Title: Informing network management using fuzzy cognitive maps

Authors: Christopher M. Baker[1,2], Matthew H. Holden[1,3,4], Michaela Plein[5], Michael McCarthy[3,6], Hugh P. Possingham[1,3,7]

Affiliations

1 School of Biological Sciences, The University of Queensland, Brisbane, QLD 4072, Australia

2 CSIRO Ecosystem Sciences, Ecosciences Precinct, Dutton Park, Brisbane, QLD 4102, Australia

3 ARC Centre of Excellence for Environmental Decisions, The University of Queensland, Brisbane, QLD 4072, Australia

4 Centre for Applications in Natural Resource Mathematics, School of Mathematics and Physics, The University of Queensland, Brisbane, QLD 4072, Australia

5 School of Earth and Environmental Sciences, University of Queensland, Brisbane, QLD, 4072, Australia

6 School of BioSciences, The University of Melbourne, Melbourne, VIC 3010, Australia

7 The Nature Conservancy, 4245 Fairfax Drive, Arlington, VA 22203, USA

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- Predicting how management will affect a network is a key challenge of modern conservation.
- Fuzzy cognitive maps are a promising method to predict the outcome of network management.
- There are two critical methodological issues with fuzzy cognitive maps.

- We describe these issues and show how to overcome them.
- We demonstrate how to use a fuzzy cognitive map to inform management on Christmas Island.

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 makes 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.

Keywords: Species interactions, ecosystem modelling, invasive species, cat control, rat control

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 & 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, Hudson, James, MacGregor, & Lindenmayer, 2013; Larrosa, Carrasco, & Milner-Gulland, 2016; Pech & 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 & Oakley, 2001) – particularly for species interactions (Dambacher, Luh, Li, & Rossignol, 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 & Norbury, 2009; Bode et al., 2016), and to help improve fisheries management (Smith, Sainsbury, & Stevens, 1999; Fulton et al., 2011; Punt, Butterworth, de Moor, De Oliveira, & Haddon, 2016). However, network models require detailed knowledge about many interactions, and different modelling software can produce qualitatively different predictions (Forrest, Savina, Fulton, & Pitcher, 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 & Salmeron, 2013), facilitated by easily accessible software (eg S. A. Gray, Gray, Cox, & Henly-Shepard, 2013). FCMs utilise expert knowledge about whether entities have positive or 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 (eg 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, Luque, & Wilcox, 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, Burgman, et al., 2012), projection (McCarthy et al., 2004), and ecological decision-making (Burgman, 2005; Holden & 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 & Norbury, 2009; Ramsey et al., 2012; Sacchelli & 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, Nally, et al., 2012), 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.

Material and methods

Christmas Island

The Australian Territory of Christmas Island is a small (135 km^2), oceanic island about 350 km south of Java and 1,550 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 & 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, Law, Schulz, & Pennay, 2011), and the loss of the Christmas Island pipistrelle was particularly frustrating, given the rescue effort (Lindenmayer, Piggott, & Wintle, 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, Green, & O'Dowd, 2014) and feral cats (Johnston, McCaldin, & Rieker, 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, Langlais, & Sugihara, 1999; Fan, Kuang, & Feng, 2005; Rayner, Hauber, Imber, Stamp, & Clout, 2007; Ritchie & Johnson, 2009; Prior, Adams, Klepzig, & Hulcr, 2018). To test if mesopredator release is possible in the Christmas Island context, we consider a network of species interactions on Christmas Island (Figure 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 (Drossel Barbara & McKane Alan J., 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.

