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A review of Bayesian belief network models as decision-support tools for wetland conservation: are water birds potential umbrella taxa?

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Abstract

Creative approaches to identifying umbrella species hold promise for devising effective surrogates of ecological communities or ecosystems. However, mechanistic niche models that predict range or habitat overlap amongst species may yet lack development. We reviewed literature on taxon-centered Bayesian belief network (BBN) models to explore a novel approach to identify umbrella taxa identifying taxonomic groups that share the largest proportion of habitat requirements (i.e., states of important habitat variables) with other wetland-dependent taxa. We reviewed and compiled published literature to provide a comprehensive and reproducible account of the current understanding of habitat requirements for freshwater, wetland-dependent taxa using BBNs. We found that wetland birds had the highest degree of shared habitat requirements with other taxa, and consequently may be suitable umbrella taxa in freshwater wetlands. Comparing habitat requirements using a BBN approach to build species distribution models, this review also identified taxa that may not benefit from conservation actions targeted at umbrella taxa by identifying taxa with unique habitat requirements not shared with umbrellas. Using a standard node set that accurately and comprehensively represents the ecosystem in question, BBNs could be designed to improve identification of umbrella taxa. In wetlands, expert knowledge about hydrology, geomorphology and soils could add important information regarding physical landscape characteristics relevant to species. Thus, a systems-oriented framework may improve overarching inferences from BBNs and subsequent utility to conservation planning and management.

Keywords: BBN, species distribution model, translational science, Netica, expert knowledge

1. **Introduction**

Biological conservation relies on identifying and connecting species with the habitat requirements important for the successful completion of life cycles. Species distribution models (SDMs) are increasingly relied upon to identify habitat elements important for conservation (Dibner et al., 2017; Phillips et al., 2017). Predictive SDMs are particularly needed for understanding how species will respond to ongoing environmental change (Wood et al., 2018). Increased access to, and advances in technology have improved our ability to understand associations between species and their habitats (Elith and Leathwick, 2009). Technological advances include Geographic Information Systems (GIS) and remote sensing technology, paired with increased computing power and the development of spatial statistical models (e.g., Guisan and Thuiller, 2005). Examples of this approach include Gap Analysis Program (GAP) models mapping land cover and predicted distributions of species, bioclimatic envelopes, habitat suitability indices, maximum entropy models (MAXENT), and genetic algorithm for rule-set prediction (GARP; Elith et al., 2006; Guisan and Zimmermann, 2000; Sowa et al., 2007). The results of SDMs are commonly used to build species-specific Habitat Suitability Indices (HSIs) that estimate the probability of species presence across a landscape and have been used extensively in conservation planning (Zajac et al., 2015). Thus, identifying the key elements of habitat for species of conservation concern is important for informing conservation actions (Lin et al., 2018).

Bayesian belief networks (BBNs) represent one form of SDM that offers a unique modeling approach by identifying explicit causal relationships among organisms and their habitats, as well as incorporating measures of uncertainty. In the ecological literature, BBNs go beyond species-habitat correlations because they explicitly consider discrete processes that influence occupancy across space and time (i.e., access and selection; Jones, 2001). BBNs consist of input, intermediate and output nodes that are linked together via conditional probability tables (CPTs) according to hypothesized causal relationships (**Figure 1**; Drew and Collazo, 2014). As graphically based probabilistic models (i.e., influence diagrams), BBNs may incorporate information gleaned from literature reviews, expert opinions and monitoring efforts to examine how all possible values of environmental variables may influence the occurrence or distribution of individuals. Bayesian belief networks approach SDMs by exhaustively exploring potential ecological variables defining a species' niche while simultaneously incorporating metrics of uncertainty surrounding estimates of habitat requirements (Marcot et al., 2006; Uusitalo et al., 2015). The inclusion of measures of uncertainty is important as many conservation decisions must be made in the absence of complete information. Thus, a BBN modeling approach can be used to inform decisions made using an adaptive management approach to reduce uncertainty (Drew and Collazo, 2014).

The umbrella species concept (Wilcox, 1984) can enhance conservation for suites of species with similar habitat requirements by countering incomplete biodiversity surveys that lack time, financial support, or adequate methods. The umbrella species concept provides a framework to improve the effectiveness of conservation action while reducing the complexity of quantifying species-specific outcomes. Umbrella species are unique in that they represent an ecologically-defined role in conservation as managing for their life history needs is expected to serve other species that co-occur or rely on the same set of resources (Roberge and Agelstam, 2004). As such, umbrella species are habitat specialists with large ranges sizes, and that are often sensitive to environmental disturbance (Kalinkat et al., 2017). Creative approaches to identifying umbrella species hold promise for devising effective surrogates of ecological communities or ecosystems

(Sattler et al., 2014), but mechanistic niche modelling for predicting overlap of species' ranges and habitat requirements can be developed by narrowing gaps in our understanding of species ecology (Kearney and Porter, 2009).

Efforts to quantitatively identify umbrella species from among multiple candidate taxa (Caro and O'Doherty, 1999; Fleishman et al., 2000; Maslo et al., 2016; Stewart et al., 2017) often focus solely on contrasting spatial overlap identified using potentially incomplete sets of environmental predictors (Andelman and Fagan, 2000; Seddon and Leech, 2008). Despite the past mixed success of umbrella species for conservation planning (e.g., successful: Fleishman et al., 2000; Roth and Weber, 2007; Suter et al., 2002, unsuccessful: Launer and Murphy, 1994; Ozaki et al., 2006), the concept continues to improve by broadening to encompass both taxonomic and functional diversity (Sattler et al., 2014). Typical approaches to identifying umbrella species have used SDMs that lacked explicit mechanistic reasoning to identify spatial ranges (i.e., beyond spatial overlap to encompass responses to similar environmental conditions) (Cayuela et al., 2009; Elith and Leathwick, 2009). As the umbrella approach to wider species conservation holds promise for identifying effective surrogate taxa (Sattler et al., 2014), we present a method to identify umbrella taxa informed by suites of BBN models that represent spatial ranges with causal reasoning.

Given the ability of BBNs to generate spatially-explicit predictions based on functionally-defined species-habitat relationships, they represent a potentially valuable approach to evaluate a species' expected performance as an umbrella species. Therefore, we took a case study and meta-analysis approach to identify potential umbrella taxa within an ecosystem using BBN models. Restricting our research to freshwater wetland ecosystems, undertook a systematic literature review to quantify the categorical overlap of habitat requirements for freshwater wetland-dependent species among existing BBNs. We reviewed existing taxon-centered BBN models to: 1) assess how BBNs were constructed, 2) describe how BBNs were used to inform biological conservation and identify the extent BBNs appeared to be used by those making biological conservation decisions, and 3) identify candidate umbrella taxa.

