2013; Raitif, Plantegenest, & Roussel, 2019) Recent surveys by Mavrommati et al. (2019) have shed light on the usefulness of an EPT index for valuing stream systems. Based on stated preference surveys among residents in the Great Bay Watershed, members of the public place a high value on habitat quality as a non-use value. An indicator of benthic macroinvertebrate community structure as a measure of a stream's potential to support biodiversity was a useful method to translate abstract values of water quality and physical stream characteristics to a metric meaningful to the members of the public (Mavrommati et al., 2019).

EPT has been linked to many physical properties of watersheds and stream systems including watershed impervious surface, nitrogen concentrations, stream bed quality, and other water quality features (Morse, Huryn, & Cronan, 2003; Qian & Miltner, 2015; Reckhow, 2010). However, the focus has been on using this indicator as a measure of current water quality and not as an indicator of the cumulative long-term effects of climate change. Understanding this relationship can help guide policies to maintain the value of ecosystem services related to the biological integrity of stream systems in response to climate change.

In this paper, we use process-based climate and water quality models combined with machine learning methods to predict future states of riverine biological integrity in New Hampshire (NH) and Vermont (VT). The result is a random forest model capable of predicting EPT richness projected 100 years in the future using inputs from land cover scenarios and hydrologic models. This work could be reasonably adapted to other regions around the US with the prevalence of EPT monitoring increasing across the country.

### 3.2 Methods

To determine the connection between climate change, land use, river health, and EPT, several datasets were combined to predict both future hydrological conditions and EPT richness. EPT data from the Agency of Natural Resources in Vermont (VT ANR) and the New Hampshire Department of Environmental Services (NH DES) were used to train a random forest model with predictor variables coming from The University of New Hampshire's (UNH's) Water Balance Model (WBM). These variables included discharge characteristics, nutrient concentrations, and physical characteristics of the river.

To predict the future conditions of EPT, downscaled climate models from CMIP3 and CMIP5 and future land management scenarios were used to forecast river conditions using the WBM. These outputs were then used to predict future values of EPT with the random forest model. The relationship between these datasets and models can be seen explicitly in Figure 10. Subsequent sections describe each component of this model in greater detail.

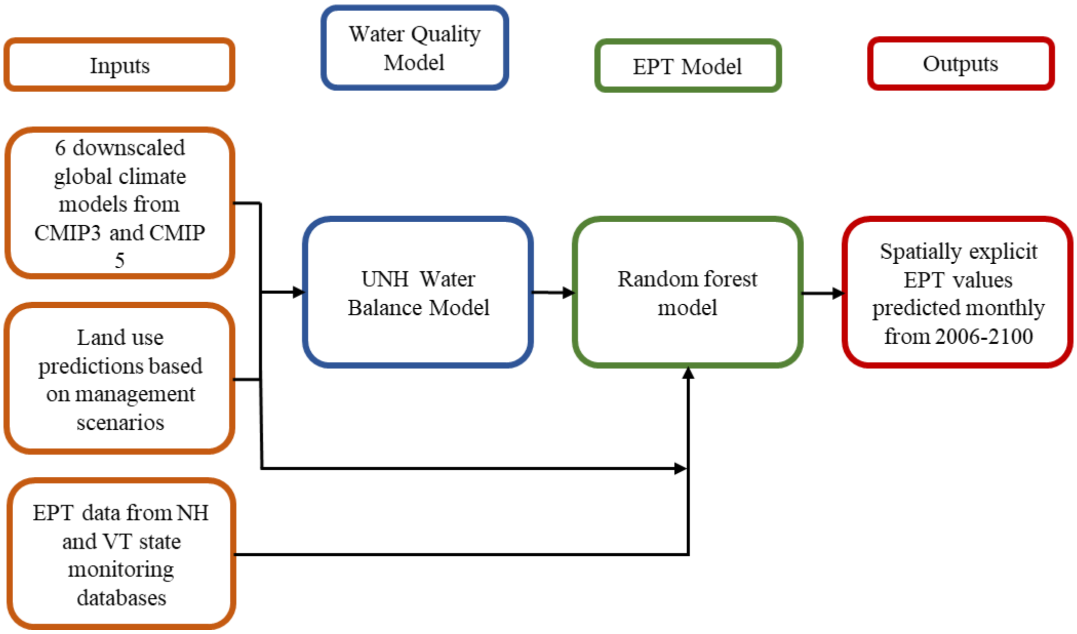


**Figure 10 Representation of the relationship between datasets and models used to predict EPT.**

### 3.2.1 Data Description

Macroinvertebrate population data were obtained from the New Hampshire Department of Environmental Services (NH DES) biological monitoring program. This dataset includes 411 macroinvertebrate population samples from 245 locations between the years of 2000 and 2015. To expand the data available for modeling, the spatial extent was expanded to include the portions of the Connecticut River watershed located in Vermont. The Agency of Natural Resources in Vermont (VT ANR) provided 74 data points of 16 locations in the Connecticut River watershed between 2010 and 2016. Using these data, a biological index based on the presence of organisms belonging to the orders Ephemeroptera, Plecoptera, and Tricoptera (EPT) was calculated. For each sample location and date, the species richness in these orders was calculated as the final index which will be referenced as EPT richness.

Hydrologic and water quality variables for corresponding time periods as the EPT data were estimated by the University of New Hampshire Water Balance Model (WBM). WBM is a gridded, process-based model that calculates the flow of water, water temperature, and nutrient fluxes across the landscape (Grogan et al., 2022). For each time and location at which EPT was sampled, WBM was used to estimate the area of the upstream watershed, channel width and depth, discharge, water velocity, dissolved inorganic nitrogen (DIN), and water temperature. These estimations required, for each sample location, the upstream watershed area classified as forest, agricultural land, developed land, and impervious surface, which were calculated using the 2006 National Land Cover Database (Homer et al., 2015) NLCD values from 2006.

### 3.2.2 Model Fitting

Random forest (RF) modeling was used to relate EPT richness to model-generated hydrological and water quality variables over the full study area. This method uses an ensemble of decision trees to predict the most likely outcome. For each tree, a random set of vectors from the input matrix is selected as the training set and the rest left as the “out-of-bag” (OOB) samples to determine the performance of the individual tree. The RF method varies from many standard methods of decision tree building in that at each split, a random number ($M_{try}$) of input variables is selected and the best split is chosen from that set (Liaw & Wiener, 2002).

There are many benefits to RF as a method for this case. Due to high levels of nonlinearity and variability in the data, linear models did not perform well in predicting the percent EPT. This model framework allows for non-linear combinations of variables while remaining robust against over fitting (Breiman, 2001). Decision trees also allow for the inclusion of correlated input variables, giving the freedom to include all potential variables in the model framework (Dormann et al., 2013).

Using the statistical software R, the Caret package was used to train the RF model predicting percent EPT using the input variables listed in Table 1 (Kuhn, 2008). The random forest model was trained and tested based on a random selection of points. 20% of the data were retained to test the model, so the model was trained on 433 randomly selected observations. The model selection criterion was the lowest root mean square error value (RMSE) when varying the features $M_{try}$ and the period over which the input variables were aggregated. $M_{try}$ was varied between 1 and 9. Four different aggregation periods were considered for the hydrologic variables as well as river depth and width: 30 days, 90 days, 180 days, and 365 days. The maximum and average value of these features over the aggregation period prior to the sample date were included in the model to account for the effects of extreme discharge events as well as changes in long-term sustained conditions. All input variables considered can be found in Table 3.

If features were found to be highly correlated with each other (>0.8), the feature with the higher mean absolute correlation was removed. Features with zero variance were also omitted.

**Table 3 Features used to predict percent EPT in the random forest model.**

| Input Variable | Data Source |
|---|---|
| Site Characteristic: | |
| River Width (m) | WBM |
| Area of the upstream watershed (km) | NLCD |
| Water Temperature (°C) | WBM |
| Hydrological Characteristics: | |
| River Discharge ($m^3/s$) | WBM |
| Water Velocity (m/s) | WBM |
| Water Quality Characteristics: | |
| Dissolved Inorganic Nitrogen (DIN) (mg DIN-N/L) | WBM |
| Percent of the upstream landscape belonging to the following categories: | |
| Forest (%) | 2006 NLCD |
| Agriculture (%) | 2006 NLCD |
| Development (%) | 2006 NLCD |
| Wetland (%) | 2006 NLCD |
| Impervious Surface (%) | 2006 NLCD |

### 3.2.3 Future Prediction of EPT

To account for the influence of land management policies in New Hampshire, future land cover conditions were based upon scenarios developed by Thorn et al. (2017). Each scenario also impacts the parameterization of WBM based on efforts to limit impacts to water quality in relation to DIN and surface runoff. The concentration of DIN is defined by a logistic function based on the developed land fraction in the catchment, which is consistent with parameterization put forth by Wollheim and Stewart (2011). Across scenarios, the asymptotic concentration of DIN and the inflection point of the model varies. Surface runoff in each scenario is impacted by the amount of impervious surface as well as the degree to which they hydrologically connected. Based on equations defined by Alley and Veenhuis (1983), the fraction of hydrologically connected impervious surface is related to total impervious cover through a power function. For each scenario, a scale factor is defined based on development of green infrastructure aimed towards reducing surface runoff. The degree to which green infrastructure is adopted also results in a proportion increase of soil storage for rainfall.

The first scenario, referred to as suburbanization, assumes an increased focus on suburban development as populations rise and no development of green infrastructure. This results in a significant increase in developed land in the Southeast region of the state expanding northward. A second scenario referred to as infill, assumes more dense mixed-use development and large-scale adoption of green infrastructure. These two alternatives were compared to the contemporary scenario in which the change in land cover remains consistent with observed rates of change between 1990-2010 and a moderate amount of green infrastructure is adopted (Thorn et al., 2017). The implications of these scenarios on the parameterization of WBM can be seen in

Table 4.

Climate projections for these scenarios were based on the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project phase 3 and 5 (CMIP3 and CMIP 5) multi-model dataset (Maurer, 2007). For each model, data were taken from RCP 8.5. Using these future conditions of temperature and rainfall, the hydrologic and water quality variables were projected through 2100 using WBM.

**Table 4 Description of land cover inputs and changes in dissolved inorganic nitrogen model parameterization for each management scenario.**

| Scenario | Asymptotic DIN Concentration (mg-DIN/L) | DIN Inflection Point (% Developed Land) | Hydrologically Connected Impervious Multiplier | Additional Rainfall Storage Capacity (mm) |
|---|---|---|---|---|
| Suburbanization | 6.1 | 51.5 | 1 | 0 |
| Infill | 4.3 | 70 | 0.1 | 25 |
| Contemporary | 6.1 | 51.5 | 0.97 | 0.75 |

Using the random forest model, EPT richness was predicted over 3-month increments between 2006 and 2099. Predictions were made at the end of March, June, September, and December based on summarized metrics of the previous 3 months. Current and future conditions were compared using 10-year averages of the March, June, September, and December predictions. At each of these points, an error term ($\sigma_{EPT\ change}$) was calculated based on the variation over the 10-year period from 2006-2015 ($\sigma_{EPT\ ave,current}$) and 2090-2099 ($\sigma_{EPT\ ave,future}$) as well as the model variation ($\sigma_{rf\ model}$). This error term was calculated based on equation 3. Differences for which two standard deviations around the mean change in EPT richness included zero were considered statistically insignificant differences.

$$\sigma_{EPT\ change} = \sqrt{\frac{\sigma_{EPT\ ave,current}{}^2}{10} + \frac{\sigma_{EPT\ ave,future}{}^2}{10} + \frac{\sigma_{rf\ model}{}^2}{10}} \qquad (3)$$

The random forest model was trained and tested based on a random selection of points. 20% of the data were retained to test the model, so the model was trained on 433 randomly selected observations. Each set was spatially distributed across the study area (Figure 11). The range of values of both the predictors and EPT richness (Table 13) show that the training and test datasets are representative of a wide range of conditions.

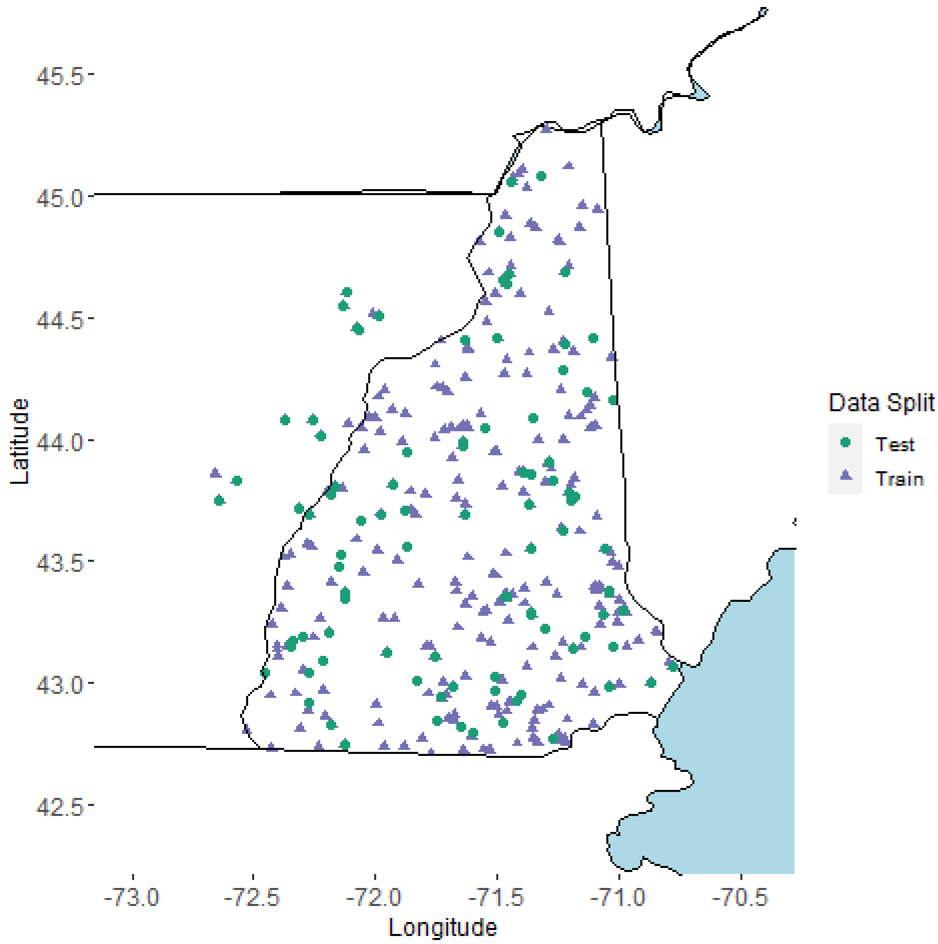


**Figure 11 Spatial distribution of data points in the test and training datasets.**

## 3.3 Results

### 3.3.1 Random Forest Model

The model that contained variables averaged over a 6-month period led to the lowest RMSE value (15.9) and largest coefficient of determination (0.41) for the test data (Figure 12). However, the 3-month averaging period was chosen despite a slightly worse fit because of its greater interpretability, allowing for comparison across seasons.