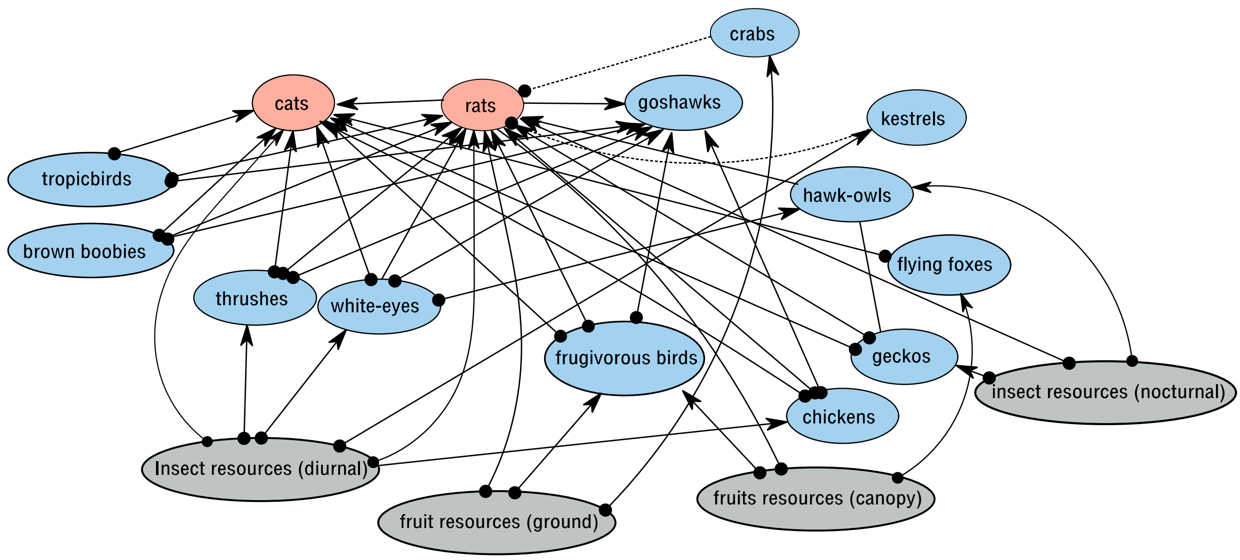

Figure 1: Interaction network for the Christmas Island case study (reproduced from Han (2016)). The species are represented by nodes of invasive (red) and native species (blue). The grey nodes represent resources on the island. Links between species are displayed by solid (direct links) and dashed arrows (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.

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 generally set to 0, though they can be set to be non-zero (Hobbs et al., 2002; Özesmi & Özesmi, 2004; Steven A. Gray et al., 2015). While predator-prey interactions are common, this framework allows for all types of interaction including commensalism, mutualism and competition (Herr et al., 2016). For example, to model mutualism between species i and j, the interactions $a_{i,j}$ and $a_{j,i}$ would both be made positive.

The value of each node is stored in a *state vector,* $\boldsymbol{n}$, and the edge weights are stored in a matrix, $\boldsymbol{A}$. The interaction effect of node j on node i is a_{ij}. For example, if $a_{ij} = -0.5$, then species j is having a negative impact on species i. The *state* of each node is given by the sum of all the interaction strengths, multiplied by the node value (see *Translating knowledge into FCMs* for further discussion about interactions). In maps representing interactions between species, the node value is some measure of the abundance of the species associated with that node, and the edges represent the per-capita influence on each other.

$$\boldsymbol{n} = f(\boldsymbol{A}\boldsymbol{n}). \tag{1}$$

The function f is the *activation function*. This function maps all states to values between 0 and 1, representing the minimum and maximum value for each node. While the true minimum and maximum abundance could be used, if known, FCMs are best used when in the absence of detailed information, (e.g. carrying capacities). If detailed knowledge is known, one should consider using a more mechanistic model. While there are a range of functions that have been used in the FCM literature, by far the most common is a logistic function:

$$f(x) = \frac{1}{1 + e^{-\lambda x}}, \tag{2}$$

where λ defines the shape of the curve. Typically λ is set to one, although other values have been explored. The choice of activation function has a major influence on results; this is discussed further in the *Activation function* section below. For a given set of interactions, $\boldsymbol{A}$, we solve for the equilibrium state by searching for the vector, $\boldsymbol{n}$, which satisfies equation (1). There are a range of ways to do this (see Supporting Information S2 for details). Once equilibrium has been obtained, we can simulate a management action by adding or removing nodes, by fixing the value of a certain node (eradicating species I would mean fixing $n_i = 0$), or changing interactions. Once we do this, we can solve equation (1) again to get the new state of every node and compare it to the original state to see the effect of management (see Supporting Information S3 for details).

In the following sections, we propose three modifications for FCMs. The first addresses model uncertainty, the second considers the distinction between the effect strength and interaction strength, while the third modification relates to the choice of activation function.

Model uncertainty

Since we have no information about the strength of most interactions, we generate every interaction (elements of $\boldsymbol{A}$) from a uniform distribution between 0 and 1 or -1 to 0, depending on whether it is a positive or negative interaction, respectively. From this distribution, we draw 100,000 parameters (discarding parameter combinations that do not satisfy any *post-hoc constraints*, as discussed in the following section). We refer to each randomly drawn matrix $\boldsymbol{A}$ that passes all model constrains as a parameter set. For each of these 100,000 parameter sets, we then simulate two management actions: 1) cat control and 2) cat and rat control, comparing the current state to the state after the management interventions. For each parameter set, we store the relative change in each species' state to obtain a distribution of change for each species across the 100,000 parameter sets – a standard approach in common network modelling procedures in conservation (Raymond, McInnes, Dambacher, Way, & Bergstrom, 2011; Baker, Gordon, & Bode, 2016).