We chose freshwater wetlands because of the important role they play for a large number of species and the widespread concern for their conservation (Dudgeon et al., 2006). Despite the numerous ecosystem services provided by wetlands, greater than 50% of wetland area in the contiguous United States (US) has been converted to agricultural and urban land use (Horvath et al., 2017). There is a growing recognition of the difficulties of wetland restoration to renew lost biodiversity and ecosystem function (Meli et al., 2014; Zedler, 2000). Multiple factors including habitat fragmentation, hydrological changes, the introduction of exotic species, and overpopulation of other native species combined with wetland loss are correlated with declines in wetland flora and fauna (Adams, 1999; Bunn and Arthington, 2002; Findlay and Houlahan, 1997; Kerbes et al., 1990; Knutson et al., 1999; Quesnelle et al., 2013; Wettstein and Schmid, 1999). Substantial wetland loss (Ramsar Convention Secretariat, 2013) and a paucity of restoration studies conducted in freshwater wetlands (Brudvig, 2011) further drive an urgency to identify conservation and restoration strategies that provide habitat for the breadth of wetland-dependent species (Galat et al., 1998; Lehtinen and Galatowitsch, 2001). Thus, approaching wetland conservation using a bottom-up framework to identify umbrella taxa in freshwater wetland ecosystems may creatively provide restoration targets (i.e., shared habitat requirements) to maximize the restoration of biodiversity in wetlands.

2. Methods

We systematically searched for and reviewed published literature to provide a comprehensive and reproducible overview of habitat requirements for freshwater wetland-dependent taxa using BBNs. We evaluated the scope of available peer-reviewed literature concerning habitat needs of freshwater wetland-dependent taxa, including identifying the presence of overlapping habitat requirements among taxa as well as collective sources of uncertainty. To do so, we searched the Google Scholar literature database using an 'abstract' search and with the publication date criteria set to 'anytime' (search undertaken in January 2018). We initially examined all English-language literature pertaining to freshwater wetland-dependent taxa, using the phrase "(wetland species AND Bayesian Belief Network AND species distribution model AND conditional probability table AND node)" (460 articles), to identify articles with published network models which we could compare. We then refined the search by including only publications that explored the distributions of species, rather than ecosystem or landscape-feature approaches. Our synthesis of the resulting publications consisted of four steps.

First, we summarized how BBNs were constructed. We compiled information on model type which included alpha-level (i.e., based on a literature review), beta-level (i.e., incorporated expert opinion), and gamma-level BBNs (i.e., included fieldwork to validate model predictions (gamma-level BBN). We also compared model features including the number of nodes (i.e., BBN complexity), the sources and amount of uncertainty. Finally, we classified each BBN as either a process model (species-habitat relationships estimated for a single season or generalized across a life cycle) or dynamic model (relationships could vary from one time-period to another).

Then, we describe how BBNs were used to inform biological conservation and identified the extent to which BBNs appeared to be used by those making biological conservation decisions. There has been a recent call for translational science; translating what is learned from empirical research on species-habitat relationships into conservation action by developing tools accessible to decision makers such as resource managers (Littell et al., 2017). Given the emphasis on translational science and the promotion of BBNs as easy to understand models, one might expect use of BBN models in natural resource management to be common. To determine if this was the case, we compiled data for each publication on: publication type (journal vs report), journal category (applied or method development), and funding source. If BBNs are easily comprehensible due to their graphical nature, (Sarah J Douglas and Newton, 2014), we expected to find evidence of their use as decision-support tools. By collecting these general criteria, we sought to identify potential gaps in the translation (i.e., from development to deployment) of the BBN approach in conservation.

Lastly, we examined the potential to identify umbrella species using BBNs. To do so, we identified important states of nodes (i.e., habitat requirements) shared across models to help identify potential umbrella taxa. Then, we summarized the BBN models that captured species-specific, mechanistically derived habitat requirements (sensu O'Hagan, 2012) to identify taxonomic groups that shared the largest proportion of habitat requirements. The taxonomic group that had the largest amount of overlap with the other taxonomic groups was considered a candidate umbrella taxa.

3. Theory

The taxon-centered BBN models used to inform our umbrella taxa investigation mechanistically identify specific habitat requirements across taxa in a given ecosystem. This approach supports future research to quantitatively distinguish priority habitat for the focus of conservation planning, as well as identifies taxa with unique habitat requirements or unique habitat types that may not benefit from conservation actions targeted at umbrella taxa.

4. Results

4.1 BBN model construction

The majority of studies followed the same three-step trajectory. The first step created an alpha-level BBN through a literature review, although few studies provided details on their literature review (n=5 studies provided literature review details). Next, all but one study elicited expert knowledge in a two-step process to refine and modify the alpha structures and build beta-level models. For the third step, over half of studies (n=26) validated their beta-level models with field data, completing the study with a published gamma-level model. The primary output nodes (i.e., response variable) for these studies were either abundance of the taxa in question or habitat suitability for the taxa in question. Nearly all studies used process models; only a single study used a dynamic model. The one temporally dynamic model (Chee et al., 2016) was also the only study to use any type of spatial statistical framework (geospatially explicit resampling between time periods). A habitat suitability response was typically represented as a binary categorical variable of suitable versus not suitable.

Few articles (n=7) discussed sources or levels of uncertainty. Articles that did estimate uncertainty surrounding the nodes that contributed the highest uncertainty in species outcomes identified the following sources: amount of flooded area, connectivity of different wetland patches, flood duration, maximum water temperature, interspecific competition, predation, and blood mercury measurements. Despite low reporting on any estimates of uncertainty (due to either data uncertainty or structural uncertainty), authors emphasized refining variable definitions if they could be interpreted in different ways by experts (i.e., structural uncertainty). Some examples of poorly defined variables included ‘water quality’ variables, determining the state of an individual plant or animal when two states are very similar, and the precise definition of outcomes following restoration.

4.2 BBNs as tools for biological conservation of freshwater wetlands

We identified a total of 53 articles with ecological BBNs for freshwater wetland-dependent taxa; consisting of 33 peer-reviewed articles, 9 reports or conference proceedings, 10 master of science theses or doctoral dissertations, and 1 book chapter (**Appendix 1**). The sources of peer-review articles were primarily ecological journals (e.g., Ecological Indicators), the modelling journal, Environmental Modelling & Software (n=6), and conservation journals such as Biological Conservation (n=2) and Conservation Biology (n=1). Lead authorship on peer-reviewed articles and reports was rarely by graduate students or early-career scientists such as postdoctoral researchers (26%), and more commonly by research fellows or senior researchers at the time of publication (**Appendix 2**).

The earliest evidence we found of BBNs being used to model habitat requirements of freshwater wetland species was from 2003, with an accelerated rate of increase in peer-reviewed literature using BBNs to explore habitat relationships of wetland taxa as years have gone on (**Figure 2**). The majority of articles focused on Australasian wetlands (including Australia, Tasmania, Papua New Guinea, and New Zealand; 42%), but wetlands from all continental regions (excepting Antarctica) have been represented by BBNs in the peer-reviewed literature. (**Appendix 1**).

The most common taxonomic subjects were fish (Actineropterygii; n=15 models), followed by macroinvertebrates (e.g., Amphipoda, Coleoptera, Gryllidae, Lepidoptera, etc.; n=10 models) and birds (e.g., Ardeidae, *Aythya affinis*, *Bucephala islandica*, *Dolichonyx oryzivorus*, *Grus canadensis*, *Hydrophasianus chirurgus*, *Megaceryle alcyon*, *Rallus elegans*, *Tympanuchus cupido*, *Tympanuchus phasianellus*, *Thryothorus ludovicianus*; n=10 models). In order of abundance, articles also included wetland plants (e.g., *Galaxiella pusilla*, *Pilularia globulifera*, *Salicaceae*, etc.; n=9 models), bacteria (e.g., *Escherichia coli*; n=5 models), fungi (e.g., *Batrachochytrium dendrobatidis*, *Bridgeoporus nobilissimus*, and *Poronia punctata*; n=3 models), mammals (e.g., *Corynorhinus townsendii*, Lutrinae, *Sus scrofa* etc.,; n=3 models), amphibians (i.e., Anura; n=2 models), reptiles (i.e., Testudines etc.,; n=2 models), and viruses (e.g., West Nile, malaria, etc.; n=2 models). Four additional studies modeled habitat requirements for invasive species found in wetlands. Articles took the form of either single- or multi-species BBNs of predominantly data-poor species, with multi-species models developed if the environmental drivers of occupancy were shared across taxa.

