A Dynamic Bayesian Approach for Integrating Climate Change into a Multi-Stressor Ecological Risk Assessment for the Mercury Contaminated South River and Upper Shenandoah River

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A Dynamic Bayesian Approach for Integrating Climate Change into a Multi-Stressor Ecological Risk Assessment for the Mercury Contaminated South River and Upper Shenandoah River

By
Lara Gaasland-Tatro

Accepted in Partial Completion
Of the Requirements for the Degree
Master of Science

Kathleen L. Kitto, Dean of the Graduate School

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MASTER’S THESIS

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Lara Gaasland-Tatro

20 May 2016
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A Thesis
Presented to
The Faculty of
Western Washington University

In Partial Fulfillment
Of the Requirements for the Degree
Master of Science

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Lara Gaasland-Tatro

20 May 2016
Abstract

Anthropogenic climate change is causing the earth to warm, and the consequences of warming will be on a continuum for species from extinction to thriving and expanding to larger ranges. There will be winners with climate change and there will be losers, and identifying species that management would benefit early makes management more effective. Environmental factors and contaminants complicate species responses to climate change. Sites with legacy contaminants, like mercury, that stay in the environment for extended periods will need to be managed for the mixed effects of climate change, environmental stressors and contaminants. In this study I use an ensemble of 10 GCMs downscaled to a 0.125-degree scale to assess the likely climate for 2071-2100. I integrate these projections into a Bayesian network relative risk model for the mercury contaminated South River in Virginia, USA. All climate change models predict increased temperatures across the South River. From my ensemble of downscaled climate projections for the South River, I predict that the Carolina wren, smallmouth bass and white sucker will all have reduced risk with warmer temperatures. This risk assessment provides early information on likely future conditions for long-term management of the South River. It also indicates future research that would increase understanding of the dynamics of contaminant uptake and temperature.

Keywords: Climate change, mercury, relative risk model, Bayesian networks, Carolina wren, smallmouth bass, white sucker, GCMs, downscaled climate projections
Acknowledgements

The South River Science Team (SRST) supplied the majority of the data for this research. Downscaled climate projections came from the CMIP3 and CMIP5 Climate and Hydrology Projections, archive at http://gdo-dcp.ucllnl.org/downscaled_cmip_projections/. The climate models (CMIP5) came from the World Climate Research Program’s Working Group on Coupled Modelling and the climate modeling groups listed.

Meagan Harris and Scarlett Graham provided fruitful discussion on the BN-RRM method. Theodore Ahlvin contributed valuable GIS knowledge.

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Note on Format
This paper outlines the human health and ecosystem services risk assessment using the Relative Risk Model. For more information on the initial biotic endpoints, refer to Landis et al. (2016). The Bayesian network files are available electronically or upon request. Download the free version of Netica to view the models without a license (https://norsys.com/netica.html).
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<tbody>
<tr>
<td>BCCA</td>
<td>Bias Corrected Constructed Analogs (downscaling method)</td>
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<tr>
<td>BN</td>
<td>Bayesian Network (sometimes called Bayes Net)</td>
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<tr>
<td>BN-RRM</td>
<td>Bayesian Network Relative Risk Model</td>
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<tr>
<td>CMIP5</td>
<td>Coupled Model Intercomparison Project Phase 5</td>
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<td>CPT</td>
<td>Conditional Probability Table</td>
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<td>IPCC</td>
<td>International Panel on Climate Change</td>
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<tr>
<td>MeHg</td>
<td>Methylmercury</td>
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<tr>
<td>NOAA</td>
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<td>PAHs</td>
<td>Polycyclic Aromatic Hydrocarbons</td>
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<tr>
<td>RCP 8.5</td>
<td>Representative Concentration Pathway 8.5 Watts/ square meter</td>
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<td>RCRA</td>
<td>Resource Conservation &amp; Recovery Act</td>
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<td>RRM</td>
<td>Relative Risk Model</td>
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<td>SRSA</td>
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<td>SRST</td>
<td>South River Science Team</td>
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<tr>
<td>TMDL</td>
<td>Total Maximum Daily Load</td>
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<td>USGS</td>
<td>United States Geological Survey</td>
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1. Introduction

Ecological risk is the chance of harmful effects to ecological systems (US EPA 2016). An Ecological Risk Assessment (ERA) determines the probability of effect from environmental, chemical and climate stressors on an endpoint of cultural value. My thesis is an ERA that uses the relative risk model (RRM) to combine multiple sources of information about a site, creating a tool for environmental management and contaminated site remediation (Landis and Wiegers 1997, Landis and Wiegers 2005). The risk assessment framework evaluates the impacts of multiple stressors on multiple endpoints across a heterogeneous landscape (Landis and Wiegers 1997). Here I use Bayesian networks (BNs) with the RRM approach (BN-RRM), to conduct quantitative, probabilistic, and spatially explicit ERAs for a contaminated site.

In this study, I incorporate downscaled climate projections for 2071-2100 into a BN-RRM based ERA (Landis et. al 2016). For my case study, I use the mercury-contaminated South River Study Area (SRSA) in Virginia which includes the South River and South Fork of the Shenandoah River watersheds, to demonstrate the applicability of using climate projections to model future risk to biota for a contaminated site. I assessed change in risk to three species of value to stakeholders, the Carolina wren (*Thryothorus ludovicianus*), the smallmouth bass (*Micropterus dolimeu*) and the white sucker (*Catostomus commersonii*). There are three primary objectives of this risk assessment:
1. Demonstrate a method for integrating climate change projections into ERA models for a contaminated site
2. Use the model to assess climate change driven future risk to SRSA biota
3. Compare effects across different climate projections, endpoints, and regions in the SRSA

1.1. Relative Risk Model
The relative risk model is used to evaluate multiple stressors and ecological parameters over landscape scale regions (Landis and Wiegers 1997, Wiegers et al. 1998). The basic form of the RRM is shown in Figure 1. Stressors and their sources are identified and compared with habitats where species or ecological services of value to stakeholders are found. When sources of stressors overlap with habitats containing the endpoints, there is risk (Figure 1).

1.2. Bayesian Network- Relative Risk Model
Bayesian network-relative risk models (BN-RRMs) combine the RRM with Bayesian networks to probabilistically assess the effect of numerous inputs on endpoints. In this research, I use the BN-RRM to compare risk over multiple timeframes. Bayesian networks are graphical models based on cause and effect relationships. They incorporate both deterministic and stochastic aspects of complex ecological systems and provide probabilistic predictions (Marcot et al. 2006). Figure 1 shows the relationship between a RRM conceptual model and the BN-RRM derived from it. As described in Tighe et al. (2013), a BN consists of the following components
Node: A variable that is divided into states
State: Conditions of a variable described through numeric ranges or ranks
Parent or input node: A node that provides input for intermediate child nodes
Child node: A node that receives information from a parent node
Link: An arrow representing a causal pathway between nodes, each link has a table of conditional probabilities based on the causal pathway.
Conditional Probability Table (CPT): Table that describes the probability of all potential output given the different combinations of input variables

Bayesian networks entered the field of ecological risk assessment in the mid-2000s (Pollino et al. 2007, Hart and Pollino 2008). Since then Bayesian networks have been successfully used to model diverse ecological systems for risk assessment and management (Marcot et al. 2001, Amstrup et al. 2008, Shenton et al. 2011). The BNs are useful for long-term studies and management because new information can be incorporated after an initial risk assessment is completed (McCann et al. 2006).