Translating knowledge into FCMs

The difference between the *effect strength* and the *interaction strength* is somewhat subtle, yet important distinction. The *interactions strengths* – the elements of $\boldsymbol{A}$ in the model – define how nodes in the network interact with each other. These *per-capita* interactions do not vary with the state. The *effect strength*, however, is the actual impact of one node on another: it is the product of the interaction strength and the state and it actually emerges from the model. For example, suppose there were 3,000 cats on an island; the impact of the cats on the bird population is the effect strength. If there were 30,000 cats the effect strength would increase, or if there were only 300 cats, the effect strength would be much smaller. In essence, the effect strength incorporates abundances, and it is what is often observed in the field. In contrast, interaction strengths are independent of the abundance; in this example, they would model the impact of a single cat on the bird population. In our framework, we assume that the impact does not change depending on how many other cats there are. Precisely how the effect of one species on another changes with abundance is known as a functional response, and there are a range of ways they are represented in the ecological literature (Holling, 1959; Liu & Tan, 2007). In this paper, the model is a Type 1 interaction. Whatever functional response is used, there must be a clear distinction about whether observations correspond to innate aspects (i.e. the interaction strength) or emergent properties (i.e. the effect strength) of the model.

This raises a problem because the model requires interactions strengths, which are notoriously difficult to estimate (Dambacher et al., 2003; Baker, Bode, & McCarthy, 2016), while effect strengths, which are much easier to estimate and observe, cannot be directly included in the model. Despite this problem, many studies ask experts to estimate effect strengths and use them as interaction strengths (eg Pacilly, Groot, Hofstede, Schaap, & Bueren, 2016; Game et al., 2017). In fact, we are not aware of any FCM study with expert knowledge that has not done this. As the effect strength emerges from the model, it is entirely possible that a node that has a 'low strength', could actually have a relatively large effect in the model, if entered as an interaction strength rather than effect strength.

The three pieces of information about the Christmas Island interactions are all about effect strengths. We include them in the model as *post-hoc* constraints, i.e., for any candidate model, we calculate the effect strength of each interaction to ensure that the model is consistent with our post-hoc constraints. For example, for each random realisation of $\boldsymbol{A}$, we multiply the cat state by the interaction strength of cats on rats and compare that to the product of the state of thrushes and the interaction strength of thrushes on rats. If the magnitude of the latter is greater than the magnitude of the former, we deem the parameter set unviable and discard it. We repeat this for each of the three post-hoc constraints, only allowing the parameter set if it satisfies each post-hoc constraint.

Activation function

The choice of the activation function is crucial to the overall results. The commonly used logistic function (Eq. 2) contains the (shape) parameter, λ, which is usually set equal to 1, but other values have been used (Buruzs, Hatwágner, & Kóczy, 2015). An informed choice for λ is critical because changing its value influences the results (Supporting Information S4). Below we suggest a structured way for choosing its value.

The maximum or minimum values of states are restricted by λ and the number of interactions, the latter is itself limited by the number of nodes. We suggest choosing λ such that the maximum allowable state for a node with an average number of interactions is p. The average number of interactions, I_n, is the number of non-zero elements of A, divided by the number of nodes. Hence, we choose λ to satisfy the following equation:

$$\frac{1}{1+e^{-\lambda I_n p}} = p,$$

which leads to:

$$\lambda = \frac{1}{I_n p} \log\left(\frac{p}{1-p}\right).$$

There is no ‘correct’ choice for p, but we suggest choosing reasonably high values. We draw it randomly for each parameter set from between 0.9 and 0.9999 using the following equation

$$p = 1 - 0.1^{Z},$$

where $Z \sim unif(1,4)$. Choosing λ in this way ensures that we account for uncertainty in a parameter which is inherently arbitrary.

Results

Christmas Island

We use our FCM method to analyse the effect of i) cat removal and ii) cat and rat removal on the Christmas Island ecosystem. We draw random parameter sets, which each conform to the network structure (Figure 1). We filter out any that don’t satisfy the three post-hoc constraints and continue drawing until we reach 100,000 that are acceptable. For each parameter set, we record the percentage change in the abundance of each species when removing cats, and when removing cats and rats (Figure 2). The removal of cats alone has a moderate benefit for many species. However, the subsequent release of rats has a slight negative impact on nocturnal insects and fruit resources. Removing cats and rats together has much greater positive impact on most species. In this case, the only clear loser are kestrels, likely due to the loss of prey.