Articles failed to identify a specific wetland type in 43% of the literature we reviewed (21/49 studies), instead simply referring to 'wetlands'. Ten out of 49 studies identified the modeled system as floodplain wetlands. In all these cases, the primary source of floodwaters was natural river connections rather than intentionally inundated through pumped water or other irrigation systems. Emergent wetlands were identified in 4/49 studies, and riparian wetlands were referred to in 3/49 studies. Other descriptive terminology used to classify wetlands included slackwater, claypan, forested (including seeps), wet meadows, polders, artificial and temporary (2% or one article, each). We found no patterns between taxonomic group and the distinction of wetland types. That is, none of the taxonomic groups had BBNs built in single wetland types that could potentially have led to the identification of an overabundance of unique habitat requirements.

Based on information in the acknowledgements sections, the majority of peer-reviewed articles were funded through government agencies with a primary mission to support applied research to improve natural resource management, such the National Climate Change Adaptation Research Facility (Australia), the United States Fish and Wildlife Service (USA), and the United States Geological Survey (USA) (**Appendix 2**). There were fewer instances of funding from government agencies with a primary mission to advance science theory, such as the National Science Foundation (USA), the National Science Council (China) or the Natural Sciences and Engineering Research Council (Canada). Very few articles cited funding from nongovernmental organizations concerned with ecological restoration or biological conservation.

4.3 Using BBNs to identify candidate umbrella taxa

We found 38 habitat requirements reported for wetland-dependent taxa in our literature review (**Table 1**). The most frequent habitat requirement was presence of or persistence of water. Persistent water during the study period was identified as an important variable driving occurrence/abundance patterns in 24% of models (n=12 models), spanning various taxonomic groups including amphibians, birds, fish, macroinvertebrates, mammals, and plants. The next most common habitat requirement was the appropriate timing (or “regularity”) of seasonal flooding, by river inundation, rainfall or by irrigation (n=10 models). Appropriate timing of seasonal flooding was required by amphibians, bacteria, fish, macroinvertebrates, plants, and viruses, although was not included in models of birds, fungi, mammals or reptiles. Other common habitat requirements (each found in n=8 models) included deferment of effluent irrigation or pollution, total flooded area available, predictability of flood timing, extent, duration and frequency, and presence of a wooded border around wetlands. Less frequent habitat variables are listed in **Table 1**, along with those mentioned above.

The responses of bird species to environmental variables were the most complex, being sensitive to the broadest set of habitat variables (n=20/38 habitat requirements were identified for bird species; **Figure 3**). Both the variables themselves and the states associated with the highest/best response value overlapped with variables identified as important and their states as required for other taxa. The habitat requirements for birds (variable states) completely overlapped with those identified for mammals (n=6), and almost entirely for amphibians (n=8 in common out of 9 identified requirements for amphibians). While fish were the most common focus of BBNs in freshwater wetlands (i.e., floodplain wetlands, wet meadows, polders, and ponds), they were also the taxa with the greatest number of unique habitat requirements (n=4 variables unidentified in studies of other taxa as important).

5. Discussion

5.1 Using BBNs to identify candidate umbrella taxa

The taxon-centered BBN models used to inform our umbrella taxa investigation for wetland conservation identified important habitat features (variables and states of variables) for freshwater wetland-dependent taxa. These shared habitat requirements across taxonomic groups can be used to leverage conservation choices that would benefit multiple species. For example, the models in our review indicated that maintaining appropriate hydrologic regimes and natural buffer areas surrounding wetlands would benefit multiple taxa. However, the top habitat features amongst taxon-centered BBNs were drawn from models built independently from one another to address specific local problems. The present lack of clarity in terminology and definitions makes it difficult to draw conclusions across taxa (e.g., Is the ‘regular flooding or irrigation’ node for one taxa equivalent to the ‘predictable timing, extent, duration and frequency of flooding’ node for another taxa?). Thus, to identify ecosystem-wide umbrella taxa, it would be beneficial to develop a standard node set with consistency of variable states that accurately represents the ecosystem in question.

In support of their use as umbrella taxa in freshwater wetland ecosystems, we found that birds had the greatest degree of overlap among habitat requirements shared with other species. Characteristics that indicate wetland birds make strong candidates for umbrella taxa representing wetland conservation include their status as habitat specialists with large ranges sizes, and that they are moderately sensitive to human disturbance (Caro, 2010; Green et al., 2002; Kalinkat et al., 2017; King et al., 2006; Roberge and Agelstam, 2004). For example, multiple bird species show sensitivity to human-caused disturbance that drives behavioral responses in vigilance, fleeing, habitat selection, mating displays and parental investment which can have population and community-wide impacts (Frid and Dill, 2002). As many wetland birds are migratory (e.g., Ma et al., 2009; Skagen, 1997), leveraging conservation efforts across entire annual ranges of wetland birds could maximize restoration of wetland biodiversity under an umbrella taxa approach.

The adoption of an umbrella taxa approach to conservation plans should, however, be made with caution as even under circumstances when umbrella taxa overlap spatially with rare or unique species, management decisions centered on umbrella taxa can cause unintended loss of non-target biodiversity (Severns and Moldenke, 2010). Although we did not consider issues of scale in our review, we recommend considering it when selecting umbrella species using BBNs or other methods to identify umbrella taxa. Unique landscape features important at regional scales continue to warrant the investigation of locally appropriate umbrella taxa (e.g., migratory fishes; Agostinho et al., 2005). Furthermore, the existence of species with unique habitat requirements or small ranges that do not overlap with umbrella taxa necessitate that conservation approaches maintain a breadth of strategies including programs surrounding focal taxa representative of unique habitats with specific threats (Lambeck, 1997).

5.2 BBN model construction

Bayesian belief network models are unique in their ability to incorporate expert opinion and refine the identification of sources of uncertainty by developing gamma models. If models rely heavily on expert opinion there is a danger that they do not adequately reflect reality due to linguistic uncertainty (when words have imprecise or different meanings to different people), overemphasis of rare cases stemming from specific memorable experiences by experts, or simply the reliance on memories and not empirical data (Meyer and Booker, 1991; Morgan and Henrion, 1990). A strength of BBNs is that they are also able to incorporate missing values in input data and perform accurate predictions with the model built from them (although not a unique to BBNs; Uusitalo, 2007). The development of gamma models (incorporating data to validate alpha or beta models) provides the opportunity to support or refute our understanding of relationships between species and their environment. Gamma models also enable refinement of identifying sources of uncertainty in resultant SDMs. To this end, we found that over half of the articles we reviewed validated their models with data. Through an iterative process of developing and updating BBN models with monitoring data, BBNs can provide an ideal modeling approach to facilitate adaptive management (Henriksen and Barlebo, 2008; Nyberg et al., 2006). Thus, a

BBN approach to understanding species distributions can be powerful due to improved accuracy in modeling species habitat relationships.

