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The Origin, Development, Application, Lessons Learned, and Future Regarding the Bayesian Network Relative Risk Model for Ecological Risk Assessment

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Special Series

The Origin, Development, Application, Lessons Learned, and Future Regarding the Bayesian Network Relative Risk Model for Ecological Risk Assessment

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EDITOR'S NOTE:

This article is part of the special series "Applications of Bayesian Networks for Environmental Risk Assessment and Management" and was generated from a session on the use of Bayesian networks (BNs) in environmental modeling and assessment in 1 of 3 recent conferences: SETAC North America 2018 (Sacramento, CA, USA), SETAC Europe 2019 (Helsinki, Finland), and European Geosciences Union 2019 (Vienna, Austria). The 3 sessions aimed at showing the state-of-the art and new directions in the use of BN models in environmental assessment, and focusing on ecotoxicology and water quality modeling. This series aims at reflecting the broad applicability of BN methodology in environmental assessment across a range of ecosystem types and scales, and discusses the relevance for environmental management.

ABSTRACT

In 2012, a regional risk assessment was published that applied Bayesian networks (BN) to the structure of the relative risk model. The original structure of the relative risk model (RRM) was published in the late 1990s and developed during the next decade. The RRM coupled with a Monte Carlo analysis was applied to calculating risk to a number of sites and a variety of questions. The sites included watersheds, terrestrial systems, and marine environments and included stressors such as nonindigenous species, effluents, pesticides, nutrients, and management options. However, it became apparent that there were limits to the original approach. In 2009, the relative risk model was transitioned into the structure of a BN. Bayesian networks had several clear advantages. First, BNs innately incorporated categories and, as in the case of the relative risk model, ranks to describe systems. Second, interactions between multiple stressors can be combined using several pathways and the conditional probability tables (CPT) to calculate outcomes. Entropy analysis was the method used to document model sensitivity. As with the RRM, the method has now been applied to a wide series of sites and questions, from forestry management, to invasive species, to disease, the interaction of ecological and human health endpoints, the flows of large rivers, and now the efficacy and risks of synthetic biology. The application of both methods have pointed to the incompleteness of the fields of environmental chemistry, toxicology, and risk assessment. The low frequency of exposure-response experiments and proper analysis have limited the available outputs for building appropriate CPTs. Interactions between multiple chemicals, landscape characteristics, population dynamics and community structure have been poorly characterized even for critical environments. A better strategy might have been to first look at the requirements of modern risk assessment approaches and then set research priorities. *Integr Environ Assess Manag* 2021;17:79–94. © 2020 SETAC

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INTRODUCTION

An extensive review of the application of Bayesian networks (BN) to ecological risk assessment can be found in Kaikkonen et al. (this issue). In this review, I specifically focus on the Bayesian network relative risk model (BN-RRM). It has been 25 y since the beginning of the development of the relative risk model (RRM) for understanding risk. My goal in this review is to present the history of the development of the relative risk model, the application of BNs to the framework, summarize the lessons learned, and to compare progress made to a list created in the early years of the research effort.

There are 5 sections in this review. The first section describes a set of my goals for ecological risk assessment that appeared in print in 2003. Meeting these goals is the impetus for the research program. The second section is a

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short comparison between the RRM as first developed and the BN-RRM as currently applied. The third section describes the history of the development of the RRM since the mid 1990s and the BN-RRM that began in the late 2000s-early 2010s. I use a number of case studies to demonstrate the changes made to methods and the variety of assessments conducted. Of particular note is the transition period from 2010–2012 when the use of BNs become a part of the RRM process. The fourth section lists the lessons learned from the 25-y process. Some are specifically in regard to the development of the BN-RRM, others are my take on the state of ecological risk assessment and the sciences that supports it. The fifth section is a scorecard of meeting the goals set in 2003. Here we go.

GOALS FOR ECOLOGICAL RISK ASSESSMENT

The year 2003 was the 20th anniversary of the publication of the Red Book, the keystone National Research Council publication describing the use of risk assessment in the Federal Government (NRC 1983). I published an invited paper for Human and Ecological Risk Assessment to review the state of ecological risk assessment (Landis 2003). At this time, the research on the RRM was well underway and we had completed a number of risk assessments. In the review, I made a list of the goals for ecological risk assessment for the next 20 y. These goals included:

1) *Universality*: Apply ecological risk assessment as a universal framework for ecological management.
2) *Organizing decision making*: Use of ecological risk assessment as the common framework, and especially the conceptual model, as the organizing principal for decision making.
3) *Observable predictions*: Make predictions and confirm the outcomes using observed patterns in the landscape, changes in community structure, alterations in population dynamics, invasion by nonindigenous species, and other means.
4) *Management alternatives*: Use scenario evaluation to evaluate management alternatives.
5) *Synthesis eco-human*: Ecological risk assessment as a synthesis of human and environmental management systems.

At the end of this manuscript I will return to this list to see how successful the RRM and BN-RRM have been in meeting these goals.

COMPARISON BETWEEN THE RRM AND THE BN-RRM

Both approaches deal with Multiple Sources, Stressors, Habitats, Effects, and Impacts or MSSHEI (Table 1). Both approaches use risk regions to compare the risk to each geographic area in a study area.

Table 1. Comparison of the RRM and BN-RRM approaches for calculating risk due to multiple stressors at large scales

Characteristic	Relative risk model including with Monte Carlo simulation	BN relative risk model
Model format	MSSHEI	MSSHEI
Risk regions	Yes	Yes
Calculation	Summing the products across the MSSHEI pathways.	BNs with the nodes appropriate to the MSSHEI structure.
Categorical	Yes	Yes
Probabilistic	With the inclusion of Monte Carlo modeling. Interaction between nodes described with filters of 0, 0.5, and 1.0 with distributions if appropriate.	Inherently probabilistic and uses conditional probability distributions to describe interactions.
Geographical	Multiple risk regions described at a variety of scales.	Multiple risk regions described at a variety of scales.
Uncertainty	Can be described by using distributions within a node to describe epistemic uncertainty. Narrative descriptions are also important.	Is inherent to the BN structure. Can use information from a variety of sources from in situ measurement and models. Narrative descriptions are also important.
Sensitivity	Nonparametric correlation analysis as part of the Monte Carlo process.	Entropy analysis-mutual information. Mutual information is based on information theory and describes the overlap in information of 2 events. Part of many software packages.
Application to Adaptive Management	Can estimate the changes by manipulating the inputs to represent alterations due to specific management alternatives.	Can manipulate the parent nodes to represent different management alternatives to calculate the resultant risk. Can also set the final child nodes to the desired state and calculate the inputs that would most likely generate those results.

BN = Bayesian network; RRM = relative risk model.