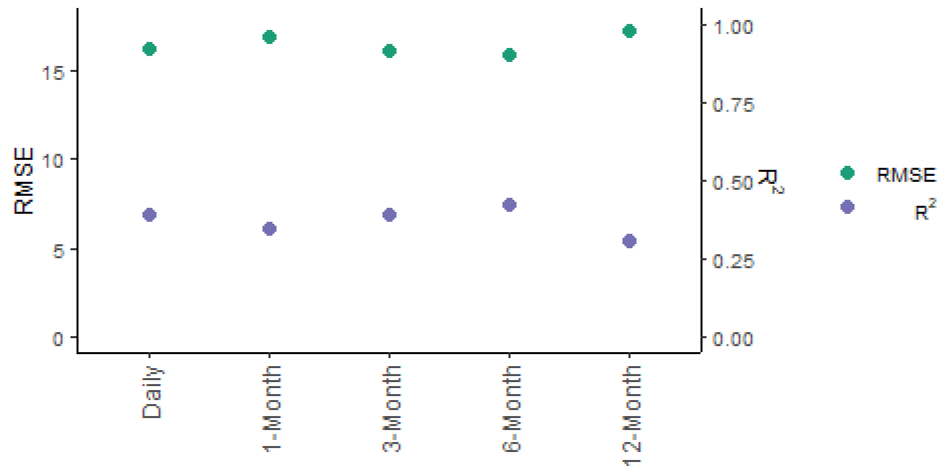


**Figure 12 Metrics for random forest models utilizing features averaged over different time periods.**

The final random forest model includes, in addition to upstream watershed area, the land cover features: percent forest, percent agriculture, percent impervious surface, and percent wetland. The features removed were the average width, maximum width, maximum discharge, and maximum dissolving inorganic nitrogen due to them being highly correlated with other features and having the higher mean absolute correlation. The other features left were average discharge, average DIN, maximum temperature, average temperature, maximum velocity, and average velocity (all over the preceding 90-day period).

As applied to the test data, the random forest model has a coefficient of determination of 0.40 and RMSE of 16.0, somewhat underpredicting EPT richness at lower values and overpredicting it at higher values (Figure 13). The third quartile is the least biased. The average ratio of the observed to predicted values is 0.92 for the test data. Average observed EPT richness in the test data is 27.4 compared to a predicted average of 26.6, indicating that average richness is slightly underpredicted. For these reasons, predicted trends in EPT richness will be evaluated primarily on large scale averages.

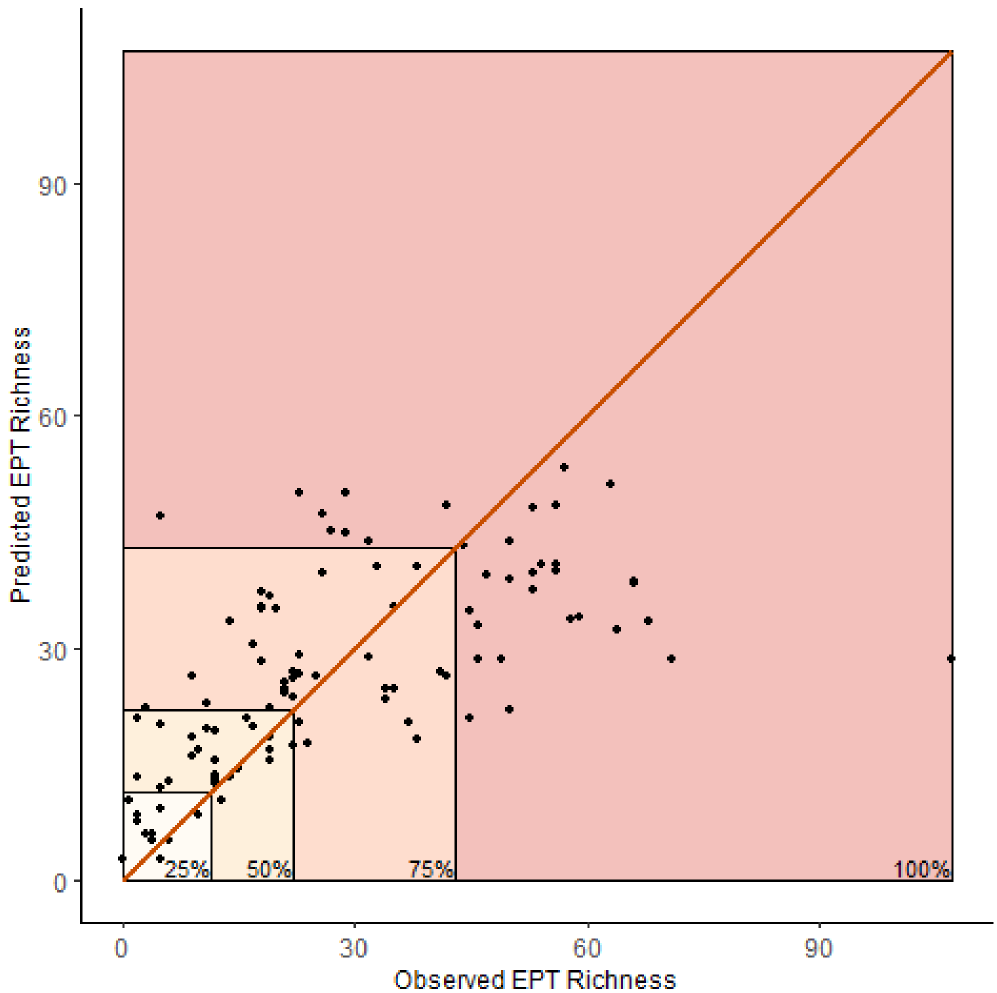


**Figure 13 Representation of EPT richness model prediction accuracy.**

**Comparison of the measured EPT richness (x-axis) and the predicted EPT richness (y-axis) in the test data set. The red line is a 1-to-1 line. The colored sections represent data quartiles.**

According to the random forest model, the most impactful predictors are average temperature, average discharge, DIN, percent land as forest, and maximum and average velocity with importance values of 100, 51, 26, 24, 21, and 21 respectively (Figure 14 A). Importance values for the remaining features quickly drop to between 0 and 5. Importance is based upon the difference of the mean square error between the predictions on OOB portion of the data and predictions based on permutations of each variable. These differences are averaged and normalized by the standard error. Therefore, higher importance values indicate a variable has a higher impact upon the accuracy of the predictions.

To determine the directionality of the influence of these features, a large data set (n = 10,000,000) was created in which each predictor was randomly generated based on a uniform distribution over its range in the training data. These simulated data were then used to predict EPT richness, and the correlations calculated between each predictor and EPT richness (Figure 14 B).

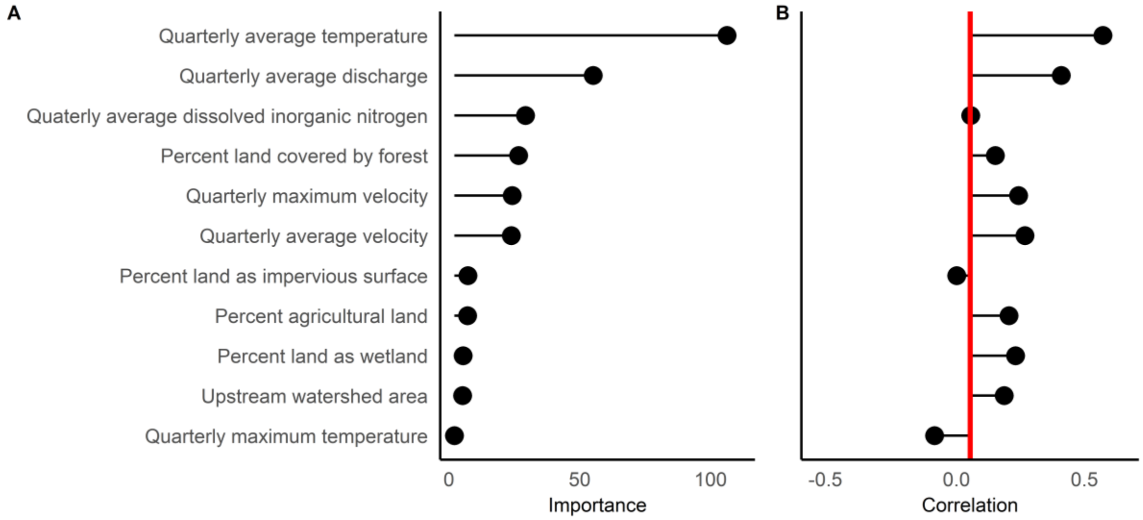


**Figure 14 Importance and correlation for the random forest model features.**

**A: The variable importance of each predictor in the random forest model, ordered from most important to least. B: The correlation between each predictor and predictions of EPT richness in a large, simulated dataset.**

Although DIN has a high importance, its correlation with predicted EPT richness is low (0.002). This could indicate a high level of variability in the directionality of the effect of DIN on EPT richness depending on the states of other variables. Quarterly maximum temperature has the lowest importance values, but demonstrates a non-zero, negative correlation with EPT richness of -0.14. Percent land as impervious surface also negatively correlates with the predicted EPT richness, but it is a weak relationship with a correlation of -0.05. The rest of the features have a positive overall correlation with EPT richness ranging between 0.1 and 0.51, with average temperature having the highest correlation followed in order by average discharge, average velocity, maximum velocity, percent land as wetland, percent area as agriculture, upstream area, and percent land as forest.

### 3.3.2 Future Predictions

EPT richness during March is projected to slightly increase under the contemporary land use scenario (Figure 15). The strength of this trend is highly variable across climate models, but the direction of change is consistent and significant in the northern half of NH (Figure 16). Under the infill scenario, the direction of change is variable across climate models and the change is highly uncertain; very few areas show a statistically significant change. The suburbanization scenario shows the highest magnitude of change consistent across climate models. Under this land use scenario, EPT richness is predicted to decrease by up to 11 species in some watersheds with most watersheds in southern NC showing a significant decline (Figure 16).

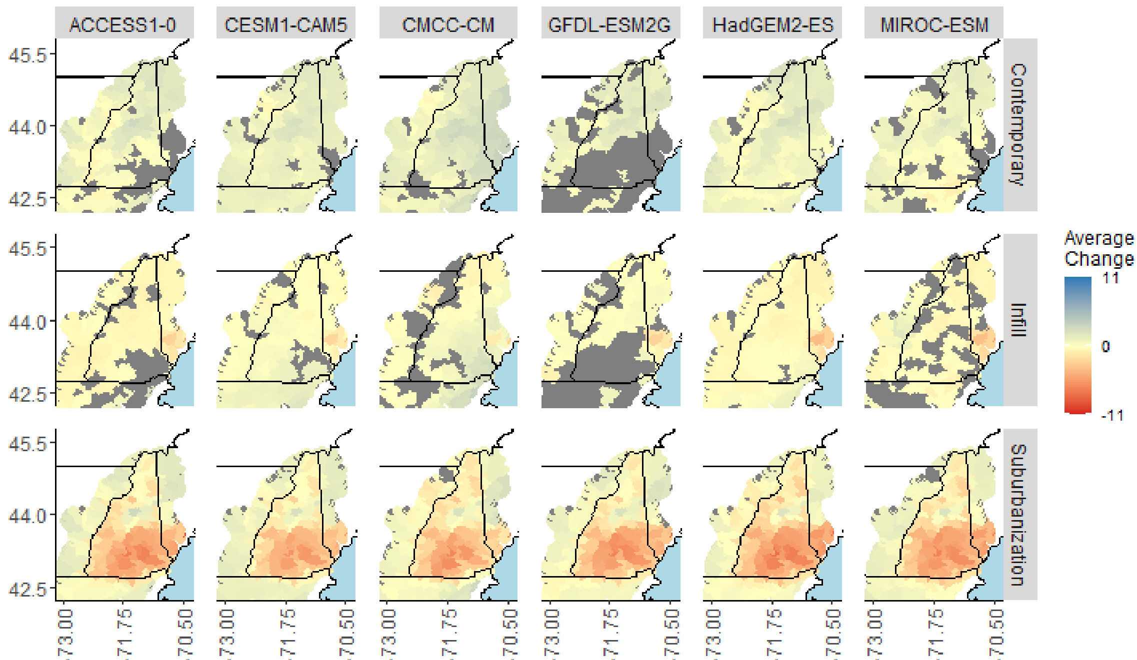


**Figure 15 Spatial representation of change in the 10-year EPT richness for each land cover scenario and climate model during March.**

**At each point, EPT richness was averaged and then differenced over the first and last ten years predicted. These differenced over the first and last ten years predicted. These differences were then averaged over each watershed defined by the 10-digit Hydrological Unit Code. Watersheds colored grey are those in which no points had a difference that was statistically significant.**

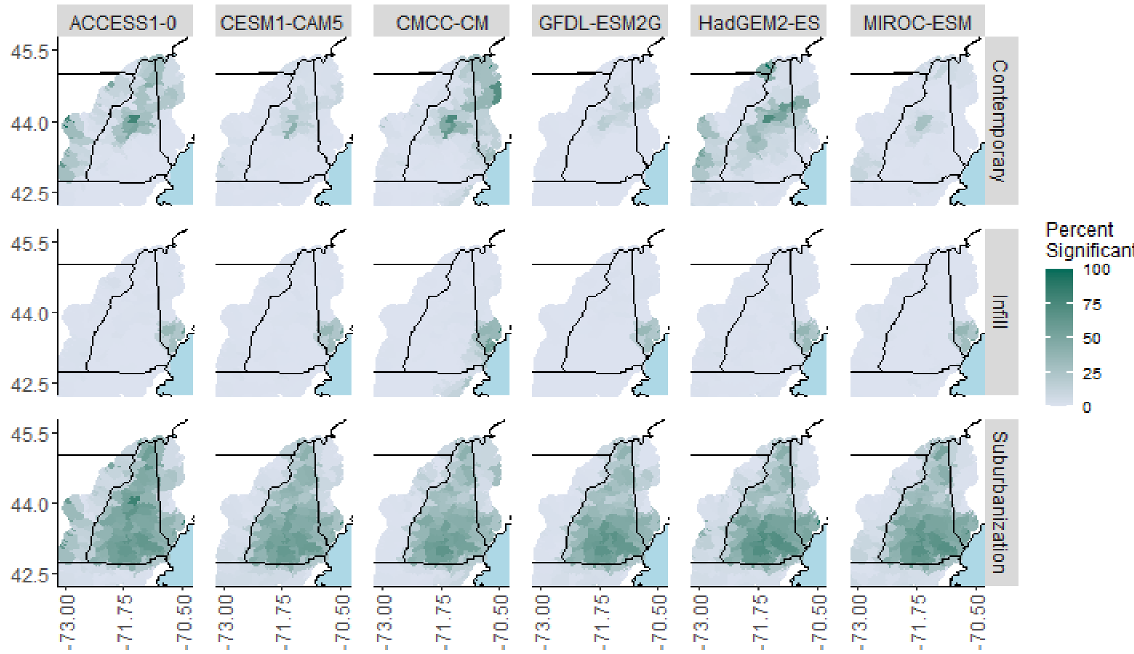


**Figure 16 Spatial representation of the proportion of sites in each watershed with a statistically significant change in EPT richness in March.**

**Significance was determined by combining the model error and the standard deviation based on averaging the points over 10 years. Sites where two standard deviations around the change in the mean did not contain zero were considered significant.**

Predictions of EPT richness for June indicate an overall increase across NH for almost all climate models and land use scenarios (Figure 17). The change in EPT richness is more spatially variable under the suburbanization land use scenario with 4 out 5 climate models indicating a decrease in richness in the northernmost parts of NH. This is also true for some of the climate models under the contemporary land use scenario. However, these watersheds are among those with the least number of sites with a statistically significant change (Figure 18). EPT richness under the infill land cover scenario shows a consistent increase across climate models most being statistically significant.

