

# Predicting the temporal response of seagrass meadows to dredging using Dynamic Bayesian Networks

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**Abstract:** Predicting temporal responses of ecosystems to disturbances associated with industrial activities is critical for their management and conservation. However, prediction of ecosystem responses is challenging due to the complexity and potential non-linearities stemming from interactions between system components and multiple environmental drivers. Prediction is particularly difficult for marine ecosystems due to their often highly variable and complex natures and large uncertainties surrounding their dynamic responses. Consequently, current management of such systems often rely on expert judgement and/or complex quantitative models that consider only a subset of the relevant ecological processes. Hence there exists an urgent need for the development of whole-of-systems predictive models to support decision and policy makers in managing complex marine systems in the context of industry based disturbances.

This paper presents Dynamic Bayesian Networks (DBNs) for predicting the temporal response of a marine ecosystem to anthropogenic disturbances. The DBN provides a visual representation of the problem domain in terms of factors (parts of the ecosystem) and their relationships. These relationships are quantified via Conditional Probability Tables (CPTs), which estimate the variability and uncertainty in the distribution of each factor. The combination of qualitative visual and quantitative elements in a DBN facilitates the integration of a wide array of data, published and expert knowledge and other models. Such multiple sources are often essential as one single source of information is rarely sufficient to cover the diverse range of factors relevant to a management task.

Here, a DBN model is developed for tropical, annual *Halophila* and temperate, persistent *Amphibolis* seagrass meadows to inform dredging management and help meet environmental guidelines. Specifically, the impacts of capital (e.g. new port development) and maintenance (e.g. maintaining channel depths in established ports) dredging is evaluated with respect to the risk of permanent loss, defined as no recovery within 5 years (Environmental Protection Agency guidelines). The model is developed using expert knowledge, existing literature, statistical models of environmental light, and experimental data.

The model is then demonstrated in a case study through the analysis of a variety of dredging, environmental and seagrass ecosystem recovery scenarios. In spatial zones significantly affected by dredging, such as the zone of moderate impact, shoot density has a very high probability of being driven to zero by capital dredging due to the duration of such dredging. Here, fast growing *Halophila* species can recover, however, the probability of recovery depends on the presence of seed banks. On the other hand, slow growing *Amphibolis* meadows have a high probability of suffering permanent loss. However, in the maintenance dredging scenario, due to the shorter duration of dredging, *Amphibolis* is better able to resist the impacts of dredging. For both types of seagrass meadows, the probability of loss was strongly dependent on the biological and ecological status of the meadow, as well as environmental conditions post-dredging. The ability to predict the ecosystem response under cumulative, non-linear interactions across a complex ecosystem highlights the utility of DBNs for decision support and environmental management.

**Keywords:** *Dynamic Bayesian Networks, predictive modelling, spatio-temporal modelling, seagrass, marine ecosystems*

## 1. INTRODUCTION

Recently, anthropogenic threats, such as urban and agricultural runoff, infrastructure development and dredging, have emerged as some of the greatest threats to the health and sustainability of marine ecosystems (Grech, Coles, & Marsh, 2011). This is especially the case for seagrass meadows, which have been declining at a rate of  $\sim 110\text{km}^2$  per year since 1980 (Waycott *et al.*, 2009). However, predicting the impact of anthropogenic activities on marine ecosystems to support decision making is challenging. This challenge arises due to uncertainty about the system and about emergent outcomes (Hughes, Bellwood, Folke, Steneck, & Wilson, 2005). Therefore, it is inadequate to look only at recent events to ascertain the ‘cause’ of a collapse or loss as the loss is likely to be precipitated through interactions and cumulative effects over time. As a result, there is an urgent need for whole-of-system predictive models that are able to deal with uncertainty and risk in managing marine ecosystems.

