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# Using the Bayesian Network Relative Risk Model Risk Assessment Process to Evaluate Management Alternatives for the South River and Upper Shenandoah River, Virginia

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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 series of regional scale risk assessments using the Bayesian Network Relative Risk Model (BN-RRM) to evaluate the efficacy of 2 remediation options in the reduction of risks to the South River and upper Shenandoah River study area. The 2 remediation options were 1) bank stabilization (BST) and 2) the implementation of best management practices for agriculture (AgBMPs) to reduce Hg input in to the river. Eight endpoints were chosen to be part of the risk assessment, based on stakeholder input. Although Hg contamination was the original impetus for the site being remediated, multiple chemical and physical stressors were evaluated in this analysis. Specific models were built that incorporated the changes expected from AgBMP and BST and were based on our previous research. Changes in risk were calculated, and sensitivity and influence analyses were conducted on the models. The assessments indicated that AgBMP would only slightly change risk in the study area but that negative impacts were also unlikely. Bank stabilization would reduce risk to Hg for the smallmouth bass and belted kingfisher and increase risk to abiotic water quality endpoints. However, if care were not taken to prevent loss of nesting habitat to belted kingfisher, an increase in risk to that species would occur. Because Hg was only one of several stressors contributing to risk, the change in risk depended on the specific endpoint. Sensitivity analysis provided a list of variables to be measured as part of a monitoring program. Influence analysis provided the range of maximum and minimum risk values for each endpoint and remediation option. This research demonstrates the applicability of ecological risk assessment and specifically the BN-RRM as part of a long-term adaptive management scheme for managing contaminated sites. *Integr Environ Assess Manag* 2017;13:100–114. © 2016 SETAC

**Keywords:** Ecological risk assessment   Adaptive management   Bayesian network relative risk model   Mercury contamination   Virginia

## INTRODUCTION

This is the second of 3 articles describing the implementation of a Bayesian Network Relative Risk Model (BN-RRM) for the South River in western Virginia, USA, for risk analysis, decision making, and adaptive management. The first installment (Landis, Ayre, et al. this issue) presents the background for the study and the initial calculation of risk to 8 endpoints from legacy Hg contamination and other stressors. The BN-RRM methodology produced a spatially explicit ecological risk assessment that estimated risk and its associated uncertainty to the endpoints. The present study investigates the change in risk for 2 potential management alternatives for the region. Finally, the third article (Landis, Markiewicz et al. this issue) demonstrates the application of this approach to an adaptive management structure that can be applied to the South River, taking advantage of the characteristics of Bayesian networks (BNs) modeling.

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Landis, Markiewicz et al. (this issue) had 3 specific findings. First, patterns of risk varied according to the endpoint and location within the watershed. Both chemical and ecological stressors influenced the spatial patterns of risk. Second, overall risk to abiotic endpoints (water quality, fishing, boating, and swimming) was greater than overall risk to biotic endpoints. Finally, although Hg reduction is the regulatory priority for the South River, Hg is not always the main contributor to risk to the endpoints. For example, in the region of highest risk to smallmouth bass, the most important factors in risk determination were river temperature and Hg in tissue.

The focus of the present risk assessment was to determine the change in risk to the endpoints for 2 management alternatives currently considered for the site. Wyant et al. (1995) suggested this approach and that ecological risk assessment could be used as part of a decision-making and adaptive management framework for ecological restoration. In their decision framework, 3 segments were delineated: Context Analysis, Management Intervention, and Risk Assessment. The Risk Assessment segment is the portion that conducts the analysis of the probability of the ecological engineering and other remediation options in meeting the objectives. One of the key principles incorporated into the Wyant et al. (1995) framework is that ecological systems are dynamic, not in equilibrium, and that the processes are affected by natural and anthropogenic activities.

In the present study, the relative risk model (RRM) developed by Landis and Wiegers (2005) provides the Risk Assessment portion of the Wyant et al. (1995) framework by incorporating management alternatives into an existing risk assessment and by calculating changes in risk with each alternative. The current RRM uses BNs for calculating risk. Conceptual models developed as part of the RRM process are used to organize and visualize multiple stressors, sources of stressors, habitats, and endpoints in a single framework. The effects of management alternatives under consideration can be incorporated into the initial conceptual model to evaluate the changes for sources, stressors, and habitats to endpoint risk.

### *Bayesian Network Relative Risk Model*

In order to describe the probabilistic nature of risk, BNs have been applied to the calculation of risk using the RRM (Anderson and Landis 2012; Ayre and Landis 2012; Ayre et al. 2014; Hines and Landis 2014; Herring et al. 2015). The BNs link cause and effects through a web of nodes using conditional probability to estimate the likely outcome (McCann et al. 2006).

The BN-RRM has been used to examine how different management strategies change risk (Ayre et al. 2014; Hines and Landis 2014; Herring et al. 2015). Hines and Landis (2014) illustrated how low-impact development adaptive management options can be incorporated into a BN-RRM to estimate prespawn mortality of Coho salmon in the Pacific Northwest under different management scenarios. Ayre et al. (2014) predicted that dams would mitigate the spread of whirling disease in cutthroat trout stocks. Herring et al. (2015) adapted the BN-RRM to calculate the risk due to nonindigenous species for the marine estuary Padilla Bay, Washington, USA, and examined the influence of ballast water treatment on the introduction and dispersal of nonindigenous species. Nyberg et al. (2006) and Howes et al. (2010) also have published other examples of using BNs to understand the effects of adaptive management options.

In our approach, the RRM framework of source → stressor → habitat or location → effect → impact pathways (Figure 1) is preserved. The initial models described in Landis, Ayre, et al. (this issue) use conditional probability to describe causality and the effect of the stressors on risk to endpoints. Post bank stabilization variables are then added to the initial models to describe how the management option will alter the transport of the stressors to the receptor. The result is a model that can calculate changes in risk from the effects of the proposed management option.

### *Study findings*

The present study uses the BN-RRM approach to evaluate how 2 management alternatives, bank stabilization (BST) and agriculture best management practices (AgBMPs), may alter the probability of risk to biotic and abiotic endpoints of the South River. The management options were being considered by South River site managers and were evaluated on the basis of their ability to lower the risk of exposure to Hg and other stressors for the 8 endpoints.

Bank stabilization did reduce risk to several of the endpoints, but only when safeguards were taken to alleviate habitat impacts. The AgBMPs did not appreciably lower risk but also did not increase risk to any of the endpoints.

Even at a study site as complex as the South River, ecological risk assessment can provide information on the efficacy of alternative management choices being considered for use in remediation. Predictions of unintended consequences can be made, and important parameters can be identified for inclusion into the long-term monitoring program to test the success of the management alternatives.

## METHODS

### *Study area*

The South River Study Area (SRSA) is the 607.6 $km^2$ South River watershed and the South Fork of the Shenandoah River. The history of the area and a description of the site have been published (Eggleston 2009; Stahl et al. 2014; Landis, Ayre, et al. this issue).

As previously described (Landis, Ayre, et al. this issue), we divided the South River watershed into 6 risk regions based on hydrological subbasins and land-use similarities (Figure 2). Risk Region 1 encompasses the headwaters of the South River, followed by Risk Regions 2 through 5. Risk Region 6 begins where the South River merges with the North River to form the South Fork of the Shenandoah River.