The BN-RRM specific framework was developed in the early 2010s (Ayre and Landis 2012) and has been used to study the impacts of grazing, wildfires and management techniques on forests (Ayre and Landis 2012); prespawn mortality of Pacific Salmon (Hines and Landis 2014); whirling disease in cutthroat trout (Ayre et al. 2014); and non-indigenous species in the Salish Sea (Herring et al. 2015). It has also been used in multiple risk assessments in the SRSA, focused on biota and ecosystem services (Landis et al. 2016), adaptive management (Johns et al. 2016), and integrated human health/ecological services (Harris 2015).
Figure 1. Transformation of conceptual model to Bayesian network, the yellow box and pathway represents climate driven temperature change addressed in this study, while the grey and green boxes represent the first risk assessment. This is the Bayesian network for the smallmouth bass for Region 5 with temperature projections for 2071-2100.
1.3 Integrating Climate Change Projections and ERA

The field of ERA has recently expanded from frameworks developed to examine particular stressors (primarily chemical) on specific receptors in small geographic areas. Now ERAs often address diverse ecological services on regional scales and include multiple chemical stressors and environmental parameters (Landis and Wiegers 1997, Wiegers et al. 1998, Cook et al. 1999). A next evolution in ERA is to integrate non-static environmental conditions (Stahl et al. 2013, Landis et al. 2013). The changing climate is creating novel climate conditions with warmer temperatures and increases in extreme temperature and precipitation events (Fischer and Knutti 2013, 2014 and 2015). Long-term management of contaminated sites will benefit from risk assessment that includes future climate projections (Landis et al. 2013, Rohr et al. 2013).

Ecological risk assessors have called for ERA of contaminated sites to include climate change (Landis et al. 2013, Stahl et al. 2013, Landis et al. 2014) but without result. In an exhaustive literature search I found no ERAs for contaminated sites that include climate change. The closest I found was ERAs focused on climate change with a contaminant stressor. Two of these focus on the effects of climate change and disappearing sea ice on Polar bears (*Ursus maritimus*) and the third focused on climate change effects on walruses (Amstrup et al. 2008, Amstrup et al. 2010 and Jay et al. 2011). All three included potential oil spills as a stressor.
The paucity of climate change stressors in ERAs for contaminated sites may be due to the challenge of working with climate projections. However, downscaled climate projections that reflect regional topography and climate patterns are becoming much more accessible with websites such as the United States Geological Survey's (USGS) Geo Data Portal (cida.usgs.gov/gdp).

It is crucial to include climate change in ERA for contaminated sites because the climate is an essential environmental factor in most determining habitat (Field et al. 2014). When assessing direct effects of temperature on organisms, each species has a specific temperature niche that can be smaller for temperature-sensitive organisms such as fish or larger for species relatively insensitive to temperatures such as birds and mammals (Magnuson 1979). Organisms that cannot tolerate increased temperatures will move to cooler areas if they can, or adapt with a shift in genetically-based tolerance, while ones that cannot do either will die, and become regionally extirpated or go extinct (Parmesan and Yohe 2003).

In this study I focus only on the direct effects of temperature change. The reasons for this are a) to isolate the effects of temperature and b) to deal with data and model limitations. Due to a lack of data and insufficient hydrological models of the South river, I do not include changes in precipitation, climate-contaminant interaction or indirect effects of temperature such as changes to predator prey relations, population demographics or behavioral attributes.
Modeling direct effects of temperature change, as I am doing, is a first step in integrating climate change into ERA. Future steps could include modeling precipitation and flooding, indirect effects of temperature and climate change-contaminant interactions. This could include both how contaminants affect organismal responses to climate change, referred to as toxicant-induced temperature sensitivity, and how temperature affects bioaccumulation and toxicity of chemicals, which is temperature-induced toxicant sensitivity (Noyes et al. 2009, Hooper et al. 2013). These climate change driven shifts will include macro-organisms down to microbes and will increase toxicant sensitivity causing effects at the individual, species population and community scale as well (Moe et al. 2013). Future work along these lines could be built on this ERA as it was built on previous work.

This work is the fourth risk assessment in a series created for the SRSA (Landis et al. 2016, Johns et al. 2016, Harris 2015). In this piece I use climate projections for 2071-2100 to assess climate change driven shifts in risk. I assess the requirements to include precipitation change and climate contaminant interactions, but find that the data for both is currently insufficient. Because of this, I focus on the effects of temperature change alone, as a first step in integrating climate change projections into ERA for contaminated sites. I isolate temperature by varying temperature parent nodes based on projections and historic data. Future temperatures are based on 10 general circulation models (GCMs) that are compared to historic temperature data for the thirty-year period of 1971-2000. Using 30-year spans of daily data and
projections reduces the effects of random variations caused by short-term anomalies on projected temperatures.

1.4 Climate Models

My future climate projections come from global coupled ocean-atmosphere GCMs. These are mathematical fluid dynamic models of the general circulation of the atmosphere, ocean, cryosphere and land surface (IPCC 2013). These models are the most advanced tools currently available for simulating future climate through simulation of the global climate system response to increased greenhouse gases (IPCC 2013). The resolution for GCMs is between 250 and 600 km, this scale is too coarse to represent climate variability at the scale of my risk regions, so I use statistically downscaled climate projections based on the GCMs.

The models I use are part of the Coupled Model Intercomparison project phase 5 (CMIP5), which are a set of coordinated model experiments (Taylor et al. 2012). The models in CMIP5 have specific requirements including hindcasts of historic climate, projections for specified time periods and a core diagnostic framework. Within this framework, each modeling group creates a model that can recreate historic climate and projects future climate (Taylor et al. 2012).

The GCMs have inputs based on representative concentration pathways (RCPs) that describe specific levels of anthropogenic greenhouse gas emissions (Riahi et al. 2011). The two required pathways are RCP 4.5 mid-range mitigation scenario with
increased radiative forcing of 4.5 watts per square meter and RCP 8.5, a high emission scenario with an increased radiative forcing of 8.5 watts per square meter (van Vuuren et al. 2011). I use the RCP 8.5 high emission scenario to assess the largest projected change, as a tool for management to see the more extreme scenario.

