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# Simple, policy friendly, ecological interaction models from uncertain data and expert opinion

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ABSTRACT

In the marine environment, humans exploit natural ecosystems for food and economic benefit. Challenging policy goals have been set to protect resources, species, communities and habitats, yet ecologists often have sparse data on interactions occurring in the system to assess policy outcomes. This paper presents a technique, loosely based on Bayesian Belief Networks, to create simple models which 1) predict whether individual species within a community will decline or increase in population size, 2) encapsulate uncertainty in the predictions in an intuitive manner and 3) require limited knowledge of the ecosystem and functional parameters required to model it. We develop our model for a UK rocky shore community, to utilise existing knowledge of species interactions for model validation purposes. However, we also test the role of expert opinion, without full scientific knowledge of species interactions, by asking non-UK based marine scientists to derive parameters for the model (non-UK scientists are not familiar with the exact communities being described and will need to extrapolate from existing knowledge in a similar manner to model a poorly studied system). We find these differ little from the parameters derived by ourselves and make little difference to the final model predictions. We also test our model against simple experimental manipulations, and find that the most important changes in community structure as a result of manipulations correspond well to the model predictions with both our, and non-UK expert parameterisation. The simplicity of the model, nature of the outputs, and the user-friendly interface makes it potentially suitable for policy, conservation and management work on multispecies interactions in a wide range of marine ecosystems.



## 1. Introduction

The marine environment and its ecosystems present major challenges for management (see reviews by Islam and Tanaka, 2004; Cicin-Sain and Belfiore, 2005; Ehler, 2005; deYoung et al., 2008; Zacharias, 2014). For example, in much of the marine environment, determining population sizes cannot be achieved by simple counts, but require mathematical models with inherent uncertainty (Hilborn and Walters, 1992). Ecological interactions are also uncertain. For example, in fisheries, top down tropic interactions have been extensively studied but data are highly variable in nature and patchy in time, space and for different species (Pope, 1991; Magnusson, 1995; Livingston and Jurado-Molina, 2000; Pinnegar and Stafford, 2007; Pinnegar, 2014). Knowledge of bottom up interactions is largely non-existent in many systems, and rarely incorporated in predictive models (see Engelhard et al., 2013 for ecological importance of bottom up effects; and Christensen and Pauly, 1992 for details of the Ecopath model, which considers biomass consumption in a bottom up context). Competition is very rarely included in species interaction models (despite initial predictions by May et al., 1979 of its potential importance).

Marine ecosystems differ from many terrestrial systems in being largely ‘natural’; albeit highly disturbed by anthropogenic activity. Food production on land, for example, is largely through agriculture, yet, despite increases in aquaculture, most marine fish are natural resources harvested directly from a natural system (World Bank, 2013). As such, predictive community based models might

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be more useful in marine environments than in terrestrial environments.

Protecting the marine environment is of paramount concern to environmental policy makers (Hallwood, 2014; Zacharias, 2014). The marine environment provides economic income through fisheries, as well as a range of other ecosystem services (Hallwood, 2014). Under international agreements such as the Convention on Biological Diversity (www.cbd.net), detailed policy documents have recently been produced by many governments to protect marine resources. For example in the North-East Atlantic, fifteen governments are contracted to establish a network of marine protected areas (OSPAR Commission, 2013). Under the European Union (EU) Marine Strategy Framework Directive (MSFD), member states aim to achieve good environmental status across European seas by 2020. To meet commitments under MSFD the UK is committed to contributing to a network of marine protected areas (JNCC, 2014). Policy documentation from the UK government on implementation of MSFD provides a wide range of targets, which for many named species or taxonomic groups indicate population level targets of 'no decrease on current levels' (DEFRA, 2012). Similarly, population management targets of 'maintain or 'recover' have been assigned to particular species within designated Marine Conservation Zones in England (Natural England, 2014). As an example, the ministerial order (second level legislation) for the MCZ in the Tamar Estuary in SW England reads: "(1) The conservation objective of each of the Zones is that the protected features—(a) so far as already in favourable condition, remain in such condition; and (b) so far as not already in favourable condition, be brought into such condition, and remain in such condition. (2) In paragraph (1), —favourable condition‖— (a) with respect to a broad scale marine habitat or a marine habitat within a Zone, means that— (i) its extent is stable or increasing; and (ii) its structures and functions, its quality, and the composition of its characteristic biological communities are such as to ensure that it remains in a condition which is healthy and not deteriorating; " (Tamar Estuary Marine Conservation Zones Designation Order, 2013). While specific species are mentioned in many MCZ ministerial orders, the idea of habitats improving or deteriorating and populations increasing and decreasing are common throughout.