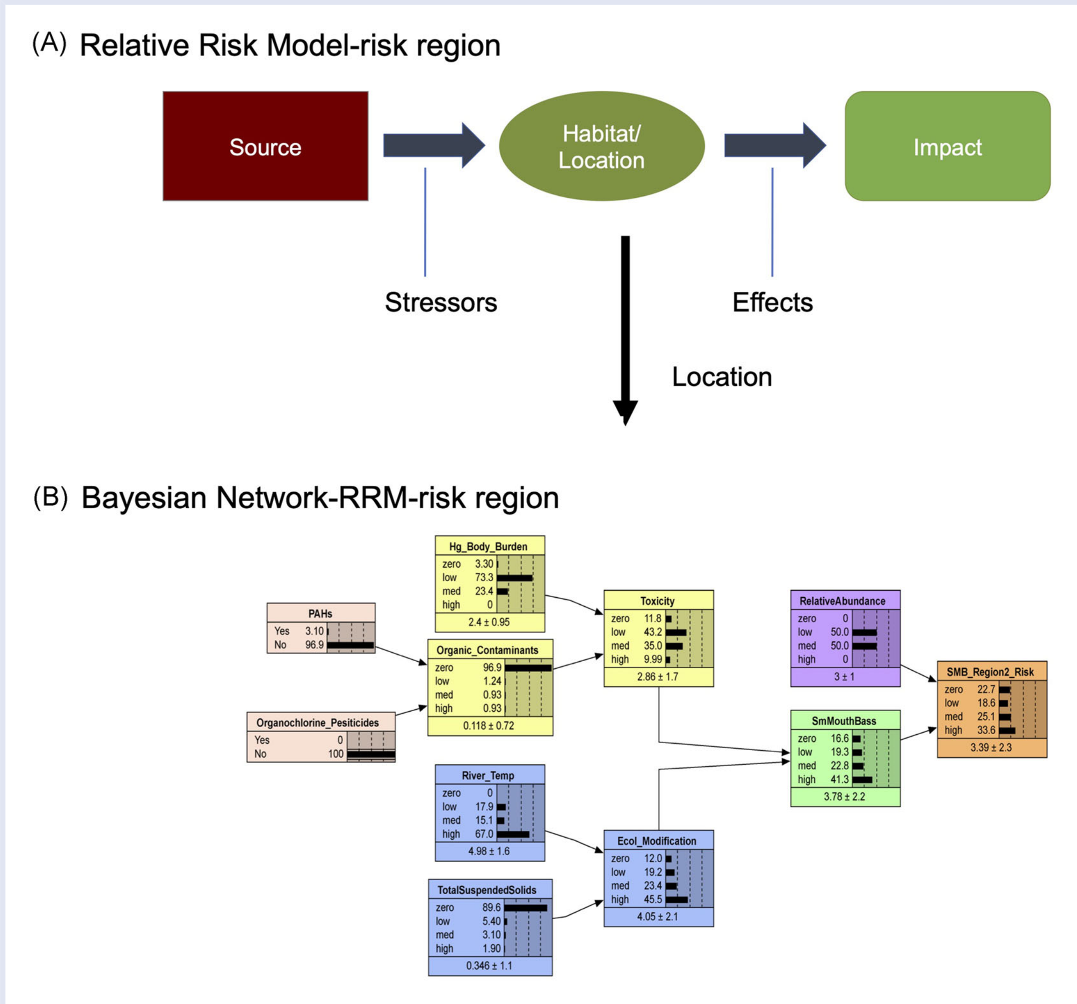

Figure 1. Comparison of the relative risk model structure and that of the BN-RRM. Figure 1**A** depicts the structure of the RRM as described by Landis and Wiegers (1997). The pathway describes a cause-effect pathway. Figure 1**B** is a BN-RRM used to calculate risk to Smallmouth Bass in the South River, VA (Landis et al. 2017a). In all instances, the models are parameterized to represent one of the risk regions. The interactions between nodes in the BN-RRM is determined by conditional probability tables.

The RRM method is described in detail in Hayes and Landis (2004) and Colnar and Landis (2007). The fundamental structure of the RRM contains sources that produced stressors that occur in habitat/regions (Figure 1). Habitats/regions are geographical areas where the stressors and endpoints may overlap and generate exposure. The effects are caused by interactions of the stressors and the endpoints, and finally the impact is the total risk to each of the endpoints. The RRM is based on ranks and the numeric values that go with each of the ranks. Ranks are none, low, medium, and high and are given values of 0, 2, 4, and 6, respectively. The final calculation is the product of the ranking along the pathways leading to a specific endpoint. The filters (0,1) describe the pathways in the calculation. If there is not a pathway then the filter is a 0, and if there is a pathway a 1 is used. The final risk calculation is the product of the rankings along the pathways leading to that endpoint. The final number for the endpoint is the risk score. When the Monte Carlo modeling is put in place, the distribution of risk scores is the end result. These risk scores can be compared between risk regions and between endpoints in a site.

The risk is calculated for a specific geographical region broken up into risk regions. Risk regions are areas of the site that are distinct by physical characteristics, sources of stressors, or the distribution of specific endpoints. In some investigations (see *The History of the Relative Risk Model* section), the risk regions depend on the change in management goals or managers for that study site. Figure 2 illustrates 2 examples of study areas and the risk regions. The risk scores are then compared between regions.

A strength of the RRM is that the information required to set the ranks and filters focuses on interactions, and calculating the cumulative risk is straightforward. However, the comparative method used to set ranks means that the scores of the RRM are interpreted best when in comparison to other endpoints, risk regions, habitats, and stressors within the same study area. The filters are also simplistic, adding model uncertainty to the results. The risk scores can also be difficult to interpret regarding specific outcomes at

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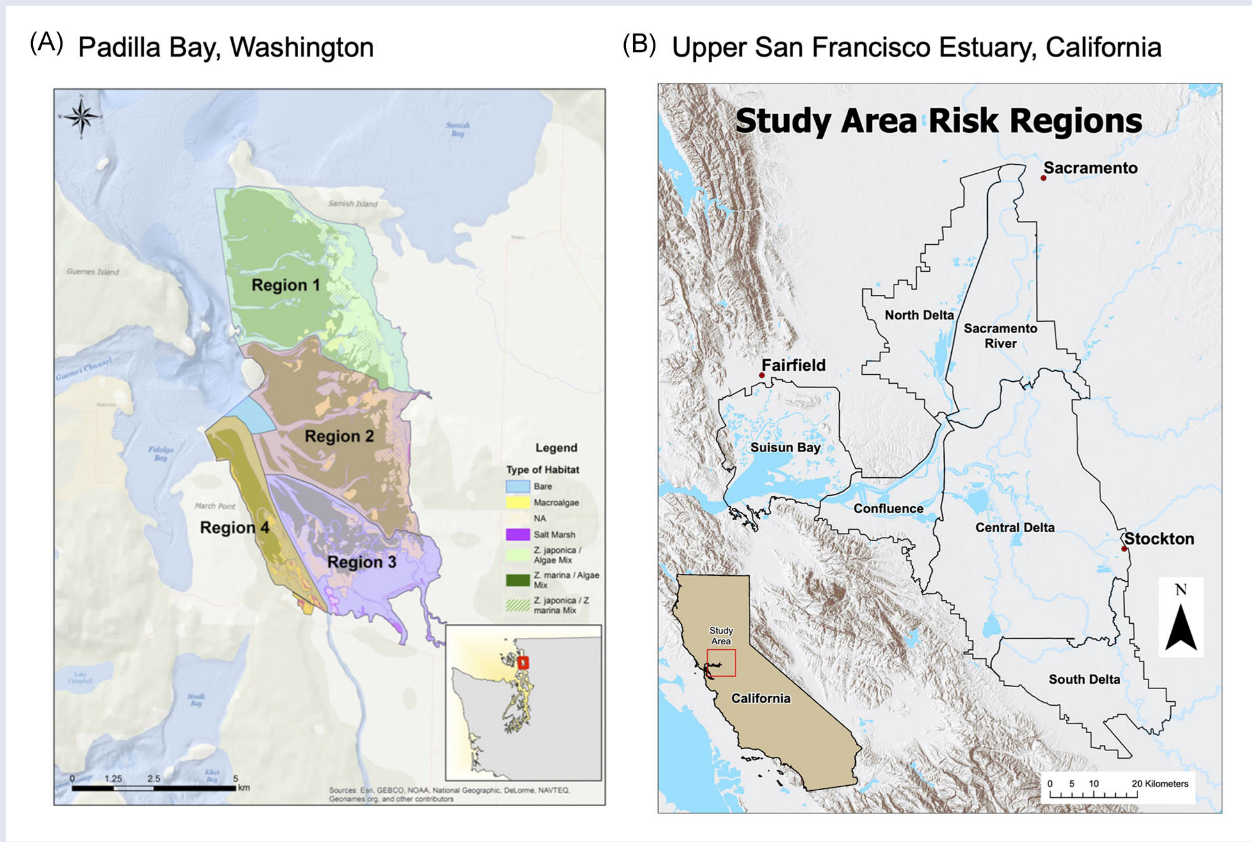

Figure 2. Examples of 2 study areas and the risk regions. The Padilla Bay map (A) is from Hines et al. (2015) and used to estimate risk due to nonindigenous species. The risk regions are dependent upon the different habitats within Padilla Bay. The Upper San Francisco Estuary (B) is for the large-scale multiple stressor risk assessment currently underway, see *New programs and questions* section. In this instance, the risk regions reflect the different watersheds and the management goals for the study.

the site. The results are in risk scores, and not, for example, the decline of a population by 50%.

The use of BNs to describe the interactions in the basic RRM allowed the calculation to be more specific and to model a variety of interactions and inputs in an inherently probabilistic manner. Invented by Pearl (1985), the method uses conditional probability tables to describe the interactions between 2 nodes. The nodes that stand alone are parent nodes. At least 2 parent nodes feed or influence a downstream or child node. The interactions between the combination of parent nodes and the child node is determined by a conditional probability table (CPT). All combinations of the states of the input nodes are included along with the outcomes.

In contrast, the BN-RRM uses the CPT to describe the interactions between variables, not the simplistic binary filter. The CPTs can describe exposure-response relationships, the effects of multiple factors to population size, how temperature affects water quality, and other interactions. There are limitations. The conditional probability tables are set by all the combinations of the different states of each of the input variables. The combinations have as the output the conditional probabilities of the multiple output states from each combination of these interactions. It is easy to have child nodes with 3 or more parents with hundreds of cells in which a probability has to be estimated. Experimental data are often not available to generate these probabilities, especially that describe the interactions among temperature, habitat extent, and several toxicants. Therefore, it is sometimes necessary to simplify the number and states of the input states and the number of output states. In some cases, models can be used to generate the CPTs. In Landis et al. (2020), models of Chinook Salmon population dynamics were used to evaluate how changes in survivorship for different life stages could result in an increase or decrease in population size. Case learning from large datasets can also be applied to describe interactions between nutrient inputs and water quality (Graham et al. 2019). Because of the widespread use of BNs in a variety of fields, there are a number of tools and strategies that can be used to address some of these issues (Marcot et al. 2006).