1.5 South River Study Area History

From 1929-1950, an E. I. du Pont de Nemours and Company (DuPont) textile factory along the river in Waynesboro caused widespread mercury contamination though accidental losses of mercuric sulfate, which was used as dye catalyst for synthetic fabrics (Bolgiano 1980, Flanders et al. 2010). This caused the South River, upper Shenandoah and adjacent flood plains to be contaminated with an estimated 26,000+ kg. of mercury (Bolgiano 1980). Impacts from the DuPont mercury contamination are present in the lower 40 km of the South River (Risk Regions 2-6) and continue for 160 km downstream in the South Fork Shenandoah River (Stahl et al. 2014). In 1984, as part of a settlement with the Virginia State Water Control Board, DuPont agreed to fund a 100-year-long monitoring and management program for the SRSA (Stahl et al. 2014). In 2001, the South River Science Team (SRST) was formed with representatives from government agencies, DuPont, consulting firms, experts in mercury contamination and academics to coordinate the numerous research projects and to assist with management of the river (Stahl et al. 2014). As of 2016, the Virginia Department of Environmental Quality is managing the
DuPont plant contamination site and SRSA under the Resource Conservation and Recovery Act regulatory requirements for mercury (Stahl et al. 2014).

1.6 Previous Risk Assessments: The South River Study Area, Virginia

This research is the fourth in a series of risk assessments on this site using the BN-RRM. The first, Landis et al. (2016), looks at selected biota and ecological services of value to local stakeholders. The second, Johns et al. (2016), assesses the effectiveness and possible repercussions of two proposed adaptive management techniques, bank stabilization and agricultural best management practices. The third assesses combined human health and ecological risk assessment in the SRSA (Harris 2015). Here I outline the portions of these studies that pertain to SRSA biota.

The first risk assessment finds that the smallmouth bass and the white sucker have a greater probability of high risk than the Carolina wren (Landis et al. 2016). Risk for the Carolina wren is driven primarily by mercury, likely because they are less sensitive to environmental factors and can range into less contaminated habitats (Cristol et al. 2008). The Carolina wren can also sequester mercury into feathers and eggs, reducing their overall contaminant body burden (Cristol et al. 2008, Jackson et al. 2011). Relative risk is highest for the Carolina wren downstream of the source because it takes time for mercury to move out into the floodplains and up the food chain (Landis et al. 2016).
For the smallmouth bass and the white sucker, risk is primarily driven by river temperature and mercury (Landis et al. 2016). The two species have distinct spatial patterns of risk due to differences in life history and probability of exposure. The smallmouth bass shows highest risk two risk regions downstream from the source (Landis et al. 2016). This spatial separation is likely due to the time it takes mercury to move up the food chain and the smallmouth bass being a high trophic level predator. The regions with highest risk correspond with the regions with highest mercury in smallmouth bass tissues. The white sucker has a very different life history; they are bottom feeders and have the greatest risk in the region closest to the source or mercury (Landis et al. 2016). This pattern reflects their increased exposure to contaminated sediments near the source (Landis et al. 2016).

The second risk assessment examines the potential changes in risk with the application of two remediation techniques. The first technique that the study assesses is bank stabilization, which may significantly reduce river mercury, but it might negatively impact the endpoints (Johns et al. 2016). Bank stabilization includes sediment and soil movement that could temporarily increase mercury and sediment in the water that would affect both white suckers and smallmouth bass (Johns et al. 2016). In addition, unless applied carefully to avoid Belted Kingfisher nests, bank stabilization could extirpate the species in the SRSA (Johns et al. 2016).

Encouraging agricultural best management practices is the other adaptive management technique assessed. Agricultural best management practices are not
predicted to reduce risk but to maintain low risk (Johns et al. 2016). The initial risks from the targeted stressors are already minimal, but it is a plausible strategy due to the low cost and low effort necessary to implement it (Johns et al. 2016).

The third risk assessment integrates human health into the ecological risk assessment for the SRSA. This study looks at human health, water quality, recreation and recreational fishing (Harris 2015). The ecological services most at risk in the SRSA are water quality and recreational fishery. Human health risk is low compared to other endpoints in the SRSA (Harris 2015).

The assessments and management options in these risk assessments assume a static environment, but the environment is changing due to anthropogenic climate change. The next step is assessing how climate change will affect the SRSA.

### 1.7 Summary of Study Results

In this study I evaluate the risk from combined future temperatures with contaminant and ecological stressors using the BN-RRM method. Results of this risk assessment are meant to show temporal patterns of risk with projected temperature change. Four key findings are listed below.

1. Air and water temperatures are projected to increase by 2071 to 2100 in all regions of the SRSA, with the greatest increase during the summer months.
2. With warmer temperatures, relative risk scores decrease for the Carolina wren (4.1-17.5% across regions) and the smallmouth bass (1.4-8.6%).
3. Warmer temperatures show no visible change in risk to the white sucker.

4. The relative change in risk is heterogeneous across the region, with only organism abundance affecting change.

The next section outlines the process for obtaining these results.
2. Methods

2.1 Study Area

The South River flows northward through Shenandoah Valley of Virginia. The South River watershed is 600 km$^2$, and includes forests (58%), agricultural land (31%) and urban areas (8%) (Eggleston 2009). The SRSA covers the watershed and is subdivided into 6 Risk Regions based on USGS hydrological sub-basins and land-use characteristics (Figure 2). Risk Region 1 contains the South River headwaters. Risk Region 2 includes the city of Waynesboro and former DuPont facility that is the source of mercury in the river. Risk Regions 3 through 5 are downstream of Waynesboro and are less urban. Risk Region 6 starts where the South River joins the South Fork of the Shenandoah River. Risk was assessed for Regions 2-6, but not for Region 1 due to a lack of site-specific monitoring data (Landis et al. 2016).
Figure 2 The SRSA, showing Risk Regions and land use.

Mercury is present in the water, sediments, floodplains and biota of the SRSA (Eggleston 2009). The inorganic mercury is primarily bound up in sediments and soil (Eggleston 2009). Organic mercury is often found as methylmercury, which is more bioavailable and therefore more toxic to organisms than inorganic mercury (Wolfe et al. 1998, Ullrich et al. 2001, Scheuhammer et al. 2007, Jackson et al. 2011). Methylmercury is known to reduce hatching success and decrease egg health in birds and also adversely affect growth, survival and embryo viability in fish (Scheuhammer et al. 2007). Though temperature drives methylation rates in many
sites, patterns for methylmercury in the sediments and water of the South River peak during moderate temperatures, indicating that methylation is limited by something other than temperature (Flanders et al. 2010). Methylmercury formation may be limited by nutrients or populations of methylating bacteria (Flanders et al. 2010). Neither inorganic or organic methylmercury rates are driven by seasonal high water periods (Flanders et al. 2010). Therefore, I have not included temperature-driven methylation rates or seasonal mercury patterns in my model.

Mercury is not the only stressor driving regulatory action and remediation in the SRSA. The site is also managed for nutrients that are part of the TMDL. Other toxicants are present as well. Land uses in the SRSA watershed include agriculture, industrial and urban development, which have introduced PAHs and organochlorine pesticides, such as aldrin, dieldrin and atrazine, into the system (Donelley and Ferrari 1998, Zappia and Fisher 1997). These toxicants, as well as environmental parameters of air and water temperature, habitat availability, turbidity, suspended solids and land use, have been identified as potential stressors to the biotic endpoints chosen to represent the SRSA (Landis et al. 2016, Johns et al. 2016).