The city of Waynesboro, VA, USA accounts for most of the urban area within the watershed and is the location of the Hg released into the South River (Risk Region 2). Urban

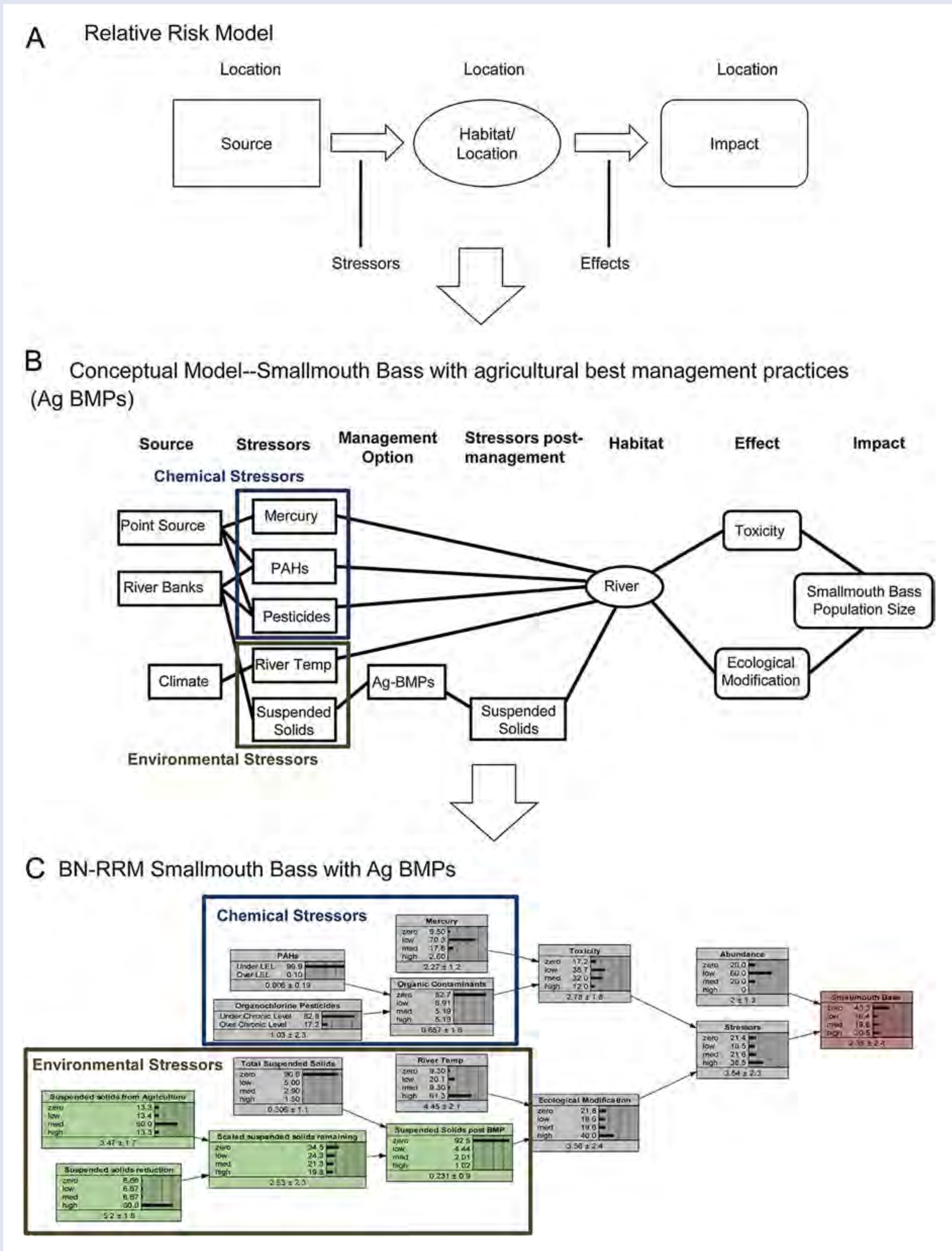


Figure 1. The structure of the relative risk model shows the causal pathway between source, stressor, habitat, effects, and impacts (A). Management actions were integrated into the cause–effect model for each endpoint to describe how the management would alter the characteristics of the stressors (B). Finally, the cause–effect model was used to derive a Bayesian network to quantify the interactions between the variables and to calculate risk (C).

and agricultural land use contributes additional stressors that are included in this risk assessment, such as pesticides, stormwater runoff, loss of canopy cover, hydrocarbons, and habitat loss.

*Endpoints*

Detailed descriptions of the endpoints and the endpoint selection rationale can be found in Landis, Ayre, et al. (this

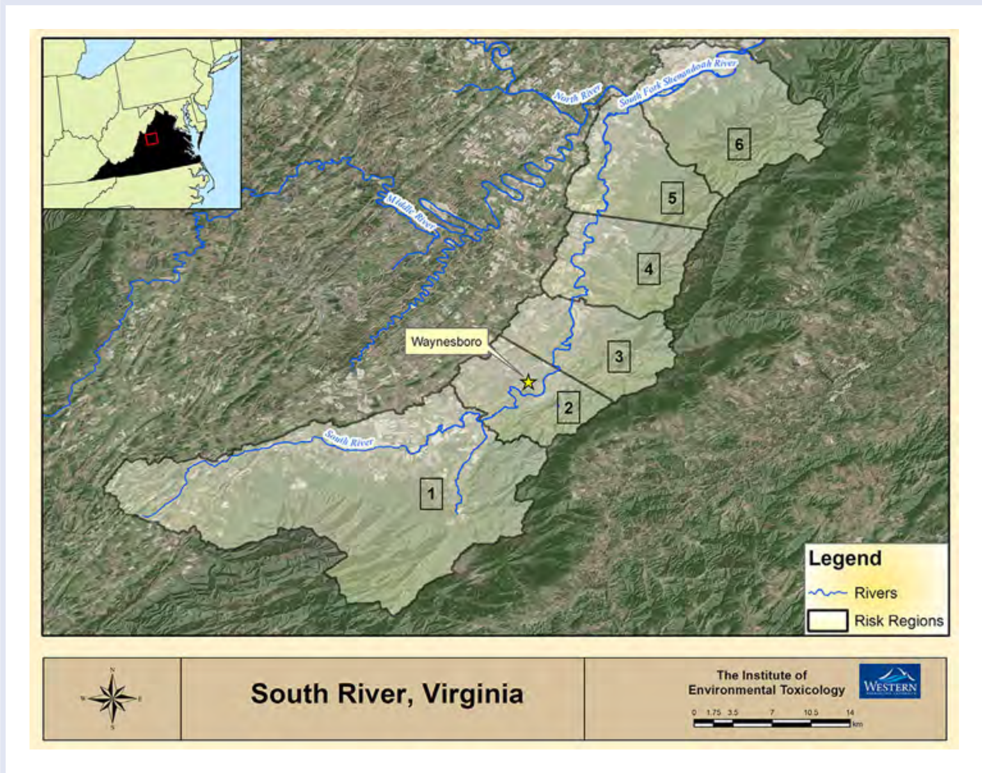


**Figure 2.** Map of the South River and South River Study Area, Virginia, USA. Waynesboro is the site of the Hg input into the South River.

issue). Eight endpoints were used for this risk assessment. The 4 biotic endpoints were Smallmouth Bass, White Sucker, Belted Kingfisher, and Carolina Wren. These 4 species are valued by stakeholders of the South River, and risk was calculated for the attribute of probability of population decline. A model was created for each endpoint that reflected species-specific pathways stressors in the South River.

The 4 abiotic endpoints were compliance with water quality standards and 3 recreational services endpoints, specifically Fishing River Use, Swimming River Use, and Boating River Use. Risk was calculated for the attributes' probability of exceeding site-specific water quality criteria and losing valued recreational uses of the river. All of the abiotic endpoints were assessed in the same model (Landis, Ayre, et al. this issue), which allows for comparison between endpoints that may be antagonistic or synergistic.

*Management practices*

Two management options were being considered by the South River Science Team (SRST) at the time of this research: BST and AgBMPs. Other management options may also be feasible for reducing risks to the endpoints in the South River, but were not actively being considered by the SRST. Brief descriptions of the 2 management actions evaluated in the present research follow.

Bank stabilization is a common management practice at sites with eroding stream banks, where flowing water exceeds the resisting forces of bank materials and vegetation. In the South River, the floodplain is contaminated with Hg from historic flood events, making stream bank erosion a mechanism by which Hg can be re-introduced into the river.

A BST pilot study was conducted in a section of the South River from 2010 to 2012, during which Hg concentrations were monitored in the water, sediment, and biotic samples pre- and post BST implementation (Anchor QEA and URS 2013). Two types of BST, enhanced vegetative and structural stabilization techniques, were applied in various combinations along the banks. Enhanced vegetative BST stabilizes an eroding bank using the existing soils and slope (Anchor QEA and URS 2013). Structural BST stabilizes a bank using the bank soils and slope but may include more invasive construction techniques such as bank reshaping, reactive amendments, slope stabilization through vegetative stabilization, and hard slope stabilization. Our assessment of the BST management option is based on the specific methodologies used in the South River pilot study.

Best management practices (BMPs) are defined as the most cost-effective, efficient, and practical methods to address a problem or guide an action (Logan 1993). Agricultural BMPs reduce environmental impacts from agricultural activities while considering agricultural productivity, feasibility and ability to implement the BMPs, and effectiveness. A wide range of AgBMPs exists, and multiple practices are described in Sheffield et al. (1997) and Cullum et al. (2006). Agricultural BMPs reduce total suspended solids, total P, and *Escherichia coli* (Sheffield et al. 1997; Line et al. 2000; Cullum et al. 2006; Meals et al. 2010).