Even in states where marine protected areas have a longer history, the fundamental principles of systems recovering or not degrading are entrenched in their policy documentation. For example, New Zealand's policy and implementation plan for marine protected areas has the following "desired outcomes for Coastal and Marine Biodiversity in 2020":

"a) New Zealand's natural marine habitats and ecosystems are maintained in a healthy functioning state. Degraded marine habitats are recovering. A full range of marine habitats and ecosystems representative of New Zealand's marine biodiversity is protected. b) No human-induced extinctions of marine species within New Zealand's marine environment have occurred. Rare or threatened marine species are adequately protected from harvesting and other human threats, enabling them to recover. c) Marine biodiversity is appreciated, and any harvesting or marine development is done in an informed, controlled and ecologically sustainable manner. d) No new undesirable introduced species are established, and threats to indigenous biodiversity from established exotic organisms are being reduced and controlled" (Department of Conservation and Ministry of Fisheries (2005)). Indeed, while there is much more detail on the comprehensive benefits of networks of MPAs in New Zealand, the overall goals are still expressed in terms of population increases and decreases.

Given the uncertainty in knowledge of marine ecosystems, and the need to adhere to what could be perceived as 'crude' policy and legislation measures, simple predictive models, with an ability to cope with sparse data and uncertainty are required (Stafford and Gardner, 2013). However, the predictions of these models can also be modest and still be fit for purpose (for example, predicting increase or decrease of population sizes). Bayesian Belief Networks are an example of such models, and have had considerable use in ecological management and in linking ecological and socio-economical outcomes (Marcot et al., 2001; McCann et al., 2006; Langmead et al., 2009).

It should be noted that nomenclature surrounding Bayesian networks in general is not consistent between authors. Many Bayesian networks are complex, requiring much data in the form of parameter distributions for use (Uusitalo, 2007). Classes of Dynamic Bayesian Networks (DBNs) can use intensive time series data to 'learn' interactions between nodes (or species, in an ecological context), and cope with feedback loops (e.g. Aderhold et al., 2012; Grzegorczyk and Husmeier, 2013). In this study we define Bayesian Belief Networks (BBNs) as static networks, which require point estimates of probabilities, such as those modelled by software such as JavaBayes or Netica. The advantage of such networks is that expert opinion, especially in the environmental sector, can be obtained by such point estimates (i.e. a 90% probability of an event happening), but is not easily obtainable in terms of more abstract 'population distributions' required by many more advanced Bayesian networks (Uusitalo, 2007). However, such BBNs cannot intuitively account for two way interactions between species (as may occur from competition, for example; Uusitalo, 2007; Norsys Software, 2015) reducing their practical value in modelling ecosystem community dynamics (Stafford et al., 2013; but see Hammond and O'Brian, 2001; Hammond and Ellis, 2002 for examples of top-down trophic dynamics). While there are often workarounds for incorporating two way interactions between competing species, these are not intuitive and not generally in common use (see reviews by Campbell et al., 2012; Schuchert et al., 2012; for further discussion of these points). Indeed, to the authors' knowledge, no ecological studies using static Bayesian belief networks (rather than DBNs) have incorporated feedback loops or interactions between species, and most focus on the links between community state (as a node) and various socio-economic factors (Campbell et al., 2012). Where various species or taxonomic or functional groups have been modelled, interactions between species have not been included explicitly in the model (e.g. Langmead et al., 2009; Allen et al., 2012).

Given the importance of species interactions in creating stable and diverse communities, it is necessary to consider these interactions when modelling the fate of any given population. In this study, we present a modified belief network model, based on simple BBNs, and encapsulating much of the usability of the technique (e.g. point estimates), but capable of simulating trophic and competitive interactions in ecological communities (by implementing mechanisms for reciprocal feedback between nodes of the network). Within this study we refer to these models as 'Belief Networks', as they capture the concept of belief of processes, but are not based solely on Bayesian inference.

The primary objective of this research is to investigate whether the simple belief networks we have developed can be useful in predicting community dynamics at a level appropriate for implementation as a policy instrument (i.e. indicating the certainty in which simple changes, such as increase or decrease, in different populations will occur as a result of an intervention). As a secondary objective, we also examine whether expert opinion can be incorporated in the network, and determine the significance of 'best guess' expert opinion on the final model predictions.

For ease of validation of results, we base our belief network on a rocky shore community in the UK. We parameterise the network based on estimates of parameters, from our knowledge of the