### 1.1. Dynamic Bayesian Networks

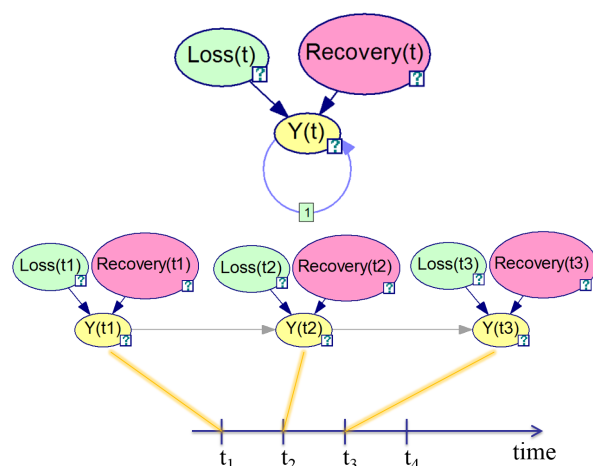
One approach to encapsulating available data and knowledge in a whole-of-systems model is with a Dynamic Bayesian Network (DBN) (Murphy, 2002). Bayesian Networks (BNs) provide a framework for knowledge representation and reasoning (Pearl, 1988). They provide a graphical representation of the system where nodes represent the variables or factors used to describe the system, and arrows describe the causal relationships between them (refer to **Figure 4** for an example). BNs are typically constructed as a state space model where each factor is discretised into states. For the example in **Figure 4**, loss could be discretised into high and low loss states and the output from the BN the probability of being in the high and low states. The relationship between a child node and its parent nodes is encoded in terms of conditional probabilities relating parent states to child node states as part of a Conditional Probability Table (CPT).

BNs have gained popularity in ecological applications in recent years as they provide a practical and scientifically credible framework for modelling complex ecological systems with uncertainty (Pollino, Woodberry, Nicholson, Korb, & Hart, 2007). They inherently provide a way to manage missing data and combine expert knowledge with data. In addition, the graphical depiction of the problem domain supports collaboration and articulate thinking about system components and interactions (Uusitalo, 2007). BNs have also demonstrated good predictive accuracy even with small sample sizes (Uusitalo, 2007). However, BNs are Directed Acyclic Graphs (DAG) which can not contain any feedback loops, a dominant feature of ecosystem dynamics. In addition, BNs can only provide an average or snapshot of a system over time. Therefore, by themselves, BNs are inadequate for the purposes of modelling the dynamics of complex ecosystems.

DBNs, however, provide a way to model cumulative effects and emergent behaviour of dynamic complex systems (Murphy, 2002). The temporal element is captured in DBNs through the discretisation of time into ‘slices’, whereby the BN is replicated at discrete points in time. It is the connections between time slices that enables the capture of feedback loops and cumulative effects as shown in **Figure 1**. Although they have been applied in other fields such as in the modelling of socio-technical infrastructure systems (Charitos, van der Gaag, Visscher, Schurink, & Lucas, 2009; Weber & Jouffe, 2003), they are not yet prevalent in the modelling and decision support of ecosystems and especially seagrass ecosystems.

### 1.2. Assessing Dredging Impact on Seagrass Using DBNs

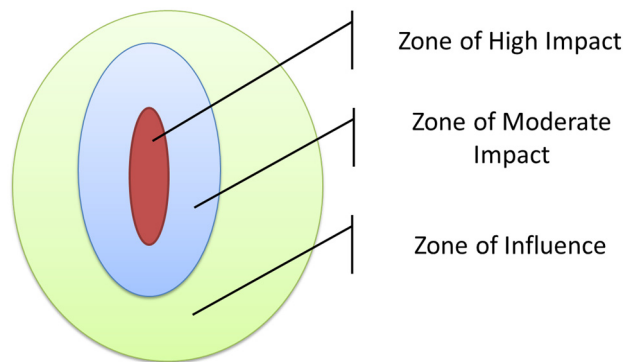
This paper specifically applies the DBN to the task of predicting the temporal response of seagrass meadows to dredging. Dredging is an integral part of port development and there are two types: capital dredging and maintenance dredging. As the names imply, capital dredging is about initially creating a navigable port for shipping and has a profound impact on the environment,



**Figure 1.** Conceptual illustration of time slicing in a DBN for three variables: loss, recovery and some metric *Y*. Note the replication of the model (top) into slices (bottom) which are joined by links between time slices.

whereas periodic maintenance dredging is of shorter duration and lesser impact (Suedel, Kim, Clarke, & Linkov, 2008).

One of the key marine habitats that are affected by dredging are seagrass meadows (Waycott *et al.*, 2009). Seagrass provides habitat for endangered species such as dugongs and green turtles as well as fishes, bird and invertebrate species. Seagrasses are also primary producers involved in nutrient uptake and cycling, providing ecosystem services of ~\$1.9 trillion per annum (Waycott *et al.*, 2009). As a result, the protection of seagrass meadows is of paramount importance worldwide.



