Notes on the report “Exploring the impact of multiple stressors on estuarine ecosystems using a Bayesian network model”

Report prepared for the Parliamentary Commissioner for the Environment
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Introduction

The report is an application of the use of a Bayesian network (BN) and expert elicitation to derive general models to predict ecological states given a variety of inputs. The study appears to be a follow on of Gladstone-Gallagher 2019, which outlines the approach.

In reviewing this research, I had access to the report and the BN built in Netica. The review was conducted as a normal peer review of a government document or journal article.

The use of Bayesian networks

The application of BNs to the estimate of impact or risk has been developed since the mid-2000s. Pollino and Hart (2005, Pollino et al 2007) pioneered the application to risk assessment, and others have since incorporated BNs (see Carriger et al and Landis et al refences; among others in the reference list). Marcot and colleagues (2007, 2012) have applied BNs to a variety of environmental management cases. Marcot (2017) is an excellent guide to common issues in building BN models and many have found it useful.

Since 2010 there have been a number of papers published using BNs to make management decisions for a variety of ecological systems. Many of these studies use some form of expert information or solicitation to inform the structure of the BN and to quantify the interactions. Notable examples include the papers by Carriger et al (Carriger and Newman 2011, Carriger and Barron 2011, Carriger, Barron and Newman 2016, Carriger, Castro, Rand 2016, Carriger, Dyson, Benson 2018, Carriger, Yee, Fisher 2019) that address toxicology, water quality, oil spill management, and coral reefs. Landis and collaborators have applied BNs in collaboration with subject experts and datasets for forests (Ayre et al), invasive species in marine environments (Herring et al 2015), urban watersheds (Hines et al 2014), a South River, Virginia contaminated site (Landis et al 2017a, Johns et al 2017) with the inclusion of an adaptive management framework (Landis et al 2017b). Graham et al (2018) examined the relationships between nutrient inputs and water quality-species diversity in a series of estuaries near Brisbane, Australia. Data and expert consultation were received via the numerous collaborators involved in data collection and estuarine management. Barton et al (2012) provided an excellent overview of the use of Bayesian statistics and BNs from a European perspective. Many of the papers summarized above incorporated the cumulative effects and overall risk due to multiple stressors of different types.

There are a number of studies that can provide operational examples of the use of BNs in environmental management that also incorporate various forms of expert interactions. In the case of Graham et al (2018), case learning (an artificial intelligence tool) was used to build the conditional probability tables describing the interactions between the nodes in a BN.

Scope of the report

This report is a description of how expert knowledge and data can be combined in the development of a BN to estimate the probability of impacts to estuarine systems. The overall approach is described in Gladstone-Gallagher (2019) and this follow-up document serves as an example of the implementation. As described above, a number of studies are now integrating expert information, extensive data sets and experimental information to build and parameterize BNs for use in environmental management. The study described here is another contribution to this growing literature and specifically addresses New Zealand environments and regulatory framework. The study has the potential to be a strong example of these types of studies and has the potential to lead to valuable peer-reviewed publications. Since the report describes the probability of impacts to key management endpoint this report will be a part of the ecological risk assessment literature.

The next sections describe the strong points of this report and also the issues that need to be resolved before release to a wider scientific community.

Strengths of the report

The application of BNs to evaluate environmental datasets has a number of advantages. The ability to use a variety of data, including ranks from expert elicitation, is a particular strength. Particularly important are the abilities to describe uncertainties as distributions and to calculate the importance (sensitivity) of variables using entropy reduction as the tool.

Another advantage of the BN is that current knowledge of cause-effect pathways can be described via the lines of influence connecting the nodes. The structure of the model can also be used to examine the model to discover variables (nodes) that are likely to be highly correlated because they are closely related.

The variety of experts involved in the estimates of cause-effect pathways and the conditional probability pathways are a strength. However, it should be known that subject area experts are likely to have a relatively limited knowledge of model development using BNs.

The datasets are extensive and enough so that the stressor scenarios can be constructed. Table 2-2 is an example of such a table. These tables should be part of every analysis and make it clear as to values in the BN.