THE HISTORY OF THE RELATIVE RISK MODEL

The development and application of the Relative Risk Model for regional scale risk assessment

The timeline for the development and application of the relative risk model and the BN-RRM is presented in Figure 3. Our research team started an ecological risk assessment funded by the Regional Citizen Advisory Council for the

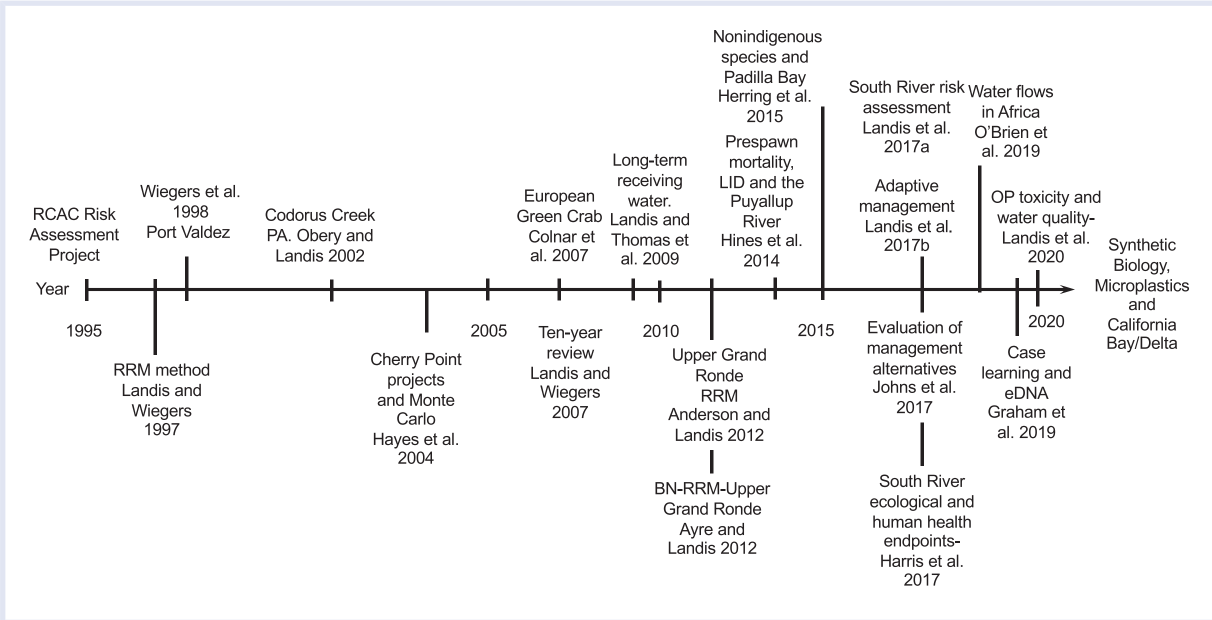

Figure 3. Timeline for the development of the RRM and BN-RRM. Papers discussed in the text are positioned in sequence.

Valdez Alaska region in 1995. We found that the existing ecological risk assessment literature and framework did not meet the requirements of conducting a multiple stressor, multiple endpoint, regional scale risk assessment. The need resulted in the structure of the relative risk model first described in Landis and Wiegers (1997) and first postulated by JK Wiegers. Within the laboratory, we compared the initial trials of the RRM with the results we were obtaining by attempting to apply the existing approaches. The application of the source-stressor-habitat-effect-impact causal pathway, with the use of ranks to describe the interactions within the conceptual model and subsequent calculations, was a clear winner in the comparison. Because the RRM breaks down the study area into risk regions for comparison, the changes in the risk and the variables that contribute to it can be compared site-to-site. This geographic component is one of the most valuable aspects of the overall method. After the initial paper on Alaska (Wiegers et al. 1998), other studies were performed for Cherry Point, Washington (Hayes and Landis 2004), and watersheds receiving effluents from pulp and paper plants (Obery and Landis 2002; Landis and Thomas 2009).

Although Landis and Wiegers (1997) is often cited to reference the method, that is not accurate. The original paper is a presentation of the basic formulation of the RRM but was not specific as to the details of the calculations and outputs. Wiegers et al. (1998) demonstrated the application of the RRM for a risk assessment of the various inputs to the fjord of Port Valdez, Alaska. This second paper demonstrated the full application of those ideas, including the ranking, filters, risk outputs, uncertainty, and sensitivity analysis. A number of papers followed that further refined the process. Of those early days, the best description of the method is Landis and Wiegers (2005) where the 10 steps of applying the RRM are delineated and the specifics of the ranking, filters, the building of a conceptual model, the use of GIS, Monte Carlo, and the importance of risk communication are presented.

Landis and Wiegers (2007) reviewed the first 10 y of the RRM and the continuing development of the method. It also serves as the touchpoint for the development of the basic RRM. As described in Colnar and Landis (2007), the estimation of risk for the nonindigenous marine species, European Crab (*Carcinus maenas*) is the definitive description of the original RRM process. In Colnar and Landis (2007), the incorporation of ranking, the use of filters with the values of 0, 0.5, and 1.0, the incorporation of the Hierarchical Patch Dynamics Paradigm, GIS, and the multiple life stages of the stressor are all described. The same RRM methods were applied of the basic RRM by Anderson and Landis (2012) on the risk assessment for the different management strategies for the Upper Grande Ronde Watershed, Oregon, USA.

The Upper Grande Ronde Watershed (UGRW) study represented the definitive application of the fundamental RRM (Anderson and Landis 2012). The transition from the RRM to the BN-RRM occurred during a project for the US Forest Service (USFS). The project was a part of the broader Interior Northwest Analysis System series of studies. One of our goals was to compare how the RRM compared to other assessment tools used by the USFS. Four watersheds were the risk regions, and the sources were sets of different goals for that forested region. Stressors were not chemicals but inputs such as grazing, insects, and wildfire; the habitat nodes were the different kinds of ecological types found in the region and included grassland, riparian zone, cold forest, and so on. The endpoints would now be considered as ecosystem services and included Hunting/Fishing, Forest

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Resources Timber, Forest Resources Recreation, and the historic ranges of Fire, Insects, Invasive Plants, and Anadromous Fish. The analysis demonstrated that total risk was similar among the 4 risk regions. The sensitivity analysis showed some differences among the risk regions, and distributions were used to describe the specific differences among the sources, stressors, habitats, and endpoints in the study. For example, in the Upper Grande Ronde risk region the warm-dry forest, riparian habitat, and rainfall had the highest correlations. In the Grande Ronde/Hilgard risk region the sources private timber/grazing and the habitats cold forest and cool-moist forest were the drivers of the risk scores.

As the UGRW study progressed, it was becoming clear that the limits of the simple system of establishing ranks and filters over such a large variety of inputs was being reached. We were already not just assigning 1 rank value to a stressor or habitat but were assigning probabilities of perhaps an 80% probability of a 4 and a 20% probability of it being a high rank with a value of 6. We were also starting to assign different values to the filters, the numbers that corresponded to whether or not the nodes of the model were connected. Instead of just a 1.0 for making a connection and 0.0 for no connection, we started using 0.5 for uncertain as to the connection.

At this time, it was becoming clear that a new language was necessary to describe the interactions in ecological risk assessment. The language had to be true to the fundamental ideas of the relative risk model and be able to describe the effects of multiple stressors from multiple sources being transported to a number of locations home to multiple endpoints that are affected in multiple ways. That tool was the BN.

The Bayesian network intervention

I had become aware of the work in the 2000s by Marcot et al. (2006), Nyberg et al. (2006), Pollino and Hart (2008), Pollino et al. (2007), and Uusitalo (2007) using BNs to describe risk and to manage natural resources. When we suggested this next step to our USFS collaborators, they were on board since Marcot worked just down the hall in the Portland office. The result was the publication of Ayre and Landis (2012), demonstrating the application of BNs to the relative risk model. The new formulation innately incorporated probability and the conditional probability tables of a BN replaced the filters, and it was clear that the conceptual models of the RRM were already acyclic graphs.

It was straightforward to set out the initial structure of the BN using the conceptual model. As noted previously, the pathways in the classic RRM represent causal pathways. The transition from the conceptual model as built for the RRM to the formulation of the BN appeared in Ayre and Landis (2012) (Figure 4). Because of our naivety to the construction of a BN, we had too many lines of influence linked to several of the nodes. We had many nodes with 3 to 4 inputs and one with 5. It was time consuming to generate the conditional probability tables and many of the relationships were generated by elicitation of our expert USFS colleagues.

