Results Summary for the Integrated Regional Risk Assessment for the South River and Upper Shenandoah, Virginia

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Project Summary

We have conducted a regional scale risk assessment was conducted using Bayesian networks (Ayre and Landis 2012) structured on the relative risk model as described by Landis and Weigers (2005). The Bayesian network relative risk model (BN-RRM) calculations were performed in three parts. Initially the risk assessment was performed using two fish species and two bird species as endpoints (Summers 2012). Concurrently a BN-RRM was constructed that applied to four water quality parameters that are specifically tied to ecosystem services delivered by the river. Finally the output of the two BN-RRM models were combined using Monte Carlo analysis to provide an overall depiction of relative risk within the South River watershed. A increasing gradient of risk was observed until the formation of the South Fork of the Shenandoah River.

In order to reduce uncertainty additional studies were conducted to better describe the toxicity of Hg to fish and the temperature tolerance of smallmouth bass. An analysis of the exposure-response data summarized in Dillon et al (2010) by curve fitting allowed a better description of the toxicity at lower levels of exposure. A detailed analysis of the temperature tolerance of smallmouth was constructed by referring to data from original publications. The analysis of this data at both high and low temperature ranges allowed the construction of an exposure-response curve that included both extremes. A calculation of risk using the updated analysis showed only small changes in risk scores for each region and the same risk gradient within the study area.

Our current efforts are focused on incorporating management alternatives into the Bayesian network. We have learned how to better calculate estimates of conditions to result in lower risk in the Netica derived Bayesian networks to target management options. The outcomes of the various management options can be expressed as a segment of our current Bayesian networks.

Introduction

In this report we summarize the risk assessment activities for the South River over the last three years conducted by the Institute of Environmental Toxicology at Western Washington University. The goal is to provide an overview of the activities and a summary of the results and conclusions. The report is organized into several sections.

The **Introduction** briefly summarizes the background on the relative risk modeling used in this analysis. The **South River Risk Assessment** section describes the research site, the development of the risk assessment model, and how Bayesian networks (BNs) were used to estimate risk. **Patterns of Risk** summarizes the current findings for risk to our eight endpoints and the overall patterns of risk in the landscape. **Updates to the Risk Assessment** discusses out re-evaluation of the effects of temperature and Hg on the smallmouth bass. **Next Steps** discusses current and future risk assessment activities.

Regional Risk Assessment using Bayesian Networks. Regional risk assessment has been specifically defined (Landis and Wiegers 2005). Regional risk assessment deals at a spatial scale that contains multiple habitats with multiple sources of multiple stressors affecting multiple endpoints and the characteristics of the landscape affects the risk assessment. Although there may be only a primary stressor of interest for the site, it is recognized that at a regional scale that other stressors acting upon the endpoints are to be considered.

Colnar and Landis (2007) introduced the current version of the basic relative risk model. This version described how the hierarchical patch dynamics paradigm (HPDP) as formulated by Wu (Wu and David 2002) could be used to conceptualize how spatial, dynamic and habitat interact at different scales. Anderson and Landis (2013) provided an extensive demonstration of how this method could be applied with the inclusion of management options for a forest system.

Bayesian network RRM (BN-RRM). Ayes and Landis (2012) incorporates the use of Bayesian networks to describe the interactions between sources, stressors, habitats, effects and impacts. Ayre and Landis (2012) demonstrated how the version of the RRM used by Anderson and Landis could be translated into a Bayesian network while retaining the basic framework of the approach. The current risk assessment for the South River uses the BN-RRM approach (Figure 1).