Similarly, the appendices demonstrate the detailed descriptions of the nodes and use of other models to set the states. An example is on page 37, Appendix A-1, Nitrogen inputs. Hydrological models were used in part to derive the states. Missing from the node state descriptions is a description of the uncertainty. Table A-2 is similarly constructed.

One of the important aspects of these tables is that it makes it clear that a large amount of data analysis went into the construction of the BNs; this is not as clear in the description of the methodology. In many instances expert elicitation is used to derive relationships when data are limited and analysis cannot be conducted. In the case of this study the data are used to inform subject area experts when it is necessary to make decisions regarding states and interactions. The tables make it much clearer than the text. Tables such as those found in the appendices are becoming common as supplemental information in journal articles. However, in appendix A-2 I do not see descriptions of uncertainty.

Figure D-1 is nice as far as it shows the structure of the BN. I was sent the Netica file so that I could evaluate the structure and the information in the tables describing the interactions between the nodes. I did not see the notes feature used in the description of each node—I often use that to make a note of the relationship or describe the derivation of the equation if one is used to construct the conditional probability table. It was very difficult to read the model structure or to evaluate changes with the size of the figure in the report. Having the Netica file allowed me to enlarge the size and be careful about noting the lines of influence.

It is clear that a careful collection of data and an appropriate data analysis was conducted. Compared to many study areas there is a wealth of data available to the researchers. From my reading it was not clear how many cases (observations with location and a collection of measurements) were involved in the data analysis. Depending on the quality of the collections I have had successful analysis with as few as 100 cases, but in other cases (see Graham et al) having thousands of cases allows a lower uncertainty in the distributions of values and in the derivations of the conditional probability tables.

Issues needing to be resolved

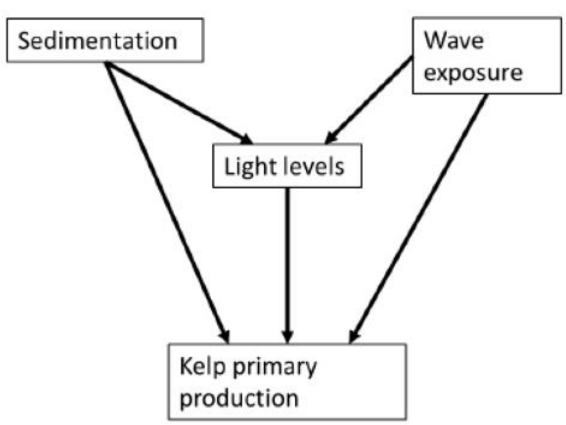
Introduction section 1.1

Please note that there have been publications covering the impacts of multiple stressors in a quantitative means since the late 1990s. The BN papers by Landis and colleagues are based on these multiple stressor papers describing the relative risk model (RRM). These models have been used across the world (including Australia) and the BN-derivations have also been used in a number of different studies. A look at these publications may provide some additional context.

Introduction section 1.2 (page 8). BN models of this type are built to create structures so that decision makers can be informed about management outcomes**.** It is not clear from this section that this is the case.

There is also a major misunderstanding of the use of probabilistic models. Page 8 has this phrase "We note that the model's purpose was to better understand the impact of multiple stressors on estuarine ecosystems in a general way using probability distributions and not to make accurate exact predictions of current or future states." I would maintain that to make the accurate prediction of current or future states would be to build a probabilistic model. Complex systems are characterized by having both deterministic and probabilistic properties, with even the deterministic interactions described by sensitivity to initial conditions. I would maintain that an accurate single point prediction would present an inaccurate impression of the system.

Description of Bayesian networks: Figure 2.1 in the report



This figure is not a diagram of a simple BN. In fact, it would not pass as a strong model. In this case the nodes Sedimentation and Wave exposure feed into the nodes Light levels and Kelp primary production. In this diagram Light levels is not a necessary node since it will be redundant with Kelp primary production. Given an appropriate conditional probability table, Sedimentation and Wave exposure are all that will be necessary. There should be another parent node that feeds into Light levels to provide information not covered in Sedimentation and Wave exposure. I can think of mean seasonal light levels or the probability distribution of the typical diurnal solar radiation during the year.