The same conceptual model used for the RRM, incorporating the same source-stressor-habitat-effect-impact, was used for the BN approach. The datasets were the same. The differences were in 2 categories, in the classic RRM the categories of sources-stressors and so on were not referred to as nodes, but the ranking schemes for those categories were transferred to the nodes of the BNs. So, the scheme for the discretization of both models were similar. The biggest difference was that the filters used to describe interactions in the classic approach were replaced by the conditional probability tables of the BN. Both methods produced distributions as outputs, the classic method via a Monte Carlo approach and the BN via the distributions as portrayed in the nodes representing the endpoints. Sensitivity analysis in the classic RRM was via correlation coefficients and in the BN approach via entropy analysis. In both methods, the structure of the models and the decisions made regarding filters or conditional probability tables were reviewed by a set of experts familiar with the research site and the UGRW study.

As noted in Ayre and Landis (2012), the results from the 2 analyses were similar in results. All 4 of the watersheds (the risk regions) had similar risk scores. In both the classic RRM and the BN model, the stressors most likely to cause risk were Forest Management and Wildfire. For endpoints at greatest risk, the classic RRM put historical range of variability (HRV) Fire at the top while the BN model estimated that the greatest risk would be to the HRV Salmon Habitat.

A major advantage of the BN-RRM was the ease with which it was possible to make a variety of simulations within the Netica software package (Ayre and Landis 2012). Through Bayesian inference it became possible to set one of the endpoints to a low risk value and then have the conditions that are most likely to result in this output calculated. Different management alternatives could be compared regarding how they changed the risks to the various endpoints. The outputs also demonstrated the trade-offs that would have to be made as the management options would benefit some endpoints and increase risk on others.

The UGRW study was our last published RRM risk assessment. However, studies using the RRM or closely related derivatives continue to be published. For example, Bartolo et al. (2012) was a case of a large-scale application. They examined the risk to the 1.1 million km^2 Northern Tropical Rivers region across Northern Australia. Risk was assessed to 18 stressors, 3 aquatic habitats, to 4 endpoints. The study is at a continental scale and one of the most extensive to use the RRM.

Wang et al. (2020) just published another example. The study focused on the relative risk of a series of wetlands in order to set management priorities. Coal mining and agriculture are 2 of the leading industries in this watershed home to 2.4 million people. The authors proposed a number of management guidelines for lowering the risk to this region.

While it is satisfying to see the RRM method continuing to be used, our mission was to push the continued

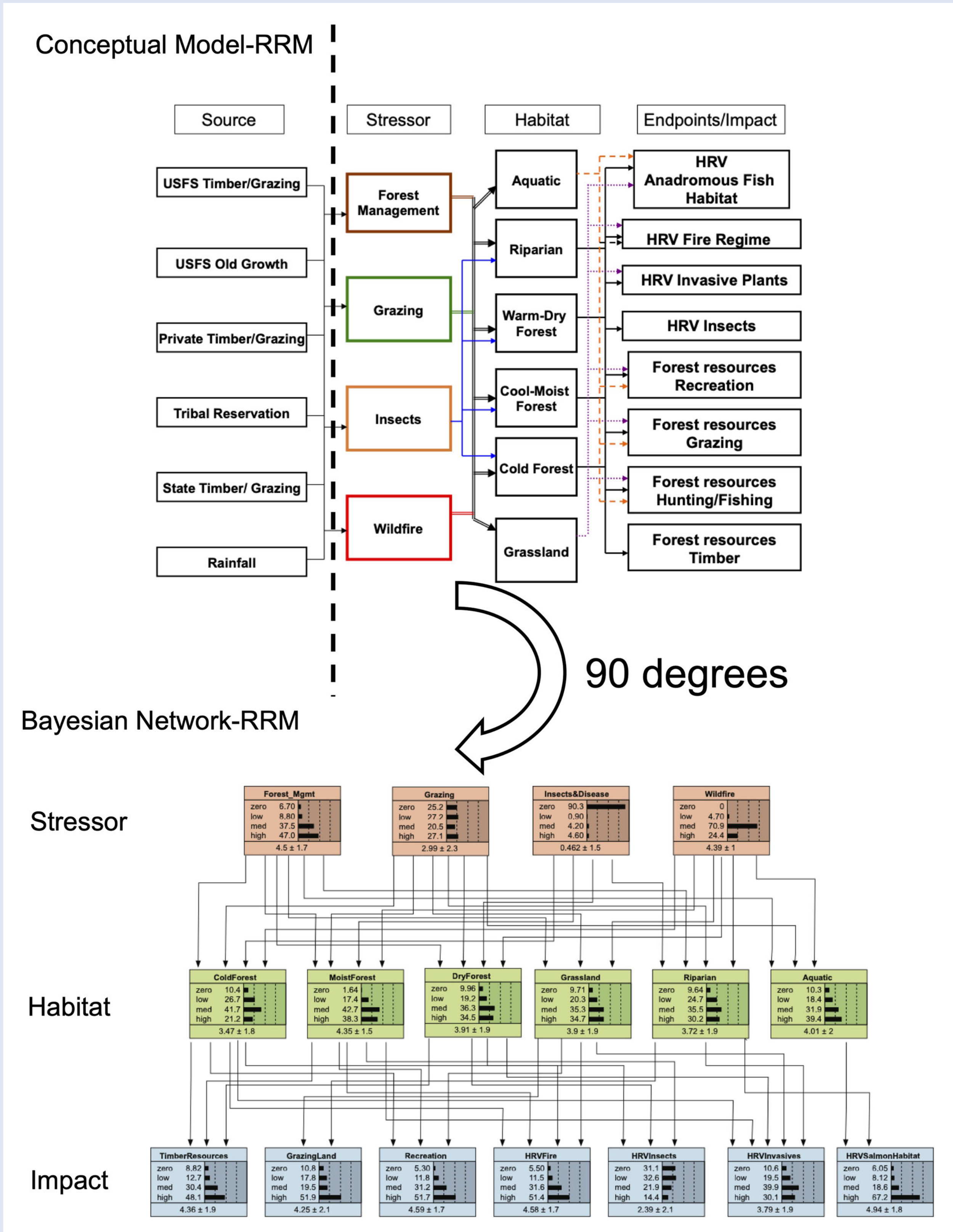

Figure 4. An example of a conceptual model as the lattice for the BN. The conceptual model for the RRM is presented at top. Since the occurrence of stressors within each of the risk regions had been determined from each source, the source layer was removed and the remainder described the interactions for the BN that followed. For convenience, the BN is rotated 90° clockwise at the bottom of the illustration. Details of the process are in Ayre and Landis (2012).

development of the approach. During the mid 2010s, our group had the opportunity to apply the BN-RRM to a number of interesting problems.

Risk assessment and management alternatives

In the fall of 2009, the lab at the Institute started to build an ecological risk assessment for the South River, Virginia, USA contaminated site. A number of papers published in 2017 described the results of that multiyear effort. During this same period, we also had projects dealing with an infectious disease, nonindigenous species, and the risk and management of prespawn mortality in Coho salmon. These diverse examples further pushed the development of the method and the application towards the evaluation of management options.

Stormwater and protected Coho salmon. Hines and Landis (2014) examined the interaction between impervious surface and the management of a valued fishery. A key question in the Puget Sound region has been the risk due to the phenomenon of prespawn mortality of Coho salmon in the region. Prespawn mortality is the observation that Coho returning to spawn in the rivers of the region die with very specific symptoms. The occurrence of the mortality corresponded to the presence of runoff from impervious surface after storm events. A proposed solution to this toxicity is the implementation of low impact development to reduce runoff and the associated toxic materials. The area of this study was the Puyallup watershed that flows from Mt. Rainier to the city of Tacoma, Washington, USA. Two sets of pathways existed in the conceptual model, 1 describing the source nodes of roads, commercial properties, and other impervious surfaces and the other focused on low impact development (LID) approaches such as LID filtration, abundance of LID, and LID retention. The amount of Coho habitat and the hydrology of the watershed were also included as nodes. We found that a risk gradient did exist from the upriver watershed that originated from Mt. Rainier to the urban watersheds in and around Tacoma, Washington. The lowest risk corresponded to the least impervious surface. The LID did reduce risk but only when applied extensively within the urban watersheds, and would result in a large number of retrofits to existing structures and landscapes. It was noted as part of the conclusions that the BN-RRM could be useful for examining water quality endpoints and the outcomes of different remediation activities. It became a standard practice to incorporate both the suggested causes of risk with the potential remediation activity.

Nonchemical stressors: Disease and nonindigenous species. The next study broke new ground incorporating an infectious agent with multiple hosts, endangered species, and the largest study area to date. Ayre et al. (2014) was a visit to the world of infectious disease and the management of endangered species, specifically whirling disease, which is caused by the parasitic myxozoan.

