Analysis of Farmers' Concepts of Environmental Management Measures: An Application of Cognitive Maps and Cluster Analysis in Pursuit of Modelling Agents' Behaviour

Livia Ortolani*, Neil McRoberts**, Nicholas Dendoncker***,
and Mark Rounsevell

1 Introduction

The Common Agricultural Policy (CAP) of the European Union (EU) recognises that agriculture is multifunctional and that its multifunctional nature should be promoted. Under this expectation, Europe's agricultural areas are required to provide a diverse mixture of market and non-market goods for the private benefit of agricultural businesses on the one hand, and public good on the other. For reasons that are very well understood, a completely liberalised agricultural market cannot be relied on to provide many of the non-market and public goods expected from a multifunctional agriculture, and, given this, some form of regulation of the market or governmental involvement in it is inevitable. One way to view the CAP, then, is as the mechanism by which the public buys non-market goods from Europe's farmers at a price which is sufficient to have them forego alternative activities which produce no public good. The aim of policy optimisation for the CAP, when viewed in this context, is to allow the public to purchase the maximum amount of good for the least cost and to compensate those farmers who are really contributing to social welfare.

Livia Ortolani · Nicholas Dendoncker · Mark Rounsevell
Center for Environmental Change and Sustainability, School of Geosciences,
University of Edinburgh, EH8 9XP, UK

Neil McRoberts
Land Economy & Environment Research Group, Scottish Agricultural College,
Edinburgh, EH9 3JG, UK
e-mail: neil.mcroberts@sac.ac.uk

* Present address: Associazione Italiana per L'Agricultura Biologica (AIAB), Via Piave, 14-00178, Roma, Italia
** Corresponding author.
*** Present address: Department of Geography, FUNDP, UC Louvain, 61 Rue de Bruxelles, 5000 Namur, Belgium

M. Glykas (Ed.): Fuzzy Cognitive Maps, STUDFUZZ 247, pp. 363–381, 2010.
springerlink.com © Springer-Verlag Berlin Heidelberg 2010

One important complicating factor in the process of policy evaluation and optimisation is that the people who generate the outcomes of policy (*i.e.* the farmers) are not the people who make the policy, and the farmers' individual and collective objectives may differ from those of the policy makers and, indeed, from each others. Under these circumstances the policy optimisation problem becomes a hierarchical (bi-level) problem and standard mathematical programming techniques are unlikely to produce optimal solutions (Candler *et al.*, 1981). A possible response to this difficulty is to use agent based modelling (ABM) to simulate farmers' responses to potential policy designs. This approach has the advantage of allowing for differences among famers' objectives while also retaining the hierarchical structure of the real world. However, in order to implement an ABM it is necessary to know the rules by which the virtual agents will behave in the model. FCMs may provide a means to describe some of those rules in a formal and structued way, as well as providing additional useful information to the analyst. This chapter is an examintation of these suggestions in the context of specific case study of agri-environment measure uptake by Belgian farmers.

The case study is discussed in later sections. In the remainder of this introduction we briefly describe some general aspects of ABMs and FCMs highlighting a mathematical connection between them; their roots in Markov process models. We then describe some generalised FCMs which have been applied to the study of agricultural intensification and environmental management. The two examples we use, together highlight the importance of the hierarchical problem structure, already noted above, which arises in the agri-environment policy area and we draw readers' attention to the similarity in problem structure discussed in this chapter and the one described by Kafetzis *et al.*, in their chapter in this volume.

1.1 ABMs in Land Use Modelling

As already noted an ABM approach preserves the hierarchical structure of the real world problem by allowing the policy-makers' objectives to configure some aspects of the ABM-world in which the modelled agents interact. The extent to which these objectives are satisfied is then an emergent property of the population of interacting agents (who are, of course, acting according to a set of behavioural rules that will include their own objectives).

ABMs are a class of simulation model which can be traced back to the pioneering work of Thomas Schelling in game theory (Schelling 1967) and the development of cellular automata (CA); starting with John von Neumann's CA models from the 1950's (Burks, 1966). The classical Schelling games and CA models are examples of finite state computational machines in which the interacting components can only take on discrete values from a finite set. In addition, there are typically a finite (and usually constant) number of interacting components and the interactions are typically modelled as discrete time, first order Markov processes (Meyn & Tweedie, 1993, see also Kafetzis *et al.* in this book). The transitions in the state of the modelled system between time points are encoded in sets of rules by which the values of the components are updated. Modern ABMs build on these basic concepts, but rather than modelling agents as cells in a fixed spatial arrangement (as in a CA) they may move over a lattice which can represent abstract or actual physical space (Bous quet & Le Page, 2004; Matthews *et al.*, 2007).

Clearly, ABMs require sets of behavioural rules to encode agent behaviour. One approach to making the rules correspond to farmers' behaviour in the real world, for agricultural systems anal;ysis, is to derive them from empirical data gathered from attitudinal or behavioural surveys. The process of moving from data to rules is recognised to be a problematic area for this type of research and is part of the process of ABM construction that might be improved by using FCMs as an intermediate step between the raw data and the final ABM rules. The rules must specify what the agent's action(s) will be depending on the values of input parameters at each time step. The input values may be from parameters that apply globally to all agents; they may be location specific (so that only agents with particular spatial references are dependent on them), or apply only to certain classes of agent at particular times. These differences essentially reduce to technical issues of implementation which are not the subject of this chapter. The main points to note about ABMs are that they are essentially rule-based and that they are typically Markov processes; these are basic characteristics which they share with *entailment projection* (see Kafetzis *et al.*, in this book) based on FCMs. It is this basic connection between ABMs and FCMs that motivates our investigation of the possibility for combining them.