As all models we reviewed were process models (with the exception of one dynamic model), seasonal processes are currently inadequately represented for the comparison of BBN models either within or among wetland types. Wetlands are, by definition, a hydrologically dynamic ecosystem defined by seasonal hydroperiod (Cowardin et al., 1979). The use of dynamic models that track habitat requirements across seasons may thus be more appropriate than the commonly used process models. However, there is an innate problem in finding convergence using Markov chains employed in dynamic BBN models which requires limiting the number of times the model can be updated (Wu et al., 2018). Further research developing BBNs as seasonal dynamic models could improve their utility in biological conservation.

Our review identified an overall lack of spatial statistical frameworks. In the absence of using spatial statistics, it may be difficult to identify when and where habitat is most likely needed to fulfill the life history needs of species within an ecosystem. Most wetland management initiatives focus on individual wetland creation, although strategic restoration planning may yield the greatest benefit using state-wide or watershed-wide perspectives (Horvath et al., 2017). Many challenges to wetland conservation planning could benefit from a spatially explicit, BBN approach. For example, wetland management remains challenging due to limited resources for acquiring new data (Margules et al., 2002), large areas of managed wetlands (Semlitsch and Bodie, 1998), limited ecological data on wetland characteristics and seasonal conditions (Zedler, 2000), and responses to changes in flow regimes in channelized river systems (Bunn and Arthington, 2002). Each of these issues could benefit from a spatially explicit risk assessment, to ease economic strain and use limited funds in the locations with the best cost-benefit ratio.

However, many small-scale species requirements remain unavailable in spatial format (e.g., topographic, geomorphic, edaphic) and so are omitted from typical SDMs (Sinclair et al., 2010). Exclusions of these species can lead to error in SDMs, and few studies quantify the uncertainty generated by these incomplete data (Beale and Lennon, 2012; Elith and Leathwick, 2009).

Approaches to identifying umbrella taxa that employ a spatial statistical framework (e.g., clustering analyses such as calculating Ripley's K statistic, or other statistics for point processes) could improve the development of finer-scale range maps that can be used to aid in identifying areas of conservation priority. The use of a spatial statistical framework in a BBN approach would include node-specific estimates of uncertainty in probabilities of species occurrence with respect to environmental data gathered from a variety of sources (e.g., expert opinion from systems experts and curated GIS layers). Some new computational tools for calculating risk assessments of alternative conservation actions; including spatial statistical approaches for identifying important areas for conservation; are currently in beta testing through the GeoNetica (GeoNetica™, Norsys Software Corporation) plug-in of the popular BBN computational tool, Netica (Netica 6.0, Norsys Software Corporation).

Building spatially scalable wetland models that can accommodate the seasonal ranges in hydrological nodes, as well as differences in mobility of wetland taxa (e.g., pollinator vs. amphibian vs. riverine fish vs. migratory bird) may also aid in efforts to identify umbrella taxa in seasonal ecosystems. The complexity of seasonally fluctuating ecosystems, such as wetlands, therefore requires either the logical integration of multiple process models, or small dynamic BBN models (e.g., four seasons) equipped with scalability options to inform conservation plans appropriate for each season and location.

Although alpha models in our review were appropriately developed using empirical literature and combined with information provided by taxonomic experts to create beta models, ecological BBNs may benefit from also interviewing ecosystem experts. Particularly in wetlands, experts knowledgeable of hydrology and geomorphology could provide information regarding systems processes that likely influence physical habitat characteristics. For example, the frequency and timing of flooding in wetlands was important in many of the BBN models that we reviewed but there was little reference to the source of floodwaters. It was unclear whether floodwater resulted from rainfall (as in playa wetlands, ombrotrophic bogs or pocosins), river connection (as in alluvial swamps, montane or streamside wetlands), groundwater discharge (as in discharge wetlands such as prairie potholes, or fens) or whether water pumped into wetlands from a municipal source was sufficient (wetland hydrological characteristics from Brinson, 1993). Similarly, pedologists or edaphologists would know the types of plants best suited to soil characteristics and identify potential wetland areas for restoration given regional soil characteristics. The current lack of distinction amongst similar nodes across taxon-centered BBN models of freshwater wetlands is a major caveat because we lack relevant take-away actions for wider conservation planning. Including systems experts in the design of ecological BBN models may improve the use of BBNs as decision-support tools for conservation planning as they would enable higher accuracy in distinguishing relevant landscape variables at the ecosystem scale.

5.3 BBNs as tools for biological conservation of freshwater wetlands

Our review produced mixed results with respect to the integration of BBNs into biological conservation. On the one hand, the majority of peer-reviewed articles were funded by government agencies with a primary mission to support applied research. On the other hand, the majority of literature sources appeared in journals contributing to conservations among modellers, not in journals likely to inform wetland management and conservation communities. In general, even when the primary purpose of developing taxon-centered BBN models is for use as a decision-support tool for conservation planning, few studies fully transition from pilot to implementation. The majority of management decisions are not developed using decision-support tools, even when the primary purpose of developing taxon-centered BBNs is for future use as a decision-support tool for conservation planning. Although there have been consistent calls in the conservation literature for mechanistic models in defining species-habitat associations (i.e., those that test a specific mechanism driving species ooutcomes; Landuyt et al., 2013; McCann et al., 2006; Nyberg et al., 2006), this failure is not unique to BBNs. In a survey of over 1000 protected areas in Australia, Cook et al. (2010) found that approximately 60% of management decisions relied primarily on experience-based information. Sutherland et al. (2004) found that only 2% of conservation actions undertaken in an English wetland were based on verifiable evidence, while 77% of actions were based entirely on experience. A major hurdle supported by statements in almost all articles in our review was that taxon-centered BBNs were not adopted as support tools by land managers responsible for conservation.

Conservation planning may understandably dismiss species-specific BBNs due to a misguided assumption (from a modelling perspective) that BBNs are built considering the inappropriate landscape settings and may fail to include relevant dynamic physical features of the ecosystem if they are built exclusively through a taxonomic lens. Disconnection between the scientific research community and area managers occurs when scientific information is acquired and assembled without consideration of management implications, the results are not easily accessible or applicable to area managers (Bouska et al., 2016; Cook et al., 2012; Pullin and

Knight, 2005), or there are perceived conflicts between single taxa model recommendations and the needs of multiple species in a complex system. Some attribute the limited adoption of decision-support tools by conservation planners to a lack of engagement between researchers and managers across multiple studies (Gawne et al., 2012; Goosen et al., 2007; Kroon et al., 2009), although adaptive resource management through collaborative efforts has been adopted in some areas (King et al., 2010; Richter and Thomas, 2007). Wetland restoration is thought to be effective at restoring both biodiversity and ecosystem services (Meli et al., 2014). Thus, the development of decision-support tools, such as BBNs, that synergize empirical data with expert knowledge from within a hypothesis-testing framework have the potential to drive critical gains in selecting effective criteria for conservation action if they were framed for more widespread utility.

5.4 Conclusion

The adoption of a systems-oriented BBN approach to conservation planning could aid the identification of effective umbrella taxa. The identification of umbrella taxa is often hindered by inconsistent methods for determining habitat requirements in species distribution models as well as inadequate prior knowledge of biotic and abiotic landscapes. As BBNs can include expert knowledge, they may provide a more robust assessment of ecosystems and improve conservation planning. As a decision-support tool for conservation planning, BBNs can be updated via monitoring to minimize uncertainties over time to achieve more rapid restoration success.