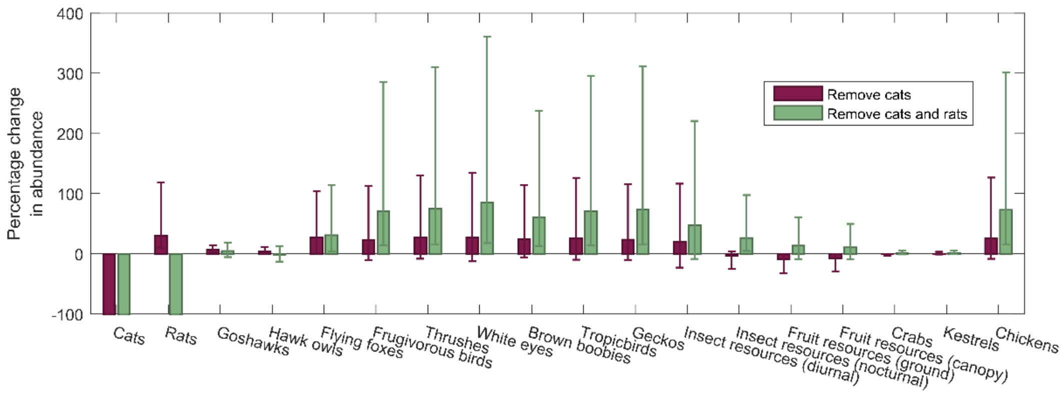

Figure 2: Percentage median abundance change for each node following cat control (maroon) or cat and rat control (green). The error bars represent the 5th and 95th percentiles across the 100,000 parameter sets.

To analyse the confidence in an increase or a decrease of a species' abundance following management, we investigated how frequently species increased in the parameter sets (Figure 3). This indicates that birds of prey (goshawks and hawk owls) are less likely to increase when both invasives are managed as compared to cat control alone, while the opposite is true for all other species.

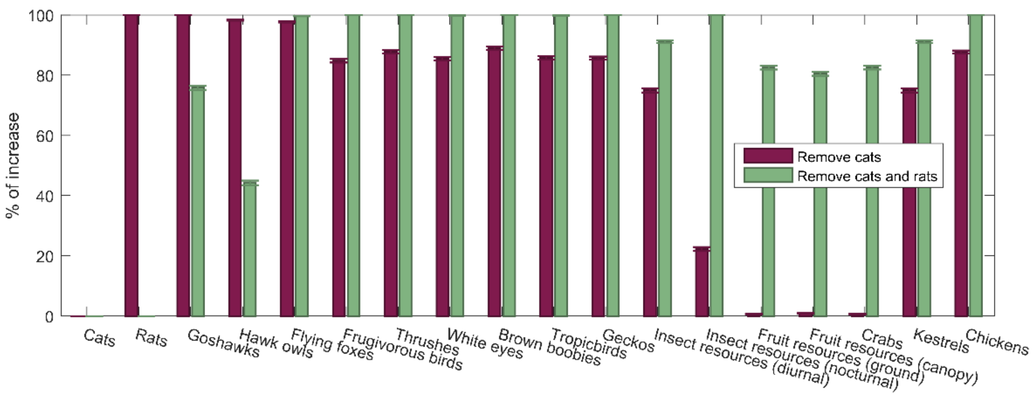

Figure 3: The percentage of simulations in which a species increases following cat control (maroon) or cat and rat control (green) across the 100,000 realisations. A bar at 0 means that this species never increased, while if the bar is at 100, it means that the species increased in every simulation. The error bars are calculated by resampling the model output with replacement 1,000 times, with

each sample containing 10,000 model outputs. We calculate the frequency of increase for each sample, and the error bars show the 5th and 95th percentile.

Post-hoc constraints

In our Christmas Island analyses we included three post-hoc constraints. Adding these post-hoc constraints increases the computational time of doing the analysis. To better understand how computational time scales with the number of post-hoc constraints, we considered a further seven arbitrary post-hoc constraints and reran the analysis using zero to ten post-hoc constraints (see Supporting Information S5 for details). We find that the model runs quickly with only a few post-hoc constraints, adding additional constraints increases computational time approximately exponentially (Figure 4). On a typical computer, drawing 100,000 parameter sets can be done within an hour for up to five post-hoc constraints. However, increasing this to ten post-hoc constraints increases computational time to around two days.

