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**Using Bayesian decision networks to guide
restoration of freshwater mussels in Illinois: a step-by-step guide
to creating and using BDNs for ecological applications**

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Using Bayesian decision networks to guide restoration of freshwater mussels in Illinois: a step-by-step guide to creating and using BDNs for ecological applications

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Background and Justification

Extirpation of species from their native ranges can occur as a result of broad scale processes such as habitat loss, land use practices, and shifts in biotic community composition. However, quantitatively linking broad scale factors to population decline can be difficult, especially for rare or cryptic species (Hamilton et al. 2015). Thereby, choosing appropriate mitigation or restoration actions can be challenging when agency resources are limited and understanding of dynamic ecological processes is imperfect. Often managers must make decisions based on personal expertise with limited empirical data. While this method is sometimes effective, it is hard to replicate. Furthermore, when such efforts fail, the reason for failure may be unclear, as factors that impact the outcome of management action may be unknown or ignored (i.e., the process is not transparent). Additionally, the perceived favorability of management outcomes may vary based on stakeholder perceptions of cost and value. Thus, there is a need for quantitative tools which are able to transparently incorporate empirical data, expert knowledge, and stakeholder values to provide a replicable framework for adaptable, structured decision making (Nyberg et al. 2006; Conroy & Peterson 2013). One approach is through Bayesian decision networks (BDNs), which incorporate multiple sources of information and provide a flexible framework for addressing questions where empirical data are limited and structural uncertainty is high (Conroy & Peterson 2013). In such situations, BDNs are an appropriate tool for aiding professionals in choosing the most appropriate management action for a specific scenario. The product of a BDN is a flexible decision-making framework that can help managers adaptively manage for variable systems over time.

The management of freshwater mussel populations is a useful application for structured decision making tools such as BDNs. Freshwater mussels are highly imperiled (e.g., Williams et al. 1993), yet play an important role in lotic systems through sediment stabilization, nutrient mobilization, and bioaccumulation of potentially harmful substances (Vaughn et al. 2007). However, knowledge gaps pertaining to ecological role and life history still exist for freshwater mussels (Haag 2012), and long term, standardized monitoring of these species is rare. Additionally, most species can live for decades or more and are largely immobile, making them highly susceptible to fragmentation and eventual extirpation in response to disturbance, as well as changes in land use or biotic community composition (Hastie et al. 2001; Galbraith et al. 2010). In regions where they persist, mussels are increasingly the focus of restoration efforts to improve water quality and biotic integrity of streams, despite high amounts of uncertainty associated with such efforts. As re-introduction of mussel species becomes more common, optimal management approaches must be determined, though targeted research of success rates is rare. Thus, Bayesian methods are particularly useful for combining prior system-specific information with expert knowledge to create a balanced and quantitative approach to managing freshwater mussel populations.

Recent collaborative efforts undertaken by Chicago Wilderness and the Illinois Natural History Survey have sought to predict the optimal method for restoration of two freshwater mussel species, Ellipse (*Venustaconcha ellipsiformis*) and Spike (*Eurynia dilatata*), within the Chicago Wilderness Area. The Chicago Wilderness Area encompasses 1,400 km² and includes the Chicago, Des Plaines, Kankakee, Kishwaukee, and Fox River watersheds. Both Ellipse and Spike were historically widespread within this region, but have suffered substantial range and

abundance reductions in recent years. Ellipse are currently a species of greatest conservation need in Illinois, and Spike are listed as threatened (Douglass & Stodola 2014; Illinois Endangered Species Protection Board 2015). Yet, recruiting populations of both species still persist within the region (INHS Mollusk Collection, unpublished data), which indicates the potential for recovery. Proposed locations for re-introduction were the South Branch Kishwaukee and West Branch DuPage rivers, as both species are presently absent in these rivers. The South Branch Kishwaukee River is located in DeKalb County, surrounded primarily by agricultural and suburban land use, and contains many areas of relatively well-preserved habitat with a variety of mussel species. The West Branch DuPage River crosses through Cook and DuPage counties, and local land use is primarily suburban or urban. A large portion of the river was contaminated by radioactive inputs during the 1930s-1970s and subsequently identified as a Superfund site (United States Environmental Protection Agency 2005). The West Branch DuPage River has undergone substantial restoration through the Superfund program, and has recently been the site of reintroduction for common mussel species (DeMartini 2017). Both target rivers historically supported Spike and Ellipse (Douglass & Stodola 2014) and have either intact habitat or undergone habitat restoration, making them good candidates for future mussel restoration.

Several options exist for facilitating restoration of mussel species to target rivers, such as translocation of adult mussels, introduction of juvenile mussels, release of inoculated host fishes, or taking no action (e.g., relying on natural recolonization). Previous introductions in the West Branch DuPage have focused on propagating and releasing juvenile mussels (DeMartini 2017), though relocation of adult mussels from source populations remains a viable option.

Releasing host fish that have been artificially inoculated with mussel glochidia has dual benefits of releasing larval mussels and boosting host fish populations. On a larger scale, removal of upstream dams is a possible management option which would seek to restore connectivity of a target area to other parts of the watershed and enable recolonization from natural sources. Finally, upon evaluating specific proposed sites for restoration, managers may seek to take no action at this time if the likelihood of a successful outcome is deemed low.

We highlight the use of Bayesian Decision Networks to formalize the decision process and suggest a management strategy for restoring *Ellipse* and *Spike* to target areas. A BDN is particularly useful in complicated situations like this, because it allows for the combination of prior knowledge of mussel distributions and habitat relationships in Illinois with expected value of management outcomes. To build the Bayesian Decision Network, we used long term mussel presence data paired with a suite of environmental and biotic variables to elucidate important factors for each focal species and structure preliminary models (Chiavacci et al. 2018). We then built multiple versions for each species using three levels of information 1) data subset (target streams, non-target streams, or both; Figure 9), 2) expert opinion values (median, minimum, or maximum), and 3) precision of mussel data (long term presence, 2018 presence or 2018 density). All model versions were compared using sensitivity analyses to determine sources of potential model performance bias and decide whether a need for quantitative mussel density sampling in future model iterations was needed.

All models built in this project were created using Netica by Norsys Software Corp., a program specifically designed to create Bayesian networks. Netica is available for download for \$285 for an individual application, or for \$600 for commercial applications (as of 2019).The

following walk-through serves as a step-by-step tutorial of how to build BDNs using Netica, while also detailing the methods and results of the Ellipse and Spike models created for this project. For each step, we outline a “General Description”, which is a broad description for managers to consider for their own projects, and “Applied Project Result” is a detailed explanation of the process completed for this project. These steps are summarized as:

Step 1. Identify Objectives

Step 2. Conduct Preliminary Analyses

Step 3. Determine possible management actions and assess preliminary costs

Step 4. Construct model

Step 5. Organize and incorporate empirical data

Step 6. Collect expert opinion responses

Step 7. Compile and validate model

Step 8. Determine sensitivity

Step 9. Test specific sites

Step 10. Assess feasibility, carry out management, and monitor results

Methods

Step 1. Identify objective(s)

General Description: Before choosing which parameters to include in a BDN, it is important to clearly articulate an objective to determine which management options should be evaluated. Be as specific as possible, and consider the appropriate timescale for management action to produce results.

Applied Project Result: Study objective: Restore Ellipse and Spike (potentially to target watersheds), resulting in 300 or more surviving adults per site, and detectable recruitment within ten years of management action.

Step 2. Conduct preliminary analyses

General Description: It is beneficial to use any existing data and/or literature values to inform the structure of a BDN, though it may not be possible to conduct targeted research to inform management decisions. If long-term data are available, using regression analysis (either simple, for each variable, or in a more comprehensive framework) can be a good starting point for determining which factors may be influencing the parameter of interest. Research in similar systems or for the same study organism may also be included when considering variables for initial models, as well as expert opinion. In cases where no known relationships have been established, another approach may be to arbitrarily include factors based only on expert knowledge, and weed out unimportant factors later in the process, through sensitivity analysis. A drawback to this method is the potential need for collecting relatively more expert opinion survey data than may ultimately prove necessary. Additionally, keep in mind that as model complexity increases so does model uncertainty. Sometimes it is better to begin with a simple model founded in empirical knowledge and add more information in the future as it becomes available, rather than starting with a very complex model that includes all possible relationships, which can quickly become unwieldy.

Applied Project Result: A large number of hydrological, water quality, and biotic variables were included in multi-stage regression analyses (see Chiavacci et al. 2018 for details)

to determine species-specific factors impacting Ellipse and Spike presence in northeastern Illinois. Five factors were significant for Ellipse (factor, relationship): number of upstream dams (-), number of pollutant dischargers (-), host fish richness (+), mean annual duration of extreme low flows [-], and number of sites unsuitable for aquatic life [-]. Four similar yet distinct factors were significant for Spike: distance to downstream dam [+], high flow variation [+], number of pollutant dischargers [-], and host fish richness [+].

Ellipse presence was negatively related to number of upstream dams and number of National Pollutant Discharge Elimination System (hereafter, NPDES) sites in the watershed. NPDES sites represent point sources of pollution and are associated with poor water quality. Duration of extreme low flows also negatively impacted Ellipse presence. Proportion of the watershed which failed to meet minimum water quality standards under section 303(d) of the Clean Water Act (Illinois Environmental Protection Agency) was also an important watershed-level predictor which negatively affected Ellipse presence. According to 303(d) regulations, sites can fail to meet water quality standards for several reasons ranging from “aesthetic quality” to “primary contact recreation”. In this study, we further specified this metric to focus on sites deemed “unsuitable for aquatic life”, using a count of sites with this designation for each stream. Host fish richness was a positive predictor of Ellipse presence. In this study, it was further modified to reflect host suitability, based on transformation success estimates gathered from literature (Luo 1993; Allen et al. 2007; Schroeder et al. 2014; see Table 1, Appendix A) for weights and scoring). As with Ellipse, Spike presence was negatively related to number of NPDES dischargers and positively related to host fish richness. However, Spike presence was also positively related to distance to nearest downstream dam and negatively related to

variation in number of annual high flow events. The above factors were included in species-specific models and were assumed to be the most likely variables affecting mussel presence for which empirical data were available.

Table 1. Weighted values for Ellipse fish hosts. Hosts with <2 successfully transformed juveniles in laboratory trials are weighted at 0.25, hosts with 2-10 transformed are weighted at 0.5, 11-20 are weighted at 0.75, and >20 are weighted at 1.