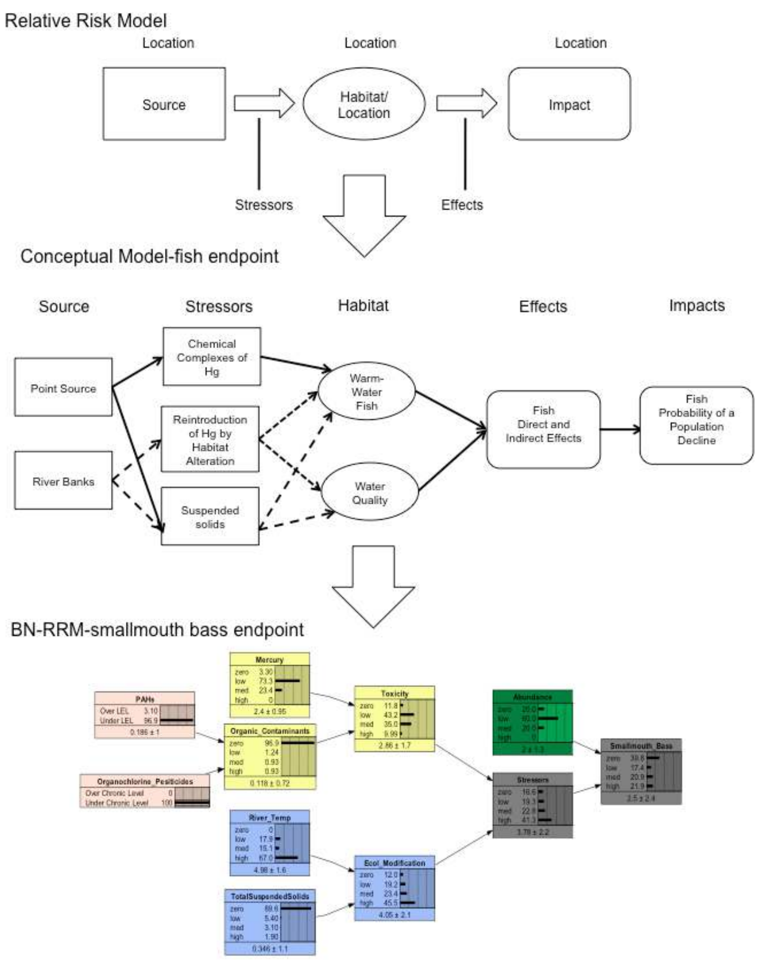

Figure 1. Derivation of a Bayesian network RRM. The basic form of the relative risk model is converted into a conceptual model that describes the cause-effect linkages that will be used to estimate risk. Finally a Bayesian network is built that describes these pathways and incorporates the likelihood distributions for each variable.

South River Risk Assessment

Research Site. 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 at total of 84.7 km to merge with the Middle River and North River in Port Republic, Virginia, to form the South Fork of the Shenandoah River. The South Fork of the Shenandoah continues flowing northward to Front Royal, Virginia, where it converges with the North Fork of the Shenandoah to form the Shenandoah River (Eggleston 2009).

We defined the South River Study Area (SRSA) as the 607.6 km^2 South River watershed and the South Fork of the Shenandoah River. We divided the South River watershed into six risk regions based on hydrological and landuse similarities. Figure 2 shows the South River watershed and division of risk regions starting upstream in region one to region six where the South River joins with the South Fork of the Shenandoah River. The primary land uses within the study area are forested (58%) and agricultural (31%) with a small portion of developed land (8%) mostly comprised of the cities of Waynesboro, Grottoes and Elkton (Eggleston 2009).

The significant amount of land used for agriculture land used within the SRSA results in other potential stressors to ecological receptors other than mercury. Because of these varied land uses, we included two of the most common chemical classes of contaminants, polyaromatic hydrocarbons (PAHs) and polychlorinated biphenyls (PCBs) as measures of potential exposure.

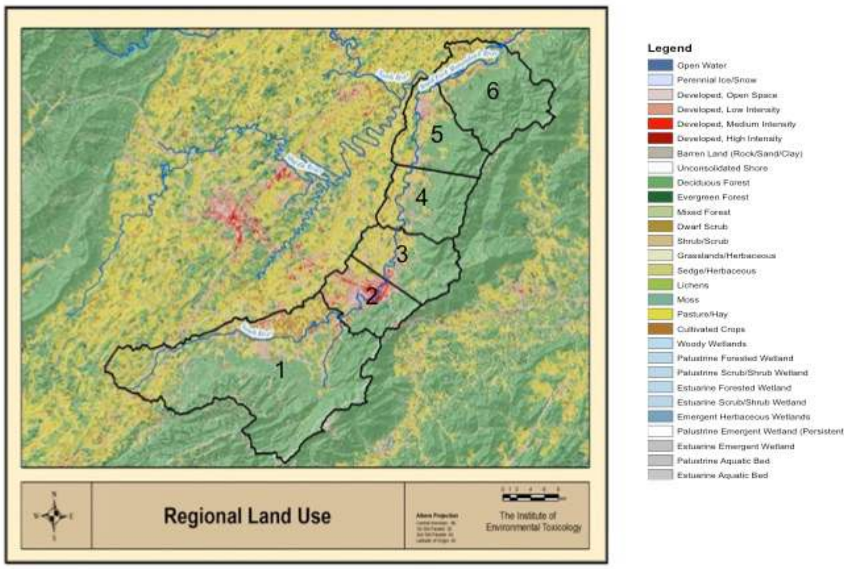

Figure 2. South River Study Area. The different land uses for the SRSA and the risk regions are depicted.