With any management option, the primary goal for the SRST is "no regrets." In other words, managers do not want to make the site worse in any way during remediation, such as reducing Hg levels at the detriment of habitat, loss of other species, degradation of water quality, or other environmental parameters. Trade-offs between risk, cost, effectiveness, and public opinion are a reality for managers. A quantitative, spatially explicit process is therefore needed to calculate the effects of implementing management options on risk and to evaluate potential unintended consequences. The BN-RRM provides a framework for this process.

*Development of the conceptual models and Bayesian networks*

The conceptual models and BNs were derived from those developed by Landis, Ayre, et al. (this issue) for the original risk assessment. Modifications were made to the input nodes to describe the influence of the 2 management options, BST and AgBMPs, to prevent Hg and other stressors from entering the river (Figure 3 and Supplemental Data Figure S1). For BST, the Hg input node was changed on the basis of pilot study data, whereas all other input nodes were modified on the basis of expert elicitation. For AgBMPs, all input stressor nodes were modified on the basis of literature values. The pilot study, expert elicitation, and literature search for applicable values are described in the *Bank stabilization models* and *Ag BMP models* sections.

In the present study, the BN is structured (from left to right) of input nodes based on region-specific data, intermediate nodes that include summary nodes reflecting combinations of intermediate nodes, and an endpoint node with the final risk calculation (score) for that endpoint. The structure and relationships in the model are the same for each risk region, but the input nodes change, depending on that region's data.

Each variable in the model is represented as a node and discretized into states. The states are assigned a numeric ranking value (zero = 0, low = 2, medium = 4, high = 6) that is used for calculating risk scores to the endpoint. The process of discretizing the nodes is important and is described in Landis, Ayre, et al. (this issue). In addition, definitions of BN

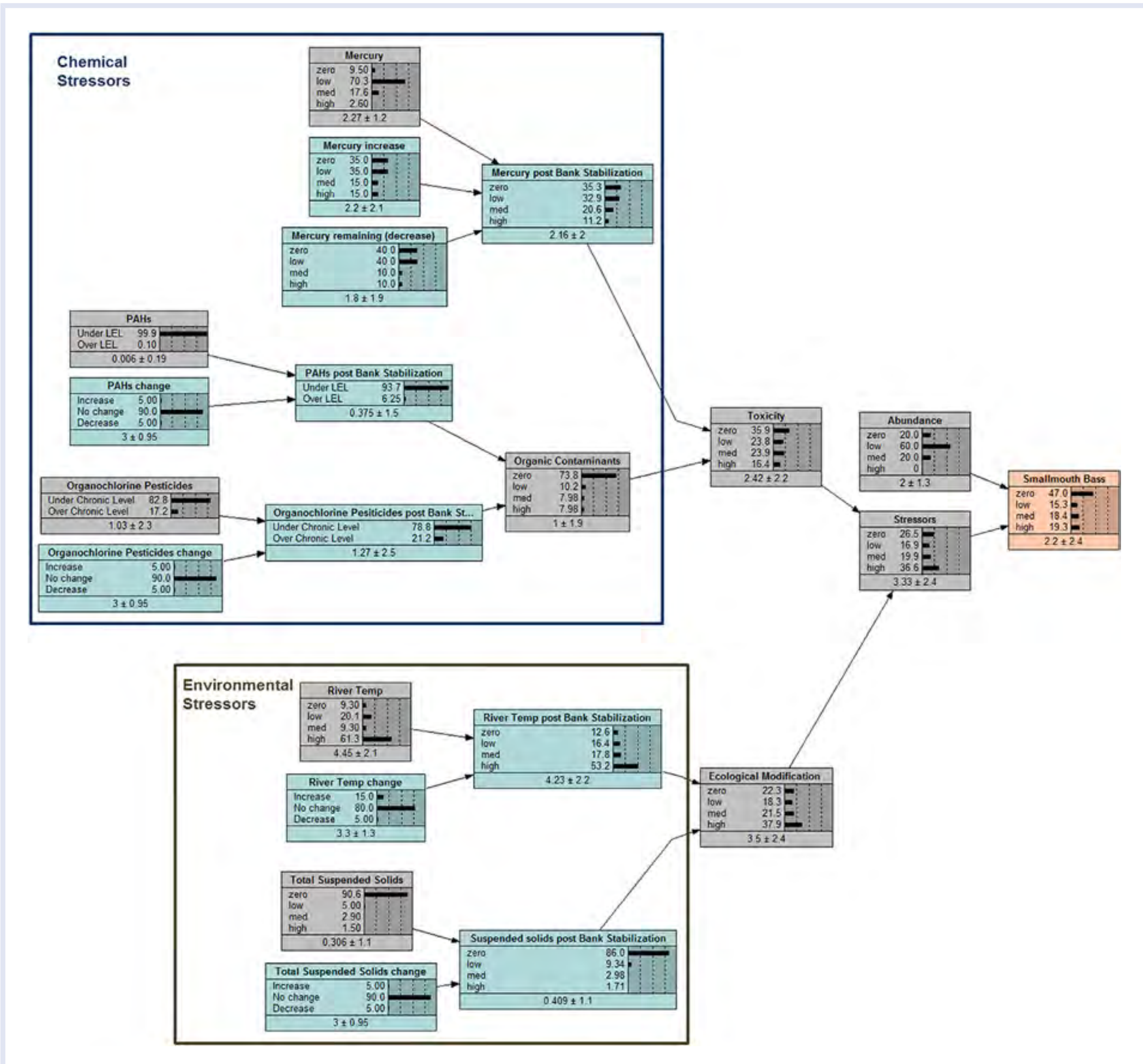


Figure 3. Bayesian network for risk to the Smallmouth Bass endpoint in Region 2 when bank stabilization is implemented. The management nodes are blue-green, the endpoint node is orange, and the other nodes are gray. LEL = lowest effect level.

components have been summarized by Tighe et al. (2013) and can be found in Landis, Ayre, et al. (this issue).

*Bank stabilization models*

The BST management treatment option was integrated into the BNs for all biotic and water quality endpoints. A combination of South River BST pilot study data (Anchor QEA and URS 2013) and expert elicitation were used in the development of the BST-related nodes. The BST pilot study entailed implementing a combination of vegetative and structural stabilization procedures along a section of the South River and monitoring Hg concentrations in the porewater, sediment, and Asiatic clam tissue before and after installation (Anchor QEA and URS 2013). In addition, upland vegetative cover and habitat quality were measured qualitatively throughout the pilot study area.

*Pilot study data.* We used the reported Hg concentration minimums, maximums, and averages for porewater from the pilot study to estimate the effects of BST on fish tissue Hg concentrations in the SRSA for the Smallmouth Bass, White Sucker, and Fishing River Use endpoints.

*Fish fillet Hg.* Changes to fish Hg body burden post BST were estimated on the basis of changes observed in porewater Hg concentration over the 3-y monitoring period of the pilot study data. The relationships between porewater Hg and fish fillet Hg can be related to each other on the basis of an equation developed by Southworth et al. (2004) and used by the Virginia Department of Environmental Quality (VDEQ 2008). Porewater Hg concentrations generally decreased over time with BST, and nearly all of the maximum porewater Hg concentrations were lower than the initial samples. On the other hand, minimum Hg concentrations increased in half of the samples, specifically those samples with the lowest initial porewater Hg concentrations (Anchor QEA and URS 2013).

To reflect these variable changes in Hg concentration with BST, Mercury Increase and Mercury Decrease nodes were added to the BN model as 2 inputs into the final Mercury Post-BST node (Figure 3). The Mercury Post BST node estimates the changes from initial region-specific Mercury node concentrations (Figure 3). The initial Hg concentrations that were ranked zero and low were assigned 50% probability of increasing and 50% probability of decreasing with BST. Initial medium and high Hg risk states had 100% probability of decreasing. The magnitude of decrease was estimated on the basis of the relative change in porewater concentration.

*Bird blood Hg.* The BST pilot study did not produce results that could be used to estimate the effects of BST on bird blood Hg concentrations. As such, the Mercury Change node was assigned probabilities of 30% for Increase, 30% for No Change, and 40% for Decrease. These probabilities reflect the uncertainty of effects from BST to Hg concentration in birds. A slightly higher chance of Decrease (40%) was assumed on the basis of Hg trends in other media (e.g., porewater and soil) from the pilot study data (Anchor QEA and URS 2013). The distribution for the Bird Blood Hg Change node could be updated if post BST upland studies are performed in the SRSA.