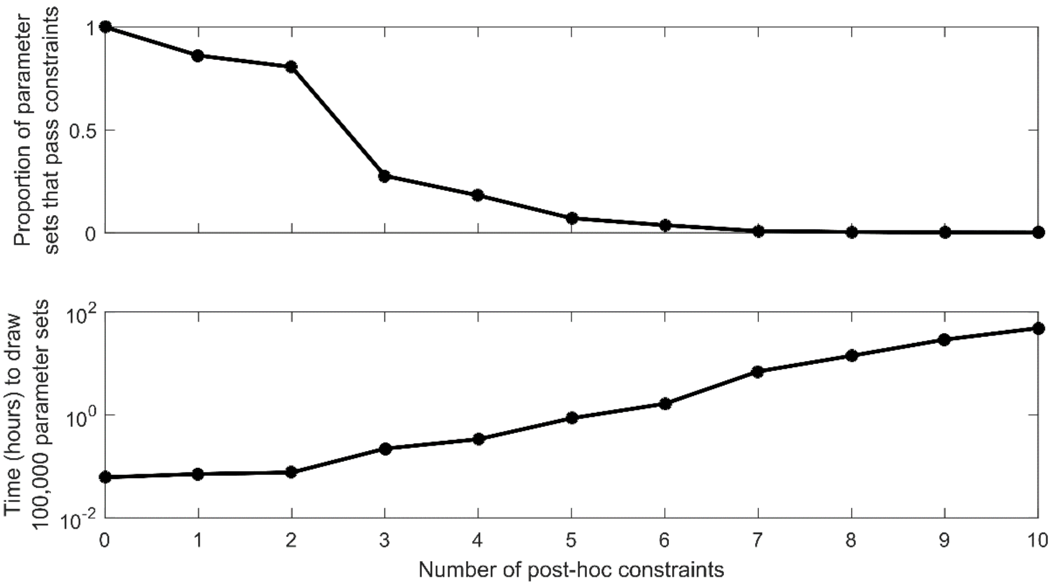

Figure 4: The effect of the number of post-hoc constraints on computational time. Top plot is the proportion of randomly drawn parameter sets that pass a set number of post-hoc constraints. For the three post-hoc constraints used in the Christmas Island example, about 25% of parameter sets

are accepted. The bottom plot shows the approximate computational time for drawing 100,000 acceptable parameter sets, running MATLAB on a computer with a 2.7GHz processor.

Discussion

In this paper, we have presented a way of altering FCM analysis to include expert knowledge of interactions and deal with parameter uncertainty. It is vital that uncertainty is modelled in conservation, and FCMs cognitive maps are no exception. We applied our FCM analysis to a species interaction network from Christmas Island to predict how feral cat and black rat management will affect the ecosystem. Despite large uncertainties in the system, we still showed that the removal of both species likely caused all other modelled species to increase, except for birds of prey, which may suffer some declines following rat removal. Our findings indicate that the system dynamics are very much a product of the network, and the precise interaction strengths are of lesser importance. Beyond making predictions about the system, which can help determine what management actions to take (removing cats vs removing cats and rats), it can inform future management of the system. For instance, in our network, if cats and rats are removed, hawk owls may decline due to a loss of food resources. Given this possibility, targeted monitoring could be implemented to track hawk owl abundance and additional feeding could be a possibility.

While we have focused on how to represent expert knowledge of interactions in a FCM and how to incorporate uncertainty, FCMs face other challenges relating to eliciting expert knowledge. While guidance is available on how to elicit which nodes should be in a network (Prigent, Fontenelle, Rochet, & Trenkel, 2008; Kermagoret, Levrel, Carlier, & Ponsero, 2016), eliciting effect strengths, combining different expert opinions and conducting linguistic sensitivity analysis requires further work. Adding post-hoc constraints reduces the probability that a randomly generated set of interaction strengths will satisfy all post-hoc constraints, which increases the computational time exponentially. Since effect strength can only be incorporated as a post-hoc constraint its estimation increases the computational difficulty of the analysis considerably. We suggest to only use effect strengths when they are known with high certainty. As our results show, we can obtain consistent results from little information.

If many effect strengths are being used in the model, we suggest that every interaction can be given a qualitative strength indicator, for example weak, medium or strong. Then, for each parameter set, it is required that all the weak interactions are smaller than the medium, which are in turn weaker than the strong. Since the probability of generating suitable parameter sets becomes very small with an increasing number of post-hoc constraints, two options exist to deal with this problem. Firstly, we may allow for an error rate; for example, if 90% of the interactions are in the correct order (ie 90% of the 'strong' effects are stronger than all of the 'moderate' effects), then it could be deemed a suitable parameter set. This in itself can be seen as a way of incorporating linguistic sensitivity into the analysis. Secondly, approaches akin to approximate Bayesian computation (Battogtokh, Asch, Case, Arnold, & Schüttler, 2002; Beaumont, 2010) could help find suitable parameter sets. Generating parameter sets and saving those that most closely meet the post-hoc constraints could help to draw new parameters. This process is repeated until parameter sets that satisfy all post-hoc constraints are obtained. Thirdly, experts can disagree about parameter values; for example, some experts might believe an interaction is strong, while others are convinced about it being medium. In these circumstances, we suggest allowing that effect strength to be either medium or strong in the model.

The increased computational time associated with adding constraints also leads to the question of how many simulations should be done. Fundamentally, this boils down to whether the results would change with more simulations. One way to tackle this is to resample the simulations with replacement, as we did in Figure 3, and compare how the results change between different sub-samples of the simulations. In our case, we found almost no variation in the frequency of increase and thus we are confident that have done enough simulations.

Interpreting model results and understanding the limitations of FCMs is critical. In our case, predictions of increase or decrease are incredibly consistent across simulations. However, for many species the potential range of abundance change is large. For these species, the only conclusion that we can reach is that the data is insufficient to give a precise prediction of abundance change. With this in mind, stakeholders can chose to accept the level of uncertainty when they are making decisions or they can chose to spend more time and resources to reduce uncertainty. For the latter, these models can help pinpoint the best way to spend those resources to reduce uncertainty most effectively.