Endpoints and model construction. The risk assessment has three different parts. The first is the development of four BNs to estimate risk to smallmouth bass (SB), white sucker (WS), Belted Kingfisher (BK) and Carolina Wren (CW). The second part is the development of a water quality BN that has four endpoints: water quality standards (WQ), fishing (WF), boating (WB) and swimming (WR). These endpoints represent ecosystem services derived from the watershed. The third part is the integration of the two sets of models to create an overall risk score. The risk distributions for all eight endpoints were combined via a Monte Carlo analysis to produce distributions representing overall risk in each risk region.

*Development of the BN-RRM***.** The basics of the methods used to create the representation of the RRM in Bayesian networks can be found in Summers (2012). A short summary is provided for the biotic endpoints and more detail can be found in Summers (2012). A more detailed section on the derivation of the water quality ranks and models follows the discussion of the biotic endpoints. Examples of a biotic endpoint and the water quality BNs can be found in Appendix 1.

<u>Biotic Endpoints.</u> Details of the process for the 4 biotic endpoints are in Summers (2012). Parameterization of the model began with selecting a dataset for each input parameter in the model. We restricted all chemical exposure datasets to data from 2005 to the present due to bank stabilization management strategies in 2005 near the former DuPont site to reduce the infiltration of mercury laden sediment to the river during flood events (Flanders et al. 2010). Input parameters for PAHs, organochlorine pesticides, turbidity and temperature (water and air) for all target species, and mercury body burden in Belted Kingfishers and Carolina Wren included all available data from 2005 onward.

Data characteristics drove the selection of literature sources for chemical stressors. Since body burden information was available for mercury in fish and birds, we used articles that reported mercury residue concentrations and their associated effects in fish species and blood mercury concentrations in birds

Once literature sources were identified, we classified the effects based on risk categories; zero or none, low, medium and high. Due to uncertainty we divided the results into fewer categories. We determined cut-offs between categories either using the suggested impact described by the author or natural breaks in the dose-response curve. When neither of these were evident, the following general rule was used: Zero ≤5% effect, Low 5 – 20% effect, Medium 20-50% effect and High ≥50% effect.

Next we determined the probability distribution for each input parameter based on the site-specific data. The following is an example of the process for Hg body burden input parameter for smallmouth bass but all followed a similar process. The source for the mercury dose-response curve for fish came from Dillon et al. (2010).

Rank	Tissue Concentration	Effect
Zero	≤ 0.2 mg Hg/kg fish tissue	<5 percent effect
Low	0.3-1 mg Hg/kg fish tissue	5-24 percent effect
Medium	1.1- 3.0 mg Hg/kg fish tissue	24-50 percent effect
High	3.1-10.0 mg Hg/kg fish tissue	>50 percent effect

Using these levels, we divided the South River smallmouth bass data by risk region and calculated the frequency of mercury residue concentrations recorded for each risk level and divided by the total number of samples in each region to determine the probability of effects in each risk level.

A similar method was used to define the input parameter probabilities for all stressors with the exception of species abundance. In order to express the potential for exposure in a geographic manner, I compared the abundance of each species within each risk regions to the total abundance in the South River study area to define risk levels for the abundance input parameter. This parameter represents the relative abundances of each region is used in the models to represent a measure of potential exposure. The abundance parameter scales the risk output by weighting regions with high abundance more heavily.

<u>Details of the water quality model.</u> 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. When considering the impact of water quality on ecological services it requires a slightly different approach. We constructed a Bayesian network model to assess the potential impacts of current conditions in the South River to achievement of water quality standards and recreational use, specifically fishing, boating and swimming. Hydrologic parameters included in the model were the magnitude of deviations in recent stream temperature, discharge and dissolved oxygen levels relative to long-term, seasonal averages. The other principle input parameters were total phosphorus and *E. coli* concentrations in the river, and methylmercury levels in fish based on their causal relationships to the ecological services of concern for communities surrounding the South River.