*Bank stabilization model expert elicitation.* Expert elicitation was used to estimate effects of BST management on the following stressors: total suspended solids or turbidity, river temperature, submerged aquatic vegetation, discharge regime, dissolved $O_2$ levels, PAHs, organochlorine pesticides, bacterial inputs, and total P. Two experts who were familiar with BST remedial technologies for contaminated sites and had site-specific knowledge of the South River were surveyed in a formal elicitation process. Finding expertise in both of these areas limited the number of available candidates for elicitation. These 2 experts also were involved in the South River BST pilot study. To minimize bias that may have been introduced into the elicitation results because of their personal experience on the South River restoration projects, our methods were based on those by McBride and Burgman (2011).

In the expert elicitation survey, the 2 respondents were asked to draw on their cumulative experience with BST to estimate the frequency, out of 10 sites, that they would expect a 50% increase, a 50% decrease, or no change in a stressor with BST management. Expert elicitation research suggests that more accurate results are obtained when experts estimate frequency instead of probability (McBride and Burgman 2011). McBride and Burgman (2011) also recommended using intervals that are perceived similarly by most individuals. In this case, 50% increase and 50% decrease were used because it was likely that the experts perceived the quantities of doubled and halved in a similar way.

The results from the BST expert elicitation are summarized in Table 1. The frequencies reported by the experts were averaged and then used as discrete input probability distributions for the BST management input nodes. Full results from the expert surveys can be found in Supplemental Data Table S1.

*Belted kingfisher habitat expert elicitation.* In addition to the BST expert elicitation described above, we conferred with Dr Dan Cristol (College of William and Mary, Williamsburg, VA, USA) to confirm our understanding of the effects of BST on belted kingfisher habitat. The 2 BST experts mentioned above were not included in this elicitation because it was not in their area of expertise. Cristol has published numerous articles on birds in the South River and the effects of Hg on birds in the SRSA (Brasso and Cristol 2008; Cristol et al. 2008; Condon and Cristol 2009; Hawley et al. 2009; Jackson, Evers, Etterson, et al. 2011; Jackson, Evers, Folsom, et al. 2011).

Cristol stated that if BST is implemented without the explicit consideration of belted kingfisher nests, the stabilization efforts will eliminate belted kingfisher habitat in the area (Dan Cristol, personal communication, 2013). However, if precautions are taken to avoid nesting habitat, BST will not have an effect on belted kingfisher habitat. Thus, 2 separate

 

Table 1. Bank stabilization expert elicitation results[a]

| Model variable | Change in variable | Average response |
|---|---|---|
| Total suspended solids | Increase 50% | 0.5 |
| | No change | 9.0 |
| | Decrease 50% | 0.5 |
| River temperature | Increase 50% | 1.5 |
| | No change | 8.0 |
| | Decrease 50% | 0.5 |
| Submerged aquatic vegetation | Increase 50% | 0.5 |
| | No change | 6.5 |
| | Decrease 50% | 3.0 |
| Discharge regime | Increase 50% | 0.0 |
| | No change | 10.0 |
| | Decrease 50% | 0.0 |
| Dissolved O | Increase 50% | 0.5 |
| | No change | 9.0 |
| | Decrease 50% | 0.5 |
| PAHs | Increase 50% | 0.5 |
| | No change | 9.0 |
| | Decrease 50% | 0.5 |
| Organochlorine pesticides | Increase 50% | 0.5 |
| | No change | 9.0 |
| | Decrease 50% | 0.5 |
| Bacterial inputs | Increase 50% | 1.0 |
| | No change | 9.0 |
| | Decrease 50% | 0.0 |
| Total P | Increase 50% | 0.0 |
| | No change | 9.0 |
| | Decrease 50% | 1.0 |

[a]The average response is from the 2 experts surveyed in the present study, estimating the probabilities of a 50% increase, no change, or a 50% decrease in the model variable. The average responses were transformed into frequency distributions for input into the Bayesian networks.

scenarios were identified for risk to the belted kingfisher: Nests Avoided and Nests Impacted. These scenarios were considered as part of the BST influence analysis.

*Agricultural BMP models*

Agricultural BMPs were integrated into BNs for 6 of the endpoints—Belted Kingfisher, Smallmouth Bass, Water Quality Standards, Swimming River Use, and Boating River Use—because pathways exist from the stressors targeted by AgBMPs to the endpoints. Only 3 stressors were expected to change as a result of AgBMP: total suspended solids, total P, and bacterial indicators (Sheffield et al. 1997; Cullum et al. 2006). The AgBMP management nodes we incorporated into the BN-RRM describe these stressors that result from agricultural land-use practices, the percent reduction of the stressors by the implementation of AgBMPs, and the amount of the stressors remaining after AgBMPs are implemented. This combination of nodes determined the reduction of the stressors due to AgBMPs based on the amount of the stressor attributable to agricultural practices.

*Data sources for the AgBMP input nodes.* The benthic impairment Total Maximum Daily Load (TMDL) study for the South River (VDEQ 2009) was used to parameterize the AgBMPs BNs. The TMDL study estimated that 70.2% of total suspended solids, 58% of total P, and 89.6% of *E.coli* entering the river come from agricultural sources (VDEQ 2009). Studies by Cullum et al. (2006) and Sheffield et al. (1997) were used to obtain data on estimated AgBMP reductions of total suspended solids, total P, and *E. coli* at other sites. Cullum et al. (2006) reported 58% reduction of total suspended solids and 32% reduction of total P, but did not monitor changes in bacterial abundance. Sheffield et al. (1997) reported a 90% reduction of total suspended solids, 64.5% reduction of total P, and 51% to 77% reduction of fecal bacteria. These data were used to define the discrete input distributions for AgBMP management nodes in the BN-RRM. Confidence limits for these data (Sheffield et al. 1997; Cullum et al. 2006; VDEQ 2009) were described by the node distributions.

*Influence analysis methodology for BST*

We completed an influence analysis (Marcot 2012) to examine the range in efficacy of the BST treatment outcome scenarios. Influence analysis is conducted by setting model input variables to a 100% probability for the highest and lowest possible states and comparing the changes in risk to the endpoints. Influence analysis is valuable to the management and decision-making process because it can quantify the degree to which input variables could affect outcome probabilities. Site managers can use the results to prioritize remedial activities and to avoid undesirable results (Marcot 2012).

The influence analysis performed for BST compares the original "Expected Risk" scenario for BST management to "Minimum Risk" and "Maximum Risk" scenarios. The Minimum Risk scenario has 100% probability of reducing input parameters influenced by BST and describes the lowest possible range of risk with high efficacy of BST and little or no additional exposure caused by stabilization activities. The Maximum Risk scenario has low efficacy in reducing inputs and 100% probability of increasing input parameters with BST and/or increasing exposure to additional stressors as a result of stabilization activities. By comparing these scenarios, we can quantify the boundaries or range of distributions that are possible with the implementation of the BST management.

To perform the influence analysis, we altered the input nodes that specifically relate to the BST treatments or management (Figure 3). In the belted kingfisher model, these parameters are Turbidity, Submerged Aquatic Vegetation Change, Organochlorine Pesticide Change, PAHs Change, and Mercury Change. We provide an example of the process using the Turbidity Change node (Supplemental Data Figure S2).

*Turbidity example.* The Turbidity Change node has 3 possible states: decreased turbidity, increased turbidity, or no overall change to turbidity. In the Expected Risk scenario for the belted kingfisher, the Turbidity Change has probabilities of 5% Increase, 90% No Change, and 5% Decrease (Supplemental Data Figure S2A). To determine the Minimum Risk scenario, in this case the greatest reduction in turbidity, we altered the probability distributions to a 100% probability of a Decrease state (Supplemental Data Figure S2B). The model was recalculated, and a reduction in turbidity in the Turbidity Post BST child node resulted. There was a shift in the zero state from 69.7% (original Expected Risk scenario; Supplemental Data Figure S2A) to 89.4% with the Minimum Risk scenario (Supplemental Data Figure S2B) for Turbidity Post BST.

The Maximum Risk scenario for Turbidity Change represents an increase in turbidity in the region when BST is implemented due to the instream activities associated with stabilizing the stream banks. To calculate this scenario, we set the Turbidity Change node to 100% in the Increase state (Supplemental Data Figure S2C) and recalculated the model. As expected, the probability distributions shifted from zero to low state in the Turbidity Post BST child node, with the low state increasing from 27.3% (Supplemental Data Figure S2A) to 85.2% (Supplemental Data Figure S2C).