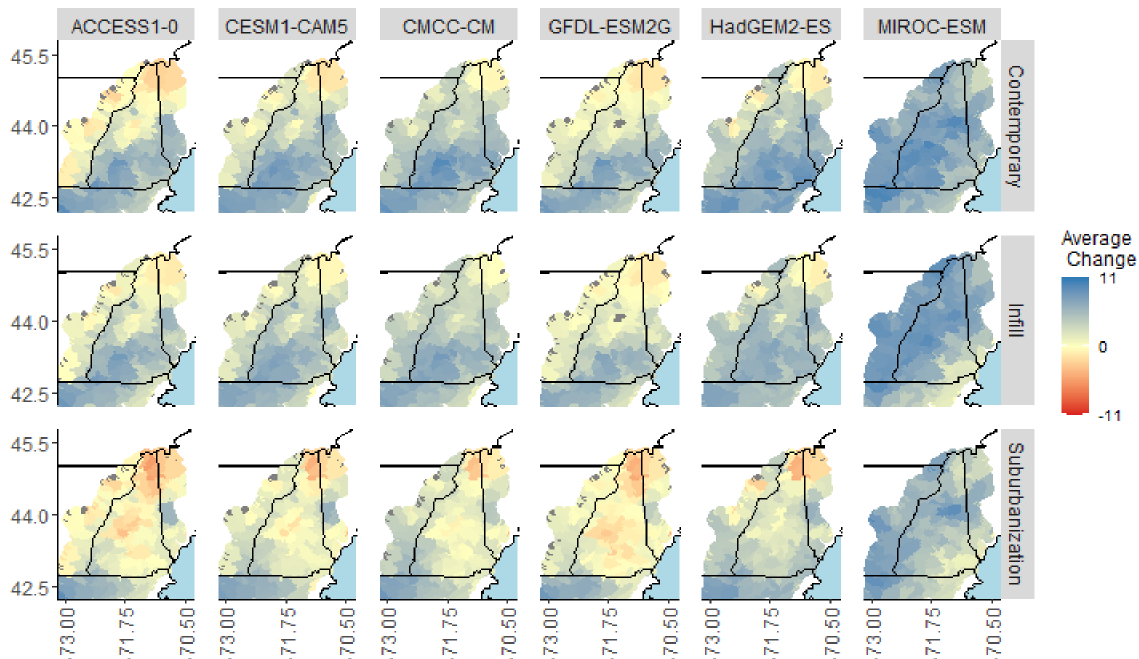


**Figure 17 Spatial representation of change in the 10-year EPT richness for each land cover scenario and climate model during June.**

**See Figure 15 for details.**

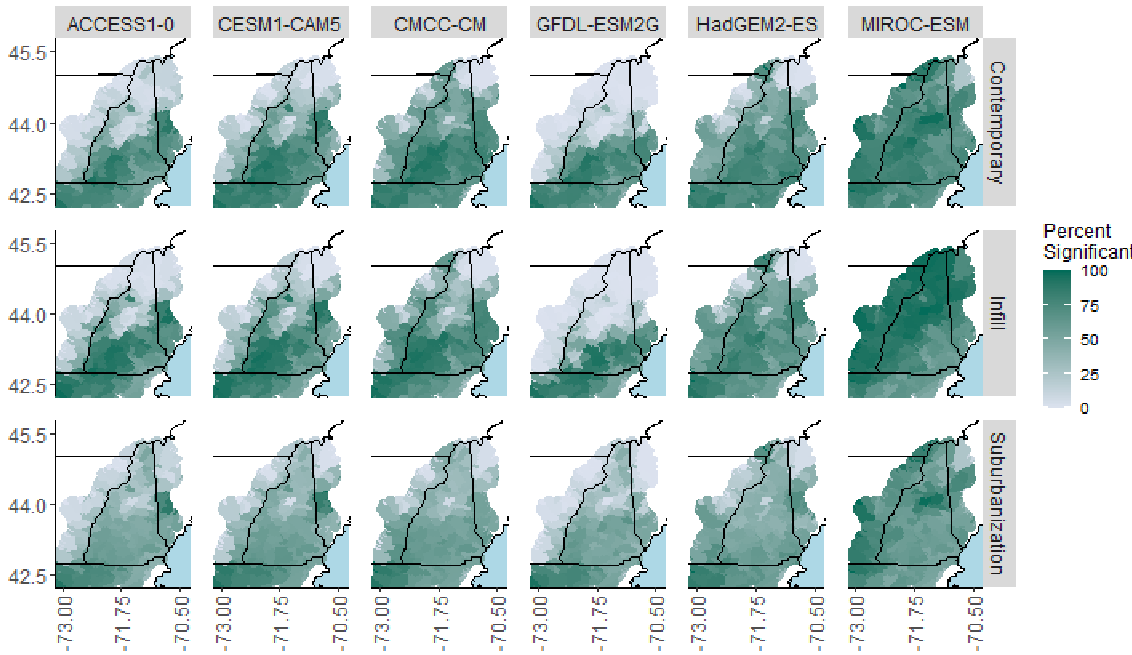


**Figure 18 Spatial representation of the proportion of sites in each watershed with a statistically significant change in EPT richness in June.**

**See Figure 16 for details.**

The trends in predicted EPT richness for September are highly varied, although most land use scenarios and climate models show a decline. EPT richness primarily decreases, with some excepts in the Connect River Basin on the western region of NH. Trends in the southern region are more variable with it primarily decreasing when conditions are predicted using the CMCC-CM, MIROC-ESM, and ACCESS1-0 climate models as is apparent in Figure 19. The response of EPT richness to future conditions in the region is less variable using the CESM and GFDL climate models. The southern region also had the smallest percentage of significant sites with many watersheds across climate models having no significant changes. September values of EPT richness in the infill land cover scenario consistently decrease. This trend is more significant in the northern regions of NH as seen by the higher percentage of sites with a significant change (Figure 20). The patterns of change in EPT richness for September based on the suburbanization land cover scenario are similar to those of the contemporary scenario (Figure 19). However, in Figure 20, it is apparent that there are a larger proportion of sites without significant change in richness in the southern region of NH.

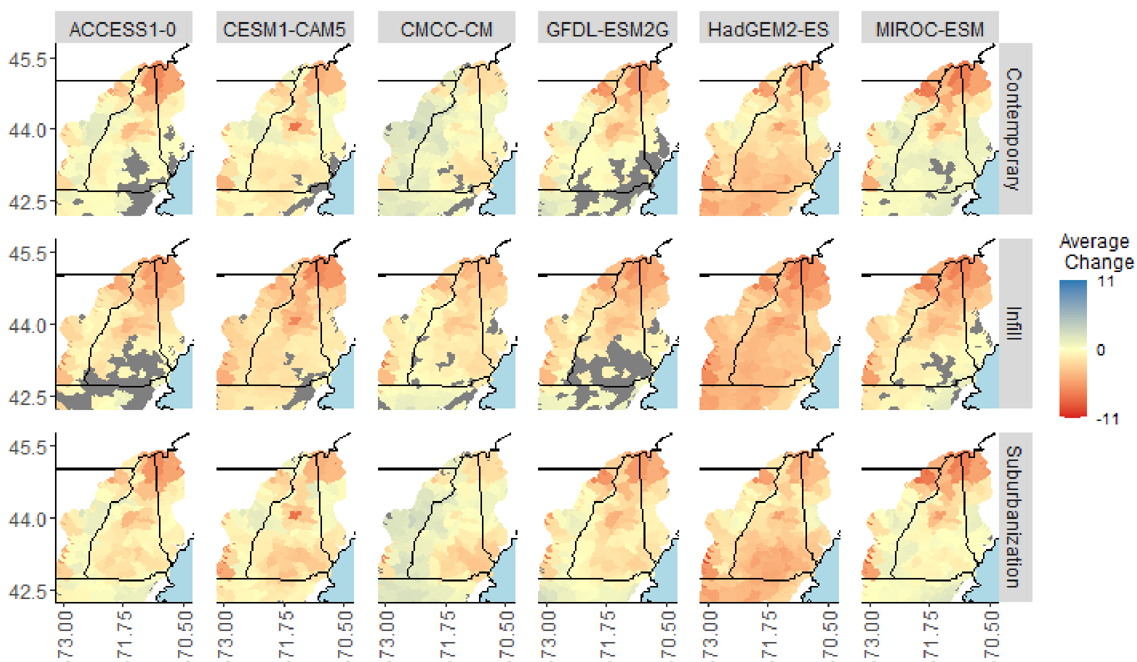


**Figure 19 Spatial representation of change in the 10-year EPT richness for each land cover scenario and climate model during September.**

**See Figure 15 for details.**

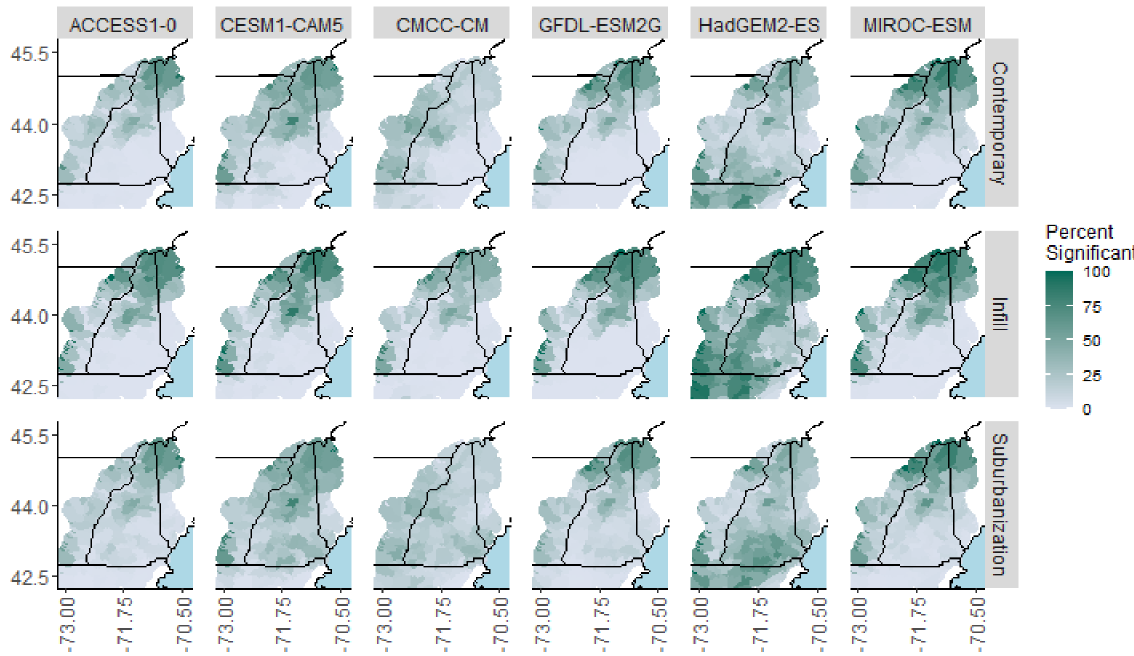


**Figure 20 Spatial representation of the proportion of sites in each watershed with a statistically significant change in EPT richness in September.**

**See Figure 16 for details.**

Changes in EPT richness for December vary between land cover scenarios. Conditions in the contemporary land cover scenario result in a somewhat positive change in EPT richness in the southeastern part of the state for some climate models (Figure 21). Under infill land cover conditions, there is very little change in richness over all climate models. For both the infill and contemporary scenarios, a very low proportion of sites were calculated to have a significant change in EPT richness (Figure 22). Lastly, the suburbanization land cover scenario shows an overall negative change in EPT richness across the state of NH (Figure 21), with most watersheds being statistically significant.

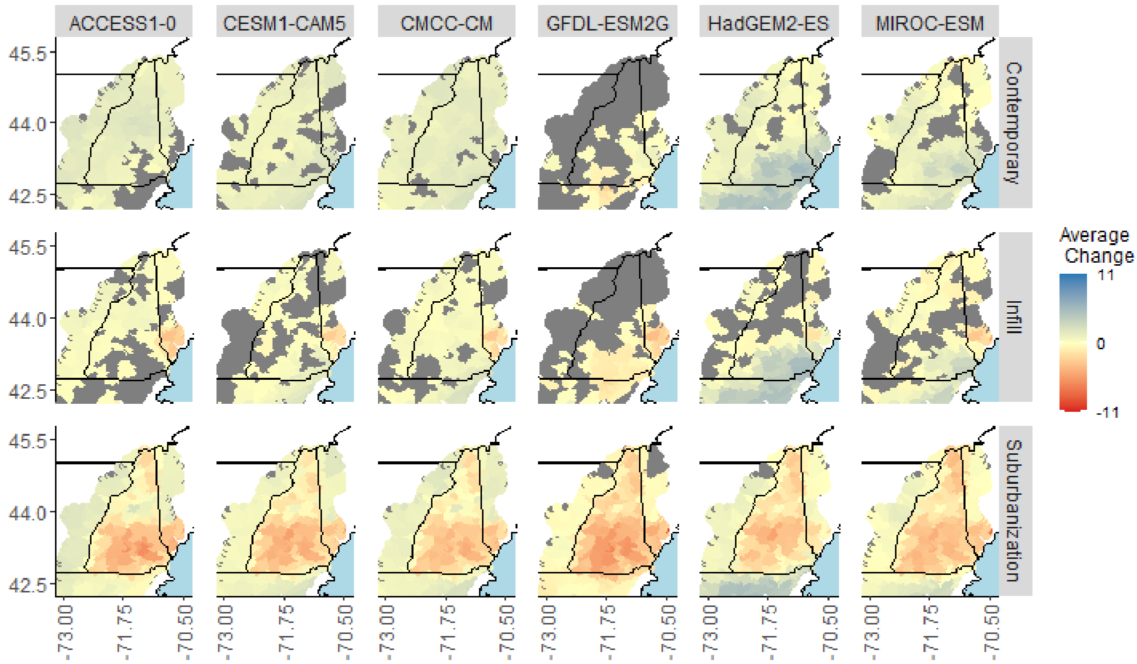


**Figure 21 Spatial representation of change in the 10-year EPT richness for each land cover scenario and climate model during December.**

**See Figure 15 for details.**

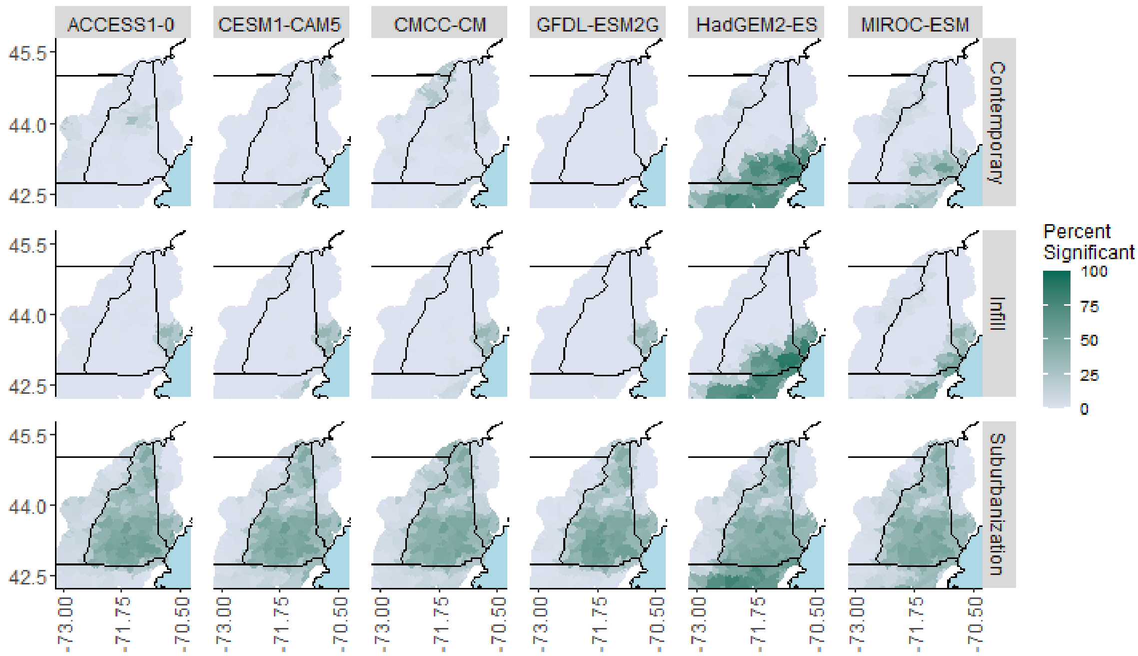


**Figure 22 Spatial representation of the proportion of sites in each watershed with a statistically significant change in EPT richness in December.**

**See Figure 16 for details.**

## 3.4 Discussion

### 3.4.1 Random Forest Model Characteristics

By modelling EPT richness, we can identify the characteristics of river systems in NH that most impact this water quality indicator and start to evaluate the ways in which future conditions of both land cover and climate change will impact macroinvertebrate populations and river health. Urban development, hydrological conditions, and non-point source pollution are typically cited as affecting EPT populations (A Woznicki & Pouyan Nejadhashemi, 2015; Kashuba, Cha, Alameddine, Lee, & Cuffney, 2010; Konrad, Brasher, & May, 2008; McLaughlin & Reckhow, 2017). This is further confirmed in our model, as the features deemed most important to model performance are water temperature, discharge, velocity and nitrogen concentration, as well as the percent land covered by forest. While impervious surface is of lower importance, it does have a negative correlation with predicted EPT richness and does exert influence over the model results.

