Short Communication

Fuzzy cognitive maps outmatch loop analysis in dynamic modeling of ecological systems

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Abstract
Modeling natural systems is challenging due to their complexity in terms of variables, interactions, and dynamics. Much of this complexity is rooted in the existence of multiple ways through which acting variables affect each other. Besides the simple direct effects, numerous indirect effects emerge in ecological systems.
Through an illustrative example, I exemplify here several advantages of fuzzy cognitive maps (FCM) over loop analysis (LA) in dynamic modeling of ecological systems. In addition to being able to incorporate information about the magnitude of variables interactions, FCM can make predictions about multiple simultaneous perturbations. Furthermore, FCM allow for the simulation of different magnitude of initial perturbations to the system. Last, FCM estimate the amount of variable increase/decrease, not just the likely direction of change. Hence, even if LA is still much more used than FCM in the scientific literature, FCM can be considered fitter than LA in modeling ecological systems.

Keywords fuzzy cognitive maps; loop analysis; interaction weights; multiple perturbations; perturbation strengths; stock increase/decrease.

1 Introduction

Understanding and predicting the dynamics of ecological and environmental systems is a central goal in ecology. When modeling ecosystems and communities, the goal is typically to find a single model that fits the system under study. System dynamics just do it, since it is an approach to modeling the behaviour of complex systems over time which deals with internal feedbacks among variables that affect the non-linear behaviour of the entire system. What makes system dynamics different from other approaches to complex systems is the use of feedback loops, stocks and flows. Qualitative system dynamics (like loop analysis) uses signed digraphs to represent a system and analyzes a system through its community matrix. Unlike traditional network analysis, which requires detailed information about the strength of direct and indirect interactions, qualitative (loop) models rely on a matrix of positive, negative and zero interactions.

In this work, I suggest that fuzzy cognitive maps, although their use is still very limited in practice, provide fitter models of ecological and environmental systems if compared to classic qualitative models, both with regard to the comprehension of their functioning and to the prevision of their dynamics, at the only expense of a bit less parsimonious model building.

2 Loop Analysis

Loop analysis (LA; Puccia and Levins, 1985) uses signed digraphs to represent networks of interacting variables. System variables are depicted as nodes in the graph, and each connection between two nodes represents a non-zero coefficient of the community matrix. Perturbations may act on ecosystems by changing one or more parameters in the growth rate of the variables. Taking the inverse of the community matrix provides an estimate of the direction of change in the equilibrium level of variables in response to these parameter changes.

The element a_{ij} of the matrix represents the effect of variable j on the growth variable i, when the following equation is solved for a moving equilibrium:

$$\frac{dX_i}{dt} = f_i(\mathrm{X}_1, \mathrm{X}_2, ..., \mathrm{X}_\mathrm{n}; \mathrm{C}_1, \mathrm{C}_2, ..., \mathrm{C}_\mathrm{h}), \qquad (1)$$

where $X_1 \dots X_n$ represent the variables and $C_1 \dots C_h$ the parameters. Responses of abundances are arranged in a table of predictions whose signs show the predicted direction of change. The entries in a table denote variations expected in all the column variables when parameter inputs affect each row variable.

LA provides predictions on the probable direction of change in variables abundances to single variable perturbations. In complex systems these predictions may be ambiguous, being the result of opposite actions exerted on the same variable by way of multiple pathways of interactions. In case of ambiguous predictions obtained from LA algorithm, thousands of simulations of the strength of interaction coefficients are used to solve ambiguities. Recent applications of LA can be found in Allesina and Pascual (2008), Berlow et al. (2004), Dambacher et al. (2007).

3 Fuzzy Cognitive Maps

One way to make link magnitude explicit in a way that can be used in qualitative analysis is used here, taking advantage of another type of system representation: fuzzy cognitive maps. Kosko (1986) introduced fuzzy cognitive maps (FCM) to illustrate the model of a system using a graph of concepts and showing the cause and effect among concepts. A FCM describes the behaviour of a system in terms of concepts; each concept represents a state, variable or a characteristic of the system. Values of concepts (nodes) change over time, and take values in the interval [0, 100]: a value of 0 means that the factor is not present, a value of 100 means that the factor is present to the maximum extent possible, while a value of 50 represents the actual level of system variables. The causal links between nodes are represented by directed weighted edges that illustrate how much one concept influences the interconnected concepts, and the causal weights of the interconnections belong to the [-1, +1] interval. The strength of the weight w_{ij} indicates the degree of influence between concept C_i and concept C_j. The value of each concept at every simulation step is calculated by applying the following rule:

$$A_j(t) = A_j(t-1) + \sum_i A_i(t-1) * w_{ij} \qquad (2)$$

where $A_j(t)$ is the value of concept C_j at time t, $A_j(t\text{-}1)$ is the value of concept C_j at time t-1, w_{ij} is the weight of the interconnection from concept C_i to concept C_j.

Although FCM is very underused to date, recent applications can be found in Kok (2009), Prigent et al. (2008), Ramsey and Veltman (2005).

4 An Example

Fig. 1 shows an example of a FCM model, and the corresponding LA model obtained by leaving out weights of interactions.