All model input parameters were discretized into categorical states, which were defined quantitatively using regulatory guidelines or established classifications (**Table 1**). We followed the methodology used in a similar water quality risk assessment (Pollino et al. 2007) to defining the categorical states for hydrologic parameters, based on comparison of current conditions to historical, long-term averages. Hydrologic data was divided into two seasons, Fall-Winter (October-March) and Spring-Summer (April-September), and the 30-year averages calculated for each season. For stream temperature and discharge we calculated 30-year averages from data collected by Virginia Department of Environmental Quality (VDEQ) monitoring stations within each risk region, and compared the seasonal averages to daily measurements from 2010-2011 that were extracted from the USGS NHDPlus database to determine the magnitude of deviations from long-term averages. Deviations in dissolved oxygen levels compared to 30-year, seasonal averages were calculated as the percent difference between the averages and daily dissolved oxygen levels for 2006-2009. The primary source of data for dissolved oxygen was VDEQ, but we supplemented these data with measurements collected by the South River Science Team (SRST). Combining the two datasets was necessary because some risk regions had limited available data.

The categorical states assigned for water phosphorus and *E. coli* levels, and fish mercury body burden were based on regulatory guidelines. Phosphorus and *E. coli* levels were included in the model because they have both been identified as TMDL pollutants that exceed water quality standards. We used concentrations of total phosphorus in our analysis, which were extracted from the same databases used for dissolved oxygen. The EPA designated 0.1 mg/L as the background level and desired regulatory for total phosphorus in surface waters, so concentrations at or below this level were assigned a zero risk state. Rivers with phosphorus levels of 0.1-0.3 mg/L typically do not develop surface algal blooms; however, above 0.3 mg/L algae and diatoms begin to flourish (Black et al. 2010). The regulatory standard for *E.coli* bacterial counts for single water samples is 235 cfu/100 mL, above this level bacteria may pose a risk to human health through exposure during recreational activities, and a comprehensive review of the relationship between recreational exposure and water quality found that the incidence of illness increases linearly with exposure to waters with bacteria concentrations above 100 cfu/100 mL (Prüss 1998). In the model bacterial concentrations measured for the South River below the regulatory standard were assigned zero risk, and concentrations above 1000 cfu/mL were categorized as high risk. The states used for fish methylmercury concentrations were the same as we used for the Smallmouth bass risk assessment, although we used the tissue sample data collected by the SRST for all fish species.

One of the assessment endpoints in the water quality risk assessment model was recreational fishing use, which is influenced by the abundance of fish in reaches of the South River. We included an input parameter in the model that impacts fish abundance directly, the presence or absence of fish stocking within a risk region. Locations for fish stocking in the South River were identified, and mapped onto our risk region delineations to determine which regions were routinely stocked with fish. This parameter is unique in that the data were qualitative, and there is a direct causality between the parameter and one of the assessment endpoints.

<u>Conditional Probability Tables.</u> Conditional probability tables describe the relationship between two or more input nodes in the Bayesian network. The conditional probability tables also describe the exposure potential geospatially, for example when the geographic distribution of a chemical contaminant intersects with a species preferred habitat.

The conditional node has the four states (zero, low, medium and high) as the input nodes. In some cases, the input node may be less well defined and contain three or even two states, making the resulting conditional probability table smaller. If data is available to describe the relationship of two stressors, then the conditional probability tables is filled in from that data. In many cases, the combination of stressors is not quantitatively defined or well understood. For conditional nodes where no quantitative description of the interaction of two or more stressors is given, we used a quantitative meta-analysis approach from an extensive literature search to define the conditional probability tables.

Table 1. Rankings of the inputs for the water quality BN models.

Variables	**Input Parameter**	**State**	**Value**
Anthropogenic Inputs	Phosphorus	Zero	<0.1 mg/L
		Low	0.1-0.3 mg/L
		Medium	0.3 to 0.5 mg/L
		High	> 0.5 mg/L
	E. coli Levels	Zero	< 200 cfu/100mL
		Moderate	200-1000 cfu/100mL
		High	> 1000 CFU/100mL
Dissolved Oxygen (DO)	Fall/Winter DO Levels	Normal	> 9 mg/L
		High	5-9 mg/L
		Low	< 5 mg/L
	Spring/Summer DO Levels	Normal	> 9 mg/L
		High	5-9 mg/L
		Low	< 5 mg/L
Mercury	Fish Mercury Body Burden	Zero	> 0.3 mg/kg
		Low	0.3 to 1.0 mg/kg
		Medium	1.1 to 3 mg/kg
		High	> 3 mg/kg
Deviation in Daily Stream Temperature from 30-year Averages	Fall/Winter Temperature	Zero	± 0-2 °C
		Moderate	± 2-4 °C
		High	>4 °C
	Spring/Summer Temperature	Zero	± 0-2 °C
		Moderate	± 2-4 °C
		High	>4 °C
Deviation in Daily Stream Discharge from 30-year Averages	Fall/Winter Discharge	No Change	76-125% of 30-yr average
		Increase	126-175% of 30-yr average
		Decrease	25-75% of 30-yr average
	Spring/Summer Discharge	No Change	76-125% of 30-yr average
		Increase	126-175% of 30-yr average
		Decrease	25-75% of 30-yr average
Input of Fish	Fish Stocking	Yes	Fish stocking in risk region
		No	No fish stocking in risk region