FCMs have a range of weaknesses, including that they do not incorporate temporal dynamics and that they are phenomenological. Lacking a temporal component, the model cannot predict how long it will take to reach the new equilibrium state, or what path the system will take to get to the equilibrium. This is important because initial observations of the system could differ from model predictions – even if the equilibrium prediction of the model is accurate (Baker, Gordon, et al., 2016). This makes it harder for monitoring populations, since it is unclear what decision is to take when a population initially decrease. For Christmas Island, understanding the timescale of recovery requires more information, and managers would need to consider growth rates of species when thinking about how long it would take to move to the new equilibrium. FCMs are designed to be phenomenological, in the sense that we can use expert knowledge of a phenomenon (one node impacts another node) to create a model. We do not have detailed quantitative information on precisely how all the nodes interact (i.e., the mechanisms), and there is no clear way to incorporate this kind of information if it were available. FCM simplifies complex interactions, and is suited to study systems where detailed information is not available, yet, decisions must be made (Martin, Nally, et al., 2012).

Our suggestions regarding the changes to the FCM methodology are not to give better 'results', but help to make FCM into a more reliable methodology that properly handles uncertainty. As we have described, actually setting accurate values for interactions parameters is incredibly difficult and, particularly in these low-information situations, uncertainty will always exist. Using point estimates of parameters can give results that are simple to communicate, but not explicitly accounting for the uncertainty means those results give a false sense of certainty about the impact of management (Baker, Bode, et al., 2016). Our methodology clearly shows the limits of what you can conclude from a FCM in a specific situation. However, learning what we don't know isn't a dead-end – in fact it can provide a clear path forward, illuminating the steps required to make an open and transparent decision.

Conservation decision-making will always involve trade-offs and carry risks (Hirsch et al., 2011; McShane et al., 2011). Networks of multiple interacting species, or different stakeholders exacerbate this complexity. Mathematical modelling can help predict management outcomes, but any model is only as good as its input data. Hence, it is vital that methods are updated to both translate expert opinion into modelling frameworks and account for the large uncertainties that are present. If this is done, FCMs can become an important decision-making tool.

Data Accessibility

Code to reproduce all of the results in this paper has been included as online supporting information. https://doi.org/10.6084/m9.figshare.5674681

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S1: Literature search

We performed a literature search to get an indication of how use of fuzzy cognitive maps has changed through time in conservation and ecology, and to quantify the prevalence of sensitivity and uncertainty analysis in the field. We conducted the search using Web of Science on the 14th of March, 2017. Our search criteria were:

TOPIC: (fuzzy cognitive map*) AND TOPIC: (ecology OR environment* OR conservation) Timespan: 1996-2017. Indexes: SCI-EXPANDED, SSCI, A&HCI, CPCI-S, CPCI-SSH, BKCI-S, BKCI-SSH, ESCI, CCR-EXPANDED, IC.

While this did not return every paper in conservation and ecology that has used fuzzy cognitive maps, it does give an indication of change in use over time. This search returned 248 records, and we removed 161 records manually which, based on the title, clearly did not relate to our search (many of which were from the education field, about e-learning environments). We then downloaded each of the remaining 87 articles and kept those which used fuzzy cognitive maps in an environmental or conservation management context, or if they were explanations on how to use fuzzy cognitive maps. We also recorded whether each article conducted any type of sensitivity or uncertainty analysis. The full list of articles is given in Supplementary Table S1. Following this, 50 articles remained. 5 of these had a sensitivity or uncertainty analysis. There has been clear increase fuzzy cognitive maps through time, although there has been no clear increase in the number of papers conducting sensitivity or uncertainty analysis (Figure 1).