The example in the preceding paragraph illustrates changes to 1 input node (Turbidity) in Region 2 for the belted kingfisher. The process was repeated for the other 4 BST treatment input nodes (Submerged Aquatic Vegetation Change, Organochlorine Pesticide Change, PAHs Change, and Mercury Change) in all regions.

### *Belted kingfisher habitat influence analysis*

Influence analysis was also used to compare the 2 belted kingfisher habitat scenarios. The Belted Kingfisher Nests Impacted scenario, in which the BST management does not avoid their nests, changes the original BN in that only the Territory and Potential Habitat stressors affect the risk to kingfisher. Under this scenario, the Toxicity and Ecological Parameters nodes are disconnected because the belted kingfishers will not be exposed to toxicological and environmental stressors if their habitat is eliminated in the region. Both the Territory and Potential Habitat nodes are assigned 100% probability of high risk to reflect the elimination of kingfisher habitat in the region.

### *Uncertainty and sensitivity analysis*

The uncertainty and sensitivity analyses are useful for quantifying to what degree variables contribute to risk to endpoints (Pollino et al. 2007; Marcot 2012; Hines and Landis 2014). Important variables and variables with high uncertainty are recommended for additional monitoring to improve the model. Uncertainty and sensitivity analyses for the original South River BN-RRM are discussed in detail by Landis, Ayre, et al. (this issue).

Uncertainty is explicitly represented in the BNs by the frequency distributions for each of the nodes (Varis and Kuikka 1999; Marcot et al. 2006). Sources of uncertainty include the simplification of relationships and interactions in an ecological system with a mathematical model, natural variation or randomness of the parameters in that ecosystem, and subjective judgment used during model parameterization (Hines and Landis 2014).

Sensitivity analysis was completed on the endpoint nodes in each BN with management alternatives using Netica™ (Norsys Software Corp. 2014). Netica's Sensitivity to Findings tool measures the mutual information between each of the input nodes and the endpoint node. A high mutual information value indicates a greater degree of influence on the endpoint node (Marcot 2012). The output from the entropy reduction analysis describes the influence that each parent and child node has on the endpoint (Pollino et al. 2007; Hines and Landis 2014). Only input nodes (intermediate nodes excluded) are reported in the sensitivity analysis results because those nodes are targeted by AgBMPs and BST.

## RESULTS

### *Bank stabilization management option*

*Biotic endpoints.* Implementation of the BST management option shifted the risk distributions for the Smallmouth Bass and Belted Kingfisher endpoints to slightly lower risk (Figures 4 and 5).

In the initial risk calculations, the probability distributions for belted kingfisher were skewed toward zero and low risk (Figure 5). When recalculated on the basis of the scenario in which kingfisher nests were not avoided during BST management, the belted kingfisher had a 100% probability of high risk. Conversely, when kingfisher nests were avoided, the recalculated risk distributions were not affected by BST management.

With BST, the initial smallmouth bass risk distributions shifted to lower risk states in Regions 3, 4, 5, and 6 (Figure 4). The probability of high risk decreased 11% and 13% in Regions 4 and 5, respectively. In Regions 3 through 6, the probability of zero risk increased by 10% to 14%.

The probability of a change in risk distributions for white sucker was less than 7% with BST management. The distributions were skewed toward zero risk, except in Region 2 where risk was split between the zero and high states at 30% and 50% probability, respectively (Supplemental Data Figure S3).

Carolina wren risk distributions showed little change with the implementation of BST (Supplemental Data Figure S4). They remained skewed toward zero and low risk in Regions 2 and 3 and peaked at low and medium risk in Regions

 

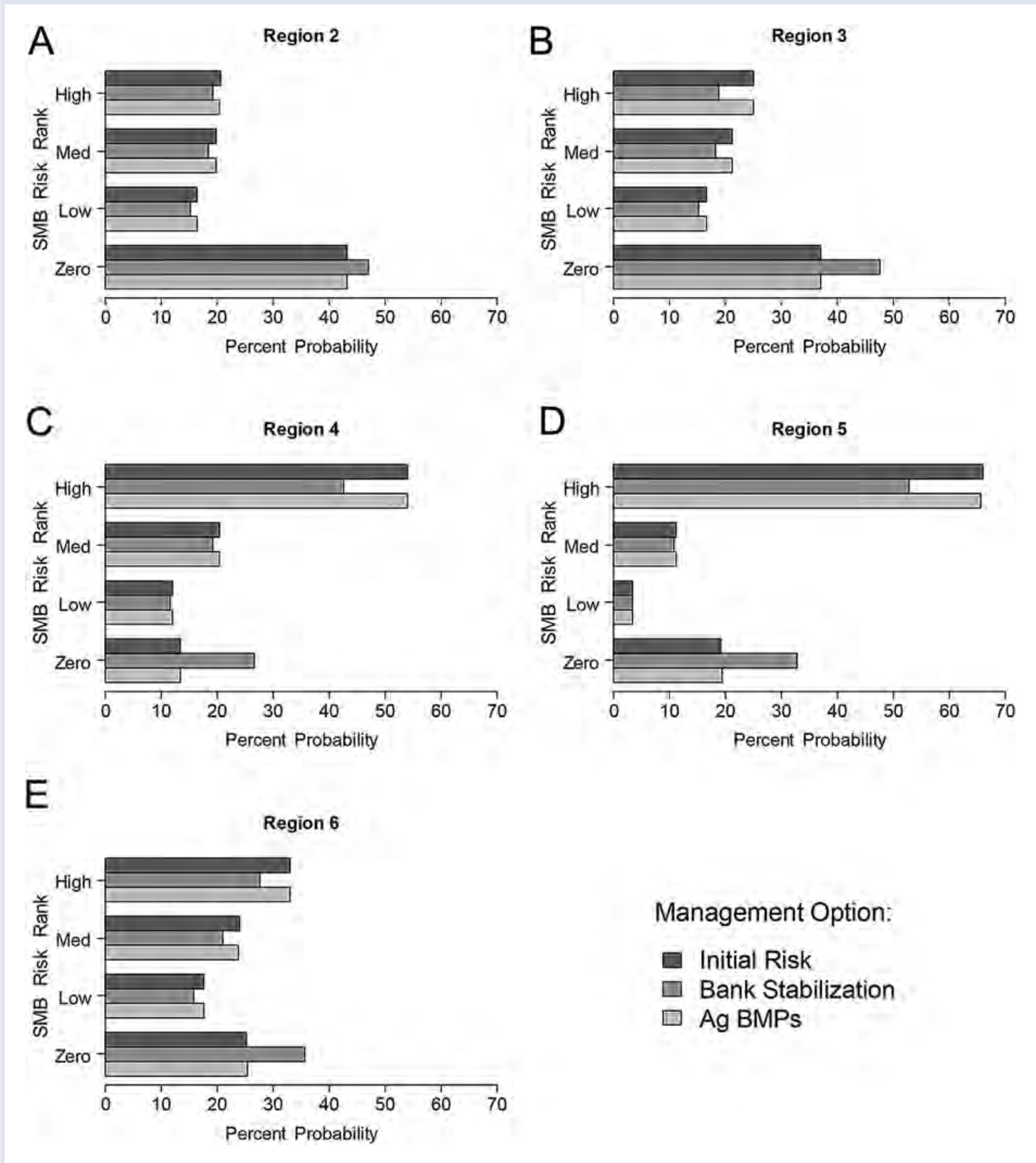


Figure 4. Smallmouth bass initial risk estimates and risk estimates with AgBMPs and bank stabilization options: Region 2 (A); Region 3 (B); Region 4 (C); Region 5 (D); Region 6 (E). Bank stabilization treatment reduced risk to SMB more than AgBMPs. AgBMP = agricultural best management practice; SMB = smallmouth bass.

4, 5, and 6 (Supplemental Data Figure S4). There was less than a 3% change in probability for risk states under BST management.

*Abiotic endpoints.* The risk distributions for the Water Quality Standards endpoint increased with BST management, and did not change at all with AgBMPs. Risk was skewed toward high with greater than 50% probability (Supplemental Data Figure S5). All regions had less than 5% probability of zero risk.