### 2.2 South River Study Area Biotic Endpoints

For the biotic portion of the first risk assessment, two fish and two birds were chosen as endpoints for their value to local stakeholders and as representatives of different routes of mercury exposure (Landis et al. 2016). Smallmouth bass is a high metabolism piscivorous fish that is popular with catch and release and harvest
anglers (DelVecchio et al. 2010). They are secondary consumers in the aquatic food chain and bioaccumulate mercury and other persistent organic pollutants. The Smallmouth bass have some of the highest body burdens of mercury in the river (Stahl 2014). White sucker represent fish at a lower trophic level than smallmouth bass (Murphy 2000). They are bottom feeders that live in direct contact with contaminated sediments (Landis et al. 2016). Both fish species are sensitive to warm and cold extremes of water temperature (Kerr 1966).

The Carolina wren is a terrestrial bird species that nests on the ground and in trees and structures in the contaminated floodplains. Wrens hunt at ground level where they eat a diet of contaminated spiders and ground insects, which causes significant bioaccumulation of mercury (Rimmer et al. 2005, Cristol et al. 2008). Carolina wrens are sensitive to cold winter temperatures (Haggerty et al. 1995). The Belted Kingfisher (Megaceryle alycon), is the final species in the first ERA. The birds accumulate mercury through their piscivorous diet (Lane et al. 2004). Because temperature was not a stressor for kingfishers in the first BN-RRM risk assessment, I excluded the species from this study.

2.3 Sources and Stressors
The stressors of focus in the first SRSA risk assessment biotic endpoints include: river and air temperature, mercury, organochlorine pesticides, PAHs, suspended solids in the river, stream cover and potential habitat (Landis et al. 2016). The first SRSA risk assessment found river temperature and mercury to be the input
parameters with greatest influence to risk for both smallmouth bass and white sucker (Landis et al. 2016). Abundance is another important parameter as it describes exposure (specifically the amount of fish present to be exposed to stressors), but is not a stressor itself. Mercury is the greatest stressor for Carolina wren, but winter air temperature was also a moderate driver of risk for Carolina wren (Landis et al. 2016). Since water and air temperature are important to these organisms and are predicted to change in the SRSA (Field et al. 2014), I ran the BN-RRMs with projected temperatures for 2071-2100.

2.4 Climate Change Stressors

I modeled future temperature stressors levels in the SRSA to assess corresponding changes in risk to endpoints. I used future air temperature projections in place of historic temperatures to calculate future risk under climate change scenarios. To assess risk to the fish species I calculated future water temperatures from projected air temperatures and historic air to water temperature relationships. To project future water temperatures, I used a multiple regression model based on historic minimum and maximum air temperature and day length to minimum and maximum water temperature. The specifics of the air to water temperature multiple regressions are in section 2.6.1.

I kept stressors other than temperature at current levels in my BN-RRMs to isolate the impact of climate change driven temperature change. I did not include changes to the ecotoxicology of mercury due to insufficient species-specific data. I also did
not include precipitation change because I lack a sufficiently detailed hydrology model for the river. Without one, I cannot model flooding and accurately predict hydrology-driven changes in risk. Including precipitation and flooding may be an important part of future climate change ERAs at this site because flooding moves contaminated sediment and is linked to higher levels of mercury in the river (Flanders et al. 2010). Likewise, I did not include potential changes in human behavior due to climate, such as organochlorine pesticide use. Human behavior changes are complex and driven by market forces for crops and pesticides, as well as climate, and the combination contains too much uncertainty to model in this study.

2.4.1 Climate Change Projections

I used climate models from the CMIP5 that were bias-corrected and downscaled to a 0.125-degree grid though the Bias Corrected Constructed Analogs (BCCA) V2 Daily Climate Projections (Maurer et al. 2007, Brekke et al. 2013). I focused on the RCP of 8.5 watts/m² increase in solar radiation, which represents continuing on the current trajectory of rising emissions (Mearns et al. 2012). I compared RCP 8.5 projected daily maximum and minimum temperatures for 2071-2100 to 1971-2000 to assess potential high warming levels and how they will affect biota in the SRSA. I selected an ensemble of 10 GCMs for independent code and modeling skill based on a literature review.
2.4.2 Selection of GCMs

Using an ensemble of multiple GCMs is important for understanding the range of climate change projections and for assessing uncertainty. Climate modeling researchers argue that a few good models give better-rated climate projections compared to a large multi-model mean or a single model (Knutti et al. 2010). An ensemble of 5 to 10 well-rated GCMs showed less root-mean-squared bias than a single model or a larger ensemble (Knutti et al. 2010). To avoid loss of signal from averaging heterogeneous model output, I analyzed the full distribution of temperature projections and combined the models’ projections into an ensemble to look at the range. For my ensemble I selected 10 models (Table 1) based on ratings from papers in my literature review that included assessment of independent code (Knutti et al. 2013), uncertainty assessment (Knutti and Sedlacek 2013), assessment of climate extremes (Wuebbles et al. 2013) and a multi factor meta-analysis (Stralberg et al. 2014). I avoided GCMs described as poor or improbable or otherwise given low rankings.
### Selected GCMs

<table>
<thead>
<tr>
<th>Model</th>
<th>Institution and Description</th>
<th>Country</th>
</tr>
</thead>
<tbody>
<tr>
<td>ACCESS1.0</td>
<td>Commonwealth Scientific and Industrial Research Organization and Bureau of Meteorology</td>
<td>Australia</td>
</tr>
<tr>
<td>CanESM2</td>
<td>Canadian Centre for Climate Modelling and Analysis</td>
<td>Canada</td>
</tr>
<tr>
<td>CCSM4</td>
<td>National Center for Atmospheric Research</td>
<td>USA</td>
</tr>
<tr>
<td>CNRM-CM5</td>
<td>Centre National de Recherches Météorologiques / Centre Européen de Recherche et Formation Avancée en Calcul Scientifique</td>
<td>France</td>
</tr>
<tr>
<td>CSIRO-Mk3.6.0</td>
<td>Commonwealth Scientific and Industrial Research Organization in collaboration with Queensland Climate Change Centre for Excellence</td>
<td>Australia</td>
</tr>
<tr>
<td>GFDL-ESM2M</td>
<td>NOAA Geophysical Dynamics Laboratory</td>
<td>USA</td>
</tr>
<tr>
<td>IPSL-CM5A-MR</td>
<td>Institut Pierre-Simon Laplace</td>
<td>EU</td>
</tr>
<tr>
<td>MIROC5</td>
<td>Atmosphere and Ocean Research Institute, National Institute for Environmental Studies and Japan Agency for Marine-Earth Science and Technology</td>
<td>Japan</td>
</tr>
<tr>
<td>MPI-ESM_MR</td>
<td>Max Plank Institute for Meteorology</td>
<td>Germany</td>
</tr>
<tr>
<td>MRI-CGCM</td>
<td>Meteorological Research Institute</td>
<td>Japan</td>
</tr>
</tbody>
</table>

**Table 1** The 10 models selected for this ERA.
Once I selected GCMs, I obtained and analyzed my climate projections with the following steps:

1. Created a GIS shapefile of each risk region
2. Selected BCCA v2 CMIP5 daily projections on USGS Geo Data Portal (cida.usgs.gov/gdp)
3. Uploaded a risk region shapefile
4. Selected a GCM and RCP 8.5 and the first run of the model available (r1i1p1)
5. Chose a date range of 2071-2100
6. Requested weighted means, where the 12-km grid cells are clipped to the area of the region and each region is given a daily mean for maximum and minimum air temperatures.
7. Repeated for each GCM and each risk region
I compared the future temperature projections with historic data to assess the likely range of temperature change in the SRSA. I used future temperatures to inform parent (stressor) nodes for the biotic endpoints (Figure 1). For the Carolina wren, I used winter temperatures for December, January and February; for the fish, I calculated future river temperature from historic air to water temperature relationships. These specifics are outlined in the following sections.