**Figure 2.** Illustration of the different impact zones as defined for a dredging EIA.

In order to plan dredging projects and perform an Environmental Impact Assessment (EIA), it is necessary to be able to predict the loss in seagrass habitat and whether it is able to recover within a specified time frame to original levels after dredging has finished. The Western Australia Environmental Protection Agency (EPA) deems an inability for seagrass meadows to come back within five years to be permanent loss (Environmental Protection Agency, 2009). Note that as part of an EIA, it is necessary to outline the zones affected by dredging as shown in **Figure 2**. In a spatial sense, the zones of interest in terms of managing impacts are the zones of influence and zones of moderate impact since losses are accepted in the high impact zone.

It can be seen then that a predictive tool that can assess the probability of recovery is of key importance to making sound management decisions about dredging.

### 1.3. Existing Models

Currently, there are very limited tools available to assist decision makers for assessing dredging impacts on seagrass meadows. Some models are conceptual and therefore do not provide a means to quantitatively evaluate or predict impact. For example, Thomas *et al.* (2005) developed a conceptual, expert elicited model that represents ecosystem factors. Some other models are quantitative but are targeted at other usage scenarios and hence do not address some of the unique concerns surrounding dredging activities. The work of (Grech & Coles, 2010) predicts seagrass presence along the Great Barrier Reef (GBR) using a data and expert elicited BN. Presence is predicted according to season, location, relative wave exposure, temperature, substrate, flood plumes, tidal range and bathymetry. However, the model does not evaluate cumulative effects as the BN only provides an average assessment over time; thus it is difficult to evaluate the loss in seagrass following dredging and subsequent recovery (if at all). This is similarly the case for the work presented by Schultz, Borrowman, and Small (2011) which is also based on a BN.

An alternative approach is presented by Sheridan (2004) which uses power law regression to predict recovery over a 5-year timeframe. Sheridan's model is in effect a time series regression focused on explaining the recovery profile for a particular dredge site and does not capture more general predictive usage scenarios involving cumulative effects. Finally, Suedel *et al.* (2008) propose a decision support method based on an outranking method entitled SMAA-III (choose between alternatives using criteria that are evaluated via pairwise preferences). In this approach, the projected impact is in effect, expert elicited and the tool provides a way to assist decision makers in making trade-offs between the multiple economic, biological, physical and water quality criteria.

As a result, it follows that despite extensive studies on seagrass meadows and their distributions and responses to disturbances in general, a quantitative 'causal influence' predictive tool (Pearl, 1988) can build upon this knowledge to provide better organised information for dredging decision support.

## 2. DREDGING IMPACT ON SEAGRASS CASE STUDY

An expert elicited DBN for evaluating dredging impacts on seagrass meadows was developed using the iterative development and expert elicitation guidelines in (Johnson *et al.*, 2010; Pollino *et al.*, 2007). At a high level, the model is concerned with loss and recovery as shown in **Figure 4**. Biological and environmental factors contribute towards the ability to resist, which then affects how much loss is incurred under different environmental conditions. Specifically, the main hazards identified were related to light

reduction, burial by sediment and sediment quality impacts (as a generic factor covering the many different types of sediment that could be exposed during dredging). On the recovery side, the main factors affecting the ability to recover include seed availability (such as whether a seed bank is present or not) as well as lateral growth from existing individuals.

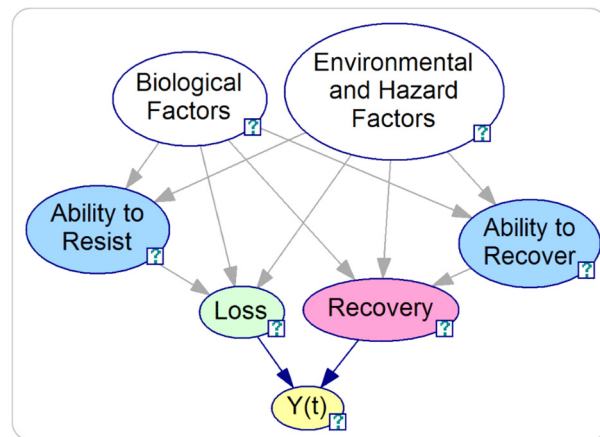
Loss and recovery are assessed with respect to metrics of interest  $Y(t)$ . The main metrics as identified from regulatory and guideline materials were shoot density, biomass and aerial extent of the meadow (ANZECC ARMCANZ, 2000; Environmental Protection Agency, 2009; Environmental Protection Authority, 2005). Each of the factors, also referred to as nodes, in the DBN are discretised into states. For example, shoot density is discretised into high, moderate, low and zero shoot density and light is discretised into above saturation and below saturation states.