Common Name	Scientific Name	Mean Transformed	Weight	Reference
Mottled Sculpin	<i>Cottus bairdii</i>	32	1	Allen et al. 2007
Slimy Sculpin	<i>Cottus cognatus</i>	48	1	Allen et al. 2007
Brook Stickleback	<i>Culaea inconstans</i>	13	0.75	Allen et al. 2007
Mud Darter	<i>Etheostoma asprigene</i>	1	0.25	Allen et al. 2007
Rainbow Darter	<i>Etheostoma caeruleum</i>	1	0.25	Allen et al. 2007
Iowa Darter	<i>Etheostoma exile</i>	5	0.5	Allen et al. 2007
Fantail Darter	<i>Etheostoma flabellare</i>	8	0.5	Allen et al. 2007
Johnny Darter	<i>Etheostoma nigrum</i>	24	1	Allen et al. 2007
Banded Darter	<i>Etheostoma zonale</i>	1	0.25	Allen et al. 2007
Logperch	<i>Percina caprodes</i>	1	0.25	Allen et al. 2007
Blackside Darter	<i>Percina maculata</i>	2	0.5	Allen et al. 2007

Step 3. Determine possible management actions and assess preliminary costs

General Description: Potential management options included in models should encompass only what is realistically feasible and applicable to the objective specified, even if this does not address all contributing factors identified in preliminary analyses. Management actions should also be as specific as possible. For example, consider the objective of improving recruitment for a fish species such as largemouth bass in an Illinois reservoir. Management actions targeted at improving habitat for this species might include “increase woody debris volume to 100m³/ha”, or “add thirty 10-ft oak logs per site”, rather than a more vague statement like “increase woody habitat”, for which cost and feasibility estimates will also be imprecise. Feasibility for a particular objective may vary based on logistical constraints of resources, as well as what the public or other stakeholders are willing to accept (which should also be a consideration).

Applied Project Result: Five possible management actions were chosen based on discussions with collaborators, experts surveyed, and propagation facilities within Illinois (Urban Stream Research Center, Warrenville, IL and Jake Wolf Memorial Fish Hatchery, Topeka, IL, Table 2). Approximate costs for each option were assessed based on literature values in the case of fish and mussel propagation (Southwick & Loftus 2018), and an average cost of proposed dam removals in the state of Illinois as of 2018 (S. Pescitelli, personal communication). An option of “No Action” was also included, for situations where the predicted probability of management success was so low that the cost of taking management action was undesirable. Costs for each option involving the release of organisms were based on

the cost of action resulting in survival of ~300 mussels to maturity, estimated from literature values (Liberty 2014; DeMartini 2017; McMurray & Roe 2017).

It is not necessary to know the precise costs for each management option before creating a BDN (but it helps!). Having a relative measure of what each management approach will cost is useful when determining the utility of potential management outcomes in various scenarios, which will be determined using expert opinion surveys or discussions (see Step 6).

Table 2. Preliminary costs for proposed management actions considered for Ellipse and Spike restoration to the South Branch Kishwaukee and West Branch DuPage Rivers.

Management Action	Cost
No Action	\$0
Release Juvenile Mussels	\$1,425
Release Inoculated Host Fish	\$1,500
Release Adult Mussels	\$20,300
Remove Dam	\$718,000

Step 4. Construct model


General Description: Choosing which parameters to include in a BDN can be accomplished in a variety of ways. The most direct approach is through preliminary analyses and/or literature review, as described above. If no empirical data are available to determine prior probabilities and inform model structure, one alternative is to build various theoretical


forms of the model, populate them with estimates of parameter distributions based on expert knowledge or simulated data, and then test each form for sensitivity to inputs. This process will determine which components might be important for inclusion in future model iterations. Often, the most thorough and practical approach is to use a combination of these methods when preparing to build a BDN. To facilitate such exercises, a detailed description of how to create and populate BDNs using Netica (Norsys Software Corp.) follows.


- a. Open Netica, and select File>New Network to begin a new project


*Note: Netica can also build Bayesian Belief Networks, which are similar to BDNs but do not include a decision or utility node and instead are used to predict relative probabilities of parameter states without incorporating a value statement.

- b. To create the graphical structure of a BDN, four buttons are necessary, and each button is located in the lower toolbar:

- i.  Nature Node: is used to add nodes that contain probabilities based on either empirical data or expert opinion, and represent variables in the model (i.e., they do not include the decision or utility node). These nodes are populated by the user and discussed in Step 7.

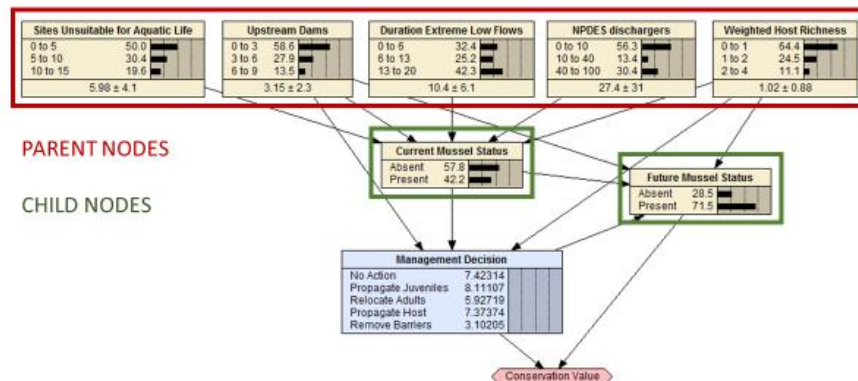
- ii.  Decision Node: is used to add a decision node. A single BDN may have multiple decision nodes, each of which must be associated with one or more utility nodes. Each decision is assigned an expected value based on the states of parameters affecting and affected by the decision node, which is calculated as a function in Netica.

iii.  Utility Node: is used to add a value statement about a decision node, based on a scale chosen by the user (usually 1-10 or 1-100). Values for this node are typically determined using survey responses or direct input from stakeholders.

iv.  Link: is used to connect nodes and describe relationships to Netica; links are what make BDNs happen! They also enable calculation of the expected value in the decision node. A few important aspects of links are listed below:

1. Nodes that have links going *from* but not *to* themselves are called **parent nodes**. Any node with a link going to itself from another node is a **child node**.

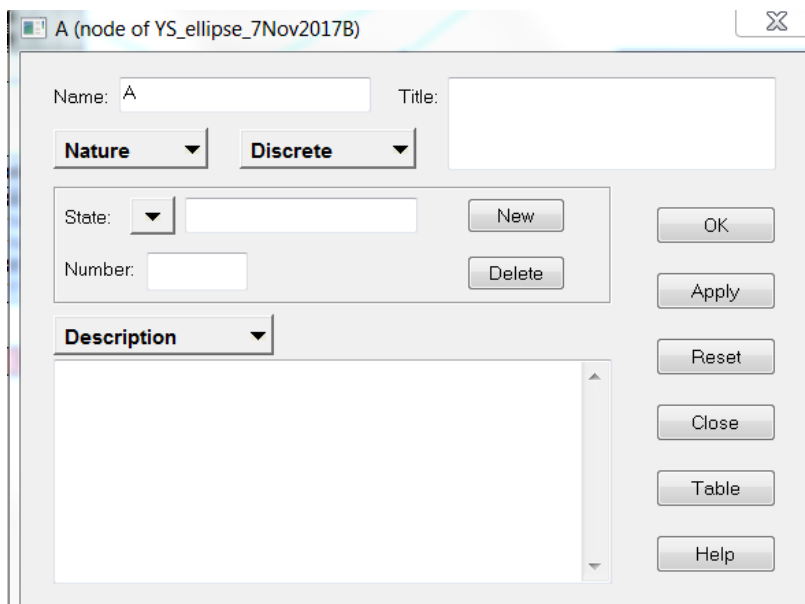
Ex)



2. Netica does not allow feedback loops between nodes because it does not incorporate time into its models (but users can adjust model parameters to reflect changes over time).
3. The utility node (“Conservation Value” in the above example) does not connect *to* any other node, but should receive connections from the decision node and any nodes representing the parameter of interest (in this case, “Future Mussel Status”).

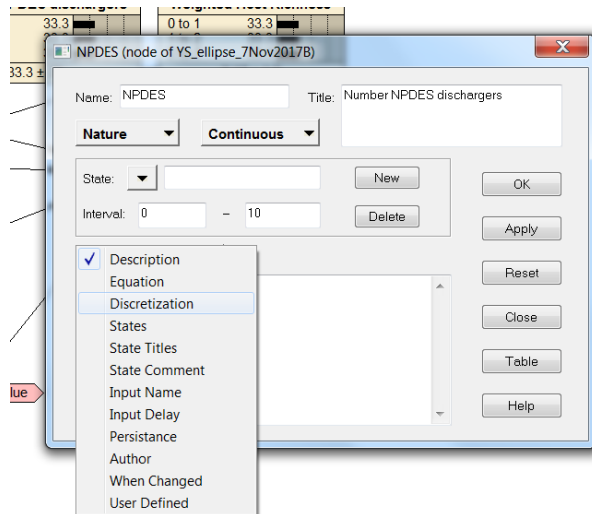
4. Nodes connected to the decision node should be only those which potential management options can alter.

c. To add a node, simply select the appropriate button, then click anywhere on the window to paste it. When a node is created, it will appear in blue, unlabeled. To specify the name and data bins for a node, right click anywhere on the node and select Properties from the menu to open the dialogue box, pictured here:

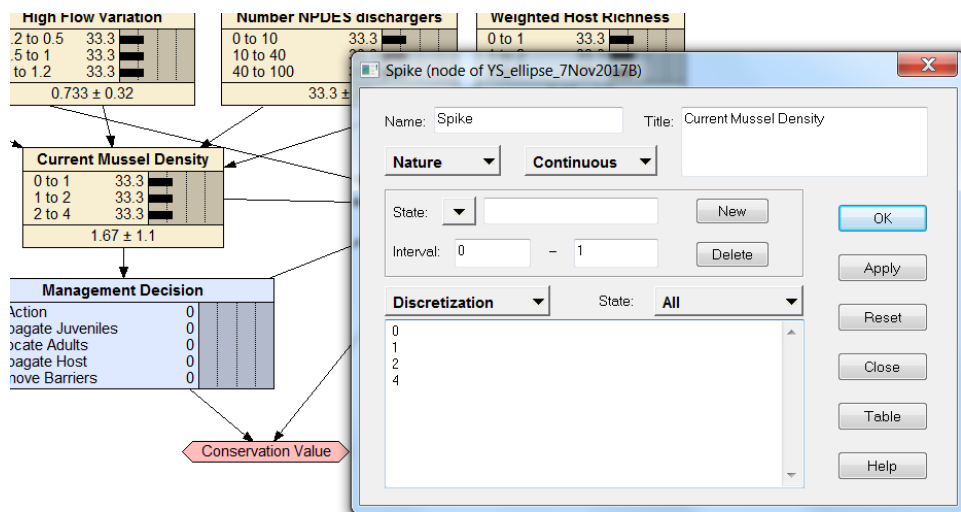


- i. The “Name” field should contain no spaces, and should be as simple as possible. This is not visible on the graphic model, but is used when specifying relationships between nodes using equations or Netica’s built-in algorithms, as described in Step 5.
- ii. The “Title” field is what will actually be displayed on the node in the graphical model, and can contain spaces.

iii. "State" specifies the levels of the parameter that will be represented by this node. These can be qualitative values such as "low, medium, high" or "yes, no", or numerical values. Continuous data will need to be discretized into bins, which can be done by changing the Description dropdown to Discretization in the Properties dialog box:



Threshold values can then be typed directly into the field to specify the bin minimum and maximum cutoffs. Netica will automatically adjust probabilities as discretization thresholds are updated.