While directionality of the impact of features is not as commonly interpreted for a random forest model, it is important to confirm that this model produces results consistent with known relationships. The negative impact of impervious surface and urban areas on EPT populations is well documented in the literature (Kashuba et al., 2010; Konrad et al., 2008; Stepenuck, Crunkilton, & Wang, 2002). It has also been found that this is compounded by subsequent the loss of forest land in many areas as well, consistent with the finding that the percent of upstream land as forest land has a high importance in predicting EPT richness (Cuffney et al., 2011; Roy, Rosemond, Paul, Leigh, & Wallace, 2003). Increased urbanization causes macroinvertebrate populations to trend towards more pollutant tolerant species as it correlates with poor water quality conditions such as increased total suspended solids, nitrogen and phosphorus concentrations, and turbidity. Our model is consistent with these findings as the portion of land as impervious surface is negatively correlated with the predicted EPT richness values. Urban land was not included as a feature as it was highly correlated with impervious surface.

The impact of nitrogen concentration has been shown to be highly variable across studies (Chambers et al., 2012; McLaughlin & Reckhow, 2017; Miltner, 2010). While our model does indicate a high importance value in predicting EPT richness, its correlation with the predicted richness values in the simulated datasets was practically zero. This would indicate that while DIN is an impactful feature, the directionality of its impact is highly variable based on the state of other features.

The hydrological features included in this model demonstrate much more significant correlations with the simulated values of EPT richness. Average river discharge was identified as one of the features with higher importance values. Discharge was highly correlated with river width, so this could be related to the fact the abundance of EPT varies with stream order. It has been theorized that EPT richness peaks at middle stream orders then decreases in larger order streams (Koster, Pytel, & Houghton, 2022). As the model was trained on points where upstream area is less than 200 $km^2$, it likely captured streams at middle to lower orders. Similar relationships have been found as the maximum possible EPT abundance has been shown to increase with base flow rate (Konrad et al., 2008).

Maximum and average velocity were also shown to be impactful upon model fit. Both positively correlated with EPT richness in the simulated data set. As EPT richness has been shown to be strongly negatively correlated with deposited sediment which is in turn strongly negatively correlated with stream velocity, it has been posited that higher stream velocity will result in increased EPT abundance (Zweig & Rabeni, 2001). These relationships were relatively weaker than that of the average discharge. It is possible that the relationship between velocity and EPT richness may also be affected by recent flood events. It has been shown that EPT species are impacted by hydrological disturbances such as variable flow and floods but recover quickly (Rolls et al., 2018; Suren & Jowett, 2006). Due to the long time-period over which the maximum velocity is calculated, it is likely that the magnitude of recent disturbance events was not captured well by the data.

The most impactful feature upon EPT richness was ambient average temperature. Given that richness of Ephemeroptera, Plecopteran, and Trichoptera has been shown to peak at a latitude of about 40°N, it is logical that in NH, which sits between 42.5°N and 45.5°N, average temperature plays a large role in EPT richness (Vinson & Hawkins, 2003).

**3.4.2 Late Winter/Early Spring Trends**

The change in predicted EPT richness between 2006-2015 and 2090-2099 vary significantly depending upon the climate model used to predict climate conditions, land cover management scenario, and time of year. The average change in EPT richness predicted for March does not deviate far from zero for the contemporary and infill scenarios. There is also not much variation in the magnitude and direction of change across climate models except that some models result in a higher year-to-year variation in EPT resulting in higher error terms. This is reflected in the differing numbers of watersheds with a statistically significant change. The high level of uncertainty for this time period could also be due to a lower predicted EPT richness compared to the predictions for June and September. The average EPT richness in NH for March is 19.9 for 2006-2015 and 20.2 for 2090-2099.

The most significant change in magnitude and direction of change in predicted EPT richness for March is seen in the land cover scenarios. While the contemporary and infill scenarios show very little change in EPT richness, the suburbanization scenario demonstrates a marked decrease in EPT richness.

### 3.4.3 Late Spring/Early Summer Trends

Changes in EPT richness predictions for June are much higher in magnitude and have a much higher proportion of sites with a significant change. Under the contemporary and infill scenarios, the primary trend is an increase in EPT richness. There is some variation in the northern regions of NH where there is little to no change depending upon the climate model with the exception of MIROC-ESM which shows a strong increase in richness across all of NH. The suburbanization land cover scenario shows very little change in EPT richness across climate models also with exception of the MIROC-ESM climate model for which richness has a large positive change. Considering there is a much lower amount of variation between land use scenarios under the same climate model, this indicates that EPT richness in June is more heavily influenced by climate.

This significant increase in EPT richness for June could in large part be due to an earlier onset of spring due to climate change. Trends over the last 20 years have shown that indicators of spring such as the last freeze date and last day the temperature falls below 5°C have been occurring earlier in Northern Hemisphere (Schwartz, Ahas, & Aasa, 2006). Others have shown that CMIP3 and CMIP5 models have demonstrated a marked increase in both precipitation and spring temperature in the Northeast United States (Demaria, Roundy, Wi, & Palmer, 2016; Lynch, Seth, & Thibeault, 2016). Given the positive correlations between the simulated predictions of EPT richness and average discharge and average temperature, it can be concluded that the positive impacts of those features overpower any negative impacts from the land cover change.

### 3.4.4 Late Summer/Early Fall Trends

For predictions in September, trends in EPT richness show an overall decrease. The regions over which it decreases and to what degree vary greatly among both land cover scenarios and climate models. The patterns of change in richness for the contemporary and suburbanization scenarios are largely the same for any given climate model. Given that the constants between these scenarios include runoff from developed areas and DIN values, this indicates there is a stronger relationship between DIN and water velocity than is suggested by the correlation between these features and EPT richness in the simulated data set. As random forest models are non-linear and the impact of any given feature is dependent on the values of the others, these correlations are not an infallible metric for directionally of influence for any given feature. As the correlations for stream velocity and DIN were close to zero, it is possible the relationships between these features and the predicted EPT richness is highly variable in directionality based on values of other features. Previous studies indicating a lack of relationship between nitrogen concentrations in rivers and EPT populations utilized either a linear or threshold value model framework, so there is a possibility that these models were not able to accurately characterize the dynamics of the system (Chambers et al., 2012; McLaughlin & Reckhow, 2017; Miltner, 2010).

There is a significant amount of variation in the change in EPT richness across climate models as well. The CMCC-CM shows the most significant difference indicating an increase in EPT richness in watersheds in the eastern region of NH. The change is small, but the portion of sites with a statistically significant change is close to 20% for many watersheds in this region. However, the other climate models do not vary in the directionality of the change but do vary significantly in magnitude of change. For all land cover scenarios and climate models, the northern watersheds of NH decrease in EPT richness. This indicates that land cover cannot counteract the negative impacts of climate change on river conditions for EPT in late Summer/early Fall.

### 3.4.5 Late Fall/Early Winter Trends

Variation in the change in EPT richness in late fall/early winter between 2006-2015 and 2090-2099 is primarily driven by the land cover management scenarios. Under the contemporary scenario of land management, EPT richness changes very little. HadGEM2-ES is the only climate model to an increase of richness over a significant portion of southeast NH. This is true for the infill land management scenario as well. Although the portion of sites with a statistically significant change is high for these watersheds, the lack of corroboration among other climate models suggests a potentially significant source of error in these predictions based on climate model.

Changes in EPT richness in NH under the suburbanization land cover scenario are consistently negative across climate models. There is some uncertainty in the magnitude of these trends across models, but the southern region of NH shows a consistent decrease. The primary difference between the suburbanization land cover scenario and the others is a marked decrease in agricultural land. Given the overall positive correlation between simulated predictions of EPT and the high importance of the land cover feature, this could be potentially driving the change in richness in early fall/late winter.

## 3.5 Conclusions

The use of EPT richness as an indicator of river health to anticipate the impacts of future changes, can be effective. However, there are confounding factors related to climate change and seasonality that need to be accounted for. Land cover management appears to be limited in its ability to counteract the impacts of climate change. A high amount of variation in climate projections results in uncertainty in the magnitude of impact land cover management can have upon river health. This sensitivity to both climate models and land cover scenarios makes EPT richness a valuable metric for analyzing the potentially compounding or conflicting impacts of the two on future conditions.

When utilizing EPT richness as an indicator of future conditions, it is important to consider the seasonality of macroinvertebrate populations. The increase in EPT richness in late spring could result in the inaccurate conclusion that river conditions are improving when the change in seasonality of the EPT could have significant impacts. In future studies, it will be important to analyze the impacts of this seasonality shift on migratory species that consume macroinvertebrates as well as local non-migratory species higher up in the food chain.

# 4. Improving Intra-agency Decision-Making for Prescribed Fire in the Ocala National Forest Through the Elicitation of a Bayesian Belief Network

## 4.1 Introduction

There are many challenges associated with the use of regulatory structures and governmental agencies to manage and protect our nation's ecosystem services. The inherent complexities of coupled human-environmental systems alone make effective policymaking a difficult and nuanced task. By modeling these social-ecological systems (SES) with the goal of understanding how policy and climate change will impact them, researchers often seek to provide information and guidance to policymakers.

This process is complicated by several factors that can cause SES models to fall short when intended for decision support. In a review of transdisciplinary SES models, Steger et al. found that less than half of studies with the stated goal of providing decision support reported success in that goal (2021). While typically not considered a primary goal, many of these studies did find success in providing opportunities for learning and communication among stakeholder participants. The recommended solutions to improve the applicability of participatory models in decision making including: a more diverse set of stakeholders, more flexibility in model structure and design, as well as the need for modelers to be cognizant of potential power dynamics in participant groups (Steger et al., 2021).

Providing decision support for a governmental agency is made more complex by the hierarchical compartmentalization of knowledge between stakeholders, managers, and practitioners. This is exacerbated by the typically linear process in which researchers provide knowledge and recommendations without significant input from these groups. There is a growing body of literature that would suggest the answer to both barriers is an approach to SES research wherein the knowledge users are part of an iterative research process (Brownell & Roberto, 2015; Lemos & Morehouse, 2005; Parviainen, Kuikka, & Haapasaari, 2022). This allows input from multiple levels of system managers into the scientific process to ensure models are informative and appropriate for specific decision-making contexts.

Boundary objects as a tool in participatory modeling can be used to facilitate this exchange of knowledge and create actionable research endpoints (Djenontin & Meadow, 2018; Parviainen et al., 2022). A boundary object is a concept or tool that allows researchers to engage in a shared space to integrate their combined knowledge of a system or process (Star, 1989, 2010). Central to the function of a boundary object is the creation of a common language and framework in which experts and stakeholders can communicate and the incorporation of different knowledge types to reach an actionable endpoint. These characteristics provide a way to bridge the gap between science and decision-making in SES.

Bayesian Belief Networks (BBNs) can be utilized as such a boundary object and have been widely used in environmental risk and decision-making literature to translate mental models into mathematical models for multi-criteria decision analysis (MCDA) (Atman, Bostrom, Fischhoff, & Morgan, 1994; Bostrom, Atman, Fischhoff, & Morgan, 1994; Bostrom, Fischhoff, & Morgan, 1992; Salliou, Barnaud, Vialatte, & Monteil, 2017). Through participatory modeling using BBNs, analysts can incorporate both quantitative and qualitative feedback from experts and stakeholders to examine the utilities of potentially conflicting management goals (M. E. Borsuk, Higdon, Stow, & Reckhow, 2001; Laurila-Pant, Mäntyniemi, Venesjärvi, & Lehikoinen, 2019; Voinov et al., 2018). Qualitative expert knowledge of a system can be incorporated into the creation of the graphical model structure, a directed, acyclic graph (DAG) where each node represents a characteristic within a system, and arrows connecting nodes indicate causality in the state of a system. Quantitative knowledge from experts as well as diverse data sets can be used to determine the relationship between nodes through the development of conditional probabilities whereby each node is assigned probabilities for each possible state based on the causal relationships represented in the model (Marcot, Steventon, Sutherland, & McCann, 2006; McCann, Marcot, & Ellis, 2006; Nadkarni & Shenoy, 2001).

In framing BBNs as a boundary object in the iterative process of the co-production of knowledge, researchers can increase communication between stakeholders and better inform environmental decision-making. Because of the graphical nature of BBN's and the simplicity of only having two requirements, directionality and acyclicality, stakeholders are able to understand, direct, and critique model structure and assumptions (Castelletti & Soncini-Sessa, 2007). This also means there is a high amount of flexibility in determining model structure with stakeholder input. Moreover, transparency and ownership in the modeling process leads to more informative model outcomes and greater likelihood of successful implementation (Laurila-Pant et al., 2019; Steger et al., 2021; Voinov et al., 2018).

Such approaches have the potential to aid in resolving management goals and optimize decision making processes within federal agencies such as the United States Forest Service and relevant stakeholders. The Forest Service manages public land for conservation, timber harvest, and recreation. This is often achieved using prescribed burning of fire dependent ecosystems. Determining where and when to prescribe burning in any forest system is a complex decision framework balancing potentially conflicting management goals of maintaining ecological integrity and reducing the potential risk due to wildfires.

To enhance evidence-based optimization of decision-making in the Forest Service, we explore the use of structured expert elicitation of a BBN as a boundary object. By engaging experts at multiple management levels within the organization we hope to determine the efficacy of this methodology to encourage the co-production of knowledge and negotiation of management goals among system managers. The second goal of this study is to engage experts in a model building exercise to better represent a decision-making framework to enhance the usability of the SES as a management tool.

## 4.2 Case Study

In the Southeastern United States, prescribed burning is an essential tool to maintain the integrity of many different ecosystems and limit the risk of uncontrollable wildfires. Many forest ecosystems depend on wildfires for seed scarification, nutrient cycling, and to maintain a diversity of wildlife and plant species in the understory of the forest (Glitzenstein, Streng, & Wade, 2003; Kirkman, Goebel, Palik, & West, 2004; Kobziar, Godwin, Taylor, & Watts, 2015). However, increased population density and development in recent history has led to suppression of wildfires to reduce risk to populated areas. Since the 1940's, prescribed fire has since been re-introduced to restore ecological integrity to these fire-dependent systems (Fowler & Konopik, 2007). Additionally, fire suppression can result in the buildup of burnable materials (i.e., fuels), elevating the risk of high-intensity fires with the potential to reach surrounding agricultural and residential areas(Mitchell, Hiers, O'Brien, & Starr, 2009). Prescribed fire is also used to reduce fuel loads in managed forests.

Managers of public lands face a particularly complex decision framework when prescribing fire to National Forest land. The goals of maintaining ecological and reducing risk associated with wildfires must be balanced with additional expectations, including outdoor recreation and timber harvest. Additionally, these lands are often surrounded by privately owned land not managed by the Forest Service and whose landowners often hold expectations for wildfire risk reduction on adjacent public lands (Sturtevant et al., 2009). The ability of land managers to further these goals with prescribed burning is limited by financial resources, manpower, and the occurrence of proper conditions under which fires can be safely managed and pose the least risk from uncontrollable spreading and potential air pollution in local areas (Calkin, Gebert, Jones, & Neilson, 2005; Hiers et al., 2003).