The discretisation of nodes into states is an implicit recognition of the uncertainty in the model and available data. Although there are datasets available, many of these contain only water quality metrics and/or overall biomass or shoot density; hence there are numerous data gaps. In addition, due to a combination of natural variability and uncertain marine environment, there is also uncertainty on the representativeness of observed measurements. Finally, there is uncertainty in the expert elicited relationships between the different factors both in terms of the structure of the model (although there was consensus in this case among seagrass and marine ecologists) and the strength of the relationships. As a result of both random and validation uncertainty (Pate-Cornell, 1996), discretisation into states provides a direct recognition of this uncertainty. Additionally, this discretisation is also useful as it provides a way to directly reflect regulatory guidelines. For example, ‘moderate’ shoot density is defined to reflect the meadow conditions necessary for moderate protection as per ANZECC ARMCANZ (2000).

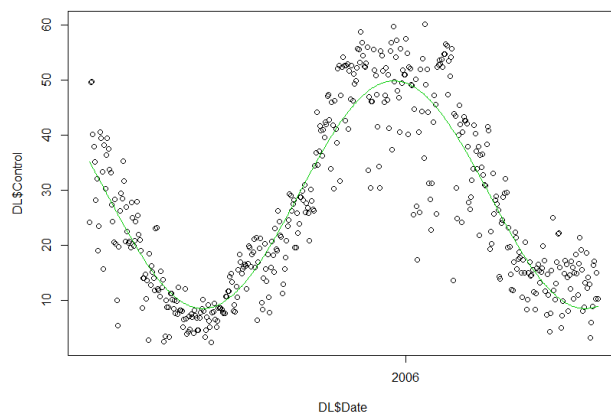
However, in order to incorporate experimental and observational data into the DBN, it is necessary to be able to transform between measurement values and these states. For this study, experimental data from the work of (Lavery, McMahon, Mulligan, & Tennyson, 2009; McMahon, Lavery, & Mulligan, 2011) was incorporated. Shoot density is measured in terms of the number of clusters or shoots per unit area, and light is captured in terms of both number of hours of saturating irradiance per day ( $H_{SAT}$ ) and the number of mols  $m^{-2}$  of benthic light per day. The expert elicited simulation time step size for the model is one month. Therefore, it is also necessary to be able to transform between different time scales. Additionally, there can be substantial natural variations in these variables even without dredging. For example, light intensity (mols  $m^{-2} d^{-1}$ ) itself follows a seasonal sinusoidal pattern as shown in **Figure 3**.

One way to transform between continuous measurements and state probabilities across different time scales is to use a Bayesian hierarchical model (Bolker, 2008). For example, a simple random effects model is used to model the probability of being above saturation for light:

$$\begin{aligned} b_i &\sim \mathcal{N}(\mu, \tau) \\ r_i &\sim \mathcal{B}(p_i, n_i) \end{aligned} \tag{1}$$



**Figure 4.** Conceptual illustration of the BN and the structure of the model.



**Figure 3.** Benthic light intensity – note the seasonal sinusoidal pattern. The (periodic) linear regression line is intensity  $Y = A\sin(2\pi t) + B\cos(2\pi t)$  where  $t$  is the date. The adjusted  $R^2 = 0.8134$ .

where  $r_i$  is the number of days of above saturation light in month  $i$ , modelled as a Binomial distribution with parameters  $p_i$  (probability of above saturation) and  $n_i$  (number of trials).  $p_i$  comes from a Normal distribution via the logit transform  $b_i = \text{logit}(p_i)$  to capture random effects and uninformed uniform priors are used. Overall, for *Amphibolis* in Jurien Bay, the probability of being above or below saturation light is captured in Table 1.

**Table 1.** Probability of above saturation light over the year for natural conditions P(control) and anticipated dredging conditions P(reduced). Derived from Bayesian hierarchical model in (1).