Although an umbrella approach to conservation may not protect habitat requirements for all species, comparing habitat requirements using a BBN approach to building species distribution models, as discussed here, allows for the identification of umbrella species. A BBN approach to identifying umbrella taxa can also quantitatively estimate which taxa may not benefit from conservation action targeted at umbrella taxa by identifying those with unique habitat requirements not shared with umbrellas. Thus, using a BBN approach to building SDMs has the potential to improve our capacity for effective biological conservation.

As BBNs are relatively easy to construct and understand due to their visual nature (Douglas and Newton, 2014), they have the potential to substantially improve coordinated efforts translating empirical research on species distributions into useable outputs in the hands of conservation planners. BBNs are flexible in their applicability and are particularly useful to build SDMs of data-poor species through the incorporation of expert knowledge (e.g., Drew and Collazo, 2014). Comparing important nodes and measures of uncertainty from multiple network models is a new methodology to identify critical habitat criteria shared across taxa. Using BBNs to identify taxa that have the highest degree of overlap in habitat requirements within an ecological community also enables a quantitative assessment of potential umbrella taxa which can then be the focus of conservation in an adaptive resource management framework.

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Figures

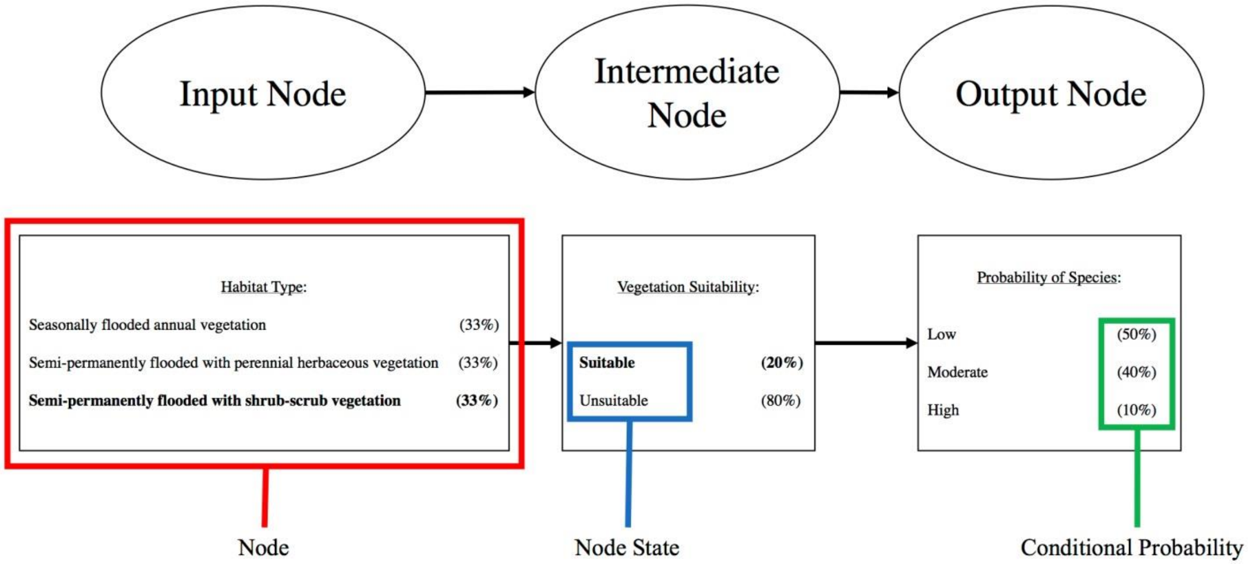

Figure 1. An illustration of a simple Bayesian Belief Network (BBN). The links between input, intermediate and output nodes (ellipses) indicate a mechanistic relationship in the direction of the arrow (i.e., the state of the input node variable drives the state of the intermediate node variable etc.). Input nodes are defined by marginal (unconditional) probability distributions defined by the range of states found in nature. Intermediate and output nodes are defined by conditional probability tables, with the probability for the node being in a specific state given by the configuration of the states of "parent" nodes. In the bottom part of the figure we demonstrate a hypothetical landscape with equal probabilities of encountering each type of habitat. In bold we represent that where there is semi-permanently flooded habitat with shrub-scrub vegetation, there is a 20% probability of finding suitable habitat (intermediate node) for an imaginary taxa. As the habitat is suitable, there is a 50% probability that the chances of encountering one individual of the species is low, a 40% probability that the chances of encountering one individual of the species is moderate, and a 10% probability that the chances of encountering one individual of the species is high. In this simplistic example, we show that the range of the probability of encountering the species (output node) changes based on the state at the input node.