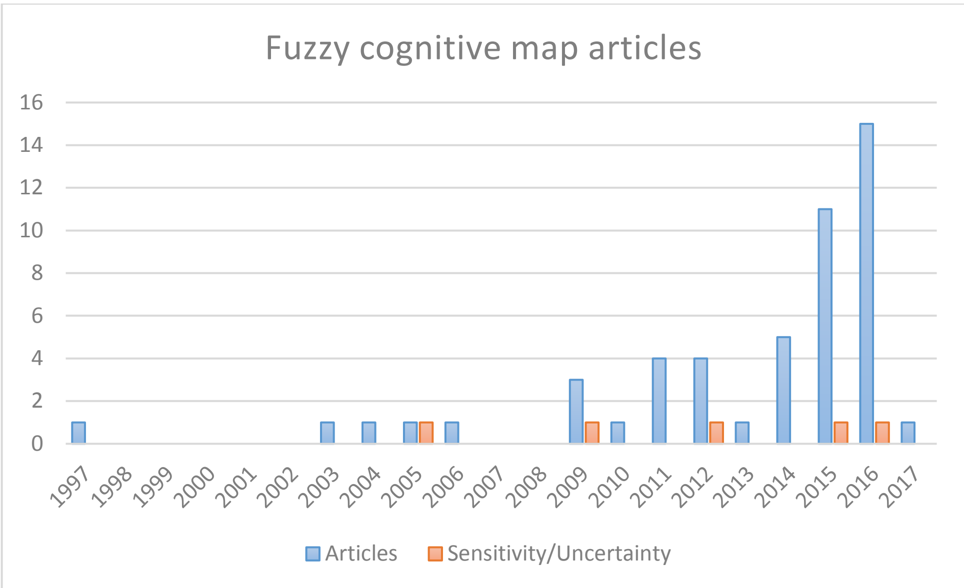

Figure 5: The number of papers published in each year using fuzzy cognitive maps since 1997. The blue bars represent the number of papers, and the orange bars are the number of papers that included a sensitivity or uncertainty analysis.

S2: Solving for steady state

The equation

$$\boldsymbol{n} = f(\boldsymbol{A}\boldsymbol{n}) \tag{3}$$

is a non-linear equation, and as such, there is no direct method to solve it. Rather, iterative methods are used. The most common method is fixed point iteration. This is done by starting from an initial guess, $\boldsymbol{n}_0$, and iterating the following

$$\boldsymbol{n}_{i+1} = f(\boldsymbol{A}\boldsymbol{n}_i) \tag{4}$$

Until $|\boldsymbol{n}_{i+1} - \boldsymbol{n}_i| < \eta$, where η is a very small number, such as 10^{-6}. Another option is to use a Gauss-Seidell scheme with the parameter $\omega < 1$:

$$\boldsymbol{n}_{i+1} = \omega f(\boldsymbol{A}\boldsymbol{n}_i) + (1 - \omega)\boldsymbol{n}_i. \tag{5}$$

This alternative method can help convergence.

Apart from these two iterative methods, most scientific programming languages include numerical methods for solving nonlinear equations that could be used. For example, the function ‘fsolve’ in MATLAB.

S3: Solving for equilibrium under management

There are three broad management situations that can be easily modelled using a FCM: node removal, node addition and node manipulation. The first two situations are easily solved. Adding or removing a node creates a new network, and to find the state of the new network, one would simply follow the procedure outlined in S2 for the new network. To run the analysis with node manipulation is a small extension. For example, from our case study, if we wanted to predict the effect of suppressing cats by 50%, we would firstly calculate the equilibrium state of the system and store the cat abundance. We would then fix cat abundance at 50% and solve Eq. (1) for all of the other node values, given the fixed cat abundance.

S4: Activation function

The activation function can have a big impact on the results. Here, we show results from a simple network (from Baker *et al.* 2016) to demonstrate this. We use a small network for this as it easier to see differences between sets of results on a small network and because this is to demonstrate what the phenomenon is and that it can arise in real networks. This network is to help understand about the role of dingoes in Australian ecosystems, and we show results the difference between network nodes when dingoes are included, compared to when dingoes are absent, using a fuzzy cognitive map. Rather than draw λ randomly, as we suggest, here we genereate results using three distinct values to show what effect λ has on model outputs (Figure 2). The absolute change in the system state varies dramatically with the value of λ.