Qualitative states can be typed directly into the field, and additional states can be added by clicking “new”. By default, the probability listed for each node state will be equal to 100 divided by the number of states specified for that node. (For example, if a node has three states, default probability of each state occurring will be 33.333%).

iv. The dropdown menu labeled “description” above has many functions which will be discussed in later steps. The Description field itself can be used to enter any working notes about the node that may be necessary for clarity. Once the node has been named and titled and states have been added, click ok to return to the network window and continue building the BDN.

- d. To connect nodes, select the link button, then click on the parent node and drag an arrow to the desired child node. A single parent node can lead into any number of children, but it is recommended that each child node have no more than five parents (Norsys Software Corp).

Applied Project Result: Two similar but distinct model structures were determined for Ellipse and Spike using preliminary analyses. A maximum of three state bins was chosen for each node to facilitate manageable expert opinion surveys, and bins were fitted to the distribution of each node’s data. For example, the “number of upstream dams” node has bins of “0 to 3”, “3 to 6”, and “6 to 9”. The scale of the utility node was specified as 1-10, with 1 being the lowest expected decision value and 10 being the highest.

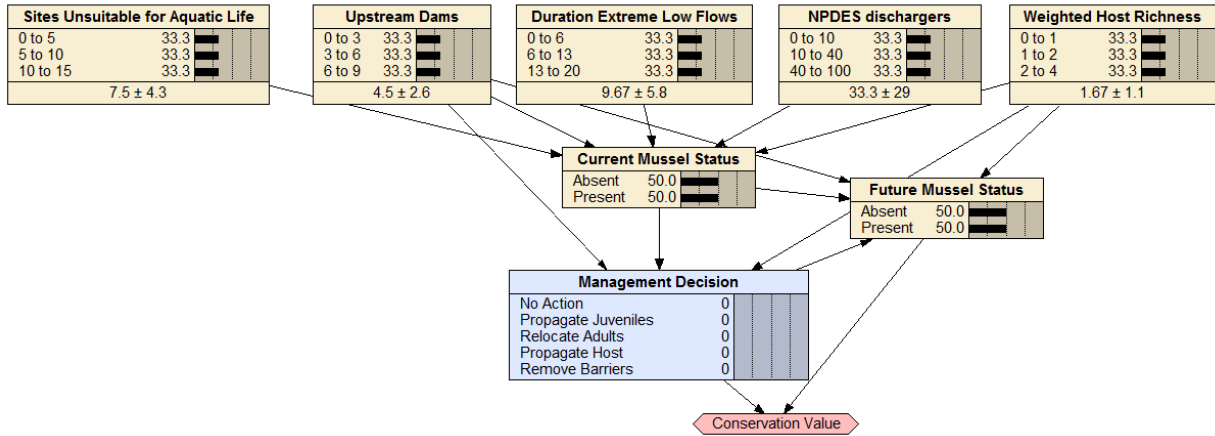


Figure 1. Default presence model structure for Ellipse. Nature nodes are pictured as tan rectangles, the decision node as a blue rectangle, and the utility node (Conservation Value), as a pink hexagonal shape. Probabilities are set to 100/number of states, as Conditional Probability Tables (CPTs) have not yet been populated.

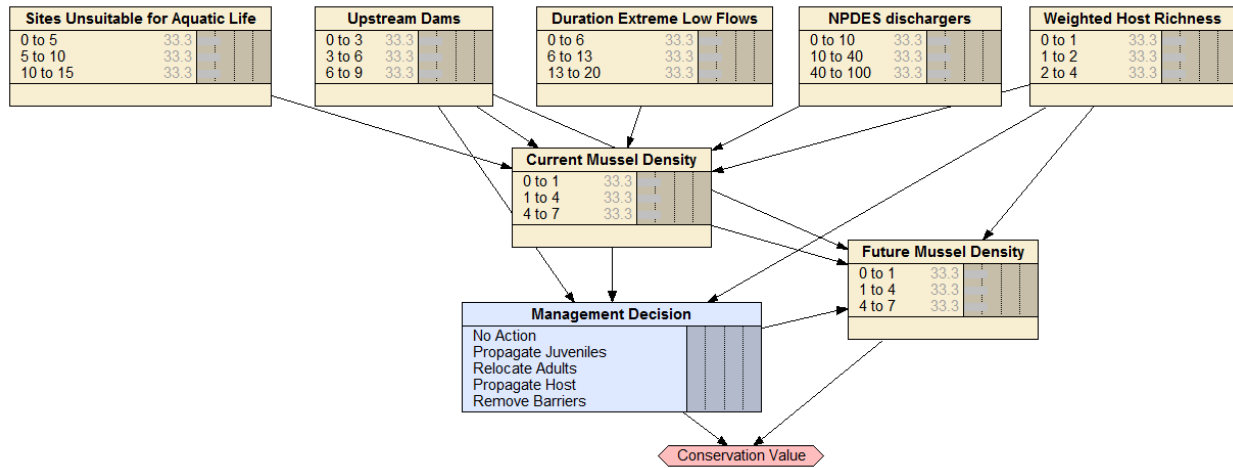


Figure 2. Default density model structure for Ellipse. Nature nodes are pictured as tan rectangles, the decision node as a blue rectangle, and the utility node (Conservation Value), as a pink hexagonal shape. Probabilities are set to 100/number of states, as Conditional Probability Tables (CPTs) have not yet been populated.

pink hexagonal shape. Probabilities are set to 100/number of states, as CPTs have not yet been populated.

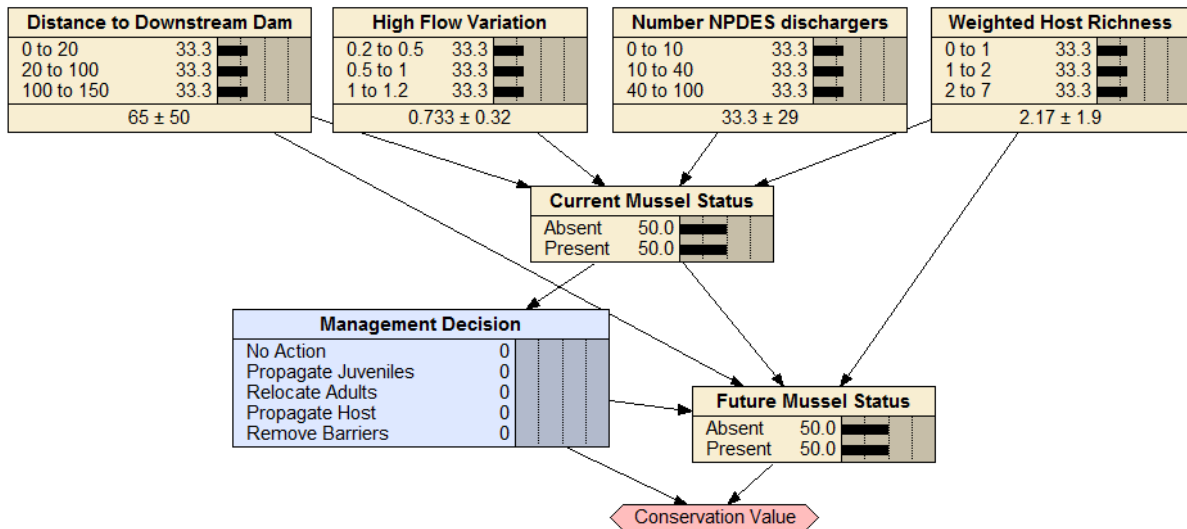


Figure 3. Default presence model structure for Spike. Nature nodes are pictured as tan rectangles, the decision node as a blue rectangle, and the utility node (Conservation Value), as a pink hexagonal shape. Probabilities are set to 100/number of states, as CPTs have not yet been populated.

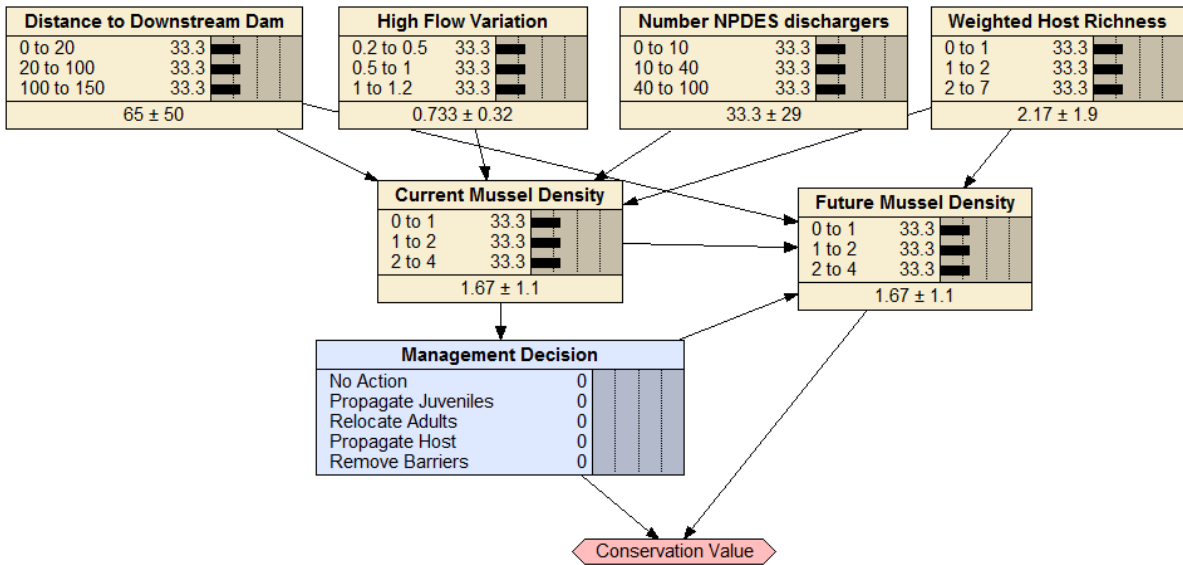


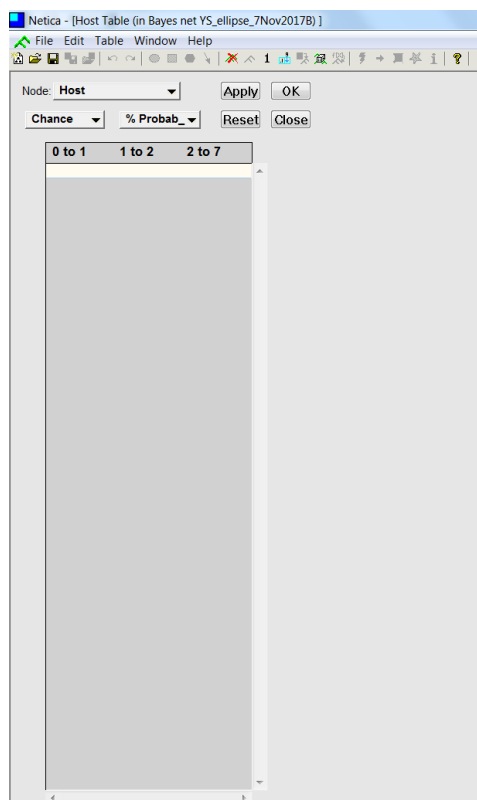
Figure 4. Default density model structure for Spike. Nature nodes are pictured as tan rectangles, the decision node as a blue rectangle, and the utility node (Conservation Value), as a pink hexagonal shape. Probabilities are set to 100/number of states, as CPTs have not yet been populated.