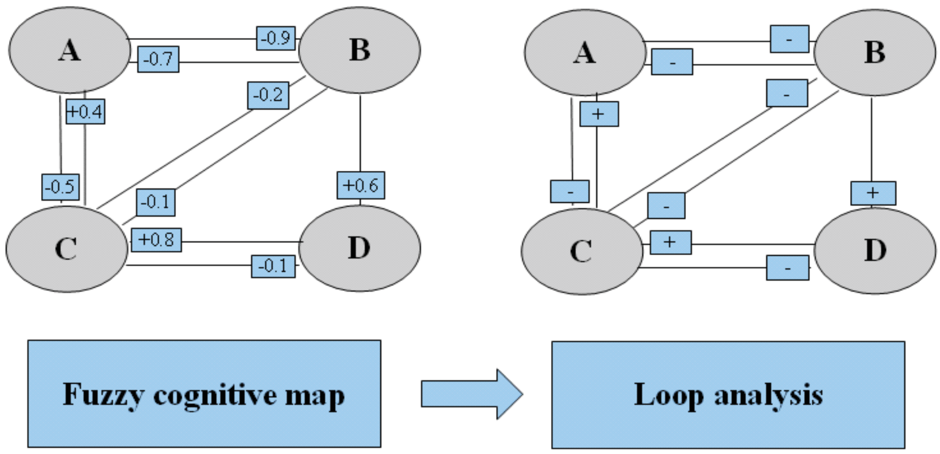

Fig. 1 On the left, the FCM model with weights of interaction. On the right, the corresponding LA model where weights have been replaced by signs (+, -, 0) of interaction.

Table 1 Prediction table of the LA model of Fig. 1. Perturbations should be read on the rows, effects on the columns. For instance, an increase in the rate of A determines an increase in the stock of A itself, and a decrease in the abundances of B, C and D.

Prediction table	A	B	C	D
A	+	-	-	-
B	-	0	0	-
C	0	0	0	-
D	+	-	-	+

Table 2 Prediction table of the FCM model with regard to initial changes of system variable A.

system variable	input change	emerging results (steady value = 50)				convergence reached?
	steady value = 50	A	B	C	D	
A	52	72	0	1	1	Yes
	60	72	0	1	1	Yes
	70	72	0	1	1	Yes
	80	72	0	1	1	Yes
	90	72	0	1	1	Yes
	100	72	0	1	1	Yes
	48	28	100	99	99	Yes
	45	28	100	99	99	Yes
	40	28	100	99	99	Yes
	30	28	100	99	99	Yes
	20	28	100	99	99	Yes
	10	28	100	99	99	Yes

The prediction table (Table 1) of the LA model has been achieved after 100,000 simulations by randomly varying the strength of interaction coefficients (number of simulations with overall feedback <0: 75,459), in order to solve some ambiguous predictions.

Table 2 shows the results of different FCM simulations on input values of variable A.

Although FCM prediction table substantiate LA outcomes, the FCM uncovers much more. Even minimal (positive or negative) changes to variable A determine drastic final changes to the other variables. Moreover, higher levels of initial change do not determine different results, meaning that the system under study is very unstable with regard to changes of variable A, but a plateau in the expected results is soon reached as well. Furthermore, Table 2 tells us that variables B, C and D are easily prone to approach 0 (i.e. disappear from the system). Instead, variable A is very stable and its lowest value (i.e. 28) is safely higher than 0; hence, even drastic negative changes on variable A are not able to make it disappear from the system. Last, Table 2 tells us that variables B, C and D are extremely correlated with regard to the way they change as a consequence of changes to variable A, i.e. they present the same direction and rate of change.

Instead, changes to the initial value of variable C are not consistent with LA results. Positive changes determine in the FCM model high level for variable A, and values close to 0 for the remaining variables. As opposite, LA predicts steady values for A, B and C itself. This is the case where the importance of interaction strengths emerges in prediction of system behavior.

But what happens to the system under study if system variables are varied simultaneously? Table 3 shows the results of 3 simultaneous simulations on input values of variables A, B, C, and D.

Table 3 Prediction table of the FCM model with regard to multiple simultaneous perturbations of system variables. Perturbations should be read on the rows, effects on the columns.

input changes	A	B	C	D
A=5, B=5, C=25, D=75	72	0	0	0
A=50, B=25, C=100, D=10	72	0	0	0
A=20, B=75, C=25, D=40	28	100	99	99

For instance, it is interesting to note that an initial negative (and strong) perturbation on A is compensated by the system when B (which damps A) decreases as well (simulation 1 in Table 3).

5 Discussion and Conclusions

Qualitative models, like LA, suffer from an all-or-nothing nature of the predictions, and a great loss of information resulting from discarding information on the strength of interactions. In this work, the approach using LA provided predictions on the probable direction of change in species abundances to single species perturbations, and resulted suitable if only the direction of the effects of perturbations is required, not their magnitude. The strength of this approach is in its generality, and its parsimony (i.e., low effort in model construction) since it doesn't require the magnitude of interactions to be known.

FCM is a halfway between fully quantitative models of system dynamics and fully qualitative models like LA. In addition to being able to incorporate information on species interactions, the further advantage of the FCM approach over loop analysis is that it can make predictions about multiple simultaneous perturbations. The effect of implementing two different perturbations at the same time is not simply the sum of implementing each perturbation separately and adding the results. Furthermore, FCM allows the simulation of different magnitudes of initial perturbation to system variables, being this a pivotal information in system dynamics. Last, it calculates the amount of stock increase/decrease, not just the likely direction of change.

Of course, a sensitivity analysis in FCM models is possible as well, by varying the interaction strengths by 1%, 5% and so on. This could be particularly useful when the values of interaction strengths are questionable. The only advantage of LA over FCM relies on its higher level of parsimony, since LA doesn't require the knowledge about the strength of interactions among system variables. As outlined by Bondavalli et al. (2008), one way to make interaction magnitudes explicit in loop analysis of ecological systems might be the use of quantitative information about interactions that comes from ecological flow networks.

Due to these methodological advantages, though LA is still much more used than FCM, FCM can be considered fitter than LA in dynamic modeling of ecological systems, and it is hoped that their use in ecological and environmental research will increase in the next years.

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