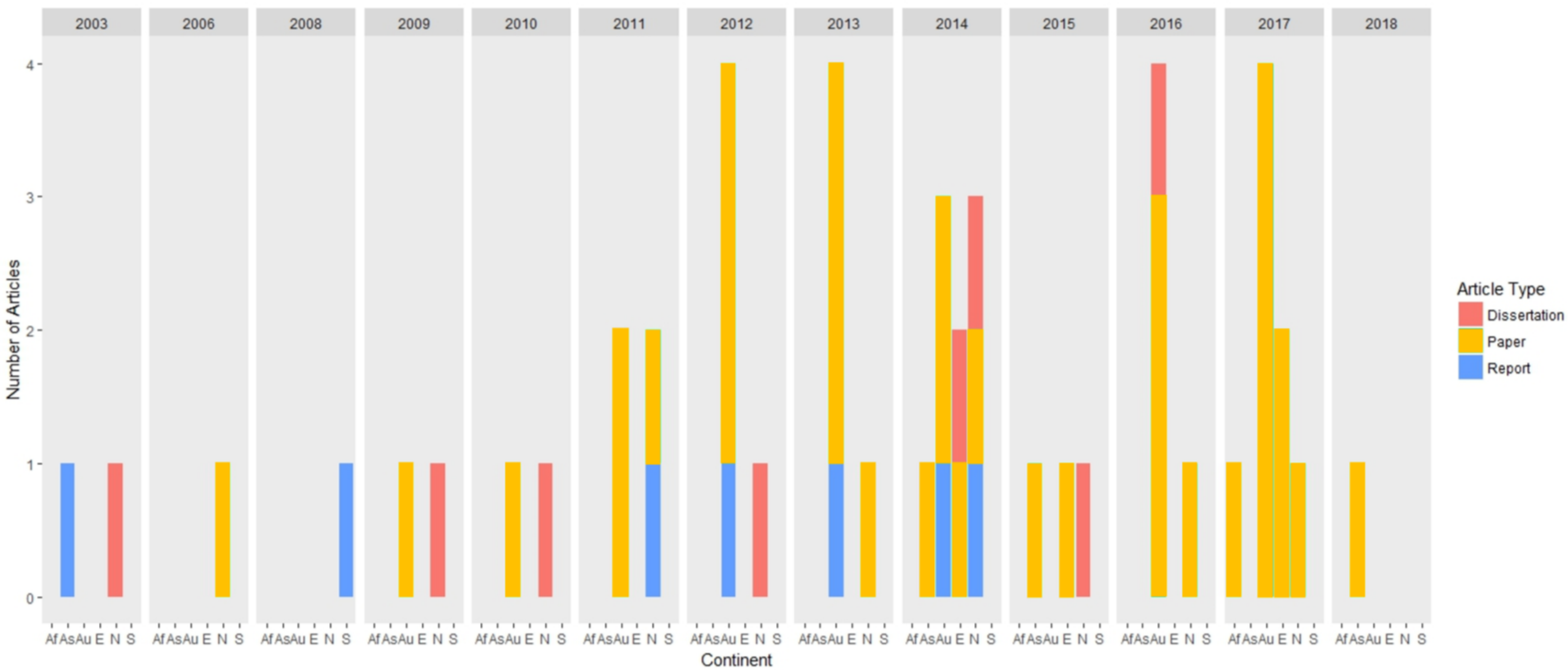

Figure 2. Distribution of article frequency, publication date, article type, and continent that BBNs were modeling based on our literature review. A book chapter published in 2008 which was theoretical in nature, and thus not affiliated with any continent, was omitted from this figure (see Appendix 1). Contributions from member countries to BBNs from each continent are as follows: Africa (Af) constituted a paper with research throughout sub-Saharan Africa; Asia (As) from Burma (Myanmar), Cambodia, China, the Lao PDR, Taiwan, Thailand, and Vietnam; Australia (Au) from Australia, Papua New Guinea, and Tasmania; Europe (E) from Belgium, England, France, Norway, Romania, Scotland, and Spain; North America (N) from Canada and the USA; and South America (S) from Chile.

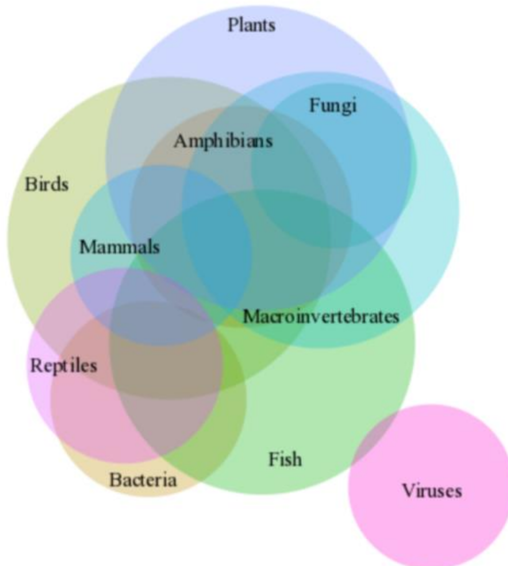

Figure 3. Venn diagram showing the proportional overlap of habitat requirements amongst freshwater wetland taxonomic groups. Lists of important habitat requirements were compiled from our review of species-specific BBN model literature (n = 38 habitat features from 50 studies; **Table 1**; **Appendix 1**).

Appendix 1

Literature summarized by this review.

Table 1. Peer-reviewed sources.

	Reference	Title	Journal	Country	Taxa
1	(Bino et al., 2014)	Maximizing colonial waterbirds' breeding events using identified ecological thresholds and environmental flow management	Ecological Applications	Australia	10 colonial waterbirds species
2	(Boets et al., 2015)	Evaluation and comparison of data-driven and knowledge-supported Bayesian Belief Networks to assess the habitat suitability for alien macroinvertebrates	Environmental Modelling & Software	Belgium	Alien gammarids (amphipod/aquatic macroinvertebrate)
3	(Bower et al., 2017)	Using a Bayesian network to clarify areas requiring research in a host-pathogen system	Conservation Biology	Australia	*Batrachochytrium dendrobatidis* (Chytrid fungus)
4	(Burgman et al., 2010)	Reconciling uncertain costs and benefits in Bayes nets for invasive species management	Risk Analysis	Australia	Red Imported Fire Ants
5	(Chan et al., 2012)	Bayesian network models for environmental flow decision making in the Daly River, Northern Territory, Australia	River Research and Applications	Australia	Barramundi (*Lates calcarifer*) and sooty grunter (*Hephaestus fuliginosus*)
6	(Chee et al., 2016)	Modelling spatial and temporal changes with GIS and spatial and dynamic Bayesian networks	Environmental Modelling & Software	USA	Invasive willow (*Salix caroliniana*)
7	(Couture et al., 2017)	Simulating water quality and ecological status of Lake Vanjo, Norway, under land-use and climate change by linking process-oriented models with a Bayesian network	Science of the Total Environment	Norway	Cyanobacteria biomass
8	(Douglas and Newton, 2014)	Evaluation of Bayesian networks for modelling habitat suitability and management of a protected area	Journal for Nature Conservation	England	Plants: Wild chamomile (*Chamaemelum nobile*), slender marsh-bedstraw (*Galium constrictum*), wild gladiolus (*Gladiolus illyricus*), pillwort (*Pilularia globulifera*); Butterflies: silver-stubbed blue (*Plebeius argus*), grayling (*Hipparchia semele*); Orthopteran: wood cricket (*nemobius sylvestris*); Fungus: nail fungus (*Poronia punctata*)
9	(Ethier and Nudds, 2017)	Complexity of factors affecting Bobolink population dynamics communicated with directed acyclic graphs	Wildlife Society Bulletin	Canada	Bobolink (*Dolichonyx oryzivorus*)
10	(Froese et al., 2017)	Modelling seasonal habitat suitability for wide-ranging species: Invasive wild bits in northern Australia	PLoS ONE	Australia	Wild pigs (*Sus scrofa*)
11	(Gawne et al., 2012)	A Bayesian belief network decision support tool for watering wetlands to maximise native fish outcomes	Wetlands	Australia	Introduced fish: common carp (*Cyprinus carpio*); native fish: carp gudgeon (*Hypseleotris* spp.), Australian smelt (*Retropinna semoni*), golden perch (*Macquaria ambigua*).
12	(Horne et al., 2017)	Using optimization to develop a "designer" environmental flow regime	Environmental Modelling & Software	Australia	Native fish: Australian Grayling (*Prototroctes maraena*), and River Blackfish (*Gadopsos marmoratus*)
13	(Jellinek et al., 2014)	Modelling the benefits of habitat restoration in socio-	Biological	Australia	Native reptile (n=22) and beetle (n=97)