Calculation of Risk. The distribution of the ranks for the input nodes each model was derived from data specific to each of the risk regions. So for each of the risk regions there were four biotic endpoint models that were specific to that particular region. Unfortunately for the estimation of risk data were often not available for the construction of a reliable BN. For the remaining five regions a total of 20 models were constructed to provide an overall pattern of risk for biotic endpoints in the study area. The water quality BN incorporated all four endpoints and a model was constructed for each risk region. A total of 25 models were built.

We used Netica™ by Norsys Software Corp (http://www.norsys.com/) to create and evaluate the Bayesian networks. Entropy analysis was used within the same software package to determine the parameters most important in determining the output.

Examples of the models for risk region 2 are provided on a CD at the October 2013 SRST meeting. It only requires the download of Netica™ as a free version to be able to view the models and to see how different inputs alter the risk results. We strongly recommend taking the online introduction to Bayesian networks at http://www.norsys.com/tutorials/netica/nt_toc_A.htm before investigating the models.

Patterns of Risk

One of the difficulties in large-scale risk assessment is the summary of the patterns of risk in the area. **Table 2** summarizes all of the relative risk scores derived by the BNs for each endpoint by each region.

Table 2. Risk Scores for the different endpoints by risk region. SMB-smallmouth bass, WS-white sucker, BK-Belted Kingfisher, CW-Carolina Wren, WQ-water quality standards, WF-fishing standards, WS-swimming standards, WB-Boating standards.

	Biotic Endpoints				Water Quality				Totals		
Region	SMB	WS	BK	CW	WQ	WF	WS	WB	Biotic	Water	Overall
2	2.5	3.3	2.5	1.1	4.9	2.2	4.5	4.4	9.4	16.0	25.4
3	2.8	2.7	1.6	1.8	4.5	3.4	4.6	4.5	8.9	17.1	26.0
4	4.5	2.7	2.0	2.9	5.0	3.7	4.8	4.8	12.0	18.3	30.3
5	5.6	2.0	2.1	2.8	4.9	3.2	4.9	4.8	12.5	17.7	30.2
6	3.6	2.1	1.7	2.0	4.3	2.3	4.7	4.6	9.5	15.9	25.4

Risk to Biotic Endpoints. The smallmouth bass had the highest risk scores with regions 4 and 5 the areas of highest risk. Carolina Wren had a similar pattern but lower risk scores. White sucker and Carolina Belted Kingfisher have the highest scores in region 2. For all biotic endpoints risk was lower in region 6 compared to region 5, Region 6 is the portion of the study area that is the South Fork of the Shenandoah.

The risk scores do not fully represent risk to the endpoints. The BNs produce a distribution that more accurately portrays the distribution of risk. **Figure 3** illustrates the differences in the risk distributions for Carolina Wren for Regions 2 and 5. The most common ranking for the Carolina Wren in Region 2 is zero or no risk. The mean of this distribution is 1.1 (**Table 2**). Region 5 has a higher risk score (2.8) and the distribution (Figure 3) shows a shift to the low and medium risk classifications. Every endpoint has an associated distribution that is summarized by the risk score.

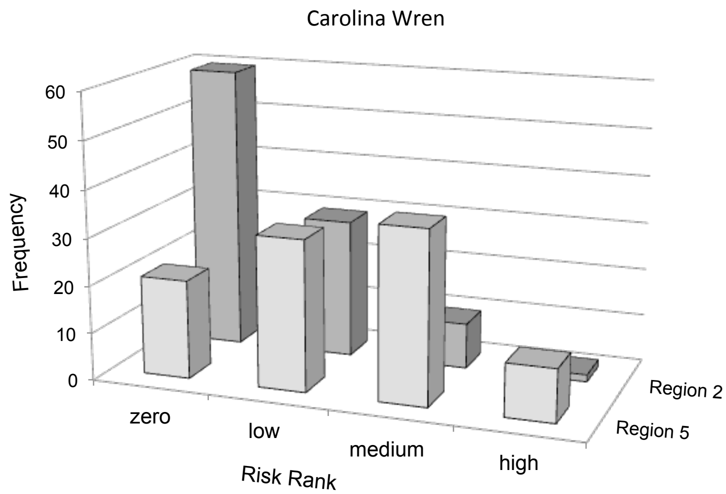

Figure 3. Comparison of the risk distributions for Carolina Wren. The risk in Region 2 is skewed towards the zero and low risk ranks. The increased risk in Region 5 is demonstrated by the shift in the distribution to the low and medium ranks.