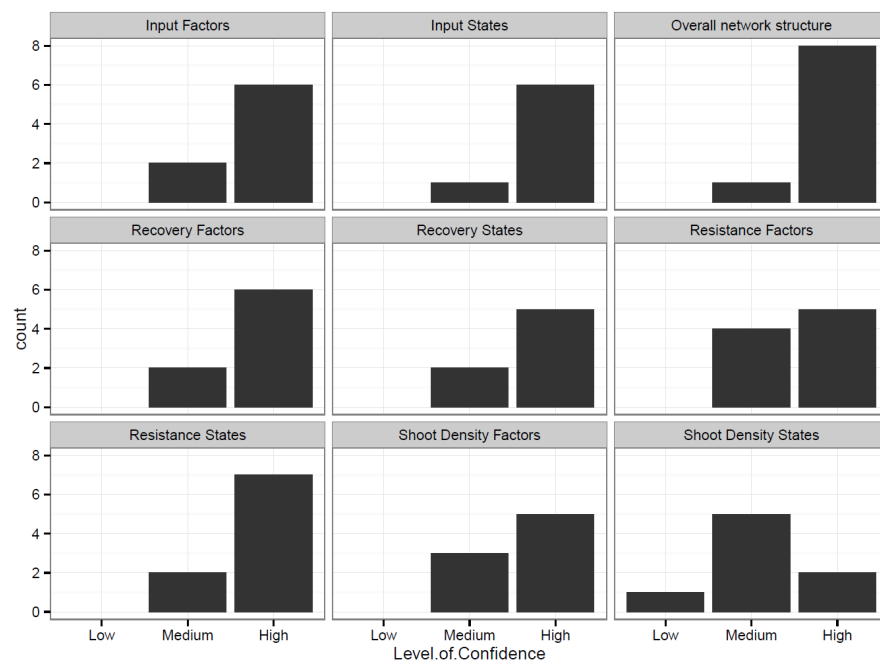
Month	P(control)	P(reduced)
Jan	0.998	0.144
Feb	0.998	0.005
Mar	0.998	0.031
Apr	0.998	0.015
May	0.890	0.003
Jun	0.771	0.003
Jul	0.998	0.004
Aug	0.998	0.004
Sep	0.998	0.004
Oct	0.998	0.004
Nov	0.998	0.005
Dec	0.998	0.054

Using the approach outlined above, the model is evaluated over a range of dredging scenarios corresponding to: (i) a tropical *Halophila* meadow using data from James Price Point (Western Australia) versus a temperate *Amphibolis* meadow from Jurien Bay (Western Australia), (ii) different durations of dredging, (iii) whether there are burial effects or not, (iv) whether there are sediment quality effects or not, and (v) whether the meadow was initially in good or poor physiological condition. The model was developed with seagrass experts and validated by a larger panel of experts

which included other seagrass experts as well as other marine ecologists/biologists. As can be seen from **Figure 5**, experts predominantly expressed moderate to high confidence in the model.

### 2.1. Results and Discussion

Consider firstly the scenario of capital dredging involving continuous dredging for twelve months. For both *Amphibolis* and *Halophila*, the meadow is driven to zero as shown in **Figure 6**. Note that the top plot shows the probability of



**Figure 5.** Count of experts and their level of confidence expressed in different parts of the model.

being in high, moderate, low or zero state over time from 2015 through 2022 and the bottom plot shows the weighted mean (assuming a uniform distribution) of the expected value and the interquartile range. Recovery occurs in both cases; however, the trajectories are markedly different. The *Halophila* meadow is in a tropical climate and has an annual meadow where the abundance declines to zero during the wet season and comes back during the dry season. This pattern is depressed during the period of dredging but comes back as soon as dredging pressures are removed. On the other hand, the *Amphibolis* meadow is a persistent one growing in a temperate climate and does not have large seasonal fluctuations. After dredging, it slowly recovers over five years to pre-dredging levels. In comparison, the maintenance dredging scenario produces a completely different response (**Figure 7**). For *Amphibolis* with good initial physiological status, the meadow is able to resist loss in that it does not go to zero and recovers faster; however, when it is in a poor physiological state initially, the meadow once again declines to zero even with a reduced dredging duration.