		ecological systems	Conservation		species
14	(Kachergis et al., 2013)	Tools for resilience management: Multidisciplinary development of state-and-transition models for Northwest Colorado	Ecology and Society	USA	Shrub-derived habitat types
15	(Kath et al., 2016)	Using a Bayesian network model to assess ecological responses to hydrological factor interactions	Ecohydrology	Australia	Riparian tree (*Eucalyptus camaldulensis*)
16	(Kragt et al., 2011)	An integrated approach to linking economic valuation and catchment modelling	Environmental Modelling & Software	Tasmania, Australia	Rare native animal and plant species, and native riparian vegetation
17	(Le Dee et al., 2011)	Envisioning the future of wildlife in a changing climate: Collaborative learning for adaptation planning	Wildlife Society Bulletin	USA	Greater Prairie-chicken (*Tympanuchus cupido*), Wood Frog (*Lithobates sylvaticus*), and Karner Blue Butterfly (*Plebejus melissa samuelis*)
18	(Li et al., 2018)	Predicting the effect of land use and climate change on stream macroinvertebrates based on the linkage between structural equation modeling and Bayesian network	Ecological Indicators	China	Macroinvertebrates (Emphemeroptera, Plecoptera, and Trichoptera)
19	(Liedloff et al., 2013)	Integrating indigenous ecological and scientific hydro-geological knowledge using a Bayesian Network in the context of water resource development	Journal of Hydrology	Australia	Native fish: Barramundi, Sawfish, Black Bream
20	(Liu et al., 2015)	Using fuzzy logic to generate conditional probabilities in Bayesian belief networks: a case study of ecological assessment	International Journal of Environmental Science and Technology	Taiwan, China	Pheasant-tailed Jacanas (*Hydrophasianus chirurgus*)
21	(Mantyka-Pringle et al., 2016)	Prioritizing management actions for the conservation of freshwater biodiversity under changing climate and land-cover	Biological Conservation	Australia	Macroinvertebrates and fish
22	(Marcot, 2006)	Characterizing species at risk I: Modeling rare species under the Northwest Forest Plan	Ecology and Society	USA	Fungus: Fuzzy Sandozi (*Bridgeoporus nobilissimuus*)
23	(McDonald et al., 2016)	An ecological risk assessment for managing and predicting trophic shifts in estuarine ecosystems using a Bayesian network	Environmental Modelling & Software	Australia	Bacteria: Chlorophyta, Bacilliariophyta, and Cyanobacteria
24	(Morrison and Stone, 2014)	Spatially implemented Bayesian network model to assess environmental impacts of water management	Water Resources Research	USA	Cottonwood and Willow tree species
25	(Murray et al., 2012)	Predicting the potential distribution of a riparian invasive plant: the effects of changing climate, flood regimes and land-use patterns	Global Change Biology	Australia	Invasive riparian species of lippia (*Phyla canescens*)
26	(Pollino et al., 2009)	Modelling ecological risks from mining activities in a tropical system	Australasian Journal of Ecotoxicology	Papua New Guinea	Fish*: Lates calcarifer, Nematalosa* sp., *Neosilurus ater, Arius* sp., other
27	(Semakula et al., 2017)	Prediction of future malaria hotspots under climate change in sub-Saharan Africa	Climatic Change	Sub-saharan Africa	Malaria (*Plasmodium spp.*)
28	(Shenton et al., 2011)	Bayesian network models for environmental flow decision-making: 1. Latrobe River Australia	River Research and Applications	Australia	Native fish: Australian Grayling and River Blackfish
29	(Shenton et al., 2013)	A Bayesian network approach to support environmental flow restoration decisions in the Yarra River, Australia	Stochastic Environmental Research and Risk Assessment	Australia	Native fish: Australian Grayling
30	(Smith et al., 2017)	Operationalising ecosystem service assessment in Bayesian belief networks: Experiences with the OpenNESS project	Ecosystem Services	Romania, Scotland	Native fish, brown trout

31	(Tantipisanuh et al., 2014)	Bayesian networks for habitat suitability modeling: a potential tool for conservation planning with scarce resources	Ecological Applications	Thailand	Otter
32	(Turschwell et al., 2017)	Riparian restoration offsets predicted population consequences of climate warming in a threatened headwater fish	Aquatic Conservation: Marine and Freshwater Ecosystems	Australia	River Blackfish
33	(Vilizzi et al., 2013)	Model development of a Bayesian belief network for managing inundation events for wetland fish	Environmental Modelling & Software	Australia	Three native fish: Golden Perch (*Macquaria ambigua*), Carp Gudgeon (*Hypseleotris* spp.), and Australian Smelt (*Retropinna semoni*); one alien fish: Common Carp (*Cyprinus carpio carpio*)

Table 2. **Reports and Conference Proceedings**. A star (*) indicates that this reference was duplicated in peer-review; The reference maintained but the content was not replicated.

	Reference	Title	Contributed to	Country	Taxa
1	(Baran et al., 2003)	Bayfish: A model of environmental factors driving fish production in the Lower Mekong Basin	Second International Symposium on Large Rivers for Fisheries	China, Burma (Myanmar), the Lao PDR, Thailand, Cambodia and Vietnam	110 fish species
2	(Barmuta et al., 2012)	Joining the dots: Hydrology, freshwater ecosystem values and adaptation options	National Climate Change Adaptation Research Facility	Tasmania	Frogs and Dwarf galaxias (*Galexiella pusilla*)
3	(Bino et al., 2013)	Adaptive management of Ramsar wetlands	National Climate Change Adaptation Research Facility	Australia	Colonial waterbirds*
4	(Collier et al., 2014)	Potential science tools to support Mahinga Kai decision-making in freshwater management	Environmental Research Institute, University of Waikato	Australia	Mahinga kai, indigenous freshwater species that have traditionally been used as food, tools or other resources
5	(Drew and Collazo, 2014)	Bayesian networks as a framework to step-down and support Strategic Habitat Conservation of data-poor species: A case study with King Rail (*Rallus elegans*) in Eastern North Carolina and Southeastern Virginia	United States Fish and Wildlife Service Raleigh Field Office	USA	King Rail (*Rallus elegans*)
6	(Dyer et al., 2013)	Predicting water quality and ecological responses	National Climate Change Adaptation Research Facility	Australia	Macroinvertebrates and six native fish species
7	(Liu et al., 2012)	Using Bayesian belief networks for ecological assessment in EIA	International Conference on Environment Science and Biotechnology	Taiwan, China	Pheasant-tailed Jacanas (*Hydrophasianus chirurgus*) *
8	(Morgan, 2011)	Standardized occupancy maps for selected wildlife in Central British Columbia	BC Journal of Ecosystems and management	Canada	Grizzly, Barrow's Goldeneye, Lesser Scaup, Long-tailed Weasel, Great Blue Heron, Sandhill Crane, Moose, Sharp-tailed Grouse, Townsend's Big-eared Bat
9	(Widén, 2008)	Evaluation of alternative discharge points from Valdivia Cellulose Plant by using Bayesian belief network system for environmental risk management	Department of Fire Safety Engineering and Systems Safety, Lund University, Sweden	Chile	Biodiversity/Black-necked Swans

Table 3. **Theses and dissertations**. A star (*) indicates that this reference was duplicated in peer-review; the reference maintained but the content was not replicated.

	Reference	Title	University	Country	Taxa
1	(Douglas, 2009)	Habitat suitability modelling in the New Forest National Park	Bournemouth University, UK	England	Plants: Wild chamomile (*Chamaemelum nobile*), slender marsh-bedstraw (*Galium constrictum*), wild gladiolus (*Gladiolus illyricus*), pillword (*Pilularia globulifera*); Butterflies: silver-stubbed blue (*Plebeius argus*), grayling (*Hipparchia semele*); Orthopteran: wood cricket (*nemobius sylvestris*); Fungus: nail fungus (*Poronia punctata*)*
2	(Ethier, 2016)	Factors affecting the abundance of a declining grassland bird: Implications for recovery strategy planning and implementation	University of Guelph, Canada	Canada	Bobolink (*Dolichonyx oryzivorus*) *
3	(Graham, 2016)	Predicting risk to estuary water quality and patterns of benthic environmental DNA in Queensland, Australia using Bayesian networks	Western Washington University, USA	Australia	Photosynthetic and heterotrophic benthos (environmental DNA)
4	(Gronewold, 2009)	Water quality models for supporting shellfish harvesting area management	Duke University, USA	USA	Bacteria (*E. coli*)
5	(Johns, 2014)	Calculating risk change with management actions using Bayesian networks for the South River, Virginia, USA	Western Washington University, USA	USA	Smallmouth Bass (*Micropterus dolomieu*), White Sucker (*Catostomus commersonii*), Belted Kingfisher (*Megaceryle alcyon*) and Carolina Wren (*Thryothorus lucovicianus*)
6	(Kashuba, 2010)	Bayesian methods to characterize uncertainty in predictive modeling of the effect of urbanization on aquatic ecosystems	Duke University, USA	USA	Macroinvertebrates: Coleoptera, Diptera, Chironomidae, Gastropoda, Oligochaeta, Other
7	(Meyer, 2014)	Parasite diversity within native and invasive terrapins: Implications for conservation	North-West University and University of Perpignan	France and Spain	Mediterranean Pond Terrapin (*Mauremys leprosa*)
8	(Summers, 2012)	The use of a Bayeian network to calculate the risks of mercury contamination to fish and birds of the South River, Virginia	Western Washington University, USA	USA	Fish: Smallmouth bass, White sucker; Birds: Belted Kingfisher, Carolina Wren
9	(Wiest, 2015)	Tidal marsh bird conservation in the Northeast, USA	University of Delaware	USA	Clapper Rail (*Rallus crepitans*), Willet (*Tringa semipalmata*), Nelson's Sparrow (*Ammodramus nelsoni*), Saltmarsh Sparrow (*A. caudacutus*), Seaside Sparrow (*A. maritimus*)
10	(Zavaleta, 2003)	Integrative risk analysis of vector-born disease	Oregon State University	USA	West Nile Encephalitis