2.4.3 Climate Projections Incorporated into the BN-RRM

The capacity of BNs to include new information allows us to use the first risk assessment of the SRSA as a base model and add projected temperature scenarios (Landis et al. 2016). I used the Bayesian network program Netica™ (Norsys Software Corp), which computes risk distributions though probabilistic inference. A free version of Netica™ is available online at http://www.norsys.com/downloads.html, along with a glossary of BN terms and tutorials.

I ran each BN with a series of inputs for the temperature parent nodes. I used historic temperatures for 1971-2000, and GCMs with lowest, median and highest temperature stressor inputs for 2071-2100. The parent nodes with past and future temperatures were combined with other ecological factors into an intermediate node through a CPT. The CPTs are based on known cause and effect pathways and represent every possible combination of probabilities from two or more parent nodes. The CPTs in this risk assessment are based on a combination of formally
elicited expert judgement, monitoring data, mathematical and biological models and literature review (Landis et al. 2016). Each row in the table sums to 100%. When making a CPT one first sets extreme cases to 0% or 100%, and then sets the most clearly known and most moderate cases (Marcot et al. 2006). The rest of the probabilities are then interpolated with the best information available (Marcot et al. 2006). An example of the CPT combining the parent nodes of smallmouth bass river temperature and total suspended solids is in the supplemental materials (Figure SF-3). All of the CPTs are viewable through Netica™ in the models provided in supplementary materials.

I created a separate set of BNs for each organism with downscaled climate projections for each risk region for a total of 60 BNs. For more details on ranking schemes, CPTs, non-climate data sources and other model methods from the first risk assessment see Landis et al. (2016).

2.5 Carolina Wren Risk Calculation

Carolina wrens are sensitive to cold winter temperatures. To see how future temperature regimes would affect the Carolina wren, I looked at December, January and February temperatures from 1971-2000 and compared them to 2071-2100 projections for the GCMs with highest, median and lowest temperature input. I divided historic and projected temperature into input bins based on Landis et al. (2016) (Supplementary Materials Table ST-1). The zero state bin is based on winter air temperatures that result in a steady increase in Carolina wren populations.
The low state bin is based on the cut off of temperatures considered suitable to Carolina wren (Haggerty et al. 1995). The medium state is based on a cold spell suspected to cause the death of many Carolina wrens, and the high state is based on extremely cold weather that decimated Carolina wren populations (Haggerty et al. 1995). The number of days in each state became inputs for BN parent nodes of Winter Temperature (Figure SF-1).

The Winter Air Temperature parent node then joined with the Nest Predation parent node though the CPT, which gives probabilities for every combination of input stress levels. The combination of inputs from both parent nodes with the CPT gives the values for the intermediate node Ecological Modification. The Ecological Modification node then combines though another CPT with the Toxicity and Habitat summary nodes to give a total risk score for the Carolina wrens (Landis et al. 2016). I ran the models for all 5 regions with historic (1971-2000) and future lowest, median and highest winter temperatures for each region. I then compared future risk to 1971-2000 risk levels.

2.6 Fish Risk Calculation

The risk assessment requires river water temperature for fish endpoints, but only air temperature projections are available for the region. I used multiple linear regressions with historic air temperature and day length to calculate water temperatures from four sites with USGS water temperature data. The specifics are described in the next section. I divided the calculated historic and projected water
temperatures into zero, low, medium and high node states based on Landis et al. (2016) (Supplementary Materials Table ST-2, ST-3). I ran all the Bayesian networks (1971-2000, future lowest, future median and future highest) for each region and compared future risk to 1971-2000 risk levels.

2.6.1 Water Temperature Calculation

Irradiance is the primary driver for both air and water temperature in most streams and rivers (Johnson 2004). Because of this, air temperature has often been used with regression to predict water temperature (Isaak et al. 2011, Mohseni et al. 1998 and Johnson et al. 2013). For water temperature projections, I used a multiple linear regression for each section of the river based on recorded air and water temperatures and local day length to the nearest hour (aa.usno.navy.mil/data/docs/My_OneYear). I used 14 months to 5 years of daily minimum and maximum water temperature data from the four sites on the South River and South Fork of the Shenandoah with USGS river gauges (USGS water data). For air temperature, I used mean daily minimum and maximum from gridded observed meteorological data (USGS GDP). The multiple linear regressions for water temperatures from day length with maximum and minimum air temperature showed good (>0.94) R² values for all USGS gauge sites and root mean square error of 1.2 to 2.1°C with a mean of 1.5°C (Supplementary Materials Table ST-4).
2.6.2 Smallmouth Bass Risk Calculation

Smallmouth bass are sensitive to both cold and warm water temperatures, and eggs, fry and juveniles are the most sensitive. Smallmouth bass zero level stressor input (22° to 26°C) is based on optimum temperatures for growth, fry survival and their preferred temperature range (Horning and Pearson 1973, Shuter 1980, Armour 1993). The low-level stressor input is based on water temperatures that are low or high enough to reduce growth rates for juvenile fish, while the medium level is based on a 30-50% (Table ST-2) reduction in growth (Horning and Pearson 1973). High-level stressor input is based on the upper temperature limit for growth and the lower limit for spawning and fry survival (Kerr 1966, Shuter et al. 1980, Armour 1993).

Past and future temperature parent nodes were combined with the total suspended solids parent node in a CPT to create the ecological modification intermediate node (Figure 1). Total suspended solids in the river affects the ability of predatory fish like smallmouth bass to catch prey (Hubert and Lackey 1960, Carter et al. 2010). The ecological modification intermediate node is combined with the toxicity node that summarizes contaminant stressors. These come together into a total stressor node. Because ecological factors and toxicity are only stressors when there is exposure to an organism, the stressors node combines with a node representing smallmouth bass abundance for each region. Abundance and stressors combine in a final CPT for the endpoint node of risk to smallmouth bass (Figure 1). I created four separate BNs for each risk region; 1971-2000, and lowest, medium and highest projections for 2071-2100.
2.6.3 White Sucker Risk Calculation

White sucker are also sensitive to warm and cold waters, but they prefer cooler water than smallmouth bass. The parent node zero stressor levels for the white sucker are based on an optimal river temperature (14°-19°C) with maximum egg hatching success (McCormick et al. 1977). The low stressor levels (Table ST-3) are based on temperatures with reduced hatching success (Horak and Tanner 1964), and medium level is based on temperatures outside the preferred range for juveniles. High temperature stressor levels are based on decreased hatching success and upper and lower lethal temperatures for juveniles and adults (McCormick et al. 1977, Twomey et al. 1984).