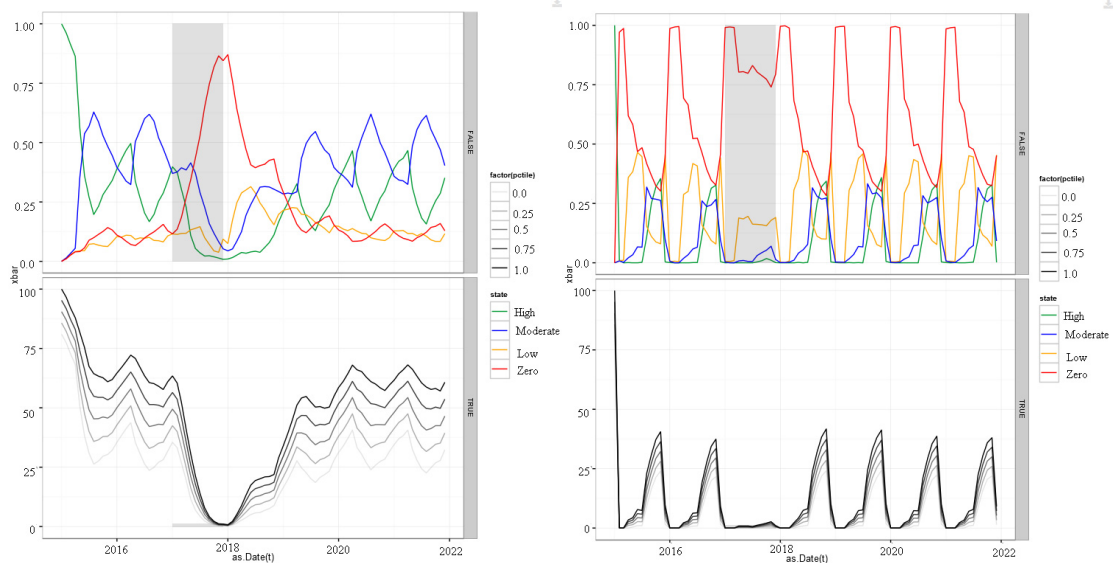
### 3. CONCLUSION

Here we demonstrate the application of DBNs to the problem of predicting complex ecosystem responses to dredging. The framework provides a tool to integrate expert knowledge with data in a whole-of-systems

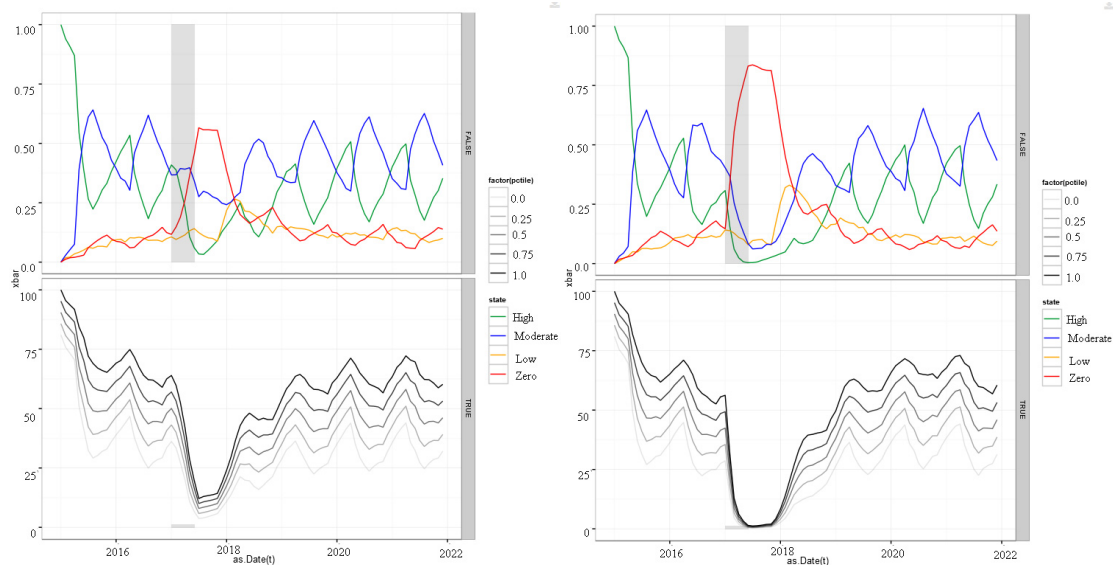
model that predicts cumulative effects in a bottom-up approach. A case study evaluation of two different types of seagrass meadows shows the utility of the approach in characterising the ecosystem response over time in a probabilistic sense as the probability of going to zero is especially important from a decision making perspective. Future work includes the adaptation of the DBN to data, analysing dynamic responses from a resilience perspective, and customising dashboards from model outputs to support decision making.

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**Figure 6.** Loss and recovery in shoot density for capital dredging for *Amphibolis* (on left) and *Halophila* (on right). The grey bar indicates a 12 month capital dredging program. Top plots are the probability of each shoot density state and the bottom plots show the weighted mean of the expected value and the interquartile range.



**Figure 7.** Loss and recovery in shoot density for a 6 month maintenance dredging program for *Amphibolis* with good initial physiological status (on left) and poor initial status (on right). Compare with **Figure 6**.

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