To work towards a solution that maximizes the utility of such management decisions in the context of potentially conflicting goals within the Forest Service as well as with surrounding landowners, the USDA Forest Service recently initiated the Landscape-level Integration and Shared Stewardship (LLISS) program. The stated goal of this initiative is to develop tools that facilitate the identification of interconnected management goals and solutions that optimize desired outcomes across stakeholder groups. In this study, we primarily focus on the former. Starting with stakeholder groups within different management levels of the Forest Service, we explore the process of expert elicitation of a BBN model structure as a boundary object through which stakeholders can identify and negotiate common management goals for prescribed fire in a National Forest in Florida.

### 4.2.1 The Study Area

The Ocala National Forest (ONF) (Figure 23) is one area in the Southeast where prescribed burning is the primary method of managing public land for productivity, ecosystem integrity, and reduction of wildfire risk. The sand pine scrub is a fire-dependent ecosystem that occurs only in Central Florida. This region is also home to many endangered species including the Red-Cockaded Woodpecker, Florida Scrub-Jay, and the Frosted Flatwood Salamander. Without frequent burns, the sand pine scrub would be taken over by xeric oak hammock and wildlife species that prefer the young, open scrub ecosystem would lose vital habitat (Outcalt & Greenberg, 1998). Additionally, wildfire is necessary for seed scarification in both long-leaf pine and sand scrub pine ecosystems and increases seed dispersion for Wiregrass, a native species that fuels recurring fires (McIntyre, Guldin, Ettel, Ware, & Jones, 2018; Outcalt, 1994).

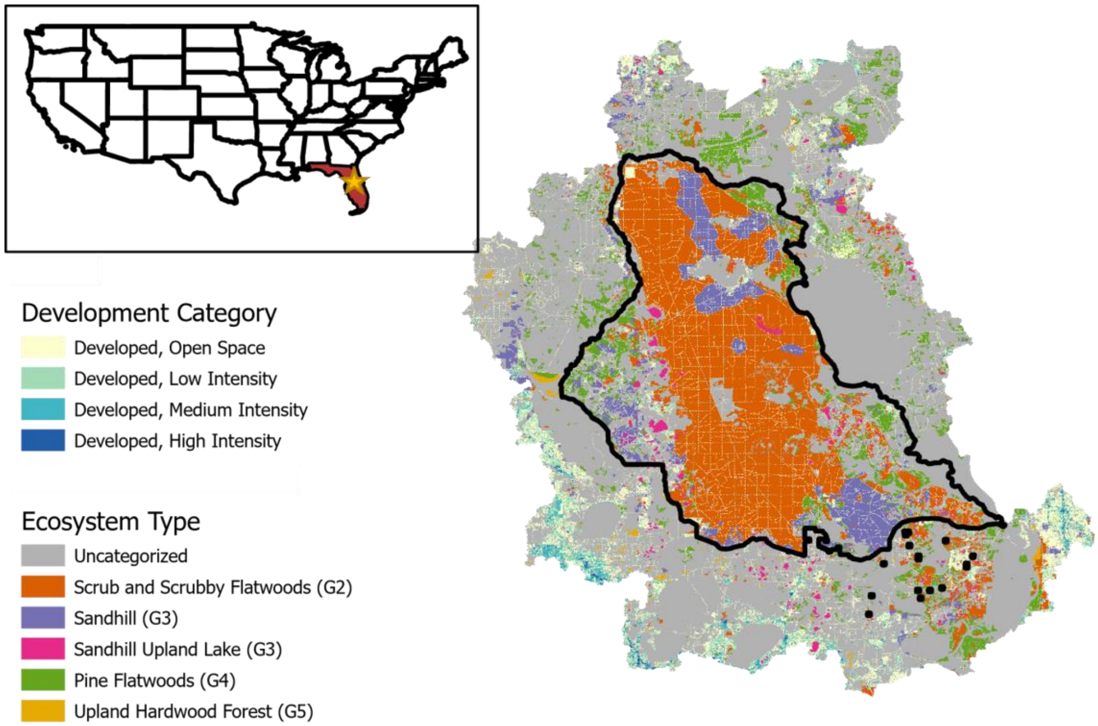


**Figure 23 Map of the Ocala National Forest.**

**The corner map displays the United States, with Florida highlighted. The yellow star denotes the approximate location of the Ocala National Forest in Florida. The larger map displays the Ocala National Forest outlined in black and includes surrounding watersheds. Development categories from the 2011 National Land Cover Database are displayed as well as the ecosystem types from the 2010 Florida Natural Areas Inventory (*Guide to the natural communities of Florida: 2010 edition*, 2010; Homer et al., 2015).**

In addition to fire being integral to ecosystem integrity within the Ocala, it is an essential function of prescribed fire to reduce risk from wildfires (Marshall, Wimberly, Pete, & Stanturf, 2008). This is of particular concern in systems such as the ONF, where private lands and residences are located within and around the National Forest (Fischer & Charnley, 2012). While fire is a necessary event in such ecosystems, extreme fire behavior can pose significant risk to these ecosystems and the services they provide, responders, and local communities (Bacciu, Sirca, & Spano, 2022). Prescribed fire is the primary tool used to reduce the risk of these extreme fire behaviors through the reduction of the hazardous fuels. While topography and weather also play a significant role in fire occurrence and behavior, fuels are considered the primary driver of fire behavior (Werth et al., 2016).

## 4.3 Approach

Expert opinion can be invaluable when creating ecological models as they have a strong influence on the decision-making process (Kuhnert, Martin, & Griffiths, 2010).To capture the complexity of the decision-making process of prescribed burning, we conducted expert elicitation to determine a BBN model structure representing the complex ecological dynamics of the ONF related to the effects of wildfires. While significant amounts of data are available to model the impacts of wildfires, the elicitation process will allow for the creation of a graphical model that represents the outcomes and environmental factors that dictate the way this landscape is managed (Voinov et al., 2018).

### 4.3.1 Model Elicitation

The elicitation of this model was conducted using a modified Delphi style process to determine key model variables and the graphical structure of the model through the use of the Bayesian Argumentation via Delphi (BARD) software (Nicholson et al., 2020). The most important aspects of the Delphi process are anonymity and iteration, which are built into the structure and workflow within BARD. Each participant is automatically provided an alias associated with each of their responses. At each step in the process, participants submit responses to prompts for decision variables and model structure, then are allowed to view the responses of the other participants. At this point, discussion is facilitated during an online workshop and participants are permitted to revise their responses. Based on the discussion and revised responses, a group response is then determined by the facilitator and released to the participants for further discussion.

While BARD supports the creation of a BBN start to finish, for the purposes of this study the following tasks were completed:

Refine the problem statement and management goals as a group

Define model variables for the system

Create a group defined structure for the system

The facilitation of these tasks was completed over Zoom. At the beginning of each session, a brief overview of the goals of the model as well as a review of previous progress was provided. Then participants were given the opportunity to submit their anonymous responses through BARD. Once responses were completed, group discussion of the results was facilitated to develop the final group response.

The group of experts were selected to be a diverse group from within the National Forest System, all of whom held positions with some degree of participation in internal Forest Service processes providing information for planning and decision-making with respect to ONF, as well as close working knowledge of forest ecosystems in Florida. Experts were chosen to represent the distributed structural organization of the National Forest System, which involves forest administration at Forest, State, and Regional levels. Two experts local to the ONF with expertise in fire management and forest planning and ecology participated in the workshops. From the statewide National Forest Supervisor's Office in Florida, two experts in ecology, management and planning participated. Lastly, two science staff from the Forest Service Region 8 (Southern Region) Regional Office participated, one with expertise in fire and fuels management and the other specializing in forest vegetation ecology.

### 4.3.2 Mockup Model

At each step in the elicitation process, experts were given a baseline from which to work. These baselines were developed in part from the BBN in Figure 24. This draft model was constructed by authors as a mockup from existing literature and data, to assist in developing the elicitation process. The BBN model as well as previous work informed the original problem statement presented, potential variable groups to initially consider, and the basis for the structure the experts were asked to critique. The full model was never presented in full to the experts.

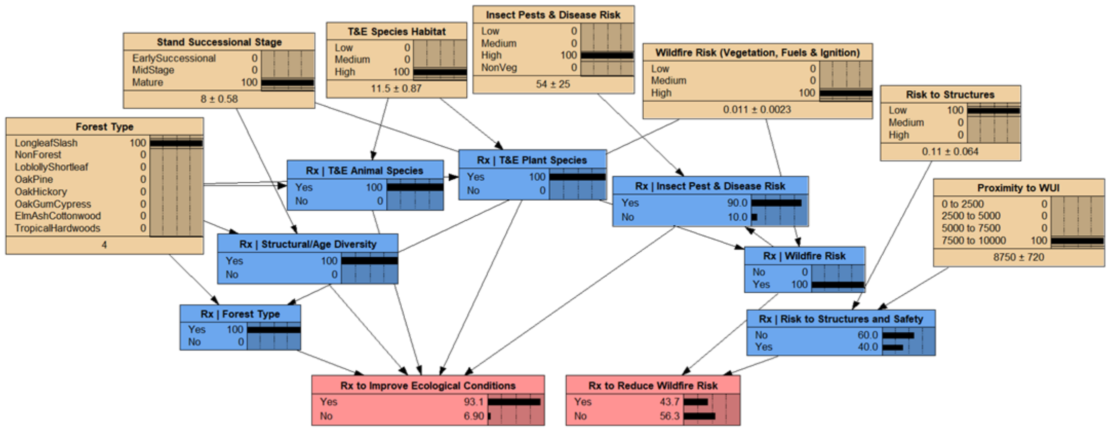


**Figure 24 Original BBN formulated to represent the decision-making process for prescribed burning.**

**Initial mockup BBN formulated to represent key processes and system elements important for understanding how prescribed burning can improve forest conditions and reduce wildfire risk.**

## 4.4 Workshop Structure and Results

### 4.4.1 Workshop 1

During the first workshop, the concept of BBNs was introduced along with the proposed problem statement in appendix D. Experts were asked to comment upon the aspects of ecological integrity within the ONF that can be managed through prescribed fire as well as the specific factors they consider related to wildfire risk. The target variables were defined as the probability that prescribed burning is the best decision, given a set of conditions, with the goal of either improving ecological condition or reducing wildfire risk. The resulting definitions of the intended goals are defined in Table 5.

**Table 5 Definitions of management goals in the Ocala.**

| Management Goal | Definition |
|---|---|
| Improvement of Ecological Conditions | Maintenance of natural disturbance regimes to prevent type conversion<br>Encouragement of stand replacement<br>Maintenance of wildlife habitat for threatened and endangered species |
| Reduction of Wildfire Risk | Hazardous Fuel Reduction<br>Reduction of tree mortality<br>Reduction in the severity of naturally occurring wildfires |

### 4.4.2 Workshop 2

The discussion resulting from the first workshop in conjunction with the mockup model was then used to develop the suggested variables listed (below) to consider during the second workshop.

Forest characteristics

Threatened and endangered species

Disease risk

Disturbance regimes

Location relative to inhabited areas or structures

During the workshop, an additional overview of BBN's and how to determine prevalent nodes was given. Then experts were asked to list the specific variables in these categories that are relevant to whether they prescribe burning to improve ecological condition or reduce wildfire risk. After combining all the variables listed by the experts into broad categories , the variables were then pared down to the most relevant ones, listed below:

Forest Stand Age

Ecosystem/Forest Type

Season of Last Burn

Time Since Last Burn

Fuel Load

Density of Structures in Proximity to Burn Area

Presence of Invasive Plants

Red-Cockaded Woodpecker (RCW) Population Status

Frosted Flatwood Salamander (FFS) Population Status

Scrub-Jay (SJ) Population Status

### 4.4.3 Workshop 3

Summarizing the discussion from workshops 1 and 2, a proposed structure was presented to the experts (Figure 25 A and Figure 26 A). They were provided with time to individually modify the structure and incorporate additional variables as they saw fit. The models for both management decisions were presented as a single model structure, so common variables in They were provided with time to individually modify the structure and incorporate additional variables as they saw fit. The models for both management decisions were presented as a single model structure, so common variables in Figure 25 and Figure 26 are the same nodes. Structures posed by the experts were much more complex (Figure 25 B-D) and often misinterpreted the target node as initially defined, instead interpreting it as a decision node of whether to prescribe burning (Figure 25 B). The results for the model structure for reducing wildfire risk, were less significantly different from the proposed model structure (Figure 26 A). One expert suggested increasing the complexity in the relationships between nodes (Figure 26 B). Another expert proposed the added connection of ecosystem/forest type to whether it is optimal to prescribe burning (Figure 26 C).

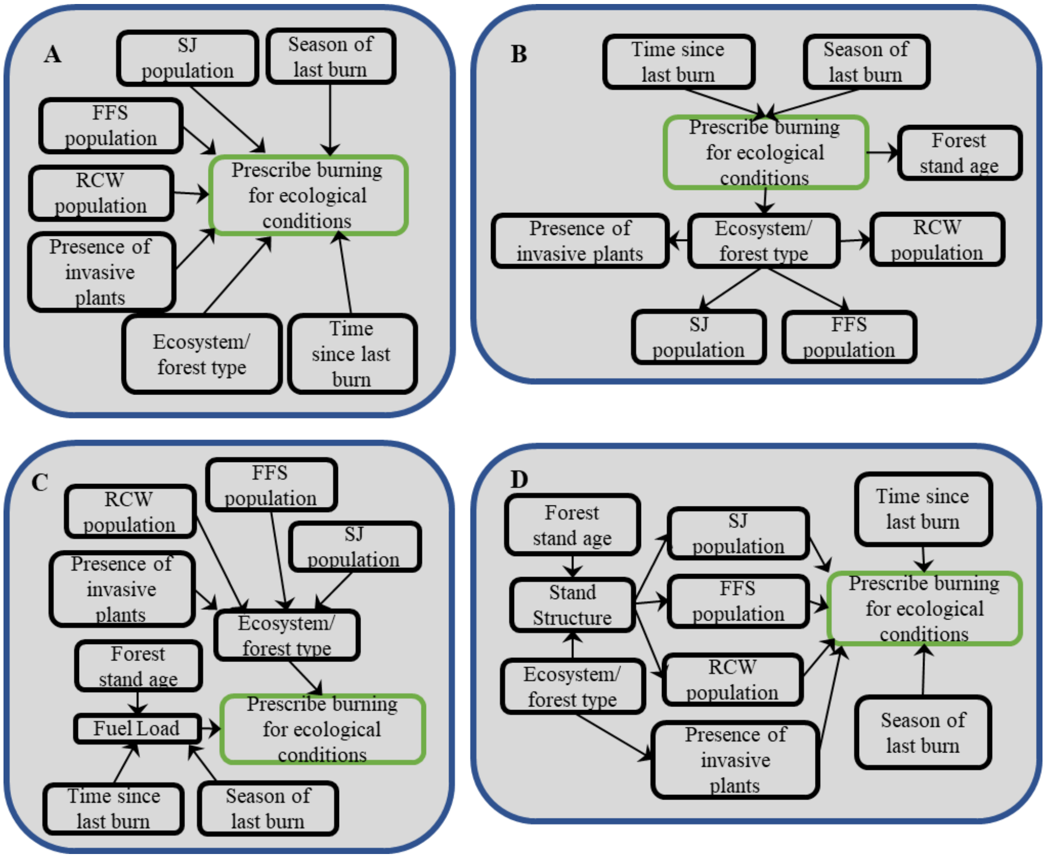


**Figure 25 BBN structures modeling the decision of whether to burn based on increasing ecological integrity reviewed during the third workshop.**