Step 5. Organize and incorporate empirical data

General Description: After preliminary analyses and/or literature have been used to determine components to be included in a BDN, and the graphical structure of the model has been configured, the next step is to use existing data to determine the prior probabilities contained in each node. Incorporating empirical data into the BDN will update the default probabilities of node states (i.e., they will no longer be 100/number of states possible as in Figure 1-4) to reflect the distribution of the data. These updated probabilities represent prior beliefs about the system being modeled, and are contained in each node's Conditional Probability Table (CPT). The CPTs of the nature nodes are ultimately what Netica uses to model

the probabilities of all possible state combinations and determine the expected value of each management option. Depending on the node complexity and data type, there are several ways to populate the CPTs of nodes.

- a. Using probability estimates: The simplest way to populate CPTs is by entering probabilities directly. To open a node's CPT, simply right click the node and select Table, which will open a dialog box like the one below.



This node is a parent node, so its CPT is simple and represents only the prior probability that the parameter (weighted fish host richness) will be in any of the three states listed. Values can be typed directly into the white data field below each state title, and must sum to 100 for each row (Netica will alert you if they don't). Entering data this way is appropriate for situations where priors may be based off of

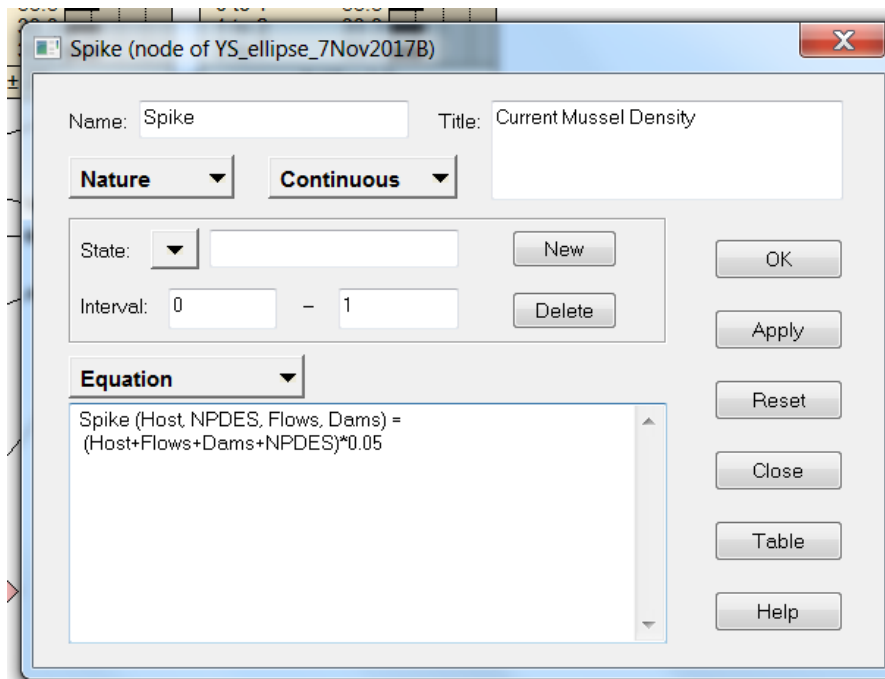
literature values and a dataset is not available, or where existing data have simply been broken into bins and summarized. This is an efficient way to populate parent nodes, but what about more complex nodes with larger CPTs?

- b. Using equations: Below is a portion of the CPT for the mussel density node, which has five parent nodes. Clearly, it is very large and would be difficult to populate by hand.

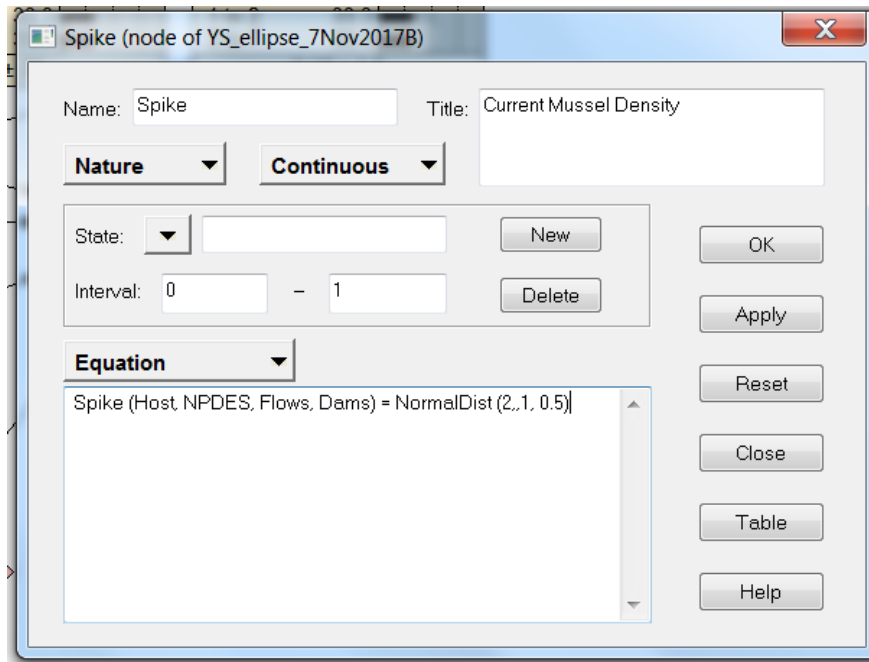
Weighted Host Richness	Number NPDES discharg...	High Flow Variation	Distance to Downstream ...	0 to 1	1 to 2	2 to 4
0 to 1	0 to 10	0.2 to 0.5	0 to 20			
0 to 1	0 to 10	0.2 to 0.5	20 to 100			
0 to 1	0 to 10	0.2 to 0.5	100 to 150			
0 to 1	0 to 10	0.5 to 1	0 to 20			
0 to 1	0 to 10	0.5 to 1	20 to 100			
0 to 1	0 to 10	0.5 to 1	100 to 150			
0 to 1	0 to 10	1 to 1.2	0 to 20			
0 to 1	0 to 10	1 to 1.2	20 to 100			
0 to 1	0 to 10	1 to 1.2	100 to 150			
0 to 1	10 to 40	0.2 to 0.5	0 to 20			
0 to 1	10 to 40	0.2 to 0.5	20 to 100			
0 to 1	10 to 40	0.2 to 0.5	100 to 150			
0 to 1	10 to 40	0.5 to 1	0 to 20			
0 to 1	10 to 40	0.5 to 1	20 to 100			
0 to 1	10 to 40	0.5 to 1	100 to 150			
0 to 1	10 to 40	1 to 1.2	0 to 20			
0 to 1	10 to 40	1 to 1.2	20 to 100			
0 to 1	10 to 40	1 to 1.2	100 to 150			
0 to 1	40 to 100	0.2 to 0.5	0 to 20			
0 to 1	40 to 100	0.2 to 0.5	20 to 100			
0 to 1	40 to 100	0.2 to 0.5	100 to 150			
0 to 1	40 to 100	0.5 to 1	0 to 20			
0 to 1	40 to 100	0.5 to 1	20 to 100			
0 to 1	40 to 100	0.5 to 1	100 to 150			
0 to 1	40 to 100	1 to 1.2	0 to 20			
0 to 1	40 to 100	1 to 1.2	20 to 100			
0 to 1	40 to 100	1 to 1.2	100 to 150			
1 to 2	0 to 10	0.2 to 0.5	0 to 20			
1 to 2	0 to 10	0.2 to 0.5	20 to 100			
1 to 2	0 to 10	0.2 to 0.5	100 to 150			
1 to 2	0 to 10	0.5 to 1	0 to 20			
1 to 2	0 to 10	0.5 to 1	20 to 100			
1 to 2	0 to 10	0.5 to 1	100 to 150			
1 to 2	0 to 10	1 to 1.2	0 to 20			
1 to 2	0 to 10	1 to 1.2	20 to 100			
1 to 2	0 to 10	1 to 1.2	100 to 150			
1 to 2	10 to 40	0.2 to 0.5	0 to 20			
1 to 2	10 to 40	0.2 to 0.5	20 to 100			
1 to 2	10 to 40	0.2 to 0.5	100 to 150			
1 to 2	10 to 40	0.5 to 1	0 to 20			
1 to 2	10 to 40	0.5 to 1	20 to 100			
1 to 2	10 to 40	0.5 to 1	100 to 150			

One alternative is to return to the Properties dialog box (by right clicking the node), and specify an equation that describes the relationship between that node and its parents. This can be used where targeted preliminary data have been collected that

are directly applicable to the system being modeled, or where strongly supported universal relationships are known. Netica has particular syntax that must be used when entering equations (described on the Norsys website here: https://www.norsys.com/tutorials/netica/secB/tut_B3.htm). Changing the dropdown option from Description to Equation opens the equation field, where the formula can then be entered. The left side of the equation will always be the node name, with all parent nodes in parentheses, and the right side of the equation must include all parent nodes. An example is shown below.

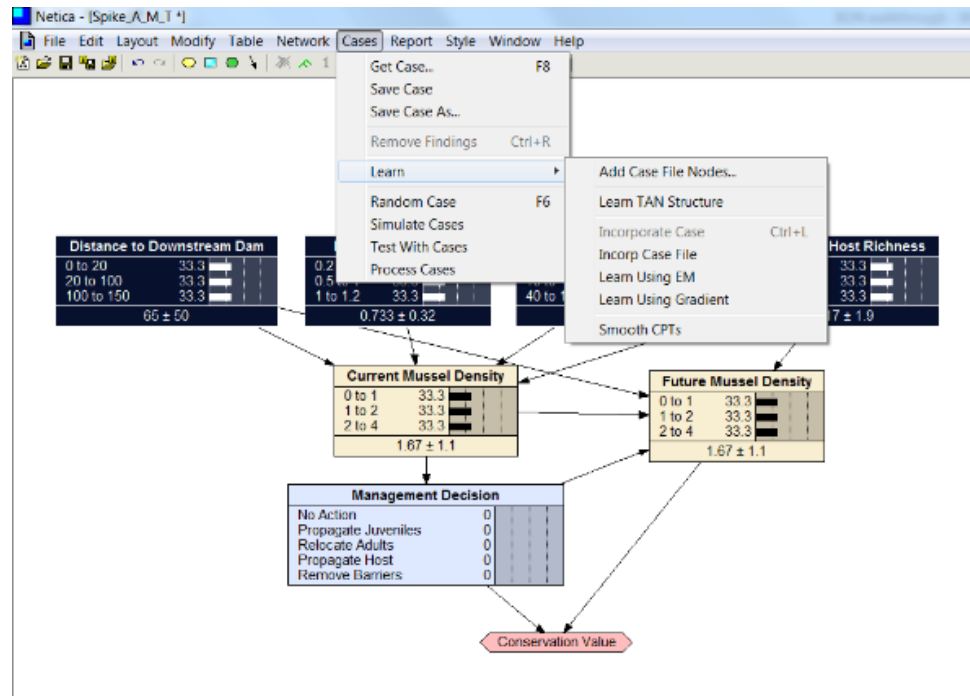


- c. Using distributions: If some information is known about the parameter, but not its relationships to other parameters, the Equation field can also be used to specify a parameter's distribution. The overall process is the same, with the right side of the "equation" being represented by a distribution. Specific syntax for distributions can also be found on the Norsys webpage listed above.



