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# The Multiple Stressor Ecological Risk Assessment for the Mercury-Contaminated South River and Upper Shenandoah River Using the Bayesian Network-Relative Risk Model

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## EDITOR'S NOTE:

This is 1 of 3 companion articles describing the ecological risk assessment for the South River and Upper Shenandoah River in Virginia, USA. The regulatory focus is Hg, and other chemicals and factors such as temperature are included in the analysis. The papers describe the foundations of the Bayesian network-relative risk model methodology and calculated risk across the landscape, evaluate how 2 management alternatives alter the risk distributions, and describe the role of risk assessment in an adaptive management process.

## ABSTRACT

We have conducted a regional scale risk assessment using the Bayesian Network Relative Risk Model (BN-RRM) to calculate the ecological risks to the South River and upper Shenandoah River study area. Four biological endpoints (smallmouth bass, white sucker, Belted Kingfisher, and Carolina Wren) and 4 abiotic endpoints (Fishing River Use, Swimming River Use, Boating River Use, and Water Quality Standards) were included in this risk assessment, based on stakeholder input. Although mercury (Hg) contamination was the original impetus for the site being remediated, other chemical and physical stressors were evaluated. There were 3 primary conclusions from the BN-RRM results. First, risk varies according to location, type and quality of habitat, and exposure to stressors within the landscape. The patterns of risk can be evaluated with reasonable certitude. Second, overall risk to abiotic endpoints was greater than overall risk to biotic endpoints. By including both biotic and abiotic endpoints, we are able to compare risk to endpoints that represent a wide range of stakeholder values. Third, whereas Hg reduction is the regulatory priority for the South River, Hg is not the only stressor driving risk to the endpoints. Ecological and habitat stressors contribute risk to the endpoints and should be considered when managing this site. This research provides the foundation for evaluating the risks of multiple stressors of the South River to a variety of endpoints. From this foundation, tools for the evaluation of management options and an adaptive management tools have been forged. *Integr Environ Assess Manag* 2017;13:85–99. ©2016 SETAC

**Keywords:** Bayesian network relative risk model   Ecological risk assessment   Mercury   South River   Virginia

## INTRODUCTION

We developed a Bayesian network relative-risk model (BN-RRM) for the South River in Virginia for risk analysis, decision making, and adaptive management. The risk assessment has been a key element in the decision making and management process for this contaminated site. This is the first of a series of 3 articles describing the approach and use of the model. The first installment describes the methods for incorporating a wide variety of site-specific information into a relative-risk framework and explains the development of the initial relative-risk submodels. The models were used to calculate spatially explicit risk to biotic and abiotic endpoints in the South River watershed from multiple stressors. In addition, the models provide a foundation for further risk analysis and adaptive management for the South River. The second installment (Johns et al. this issue) describes the adaptation of the initial risk models to investigate potential changes in risk with 2 management alternatives for the region. A third article (Landis et al. this issue) will demonstrate the application of the BN-RRM approach to an adaptive management structure that can be applied to the South River, taking advantage of the characteristics of Bayesian network (BN) modeling.

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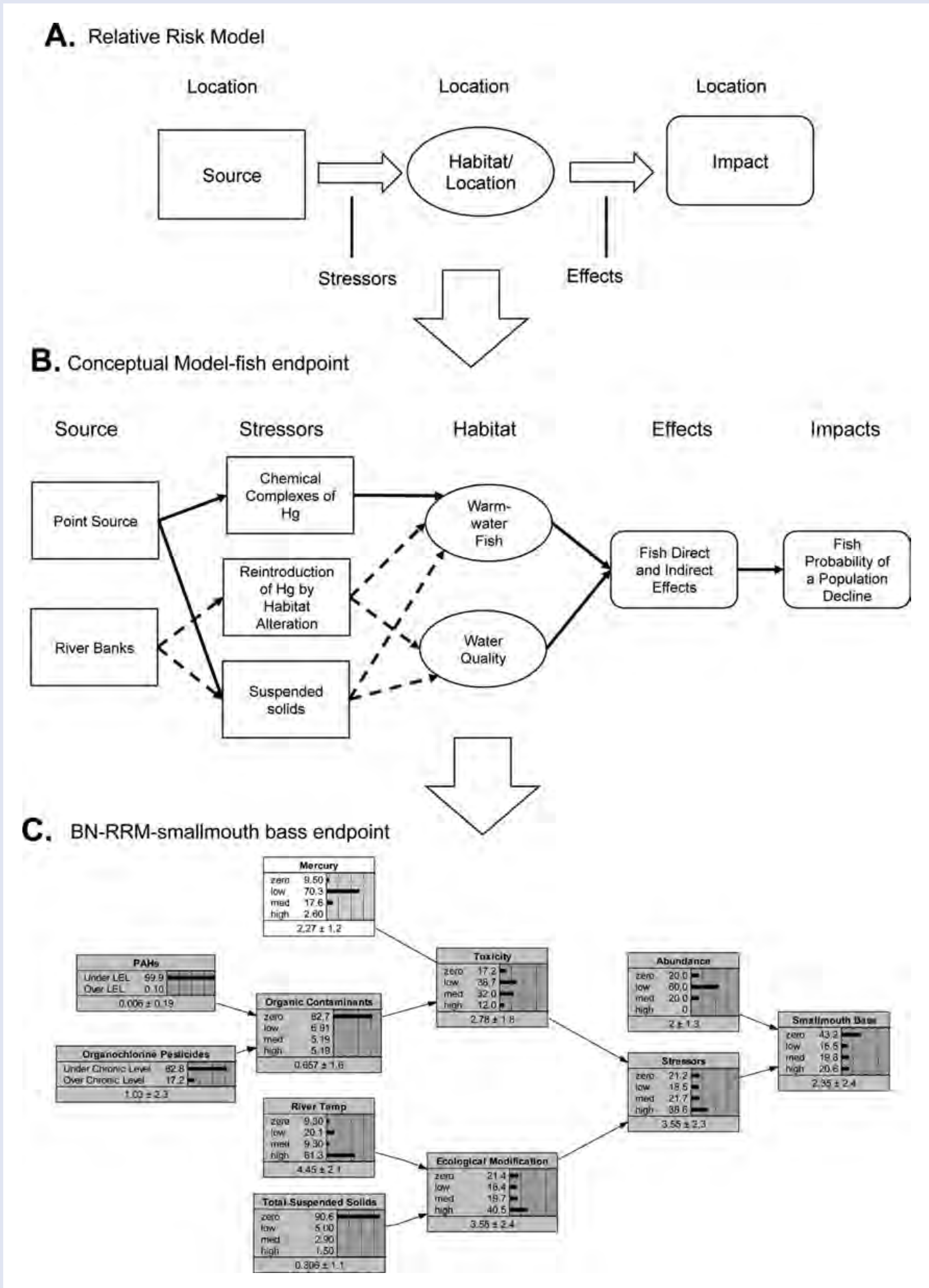


Figure 1. The RRM is used to develop a conceptual model that becomes the template for the Bayesian network. In this example, the conceptual model represents all fish endpoints and the BN is specific to the smallmouth bass endpoint.

*Regional scale risk assessment and the relative risk model*

Hunsaker et al. (1990) described the need for landscape-scale approaches during the early formulations of ecological risk assessment. Realizing that requirement has been a challenge. The assessment of the fjord of Port Valdez by our research group led to the development of the relative-risk model (RRM) (Landis and Wiegers 1997, 2005, 2007; Wiegers et al. 1998) (Figure 1A). The impetus for the development of the RRM was the necessity of incorporating multiple sources with multiple stressors within multiple, diverse habitats that were potentially affecting multiple endpoints within the fjord, as well as in the surrounding watershed. At that time, there was not a suitable framework to use on such a complex site at a landscape scale. The RRM has now been used at multiple locations and for marine, freshwater, and terrestrial environments (Landis and Wiegers 2007).