Risk to Water Quality Endpoints. The risk to water quality endpoints did not demonstrate the range of values found in the biotic endpoints (**Table 2**). WQ, WS and WB all demonstrated similar scores and patterns of risk in the study area. WF (fishing standards) were at a lower risk throughout the study area compared to the other endpoints. Regions 2 and 6 had lower scores for WF and regions 3-5 were similar.

*Overall Risk***.** Water Quality endpoints were at higher total risk than the biotic endpoints in each risk region (**Table 2**). This pattern is reflected in **Figure 4**. The biotic endpoints are a larger portion of the overall risk in Regions 4 and 5. But as the risk to the biota is reduced the portion of risk due to water quality increases in Region 6. The water quality endpoints are more consistently at risk compared to the biotic endpoints. Because of the increased risk to biotic endpoints in Regions 4 and 5 the highest overall risk is in those regions. To provide perspective for the total risk scores a maximum risk score would be 48, medium 32, low 16 and zero would have a score of 0.0.

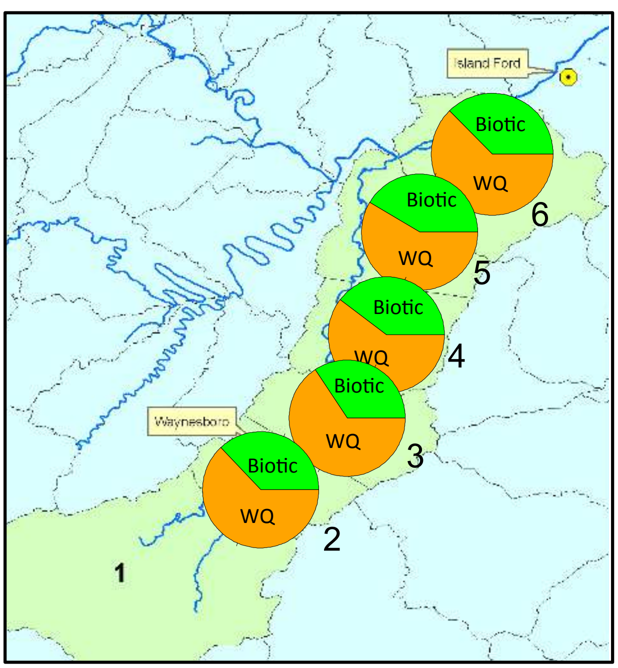

Figure 4. The proportion of risk from the biotic and water quality (WQ) endpoints in the different regions. WQ is the major contributor to risk in all regions. In regions 4 and 5 risk to biotic components is a larger percentage compared to the other regions.

Updates to the Risk Assessment

Two projects have been completed to reduce the uncertainty of the exposure-response relationship. The first is the relationship between temperature and the smallmouth bass. The second in an effort to better characterize the relationship between Hg and fish toxicity.

Smallmouth Bass Temperature Tolerance. A literature search analyzing the effects of temperature on smallmouth bass, *Micropterus dolomieui,* was completed to address questions concerning temperature rankings presented in the original Bayesian model and report. Four articles (Casselman et al. 2002, Smith et al. 2005, Sharma et al. 2007, Sharma and Jackson 2008) were used as a starting point in the search for temperature data. These initial articles presented lethal temperature data from earlier work, thus we used a tree search to find the original articles and experiments.

In ranking temperature, we considered each life stage of the smallmouth bass, as well as the time of year and likely temperatures for shorter events like spawning. Upon completion of this literature search, we decided to no change was necessary for the upper temperature bounds for all ranks. These ranks were consistent with the preferred and avoidance temperatures of many of the life history stages of smallmouth bass (Cherry et al. 1975 and 1977). However, two additional scenarios were created for the lower temperature bounds. In these scenarios, the lower thermal limits were expanded to encompass spawning temperatures (Shuter et al. 1980, Wrenn 1984) and preferred temperatures of juvenile (20.2-30.9°C) and adult (18-21°C) smallmouth bass (Zweifel et al. 1999). **Figure 4** displays the thermal lethal limits for the eggs and fry life history stages of smallmouth bass.