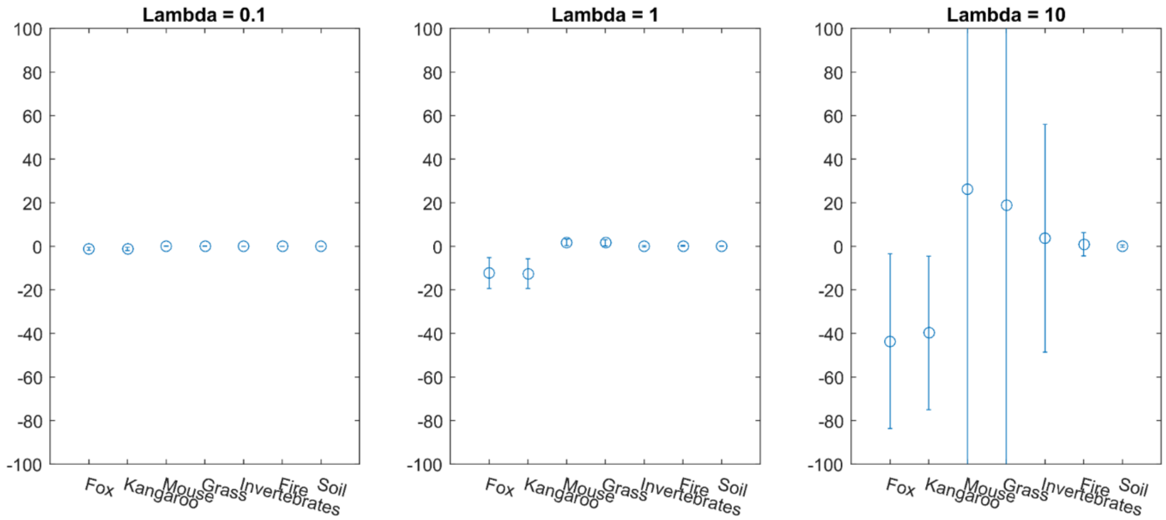

Figure 6: The percentage change in state for each node, after the introduction of the dingo to the network for different values of $\boldsymbol{\lambda}$. The circles show the median and the error bars depict the 5^{th} and 95^{th} percentile.

Next, instead of considering percentage change, we look at how frequently a node increased with dingo introduction (Figure 3). We find that this is remarkably robust to changing λ. Hence, predictions about whether nodes increase or decrease with management appear to be much more robust, compared to predictions of the change in the state of nodes.

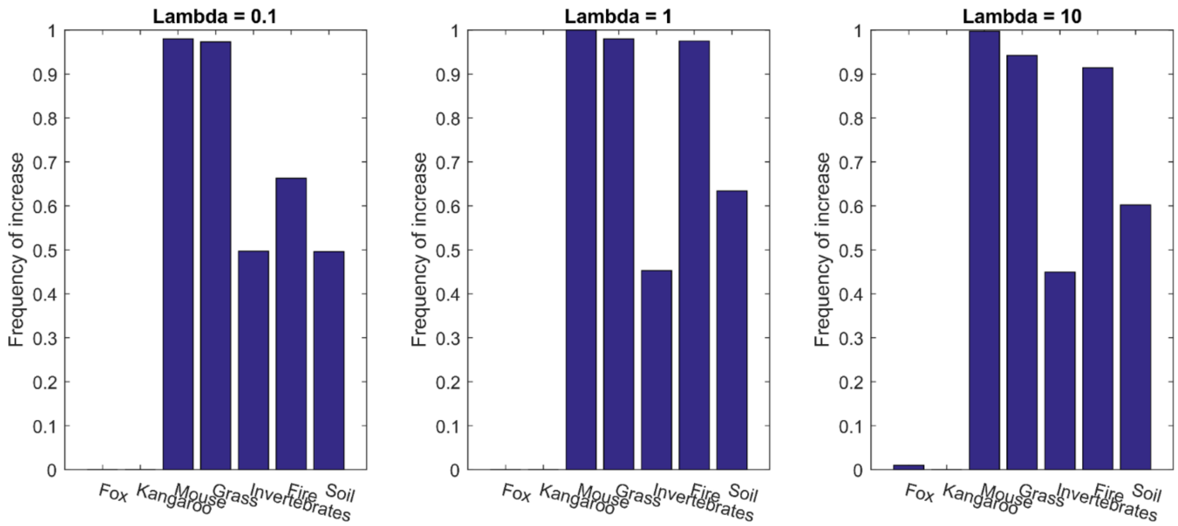

Figure 7: The frequency that nodes increase with the introduction of dingoes in the dingo network (Baker et al. 2016) across 10,000 parameter sets for varying values of $\boldsymbol{\lambda}$.

S5: Computational impact of post-hoc constraints

To test the computational burden of adding post-hoc constraints, we supplement the list of Christmas Island post-hoc constraints to get a list of 10:

1) Cats have a bigger (negative) effect on rats than thrushes have a (positive) effect.
2) Fruit resources (canopy) have a larger positive effect on flying foxes than flying foxes have a positive effect on cats; Thrushes are more strongly predated by rats than cats.
3) Brown boobies have a larger positive effect on cats than on rats.
4) Goshawks have a bigger impact on Tropicbirds than Rats do.
5) Insects (diurnal) have a bigger positive for Thrushes than on white eyes.
6) Fruit has a bigger positive impact on frugivorous birds than cats have negative impact on frugivorous birds,
7) Rats have a bigger impact on geckos than on insects.
8) Thrushes have a bigger impact on insects than white eyes do.
9) Cats benefit more from tropicbird than from gecko.

We emphasise that these are simply to test computational times, and are not representative of Christmas Island.

We test the computation time to generate acceptable parameter sets for 0 through 10 constraints. For each number of constraints, we generate 10,000 acceptable parameter sets. For each parameter set, we also randomise which constraints are being used (e.g. if we are using four constraints, we randomly sample four from the above list each time). We only draw 10,000 parameter sets due to the computational time required, particularly with many constraints. For each number of parameter sets, we record the number of attempts were required to get 10,000 acceptable sets. To estimate the time required to generate 100,000 parameter sets, we divide the time to get 100,000 parameter sets with not constraints by the proportion of acceptable parameter sets for each number of constraints.