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

*Bayesian networks and the Bayesian network relative-risk model*

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

- *Node*: A variable that can be divided into a number of states
- *State*: Conditions of the variable often depicted as numerical ranges or ranks
- *Parent or input node*: A node that provides information to another node
- *Child or conditional node*: The node that receives information from a parent node
- *Link*: The graphical representation of the causal link between parent node(s) and child node(s).
- *Conditional Probability Table (CPT)*: This table describes the conditional probabilities between the occurrence of states in the parent nodes and the resulting probabilities of states in the child nodes.

In the mid-2000s, Bayesian networks (BNs) were introduced as a tool for ecological risk assessment (Pollino et al. 2007; Hart and Pollino 2008) and natural resource management (Marcot et al. 2006). Since then, BNs have been used in a variety of ecological risk assessment and natural resource management applications. For example, Bayliss et al. (2012) used BNs to describe the sources of risk in the Kakadu National Park and to demonstrate that nonpoint sources contributed the most risk to the valued components of that region. Bayesian networks are now used increasingly in risk assessment (Uusitalo 2007; Hart and Pollino 2008) because they inherently deal with cause–effect relationships and uncertainty and also use combinations of available data and expert knowledge (Uusitalo 2007).

Ayre and Landis (2012) demonstrated how BNs could be used in conjunction with the RRM for forest management. The causal framework of the RRM can be directly translated into the tiered node structure of a BN (Figure 1) (Ayre and Landis 2012; Hines and Landis 2014). In addition, the application of BNs to evaluate management scenarios and to set management guidelines was immediately apparent. Since 2012, the integrated Bayesian network relative risk model (BN-RRM) has been used for a variety of assessments. Ayre et al. (2014) used the BN-RRM to estimate risk due to whirling disease in cutthroat trout in the Southwestern United States. Hines and Landis (2014) and Herring et al. (2015) applied the BN-RRM to estimate both risk and the efficacy of suggested management tools to a large watershed and a marine reserve, respectively.

*The South River case study*

Stahl et al. (2014) presented the background for the South River and a general approach for conducting ecological risk assessment for the Resource Conservation and Recovery Act (RCRA) site. In summary, the South River and its watershed is a legacy site contaminated with Hg that was released to the river as a waste product during a manufacturing process from the late 1920s to the early 1950s. Urbanization and agriculture in the South River watershed have introduced other stressors to the region. In 2001, E.I. du Pont de Nemours and Company (DuPont) and the Commonwealth of Virginia established a multi-stakeholder and collaborative group, the South River Science Team (SRST), to address the assessment and management of the South River. The use of regional scale risk assessment for the South River is summarized in Stahl et al. (2014).

*Study findings*

There are 5 specific findings that are presented in the body of this report.

1) The BN-RRM models allowed us to 1) calculate risk from contaminants and environmental stressors to 8 endpoints, and 2) quantify uncertainty and conduct sensitivity analyses across the entire study region.
2) Risk varied among risk regions according to location, type, and quality of habitat, and exposure to stressors within the

 

landscape. Both chemical and ecological stressors influenced the spatial patterns of risk.
3) Overall risk to abiotic endpoints was greater than overall risk to biotic endpoints and less spatially variable than risk to the biotic endpoints. By including both biotic and abiotic endpoints, we are able to compare risk to endpoints that represent a wide range of stakeholder values.
4) Although Hg reduction is the regulatory priority for the South River, Hg is not the only stressor driving risk to the endpoints. Ecological and habitat stressors contribute risk to the endpoints and should be considered when managing this site. Additionally, areas of higher risk do not necessarily correspond to the initial site of Hg contamination.
5) The findings of this analysis have provided a framework for decision making regarding management options and delineated long-term monitoring priorities in the study area.

## MATERIALS AND METHODS

### *Study area*

The South River is located in Augusta County, Virginia in the Shenandoah Valley (Figure 2). The headwaters of the South River form southwest of Waynesboro, Virginia and flow northward for 84.7 km until merging with the Middle River and North River in Port Republic, Virginia to form the South Fork of the Shenandoah River (Eggleston 2009).

The South River Study Area (SRSA) encompasses the approximately 600 km$^2$ South River watershed and a portion of the South Fork of the Shenandoah River. We divided the SRSA into 6 risk regions based on hydrological sub-basins and land use similarities (Figure 2). Risk Region 1 encompasses the headwaters of the South River. Risk Region 2 includes the town of Waynesboro and the former DuPont facility. Regions 3 through 5 are downstream of Waynesboro, and Risk Region 6 begins where the South River merges with the North River to form the South Fork of the Shenandoah River. Risk was assessed in Regions 2 through 6; risk was not assessed in Region 1 due to lack of site-specific monitoring data.

The primary land uses in study area are forestry (58%), agricultural (31%), and urban (8%) (Eggleston 2009). The eastern portion of the watershed is forested and the western portion is composed of the urban and agricultural land uses (Figure 2). The city of Waynesboro accounts for most of the urban area and is the location of the Hg released into the South River.

### *Endpoints*

Eight assessment endpoints were selected for this risk assessment. The 4 biotic endpoints were smallmouth bass (SMB), white sucker (WS), belted kingfisher (BK), and Carolina wren (CW). The 4 abiotic endpoints were compliance with Water Quality standards (WQ) and 3 recreational services endpoints, specifically Fishing River Use (WF), Swimming River Use (WS2), and Boating River Use (WB). Further discussion of the endpoints follows.

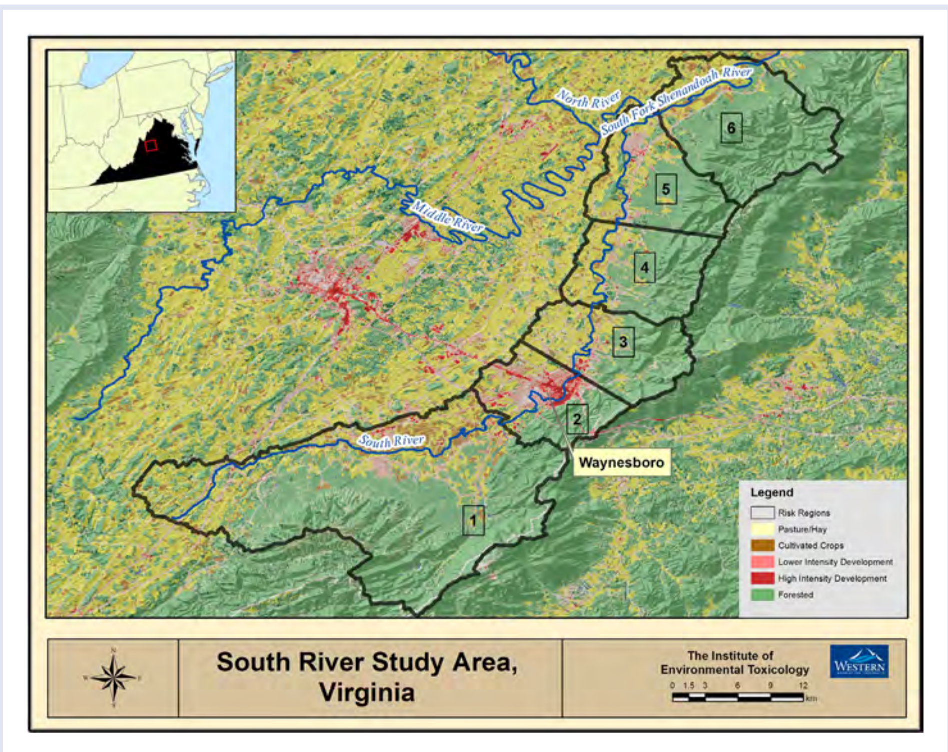


Figure 2. South River and South River Study Area, Virginia, USA with risk regions and land use. Waynesboro in Risk Region 2 is the site of the Hg input into the South River and also the largest urbanized development in the study area.