The risk distributions for Swimming River Use and Boating River Use remained relatively the same with BST; however, all distributions were skewed toward high risk with a slight increase in risk in the high state. There was more than 40% probability of high risk and more than 35% probability of medium risk for both endpoints (Supplemental Data Figures S6 and S7).

Risk distributions for the Fishing River Use endpoint changed the most in Region 6 with BST implementation (Supplemental Data Figure S8). The initial risk distribution

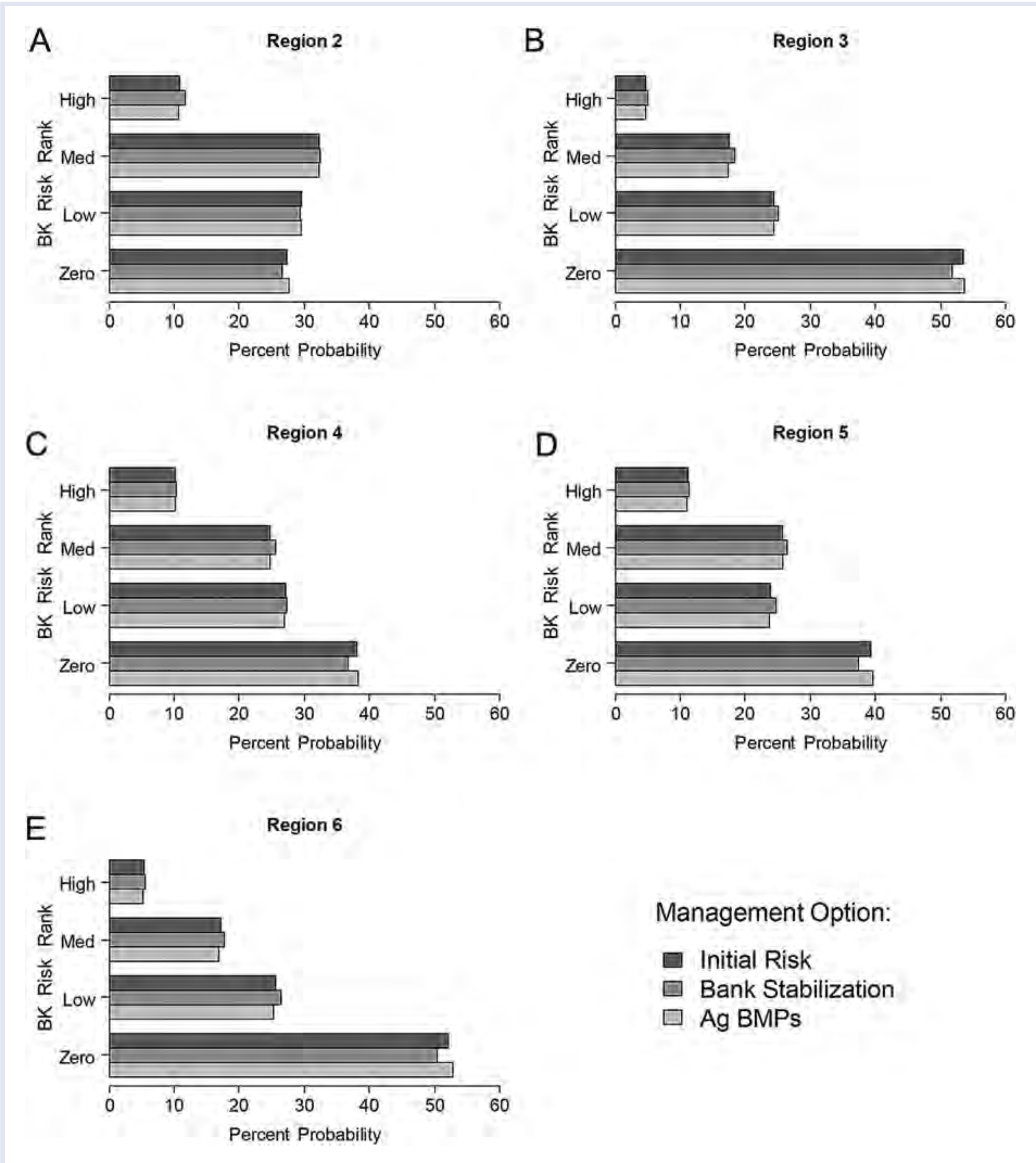


Figure 5. Belted kingfisher initial risk estimates and risk estimates with bank stabilization and AgBMPs management options: Region 2 (**A**); Region 3 (**B**); Region 4 (**C**); Region 5 (**D**); Region 6 (**E**). AgBMP = agricultural best management practice; BK = belted kingfisher.

was skewed toward zero. Under BST management, the distribution remained skewed, but the probability of zero risk decreased by 18%, and the high-risk probability increased from 2% to 15% (Supplemental Data Figure S8). The general upstream–downstream risk pattern also changed with BST management. Initially, risk was highest in Region 4 with a probability of 34% in the combined medium- and high-risk states and lowest in Regions 2 and 6 (19% and 12% combined medium and high risk, respectively). With BST, risk remained high in Region 4 (38% combined medium and high risk), but also was high in Region 6 (36%). Risk increased slightly in Region 2 (23%), but remained low relative to the other regions.

*Influence analysis results for BST*

The results for the Smallmouth Bass (Supplemental Data Figure S9), Fishing River Use (Supplemental Data Figure S10) and Water Quality Standards endpoints (Supplemental Data Figure S11) are presented graphically. These endpoints had the greatest percentage change for the biotic (Smallmouth Bass) and abiotic (Fishing River Use and Water Quality Standards) endpoints. Risk distributions for belted kingfisher and Carolina wren did not change. Additional tables describing the percentage change calculations for the other endpoints are located in Supplemental Data Table S2.

*Bank stabilization maximum risk scenarios*

The BST Maximum Risk scenario defined the upper range of possible risk to the endpoints from low efficacy of the stabilization efforts and/or additional exposure to stressors as a result of stabilization activities. In the Maximum Risk scenario, risk distributions for most endpoints shifted toward higher risk compared to the original risk calculations that included BST management; however, the degree of this shift differed between endpoints.

Under the Maximum Risk scenario for smallmouth bass, risk increased in all regions (Supplemental Data Figure S9). In Region 5, there was a 25% increase in probability of high risk, resulting in a total high-risk probability of 77%. The smallmouth bass risk distribution for Regions 4 and 6 shifted toward high risk by 17% and 14%, respectively (Supplemental Data Table S2A).

Risk distributions for Fishing River Use, which were skewed toward zero and low risk in the original Expected Risk scenario, shifted to the medium- and high-risk states under the Maximum Risk scenario (Supplemental Data Figure S10). As a result, the probability of medium and high risk increased 8% to 12% and 7% to 20%, respectively (Supplemental Data Table 2A). For Water Quality Standards, the probability of high risk increased by 17% to 20% (Supplemental Data Table S2A). Water Quality Standards, Swimming River Use, and Boating River Use risk distributions were skewed toward high risk under both the Expected and the Maximum Risk scenarios.

*Bank stabilization Minimum Risk scenarios*

The BST Minimum Risk scenario described the lowest range of possible risk, given high efficacy of the stabilization efforts and little or no additional exposure caused by stabilization activities. The skew of the risk distribution for Belted Kingfisher and Carolina Wren endpoints did not change under this scenario. Smallmouth bass risk distributions shifted from the medium or high states to zero by 8% to 15% depending on the region (Supplemental Data Table S2B and Figure S9). Similarly, the white sucker risk distributions shifted toward zero risk by 6% to 8% for all regions (Supplemental Data Table S2B). Risk distributions for the Fishing River Use endpoint became more skewed toward zero risk with 16% to 20% greater probability of zero risk (Supplemental Data Table S2B and Figure S10). The Water Quality Standards endpoint risk distributions remain skewed toward high risk, but there was a greater probability of risk falling into the zero-, low-, or medium-risk states than under the Expected Risk scenario (Supplemental Data Figure S11). Swimming and Boating River Use endpoint's risk distribution skews did not change.

*Belted kingfisher habitat scenarios*

If precautions are taken during BST to avoid kingfisher nests (Nests Avoided scenario), BST does not alter the risk to the belted kingfisher. If nests are not explicitly avoided, as is the case in the Nests Impacted scenario, risk to the belted kingfisher increases to 100% in high risk for any region in which BST is implemented. Currently, BST efforts are focused in Region 2, but future BST in other downstream regions would have the same effect on risk to this bird species. We have not evaluated the extent to which loss of belted kingfisher habitat in 1 region would alter risk to the belted kingfisher adjacent regions.