The white sucker river temperature parent node combines with the stream cover parent node. Stream cover provides habitat and predator avoidance (Figure SF-2). As with smallmouth bass, the two environmental parent nodes are summarized in an intermediate ecological modification node. The ecological modification node combines with the toxicity node into a node that summarizes stressors. Regional abundance is used to assess exposure, so the abundance and stressor nodes come together with a final CPT to create the total risk to white sucker endpoint node (Figure SF-2).

2.7 Model Ranking

The risk states in my models are zero, low, medium and high based on Landis and Wiegers (2005). The final risk scores are on a 0-6 scale and summarize overall risk to an endpoint, but the distribution is also a key descriptor of the risk result.
2.8 Uncertainty

Scientific uncertainty describes how well something is known and also extends into how clearly it is communicated (Regan et al. 2002). The BN-RRM uses probabilities to combine deterministic and stochastic data in fashion where it is easy to see what is known or unknown. Input parameters are represented as frequency distributions derived from climate model output, monitoring data, peer-reviewed literature and expert elicitation. If data are lacking to inform the model, then the input parameters are set to an even distribution. This translates uncertainty into a wider spread of probabilities throughout the model (Landis et al. 2016). Sensitivity analysis of the first model found that river temperature was a strong driver to smallmouth bass risk, and more water temperature data was analyzed to reduce uncertainty for the node (Landis et al. 2016).

I address the uncertainty in the temperature projections that inform our models by using an ensemble of 10 GCMs over a 30-year period. When using the climate projection ensemble, I looked at the climate models with temperatures that created maximum, minimum and median input levels for each organism.
3. Results

3.1 South River Study Area Temperatures

At RCP 8.5 the SRSA will be warming by 2071-2100, with all 10 models in agreement (Figure 3). Summer temperatures will increase more than winter temperatures (summer daily max temperature +3.0° to +9.3°C and min temperature +3.7° to +8.1°C; winter daily max temperature +0.8° to +7°C and min temperature +1.7° to +6.2°C). The GFDL-ESM2M model (Table 1), shown as max GFDL and min GFDL (Figure 3), predicts the warmest levels for summer months and MRI-CGCM predicts the coolest temperatures year round (Figure 3).

As with air temperatures, water temperatures in the South River will increase overall, though to a lesser extent (summer daily max water temperature +1.5° to +5.1°C and winter daily temperature +0.6° to 4.4°C). Water temperatures in my model are calculated from air temperatures and day length, so the models projecting highest and lowest future air temperature are the same.
Figure 3. Monthly means of maximum and minimum air temperature change. The dashed lines represent historic 1971-2000 minimum and maximum temperatures, the blue and green lines represent projected minimum temperatures for 2071-2100 and the red and yellow represents projected maximum temperatures for 2071-2100.
3.2 Change in Risk

When the models are run with projected temperatures for the SRSA for 2071 to 2100 at RCP 8.5, risk decreased for the Carolina wren and the smallmouth bass but was unchanged for the white sucker. Though these models do not include all the complex factors of climate change, they do give a starting point to see how organisms may be affected.

3.2.1 Change in Risk to the Carolina Wren due to Air Temperature

Carolina wren risk scores decrease (mean of 0.17 points out of 6 risk score change or 8.6%) with warmer winter temperatures for all regions in 2071-2100, with the lowest risk corresponding to the warmest projections (Figure 4). Probability of zero risk state for the Carolina wren increases in all regions (Figure SF-4). Low, medium and high-risk states decrease with warmer winters and the zero risk state increases (Figure SF-4). Region 2 has the greatest percent change in risk (10.5-17.5% reduction) and Region 4 has the smallest change (4.1 to 7.3% reduction). The GFDL-ESM2M model (Table 1) has the warmest December, January and February, projections leading to the greatest reduction in risk score across all regions (7.0-17.5% reduction). CanESM2 (Table 1) represents the median temperature projections and median reduction in risk scores (5.6-14.3% reduction). MRI-CGCM (Table 1) predicts the least warming in winter and the smallest reduction in risk scores (4.2-10.5% reduction). All of the reductions in risk scores for the Carolina wren exceed the variability in projected temperatures from the 10 GCM models.
Figure 4. Risk scores for the Carolina wren for 1971-2000 with observed temperatures compared to 2071-2100 with projected temperatures show a moderate decline in risk. The bars represent variability between the future scenarios with warmest and coolest winters.

### 3.2.2 Change in Risk to Smallmouth Bass Due to Water Temperature

Smallmouth bass risk scores decrease (a mean of 0.14 points out of six risk score change or 4.1%) in all future scenarios (Figure 5). Region 2 has the largest decrease in risk score (4.3% for the coldest winter to 8.6% decrease with the warmest winter) and Region 4 has the smallest decrease (1.4-2.3%). The GCM inputs resulting in highest and lowest projected risk scores differ across regions. Model GFDL-ESM2M results in the lowest risk score and MRI-CGCM results in the highest risk scores for all regions except region 4. For region 4 models the MPI-ESM_MRI input shows the
highest risk score and CCSM4 showed the lowest risk score. The change in risk scores for smallmouth bass exceed the variability for the 10 GCMs.

![Smallmouth Bass](image)

**Figure 5.** Risk score changes for the smallmouth bass for 1971-2000 compared to 2071-2100 show moderate decreases. The bars represent variation between climate models.

### 3.2.3 Change in Risk to White Sucker Risk due to Water Temperature

White sucker risk scores decreases are so small (a mean of 0.03 or 1.6% decrease in risk in all regions) that any changes are unlikely to be measurable in the field (Figure 6). The changes for white sucker are so small that they are eclipsed by the model uncertainty, unlike the changes for Carolina wren and smallmouth bass.
Figure 6. Risk score comparison for the white sucker for 1971-2000 compared to 2071-2100, showing no decline in risk.

3.2.4 Risk Change Trends by Region

The Carolina wren shows a homogenous decrease in risk scores across all regions. Smallmouth bass shows a smaller decrease in Regions 3 and 4 compared to other risk regions. Risk Regions 3 and 4 are the same regions that have low abundance. In this model abundance is a measure of exposure: the more fish that are present, the larger probability of effect of stressors on endpoints.
4. Discussion

At RCP 8.5 temperatures increase throughout the SRSA area by 2071-2100 (Figure 3). Summer mean temperatures for the SRSA in 2071-2100 will rise up to 8.7 degrees (August model GFDL-ESM2M). This is enough of an increase to cause significant ecological effects from the organism level (stress to an individual) to large community shifts (Moe et al. 2013). Due to data and model limitations, this risk assessment only addresses the direct effects of projected future air and water temperatures. The models do not include precipitation change, climate-contaminant interactions, organism interactions or indirect effects on habitat quality.