*Biotic endpoints.* Smallmouth bass (*Micropterus dolomieu*) are a resident piscivorous fish species of the South River. They are an important recreational fish in this watershed and are valued by both harvest and catch-and-release anglers (DelVecchio et al. 2010). Smallmouth bass are secondary consumers in the aquatic food chain; through dietary exposure, smallmouth bass biomagnify methylmercury (MeHg) and other persistent organic pollutants. White sucker (*Catostomus commersoni*) were selected as an endpoint to represent fish species at a lower trophic level than SMB (Murphy et al. 2005). As bottom feeders, WS represent a different Hg exposure pathway than SMB because they are in contact with sediment-associated contaminants.

The belted kingfisher (*Megaceryle alcyon*) and Carolina wren (*Thryothorus ludovicianus*) were chosen as endpoints for their value to recreational bird watchers and outdoor enthusiasts. They are unique endpoints in that they differ in life histories, diet, and habitat preferences. Belted kingfishers are found along the shores of rivers, lakes, streams, and marshes, where they nest and feed on crustaceans, amphibians, insects, and fish. They make nests by burrowing in the banks of lakes and rivers. As such, they acquire and biomagnify MeHg from aquatic food sources and contact with contaminated soils and sediments in nesting areas. The Carolina wren represents a different pathway of MeHg exposure from the BK. They are found on or near the ground or in understory vegetation and obtain MeHg primarily by eating contaminated ground insects and spiders (Rimmer et al. 2005; Cristol et al. 2008). Wrens nest on the ground, in trees, and even in barns or abandoned buildings.

*Abiotic endpoints.* The 4 abiotic endpoints (WQ, WF, WS2, and WB) represent the respective risks of exceeding site-specific water quality criteria for the protection of aquatic life under the Clean Water Act, as well as recreational use of the river. The recreational endpoints include popular recreational uses of the South River: fishing, boating, swimming, and observing wildlife (Bugas 2005, 2011).

### *Sources and stressors*

We identified stressors and sources of stressors in the SRSA that were most likely to affect the selected endpoints, and result in risk to both aquatic life and recreational users. These included the Hg contamination, as well as chemical and ecological stressors from past and current urban and agricultural land use.

*Mercury.* Mercury contamination in the South River originated from a textile manufacturing plant located in Waynesboro, Virginia that was owned and operated at the time by DuPont. Mercury sulfate was used as a catalyst in the manufacturing process from 1929 to 1950, and inadvertent releases resulted in widespread Hg contamination of the river and floodplain (Bolgiano 1980). Agricultural fungicides, atmospheric deposition, and leaking hydraulic seals in industrial equipment were other documented sources of Hg but were all considered insignificant sources compared to the amounts of Hg released from the plant (Stahl et al. 2014).

Mercury on soils and sediments continues to be a source to the watershed through stormwater runoff, flooding, and erosion of river sediments and floodplain soil (Stahl et al. 2014). Fish tissue Hg concentration in the South River exceeds the guideline of 0.3 mg/kg wet weight (Eggleston 2009), and as such, there is a fish consumption advisory. Contaminant concentrations measured in the biotic receptors and environmental media (surface water, sediment, and soils) were used as measures of exposure or potential exposure to these stressors.

*Chemical stressors.* Two common classes of contaminants that are associated with urban and agricultural land use were included in this risk assessment: PAHs and organochlorine pesticides. Similar to the Hg data, site-specific contaminant concentrations were used as measures of exposure or potential exposure to these stressors.

*Ecological stressors.* Regulation and management of river water quality is often based on measurements of physical, chemical, and biological characteristics, because these metrics can be easily monitored and compared to established benchmarks for protecting human health. Not all of these metrics have the same influence on valued ecological resources, with some having a more direct influence than others. An extensive literature review was conducted to determine which metrics, or stream attributes, had causal pathways connecting them to one or more of the assessment endpoints. River temperature, total suspended solids (TSS), avian nest predation, available habitat, submerged aquatic vegetation, dissolved $O_2$, bacterial indicators, total P, and river discharge regime were included as potential stressors. The most applicable stressors were evaluated for each endpoint.

### *Derivation of the BN-RRM models for the South River*

Using the BN-RRM approach (Figure 1), the basic form of the RRM (Figure 1A) is converted into a site-specific conceptual model for the South River study area (Figure 1B). The conceptual model describes the cause–effect linkages that will be used to estimate risk. In this study, we developed 5 conceptual models: 1 for each of the 4 biotic endpoints, and a single model for the 4 abiotic endpoints. Individual models for the endpoints were then created for each risk region. The structure and relationships of the model remain the same for each risk region, but the input parameters change based on region-specific data. In total, risk was calculated for 8 endpoints and 5 risk regions, for a total of 25 models.

We used Netica$^{TM}$ by Norsys Software (http://www.norsys.com/) to build BNs with the same structure as the conceptual models (Figure 1C). Within Netica, probabilistic relationships between variables are defined with CPTs, ranks and appropriate inputs are specified, and risk probabilities and scores are calculated. We present 2 BN models for Risk

 

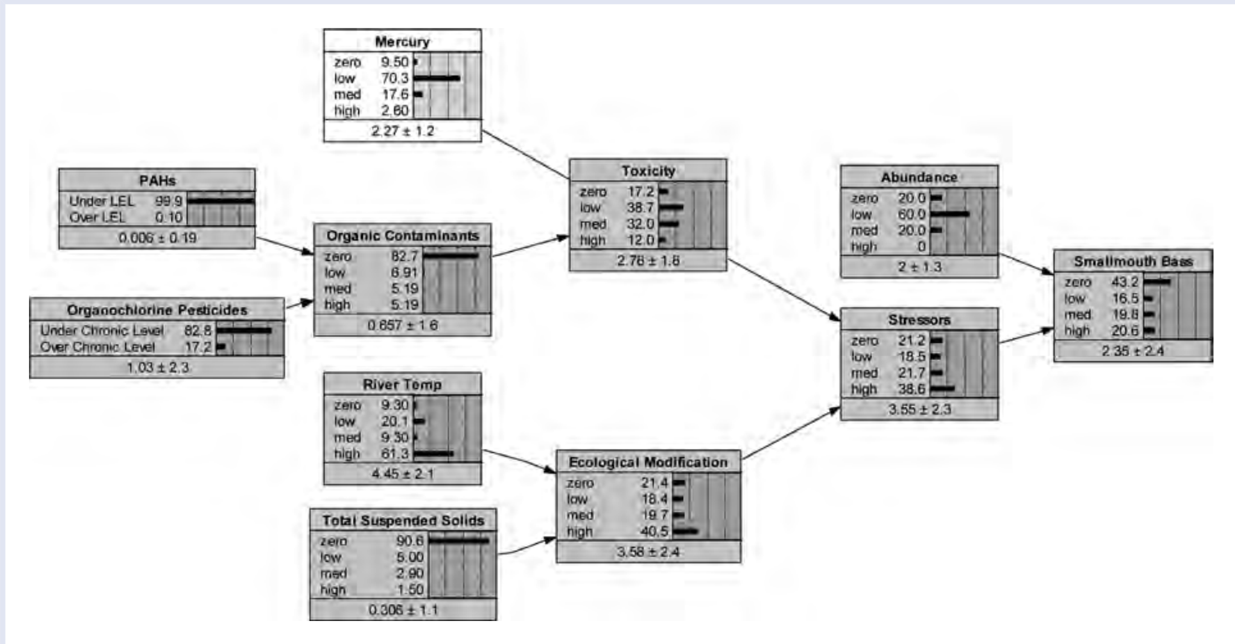


Figure 3. The smallmouth bass Bayesian network for Risk Region 2.