Myxobolus cerebrali. Myxobolus cerebrali has decimated cutthroat trout populations as it has moved westward from its original introduction from Europe. The infection rate in wild fish is dependent on the occurrence of the intermediate tubifex worm host, *Tubifex tubifex,* and a susceptible salmonid. Whirling disease has been implicated in the decline of trout populations in Colorado, Montana, Utah, and Wyoming, USA. The spatial extent of our study area extended from Southwestern Wyoming to Northern Arizona and New Mexico. The Colorado River cutthroat trout and Rio Grande cutthroat trout were the species under management. The risk regions were designated geographic management units (GMUs) for each species. Generally, the GMUs corresponded to the hydrographic subbasins, 8 for the Colorado River cutthroat and 4 for the Rio Grande species. Extensive datasets on water quality, fish distribution, the occurrence of whirling disease, and other factors were available from US Geological Survey, Cooperative Fish and Wildlife Research Unit at New Mexico State University (Ayre et al. 2014).

The conceptual model and resulting BN were markedly different from the usual construct. There was 1 layer of parent nodes and 2 layers of child nodes. The layer of parent nodes described the occurrence of the suitable *T. tubifex* habitat, the co-occurrence of rainbow trout with the managed species, and the co-occurrence of the spawning habitat. The final set of parent nodes described the occurrence of barriers to fish migration. The barriers determine the mixing of the rainbow trout with the managed species and the proximity of the infected population. The barriers were a management option to prevent the spread of whirling disease.

The risk of infection was relatively low for the Colorado River cutthroat trout, especially in the Northern part of its range. The Upper Colorado GMU had a 77% probability of a 0-risk level and an 8% probability of high risk. Rio Grande cutthroat also had a low relative risk of infection but were more variable than the Colorado cutthroat trout. The Rio Grande cutthroat in the Rio Grande GMU had a higher low risk probability than the 3 other GMUs, In contrast, the Pecos GMU had the highest probabilities in the high and medium risk categories.

The sensitivity analysis demonstrated that for both species the probability of infection was most strongly influenced by the presence of the habitat suitable for the tubifex worm that releases the triactinomyxon life stage (TAM habitat pathway) and the amount of spawning habitat. There was a lack of site-specific data for the various management units. The third important factor was the proximity of barriers to fish passage and was important across all of the species and the GMUs.

While several factors influenced the risk due to whirling disease, barriers were the 1 potential management option. The greater the barrier to fish migration, the lower the risk. Given the constraints on resources common in wildlife management, we proposed a 2-step process. First, reduce the uncertainties in risk to identify those fisheries to be protected.

Second, improve the construction and maintenance of the barriers to prevent migration of infected fish to naïve populations. Yes, in this instance, the barriers are protective for preventing exposure to the pathogen. Implementation of this strategy would lead to a long-term interactive management approach for the cutthroat trout species across a large proportion of the habitat in the American West.

Management of nonindigenous species (NIS) in a marine reserve. Continuing the theme of estimating risk to nonchemical stressors was an investigation of the risk due to nonindigenous species (Herring et al. 2015). There has been an ongoing discussion about how to best protect regions against nonindigenous species and the change to community structure and function. In this study, we used the Padilla Bay National Estuarine Research Preserve (PBNERR) as the study site. The PBNERR has been extensively mapped as to the extent of the species at the reserve. We had 3 goals in this study: 1) to determine if the BN-RRM could be used to estimate risk due to nonindigenous species (NIS), 2) to estimate risk to the risk regions and endpoints due to NIS, and 3) to test the effect of management options on reducing risk to this site.

In summary, the studies using the BN-RRM from the UGRW forest to Padilla Bay all had specific management goals. The UGRW concerned the application of different forest management practices and how they affected the delineated resource management goals. The work on the Puyallup was oriented toward the amount of low impact development necessary to reduce the risk of urban runoff to Coho salmon. The whirling disease study was also directed toward those factors that could control the spread of the infection to valued populations of cutthroat trout over a large geographic region. Most recently, the investigation of the factors contributing to the risk of NIS to Padilla Bay was a determination that NIS already in Puget Sound were a larger contributor than that posed by ballast water from shipping. Our next study was an application of the interaction between risk assessment and potential risk management for a contaminated site managed under Resource Conservation and Recovery Act (RCRA).

The South River, VA studies. The South River program began in late 2008 and continued until the publication of the series of papers describing the results. The risk assessment focused on the Hg released as part of the process of making synthetic fiber at the plant in Waynesboro, VA, USA to the South River. The series of 4 papers (Harris et al. 2017; Johns et al. 2017; Landis et al. 2017a, 2017b) presented the methods, structure and results of the initial risk assessment (Landis et al. 2017a), the assessment of alternative management strategies (Johns et al. 2017), a method of integrating ecological and human wellbeing risk estimates and the results for the South River (Harris et al. 2017), and how the risk assessment would fit into an adaptive management process (Landis et al. 2017b). Strong funding support (DuPont), the support of the South River Science Team (SRST), the collaboration of many of the regional scientists, local, state, and federal agencies, nongovernmental agencies, and the citizens of Waynesboro and surrounding region made this our most comprehensive use of the relative BN-RRM to that date. The series of publications describe the specifics. The next paragraphs summarize what we learned about the application of BN-RRM to the study and the foundation it has served for our current research.

Landis et al. (2017a) set the stage by providing the description of the problem, the construction of the risk assessment, and the resulting risks and uncertainties. The identification of the endpoints, the description of the Hg contamination and the other stressors, and the derivation of the conceptual model were described in detail. Endpoints were derived from discussions with the diverse stakeholders from the South River Team. Unlike many of our previous studies, 5 sets of BNs were developed. One was for the abiotic pathways and the other set was for the 4 biotic pathways and endpoints. Abiotic pathways described the cause-effect models for the endpoints Water Quality Standards, Fishing River Use, Swimming River Use, and Boating River Use. These interactions were described by 1 dedicated BN. The biotic endpoints were Smallmouth Bass, White Sucker, Belted Kingfisher, and Carolina Wren. Separate BNs were generated for each of the 4 biotic endpoints. For each of the 5 risk regions that had sufficient information to calculate risk, the models were parameterized and calculated for a total of 25 sets of outputs.

The risk patterns for the South River were described as risk distributions within each of the regions. Risk region 2 was the site of the initial Hg input, risk region 5 was the furthest downriver. The Smallmouth Bass was at highest risk in regions 4 and 5, the downriver stations. Similarly, the risk to the Carolina Wren was highest in the same regions but still was lower than the other endpoints. White Sucker and Belted Kingfisher were at highest risk in region 2.

The abiotic endpoints Water Quality Standards, Swimming River Use, and Boating River Use had similar risks for each region. Risk to Fishing River Use was low in all of the risk regions.

The sensitivity analysis showed that the stressors most important to the biotic endpoints were a mixture of chemical and biological stressors and varied by endpoint. For Belted Kingfisher and Carolina Wren, Hg was the most important input. River temperature and Hg were most important for the Smallmouth Bass endpoint. For the White Sucker, River temperature and stream cover were the 2 highest inputs, with Hg concentration being the third.

The inputs important to the abiotic endpoints were highly variable. Dissolved O was the most important input for Water Quality Standards and Fishing River Use. The $[CH_3Hg]^+$ concentration was important to only fishing river use. River temperature was important to every abiotic endpoint but was never the most important in determining a risk score.

At the end of this phase, a detailed description of the effects of multiple stressors to the risk to these 8 endpoints had been determined and the key inputs identified. The next step was to evaluate 2 management scenarios identified for potential application to the study area.

Johns et al. (2017) used the models previously developed to examine how 2 management strategies would alter the risks calculated for the South River. The proposed strategies were the use of agricultural best management practices (AgBMP) and bank stabilization (BST). For both management strategies the estimated changes in the stressor inputs were used to parameterize the models previously used in the initial risk assessment. The stakeholders also stipulated that that the primary goal was "no regrets," meaning that the site should not be made worse during remediation. This meant that a reduction in Hg concentration was not to come at the expense of habitat for one of the biotic endpoints or an increase in any factor increasing abiotic risk. This was the criteria to be used by managers to examine the trade-offs between the use of this management options along with cost, effectiveness, and public opinion.

A novel aspect of this program was the use of expert elicitation to evaluate the effectiveness of BST along with potential effects. Two experts familiar with BST and the South River program were consulted. Specific methods, as described in the full report, were used to account for potential personal bias. Dan Cristol (College of William and Mary, Williamsburg, VA, USA), an expert in the toxicity of Hg to birds, was consulted to confirm our understanding of the effects of BST to the bird endpoints.

Bank stabilization was projected to reduce Hg concentrations and the Smallmouth Bass risk distributions were lowered to the lower risk states in regions 3, 4, and 5. The changes to the risk for the White Sucker was not as high, but it was lowered. Risk to Carolina Wren distribution showed little change after implementation of BST. Risk to Belted Kingfisher did decrease slightly with BST, but AgBMP did not lower risk.