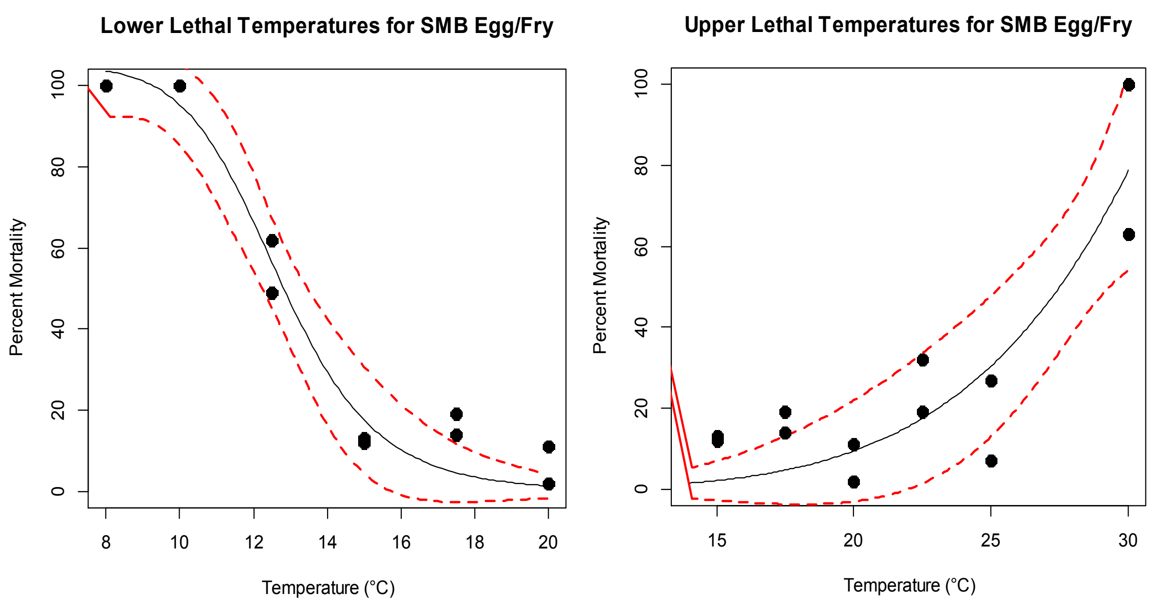

Figure 4. Temperature and Mortality for Smallmouth Bass. These graphs summarize the data for lethal temperatures for egg and larval stages of smallmouth bass. This is a log-logistic model, dashed lines indicate 95% CI. The 63% mortality point at 30°C represents eggs that hatched, but larvae died soon after hatching. Data source: Kerr 1966, also see Shuter et al. 1980. These figures were created in R with the 'drc' package.

After applying the alternative ranking schemes to the Bayesian models, very little change was observed to the smallmouth bass in any risk region. The greatest shift in distribution was occurred in the zero rank, with a maximum increase of 4% probability, and in the high rank, with a maximum decrease of 1.8% probability. The low and medium distributions remained similar to the original Bayesian network model values.

Mercury Exposure-response for Fish. The original risk assessment used the log transformed dose-response curve from Dillon et al. (2010) to estimate total mercury concentrations associated with different levels of adult/juvenile fish injury. For the re-evaluation, we fit a model to the raw data, not the log of total mercury concentrations. We only included data for total mercury concentrations less than 6 mg/kg wet weight. This allowed the model to have an improved fit of the dose-response data at lower total mercury concentrations. Decision makers are most interested in the lower portion of the curve because the target total mercury concentration for fish in the South River is 0.3 mg/kg wet weight (USEPA 2010). After censoring the data as described, we fit a three parameter log-logistic model using the drc function in the drm package in R. We included 95% confidence intervals.

We evaluated three different scenarios: upper confidence interval, lower confidence interval and model predicted. The total mercury concentration range for each state was obtained by calculating the concentration associated with the injury percentage that represents the break between the four possible “Mercury” node states. This method was used for the upper confidence interval, lower confidence interval and the predicted model. A Mercury node state of zero is defined as less than 5% injury; low represents 5-24% injury; medium represents 24-50% injury; and high represents greater than 50% injury (Summers 2012). We used the original mercury state definitions our analysis. Mercury was the only node altered for each alternative scenario.