*Agricultural BMP option*

Agricultural BMPs did not change the probability of risk states by more than 5% (Figures 4 and 5, Supplemental Data Figures S3 to S7). The probability of risk to belted kingfisher decreased in the high-, medium-, and low-risk states and increased in the zero-risk state (Figure 5). Similarly, the probability of risk to the Smallmouth Bass, Water Quality Standards, Swimming River Use, and Boating River Use endpoints increased in the low- and zero-risk states (Figure 4 and Supplemental Data Figures S3 to S7). On the landscape scale, the spatial pattern of risk to the endpoints in the risk regions was also unchanged, compared to initial risk estimates.

*Uncertainty and sensitivity analysis*

The results of the sensitivity analysis are presented graphically in Figure 6 and Supplemental Data Figures S12 to S14. Detailed scores are listed in Supplemental Data Table S3.

*Biotic endpoints.* Mercury was the top contributor of risk to the Carolina Wren and Belted Kingfisher endpoints in most risk regions, even after AgBMPs and BST options were included in the modeling. The management options did not change the other contributors of risk to the bird endpoints. River temperature was the primary factor influencing smallmouth bass and white sucker in the initial BN models. Mercury had the second-highest influence on smallmouth bass and third-highest influence on white sucker. In many regions, river temperature was twice as influential as Hg on the fish species. Agriculture BMPs did not alter the influence of input parameters on smallmouth bass. For both fish species, the river temperature remained an influential parameter, along with stream canopy and vegetative cover for the white sucker in the BST management option scenario.

*Abiotic endpoints.* Overall, summer dissolved-$O_2$ concentrations, deviations from average river temperature, and bacteria indicators most strongly influenced risk to the water quality endpoints in the initial risk estimates. Additionally, Hg body burden in fish was consistently one of the main risk contributors to Fishing River Use. The integration of AgBMPs did not change the top risk factors influencing Water Quality Standards, Swimming River Use, and Boating River Use (Supplemental Data Figure S13).

 

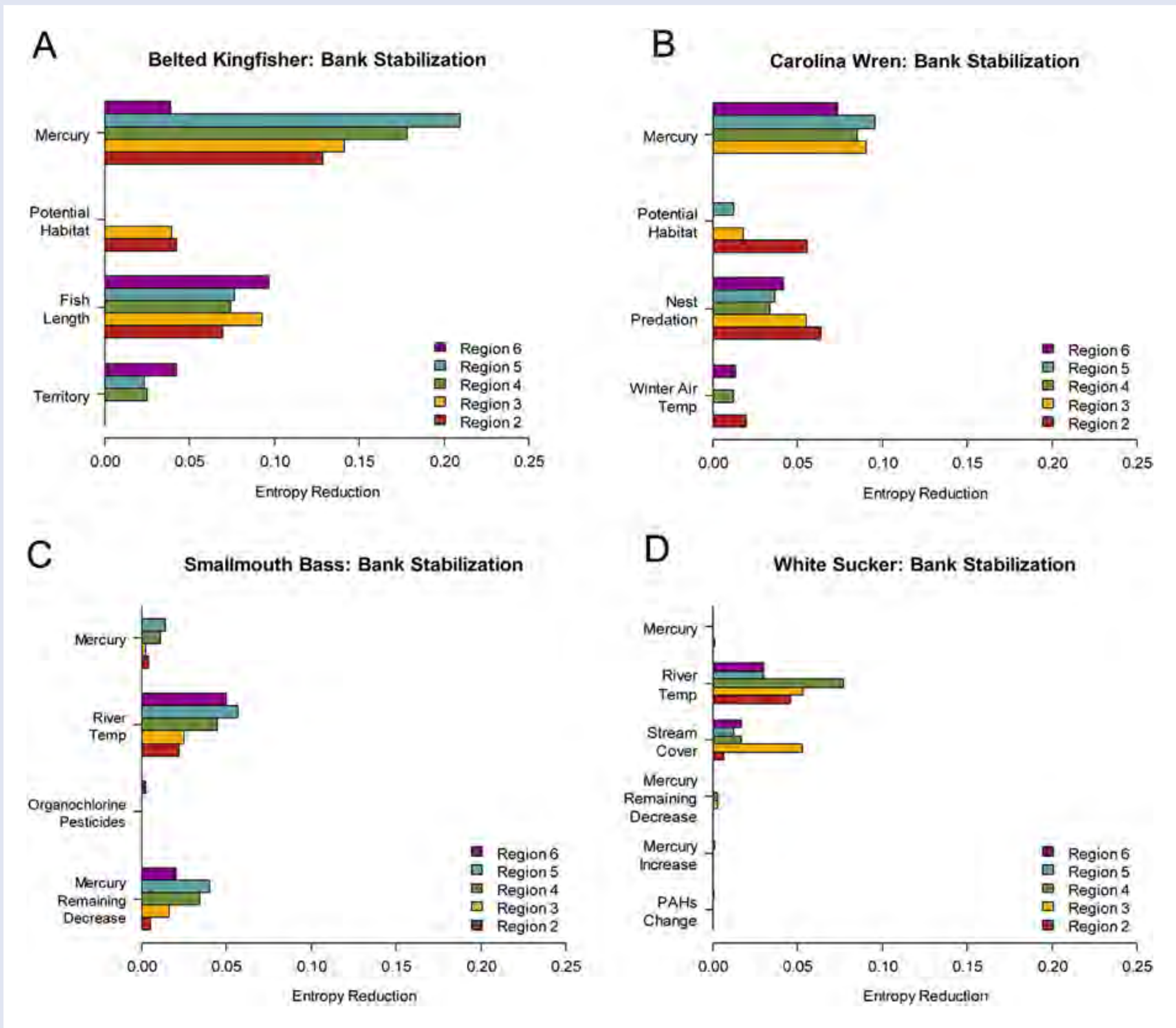


Figure 6. Sensitivity analysis as measured by entropy reduction for the biotic endpoints with the bank stabilization option: Belted Kingfisher (**A**); Carolina Wren (**B**); Smallmouth Bass (**C**); White Sucker (**D**).

For the Water Quality Standards endpoint, summer dissolved-$O_2$ concentrations and bacterial contamination remained the inputs that contributed the greatest risk. Although deviations from summer and winter discharge were important parameters in the initial model for water quality, deviations in river temperature became a greater driver of risk under the BST management option. For Fishing River Use, summer dissolved-$O_2$ concentrations became the most important risk factor with the implementation of BST management option in all regions (Supplemental Data Figure S14B). For the Swimming and Boating River Use endpoints, there was little to no change in the sensitivity of input parameters with BST (Supplemental Data Figures S14C and D).

## DISCUSSION

The purpose of the present article was to apply risk assessment and specifically the BN-RRM in evaluating management alternatives to the South River. In the following sections, we discuss both of the alternatives and how they meet the criteria as management tools. Then we broaden the discussion of how risk assessment can be used at other sites to evaluate the potential success of management strategies.

### *Bank stabilization*

Bank stabilization would not meet the "no regrets" management criteria for belted kingfisher if it were implemented without explicit avoidance of kingfisher nests. The ability of BST to achieve "no regrets" for most of the remaining endpoints is less clear. In looking at overall risk patterns, the skew of the risk distributions for Carolina Wren, White Sucker, Water Quality Standards, Swimming River Use, and Boating River Use endpoints would not change. For instance, the Water Quality Standards and the Swimming and Boating River Use endpoints still have a pattern of risk skewed to the medium- and high-risk states. If, however, we look more closely at the predicted probability distributions with the implementation of BST, we see an increase in risk up to 7% in the high-risk state for many endpoints and regions.

This brings up the question of acceptable risk and what constitutes "no regrets" as determined by the stakeholders of the South River. Stakeholders must also decide whether the "no regrets" goal is applied similarly to all endpoints or is more important for some endpoints than for others. These are things to consider when moving forward with the implementation of these or any management option.

The BST Minimum and Maximum Risk scenarios bracket the risk outcomes for this management option and allow further evaluation of the potential for unintended consequences. The skew in the risk distributions for Belted Kingfisher, Carolina Wren, Water Quality Standards, Swimming River Use, and Boating River Use endpoints would not change under either scenario, meaning there is greater certainty as to the effects of BST on these endpoints. Risk would remain skewed toward zero or high risk, depending on the endpoint in question.