**The BBNs for the two management goals are separated for readability but are considered part of the same model. A: The structure presented as a baseline to experts. B-D: Structures proposed by experts during the workshop.**

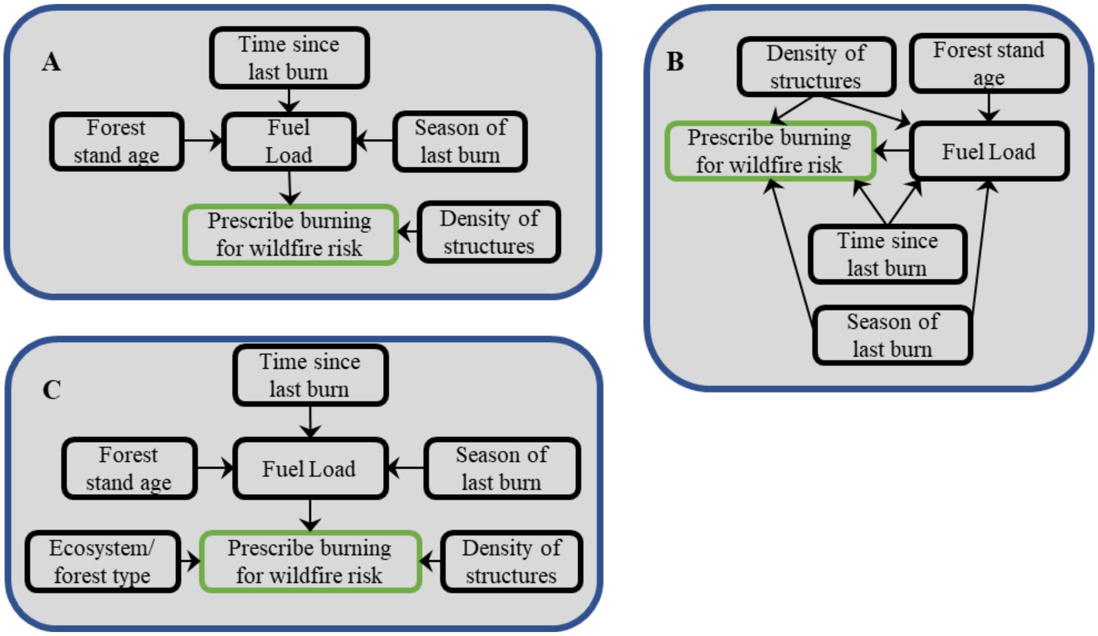


**Figure 26 BBN structures modeling the decision of whether to burn based on reducing wildfire risk reviewed during the third workshop.**

**The BBNs for the two management goals are separated for readability but are considered part of the same model. A: The structure presented as a baseline to experts. B-C: Structures proposed by experts during the workshop.**

To reach consensus on a final model at the end of workshop 3, each connection was discussed in detail. This included an explanation of the interpretation of each connection to ensure experts understood the use of arrows to imply causality.

### 4.4.4 Workshop 4

Following the third workshop, it became clear that the proposed model structure was not compatible with the mental models of the experts. Therefore, the graphical structures generated in workshop 3 were adapted to an adjusted structure. This new structure used prescribed burning as a decision node for which the specific outcomes for ecological integrity and wildfire risk could be modeled (Figure 27). This structure was based on the discussion during the previous three workshops and the structures created by the experts.

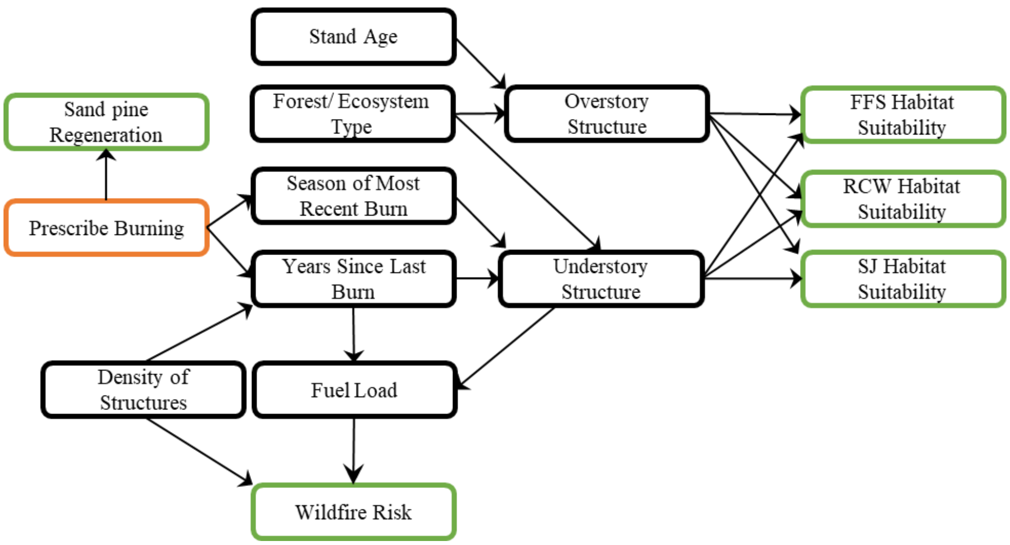


**Figure 27 BBN graphical structure presented to experts during the fourth workshops.**

For the fourth workshop, we split it into three separate sessions to speak separately to the local, state, and regional experts. First, each group was presented with the adapted model and asked for any critiques on the structure. After this, each node was examined to increase its specificity and gain surface level insight into possible numeric relationships between nodes. This was limited to discussing potential discretization of parameters and validity of any specific, measurable variables used to represent the concepts included in the BBN (i.e. using canopy cover to describe overstory structure).

The final BBN did not change significantly from that which was presented to the experts at this stage. The most significant change was to remove sand pine regeneration as an ecological goal for prescribed burning. It was concluded that while prescribed burning can aid in the preparation of planting a stand of sand pines, their regeneration is primarily controlled through artificial seeding. Most progress was made in developing more specificity for each node (Figure 28). For example, wildfire risk was defined as the risk to the wildland urban interface (WUI) given that the majority of risk arises when wildfires gain traction in populated areas.

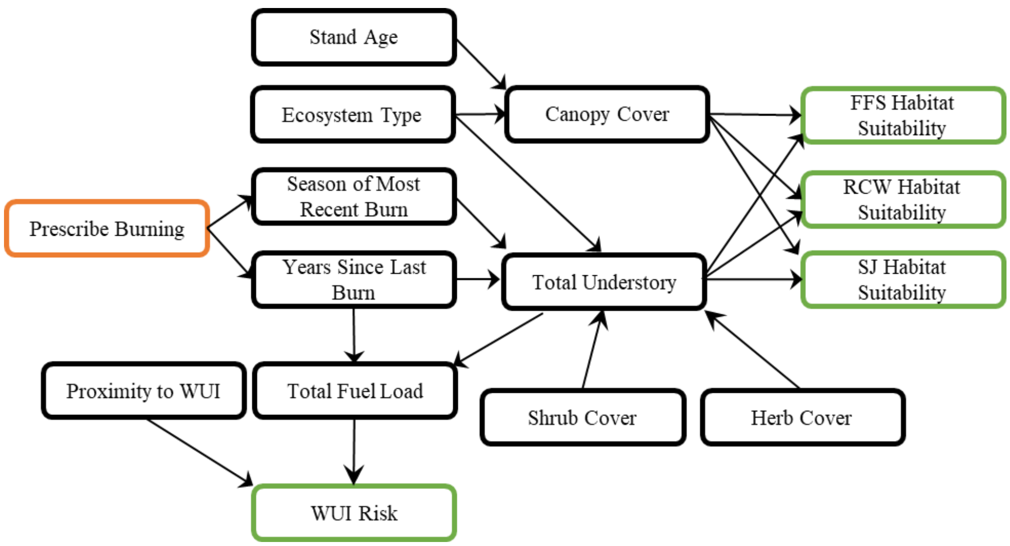


**Figure 28 Final BBN graphical structure agreed upon by all experts.**

## 4.5 Discussion

### 4.5.1 Model Evolution

Over the course of the elicitation workshops, the graphical model changed significantly from the mockup model created through a traditional research process. The original model was simplistic and straightforward but provided the base framework from which to develop an informative decision-making tool. While the model was never presented in full to the experts, it provided the basis from which we developed the problem statement, proposed variable categories, and the basic structure presented to the experts.

Given the initial problem statement, experts were able to identify the values relevant to the decision of prescribed burning specific to the ONF. While it is widely understood that fire-dependent ecosystems require regular disturbance regimes, not all these ecosystems operate under the same dynamics, and many are managed with different ecological goals in mind (Fernandes & Botelho, 2003; Haines, Busby, & Cleaves, 2001). The Forest Service in the ONF, specifically, has goals to conserve local, unique ecosystems and threatened and endangered species as well as sustainable timber production. During the workshops, we identified the key aspects that are managed through prescribed fire, which are the maintenance and improvement of habitats suitable for Red-cockaded woodpeckers (*Picoides borealis*), Scrub-Jays (*Aphelocoma coerulescens*), and Frosted Flatwoods Salamanders (*Ambystoma cingulatum)*. While production of timber is an important management tool for the ONF, and the pine species harvested require fire for seed scarification, stand replacement is primarily managed through artificial seeding.

When defining risk for natural disasters such as wildfires, there are many aspects to consider and ways in which that risk can be defined (Finney, McHugh, Grenfell, Riley, & Short, 2011; Preisler, Brillinger, Burgan, & Benoit, 2004). For this model, we were able to work with the experts to define a BBN in a way that is applicable and meaningful to their decision-making process. Because the ONF has private residences and pasture lands interspersed within Forest Service land and very close to the boarders of the forest, determining the potential for damage to people and resources is primary consideration in limiting the risk of wildfires. Reducing the occurrence of tree mortality resulting from wildfires is an important consideration in reducing wildfire risk as well but is secondary. This motivated the selection of the WUI risk metric over others, as it focuses primarily on risk to populated areas. Other metrics considered focus primarily on evaluating fire characteristics associated with high risk, such as intensity and rate of spread, that does not account for its potential for impact on resources and people (Dillon, Menakis, & Fay, 2015).

By engaging with experts in selecting appropriate model variables, we were able to add important context without over complicating the model. For example, it was identified that an essential link between ecosystem type and stand age to the habitat of threatened and endangered species were the overstory and understory forest structure. These two variables are the primary attributes observed on the ONF to monitor the state of threatened and endangered species habitat and may be influenced by fire, making them highly relevant in this decision-making context. The incorporation of such system characteristics that are readily monitored and understood by managers of the system, the model becomes much more applicable (Steger et al., 2021).

The model structure was significantly altered through the elicitation process. While many changes were suggested based on the relationship between the system characteristics, the most significant was to the basic structure of the model. In the original mockup model, the model end points were the probability that a manager would prescribe burning based on each management goal. When the problem statement was formulated, this was updated to represent the probability that prescribed fire is the optimal decision based on the given conditions and desired outcome. However, during the first three workshops, it became clear that this model structure was incompatible with the mental models of the experts. Therefore, the structure was changed to instead include prescribed burning as a decision node which impacts the state of the system and specific desired outcomes. The final model structure resonated much more with the experts and increased their understanding of the model assumptions and formulation.

The next step in completing this model is to fully parameterize the relationships between nodes using existing data. Outputs of the model will be spatially explicit values of habitat suitability and WUI risk. Once parameterized, the revised model allows end users to evaluate the utility of prescribed fire based on the expected changes in habitat suitability and WUI risk at each spatial unit, predicated on the decision to prescribe burning given the current landscape conditions. Managers can prioritize locations that will most benefit from burning on the basis of this forest-wide information.

### 4.5.2 Reflection on Methodology

The scope of this study was to elicit the BBN model structure, but the next step in this work is to fully parameterize this model. With this goal in mind, the model was framed as a BBN to the experts. Time was spent during the first workshops explaining the anatomy and probability structure of a BBN. However, this information introduced more confusion than it resolved. It hindered the expert's ability to focus solely on formalizing their mental models of the system. The original purpose of influence diagrams was to prompt the decision-makers and content experts to translate their knowledge to a graphical model structure without engaging them in the complex mathematical representations of systems (Howard & Matheson, 2005).

By introducing these diagrams as a Bayesian Statistics tool, even without presentation of formulas or probability tables, it implies there is a complex mathematical concept the experts must understand to correctly build the graphical structure. This hindered the understanding of what information we as analysts were asking them to provide. In retrospect, we would revert to more approachable terms such as "concept map" or the original "influence diagram" and present the concepts of acyclicality and directionality independent of the term Bayesian Belief Network.

Due to this barrier, the primary method of this study was indirect elicitation with iteration by the experts (Carley & Palmquist, 1992; LaMere, Mäntyniemi, Vanhatalo, & Haapasaari, 2020). As described, the lists of model variables were constructed using a combination of those provided by experts as well as those interpreted from previous workshop discussions. Similarly, the original structure presented to the experts was one built based upon the discussion transcripts from previous workshops and the mockup model. While this may have resulted in anchoring effects (Tversky & Kahneman, 1974), the utilization of the variable list and graphical structure as boundary objects provided the opportunity for experts to contextualize their knowledge of the system within the framework we were proposing (Alberto Franco, 2013). With a baseline model and list of variables established, experts focused on providing detailed feedback and information on the system that could be incorporated into the model formulation.

A limitation of this methodology is that it requires the analyst or facilitator to have a degree of knowledge about the system prior to the workshops. This introduces at least some level of bias based on the facilitators previous knowledge and values associated with the system (Voinov et al., 2016). This could interfere with one of the goals of participatory modeling which is to instill a sense of ownership over the model to empower experts in a specific decision-making context (Voinov et al., 2018). Facilitators must be careful to incorporate the input of participants to establish trust in the model building process. Occasionally over the course of this study, information was lost between workshops and left unincorporated into the model structure. We suspect this could have resulted in some of the observed hesitance to disagree or assert opinions in discussion.

This hesitance could have been attributed to power and professional dynamics amongst experts. Over the course of the workshops, the local forest managers provided the bulk of information during the discussion stages. As the ones most familiar with the specific dynamics within the ONF, they have the most thorough knowledge of the system in the field. State-level managers were able to provide the next most context-specific knowledge, but often deferred to the local managers to confirm their statements. At the regional level, experts were more able to provide information on broader dynamics and considerations across forests in the region. However, it was a consistent pattern that confirmation of information was always requested of local managers, who were often asked to have the final say on model critiques.

This was evident not only in asking the experts to correct or critique the details of the model, but also in the determination of final management goals. At the regional level, the understanding of management goals can be much broader. In this case study, this was demonstrated in the discussion around threatened and endangered species, insect, pest and disease risk, and invasive species. While these aspects of ecological integrity are all considered high importance at the regional level, managers at the local level were primarily focused on the management of threatened and endangered species in the context of prescribed burning. These negotiations and communication of appropriate management goals in the context of a boundary object can promote synergy amongst management levels within organizations such as the Forest Service (Etienne, Du Toit, & Pollard, 2011).

## 4.6 Conclusion

To maximize the utility of Bayesian Belief Networks, they should not only be thought of as a mathematical representation of a system, but also a boundary object through which policy makers can participate in the co-production of knowledge. While models created to represent decision frameworks without stakeholder, expert, or policymaker input are mathematically sound, without incorporating that feedback these models can only be of limited use. Participation of experts in the modeling process increases the applicability of a model to decision-making by 1) ensuring the graphical structure of the model is consistent with the mental models of the system managers and the practicalities of the decision framework and 2) strengthening system managers trust in the formulation and applicability of the model. Elicited graphical model structures such as these provide valuable insight into the scientific questions in need of answering to inform policy and decisions.

