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Informing network management using fuzzy cognitive maps

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ABSTRACT

Modern conservation requires robust predictions about how management will affect an ecosystem and its species. The large uncertainties about the type and strength of interactions make model predictions particularly unreliable. In this paper, we show how fuzzy cognitive maps can produce robust predictions in complex and uncertain ecosystems. The use of fuzzy cognitive maps has been increasing markedly, but there are two critical issues with the approach: translation of expert knowledge into the FCM is often done incorrectly; and sensitivity analyses are rarely conducted. Translating expert knowledge is a constant challenge for ecological modellers, often because experts know about the behaviour of a system, but modellers need to know model parameters, which subsequently lead to system behaviour. We describe how to correctly incorporate expert knowledge into FCMs, and we describe how to appropriately conduct uncertainty and sensitivity analysis. We illustrate this process with a previously published network for feral cat and black rat control on Christmas Island. Perverse indirect effects of conservation management are a key concern, and methods to help us make informed decisions are required. Fuzzy cognitive maps are a promising approach for this, but it requires the methodological improvements that we present here.

1. Introduction

Environmental systems are complex and interconnected, so even small changes to local processes can substantially change the future state of populations, ecosystems, and the environment (Shears and Babcock, 2003; Fortin et al., 2005; Holdo et al., 2009). Conservation initiatives are better resourced than ever before, but despite best intentions, unintended negative consequences of management sometimes occur (Dexter et al., 2013; Larrosa et al., 2016; Pech and Maitland, 2016). To avoid such perverse outcomes, we must account for species interactions that govern the dynamics of complex ecosystems. However, detail about how species affect each other is often lacking, and gathering ecological information can be expensive and time consuming (Caughlan and Oakley, 2001) – particularly for species interactions (Dambacher et al., 2003). Since this cost is high, it's important to know whether data already exists to proceed with management, or whether more data is required. Making robust predictions about how any action will affect a whole system is vital for informed management decisions, but, doing this has been a key methodological challenge.

Network models are important for informing system management, as they can predict how changes will proliferate throughout a complex system. For example in ecology and conservation, they have been applied to manage ecosystems for threatened species conservation (Ramsey and Norbury, 2009; Bode et al., 2016), and to help improve fisheries management (Smith et al., 1999; Fulton et al., 2011; Punt et al., 2016). However, network models require detailed knowledge about many interactions, and different modelling software can produce qualitatively different predictions (Forrest et al., 2015). Hence, we must develop methods to make predictions in systems where data are scarce and the nature of interactions is unknown; fuzzy cognitive maps (FCMs) are a promising solution.

A growing body of literature uses FCMs to analyse networks (see Supporting information S1), and they have been applied broadly in conservation and ecology (Papageorgiou and Salmeron, 2013), facilitated by easily accessible software (e.g. Gray et al., 2013). FCMs utilise expert knowledge about whether entities have positive or

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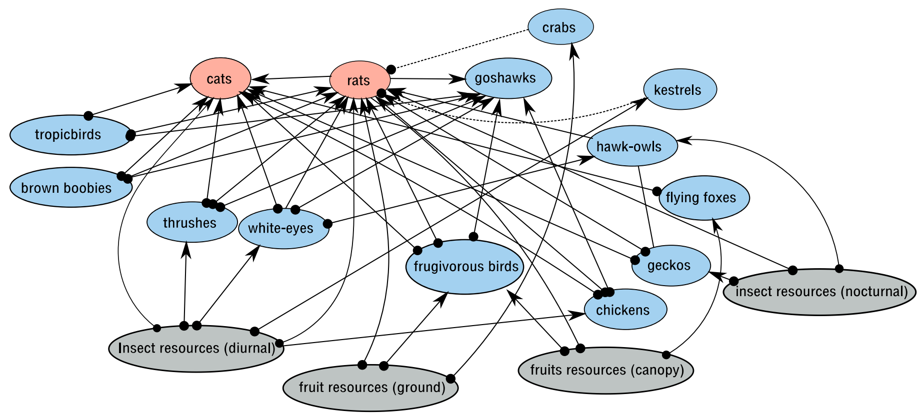

Fig. 1. Interaction network for the Christmas Island case study (reproduced from Han (2016)). The species are represented by nodes of invasive (red) and native species (blue). The grey nodes represent resources on the island. Links between species are displayed by solid (direct links) and dashed arrows (uncertain links). For the analysis in this paper, we assume that the uncertain links exist. The pointy end of an arrow indicates the species that receives a benefit from this interaction, the round end indicates a species that is harmed by the interaction. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

negative interactions on each other to predict how changes will proliferate throughout a system (Kok, 2009). Ideal for systems with little data, they can help formalise expert reasoning and predictions (e.g. Game et al., 2017). For systems where highly parameterised models are unsuitable, they openly and transparently display the logic behind expert predictions - an important aspect of conservation decision-making (Blomquist et al., 2010; Donlan et al., 2014).