- d. Using learning algorithms: Finally, when a more complete dataset is available for informing priors, it may be most useful to use Netica's built-in learning algorithms to estimate probabilities. Generally, learning algorithms use an iterative process of adding observed values (cases) to update predicted probabilities for each node in the model. This is done using what the program calls "case data", and requires some preparation.
- i. Case data can include observations of some or all nature nodes (those that are not decision or utility nodes), and may include missing data.
 - ii. Data can be loaded into Netica from a csv file, which should contain only the variables to be included in the model (e.g., remove any label columns that do not contain actual observations). Any cells with missing data should be filled with an asterisk (*).

- iii. To incorporate case data for one or more nodes, first select the node by either left-clicking on the node, or left clicking and dragging a box around multiple nodes. From the upper toolbar, select Cases>Learn.



There are three options for loading cases: incorporate case files, learn using expectation maximization (EM), and learn using gradient. It is simplest to choose to incorporate case files directly. Typically the EM algorithm is used where missing data occur, and the gradient descent algorithm should be used where latent variables are known to exist (for more information on the three learning algorithms, see here:

https://www.norsys.com/WebHelp/NETICA/X_Algorithms.htm).

- iv. Select the desired learning method, and choose a file to upload. Next, Netica will ask you to choose a number of degrees. Typically the default,

1, is selected, unless previous learning is being undone (but there are easier ways to do that anyway). After the number of degrees is specified, Netica will use an iterative process to build CPTs for all the selected nodes based on the case data. This may take a few minutes, depending on the size of the case file.

- v. Case data can also be unlearned, which may be necessary when building different model versions for comparison, or over time as new data become available. This can be accomplished by either repeating the learning process (Netica will then ask if you would like to remove old CPTs first), or by right clicking the node and selecting Modify>Remove Table.
- vi. When possible, comparing learned values to raw data distributions can be a useful check on model learning. Predicted probabilities based on learning should be similar to raw values. Drastic differences may indicate that the dataset being used is highly variable or of insufficient size.

Applied Project Result: We used empirical data to populate six nodes in Ellipse models (Figure 5), and five nodes in Spike models (Figure 6). Because data were pooled from multiple sources and included missing observations in some cases, we used the EM algorithm to learn from cases when populating these nodes, then compared learned probabilities to observed data distributions to assess similarity. Learned probabilities were similar to observed probabilities for all nodes, thus learning was considered successful. Because 27 model versions

were built for each species during model validation, only one example for each species is shown below (see Step 7 for more detail on version comparisons).

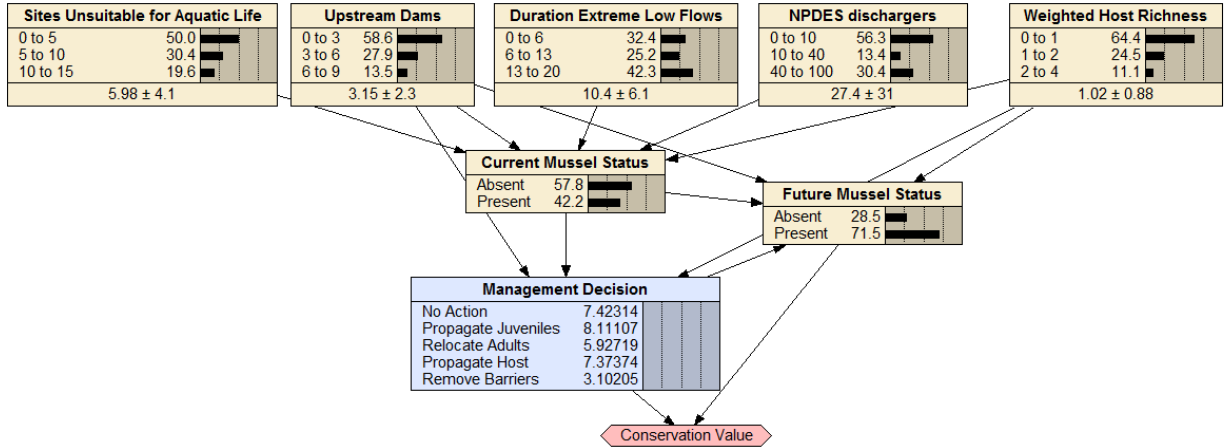


Figure 5. Ellipse presence model with priors, using long term data, median expert opinion values and all streams cases. CPTs have been updated to reflect empirical data distributions.

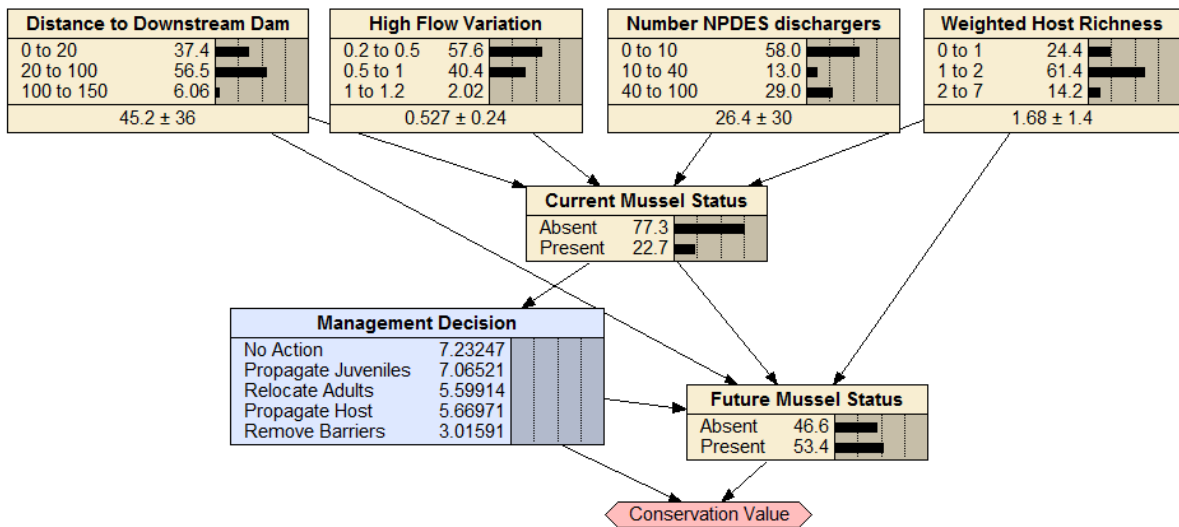


Figure 6. Spike presence model with priors, using long term data, median expert opinion values and all streams cases. CPTs have updated to reflect mussel empirical data distributions.

Step 6. Collect expert opinion responses

General Description: Like many simulation-based models, BDNs offer a framework that is able to incorporate a mix of data sources, including expert opinion for cases where relationships are known to exist, but empirical data are lacking. The inclusion of a utility node in BDNs also creates a particular type of node where expert opinion (or stakeholder input, depending on the desired application), influences the decision outcome by attributing value to each possible management action and outcome combination. Thus, there are two ways to collect expert opinion or stakeholder input for use in BDNs.

- a. For knowledge gaps: Collecting expert opinion to populate CPTs of nodes with no empirical data can be accomplished in a few ways. Gathering experts in a workshop setting and holding discussions to determine prior probability estimates is one way, which may be the most efficient. Experts can be interviewed or complete surveys, which may be table or text based, depending on the complexity of the node for which opinions are being collected. Text based questions may be easier for experts to interpret, eliciting faster response time. However, they must be translated back into probabilities to populate the model, so this process can be less precise. No matter how they are collected, expert opinion data should be summarized and compared among experts to assess potential bias and level of agreement among individuals surveyed, as this may impact decision outcomes (Death et al. 2015; Hamilton et al. 2015). Assessing agreement can be accomplished by building model

versions using each individual expert's responses (usually in cases where the number of experts surveyed is <5), or through use of summary statistics such a mean, median, minimum, and maximum values.

- b. For value assessment: Perhaps the most important application of survey data in BDNs is within the utility node, which determines optimal decision. Parents of the utility node should be the decision node and the parameter of interest (in the case of our mussel models, future mussel status or density). Utility values give a sense of relative satisfaction of different management action and outcome combinations, usually determined by the cost of each action. For example, on a scale of 1-10 a high cost option may be rated as 5 if it is successful, but 1 if it is not, where a low cost option may be rated as 10 if it is successful, but 3 if it is not. Decisions are then calculated as the utility value multiplied by the probability of an outcome occurring. Thus, the optimal decision of a model outcome can change drastically depending on the utility attributed to each management scenario, even if nature node inputs and the likelihood of each parameter state has not changed. When dealing with management scenarios involving conflicting stakeholder views, it is useful to construct multiple versions of models incorporating utility nodes that reflect each group's values, to compare, for example, differences in perceived optimal decision between natural resources professionals and the public. This can be used as a measure of public support for a management action. If decisions do not change, the action is likely to receive little backlash, whereas if decision outcomes differ

drastically, there may be a need for continued public outreach to make proposed management actions more palatable.

Applied Project Result: Expert opinion was used to inform two nodes in each model: “Conservation Value” (the utility node) and “Future Mussel Status” (the parameter of interest). This was accomplished by distribution of surveys to experts, including malacologists, ecological researchers, hatchery supervisors, and agency biologists. All participants were experts in aquatic ecology and/or mussel taxonomy, ranging from 7-35 years of experience in these areas. A total of 16 experts were invited to participate, with 13 ultimately returning surveys during the allotted nine month period. Surveys were table-based and asked participants to enter their best approximation of the likelihood of an event occurring (e.g., mussel presence at a given site), given some number of other conditions (e.g., number of upstream dams, host fish richness, management action; Figure 7). Responses were then summarized by median, minimum, and maximum and used to populate CPTs of model iterations corresponding to each combination of expert opinion, data set, and stream subset tested.

For the utility node, preliminary costs were assessed as described in Step (6), and experts were asked to rank management outcomes based on the cost of each management decision, on a scale of 1-10 (Figure 8).