The upper confidence interval scenario increased slightly the probability of high risk to smallmouth bass and decreased the probability of zero risk while other state probabilities remained the same compared with the risk probability distribution in the original model. The probability of low and medium risk from mercury remained approximately the same. This resulted in an increased in the total risk score for all risk regions under the upper confidence interval scenario. The lower confidence interval scenario yielded a minor decrease in high-risk probability and an increase in zero risk probability from mercury accompanied by a one or two percent change in probability of low or medium risk. Therefore the total risk score to smallmouth bass decreased for each risk region. The model prediction scenario changed the probability of a state by only a few percent in each risk region, and there was no consistent increase or decrease in a specific state probability with the application of this scenario, thus no consistent change in total risk score across risk regions was observed.

Risk from Combining Alternative Mercury and Temperature Scenarios. We also explored combinations of the alternative temperature and mercury scenarios to identify the highest and lowest probabilities of risk associated with each risk region. The combination with the coldest temperature scenario and upper confidence intervals of mercury concentrations resulted in findings similar to the original Bayesian models. The higher toxicity associated with the upper confidence intervals was essentially ‘canceled out’ with the coldest temperature scenario. However, when applying the coldest temperatures with lower confidence intervals, we observe a shift in the distribution risk from high to lower risk. Region 6 experienced the greatest change, with the high-risk distribution changing from 38.0 to 25.5% probability. The zero risk distribution changed from 19.5 to 39.3% probability. Again, low and medium distributions remained fairly consistent with the original model and the greatest changes occurred in the zero and high distributions. Results from this last scenario (lower CL and coldest temperature) describe the lowest risk distribution scenario for smallmouth bass. Next we need to finish the sensitivity analysis for the alternate Hg and temperature scenarios.

Next Steps

The next step is the integration of the risk assessment with different management options. This project will examine how the management scenarios, such as bank stabilization or best management practices (BMPs) for agriculture, change the risk throughout the watershed. Currently the smallmouth bass and Belted Kingfisher models have agricultural BMPs integrated into the BN. The integration of the agricultural BMPs into the water quality model is now underway.

The integration of the management programs into the BNs will have three benefits to the future management of the South River. First, the efficacy of the management option in reducing risk can be examined for each endpoint and risk region. Second, negative effects may occur due to a particular management strategy so the risk assessment can add in preventing unexpected consequences. "No regrets" is an overriding theme in the discussions of the management of the SRST. Third, the risk assessment can provide information on the changes in the watershed and their likelihood, aiding in the development of a long term monitoring program.

Next year it is planned to initiate the integration of the ecological risk assessment with the human health assessment. Fish, water and soil are routes of exposure of Hg to the human population. The current ecological assessment covers risks to two of these pathways, fish and water. So our current plan is to closely examine the fish, water and soil pathways as routes of human exposure. Then current guidelines on the risks of Hg exposure to humans will be compared across the study area.

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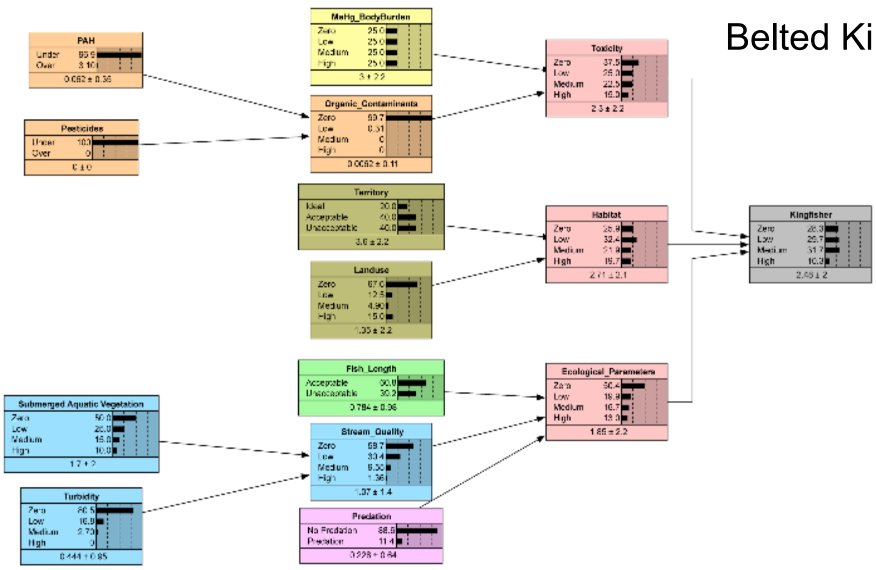
Appendix 1. Representation of a typical biotic (Belted Kingfisher) the water quality BN. There are 4 specific models for each biotic endpoint for each risk region. So there are a total of 20 biotic BN models for this assessment. In the water quality model all 4 endpoints are included for each risk region for a total of five models.

Belted Kingfisher



Water Quality