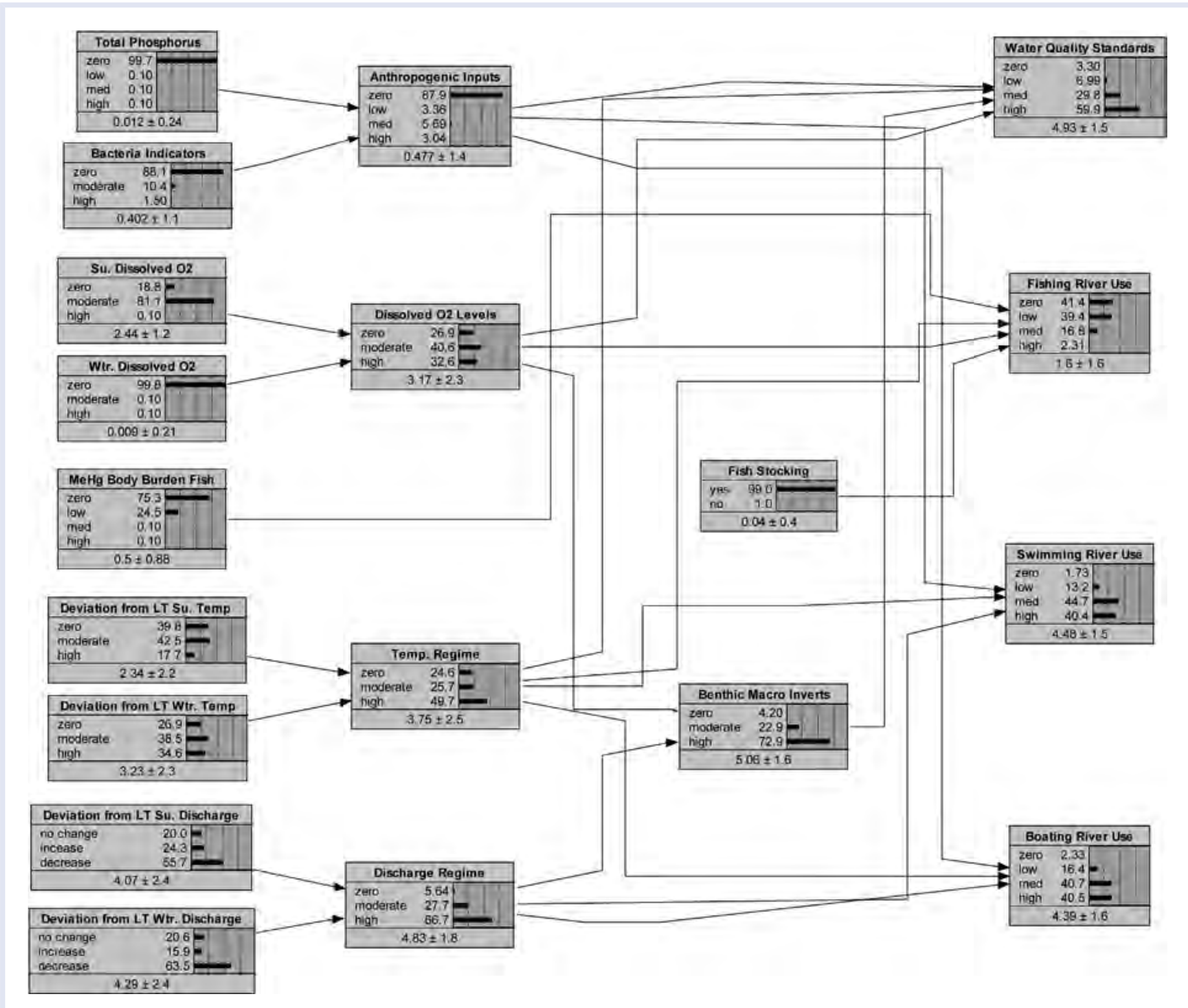


Figure 4. Bayesian network to calculate risks to the abiotic endpoints in Risk Region 2.

Region 2 as examples: the SMB BN (Figure 3) and the abiotic BN (Figure 4). The complete set of BNs for each endpoint for Region 2 are available in the Supplemental Data as Netica files. Directions for reading the files can be found in the section *"Notes for viewing the BN models."*

*Development of the biotic conceptual models.* We used the same basic structure for all target species (SMB, WS, BK, and CW) and selected the stressors most applicable to each endpoint. Stressors were grouped into 3 categories of inputs: 1) chemical stressors, such as Hg, PAHs, and organochlorine pesticides; 2) ecological stressors, such as temperature, turbidity and TSS, submerged aquatic vegetation, and nest predation; and 3) exposure, which was measured through abundance for the fish endpoints and potential habitat and territory size for the bird endpoints. Organisms must be present to be exposed before a toxic or ecological modification effect can develop. To express the potential exposure of the fish species to a contaminant in a spatially explicit manner, we compared the abundance of each species within each risk region to the total abundance in the SRSA. The proportion represents the relative species abundance in each region and is used in the models to represent potential exposure.

In most cases, site-specific data were available for the input nodes (i.e. the stressors and measure of exposure) in the model (Figures 3 and 4). Summary or intermediate nodes (i.e. the Toxicity and Ecological Modification nodes) were used to organize information, summarize the effects of stressors in each category, and balance the structure of the model. All of the nodes feed into a final endpoint node.

*Derivation of the abiotic model.* The chemical and biological parameters were known to cause direct or indirect effects on fish or other biota, and they included fish MeHg body burden, dissolved $O_2$, fecal coliform bacteria (*E. coli* concentrations), and total P concentrations (Figure 4). Physical or hydrologic parameters included in the model were the magnitude of deviations in stream temperature and water discharge relative to long-term seasonal averages. Similar to the biotic model, summary nodes were used in the abiotic model to organize and summarize the model inputs (Figure 4). The 4 endpoints (WQ, WS2, WF, and WB) summarized the effects of 3 to 4 nodes and described the risk to the endpoint.

*Informing the model.* The BN-RRM framework uses multiple types of data to inform the variables and relationships in the model. Informing the model can be broken down into 3 steps, which are described in further detail in the following paragraphs. The sources of data and information used in this model are documented in Supplemental Data Tables S1 and S2.

1) Set a ranking scheme for each node (parent and child nodes).
   Each variable (node) in the models was discretized into states, or ranks. In most cases, we created 4 states and designated them as zero, low, medium, and high; a method used in previous risk assessments by Hayes and Landis (2004), Colnar and Landis (2007), Hines and Landis (2014), and Herring et al. (2015). The states were assigned a numeric ranking value (zero = 0, low = 2, medium = 4, high = 6) that is used for calculating risk scores to the endpoint.
   Ranking schemes were set using regulatory criteria, published adverse impacts data, or natural breaks in the dose-response curve data. When none of these were available, the following general rule was used: zero = <5% effect; low = 5% to 20% effect; medium = 20% to 50% effect; and high = ≥50% effect. For some nodes, such as PAHs and organochlorine pesticides, we used fewer ranks because our literature search did not produce information to support a dose–response relationship. Therefore, a single benchmark such as the National Oceanic and Atmospheric Administration's (NOAA) low effects limit screening reference value was used to create 2 ranks: above or below the benchmark. A detailed justification for each input node is presented in Tables S1 and S2.