The BST increased the risk to the abiotic endpoints Water Quality Standards, Swimming River Use, and Boating River Use. Fishing River Use did decrease with BST. The AgBMP did not alter risk appreciably for any of the endpoints. The issue with BST was that it requires the modification of the bank in order prevent the erosion from releasing Hg into the river. Belted Kingfisher used banks for nesting, and modification using BST would eliminate those habitats. So, to implement BST approach, there would have to be a Nest Avoided scenario to prevent an increase in risk to this endpoint.

Two key points were made in the discussion. First was that there was a paucity of information in the technical literature of the efficacy of various management schemes. Applying a framework such as the BN-RRM was suggested as a tool in which to frame the various management alternatives. The second point was that the BN-RRM could be applied to an adaptive management strategy as suggested by Holling (1978).

The last risk assessment paper in this series was by Harris et al. (2017). In this study, the risk due to cumulative stressors was applied to biotic, ecosystem services, and human health endpoints. There were 3 goals: 1) to demonstrate the integration of ecological and human health risk assessment (ERA-HHRA), 2) the incorporation of ecological services into an ERA-HHRA as endpoints, and 3) apply the BN-RRM approach in the calculation of human health and ecological services to the South River. Risk was calculated for 14 biotic, human health, recreation and water quality endpoints due to chemical and ecological stressors for each the 5 risk regions downstream of the Hg source. In this study, Water Quality was at highest risk and Human Health was the lowest. Risk to the Recreational Fishery was the most variable between the risk regions.

A key advance in this study was the incorporation of human health and different exposure scenarios. The 5 pathway scenarios were: All Pathways of Exposure, Hunter/Fisher, Fisher, Farmer, and Recreational User. The All Pathways is the highest exposure scenario for Human Health risk, but the low risk score was the most likely and the high risk score only a 2% to 11% probability. As pathways decreased, so did risk, but it did not disappear through the study area. Given sufficient data, the incorporation of human health as a factor in an ecological risk assessment is possible.

Since the beginning of the development of the RRM and now the BN-RRM, the long-term goals were to be able to manage ecological structures in an integrated fashion. The UGRW project had at its core a series of management alternatives designed to be applied to forests. Both the projects in the Puyallup and Padilla Bay evaluated the usefulness of low impact development and the treatment of ballast water, respectively. In both instances, the weaknesses of each approach was demonstrated. In the case of whirling disease, dams and barriers to migration were demonstrated to be potential management tools to slow the infection. Finally, the South River studies demonstrated that is was possible to integrate risk, evaluate management alternatives, and mesh ecological endpoints with human health and ecological services. As suggested in Johns et al. (2017), the next step was to achieve the long-sought goal of adaptive management. Landis et al. (2017b) described using the South River as an example of how risk assessment can be the linchpin of an achievable adaptive management process.

Estuaries of the State of Queensland, Australia

A consistent goal of the BN-RRM program has been to integrate a variety of types of endpoints into a common risk framework. Graham et al. (2019) integrated the estimation of risk to water quality endpoints and to the change in benthic community structure (using eDNA) in the Noosa, Pine, and Logan Estuaries in Southeast Queensland, Australia. Each of the estuaries were broken into risk regions. In the Noosa and Pine Estuaries, the State of Queensland sets different water quality criteria depending on the salinity of the system. So those estuaries were divided into 2 risk regions. The Logan Estuary has only 1 set of water quality criteria so other criteria were used to divide it into 2 risk regions.

This site had an extensive dataset in which relationships between stressors and endpoints could be explored. These data meet the quality control criteria for the monitoring program. For the water quality endpoints, a unique case file for each estuary model was used to derive the CPTs. The case files for each estuary consisted of Southeast Queensland's Environmental Health Monitoring Program data collected monthly from 1999 to 2014 at specific locations. Each record (case) in the file was matched to the corresponding previous 30-d rainfall total and percentage intensive land use ($n = 5032$, $n = 6204$, and $n = 3621$ cases for Noosa, Logan, and Pine, respectively). These case files were used to parameterize the CPTs between the water quality nodes.

In the case of the of the benthic evaluations, the 18s rDNA gene (for eukaryotes) and matching the sequence to the organisms were used to characterize taxa groups. The dataset is not as extensive as in the case of the water quality parameters. The benthic endpoint nodes of the model were parameterized by using a single separate benthic data case file for all estuaries ($n = 287$).

The 3 estuaries were different in the distribution of risk. The water quality and benthic assemblages of the Noosa are more homogenous than the other 2 estuaries. The Noosa is also at the lowest risk with an estimated 73%to 92% probability of achieving water quality targets. In comparison, the middle Logan, middle Pine, and lower Pine regions have only a 15% to 55% probability of meeting the objectives. A high richness of fungi species was also consistently associated with a higher risk to water quality in the study area.

Three major findings summarized this work. First, it was demonstrated that the BN-RRM approach can be used to couple a variety of stressors to water quality and benthic endpoints in a diverse set of estuarine environments. Case learning (a machine learning technique) was used to parameterize the relationships between land use, water quality, and benthic community structure. The structure of the model can be used to evaluate future land use scenarios as to their ability to alter risk. Second, the results predicted that the subregions nearest the mouth have a higher probability of meeting the water quality objectives than the middle or upper subregions for each estuary. The network predicts dissolved O (DO) more accurately that the chlorophyll-a water quality endpoint and photosynthesizing benthos species diversity (Diatoms and Green Algae) were more accurately than heterotroph diversity (Fungi or Meiofauna). Third, eDNA data were incorporated in the risk assessment to evaluate the relative richness of the 6 benthic groups. As the use of eDNA has increased in ecological monitoring, this information can be applied to risk assessment and subsequent decision making.

Pesticides, water quality, and Chinook population dynamics

A key set of studies has been the ongoing work describing the connection between molecular interactions described as biomarkers, such as the inhibition of acetylcholinesterase, with water quality paraments and the population dynamics of Chinook salmon. Landis et al. (2020) and Mitchell et al. (this issue) have produced a framework for integrating such disparate factors into a risk assessment. Water quality as determined by DO and water temperature are key drivers. Pesticide concentration was an important variable when water quality parameters were not important variables in contributing to risk, as in the winter season. Mitchell et al. (this issue) demonstrated that a similar situation occurred in the Yakima River, but the was able to identify the importance of the dynamics among the various Chinook patches in that basin. Metapopulation dynamics was a factor in risk estimation. The different connections between the connected populations along the Yakima changed the responses of each.

Adaptive management and the BN-RRM

As part of the South River series, Landis et al. (2017b) described a framework for adaptive management in which ecological risk assessment plays a key role. While not directly about the BN-RRM, the paper described the context of the process in a broader, adaptive management framework.

Wyant et al. (1995) was the earliest proposed scheme in which ecological risk assessment was vital to the adaptive management and restoration of ecological structures. As in the RRM process, the process had at its center the definitions and objectives of the management effort. These criteria were defined by context analysis consisting of ecological state and dynamics, as well as cultural contexts. The objectives defined the endpoints, the scope of the assessment, and specific goals. The risk assessment then calculated current risks to the endpoints and predicted changes in risk because of management intervention. Using this scheme, as post management data are collected, the ERA can be updated to provide new risk estimates. A number of additional management options can be considered at this stage. Different management options may have different costs, risks, and efficacy, and this information can be communicated to the decision makers.

We began Landis et al. (2017b) by providing a history of adaptive management and the historical issues precluding its adoption as the standard method for environmental decision making. Next is the formulation of an approach detailing the 3 components of the adaptive management framework. The 3 parts are public engagement and governance; research, engineering, risk assessment, management; and change in externalities (Figure 5). In this formulation, it was assumed that the BN-RRM process conducting the ecological risk assessment of the Engineering, Risk Assessment, and Management segment. There are 2 segments where ecological risk assessment played a role. The *Introduction* section was where the ecological risk assessment is valuable to set the scope and endpoints assuming multiple stressors, habitats, effects, and endpoints. The second section is where the estimates of risk are produced in concert with the uncertainty and sensitivity analyses. Predictions about future outcomes are made including those representing different management options. The