Current Mussel Status	Management Decision	Host Richness	Number upstream dams	Future Mussel Status	
				Present	Absent
Absent	Release Juvenile Mussels	Low	Low		
			Medium		
			High		
		Medium	Low		
			Medium		
			High		
		High	Low		
			Medium		
			High		
	Release Adult Mussels	Low	Low		
			Medium		
			High		
		Medium	Low		
			Medium		
			High		
		High	Low		
			Medium		
			High		
	Release Host Fish	Low	Low		
			Medium		
			High		
		Medium	Low		
			Medium		
			High		
High		Low			
		Medium			
		High			
Remove Barriers	Low	Low			
		Medium			
		High			
	Medium	Low			
		Medium			
		High			
	High	Low			
		Medium			
		High			

Figure 7. Example of expert elicitation table-based survey used for future mussel status node in Ellipse presence models. Experts were not asked to provide estimates for parts of the table where mussels were already present, as it was assumed that if mussels currently persist at a site, they will continue to do so under current conditions or with management action. Probabilities for these scenarios were uniformly set to 99% for continued presence, and 1% for possible future absence (to account for potential stochastic events).

Future Mussel Status	Cost	Utility
Absent	\$0	
Absent	\$1,425	
Absent	\$1,500	
Absent	\$20,300	
Absent	\$718,000	
Present	\$0	
Present	\$1,425	
Present	\$1,500	
Present	\$20,300	
Present	\$718,000	

Figure 8. Survey template used for utility node estimates.

Step 7. Compile and validate model

General Description: After all CPTs have been populated, the model must be compiled to update prior probabilities. This can be accomplished by clicking the compile () button in the lower toolbar. A major function of BDNs and other simulation models is that they give users a way to compare multiple model structures and datasets to identify sources of uncertainty and variance. Part of this process should include some form of model validation, where multiple versions of each overall model structure arrangement are compared using variations in data subset. This can be achieved through various approaches.

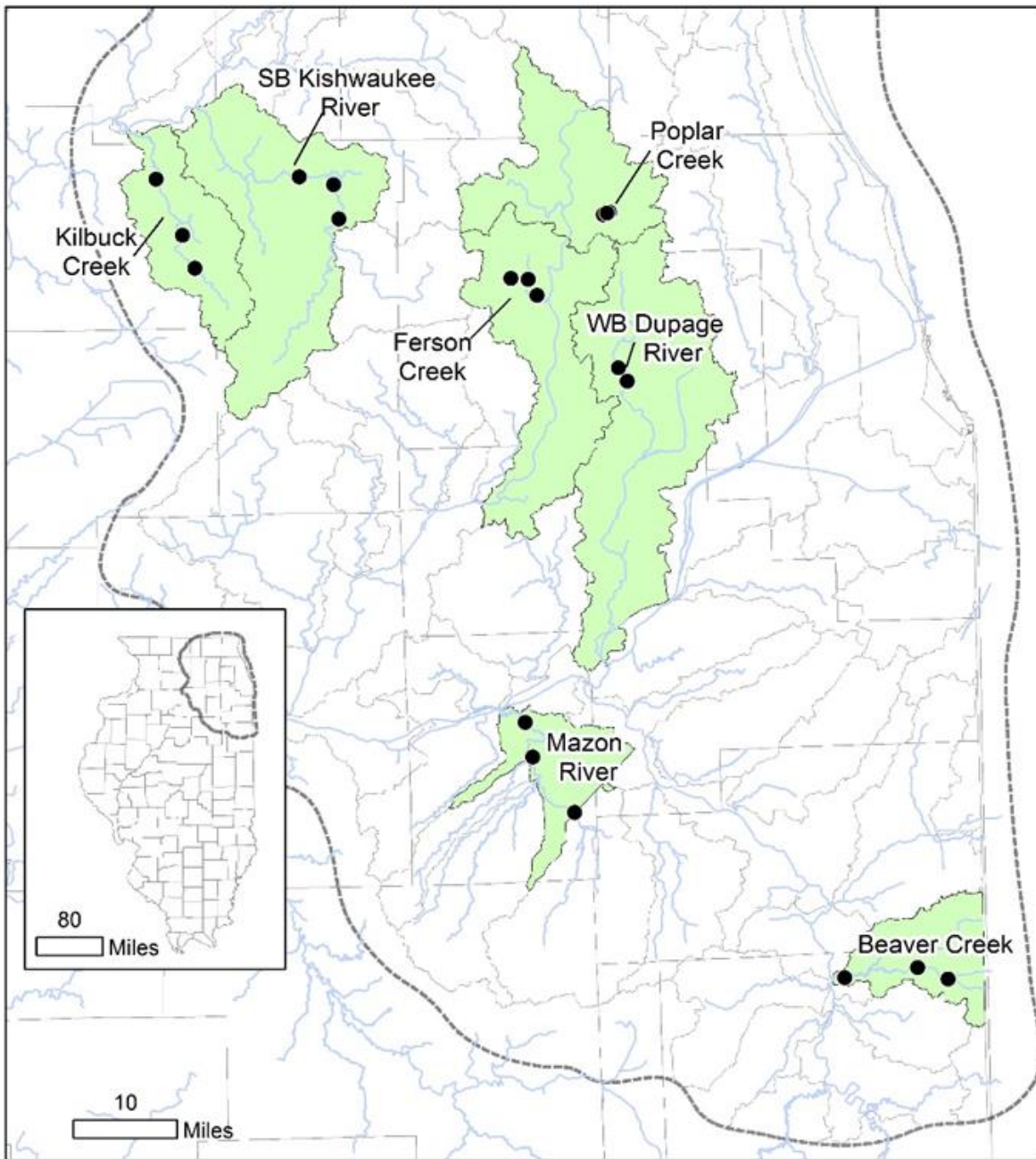
For large datasets of several hundred observations or more, cross-validation methods such as bootstrapping (comparing model versions using randomly selected subsets of data) or

using holdout data (building models with a random subset of data and testing with the remaining subset) can be used. If the dataset used is not large enough for cross-validation to be effective (i.e., resulting random subsets of data would be small [$n < 100$]), another method is to divide data based on known sources of variation. For example, models using subsets of data from differing geographic regions or time periods may be compared to evaluate the impact of known sources of variation on model outcome. For BDNs in particular, it is also important to address variation in expert opinion inputs, since they may strongly affect the utility node and thus expected value of decisions. In cases where expert responses are variable, it may be useful to omit responses that are outliers, or apply a weighting system to account for differences resulting from varying levels of applicable expertise. After multiple models have been created, differences can be assessed using sensitivity analysis (see Step 8).

Applied Project Result: To assess sources of bias and variance in our models, we built 27 versions for each mussel species, incorporating three levels of data precision, data subset, and expert opinion statistics, and compared optimal decision outcomes and sensitivity of nodes among model versions.

- a. Data precision: We initially built models using long-term presence data collected from 1990-2017. To test for differences in outcome driven by data precision, we also performed quantitative field surveys during 2018 to collect density estimates of target species at all sites included in our models. Thus we were able to construct model versions including long-term presence data, 2018 presence data, and 2018 density data to test for differences in decision outcome related to sampling method and data precision.

b. Data subset: To maintain specificity of data included in modeling efforts to our target rivers, we included long-term and 2018 data from seven streams and rivers. These included our target rivers, the South Branch Kishwaukee and West Branch DuPage, and five non-target rivers that were also within the Chicago Wilderness Area and contained varying levels of target mussel species (Figure 9). Non-target streams were the Mazon River, Kilbuck Creek, Beaver Creek, Poplar Creek, and Ferson Creek. Estimates of abundance from long term data were used to determine which streams would be chosen to represent low (absent), moderate, and high densities of each species. These estimates were confirmed in most cases during the 2018 field season, although Ellipse densities were higher at some sites than anticipated (Table 3). Models including data from target rivers only, non-target rivers only, and both target and non-target rivers were compared.



Legend

- Mussel abundance samples
- Watersheds for abundance calibration
- HUC 10 watershed
- ⋯ Chicago Wilderness Boundary



Figure 9. Map of sites sampled during 2018 field season.

Table 3. Expected and observed densities of Ellipse and Spike at each target and non-target stream. Expected values were relative estimates based on previous qualitative sampling of sites. Observed values were maxima (per grid) densities observed during 2018 sampling.

Stream	Expected Density (#/m ²)		Max Observed Density (#/m ²)	
	Ellipse	Spike	Ellipse	Spike
South Branch Kishwaukee River	Absent	Absent	0	0
West Branch DuPage River	Absent	Absent	0	0
Mazon River	Absent	Absent	0	0
Poplar Creek	High	Low	3.5	0
Beaver Creek	Low	High	0	3.47
Kilbuck Creek	Moderate	Moderate	6.9	0.8
Ferson Creek	Low	Low	8	0.53

Step 8. Determine sensitivity

General Description: Sensitivity analyses offer a means of comparing the relative importance of each factor included in a model to determining the outcome of that model. They can also be used as a way of comparing relative performance of different model versions, and thus the influence various datasets have on model outcome. For BDNs in Netica, sensitivity analysis must be performed by hand for each model. To do this, first the lowest value and then the highest value state of each node must be selected, and the optimal default decision (whichever one has the highest expected value) should be recorded for each, as well as any changes in optimal decision. The difference between expected value for the minimum and maximum state value of each node equals the sensitivity of that node. This is repeated for each

node, for each model version, resulting in a table of values for each model (Table 4). These individual sensitivity tables can then be summarized further for ease of interpretation (Table 5).

Applied Project Result: Optimal decision outcomes were sensitive to changes in expert opinion statistic, data precision, and stream subset, to varying degrees. General trends are described below, and a complete breakdown is given in Tables 5 and 6.

- a. Data precision: In general, no major differences in model performance were observed between long-term and 2018 presence models, indicating that 2018 data are not anomalous compared to long-term data. Models built using density data did not produce drastically different results from those using presence data (with all else held equal) in most cases, although there were differences in some scenarios (see Step 9 for more details). Because some differences were evident, we recommend using density data when available. However, presence models may still offer some insight to management scenarios where density estimates are not available, and should still be considered.
- b. Data subset: Differences in optimal decision choice and Future Mussel Status likelihoods were evident, primarily when using target stream data only. Because target species were almost always absent from target streams in both long term and 2018 data, models using only target stream data tended to predict very low probability of establishment after management, regardless of approach. However, these species do persist in nearby streams and have previously survived in the target systems, thus this output is likely not accurate and may be overly pessimistic. Both non-target and all streams data produced more balanced models that had higher

sensitivity to input and produced results that were more reflective of observed densities in the field. There were no major differences in outcomes using non-target streams or all streams data, so for future management purposes we recommend using all streams data to increase empirical data sample size.