The participatory modeling process provides neutral ground over which differences in desired management endpoints can be negotiated and discussed across levels of management given potentially conflicting goals. However, within an organization there are important power and professional dynamics of which to be cognizant. Local managers can have different goals based on the practicalities of the day-to-day in the field operations compared to the broader, landscape scale goals of the regional managers. Additionally, because local and state managers have more context specific knowledge, they can monopolize the conversation around these decision frameworks. It is essential to structure workshops or expert elicitations in a way that allows for collaborative discussion and equal input from all management levels.

# 5. Conclusion

Many solutions have been proposed to bridge the science policy gap, but there are still significant barriers between the fields of research and policy making it difficult, if not impossible, to create effective, evidence-based policy. Much of the disconnect between these groups results from a fundamental lack of understanding of scientific uncertainty from policymakers and a lack a appropriate research communication methods from the field of research (Bradshaw & Borchers, 2000). This has garnered two reactions, 1) Researchers have sought to resolve uncertainties to a reach near-zero levels of uncertainty, 2) Encouragement of broader communication methods for policy-related research. However, these solutions are incomplete and have not thus far resulted in more effective policymaking (Brownell & Roberto, 2015; Steger et al., 2021).

There is a greater need to rethink the highly linear process through which research is expected inform policy. To expect all environmental researchers to also play the role of political scientist and policy expert is unreasonable. Instead, we as a research community need to re-examine the role of individual studies in the policy-making process. In this thesis, I explored three case studies of environmental modeling, their representation of uncertainty, and how they can be applied to policy (Boswell & Smith, 2017; Brownell & Roberto, 2015).

In my second chapter, "Patterns of co-contamination in freshwater and marine fish of the northeastern United States", I used a novel statistical modeling framework to develop a multivariate Bayesian model of current fish tissue co-contamination in the Northeast United States. Data were aggregated from three publicly available datasets from the Environmental Protection Agency (EPA) to assemble a large enough dataset to make broad policy recommendations on regional and state levels for fish consumption advisories in lakes, rivers, and coastal waterways. The large amount of data across a wide spatial scale allows the model to capture a higher level of variation in contamination patterns, making for better future predictions to inform policy. The multivariate structure of this model allows me to draw conclusions about the prevalence of multi-contaminant exposure when consuming fish and the potential public health concerns. The results of my work show a significant positive covariance of organic contaminants in surface waters of the Northeast US, indicating that fish consumption advisories based on single contaminant exposures are likely inadequately protective of human health.

This study manages to make important observations in the patterns of co-contamination across a broad spatial scale. The complexity of a multivariate model structure which provides valuable insight into covariance structures of these fish tissue contaminants and allows for a detailed mathematical representation of uncertainty. To place this work within the boundary between science and policy, I frame the result in terms of its proposed impacts on fish consumption advisories. However, this method falls short of making directly applicable policy recommendations. The large spatial extent means there is no clear individual or small group of policymakers who should be accounting for this information in their decisions. This is compounded by the complex mathematical nature of the model, which could exacerbate the science policy gap through the non-intuitive representation of uncertainty that would require careful explanation. Additionally, this is only a small piece of information in a larger social context in which one must consider risk-risk tradeoffs between the consumption of fish and potential alternative food sources (Calder, Bromage, & Sunderland, 2019).

For my third chapter, "Predicting the effects of climate and land use change on water quality in the river systems of New Hampshire and Vermont", I use a combination of state monitoring data from New Hampshire and Vermont state agencies and outputs from a gridded hydrology model from the University of New Hampshire to model the effect of different climate and land management scenarios on future indicators of water quality. I use the Random Forest machine learning approach to model the effect of land use, water quality, and hydrological patterns on the presence of species of the orders Ephemeroptera, Plecoptera, and Tricoptera (EPT). These orders are particularly sensitive to poor water quality and hydrological disturbances, making them a good indicator of overall river health. By using detailed data from the gridded hydrological model from UNH, I was able to accurately predict current conditions of EPT populations and project the state of these populations 100 years into the future. The results of my work show that without increased management of urban development and nutrient pollution from agricultural land, river conditions will continue to worsen overall during the summer months. However, the implications for water quality in spring months are more complex as the benefits of earlier springs for organisms that thrive in warmer weather overshadow any negative effects from increased suburbanization and hydrological impacts of climate change. While stakeholder input was not directly used to determine model structure in this paper, the results of stakeholder workshops in the Great Bay area of New Hampshire were used to determine the extent to which the presence of EPT resonates with the public as an indicator of overall water quality.

The goal of this model was not to develop fundamental knowledge of the dynamics of macroinvertebrates, but to examine the trends in water quality over the next century using an indicator that resonates with both the public and policy makers. While uncertainty is quantified to an extent in this study, it is largely considered through a qualitative lens comparing outcomes across New Hampshire and Vermont under different climate models and land cover scenarios. This work has much more direct applicability to policy-decision making but there are still several more considerations to be make before that point. EPT is but a single management indicator and while it encompasses many aspects of river quality, it must be considered holistically with all other management goals should there be significant tradeoffs in outcomes.

In the fourth chapter of this thesis, "Expert elicitation of a graphical model defining the decision-making framework for prescribed burning in the Ocala National Forest", I led a structured elicitation of a Bayesian belief network to modeling the ways in which managers of forest systems prioritize locations for prescribed burning. Wildfires are necessary for many ecosystems to thrive, but these fires also pose significant risk to nearby populated areas. For this reason, fires are deliberately set and managed on public lands to reduce the risk of uncontrollable and unexpected wildfires and maintain ecological integrity. Using the Ocala National Forest (ONF) as a case study, I surveyed forest experts to determine the factors considered when deciding the priority level of a site for prescribed burning and the desired outcomes. Given the smaller spatial scale of the potential policies recommended, this project has much lower data requirements and can instead be driven more by expert opinion and input on the model structure. By better understanding forest management decisions and its outcomes, allocation of resources can be optimized based on expected outcomes for multiple management goals.

The primary goal of this study was to provide a tool to be directly used by system managers. The smaller spatial extent of this study allowed for direct collaboration with the experts and managers interacting with this system. This not only affords the opportunity to incorporate multiple forms of data in the model including expert elicited values but resulted in a model structure better matched to the experts pre-existing mental models of the system. While the model may lack in detailed representation of all the dynamics within the system and result in high uncertainty, it is much more interpretable by decision-makers and their involvement in the model creation process will engender greater trust in its outcomes.

Although the ONF graphical model framework is the most directly applicable to policy decision, each model plays an essential role in the research to policy pipeline. The models presented in chapters 2 and 3 provide valuable information on the dynamics of regulated systems and can inform directions for further policy research and identification of policy goals. However, for it to play a direct role in decision making, this knowledge needs to be downscaled and contextualized within local dynamics. Many researchers have taken on this role through the creation of locally relevant Bayesian belief networks incorporating expert knowledge, but they often fail to account for complex political and social implications (M. Borsuk, Clemen, Maguire, & Reckhow, 2001; McLaughlin & Reckhow, 2017).

As demonstrated in the chapter 5 of this thesis, models developed by researchers can misrepresent the system as viewed by decision makers and ignore the practicalities associated with managing a system. This is compounded by the potential to create over complex models that do not resonate with non-researchers. Simpler models with potentially higher levels of uncertainty can be more impactful in a decision context when they are built through collaboration with policymakers, stakeholders, and practitioners. Through the co-production of knowledge between these groups to create simpler graphical model structures, researchers start from a place of mutual understanding and the barriers to communicating model uncertainties and outcomes as they relate to policy are lowered significantly (Boswell & Smith, 2017; Hoffmann, Deutsch, Klein, & O'Rourke, 2022; Steger et al., 2021).

As a research community we need to acknowledge the need for the proposed novel role of research integrator, researchers who can resolve policy goals across research, social, and political boundaries (Hoffmann et al., 2022). Uncertainty is an essential part of the research process and will never be fully resolved to the satisfaction of policymakers and to put the onus on researchers to simply communicate more effectively is unreasonable. By instead building integrative model frameworks or boundary objects, we can improve upon the success of the research to policy pipeline.

# Appendix A

**Table 6 Description of data used for the trophic level predictor variable.**

| Species | Common name | Carbon fraction (‰) | Nitrogen fraction (‰) | Estimated Trophic Position | Sources |
|---|---|---|---|---|---|
| *Ambloplites rupestris* | Rock bass | -17.5 to -16; -14.9 to -17.7 | 11 to 11.5; 10.3 to 12.1 | 3.5-4.4; 3.45 to 4.08; 3.4 ±0.2 se | (Cabana & Rasmussen, 1996; Paterson, Drouillard, & Haffner, 2006; Vander Zanden, Cabana, & Rasmussen, 1997) |
| *Micropogon undulatus* | Atlantic croaker | -22.4 | 10.2 | 4±0.5 | (Sullivan & Moncreiff, 1990) |
| *Microgadus tomcod* | Atlantic tomcod | -12.8 to -12.9; -16.92 to -18.95 | 13.87 to 14.65 | 4.2 to 4.5; 3.8 ±0.5 se | (Pastershank, 2001; Schwingham er, Tan, & Gordon Jr, 1983) |
| *Ictalurus furcatus* | Blue catfish | -22.3 to -23.25; -21.7 | 16.3 | 3.4±0.44 | (S. MacAvoy, Macko, McIninch, & Garman, 2000; S. E. MacAvoy, Macko, & Garman, 2001) |
| *Callinectes sapidus* | Blue crab | -20.4 to -26.9 | 8.8 to 12.5 | 2.98 ± 0.08 sd to 4.22 ± 0.19 sd (outside | (Bucci, Showers, Rebach, DeMaster, & |

| | | | | | |
|---|---|---|---|---|---|
| | | | | US) | Genna, 2007; Carrozzo et al., 2014) |
| *Pomatomus saltatrix* | Bluefish | – 17.33; -16 to -18.5 | 15.58 to 16.09 | 3.55 to 3.71; 4.5±0.3 se | (Melville & Connolly, 2005; Szczebak & Taylor, 2011) |
| *Lepomis macrochirus* | Bluegill | -8; -12.3 to -16.4 | 9 to 10.5; 10.6 to 12.1 | 2.8; 3.2±0.2 se | (Gu, Schelske, & Hoyer, 1996; Paterson et al., 2006) |
| *Salvelinus fontinalis* | Brook trout | 33 to -23.5; -27.76 to -41.10 | 5 to 10; 6.85 to 10.15 | 3.5-3.7; 3.3 | (Jardine, Gray, McWilliam, & Cunjak, 2005; Power, Power, Caron, Doucett, & Guiguer, 2002; Vander Zanden et al., 1997) |
| *Ameiurus (formerly Ictalurus) nebulosus* | Brown bullhead | -31.2 to -28.1 | 10.5 to 11.8; 10.1 to 10.6 | 3 | (Gu et al., 1996; Keough, Sierszen, & Hagley, 1996) |
| *Salmo trutta* | Brown trout | -26 to -33 | 8.7 to 10.5; 5.8 to 8.5 | 3.5-3.7; 3.4±0.1 se | (French, Vondracek, Ferrington Jr, Finlay, & Dieterman, 2014; McHugh, Budy, Thiede, & |

| | | | | | |
|---|---|---|---|---|---|
| | | | | | VanDyke, 2008; Vander Zanden et al., 1997) |
| *Catostomus commersoni* | White sucker | -28.1 to -31.6 | 4.66 to 7.26; 8.2 to 9.1 | 3.5; 2.8±0.2 se | (Garcia & Carignan, 2005; Sierszen, Keough, & Hagley, 1996; Vander Zanden et al., 1997) |
| Esox niger | Chain Pickerel | -23.70 to -26.30 | 9 to 11.2 | 3.38-4.51; 3.3±0.46 se | (Fry et al., 1999; Vander Zanden et al., 1997) |
| *Ictalurus punctatus* | Channel Catfish | -22.58 to -23.85 | 8.53 to 9.32 | 4.2; 4.2±0.3 se | (Fry et al., 1999) |
| *Erimyzon oblongus* | Creek chubsucker | -28.1 | 10.9 | 3.0 ±0.38 se | (S. MacAvoy et al., 2000) |
| *Esox lucius* | Northern pike | -27.8 to -30 | 11.5 to 12 | 3.38-4.51 | (Sierszen et al., 1996; Vander Zanden et al., 1997) |
| *Ictalurus natalis (new name: Ameiurus natalis)* | Yellow bullhead | -24.20 to -25.40 | 8.40 to 10.40 | 3.3 ±0.46 se | (Fry et al., 1999) |
| *Salvelinus namaycush* | Lake trout | -24.96 to -25.08 | 9.49 | 3.5-3.7; 4.3± 0.5 se | (Harvey & Kitchell, 2000; Vander Zanden et al., 1997) |
| *Micropterus salmoides* | Largemouth Bass | -21.93 to -25.94 | 9.32 to 12.23 | 3.55-4.49; 3.8± 0.4 se | (Fry et al., 1999; Vander Zanden et al., 1997) |

| | | | | | |
|---|---|---|---|---|---|
| *Lepomis gibbosus* | Pumpkinseed | -26.1; -24.5 | 13.4 | 2.81-4.15; 3.3± 0.1 se | (S. MacAvoy et al., 2000; Vander Zanden et al., 1997; Vander Zanden & Vadeboncoeur, 2002) |
| *Homarus americanus* | American Lobster | -14.9 to -17 | 12 | 3.2 | (Steneck, Vavrinec, & Leland, 2004; Stephenson, Tan, & Mann, 1986; Tucker, Sheats, Giblin, Hopkinson, & Montoya, 1999) |
| *Margariscus margarita* | Allegheny pearl dace | -27 | 10.56 | 3.1 ±0.36 SE | (Freedman, Curry, & Munkittrick, 2012) |
| *Micropterus dolomieu* | Smallmouth bass | -23.4 | 13.5 | 3.46-4.73; 3.6±0.2 se; | (Tom, Newman, & Schmerfeld, 2010; Vander Zanden et al., 1997; Vander Zanden & Vadeboncoeur, 2002) |
| Mixed Salmonidae (Family) | Atlantic salmon; Rainbow trout; Brown trout; Brook | | | 4.5±0.3; 4.1±0.3; 3.4±0.1 se; 3.3; 4.3± 0.5 se | (Froese, 2014) |

| | | | | | |
|---|---|---|---|---|---|
| | trout; Lake trout | | | | |
| *Pomoxis annularis* | White crappie | -27 | 15.2 ±0.1 | 4.4 ±0.6 se | (Dodder, Strandberg, & Hites, 2002; Zeug & Winemiller, 2008) |
| *Pomoxis nigromaculatus* | Black crappie | -22.53 to -23.37 | 10.97 to 12.93 | 3.8±0.62 | (Fry et al., 1999) |
| Sparidae (Family) | Porgy-scup; grass porgy only in gulf coast/FL coast; spottail seabream; red porgy; longspine porgy; pinfish; | | | 2.3; 3.9± 0.2; 3.4±0.1; 4.4 | (Froese, 2014) |
| *Oncorhynchus mykiss (AKA Salmo gairdneri)* | Rainbow trout | -26 to -27.5 | 10.5 to 13; 15 to 17 | 4.1±0.3 | (Angradi, 1994; Heady & Moore, 2013) |
| *Salmo salar* | Atlantic salmon | -20.51 ± 0.23 | 12 ± 0.38 | 4.5±0.3 | (Dempson & Power, 2004) |
| *Stenotomus chrysops* | Scup | -13.61 to -18.12 | 12.88 to 16.33 | 3.8±0.1 | (Piraino & Taylor, 2009) |
| *Leiostomus xanthurus* | Spot | -19.9; –13.5 ± 0.1 | 13.3 ± 2.0 | 3.2±0.1 | (Hughes & Sherr, 1983; Winemiller, Akin, & Zeug, 2007) |
| *Stizostedion vitreum* | Walleye | -23 to -27 | 15.3 to 19.2 | 3.91-4.86; 4.5 | (Overman & Parrish, 2001; Vander Zanden et |

| | | | | | |
|---|---|---|---|---|---|
| | | | | | al., 1997) |
| *Paralichthys dentatus* | Summer flounder | -17.48 ±0.37 | 15.55 ±0.57 | 4.5±0.3 | (Buchheister & Latour, 2010) |
| *Cynoscion regalis* | Weakfish | -24 to -15 | 10 to 17 | 3.8±0.2 | (Weinstein, Litvin, Guida, & Chambers, 2009) |
| *Ameiurus catus* | White catfish | -6 to -7.5 | 10.5 to 11.0 | 3.2±0.45 | (Gu et al., 1996) |
| *Morone americana* | White Perch | -27.4 to -32.6 | 8.8 to 11.2 | 3.1±0.35 | (Sierszen et al., 1996) |
| *Pseudopleuronectes americanus* | Winter flounder | -16.8±0.6 | 11.1±1.6 | 3.6 ±0.1 | (Fry, 1988) |
| *Perca falvescens* | Yellow Perch | -26.5 to -29.1 | 10.6 to 11.7 | 2.99-4.47; 3.7±0.2 se | (Sierszen et al., 1996; Vander Zanden et al., 1997) |