Table 4. Book Chapters

	Reference	Title	Country	Taxa
1	(Orme-Zavaleta and Munns, 2008)	Chapter 38: Integrating Human and Ecological Risk Assessment: Application to the Cyanobacterial Harmful Algal Bloom Problem	aspatial	Cyanobacteria

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Appendix 2

Employment and funding for authors of BBNs.

Table 1. Employment of first authors at the time of publication for peer-reviewed articles in our review.

Reference	First Author	Employment
(Bino et al., 2014)	Gilad Bino	Adjunct Research Fellow, Charles Sturt University; Research Fellow, University of New South Wales
(Boets et al., 2015)	Pieter Boets	*Unknown*
(Bower et al., 2017)	Deborah Sheena Bower	Postdoctoral Researcher
(Burgman et al., 2010)	Mark A. Burgman	Managing Director, The Australian Centre of Excellence for Risk Analysis
(Chan et al., 2012)	Terence U. Chan	Research Fellow, Monash Sustainability Intstitute
(Chee et al., 2016)	Yung En Chee	Senior Researcher, University of Melbourne
(Couture et al., 2017)	Raoul-Marie Couture	Senior Researcher, Norwegian Institute for Water Research
(Douglas and Newton, 2014)	Sarah J. Douglas	Stay at home Mother
(Ethier and Nudds, 2017)	Danielle M. Ethier	Postdoctoral Researcher, University of Guelph
(Froese et al., 2017)	Jens G. Froese	Research Associate, The University of Queensland
(Gawne et al., 2012)	Ben Gawne	Director of the Murray Darling Freshwater Research Centre
(Horne et al., 2017)	Avril Horne	Research Fellow, University of Melbourne
(Jellinek et al., 2014)	Sacha Jellinek	Restoration project officer, Department of the Environment, Water and Natural Resources, South Australia
(Kachergis et al., 2013)	Emily J. Kachergis	Landscape Ecologist, Bureau of Land Management, Denver, Colorado
(Kath et al., 2016)	Jarrod M. Kath	*Unknown*
(Kragt et al., 2011)	M. E. Kragt	Senior Lecturer, The University of Western Australia
(Le Dee et al., 2011)	Olivia E. LeDee	Research Associate and Assistant Scientist, University of Wisconsin-Madison
(Li et al., 2018)	Xue Li	*Unknown*, Tiajin Normal University
(Liedloff et al., 2013)	A. C. Liedloff	*Unknown*
(Liu et al., 2015)	Kevin Fong-Rey Liu	Deputy R & D Chief, Ming Zhi University of Science and Technology Research and Development
(Mantyka-Pringle et al., 2016)	Chrystal S. Mantyka-Pringle	Postdoctoral Research Fellow, University of Saskatchewan
(Marcot, 2006)	Bruce Marcot	Research Wildlife Biologist, USDA Forest Service
(McDonald et al., 2016)	K.S. McDonald	*Unknown*
(Morrison and Stone, 2014)	Ryan R. Morrison	Postdoctoral Fellow, University of New Mexico
(Murray et al., 2012)	Justine V. Murray	Postdoctoral Fellow, CSIRO
(Pollino et al., 2009)	Carmel A. Pollino	Fellow, The Australian National University
(Semakula et al., 2017)	Henry Musoke Semakula	*Unknown*, Dalian University of Technology
(Shenton et al., 2011)	W. Shenton	*Unknown*
(Shenton et al., 2014)	W. Shenton	*Unknown*
(Smith et al., 2017)	Ron I. Smith	*Unknown*
(Tantipisanuh et al., 2014)	Naruemon Tantipisanuh	Ph.D. student
(Turschwell et al., 2017)	Mischa P. Turschwell	Research Fellow, Griffith University
(Vilizzi et al., 2013)	Lorenzo Vilizzi	Senior Research Scientist, Mugla Üniversitesi

Table 2. Funding sources for BBNs of freshwater wetland-dependent species from peer-reviewed literature sources.

Type of funding source	Funding agencies (alphabetical order)
Non-governmental agency	Nature Conservancy
Private funders	Canadian Forest Products, Conifex Inc., C&C Forest Products, Albert Shimmins postgraduate award, Norman Wettnhall research grant, ARC Linkage Project, Gouldburn-Broken, TRACK program
Research institutions conducting their own research (privately funded)	College of Agriculture & Natural Resources (Delaware), Tropical Rivers and Coastal Knowledge research programme, Environmental Economics Research Hub and Landscape Logic (Australian Commonwealth Environmental Research Facility), Commonwealth Scientific and Industrial Research Organization Climate Change Adaptation Flagship Scholarship, Australian Centre for Excellence for Risk Analysis, Flemish Institute for Technological Research
Local government agencies (competitive, publicly funded)	Northern Rivers Catchment Management Authority (Australia), Port Macquarie Hastings Council (Australia), State Wildlife Grant (Delaware), State of Delaware, Queensland Government Mart Futures PhD Scholarship, USGS Winsconsin Coop Wildlife Research Unit, Wisconsin Department of Natural Resources, Colorado Agricultural Experiment Station, Melbourne Water, Department of Sustainability and Environment (Australia), Queensland Department of Natural Resources and Water, East Gippsland and West Gippsland CMAs, Ontario Ministry of Natural Resources and Forestry
Federal government agencies	USDA Economic Research Service, NSF EPSCoR, USFWS, USDA National Institute of Food and Agriculture Managed Ecosystems Program, Natural Resource Conservation Service of Colorado, Land and Water Australia, Managing Aquatic Ecosystems and Water Resources under Multiple Stress (MARS program – Norway), Ministry of Business (New Zealand), Department of Climate Change and Energy

	Efficiency (Australia), National Water Commission (Australia), National Climate Change Adaptation Research Facility (Australia), USGS, USFWS, Australian National Water Commission
Research grants from federal government (competitive, publicly funded grants)	NSF (USA), NRF (South Africa), CNRS (South Africa), Australian Government Postgraduate Award, Australian postgraduate award, Conservation Innovation Grant, National Environmental Research Program (Australia), Australian Research Council, National Science Council of the Republic of China, Natural Sciences and Engineering Research Council of Canada, Research Council of Norway project 'Lakes in Transition', ARC discovery grant (Australia)

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