- c. Expert opinion: Model outcomes differed most drastically in response to differences in expert opinion statistics. For example, one expert in particular tended to choose higher than average utility values (e.g., 9 or 10 where others surveyed chose values closer to 5), which resulted in a less responsive model that valued all possible outcomes similarly highly. This highlights the importance of surveying multiple experts to assure that one individual is not biasing model output and to assess the level to which most experts agree. Minimum and maximum expert opinion values did not usually cause major differences in model performance, although minimum models tended to choose No Action as the best management action more often than did median models. In general, we recommend use of median models because they offer the most representative and least skewed measure of expert opinion responses, although in cases where it is necessary to be particularly conservative when choosing management options, using minimum models may be preferred.

Table 4. Example of sensitivity analysis table, for the Ellipse model including long-term data, all streams data, and median expert opinion values. Optimal decision for each model component is that which had the highest expected value when either the minimum or maximum state value was selected. Difference is the difference between expected value for each state selection for each component, and asterisks denote cases in which optimal decision changed when switching from minimum to maximum state selection.

Model Component	Minimum		Maximum		Difference	
	<i>Optimal Decision</i>	<i>Expected Value</i>	<i>Optimal Decision</i>	<i>Expected Value</i>		
Future Mussel Status	No Action	7	Juveniles	9	2.00	*
Current Mussel Status	Juveniles	7.5	Juveniles	8.96	1.46	
Duration Extreme Low Flows	Juveniles	8.19	Juveniles	8.05	0.14	
Number NPDES Dischargers	Juveniles	8.07	Juveniles	8.13	0.06	
Number Upstream Dams	Juveniles	7.88	Juveniles	8.58	0.70	
Weighted Host Richness	Juveniles	8.35	No Action	7.41	0.94	*
Number 303(d) Sites	Juveniles	8.1	Juveniles	7.98	0.12	

Table 5. Summary of node sensitivities and decision changes for all default Ellipse models. Cells highlighted in yellow indicate decision changes during sensitivity testing for that node.

Data Precision	Expert Opinion	Streams	Optimal Decision	Expected Value	Future Mussel	Current Mussel	Flows	NPDES	Dams	Host	303d	Decision Changes
long-term presence	Med	All	Release juveniles	8.11	2	1.16	0.14	0.06	0.7	0.94	0.12	2
long-term presence	Min	All	No Action	7.42	2	1.95	0.08	0.01	0.17	0.07	0.06	4
long-term presence	Max	All	Release juveniles	8.39	2	0.99	0	0.05	1.22	0.24	0.02	1
long-term presence	Med	Non-target	Release juveniles	7.83	2	1.93	0.23	0.01	0.58	0.45	0.15	2
long-term presence	Min	Non-target	No Action	7.4	2	1.95	0.32	0.02	0.04	0.16	0.01	5
long-term presence	Max	Non-target	Release juveniles	8.48	2	0.79	0.02	0.03	1.11	0.21	0	1
long-term presence	Med	Target	No Action	7.34	2	1.94	0.23	0.23	0.63	0.52	0.01	6
long-term presence	Min	Target	No Action	7.34	2	1.95	0.09	0.09	0.15	0.04	0.01	3
long-term presence	Max	Target	Release juveniles	8.12	2	1.27	0.25	0.25	1.46	0.34	0	2
2018 presence	Med	All	Release juveniles	8.01	2	1.71	0.09	0.02	0.69	0.85	0.09	2
2018 presence	Min	All	Release juveniles	7.49	2	1.95	0.11	0.01	0.24	0.29	0.06	4
2018 presence	Max	All	Release juveniles	8.52	2	0.78	0	0.02	1.16	0.22	0.01	1
2018 presence	Med	Non-target	Release juveniles	7.88	2	1.91	0.15	0.06	0.65	0.47	0.1	2
2018 presence	Min	Non-target	Release juveniles	7.45	2	1.95	0.19	0.07	0.2	0.3	0.16	6
2018 presence	Max	Non-target	Release juveniles	8.51	2	0.8	0.02	0.02	1.18	0.19	0.02	1
2018 presence	Med	Target	Release juveniles	7.94	2	1.69	0.05	0.05	0.7	0.58	0.17	2
2018 presence	Min	Target	Release juveniles	7.46	2	1.95	0.05	0.16	0.1	0.28	0.3	3
2018 presence	Max	Target	Release juveniles	8.57	2	0.64	0.03	0.05	1.13	0.34	0.03	1
2018 density	Med	All	Release juveniles	9	3	2.13	0.16	0.01	0.93	0.11	0.04	1
2018 density	Min	All	Release juveniles	8.27	3	2.91	0.18	0.04	0.43	0.37	0.06	3
2018 density	Max	All	Release juveniles	9.27	3	1.45	0.04	0.04	0.76	0.21	0.02	1
2018 density	Med	Non-target	Release juveniles	8.92	3	2.28	0.29	0.07	0.5	0.26	0.23	1
2018 density	Min	Non-target	Release juveniles	8.92	3	2.28	0.29	0.07	0.5	0.74	0.23	1
2018 density	Max	Non-target	Release juveniles	9.25	3	1.44	0.11	0.02	0.73	0.2	0.08	1
2018 density	Med	Target	Release juveniles	9.04	3	1.82	0.01	0.31	0.32	0.15	0.34	1
2018 density	Min	Target	Release juveniles	8.17	3	2.9	0.08	0.27	0.21	0.45	0.48	3
2018 density	Max	Target	Release juveniles	9.25	3	1.3	0.06	0.01	0.67	0.3	0.14	1

Table 6. Summary of node sensitivities and decision changes for all default Spike models. Cells highlighted in yellow indicate decision changes during sensitivity testing for that node.

Data Precision	Expert Opinion	Streams	Optimal Decision	Expected Value	Future Mussel	Current Mussel	Flows	NPDES	Dams	Host	Decision Changes
long-term presence	Med	All	Release juveniles	7.83	2	1.35	0.4	0.13	1.36	0.57	3
long-term presence	Min	All	Release juveniles	7.87	2	1.42	0.38	0.52	1.07	0.67	2
long-term presence	Max	All	Release juveniles	7.83	2	1.29	0.48	0.07	1.26	0.48	3
long-term presence	Med	Non-target	Release juveniles	7.96	2	1.33	0.27	0.37	1.24	0.32	2
long-term presence	Min	Non-target	Release juveniles	7.44	2	1.95	0.38	0.39	0.63	0.48	3
long-term presence	Max	Non-target	Release juveniles	8.03	2	1.31	0.29	0.36	0.99	0.36	2
long-term presence	Med	Target	Release juveniles	7.96	2	1.42	0.03	0.36	1.25	0.27	3
long-term presence	Min	Target	Release juveniles	8.07	3	2.91	0.7	0.63	0.94	0.5	2
long-term presence	Max	Target	Release juveniles	8.55	3	2.08	0.51	0.68	1.05	0.08	2
2018 presence	Med	All	Release juveniles	8.24	3	2.9	1.66	0.85	0.43	0.71	2
2018 presence	Min	All	Release juveniles	8.24	3	2.9	0.66	0.85	0.43	0.71	2
2018 presence	Max	All	Release juveniles	8.61	3	2.06	0.52	0.76	0.62	0.09	2
2018 presence	Med	Non-target	Release juveniles	8.09	3	2.91	0.26	0.68	0.12	0.1	3
2018 presence	Min	Non-target	Release juveniles	8.65	3	2.19	0.1	0.61	1.21	0.16	2
2018 presence	Max	Non-target	No Action	7.23	2	1.95	0.4	0.01	0.57	0.41	4
2018 presence	Med	Target	No Action	7.23	2	1.95	0.24	0.01	0.09	0.09	4
2018 presence	Min	Target	No Action	7.3	2	1.95	0.44	0.45	0.66	0.54	6
2018 presence	Max	Target	No Action	7.3	2	1.95	0.22	0.25	0.29	0.2	4
2018 density	Med	All	No Action	7.36	2	1.95	0.15	0.23	0.62	0.54	4
2018 density	Min	All	No Action	7.23	2	1.95	0.31	0.17	0.02	0.04	2
2018 density	Max	All	No Action	7.35	2	1.95	0.4	0.25	0.65	0.48	5
2018 density	Med	Non-target	No Action	7.35	2	1.95	0.15	0.09	0.26	0.16	4
2018 density	Min	Non-target	No Action	7.38	2	1.95	0.13	0.15	0.28	0.26	4
2018 density	Max	Non-target	No Action	7.36	2	1.95	0.15	0.23	0.62	0.54	4
2018 density	Med	Target	No Action	7.36	2	1.95	0.08	0.1	0.23	0.01	4
2018 density	Min	Target	No Action	7.65	3	2.91	0.54	0.16	0.49	0.1	4
2018 density	Max	Target	No Action	7.73	3	2.91	0.31	0.19	0.62	0.14	4

Step 9. Test specific sites

General Description: Finally, after model structure, prior probabilities, and sensitivity have been determined, the BDN can be used to choose an optimal decision for a specific site of interest. To do this, the most recent available data should be used to select the appropriate current state of each node in the model for which information exists. This acts as the observation that informs the prior probabilities already added to the model, and the decision

node adjusts its expected values accordingly. To enter an observation for a node in the model, left click on the desired state to select it. The probability for that state will change to 100 (since it is no longer a probability but an observation, there is 100% certainty), and a black bar will appear (Figure 10). This can be repeated for as many sites as desired to obtain real-world expected values of management decisions.

Applied Project Result: To begin with, we have applied both Ellipse and Spike models for one site at each of our target rivers. In keeping with recommendations, we used only median expert opinion models and all streams datasets. However, we used density and presence models to highlight potential differences between these levels of precision. Because there were no differences between long-term and 2018 presence models, long-term presence data have been omitted here for simplicity. See Table 7 for a comparison of Ellipse and Spike optimal decision outcomes at initial sites in each target river.

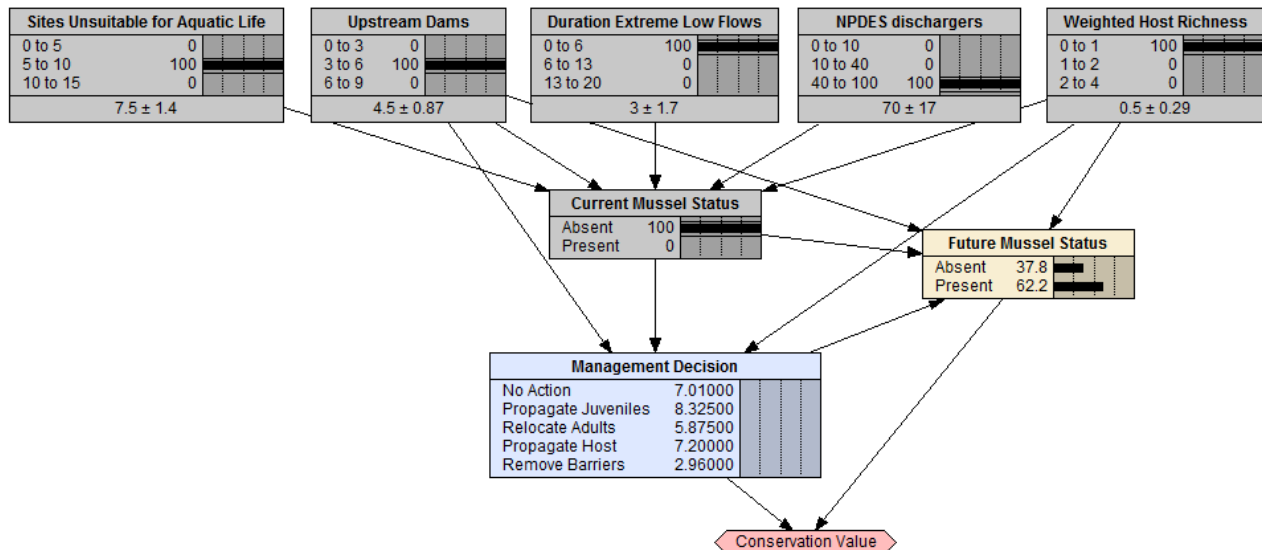


Figure 10. Example of BDN with site-specific values selected. This model included long-term presence data, median expert opinion values, and all streams data. The site specified is a

portion of the West Branch DuPage River located in Warrenville, IL; a site of previous mussel restoration for juvenile *Lampsilis* spp.