**Table 7 Detailed description of predictors utilized for the EMAP dataset model.**

| Variable | Description |
|---|---|
| Estimated Trophic Level | See table A.1 for trophic level data description |
| Species | Fish genus and species as recorded |
| Lipids | Percent lipids of sample |
| Tissue Type | A whole fish sample was used to analyze contaminant concentrations |
| Total Zooplankton Abundance | The total number of zooplankton individuals within a water column of the lake |
| Alkalinity | Calculated alkalinity based on sample (μeq/L) |
| DOC | Dissolved organic carbon measured in single grab sample (mg/L) |
| Chlorophyll a | Trichromatic chlorophyll a measured in single grab sample (μg/L) |
| Total Human Disturbance | Percent of watershed that agriculture, urban, and mining |
| Percent Mining | Percent mining within the watershed |
| Watershed Area | Total area of the watershed |
| Percent Agriculture | Percent of the watershed that is agriculture |
| Latitude | Latitude coordinate of sample location |
| Longitude | Longitude coordinate of sample location |

**Table 8 Detailed description of predictors utilized for the NRSA dataset model.**

| Variable | Description |
|---|---|
| Fish Length | Length of each fish taken for sampling (mm) |
| Species | Both common names and scientific names were collected for each sample |
| Fish Tissue Type | All samples were measured from the filet. |
| Percent Ephemeroptera | Percent of Ephemeroptera taxa |
| Total Nitrogen | Total nitrogen measured in lake (μg/L) |
| pH | Laboratory measured pH |
| DOC | Dissolved organic carbon (mg/L) |
| Watershed Area | Area of the watershed in which the river is located |
| Percent Agriculture | Percent area of the watershed classified as pasture/hay or row crops by the National Land Cover Database (NCLD) |
| Percent Urban | Percent area of the watershed classified as low or high density residential, commercial/industrial/transportation, or developed high intensity by NCLD |
| Percent Shrubgrass | Percent area of the watershed classified as shrub/scrub or grasslands/herbaceous by NCLD |
| Percent Wetland | Percent of watershed classified as woody wetlands or emergent herbaceous wetlands by NCLD |
| Percent Impervious | Mean percent impervious surface classified by NCLD |
| Barrier Disturbances | Presence of walls/dikes/revetments weighted by distance |
| Riparian Vegetation | Total canopy, mid, and ground layer areal cover |
| Longitude | Latitude coordinate of sample location |
| Latitude | Longitude coordinate of sample location |

**Table 9 Detailed description of predictors utilized for the NCA dataset model.**

| Variable | Description |
|---|---|
| Chlorophyll a | Chlorophyll a concentration in the surface layer of the water. For shallow areas, a single measurement was taken and used for analysis. (μg/L) |
| Total Nitrogen | Total nitrate in surface layer of the water. For shallow areas, a single measurement was taken and used for analysis. (mg/L as N) |
| Sediment Toxicity | Toxicity based on *Ampelisca abdita* survival during a ten-day exposure to sediment. (% survival) |
| Abundance Tolerant Benthic Organisms | Each benthic species was ranked between 1 and 5. 1 being least tolerant and 5 being most tolerant. All ranked as a 4 or 5 were considered tolerant species and the abundance of all such species was summed. |
| Abundance Sensitive Benthic Organisms | Each benthic species was ranked between 1 and 5. 1 being least tolerant and 5 being most tolerant. All ranked as a 1 or 2 were considered tolerant species and the abundance of all such species was summed. |
| Tissue Type | Tissue analyzed for sample: Filet, Offal, or Whole |
| Percent Agriculture | Data was collected using GIS and the NCLD database from the survey closest in time to the sample taken. All land within a 200 mi radius of the sample point was used to determine percentages. This was to maintain consistency with the standard practice for the NRSA dataset. |
| Percent Forest | Data was collected using GIS and the NCLD database from the survey closest in time to the sample taken. All land within a 200 mi radius of the sample point was used to determine percentages. This was to maintain consistency with the standard practice for the NRSA dataset. |
| Percent Impervious | Data was collected using GIS and the NCLD database from the survey closest in time to the sample taken. All land within a 200 mi radius of the sample point was used to determine percentages. This was to maintain consistency with the standard practice for the NRSA dataset. |
| Percent Urban | Data was collected using GIS and the NCLD database from the survey closest in time to the sample taken. All land within a 200 km radius of the sample point was used to determine |

| | |
|---|---|
| | percentages. This was to maintain consistency with the standard practice for the NRSA dataset. |
| Percent Wetlands | Data was collected using GIS and the NCLD database from the survey closest in time to the sample taken. All land within a 200 mi radius of the sample point was used to determine percentages. This was to maintain consistency with the standard practice for the NRSA dataset. |
| Latitude | Latitude coordinate of sample location |
| Longitude | Longitude coordinate of sample location |
| Lipids | Percent lipid content in sample |
| Length | Length of fish in sample (mm) |
| Species | Fish genus and species as recorded |

# Appendix B

**Table 10 $R^2$ values calculated for the model of the EMAP dataset.**

| Contaminant | $R^2$ |
|---|---|
| 4,4-DDE | 0.38 |
| 4,4-DDD | 0.29 |
| 2,4-DDT | 0.51 |
| 2,4-DDD | 0.35 |
| Hexachlorobenzine | 0.41 |
| Oxychlordane | 0.69 |
| Alpha Chlordane | 0.72 |
| Gamma chlordane | 0.65 |
| Dieldrin | 0.51 |
| Aldrin | 0.39 |
| Total PCBs | 0.54 |
| cis-Nonachlor | 0.66 |
| trans-Nonachlor | 0.69 |
| Mercury | 0.35 |

**Table 11 $R^2$ values calculated for the model of the NRSA dataset.**

| Contaminant | $R^2$ |
|---|---|
| Mercury | 0.59 |
| Oxychlordane | 0.38 |
| Endrin Ketone | 0.54 |
| Total PFCs | 0.3 |
| Heptachlor | 0.46 |
| Heptachlorepoxide | 0.52 |
| Endosulfan II | 0.16 |
| Total PCBs | 0.29 |
| trans-Nonachlor | 0.54 |
| cis-Nonachlor | 0.45 |
| Endrin | 0.34 |
| Dieldrin | 0.30 |
| Gamma chlordane | 0.57 |
| Alpha chlordane | 0.50 |

**Table 12 $R^2$ values calculated for the model of the NCA dataset.**

| Contaminant | $R^2$ |
|---|---|
| Total PCBs | 0.64 |
| Mercury | 0.30 |
| Benzo(b)fluoranthene | 0.05 |
| 2,6-Dimethylnaphthalene | 0.12 |
| Biphenyl | 0.18 |
| trans-Nonachlor | 0.54 |
| Pyrene | 0.05 |
| Methylnaphthalene | 0.10 |
| Fluoranthene | 0.10 |
| Chrysene | 0.04 |
| Anthracene | 0.22 |
| Acenaphthylene | 0.22 |
| 2,4-DDE | 0.25 |
| 2,4-DDT | 0.06 |
| 4,4-DDT | 0.46 |
| 4,4-DDE | 0.66 |
| 4,4-DDD | 0.63 |
| Naphthalene | 0.09 |

# Appendix C

**Table 13 Mean, minimum, and maximum values for all features used to train the Random Forest model.**

| | Training Data | | | Test Data | | |
|---|---|---|---|---|---|---|
| Variable | Mean ± standard deviation | Min | Max | Mean ± standard deviation | Min | Max |
| Average Discharge ($m^3/s$) | 0.74 ± 1.03 | 0.00036 | 11.2 | 0.80 ± 1.17 | 0.00102 | 8.35 |
| Max Discharge ($m^3/s$) | 1.97 ± 2.39 | 0.0012 | 22.0 | 2.18 ± 2.91 | 0.010 | 16.85 |
| Average Velocity (m/s) | 0.39 ± 0.13 | 0.0013 | 0.85 | 0.40 ± 0.13 | 0.013 | 0.78 |
| Maximum Velocity (m/s) | 0.71 ± 0.23 | 0.0056 | 3.47 | 0.71 ± 0.17 | 0.061 | 1.18 |
| Average Dissolved Inorganic Nitrogen (mg DIN-N/L) | 1094.6 ± 12467.8 | 0 | 241338.9 | 96.6 ± 589.8 | 0 | 4437.9 |
| Maximum Dissolved Inorganic Nitrogen (mg DIN-N/L) | 3826.0 ± 46043.8 | 0 | 897956.8 | 273.6 ± 1659.3 | 0 | 12256.6 |
| Average Width (m) | 6.54 ± 4.40 | 0.213 | 19.9 | 6.71 ± 4.23 | 0.39 | 19.2 |
| Maximum Width (m) | 7.46 ± 4.96 | 0.25 | 22.8 | 7.7 ± 4.9 | 0.52 | 21.8 |
| Average Temperature (°C) | 15.0 ± 3.74 | 2.32 | 24.2 | 14.3 ± 4.1 | 2.23 | 22.1 |
| Maximum | 22.2 ± 3.26 | 8.93 | 35.6 | 22.0 ± | 12.0 | 31.1 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Temperature (°C) | | | | 3.11 | | |
| Upstream Area ($km^2$) | 46.1 ± 48.9 | 0.20 | 194.7 | 47.4 ± 50.7 | 0.3 | 194.7 |
| Forest (%) | 84 ± 26.9 | 0 | 100 | 85.3 ± 15.4 | 0 | 100.0 |
| Agricultural Land (%) | 4.6 ± 4.8 | 0 | 31 | 4.2 ± 4.7 | 0 | 20.8 |
| Developed Land (%) | 7.0 ± 11.4 | 0 | 100 | 6.2 ± 11.3 | 0 | 75.1 |
| Impervious Land (%) | 1.9 ± 5.0 | 0 | 61 | 1.6 ± 4.7 | 0 | 33.1 |
| Wetland (%) | 1.9 ± 4.0 | 0 | 30.6 | 3.3 ± 4.3 | 0 | 30.6 |
| EPT Richness | 26.8 ± 19.3 | 0 | 91 | 27.4 ± 20.7 | 0 | 107 |

**Table 14 Climate scenarios utilized in predicting EPT richness over the next 100 years.**

| Climate Model | Information | Primary Reference |
|---|---|---|
| MIROC-ESM | Center for Climate System Research (The University of Tokyo), National Institute for Environmental Studies, and Frontier Research Center for Global Change, Japan | (Developers, 2004) |
| ACCESS1-0 | Commonwealth Scientific and Industrial Research Organization and Bureau of Meteorology, Australia | |
| CESM1-CAM5 | Community Earth System Model Contributors | |
| CMCC-CM | Centro Euro-Mediterraneo per I Cambiamenti Climatici | |
| GFDL-ESM2G | U.S. Dept. of Commerce/NOAA/ Geophysical Fluid Dynamics Laboratory, USA | (Delworth et al., 2006) |
| HadGEM2-ES | Met Office Hadley Centre (additional HadGEM2 ES realizations contributed by Instituto Nacional de Pesquisas Espaciais) | |

# Appendix D

Case Study: Ocala National Forest

The goal of this project is to determine the viability of an expert elicited Bayesian model to aid in the decision making across a landscape. Our current aim is to consider this first on a small scale by using the Ocala National Forest as a case study. Future applications will consider larger spatial scales, a wider range of stakeholders, and potentially more management options and end goals. The expert elicitation is meant to foster the creation of a robust model framework and provide a structure in which managers can explore decision frameworks holistically. In this case study, we will be specifically focusing on this method to balance tradeoffs based on potentially conflicting end goals.

This is the first step in testing expert elicitation of bayes networks as a process to encourage collaboration of diverse stakeholders to make optimal management decision on a landscape scale. The goal of this specific exercise is to gauge the feasibility of this approach as a decision tool for managers, not to create a complete model of the decision process. This model can be expanded upon in later iterations to include other management decisions or outcomes.

**Case Study**

For this exercise, we are asking you to consider the decision-making framework you, as an expert or manager of this ecosystem, would use to prescribe burning in the Ocala

National Forest. The management goals for this scenario are either to reduce wildfire risk or to improve ecological conditions. These do not have to be mutually exclusive goals, one or both can be considered an end goal in any specific conditions. For the purposes of this exercise, it is assumed the following factors into ecological condition:

- Diversity of flora and fauna
- Quality of the long leaf pine ecosystem
- Protection of habitat for the Cockaded Woodpecker
- Protection of habitat for Scrub-Jay populations
- Maintain disturbance regimes for the Florida sand pine scrub

The land area will be divided into 500-acre units, which will be individually assigned two probabilities that fire will be prescribed based on each of these management goals. Although these decisions are not made on the scale of 500-acre plots, this level of granularity will allow decision makers to view broader spatial patterns across the study area.

The goal is to consider these decisions based on landscape characteristics, independent of short-term conditions such as logistics or day-to-day risk of catastrophic failure. Below is a list of potential factors to consider. Based on your expert opinion, variables will be added or removed from this list and utilized in the final model.

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# Biography

Kimberly Bourne is a native of rural western North Carolina. In 2010, she was accepted into and attended the North Carolina School of Science and Mathematics in Durham, North Carolina from which she graduated in 2012. At this point in time, she began her undergraduate education at Clemson University where she earned a Bachelor of Science in Environmental Engineering.

At Duke University, she was primarily funded by grants provided by the USFS, EPA, and NIEHS. She also earned a scholarship from Anchor QEA consulting in 2019. She has pursued a multitude of interests in research, mentorship, and teaching. Her research interests have been diverse including analyzing the behavior of Lionfish prey preferences and exploring the impact of climate change on the bioaccumulation of mercury in addition to her environmental policy-related research. She has also acted as a project manager for an undergraduate research experience in both Bass Connection and Data+ programs at Duke. Working with the International Institute for Sustainable Development, she collaborated with other graduate students, professors, and undergraduate students to build creative data visualizations and learning modules from data taken from the Experimental Lakes Area.

She continued to develop her passion for mentorship and teaching through her involvement with the North Carolina School of Science and Mathematics. Working with the Mentorship program for two years in addition to her graduate studies, she guided high school students through the research process as they completed independent projects with local researchers. She also had the opportunity to aid in the design and implementation of an environmental systems thinking course. Additionally, she has taught honors-level Environmental Engineering multiple times to online students of the school.

The publications on which Kimberly Bourne has been included as an author are "Effects of temperature, salinity, and sediment organic carbon on methylmercury bioaccumulation in an estuarine amphipod" which features in Science of the total environment, 2019, and "Diet choice in a generalist predator, the invasive lionfish (Pterois volitans/miles)" in Journal of Experimental Marine Biology and Ecology, 2020.