Title: Applying Bayesian Networks to Inform Public Decision-Making for Improved Water Quality

Keywords: Bayesian Networks; Artificial Intelligence; Public Policy; Water Quality

Extended Abstract

THE APPLICATION DOMAIN

Port Phillip Bay is a 1930km^2 water body ringed by the large capital city of Melbourne and numerous regional communities. In addition to the economic value it supports through housing Australia's primary trading port and numerous localised business, the Bay holds inherent environmental, spiritual, and recreational values that are much appreciated by the community. Nutrient cycling is one such value, critical to the ecological balance within and adjacent to the Bay. Numerous models have been built that estimate, predict, analyse or monitor aspects of the nitrogen cycle of Port Phillip Bay (PPB) and have contributed to strong understanding of the sources and pathways that contribute to nitrogen inflows. However, prioritising interventions to optimise these inflows is problematic given the complexity of pathways, and multifaceted considerations that inform policymaking. In 2017 an Environment Management Plan (EMP) (DELWP, 2017) was developed for PPB identifying priority areas, including nutrients and pollutants, and habitat and marine life. Water quality in the Bay is also monitored by the Commissioner for Environmental Sustainability (CES) through the State of the Bays reports (Commissioner, 2016). While the EMP outlines goals and priority areas, it is not possible to address all of them and thus an approach that supports policy decision makers to prioritise interventions is required.

We conducted a 3-month feasibility assessment to determine the viability of leveraging Bayesian networks (Pearl, 1988; Korb & Nicholson, 2011) to provide a decision support tool that could not only support the prioritisation of public spending to maximise water quality gains but also to provide a structured and transferrable approach to decision-making through the creation of the Bayesian network (BN).

THE BN KNOWLEDGE ENGINEERING METHODOLOGY

The BN was developed primarily by expert elicitation from Department of Environment Land and Water Planning (DELWP) subject matter experts and to a lesser extent from reports and literature provided by DELWP and other reliable sources. Broadly the methodology of this project followed the KEBN (Knowledge Engineering with Bayesian networks process) (Korb & Nicholson 2011, Chapter 10). Knowledge engineering is the structured process of collecting and transforming data into meaningful, problem specific knowledge, starting with the collection from documentation and expert elicitation. Knowledge is then represented graphically and probabilistically in Bayesian Network models. Four elicitation workshops were held with different aspects of the BN model being elicited at each workshop. The respective purpose of each of the four workshops was as follows: 1) Variable and structure elicitation; 2) Aggregated model validation and expansion and intervention elicitation; 3) Parameter elicitation; and 4) Final feasibility model validation and scenario elicitation. The Zoom platform was used to conduct all workshops remotely and a Zoom recording of the workshop was captured for reference. The BARD platform (Nicholson, et al., 2020) was the tool used to elicit variables and structure and was only used for this first workshop.

RESULTS AND DISCUSSION

Figure 1 shows the conceptual BN which was the basis for the parameterized model. There are four layers in this model: 1) (grey) a context layer housing the background factors relevant to the model; 2) (light blue) a pathway layer of nodes connecting background factors and interventions to the model outputs; 3) (orange) an intervention layer of nodes representing levers that policymakers can act on; and 4) (aqua) the target layer of the models desired output nodes.

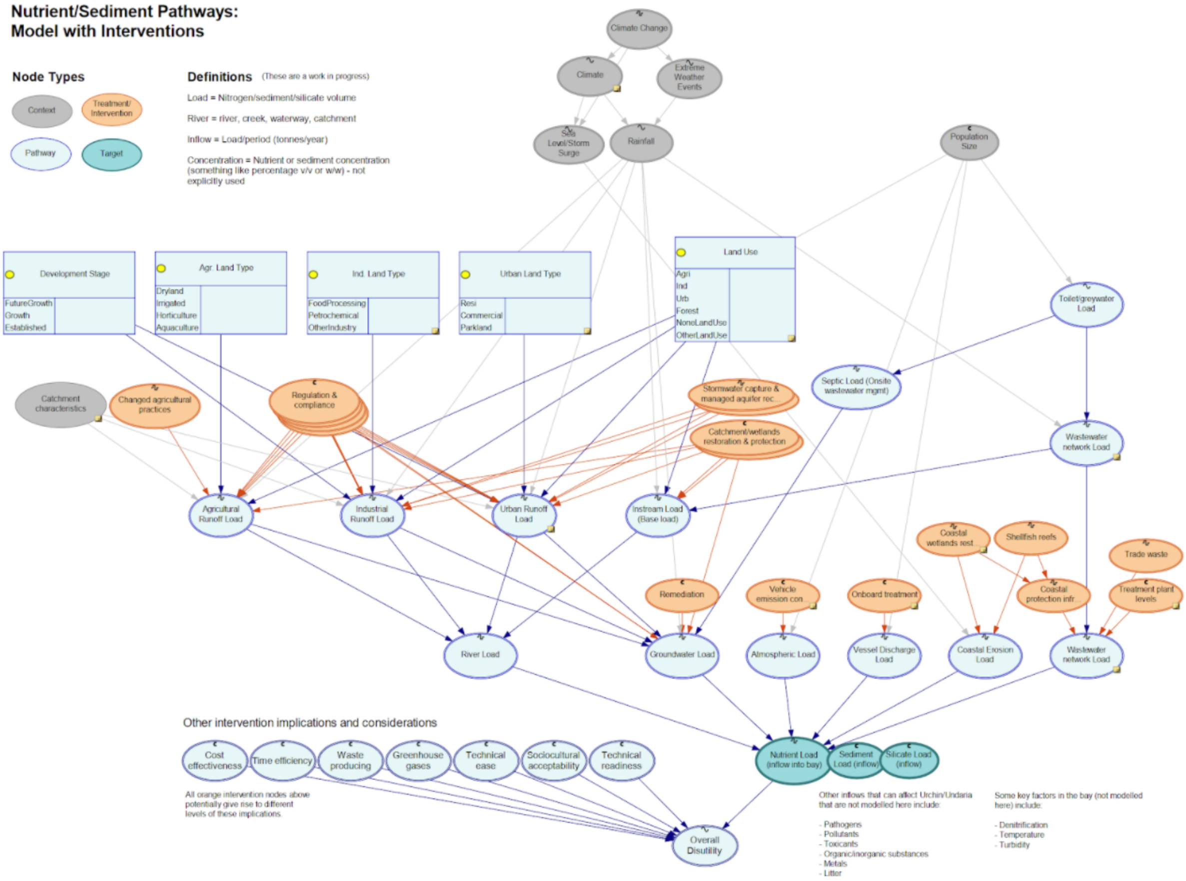

Figure 1 – The conceptual model of PPB nutrient inflow pathways (screenshot from GeNIE)

Parameters and scenarios were elicited from subject matter experts and were used to create the parameterized model. While experts found estimating parameters challenging, we found that mean estimates matched well with recorded estimates found in the literature (where available). The results showed which interventions had the greatest impact on various dimensions. The dimensions that we reported on included: tonnes of nitrogen within PPB each year, tonnes of silicate and tonnes of sediment. We found that the model structure generalised well for each of these dimensions. The resultant output from the BN which was extracted into tabular format, demonstrated how the model could evaluate different scenarios and summarise the impact of each along with other implications (such as cost effectiveness) and provided a view for prioritisation consideration, which can be further developed through the addition of historical datasets to enable direct guidance on how best to achieve desired EMP outcomes.

This case study demonstrates that Bayesian networks are a viable decision support tool that can not only support the prioritisation of public spending to maximise water quality gains but also provide a structured and transferrable approach to decision-making.

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