2) Calculate a frequency distribution for each input (parent) node using site-specific data.
   Based on the ranking scheme, a frequency distribution for each of the inputs nodes was calculated for each risk regions. As such, each risk region had its own set of 4 biotic BN models and an abiotic model with different inputs. The SMB and abiotic BNs with parameterized input distributions for Risk Region 2 are shown in Figures 3 and 4, respectively.
   The input data used in this research were spatially explicit, which was useful for analysis and communication of risk results. Land use data from the United States Geological Survey (USGS) and Light Detection and Ranging (LIDAR) images from the SRST were used in the analysis and cartography. Most of the biotic and water quality data were provided by the SRST from site-specific studies conducted over several years. Additional stream data were obtained from USGS gauges (USGS 2014a, 2014b, 2014c, 2014d) and NOAA (2014).
   Because of the bank stabilization strategies implemented in 2005 (Flanders et al. 2010), we targeted using chemical exposure data sets collected after 2005. For some chemicals, however, there were not enough data collected during that time frame to adequately parameterize the model. As a result, input parameters for PAHs were expanded to included data collected from 2003 to 2010, and for organochlorine pesticides from 2003 to 2007 for all target species. Input parameters for MeHg body burden in BK and CW included all available data collected from 2003 onward.

3) Complete a conditional probability table (CPT) for each intermediate and endpoint node to describe and quantify the relationships between two or more variables.

| River Temp | Total Suspended Solids | zero | low | med | high |
|---|---|---|---|---|---|
| zero | zero | 100 | 0 | 0 | 0 |
| zero | low | 70 | 30 | 0 | 0 |
| zero | med | 20 | 30 | 40 | 10 |
| zero | high | 10 | 15 | 30 | 45 |
| low | zero | 50 | 50 | 0 | 0 |
| low | low | 25 | 50 | 25 | 0 |
| low | med | 10 | 30 | 45 | 15 |
| low | high | 0 | 15 | 25 | 60 |
| med | zero | 5 | 30 | 45 | 20 |
| med | low | 0 | 20 | 50 | 30 |
| med | med | 0 | 10 | 40 | 50 |
| med | high | 0 | 5 | 20 | 75 |
| high | zero | 5 | 10 | 25 | 60 |
| high | low | 0 | 5 | 20 | 75 |
| high | med | 0 | 0 | 15 | 85 |
| high | high | 0 | 0 | 0 | 100 |

Figure 5. Conditional probability table (CPT) from the Netica$^{TM}$ software for the Ecological Modification summary node. To complete the CPT, the corners (zero, zero and high, high) were assigned values of 100%, the moderate states were filled in with River Temp having a greater influence than TSS on Ecological Modification. The remaining probabilities were interpolated.

Links, or arrows, in the BNs were based on known cause–effect pathways. In the BNs, each link connecting 2 or more parent nodes to a daughter node relied on a CPT to quantify the relationship and calculate the distribution of the daughter node. The CPTs are shown as matrixes in Netica and contain the probabilities of the daughter node states given all possible combinations of the parent node states (Figure 5). Each possible combination is shown as a row, and the row must sum to 100%. The CPTs can be viewed by opening the Netica files provided in the Supplemental Data.

Conditional probability tables can be completed using a variety of methods depending on the data available. These methods can be broken down into 4 categories: expert judgment, empirical evidence, mathematical or biological equations, and case file learning (Marcot et al. 2006; Pollino et al. 2007; Chen and Pollino 2012). The BN approach is easily adapted depending on the data available. In a single model, CPTs for different nodes may be completed using different methods (Chen and Pollino 2012) or combination of methods may be used within a single CPT (Pollino et al. 2007).

The South River BN-RRM models relied predominantly on expert judgment, feedback from the SRST, and empirical evidence from an extensive literature search to define the CPTs. Figure 5 depicts the CPT for the Ecological Modification node as shown in Netica. Marcot et al. (2006) described an approach for filling out CPTs that was often used; where first the extreme cases are set to 0% or 100%. Then, the probabilities for either a known combination of states or the most moderate combination is set. The remaining combinations are interpolated between the known or moderate case and the extreme cases (Marcot et al. 2006). This method is particularly useful for the initial construction of BNs and when incorporating a breadth of information as in the case of the South River.

Some variables are known to have more influence on an endpoint; those variables were identified through analysis of pertinent literature and elicitation from the SRST. This effect is reflected in the daughter node CPT with that parent node state having a greater influence on the resulting state. As a specific example, in the SMB BN (Figure 3), the interactions between the River Temperature node and Total Suspended Solids node are described by the Ecological Modification node. River Temperature affects both spawning and growth of SMB whereas TSS mainly affects prey consumption; thus River Temperature had a greater influence on the CPT (e.g., if River Temperature is high, Ecological Modification is more likely to be high even when TSS is zero). In summary, the Ecological Modification node describes the overall impact of both factors.

Once all of the CPTs are complete, the model can be run and the results evaluated. Multiple iterations of the CPTs (beta models) were created to test the behavior of the model before a model was finalized. In addition, sensitivity analysis (described later) was used to test and adjust the CPTs to reflect site specific knowledge and known relationships.

*Risk calculation and model evaluation*

Netica uses probabilistic inference to update the intermediate and endpoint nodes based on the input probabilities and CPTs (Norsys Software 2014). The final result for each endpoint is a risk distribution and a risk score (the mean of the distribution). Risk scores are continuous; in these models, risk scores range from 0 to 6. Very different distributions may have similar mean values, hence the risk scores should be considered in that context. Although risk scores facilitate the communication of general trends, risk distributions are useful for conveying specific information about patterns of relative risk and comparing differences in risk by region or by year. There is no assumption of a normal distribution of the risk results; rather, distributions reflect the actual frequencies from the model calculations.

*Uncertainty evaluation.* Uncertainty in any model input was incorporated into the input frequency for that node. When data were unavailable for a particular input parameter, equal probabilities were assigned to each of the states for that node (25% in the zero, low, medium, and high states). Uncertainty in the model inputs was translated through the model as wider probability distributions of the intermediate and endpoint nodes.

Feedback was provided from the SRST on model structure. For example, concerns were raised on the importance of water temperature in the estimation of risk to smallmouth bass. Given that the fish was native to the region, risk due to temperature seemed unwarranted. A further analysis of this input was conducted that demonstrated that temperature tolerances at both the cold and warm temperature ranges were being exceeded. On presentation of these results to the SRST the experts concurred with the analysis. Details of the determination of the Smallmouth Bass Temperature Node are included in the Supplemental Data section.

*Sensitivity analysis.* Sensitivity analysis compares the relative influence of input nodes on the endpoint (Pollino et al. 2007; Marcot 2012). It can be used to understand which variables contribute the most risk to the endpoint (Pollino et al. 2007; Marcot 2012; Hines and Landis 2014).

We performed a sensitivity analysis on each BN that was created for the study (25 BNs total). The "Sensitivity to Findings" tool within Netica was used to run this analysis. "Sensitivity to Findings" measures mutual information between each of the input nodes and the endpoint node (Pollino et al. 2007; Norsys Software 2014). A high value of mutual information for an input indicates a greater degree of influence on the endpoint node (Marcot 2012). Mutual information is a function of both the findings in the node (input frequency) and the relationship described in the CPT (Marcot 2012; Norsys Software 2014).

Results of the sensitivity analysis were used evaluate the model structure, interpret the risk results, and provide further information to the risk managers as to the sources of risk to the endpoint.

## RESULTS

### BN-RRM models

Figures S1A through S1E present images of the BNs for the biotic and abiotic endpoints respectively using Region 2 as an example. The BN figures show the probability distributions of input nodes, intermediate nodes and endpoint nodes. The Netica file for each BN model is also available in the Supplemental Data. These models can be examined using the free version of Netica software.