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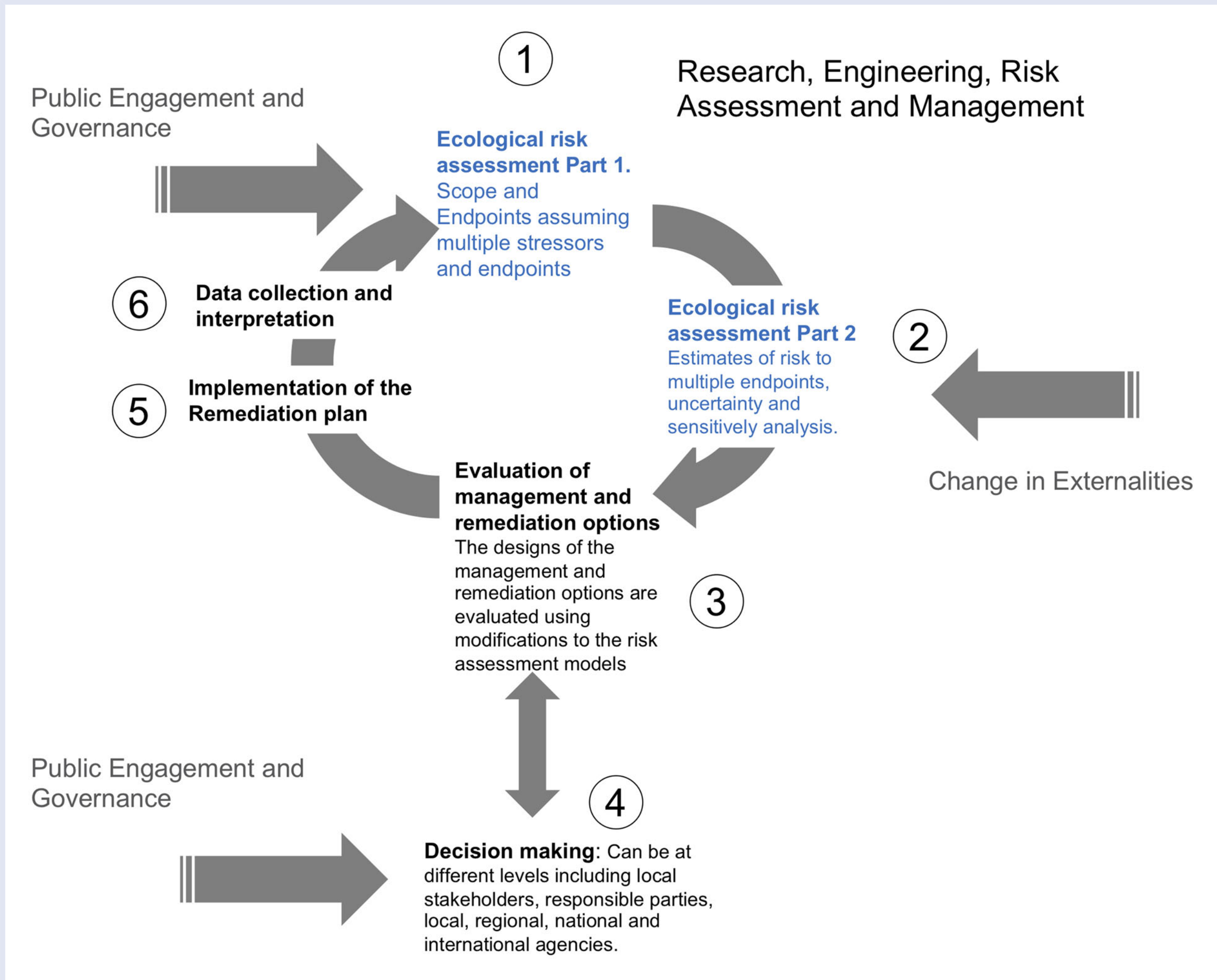

Figure 5. Adaptive Management Process. The diagram is derived from Landis et al. (2017b). The highlighted areas are those where ecological risk assessment plays a key role in what is an observed-orient-decide-act (OODA) loop for adaptive decision making.

Comparison Between the RRM and the BN-RRM section and *The History of the Relative Risk Model* section are central to the decision-making process where Public Engagement and Governance determines the next steps. The *Lesson Learned* section is the implementation of the remediation or management plan. Finally, the *Did We Meet the Goals of Landis (2003)* section is the data collection and analysis process that determines if we hit the target or have to go around the loop another time.

The framework was the same that we used the South River site and the associated RCRA process to illustrate the application of the process proposed adaptive management scheme. I regard the adaptive management process as described in this process as being one of the key developments of the research program. Adaptive management following this outline has become a common theme in all of our current and future research.

New programs and questions

We have 3 programs that are continuing the research on the use of the BN-RRM to address a diversity of topics. Synthetic biology, especially the use of gene editing, is a technique with a number of potential uses and 2 case studies have just been completed. Second is a microplastic risk assessment now underway for the San Francisco Bay. The third program evaluates the risks due to nutrients, pesticides and other factors to the Upper San Francisco Estuary, commonly called the Delta.

Synthetic biology is a research focus. These studies are inspired by the recommendations of NASEM (2016) in *Gene Drives on the Horizon* (Landis et al. 2020). Former graduate students, Steven Eikenbary and Ethan Brown, have been exploring the methods on how to apply the BN-RRM method to the evaluation of gene drive organisms derived by the use of CRISPER Cas 9. The insertion of specific genetic sequences using CRISPER Cas 9 is a widely used tool of synthetic biology and if the construct includes a gene drive, there may be a rapid increase in frequency of that sequence.

Brown (2020) developed a quantitative framework to describe how a gene drive modified house mouse could be introduced to Southeast Farallon Island to reduce the impact of the invasive mouse population to introduced species. The BN-RRM was used as the framework. The R-based MGDrivE model (Sánchez et al. 2020) was used to simulate both the population genetics and dynamics of the introduced sequence and the invasive mouse. Twelve different scenarios including 2 different gene drive homing rates, 3 unique gene drive mouse release schemes, and 2 levels of rodenticide use were investigated. Resistance to the gene drive by the mice was also incorporated. The sensitivity analysis demonstrated that the homing rate of the gene drive was more important to the elimination of the invasive mouse than the application of the rodenticide. The model suggested that the mice could be eliminated from the island in as little as 7 y and a high probability of eradication would be accomplished in 10 y.

Eikenbary (2020) examined the introduction of modified mosquitoes to suppress the populations of *Aedes aegypti* and *Aedes albopictus*, the hosts for Zika and dengue. The case study is based on the conditions in Ponce, Puerto Rico and incorporates GIS descriptions of habitat, human population density, and land use. The gene drive construct is assumed to be designed to prevent the reproduction of the mosquitos. The MGDrivE (Sánchez et al. 2020) again is used to model the population genetics and population dynamics of the species of interest, *A. aegypti*. A key finding of the study is that while mosquito populations initially decline, the development of resistance results in a mosquito population as large as before and composed of a preponderance of resistant insects. These studies demonstrate that the BN-RRM can be applied to situations far afield of conventional risk assessments.

Microplastics is a diverse set of stressors that are in need of a demonstrated quantitative probabilistic risk assessment. One of our current case studies is a microplastic ecological risk assessment for San Francisco Bay. Research support is provided by the National Science Foundation. Oregon State University is the lead university concentrating on the characterization of micro- and nanoplastics, the fate and transport of these materials, and their toxicological properties. The Western Washington University segment of the project is responsible for the development of a risk assessment and adaptive management framework for the prediction of effects to valued endpoints. The San Francisco Bay is the case study in collaboration with the San Francisco Estuary Institute (SFEI). The SFEI has recently completed a detailed analysis of the occurrence, transport, and exposure of the biota to the materials. The identification of the endpoints, the building of the conceptual model in a BN-RRM format, data acquisition, and the design of appropriate toxicity tests are underway. The collaboration is also building a microplastic risk assessment framework that reflects the current state of the art in the calculating risk. The microplastic program is scheduled to continue for 5 y.

The Upper San Francisco Estuary program is an ecological risk assessment focused on 3 endpoints: Chinook salmon survivorship as they pass through the region, the Delta Smelt, and macroinvertebrate community structure. Compared to the 2 programs described above, this is a more conventional risk assessment comparable to the South River, VA series of papers. The difference is the extent of the geographic region, the complexity of the landscape, and the large size of the dataset. We have now completed the general conceptual model, the data resources have been compiled, and the BNs are under construction. Innate to this process is the context of the adaptive management process as described in Landis et al. (2017b). Several California agencies are funding and providing technical expertise for this program.

LESSONS LEARNED

Lists of lessons learned are challenging, there are so many that are required to even begin the use of BNs to risk assessment. These are the ones that apply to the results pertaining to the risk assessment calculation and communication.

Lesson 1. The framework is adaptable to a wide range of scenarios. Over 25 y, the source-stressor-habitat-effect-impact coupled with a ranking approach has been used successfully to describe cumulative effects of multiple diverse and interacting stressors within a variety of environments, incorporating various effects to multiple endpoints. The method has incorporated a broad range of data, addresses uncertainties, and supports adaptive management.

Lesson 2. The integration of BNs to the basic RRM have improved the ability to estimate risk and to incorporate ecological risk assessment into an adaptive management process. The application of BNs was a key step in facilitating the advance of the RRM approach. Although studies on chemical contamination, nonindigenous species, habitat alteration, water quality, and so on had already been performed, dealing effectively with exposure-response and uncertainty was becoming challenging. The integration of the BNs with the relative risk model address some of the critique that the original RRM process was not sufficiently quantitative.