While using expert knowledge to build a network model posits many advantages, relying on opinions of individuals has drawbacks: experts can be biased; translation of knowledge into the FCM can be non-intuitive; and appropriate sensitivity and uncertainty analysis must be conducted. This is important because people are biased in factual estimation (Martin et al., 2012a), projection (McCarthy et al., 2004), and ecological decision-making (Burgman, 2005; Holden and Ellner, 2016). Translating expert opinion into models is challenging because we intuitively interpret interactions as the effect of one node on another, rather than the per-capita interactions, as required for population models. Given these challenges, it is vital that appropriate sensitivity and uncertainty analyses are conducted. Unfortunately, these points are very rarely addressed in FCM analyses (but see Ramsey and Norbury, 2009; Ramsey et al., 2012; Sacchelli and Fabbrizzi, 2015). Given their widespread use and the potential for misinterpretation, accurate and robust results require updating of current methods.

In this paper, we describe how use of fuzzy cognitive maps must change to produce robust predictions in complex systems. First, we offer an overview of the FCM method and describe the methodological issues in detail. We then suggest ways that help translate expert knowledge for FCMs and help to appropriately account for uncertainty. Finally, we illustrate the application of FCM with a case study of an invaded ecosystem on Christmas Island, Australia. We often need to act fast in conservation (Martin et al., 2012b), but quantitative data is lacking frequently. Utilising expert opinion is a potentially powerful way for making robust predictions in complex systems, and FCMs are a valuable tool for this.

2. Material and methods

2.1. Christmas Island

The Australian Territory of Christmas Island is a small (135 km^2), oceanic island about 350 km south of Java and 1550 km north-west of mainland Australia. Being the top of an extinct underwater volcano the basalt island has never had a connection to the mainland and hence harbours a number of endemic species (James and McAllan, 2014), such as the Christmas Island flying fox (*Pteropus natalis*), the blue-tailed skink (*Cryptoblepharus egeriae*), the giant gecko (*Cyrtodactylus sadleiri*) and the Christmas Island imperial pigeon (*Ducula whartoni*), only to name a few. Having naturally small population sizes, endemic species are threatened by habitat loss, degradation, introduced diseases and invasive species (Misso and West, 2014). These threats have already caused several extinctions on the island (Wyatt et al., 2008; Lunney et al., 2011), and the loss of the Christmas Island pipistrelle was particularly frustrating, given the rescue effort (Lindenmayer et al., 2013). To avoid further extinctions, threatened species on Christmas Island now receive priority attention with management acting on the conservation of individual species, the restoration of degraded land and the removal of damaging invasive species, such as yellow crazy ants (Abbott et al., 2014) and feral cats (Johnston et al., 2016).

Well-documented and wide-ranging impacts of predator control indicate the potential for mesopredator release following the removal of the top-predator from the system. For example removing feral cats has been found to increase the predation pressure on native birds by releasing other invasive species from predation pressure, such as omnivorous black rats (*Rattus rattus*) (Courchamp et al., 1999; Fan et al., 2005; Rayner et al., 2007; Ritchie and Johnson, 2009; Prior et al., 2018). To test if mesopredator release is possible in the Christmas Island context, we consider a network of species interactions on Christmas Island (Fig. 1) and test the impact of removing feral cats on threatened species and whether rat control would be necessary. The Christmas Island species network, adapted from Han (2016), is a simplification of the real ecosystem, and as with many interaction networks, it was generated to capture the most important and relevant interactions for conservation management (Barbara and McKane, 2005).

The paucity of information on the strength of interactions between the species in the network makes analysing it particularly challenging. Hence, throughout our analysis we only use directional knowledge of species interactions – whether a species has a positive or negative affect on another – and three pieces of information about species impacts (expert opinion of Sarah Legge, Caitlyn Pink and Rosalie Wilacy):

1) The negative effect of cats on rats is bigger than the positive effect of thrushes on cats;
2) Fruit resources (canopy) have a larger positive effect on flying foxes than flying foxes have a positive effect on cats;
3) Brown boobies have a larger positive effect on cats than on rats.

Given the large uncertainties, FCM is an appropriate way to proceed.

2.2. FCM method

A FCM map consists of *nodes* representing species or other entities, which are connected by *edges*, representing the interactions between the nodes. The value of each node is typically restricted to be between 0 and 1, and the interactions strengths are between −1 and 1. A positive value means that a node has a positive impact on the target node, and a negative value shows a detrimental impact. Self-interactions are