### Risk patterns for the South River

One of the challenges in large-scale risk assessment is summarizing the patterns of risk in the landscape. This section presents the relative risk estimates for the biotic and abiotic endpoints in Regions 2 through 6. The results are presented in 2 ways: as risk scores and risk distributions. For the first, the advantage of using risk scores is that it gives an overview of the patterns in a user-friendly format for those not familiar with interpreting distributions. These findings are summarized in Table 1. In the second, we present the results as probability distributions of risk in each of the risk regions. Two examples of risk distributions are given in Figure 6; the remaining distributions are provided in the Supplemental Data. The results are similar between the 2 presentations, but the risk distributions provide more information.

*Risk scores.* Among the biotic endpoints, SMB had the highest risk in Regions 4 and 5 (risk scores of 4.3 and 4.5, respectively; Table 1). Carolina wren had a similar pattern of risk as the SMB (highest risks in Regions 4 and 5), but with lower risk relative to the other endpoints. White sucker and BK had the highest scores in Region 2. All biotic endpoints except WS had lower risk in Region 6 compared to Region 5.

For the abiotic endpoints, WQ, WS2, and WB had comparable risk scores in every region. Risk to WQ was higher than risk to WS2 and WB in Regions 2 and 5; risk to WB and WS2 was higher than risk WQ in Region 6. Risk to WF was low in all regions with risk scores ranging from 1.2 to 2.1 (Table 1).

Table 1. Mean risk scores for the endpoints by risk region

| | Biotic endpoints | | | | Abiotic endpoints | | | | Totals | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Region | SMB | WS | BK | CW | WQ | WF | WS2 | WB | Biotic | Abiotic | Overall |
| 2 | 2.4 | 3.6 | 2.5 | 1.1 | 4.9 | 1.6 | 4.5 | 4.4 | 9.6 | 15.4 | 25.0 |
| 3 | 2.7 | 3.1 | 1.5 | 1.9 | 4.5 | 1.5 | 4.6 | 4.6 | 9.2 | 15.2 | 24.4 |
| 4 | 4.3 | 2.4 | 2.1 | 3.0 | 4.5 | 2.1 | 4.3 | 4.2 | 11.8 | 15.1 | 26.9 |
| 5 | 4.5 | 1.3 | 2.2 | 2.9 | 4.8 | 1.9 | 4.8 | 4.7 | 10.9 | 16.2 | 27.1 |
| 6 | 3.3 | 1.7 | 1.5 | 2.5 | 4.3 | 1.2 | 4.6 | 4.5 | 9.0 | 14.6 | 23.6 |
| Totals | 17.2 | 12.1 | 9.8 | 11.4 | 23.0 | 8.3 | 22.8 | 22.4 | 50.5 | 76.5 | 127.0 |

BK = Belted Kingfisher; CW = Carolina Wren; SMB = Smallmouth Bass; WB = Boating River Use; WF = Fishing River Use; WQ = Water Quality Standards; WS = White Sucker; WS2 = Swimming River Use.

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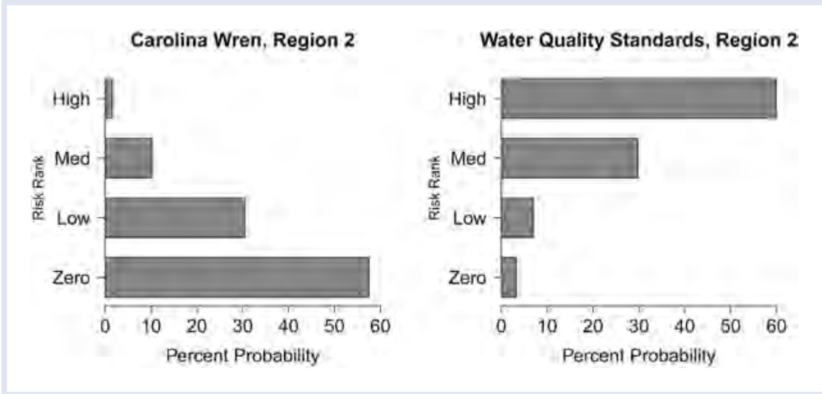


**Figure 6.** Comparison of probability distributions for 2 endpoints: Carolina Wren and Water Quality Standards in Risk Region 2.

*Risk state distributions.* Figure 6 provides examples of the risk distributions for the CW and WQ endpoints. The distribution of risk for each endpoint is represented by the horizontal bands in each of the 4 discrete risk states and characterizes the percent probability of any given risk state. The risk distributions for all endpoints by every risk region are presented in Figure S2.

Similar to the risk scores results, SMB were at greatest risk among the biotic endpoints, with 74% and 77% probability in the medium and high-risk states for Regions 4 and 5, respectively. White sucker had the second highest risk with probabilities of 54% and 64% in the medium and high-risk states. Elevated risk (measured as the combined medium and high-risk states) varied most for the WS and CW between the 5 risk regions. Similar again to the risk score results, the risk distributions showed elevated risk to both fish endpoints when compared to the bird endpoints in all the risk regions. Risk to the biotic endpoints was not localized in any one risk region, but varied across the study area landscape.

The probability distributions for the risk states of the WQ, WS2, and WB endpoints were skewed toward the medium and high risk states. For instance, the probability of combined medium and high risk ranged from 77.9% to 89.7% for WQ, 80% to 90% for WS2, and 78% to 88% for WB among the 5 risk regions. Water quality, Boating, and Swimming endpoints had similar risk patterns in Regions 3 and 5; Swimming and Boating were also similar to one another in Region 6. Fishing River Use was at a lower risk throughout the SRSA compared to the other endpoints, with the probability of combined medium and high risk ranging from 12% to 33% across regions. Risk to WF was lowest in Regions 2, 3, and 6, with distributions of risk skewed to the zero and low-risk states (66%–87.7%; Figure S2).

*Overall risk to biotic and abiotic endpoints*

To understand spatial patterns in overall risk, we summed risk to the endpoints to obtain overall risk scores for each region. For all biotic endpoints combined, Region 4 had the greatest risk and Region 5 had the second greatest risk (Table 1). For all abiotic endpoints, Region 5 had the greatest total risk and Region 6 had the least risk (Table 1). When considering all 8 endpoints (biotic and abiotic), Region 5 had the greatest overall risk. Region 4 and 2 had the next greatest risk, Region 3 was intermediate, and Region 6 had the lowest risk overall (Table 1).

By summing risk across regions, we can compare risk to each endpoint for the entire SRSA. The SMB was the biotic endpoint at the highest risk in the SRSA and the BK was at the lowest risk overall (Table 1). There was risk associated with the fish species (SMB and WS) when compared to the bird species (BK and CW). The abiotic endpoint at highest risk was WQ, though the overall risk to WS2 and WB were comparable (Table 1). Overall, the abiotic endpoints were at higher total risk than the biotic endpoints for every risk region individually and for the SRSA as a whole.

*Results of the sensitivity analysis*

The sensitivity analysis revealed that the stressors most important to the biotic endpoints were a combination of chemical and ecological stressors and varied by endpoint. A full summary of the top parameters determined in the sensitivity analysis can be found in Table 2.

Figure 7 provides the sensitivity analysis results for 2 biotic endpoints, SMB and CW, and 2 abiotic endpoints, WQ and WF for all risk regions. The input parameters with the greatest influence on the SMB were River Temperature and fish tissue Hg, with River Temperature having a slightly greater influence. For the CW, fish tissue Hg and Nest Predation were important parameters influencing risk. Mercury in tissue was the largest contributor of risk to both CW and BK in Regions 3, 4, and 5.

The sensitivity analysis for the abiotic endpoints (Figure 7; Table 2) indicated that most of the endpoints were influenced by the Summer and Winter River Temperatures, as well as by discharge. The WQ endpoint was most influenced by Summer Dissolved $O_2$ and Bacteria Indicators. The WF endpoint was also affected by the Summer Dissolved $O_2$ levels, as well as by Hg in fish.