Bayesian networks had already been used for risk assessments—notably in Australia—and for ecosystem management. Applying the BN to the RRM provided a number of important features to the framework.

The BN method connects the variables (nodes) in a manner that has deterministic and probabilistic attributes. The conditional probability tables replaced the filters of the RRM and allowed a broadening of the types of interactions that could be described.

The BN method kept the discrete and categorical nature of the ranking system and the innate connection to the decision-making process. The necessity of using categories is not a liability in this application as is so often assumed. Recall that the basic RRM formulation was based on the idea of ranks in order to describe different management alternatives and the description of the effects on endpoints into acceptable or unacceptable classifications. Given the nature of much of the data that we have analyzed over the 25 y, ranking coupled with an observed distribution provides a clearer picture of the information, its precision, and its accuracy with regard to it affecting the endpoints.

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My observations have been that the world is lumpy, with measurements reflecting the heterogeneity and spatial clustering of the environment. Species that are endpoints are clustered depending on habitat. Stressors are often introduced to the environment at the end of a pipe or a spill site. A risk assessment should reflect the heterogeneity of the risk in the study area.

The ability of BNs to be interactive has been another key attribute of the use of BNs to describe risk. It has proven possible to demonstrate in real time to stakeholders how different management options affect the risk calculation. If there is an intense discussion regarding the concentration of a chemical or the importance of a variable, it has been straightforward to demonstrate how those alternative assumptions affect the risk calculation. It has also been informative to interact with the model in real time with decision makers and engineers to apply different management alternatives to the model and demonstrate the changes in the endpoints. Often it has proven that a magic bullet approach is not the answer because of unintended consequences to other endpoints. The effect of subtle changes to a number of inputs has been demonstrated.

The potential of applying risk assessment to evaluate management options and its place in an integrated adaptive management framework has been demonstrated. Since the UGRW study management has always been an interest. A process was described (Landis et al. 2017b) and its application to the South River study area described. In our current research on the California Upper San Francisco Estuary and the microplastics in San Francisco Bay, the context of adaptive management is a given. In the application of the BN-RRM in synthetic biology, our case studies focus on mosquito control or the control of an invasive rodent. It is now not clear to me how a risk assessment can be performed without a clear recognition of its role in adaptive management.

A major perceived disadvantage to the use of BNs has been the learning curve of students and risk assessment practitioners. The issue has not been a property of the method as much as the training of a population of scientists used to frequentist approaches and unfamiliar with conditional probability. Fortunately, there have been a number of papers that demonstrate the applicability of BNs for environmental management and have derived best practices, approaches for solving common problems, describing sensitivity and uncertainty, and interpreting the outputs. It does mean that risk assessors wanting to apply the method have to learn new skills. My experience has been that it is normal for new graduate students to learn the basics and to start applying BN models to risk assessment questions within a short period of time.

Lesson 3. Stakeholders and decision makers are key and need to be involved during the entire risk assessment and management process. At the origin of the RRM, we had a close interaction with the Rural Community Assistance Corporation (RCAC) and the broad range of decision makers, stakeholders, and scientists that were part of the process. The interaction was key to the success of that process. The series of risk assessments for Codorus Creek, the Cherry Point region of Washington State, the South River program, and now the Upper San Francisco Estuary have all had strong interactions with organizations similar to the RCAC. In the case of whirling disease, the program had interactions with the managers across the West, scientists from the region, and an exceptional dataset from which to work as assembled by this team. The risk assessment for the UGRW site also involved the close collaboration with USFS managers and the scientists in the Western region.

The SRST was a classic example of the value of engagement with stakeholders and decision makers. The meetings of the organization were attended by local academics, regulators from Region 3 EPA and Virginia state government, members of NGOs, scientists from state and federal agencies, representatives of the city of Waynesboro, and others. The SRST served to establish endpoints, provide access to data, were experts in the management options, and provided technical reviews. The interaction also facilitated the BN-RRM model and resulted in it becoming one of the evaluation tools for the continued management of the site.

The same kinds of collaboration are underway in the risk assessments for the Upper San Francisco Estuary and the microplastics risk assessment for the San Francisco Bay. For the Upper San Francisco Estuary, there is a technical advisory team composed of representatives from state agencies, Federal agencies, NGOs, and key stakeholders. We have routine meetings regarding the status of the risk assessment, we answer numerous questions regarding the approach and progress, and we ask questions about datasets, endpoints, and management plans. The graphical nature of the BN-RRM process and the mapping of relative risk in the study areas facilitates the communication between risk assessors and stakeholders in this diverse environment.

We are following a similar process for the microplastic risk assessment for the San Francisco Bay. There are 2 sets of collaborators, the first is the San Francisco Estuary Institute, a leading scientific NGO in the region. They are providing extensive datasets on microplastic concentrations, simulations of transport of these particles, and information on land use. The second set of collaborators is the Pacific Northwest Consortium on Plastics. The consortium is organized by Oregon State University, funded by NSF, and consists of interested scientists, managers, and stakeholders from Northern California, USA to British Columbia, Canada. This second group broadens our focus to meet the eventual goal of having a risk assessment process for microplastics across the region.

In all of these examples, the interaction with stakeholders and decision makers improves the ability to gather datasets, establish endpoints, and produce results to inform the decision-making process.

Lesson 4. Contrary to many claims, much research in the field of environmental toxicology is not done in a manner appropriate to the quantitative management of ecological structures. The issues with the reporting of exposure-response information using hypothesis testing or single point estimates in the field of environmental toxicology has been extensively documented. Exposure-response interactions are best described as functions with a most likely estimate with a confidence interval and also a predictive interval that describes the probability of a single observation. Most decisions are made at the low exposure/low response portion of the function (EC5, EC20), not the midrange (EC50). As demonstrated by the research on pesticides, water quality, and Chinook salmon populations, small differences in survivorship can have long-term consequences to population dynamics. So why do we not do a better job of mapping the lower tails of the exposure-response interactions? What use is an EC50 or other point value, or a treatment result that is statistically significant at an arbitrary *p* value? If an EC value is reported, then it should be trivial to then report the entire curve along with confidence intervals. The BN-RRM can apply the entire exposure-response relationship to estimate risk to endpoints, time to report the equation for the curve, not estimated points along the curve. Turns out that many reports of toxicity have been at best scoping studies with only a few exposures and extraneous replication. The studies should be followed up with studies with numerous exposures and measured effects reported with the necessary confidence and predictive estimates.

In reading the manuscript, note that there are no mentions of reference/control sites, unimpacted sites, pristine sites, or other terms signifying unimpacted systems that should be compared to the "impacted" sites or systems. Such constructs have been demonstrated to be unnecessary to perform ecological risk assessments. Our experience is that such sites do not exist, the environments that we work in are all highly modified and managed. Instead, we have learned to look at gradients of exposure and effects of the multiple stresssors that modify the area to be managed.

DID WE MEET THE GOALS OF LANDIS (2003)?

Did I and my colleagues make progress along the goals set in 2003? Progress yes, but to satisfaction, not yet. Here is my status report.

Universality

I would mark this one as *in progress*. The case studies in this paper are highly varied. O'Brien et al. (2018) have used the BN-RRM to evaluate environmental flows in South Africa. But only a few researchers use ecological risk assessment as a management tool.

Organizing decision making

Again, I mark this *in progress*. It seems that building a conceptual model to describe cause-effect in a quantitative manner is not a priority. How can you organize decision making without at least an outline of causality? My experience says that it is possible to construct such frameworks for a diverse set of questions.

Observable predictions

Little progress if at all. Predictions are made by the series of risk assessments described in this review and by others. The question is about having monitoring programs established to test those predictions. They will be expensive, but many sites are already doing long-term monitoring as part of agreements and as part of the cleanup of contaminated sites and those involving sites of special cultural interest such as Puget Sound. Sites such as those at South River, the Queensland estuaries around Brisbane, Australia, and the Upper San Francisco Estuary are information rich, but can they be modified to test the results of management actions as in an adaptive management process? Time will tell.

Management alternatives

In progress. It is possible using risk assessment to calculate the results of management alternatives and even calculate targets for controlling chemical inputs or water quality measurements. At the South River site, we did present our findings to the SRST as part of the management process. Are others applying risk assessment to determine management alternatives and then act on them?

Synthesis eco/human

There is Harris et al. (2017) that demonstrates the potential. So I mark this as in progress, but it is difficult to find other papers attempting the same goals. Maybe this is *barely off the starting line*? With the detailed discussions regarding ecosystem services and human wellbeing, I would have thought this to be an increasingly important area of research.

In 17 y we are only 3 y away from the 20-y time horizon I set. I thought we would be further along, but perhaps I am not using the correct search terms after seeing the special series that this paper is part of, I would reevaluate this analysis. I am looking forward to it.

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