In my models, warmer temperatures in the SRSA will reduce risk for both the Carolina wren and the smallmouth bass, but have no influence on the white sucker. The risk scores show little variation across the landscape, but do vary with organism’s life history. Warmer temperatures result in the greatest change for Carolina wrens as they experience lower risk with warmer winters (Figure 4). The same change in temperature results in a smaller reduction of risk scores for smallmouth bass as they are sensitive to both very warm as well as cold water temperature (Figure 5). The white sucker change is less than the model uncertainty (Figure 6).

4.1 Risk to Carolina Wren

Risk will decrease for Carolina wrens with less frequent cold winter temperatures that can kill wrens outright or sap their metabolic energy (\(<-2.7^\circ\text{C}\)) (Haggerty et al.
1995). With future warming scenarios, Carolina wrens will experience less cold winter days. With warming winters, populations may become more numerous if winter temperature is a limiting factor for their density (Haggerty et al. 1995). However, prey availability, predation, habitat, synergistic effect of temperature and mercury or another factor may be more important to Carolina wren populations in the SRSA. Any of these factors may shift with climate change.

There may also be interactions between temperature and mercury that impact the Carolina wren’s nesting success. Hallinger and Cristol (2011) found that tree swallows (*Tachiana bicolor*), which have a similar life history to Carolina wrens, have reduced nesting success when warm temperatures are combined with mercury exposure during early nesting periods. This result demonstrates one example of the complex contaminant and climate interactions that may come into play with long-term changes in climate.

### 4.2 Air to Water Temperature Relationship

There is uncertainty in modeling water temperature due to the large number of drivers affecting river temperature. These drivers include: relative humidity, shade, cloud cover, wind speed, heat exchange through the water surface, heat conduction and convection between the water and land, and water flow (Stefan and Sinokrot 1993). Because sufficient data was not available to model the drivers described, I used air to water historical relationships with day length to represent seasonal patterns in irradiance. My multiple linear regression based on air temperature, water
temperature and day length represents future temperatures with a $R^2 > 0.94$
indicating that model explains 94% of the variability. It also has a root mean square
error averaging 1.5°C indicating that the uncertainty of my air to water temperature is
smaller than the overall model uncertainty.

4.3 Risk to Smallmouth Bass
Risk decreases for smallmouth bass with warmer river temperatures in 2071-2100
compared to 1971-2000. Though the fish are sensitive to warm as well as cold water
temperatures, the frequency of their preferred water temperatures will increase with
climate change. This outcome was unexpected as there is no spawning or fry
survival when water temperature is over 32°C (Horning and Pearson 1973, Shuter et
al 1980, Armour 1993, Kerr 1966), and the upper projections for July and August
translate to water temperatures above 32°C (35.9°C to 37.2°C). Regions 3 and 4
have a smaller change in risk due to smaller abundance of smallmouth bass. Where
there are few fish, there is less effect from a stressor. Smallmouth bass populations
are an ecological resource that provides economic benefits to the area through
recreational fishing. Where the habitat doesn’t support smallmouth bass, there is no
fisher to lose.

4.4 Risk to White Sucker
The change to risk scores for white sucker is smaller than model uncertainty (Figure
5). A lack of change was unanticipated, as white suckers prefer water temperatures
between 14-19°C, and projected summer water temperatures are well above their
preferred range (McCormick et al. 1977, Horak and Tanner 1964). However, with the increase in risk from thermal stress, there is a concomitant decrease in stress from cold temperatures during the winter (Figure SF-4).

There are interactive effects of increased temperature and toxics on fish that are beyond the scope of my current models. For example, warmer temperatures increase metabolic rates and Methylmercury (MeHg) accumulation for killifish *(Fundulus heteroclitus)* (Dijkstra et al. 2013). Other fish, including smallmouth bass and white sucker, may have similar bioaccumulation increases with warmer temperatures. Also, elevated temperatures have been shown to increase the toxicity of pesticide mixtures in juvenile coho salmon (*Oncorhynchus kisutch*) (Laetz et al. 2014), and similar synergistic effects may occur in the SRSA. Field and laboratory studies of temperature-toxicant interactions in the SRSA will be necessary to better understand how climate change will affect SRSA biota.

**4.5 Risk Change by Region**

For all species, risk scores changed homogenously across most to all regions. This is the case because climate change driven temperature shifts are on a larger scale than mercury contamination or most of the environmental parameters. With the Carolina wren, risk scores declined homogenously across all regions at a similar rate for each warming scenario. Risk scores also declined evenly for smallmouth bass across most regions, except Regions 3 and 4, which had smaller change. These
regions have lower smallmouth bass abundance, so there was a lower probability of exposure because there were fewer fish.

4.6 Sources of Uncertainty

Due to the scale of climate change and the similarity in temperature projections between regions, the uncertainty associated with climate change is homogenous across the SRSA. Climate models include inherent uncertainty, which I addressed by using an ensemble of climate models. I only assessed one forcing scenario - RCP 8.5. This scenario represents an increase in solar radiation of 8.5 watts/meter, which is the projection for emissions increase at the current rate (Field et al. 2014). If global carbon emission rates are reduced, we may have a smaller increase in solar radiation and therefore smaller increase in warming. However, scenario RCP 8.5 is the highest of the IPCC warming scenarios, and I chose it to look at the largest likely change in risk.

The SRSA biota will be affected by other stressors that are a product of climate change, such as precipitation, and bioavailability and uptake of contaminants. Precipitation changes will alter the flood regimes of the South River and Shenandoah, causing change in the transport of mercury throughout the river and into the floodplains. Warmer temperatures will increase metabolisms of most fish species, with concomitant increases in bioaccumulation of methylmercury and other contaminants (Dijstra et al. 2013). Conversely warmer temperatures and higher metabolism rates may reduce an organism’s lipid stores resulting in depuration and
less bioaccumulation (Trudel and Rasmussen 1997). Synergistic interactions between temperature and contaminants may cause reduced fitness for organisms (Laetz et al. 2014, Hallinger and Cristol 2011). There are also complex indirect changes that are beyond the scope of this model. Though these organisms will have reduced risk or no change with warmer temperatures, the temperature shifts can cause myriad other ecological shifts. These include but are not limited to, change in prey availability, competition from other organisms shifting their range, new pathogens, and new parasites (Parmesan and Yohe 2003, Marcogliese 2008).

4.7 Model Improvement

My models would better represent the SRSA ecological system if the following were available to inform model inputs:

1. A hydrologic model for the South River and Shenandoah with precipitation projections to characterize how mercury movement will change in the SRSA. Modeling future hydrology would also be useful for assessing long-term effectiveness of bank stabilization projects (Johns et al. 2016).

2. Field and laboratory studies on interactions between temperature and Hg for SRSA specific species, especially changes in mercury biotransformation, uptake and bioaccumulation in fish and mercury/temperature dynamics affecting nesting success of the Carolina wren.

3. A more complete air temperature to water temperature model with relative humidity, shade, cloud cover, wind speed, heat exchange through the water
surface and heat conduction between the water and discharge. Greater water temperature data sets would also reduce uncertainty.