So far this is a diagram of an acyclic graph. It is the inclusion of the conditional probability tables that would make this a BN.

I have spent a great deal of time to understand the structure of the BN used in this study. I did not find a diagram of the conceptual model used to inform the structure of the BN. There does not seem to have been a clear cause-effect diagram produced. Many of the papers cited above use a source-stressor-habitat-effect-impact framework (see Graham et al 2018).

The final model is composed of 28 nodes, 102 lines of influence and at least 127,275 conditional probabilities describing the interactions. One node in particular, Denitrification, has 6 inputs creating a particularly large conditional probability table. Experience suggests that it is difficult to evaluate the accuracy and uncertainty of such a large table. Other nodes also have large – but not as large – numbers of inputs.

The Suspended Sediment node (upper left-hand corner of figure 2-2) has 10 outgoing lines of influence and appears to have the largest number. Does this actually seem reasonable? Given these multiple lines one would think it to be a key node.

Figure 2-2 is virtually impossible to read, as are the rest of the illustrations depicting the other scenarios. This appears to be a screenshot from Netica and has no labels to identify the layers as outlined in the text. The way the Netica model is drawn has lines of influence being blocked by nodes, making it difficult to follow the paths across the diagram. Such issues can be resolved by moving the nodes and putting bends in the lines of influence to avoid being blocked. It is also possible to color code the nodes to illustrate pathways or levels of integration.

I note that in Figure 2-2 that the top nodes are all set at the lowest setting for the no stressor case. I know of no systems without stressors. I understand that in this case the BN was set at the lowest state for each of the inputs.

A critical missing piece to the analysis of the BN is an analysis of the sensitivity of the various bottom nodes in this model to the rest of the nodes. The methodology is described in the Netica software at https://www.norsys.com/WebHelp/NETICA/X_Sensitivity_Analysis.htm. I would doubt that all nodes are important in determining the results in the final child nodes. Such an analysis can also point to nodes that can be removed from the model. I have found that the sensitivity analysis is one of the most important evaluation tools in the Netica software.

The lack of a clear description of uncertainty or a sensitivity analysis makes it difficult to have confidence in the results described in section 3.3. Section 3.3.1 Increasing stress levels would be better described as Increasing the ranks of the stressors. In some ways this is a sensitivity analysis. Changes in output for each change in one or a combination of stressors (top set of nodes) may describe which stressors are driving the outputs (bottom set of nodes). The authors did this a bit in Figure 3-2, but it was checking all of the nodes changing to the same state in an increasing fashion. This will not determine which of the nodes is the most important.

The same notes can be made of the analyses illustrated in Figures 3-3 and 3-4. Essentially these outputs demonstrate that the nodes are connected. In both cases it does seem that, when the stressors or other nodes are changed, other changes downstream do occur. In my experience it is the changes in the output distributions that is the key output in judging how effects may be altered. The authors note in the text that even with low states of stressors, there is a probability of the highest state occurring. This sounds completely normal in the dynamics of real systems. So, it is the change of the distribution that is the key output.

Describing and summarizing the key results of BN models of this size is problematic and each author struggles with how to communicate such information. I suggest examining a number of publications for examples. Which approach best illustrates the main findings of the study? That is the question.

Discussion

Given the numerous comments on the construction of the BN, and the lack of a detailed uncertainty analysis and sensitivity evaluation, I did not spend much time on the discussion section. The main points may be altered after a further investigation of the BN.

I found section 4.4 to be a particularly useful section, which probably belongs in its own section on uncertainty rather than part of the discussion. Items 1-7 all discuss sources of uncertainty in the model structure and parameterization. I thought that the analysis is strong.

Summary

This study has a strong potential to be a key study and subsequent peer-reviewed publication. The methodology and results would complement the existing literature and be an important case study. I suggest reviewing some of the current publications in the field and applying the lessons learned to the analysis and summary of the data, BN and the outputs.

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