Table 7. Ellipse and Spike optimal decision outcomes for two potential reintroduction sites: for the West Branch DuPage River, in Warrenville, IL, and for the South Branch Kishwaukee River, near Kingston, IL. For simplicity and because no differences in decision were observed between long-term and 2018 presence datasets, only 2018 presence and density are shown here.

Dataset	River	Species	Decision
Presence	WB DuPage	Ellipse	Release juveniles
Presence	WB DuPage	Spike	No Action
Presence	SB Kishwaukee	Ellipse	No Action
Presence	SB Kishwaukee	Spike	No Action
Density	WB DuPage	Ellipse	Release juveniles
Density	WB DuPage	Spike	No Action
Density	SB Kishwaukee	Ellipse	Release juveniles
Density	SB Kishwaukee	Spike	No Action

Step 10. Assess feasibility, carry out management, and monitor results

General Description: Before enacting any on-the-ground management, feasibility of proposed action should be assessed. Parameters at proposed restoration sites supported by model findings should be measured to ensure real-time suitability. Utility nodes may also need to be updated to reflect site-specific restoration costs including things like paid labor or cost of supplies, if needed. In some cases, this may alter decision outcomes, especially for BDNs in which two or more decision options have similar expected values. It is important to remember that BDNs offer a useful tool in decision-making, but decisions are not final and model parameters should be updated as often as needed to reflect management needs.

The ultimate goal of creating a BDN to inform management decisions is to help professionals choose the most efficient and promising management option for a specific scenario. Thus, the initial product of a BDN is a management decision which can then be carried out. Further, BDNs should ideally be used as a tool for facilitating adaptive management practices, i.e., they can be updated with additional observations after management action is taken, adding information which may change expected value of outputs. Accordingly, if management is successful, the BDN functions as a decision-making map that can be used in future scenarios to reduce uncertainty. If management fails despite being chosen by the BDN as optimal, structural changes may be needed to help elucidate areas where research should be focused to better inform future management efforts. For example, consider a case where survival of propagated mussels in the wild is unknown (e.g., Plain Pocketbook, *Lampsilis cardium*). Utility of this model will be impacted by prior probability estimates of survival, which will likely be low for the sake of being conservative. However, if juveniles are released at a particular site and a five year follow up survey finds higher survival than anticipated, the utility of the option to release juveniles in this management scenario can be updated to reflect this new and more specific information, which may in turn impact future model applications. Overall, the implementation of a BDN is often the first step in adaptive management, and should be used as a baseline for ongoing efforts when attempting to understand and manage the system under consideration, or other similar scenarios.

Applied Project Result: Our model outputs will be expanded to consider additional sites following working group meetings in spring 2019, and may be used to evaluate the potential of other streams besides the original targets, particularly for Spike. Propagation approval and

methods for Ellipse are still being developed, meaning that it will likely be necessary to update cost estimates for restoring this species moving forward. However, general cost trends are not expected to change (i.e., release of adult mussels will be significantly more expensive than releasing host fish or juvenile mussels, and dam removal will be the most expensive option).

Ellipse and Spike models will be used to guide reintroduction of these species within the Chicago Wilderness Area in the near future. Based on model results, it is not likely that restoration of Spike will be undertaken at this time. However, because Ellipse results were promising and there is sustained interest in the ecology and management of this species, it will continue to be a focus of reintroduction efforts.

Conclusions and Future Directions

Overall, BDNs tended to choose release of juvenile mussels as the optimal decision, except for in situations where probability of future mussel establishment was low, in which case No Action was suggested. When applied to specific target sites, No Action was always the optimal decision for Spike, indicating that Spike may be too sensitive to real-world conditions at these sites to be suitable for reintroduction at this time. Models predicted that release of juvenile Ellipse in the West Branch DuPage River should be successful. However, results for the South Branch Kishwaukee River were conflicting, depending on use of presence vs density data. From a modeling standpoint, this may be due to variations in Ellipse density. In long-term data and during the 2018 field season, it has been observed that where Ellipse occur, they tend to be highly abundant and often dominate the mussel fauna at that site (Illinois Natural History Survey, unpublished data). However, this is not accounted for in BDNs using only presence data.

In such cases, the model must weigh the probability of mussel presence compared to the cost of each management option. In this case, if probability of future mussel presence is much lower than 50%, No Action becomes the best option. Yet density models attribute more value to high density establishment in the utility node, which may outweigh the negative impact of probability of low or no density, especially for sites where probabilities of absence are near 50%.

Indeed, density was an influential factor when considering Ellipse in the South Branch Kishwaukee River. For most model versions, probability of establishment after management was around 40%, which was low enough to result in No Action as the optimal decision for presence models. However, in density models, while probability of absence after management was still around 60%, probabilities of moderate and high densities were each around 20%, with the value of a high density population being relatively higher than that of a moderate density population in the utility node. Thus, when BDNs were able to calculate utility using a finer scale, decision outcomes shifted. Simply, it was considered less risky and more favorable to attempt management even at a 60% rate of failure, if there was also a 20% chance of a very favorable outcome. However when all presence was considered equal, the risk of failure was too high for the model to consider any management decision worth implementing.

Future restoration efforts for Ellipse and Spike will seek to identify other environmental or biotic variables that have not been previously included. Habitat is one such intuitively important factor which is somewhat difficult to quantify for freshwater mussels due to the ever-shifting nature of stream sediments and hydrology. Further topics of consideration also include propagation practices for both host fish and mussels themselves, as there is past

evidence to suggest that not all fish hosts are created equal for a particular population of mussels, even within a species (Riusech & Barnhart 1998; Bigham 2002). Additional surveys during the 2019 field season will be aimed at creating broader BDNs which evaluate potential large-scale management approaches and their effects on overall mussel community richness in central Illinois. Generally, the development of a structured decision making method for freshwater mussel management is needed, and should be a focus of ongoing effort and selected research, when possible.

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Appendix A. Weighted values for Spike fish hosts. Hosts with 0-20 successfully transformed juveniles in laboratory trials are weighted at 0.25, hosts with 21-50 transformed are weighted at 0.5, 51-100 are weighted at 0.75, and >100 are weighted at 1.

Common Name	Scientific Name	Mean Transformed	Weight	Reference
Eastern Sand Darter	<i>Ammocrypta pellucida</i>	10	0.25	Schroeder, Ellipsaria 2014
Rock Bass	<i>Ambloplites rupestris</i>	15	0.25	Schroeder, Ellipsaria 2014
Rock Bass	<i>Ambloplites rupestris</i>	1	0.25	Luo 1993
American Eel	<i>Anguilla rostrata</i>	13	0.25	Schroeder, Ellipsaria 2014
Holston Sculpin	<i>Cottus baileyi</i>	164	1	Luo 1993
Banded Sculpin	<i>Cottus carolinae</i>	3	0.25	Luo 1993
Brook Stickleback	<i>Culaea inconstans</i>	39	0.5	Schroeder, Ellipsaria 2014
Northern Pike	<i>Esox lucius</i>	21	0.5	Schroeder, Ellipsaria 2014
Rainbow Darter	<i>Etheostoma caeruleum</i>	21	0.5	Schroeder, Ellipsaria 2014
Rainbow Darter	<i>Etheostoma caeruleum</i>	3	0.25	Luo 1993
Iowa Darter	<i>Etheostoma exile</i>	9	0.25	Schroeder, Ellipsaria 2014
Johnny Darter	<i>Etheostoma nigrum</i>	103	1	Schroeder, Ellipsaria 2014
Banded Darter	<i>Etheostoma zonale</i>	3	0.25	Schroeder, Ellipsaria 2014
Banded Killifish	<i>Fundulus diaphanus</i>	11	0.25	Schroeder, Ellipsaria 2014
Blackspotted Topminnow	<i>Fundulus olivaceus</i>	57	0.75	Schroeder, Ellipsaria 2014
Longnose Gar	<i>Lepisosteus osseus</i>	17	0.25	Schroeder, Ellipsaria 2014
Green Sunfish	<i>Lepomis cyanellus</i>	12	0.25	Schroeder, Ellipsaria 2014
Pumpkinseed	<i>Lepomis gibosus</i>	19	0.25	Schroeder, Ellipsaria 2014
Bluegill	<i>Lepomis macrochirus</i>	7	0.25	Schroeder, Ellipsaria 2014
Longear Sunfish	<i>Lepomis megalotis</i>	13	0.25	Schroeder, Ellipsaria 2014
Burbot	<i>Lota lota</i>	3	0.25	Schroeder, Ellipsaria 2014
Smallmouth Bass	<i>Micropterus dolomieu</i>	39	0.5	Schroeder, Ellipsaria 2014
Largemouth Bass	<i>Micropterus salmoides</i>	148	1	Schroeder, Ellipsaria 2014
Golden Shiner	<i>Notemigonus crysoleucas</i>	1	0.25	Schroeder, Ellipsaria 2014
Yellow Perch	<i>Perca flavescens</i>	59	0.75	Schroeder, Ellipsaria 2014
Logperch	<i>Percina caprodes</i>	63	0.75	Schroeder, Ellipsaria 2014
Gilt Darter	<i>Percina evides</i>	7	0.25	Schroeder, Ellipsaria 2014
Blackside Darter	<i>Percina maculata</i>	21	0.5	Schroeder, Ellipsaria 2014
Slenderhead Darter	<i>Percina phoxocephala</i>	5	0.25	Schroeder, Ellipsaria 2014
River Darter	<i>Percina shumardi</i>	2	0.25	Schroeder, Ellipsaria 2014
Black Crappie	<i>Pomoxis nigromaculatus</i>	51	0.75	Schroeder, Ellipsaria 2014
Longnose Dace	<i>Rhinichthys cataractae</i>	3	0.25	Schroeder, Ellipsaria 2014
Sauger	<i>Sander canadensis</i>	72	0.75	Schroeder, Ellipsaria 2014
Walleye	<i>Sander vitreus</i>	296	1	Schroeder, Ellipsaria 2014