*Interactive use of the BN-RRM*

Using the results of the sensitivity analysis, we calculated the reduction in risk when input parameters that had the greatest influence were set to the lowest possible state (100%

 

Table 2. Summary of sensitivity analysis to biotic and abiotic endpoints

| Endpoint | Input parameter |
|---|---|
| Belted Kingfisher | Hg (5) – blood samples |
| | Fish length (5) |
| | Potential habitat (2) – land use type (%) |
| | Territory (3) – nests per length of river section (m) |
| Carolina Wren | Hg (4) – blood samples |
| | Nest predation (5) |
| | Potential habitat (2) – land use type (%) |
| | Winter air temperature (4) |
| Smallmouth Bass | River temperature (5) |
| | Hg (5) – Fish fillet Hg concentrations |
| White Sucker | River temperature (5) |
| | Stream cover (5) – submerged aquatic vegetation cover (%) |
| | Hg (4) – fish fillet Hg concentrations |
| | PAHs (1) |
| Water Quality Standards | Dissolved $O_2$ (5) – Summer dissolved $O_2$ |
| | Bacteria (4) – bacteria indicators (*E. coli*) |
| | River temperature (3) – Winter temperature |
| | River discharge (3) – Summer and Winter discharge |
| Fishing River Use | Dissolved $O_2$ (5) – Summer dissolved $O_2$ |
| | Methylmercury (4) – fish fillet Hg concentrations |
| | River temperature (5) – Summer and Winter temperature |
| Swimming River Use | Bacteria (4) – bacteria indicators (*E. coli*) |
| | River temperature (5) – Summer and Winter temperature |
| | River discharge (1) – Summer discharge |
| Boating River Use | River temperature (5) – Summer and Winter temperature |
| | Bacteria (4) – bacteria indicators (*E. coli*) |
| | River discharge (1) – Winter discharge |

The input parameters listed are those that had the greatest reduction in entropy for each endpoint. The number following the input parameter (e.g., Hg (5)) indicates the number of regions in which that parameter was important in the sensitivity analysis.

in the zero state). For instance, if remediation achieved the 100% zero risk state for Hg in fish, we could see an 8% to 42% reduction of risk to the BK, and a 16% to 35% reduction to SMB. If we achieved the zero state of low Summer Dissolved $O_2$, we would expect to see an 11% to 27% decrease in risk to the WQ endpoint and a 38% to 68% reduction of risk to the WF endpoint.

*Results with low Hg.* We set the Hg nodes in all of the models (all endpoints, all regions) to 100% probability of the low-risk state and recalculated risk. There was a decrease in risk to all biotic endpoints from 6% to 16% and a decrease in risk for the WF endpoint by 18% to 25% for Regions 3, 4 and 5. There was no change to the other abiotic endpoints, WS2, WB, and WQ.

## DISCUSSION

*Risk estimates for biotic endpoints.* The patterns of risk in the landscape varied by endpoint. Risk to smallmouth bass was highest in 2 risk regions further from the original Hg source. In contrast, white sucker was at highest risk in the regions closest to the Hg source. These patterns were likely attributed to environmental conditions, differences in species life history, sensitivity to stressors, and probability of exposure. The greatest contributors of risk to smallmouth bass risk were River Temperature and Fish Tissue Hg. We hypothesize that the concentration gradient of Hg body burden, which peaks in Regions 4 and 5, explains the increased risk to SMB in Region 5, downstream of the Hg source.

Carolina wren and belted kingfisher were generally at lower risk than the fish species (SMB and WS). Based on the sensitivity analysis, bird species are less sensitive to ecological stressors than the fish species, meaning that risk is largely a function of Hg exposure. Bird species have a greater ability to sequester and eliminate Hg from their bodies by depositing Hg in their eggs and feathers, whereas fish do not have as sophisticated a method for Hg elimination (Cristol et al. 2008; Jackson et al. 2011). The birds are generally thought to overwinter in the study area, but have access to nearby, less contaminated river systems such as the Middle and North rivers. The prey organisms in these near-by systems have much lower levels of Hg and MeHg (White 2007; Cristol et al. 2008), resulting in the birds having reduced exposure compared to the fish confined in the more contaminated South River.

*Risk estimates for abiotic endpoints.* Risk to the abiotic endpoints exceeded risk to the biotic endpoints, with the exception of WF that had lower risk than the other water quality endpoints. Risk to the abiotic endpoints was less spatially variable than risk to the biotic endpoints and was driven primarily by ecological stressors. Fecal coliform bacteria and deviations from historic river temperature and stream flow conditions contributed risk to the abiotic endpoints. Risk to the WQ was most influenced by Spring and Summer dissolved $O_2$ levels and fecal coliform bacteria contamination.

The South River was first listed as an impaired river under section 303(d) of the Clean Water Act in 1996 for failure to meet the federal standard for benthic macroinvertebrate

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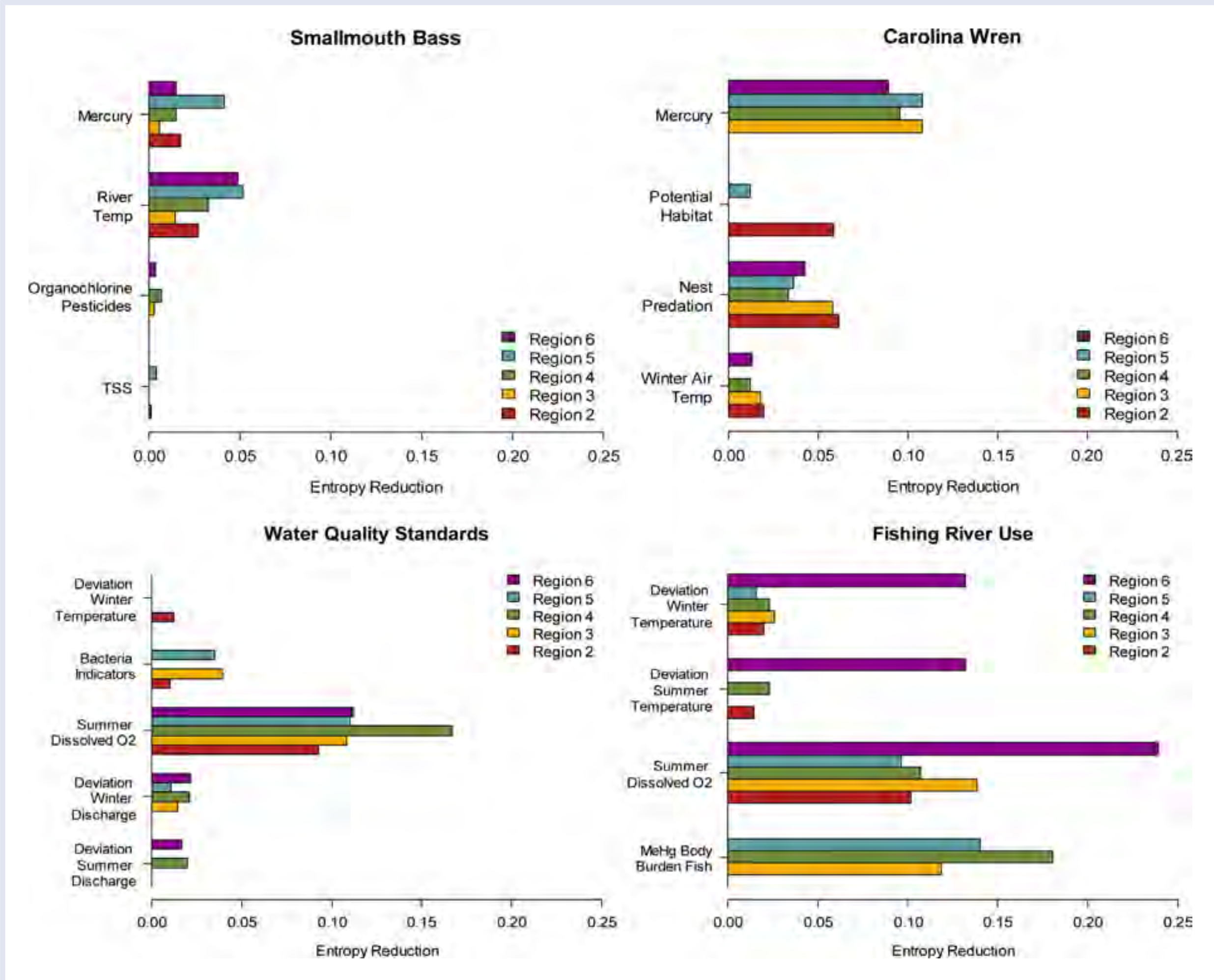