For the other endpoints, the effects of BST are less certain and the scenarios lead to different possible distributions of risk. The Minimum and Maximum Risk scenarios provide a range of possible risks to these endpoints. Although the original Expected Risk scenario represents our best estimation of the effects of BST on these endpoints, the Minimum and Maximum Risk scenarios provide possible alternative outcomes and should be considered in decision making. For example, risk to smallmouth bass in Region 6 would be considerably higher in the Maximum Risk scenario than in the Expected Risk scenario, but would be even lower (and more skewed toward zero) under the Minimum Risk scenario. The Fishing River Use risk distributions, which are zero to low in all risk regions under the Expected Risk scenario, shift toward medium and high risk under the Maximum Risk scenario.

In short, a wide range of risk outcomes could occur with the implementation of BST management for these endpoints. In the Minimum Risk scenario, BST is highly effective at reducing stressor loads or exposure to the endpoints from these stressors. In the Maximum Risk scenario, BST is ineffective at reducing risk, and activities associated with BST may in fact increase stressor loading and/or exposure to the endpoints.

*Agricultural BMPs*

The integration of AgBMPs in the BNs had little impact on risk. Implementing AgBMPs would not reduce the moderate to high risk to the abiotic endpoints, but it would maintain the low risk to the belted kingfisher and smallmouth bass, which aligns with the "no regrets" management goal. Agricultural BMPs are a plausible management option (low cost, low effort); however, initial risk from the targeted stressors is already minimal. The input distributions (priors) for total suspended solids, turbidity, and bacteria are primarily in the zero- and low-risk states, indicating that these stressors are not the main risk drivers. This was confirmed by the sensitivity analysis.

Agricultural BMPs align with the stakeholders' goal that there be "no regrets" when a management action is implemented, that is, that risk to the endpoint did not increase as a result of the management action. Risk, however, was not reduced with the implementation of this management option either. This management option should therefore be evaluated by managers in terms of benefit versus cost. As a preventative measure to reduce potential risks from future agricultural practices, it may be worth the cost, especially in achieving TMDL goals for the South River.

*Application of BNs in South River management*

Using these BNs, South River managers can evaluate management scenarios and identify those alternatives that are the most effective in reducing risk. They can then implement one or more options, monitor key risk factors known for impacting other variables, and use the data to update the BNs to initiate the next decision cycle in adaptive management. An example of updating the BNs to inform future management is provided in Supplemental Data Figure S15. In this example, the smallmouth bass BN for Region 6 was updated 3 subsequent times on the basis of changes to the stressor node probability distributions when BST was included in the model (Supplemental Data Figure S15B). The risk distributions changed over time with the updated inputs (Supplemental Data Figure S15B). In this simulation, smallmouth bass risk decreased the most in the first iteration, and continued to decrease through the next 3 iterations, but at a slower rate. Mercury was the stressor used in this example; however, we also updated the input distributions using the "post BST" nodes to include the other stressors: PAHs, organochlorine pesticides, river temperature, and total suspended solids.

The sensitivity analysis for each endpoint provides a list of monitoring parameters in the order of their influence on an endpoint's risk. Monitoring these stressors is important for informing the adaptive management process. From the sensitivity analysis, it is clear that river temperature must be monitored more extensively to calculate risk to fish species. Mercury was the most important risk factor to the avian species, but was also a risk driver to the fish species and Fishing River Use endpoint. Suggested monitoring parameters for the other water quality endpoints are summer dissolved-$O_2$ levels and deviation from summer and winter average river temperature. River temperature is a major risk factor influencing water quality endpoints, as well as both fish species. Managers of the South River should consider options that may reduce risk from this stressor.

Bayesian network models can also be used interactively to visually communicate responses of endpoints to variables and to compare risk regions. Influence analysis, in particular, can be used as a risk communication tool to compare risk under theoretical scenarios. During a number of presentations to the SRST, we have demonstrated the influence analysis in real time, allowing stakeholders to suggest theoretical scenarios that we then run through the models as a part of the presentation. Because results are instantaneous, they can be used to facilitate discussion and answer "what if" questions that the stakeholders may have. In addition, we make the Netica files available to the SRST and the general public so that anyone may access the BNs and view all components of the models.

*Next steps for management along the South River*

Current plans are to implement BST along sections of the South River as part of the remediation plan. Our BNs can be used to identify areas where BST is likely to cause increased risks, as well as help managers prioritize monitoring parameters. Because management of the South River has been and will be a very long-term process, an adaptive management implementation cycle may span 10 to 15 y; however, the BNs can be updated more frequently to provide revised estimates of risk as more data are collected postremediation.

Every site has multiple stressors, and trade-offs are a reality for managers. Other factors beyond ecological risk may be considered in the decision-making process, including cost, human health risk, and stakeholder approval (Kiker et al. 2008). The BNs in the present study have incorporated 2 management options into a risk assessment framework. In doing so, we have created a method by which other factors that may be considered in the decision-making process can be incorporated into the model as well.

We have found that there is a paucity of peer-reviewed data on the performance of various site remediation and restoration methods within a risk assessment framework. A framework such as the BN-RRM would greatly facilitate evaluating the efficacy of the management option in reducing a stressor, its potential impact on habitat quality, and the potential stressors introduced as part of its construction or implementation.

*Adaptive management and the role of ecological risk assessment*

Holling (1978) proposed adaptive management as a strategy for restoring and then managing the environment. Wyant et al. (1995) proposed that risk assessment could be a critical part of the decision-making process that is key to adaptive management. In the BN-RRM method we use, current risk can be profiled and the change in risk due to a management strategy can be calculated. The new estimates of risk can then be evaluated in a multiple criteria decision analysis (MCDA).

Foran et al. (2015) discuss how a reduction in Hg concentration for the South River could be employed in an MCDA process. However, Hg concentration is not the probability of exposure or effect that is innate to a computation of risk. As has been demonstrated in the present study, a decrease in Hg concentration does not reduce risk to some of the endpoints.

In the concluding article of this series, Landis, Markiewicz et al. (this issue) demonstrate how risk assessment using the BN-RRM can be applied to the framework of Wyant et al. (1995) for adaptive management. We detail how remediation options are placed into an ecological context in which the efficacy is presented as a change in risk throughout the landscape and not merely as a change in concentration of a toxicant. Because the options are put into the ecological context of the site, unintended consequences can be evaluated as part of the overall costs associated with restoration.

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*Data availability*—The data are available at two locations online, at the South River Science Team website (http://southriverscienceteam.org/) and at the WWU CEDAR library server site (http://cedar.wwu.edu/).

## SUPPLEMENTAL DATA

Two kinds of files: 1) Supplemental tables and figures specifically called out in the text of the main manuscript and 2) examples of the Bayesian networks that were derived for this study as Netica files (.neta).

**Table S1.** Survey results from the bank stabilization expert elicitation

**Table S2.** Bank stabilization influence analysis

**Table S3.** Sensitivity analysis: Entropy reduction results for adaptive management

**Figure S1.** Bayesian network to calculate risk to Smallmouth Bass endpoint in Region 2 with AgBMPs implemented.

**Figure S2.** Bayesian network example of the scenarios used for the influence analysis of turbidity change to the belted kingfisher.

**Figure S3.** White sucker (WS) initial risk estimates and expected risk with the bank stabilization option.

**Figure S4.** Carolina wren (CW) initial risk estimates and expected risk with the bank stabilization option.

**Figure S5.** Water Quality Standards (WQ) initial risk estimates and expected risk with both bank stabilization and AgBMP options.

**Figure S6.** Swimming River Use (WS2) initial risk estimates and expected risk with bank stabilization and AgBMP options.

**Figure S7.** Boating River Use (WB) initial risk estimates and expected risk with both bank stabilization and AgBMP options.

**Figure S8.** Fishing River Use (WF) initial risk estimates and expected risk with bank stabilization option.

**Figure S9.** Bank stabilization scenarios influence analysis for the Smallmouth Bass endpoint.

**Figure S10.** Bank stabilization scenarios influence analysis for the Fishing River Use endpoint.

**Figure S11.** Bank stabilization scenarios influence analysis for the Water Quality Standards endpoint.

 

**Figure S12.** Entropy reduction results for the biotic endpoints with the AgBMPs option included in the model.

**Figure S13.** Entropy reduction results for the water quality endpoints with the AgBMPs option.

**Figure S14.** Entropy reduction results for the water quality endpoints with the bank stabilization option.

**Figure S15.** Graphical representations from Netica showing the risk distributions for the Smallmouth Bass endpoint with bank stabilization management through three time steps.

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