4. More studies of the effects of temperature on Carolina wren and white sucker.

5. These models run with inputs for other RCPs.

Carolina wren, smallmouth bass and white sucker are only three species found in the SRSA. Risk assessments of other species would benefit the long-term management of the river. For example, another step in this work would to model climate change adaptive management including future extreme precipitation events and their effect on mercury movement and bank stabilization effectiveness.
5. Conclusions

In this study I incorporated climate change projections into an ERA for the SRSA RCRA site demonstrating a methodology useable at any site. The applicability of this method to other sites is due to the RRM-BN framework. The RRM-BN framework has been used on sites including rivers, estuaries and forest (Ayre and Landis 2012, Hines and Landis 2014, Ayre et al. 2014, Herring et al. 2015, Landis et al. 2016, Johns et al. 2016). Downscaled climate projections for chosen regions are available for the US through the USGS geo data portal. The combination of the RRM-BN and downscaled climate projections makes ecological risk assessments with integrated contaminant, environmental and future climate stressors very accessible for any region, watershed or site in the country.

The SRSA site by 2071-2100 (at RCP 8.5) will likely have-

1. Increased summer daily maximum air temperatures (+3.4°C to +8.7°C monthly mean), and increased summer daily minimum air temperatures (+4°C to +7.8°C monthly mean) with smaller warming in winter.

2. Water temperature will correspond with warmer air temperatures (+0.6°C to +5.1°C maximum daily mean)

3. Warmer winter air temperature reduces risk scores for Carolina wren (4-18%).

4. Warmer water temperatures reduce risk scores for smallmouth bass (0.2-9%).

5. Warmer water temperature has no effect on white sucker.

6. The relative change in risk is heterogeneous across the region, with only organism abundance affecting change.
This study demonstrates with temperature change how downscaled climate change projections and toxicological focused ecological risk assessment could be combined in a clearly defined and quantitative method. The results are meant to show temporal patterns of risk with projected temperature change. This assessment also directs attention to where more research is needed and is available to inform early adaptations for long-term management.
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7. Supplementary Information

Figure SF-1 Bayesian net for the Carolina wren, Region 2 with temperatures based on 2071-2100 from model GFDL-ESM2M.

Figure SF-2 Bayesian net for the white sucker, Region 2 with temperatures based on 2071-2100 from model MRI-CGCM.
Figure SF-3 Conditional probability table combining river temperature and suspended solids for smallmouth bass Region 2 for 2071-2100 temperatures based on model MRI-CGCM.

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Risk Probabilities in the South River 1970-2000 vs 2070-2100

Figure SF-4 Risk distributions for Carolina wren, smallmouth bass and white sucker at historic and projected temperatures.
### Table ST-1 Temperature bins for Carolina Wren (Haggerty et al. 1995) from Landis et al. (2016).

<table>
<thead>
<tr>
<th>Winter Air Temperature</th>
<th>Zero</th>
<th>&gt;2.7 °C</th>
<th>Steady increase in populations when winter temperatures were above average</th>
<th>Haggerty et al. 1995</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>-12 to 2.7 °C</td>
<td>Average min. Jan temperatures drop below -12° C not suitable for C. wren</td>
<td>NOAA National Climatic Data</td>
<td></td>
</tr>
<tr>
<td>Med</td>
<td>-20.83 to -12 °C</td>
<td>Indiana, Jan cold spell (-21° to -24°C for 3 d) suspected cause of many CW deaths</td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>-27 to -20.83 °C</td>
<td>W. Virginia populations decimated in winter of 1935–1936 owing to extremely low temperatures (-27 to -34°C)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>


<table>
<thead>
<tr>
<th>River Temperature</th>
<th>Zero</th>
<th>20-26 °C</th>
<th>Ideal temps for spawning &amp; growth; Temp optimum for juvenile growth &amp; fry survival; Preferred adult temp range</th>
<th>Horning and Pearson 1973, Shuter et al. 1980, Armour 1993</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>17-19.9 or 26.1-29 °C</td>
<td>Spawning occurs at lower temp range, however we have reached upper temp limit for spawning (27°C); Positive growth rates for juvenile &amp; fry (upper temps)</td>
<td>Kerr 1966, Horning and Pearson 1973, Shuter et al. 1980</td>
<td></td>
</tr>
<tr>
<td>Med</td>
<td>15-16.9 or 29.1-31.9 °C</td>
<td>Reaching min. spawning temps, survival rates of egg/fry start to decrease; Nearing the upper avoidance temps by SMB (31°C); 100% mortality of egg/fry at upper temps (&gt;30°C)</td>
<td>Kerr 1966, Stauffer et al. 1976, Shuter et al. 1980</td>
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</tbody>
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### Table ST-3 Temperatures bins (McCormick et al. 1977, Horak and Tanner 1964, Marcy 1976, Twomey et al. 1984) from Landis et al. (2016).

<table>
<thead>
<tr>
<th>River Temperature</th>
<th>Zero</th>
<th>14-19 °C</th>
<th>Maximum hatching success</th>
<th>McCormick et al. 1977</th>
</tr>
</thead>
<tbody>
<tr>
<td>Low</td>
<td>11-14 or 19-22 °C</td>
<td>Preferred temperature for adults</td>
<td>Horak and Tanner 1964</td>
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</tr>
<tr>
<td>Med</td>
<td>9-11 or 22-29 °C</td>
<td>Preferred temperature for juveniles</td>
<td>Marcy 1976</td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>≤ 9 or ≥ 29°C</td>
<td>Upper lethal temperature limits for juvenile white suckers of 26 to 31° C and lower lethal temperatures of 2 to 6° C; decreased hatching success at temperatures &lt; 9° C or &gt; 17° C.</td>
<td>McCormick et al. 1977; Twomey et al. 1984.</td>
<td></td>
</tr>
</tbody>
</table>
Table ST-4 Multiple regression to calculate daily water temperature from air temperature and day length.

<table>
<thead>
<tr>
<th>Equation</th>
<th>$R^2$</th>
<th>P-value</th>
<th>RMSE</th>
<th>95% CI</th>
<th>2.5%</th>
<th>97.5%</th>
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</thead>
<tbody>
<tr>
<td>R2 Max</td>
<td></td>
<td></td>
<td></td>
<td>Intercept</td>
<td>-4.266</td>
<td>-3.088</td>
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<tr>
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<td></td>
<td>Max Air</td>
<td>0.192</td>
<td>0.232</td>
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<tr>
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<td></td>
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<td></td>
<td>Min Air</td>
<td>0.252</td>
<td>0.292</td>
</tr>
<tr>
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<td></td>
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<td>Day Length</td>
<td>0.974</td>
<td>1.079</td>
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<tr>
<td>R2 Min</td>
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<td></td>
<td></td>
<td>Intercept</td>
<td>-0.666</td>
<td>0.371</td>
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<td>Max Air</td>
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<td>Min Air</td>
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<td>Day Length</td>
<td>0.534</td>
<td>0.627</td>
</tr>
<tr>
<td>R3 Max</td>
<td></td>
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<td>Intercept</td>
<td>-3.530</td>
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<td>Min Air</td>
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<td>Day Length</td>
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<tr>
<td>R3 Min</td>
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<td>Day Length</td>
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