Figure 7. Comparison of entropy reduction (sensitivity analysis) results for Smallmouth Bass, Carolina Wren, Water Quality Standards, and Fishing River Use endpoints.

assemblages. Impaired sediment quality and excess P were identified as the most probable stressors (USEPA 2009). Our assessment implicated low stream flows relative to historic conditions and seasonally depressed dissolved $O_2$ levels (due to excess P) in the summer as other potential stressors on aquatic life in the South River.

Reduction in stream flow and deviations from historic river temperature increased risk to recreational swimming and boating. Recreational use and satisfaction are influenced by numerous social and environmental conditions, and stream discharge has been shown to exert a strong influence on the perception of stream conditions and suitability for recreation (Brown et al. 1992; Prüss 1998). River recreational use increases with discharge up to a point and then declines at high flow (Brown et al. 1992).

Perceptions of water quality influence the user's willingness to participate in river-use recreation and the satisfaction derived from these recreational activities. Perceived water quality encompasses the visual landscape, habitat structure for aquatic life, navigational safety, and visual and olfactory characteristics of the water and shoreline (Lant and Mullens 1991). Perception of a stream segment's suitability for recreational swimming has been shown to be the most sensitive indicator with regard to perceptions of water quality, although stream temperature and discharge are also factors considered. Although perceptions of "suitable" water quality may align with regulatory compliance, these factors are not necessarily interdependent.

### *BN sensitivity analysis*

Although Hg is a stressor for all the species studied, it was not always the greatest contributor of risk in all regions. Other environmental stressors, such as river temperature, may be affecting fish species as much or more than the Hg. Stream temperature directly affects aquatic organisms through impacts on metabolic rates, activity levels, and life history traits (Kerr 1966; Horning and Pearson 1973; Shuter et al. 1980; Armour 1993; Murphy et al. 2005). Stream temperature is a function of a river's heat load and discharge, both of which are influenced directly or indirectly by anthropogenic activities. Alteration of the stream environment is a consequence of managing rivers for flood control and multiple uses, but surrounding land use patterns can indirectly alter the temperature regime (Whitledge et al. 2006). Removal of upland vegetation can lead to increased sediment volumes, changing channel morphology, alteration or removal of riparian vegetation, and increased convective and advective heat transfers between the atmosphere and stream surface (Poole and Berman 2001).

To reduce risk to biotic and abiotic endpoints for this site, it will be necessary to consider all of the stressors, not just those that initiated the management action. Remediation that focuses on multiple stressors will have the greatest effectiveness for reducing risk to endpoints of the South River. Restoration of the riparian habitat surrounding the South River, especially in the high-risk regions, would likely improve both actual water quality and perceived water quality. The South River Total Maximum Daily Load (TMDL) for Aquatic Life Use (General Standard–Benthic) recommended revegetation of barren areas and development of riparian buffers among other strategies to reduce erosion and sediment loading into the South River (USEPA 2009).

### *Using sensitivity results to inform the monitoring plan*

One of the benefits of the sensitivity analysis is that it can identify the variables that contribute the greatest risk to the endpoints. This information can be used to prioritize and direct future monitoring plans. For example, given the importance of river temperature for SMB, we can recommend that water temperature is collected when the fish are sampled for MeHg. The results of our sensitivity analysis are presented in Table 2. Many of these parameters are now included in the multidecadal monitoring plan for the SRSA.

Gaps in information were also identified during the model evaluation process. This information about important and missing variables can be used in planning future monitoring and remediation programs. Additional data and more information on certain causal pathways would reduce the uncertainty in the model.

### *Application of the BN-RRM*

The development of the biotic and abiotic risk models and the calculation of current risk within the study area was the first step in evaluating risk to the biota, water quality, and recreational uses in the SRSA. The extensive sampling program conducted by the SRST provided site-specific data to inform the model parameters. As new data are collected in the SRSA, the risk models can be updated to reflect new knowledge of the system. Input parameters and CPTs can be refined to reflect our greater knowledge of the system, thereby reducing the uncertainty in the risk estimates. For example, although Region 4 was one of the regions with higher risk, it was also a region for which we did not have complete data. More sampling and measurements will provide the data needed to reduce the uncertainty and assess risk to the endpoints in this area with greater accuracy.

The BN-RRM risk assessment can play a critical role in an adaptive management scheme. The models created in this research provide a foundation for assessing the impacts of adaptive management strategies. These models can now be applied to assess changes in risk from management activities in the SRSA. As the SRST plans management and implements Hg reduction strategies, regional scale ecological risk assessment scan be used to evaluate the efficacy of proposed management alternatives in achieving risk-based goals and understand potential tradeoffs (Nyberg et al. 2006; Johns 2014; Johns et al. this issue). For example, the models can be used to calculate the conditions that lead to the highest probability of meeting the management goals (Nyberg et al. 2006).

This research provides the foundation for evaluating the effects of multiple stressors of the South River on a variety of assessment endpoints over a regional spatial scale and incorporating a breath of site-specific information. Future risk analysis for the South River will build on this foundation to assess risk to human health and wellbeing endpoints. Other chemical or ecological stressors can be incorporated into this risk framework; for example, the models can be used to evaluate the effects climate change stressors on the endpoints of the SRSA.

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*Disclaimer*—The peer-review process for this article was managed by the Editorial Board without the involvement of W Landis.

*Data availability*—The data are available at the South River Science Team website (http://southriverscienceteam.org/). The models will be made available at the WWU CEDAR library server site (http://cedar.wwu.edu/).

## SUPPLEMENTAL DATA

**Notes for viewing the BN models.** The BN models are labeled by endpoint and then risk region. For example, the model for SMB risk for Risk Region 2 is SmallmouthBass_R2.neta. The files are written in Netica$^{TM}$, which can be downloaded from the Norsys Web site (https://www.norsys.com/netica.html). Download and purchase instructions can be found on this Web site as well. The free version of Netica allows the reading and saving of models up to a certain size (15 nodes). The reading of the model includes access to the conditional probability tables for each child node. We also recommend reading the introductory tutorial at https://www.norsys.com/tutorials/netica/nt_toc_A.htm.

**Table S1.** Biotic model parameterization tables describing input parameters, states, ranking schemes, justification, and data sources or references

 

**Table S2.** Water Quality model parameterization tables describing input parameters, states, ranking schemes, justification, and data sources or references

**Figure S1.** Diagrams of the biotic and abiotic Bayesian networks for Region 2. For a given endpoint the structure of the model is the same for each of the other risk regions except for the inputs specific to that region. (A) Belted kingfisher, Region 2. (B) Carolina wren, Region 2. (C) White sucker, Region 2.

**Figure S2.** Risk distributions for each endpoint in each risk region. (A) Smallmouth bass. (B) White sucker. (C) Belted kingfisher. (D) Carolina wren. (E) Water Quality Standards. (F) Swimming River Use. (G) Boating River Use. (H) Fishing River Use.

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