1.2 FCMs: Generic Features and Specific Applications in Agri-Environment Analysis

FCMs are directed cyclic or acyclic graphs. (Axelrod, 1976) introduced binary cognitive maps and the subsequent development of FCMs was led by Kosko (1986; 1987). In FCMs the graph nodes refer to events, concepts, or quantities in the world while the graph edges represent causal connections between the nodes. A FCM is, then, a graphical summary of a set of entailments, or causal statements. The numerical values of the edges are the fuzzy weights, fuzzy degrees of belief, or fuzzy entailments. In a standard FCM these weights are typically crisp, real numbers in the interval [-1,1], meaning that FCMs are deterministic mathematical models which generate the same output every time a specific set of inputs is supplied. Specifically, as noted in Kafetzis *et al.* in this volume, FCMs are usually employed as first order Markov processes using matrix multiplication (see also Taber, 1981). Matrix Markov process models occur in a wide range disciplines as discussed by Kafetzis *et al.* FCMs, as a specific sub-group of matrix Markov models, have been used for, (among other thing)s: analysis of the sensitivity of the building construction process to different sources of problem (Dissanayake & AbouRizk, 2007); representation of biological processes in bioinformatics (Ettinger, 2002); development of automated supervisory process control systems (Stylios & Groumpos, 1998); medical diagnosis (Froelich & Wakulicz-Deja, 2008, Stylios *et al.*, 2008), analysis of socio-economic problems (Taber, 1981) and; failure mode and effect analysis (Paelaz & Bowles, 1996).

The focus of this chapter is on the value of FCMs as a tool in environmental and ecological modelling. The debate over sustainability and resilience of human activities has led to an increasing awareness of the need to analyse human-environment interactions in an holistic way; as socio-ecological systems (SES) (Gunderson & Holling, 2002; Giampietro, 2004). A feature of SES is that they combine many different types of process, including biophysical, economic and information flows.

This multiplicity of characteristics makes traditional approaches to modelling difficult to implement (Giampietro, 2004). In this situation, the focus which FCMs place only on cause and effect rather than mechanism is an advantage in making headway in understanding the possible dynamics of such systems.

Agriculture is one of the most obvious and important classes of SES, and one in which purposeful human management of the environment is being attempted on a huge scale. In industrialised countries there is a near-universal recognition that intensive agriculture has become unsustainable and active measures are being implemented to attempt to balance food production and environmental health. The balancing act being attempted in the EU, for example, through its CAP (as described above) is one of the most notable examples of these efforts. Aspects of the trade-offs entailed in this balancing act have been studied using FCMs at different scales.

McRoberts *et al.*, (1995), for example, used an FCM derived from a cause and effect diagram drawn by Verijken (1992) to illustrate the factors involved in the intensification of agriculture. The dynamic analysis conducted on the FCM by McRoberts *et al.* (1995) supported Verijken's (1992) original contention that the relationship between agriculture and free markets for food, leads to a closed, positive feedback loop of technological development and intensification. The knock-on effects of this closed loop are a reduction in social welfare resulting from increased unemployment and decreased income, and an increase in pollution. We examine Verijken's (1992) model here in more detail.

Verijken's (1992) cognitive model is reproduced in the upper half of Figure 1 together with the projected state activations when the model is projected as a three-valued cognitive map (i.e. fuzzy weights on the edges take only values of -1, 0, or 1 depending on the direction or existence of causality between concepts) The analysis supports Verijken's (1992) contention that the system is locked in a feedback loop of undesirable effects. In fact, this qualitative result can be inferred directly from the map since it is clear that there is no causal feedback from either of the regulatory policy nodes (*i.e.* Subv and Restr) to the feedback loop at the top of the map. In the lower half Figure 1, we have added such causal links and repeated the projection from the same initial state vector. The added connections are between the community cost and the two regulatory policy nodes and between these nodes and intensification and technology. The interpretation of these changes is to introduce a "polluter pays" feedback into the system: The higher the cost of market driven intensification, the greater the input to subvention and regulatory policies and the more these act to restrict intensification and technology. Note that no direct feedback is applied to the market itself in this analysis. The middle set of projections shows the result of maintaining this pattern of feedback throughout the simulation. The final set of projected data starts with the policy feedback mechanisms just described. In the projection process, thresholding was used so that states with values >0 are depicted as active (solid) while those with values ≤0 are depicted as inactive (open).

After 10 cycles the system enters a stable state in which only subvention policy and community cost nodes are active; the real world interpretation of this result being that imposition of the feedback "polluter pays" policy eventually suppresses the cycle of intensification. Since continuing to enact a costly policy is itself a cost on the community, it would be beneficial if the policy could be de-activated, provided that the system did not return to its previous, damaging configuration. This issue is assessed in the final set of output by using the orginal FCM to project state vector forwards after cycle 10. It can be seen that the damaging positive feedback loop does not become active again. A ranking of the relative cost of these different projections can be made by calculating the proportion of cycles in which the cost node is active (making the assumption that within each cycle, cost is a constant value). The ratio of these cost values, following the sequence from the upper (original Verijken model) to the middle (continuous policy) to lower (discontinued feedback) projections is: 1: 2.14: 1.32.

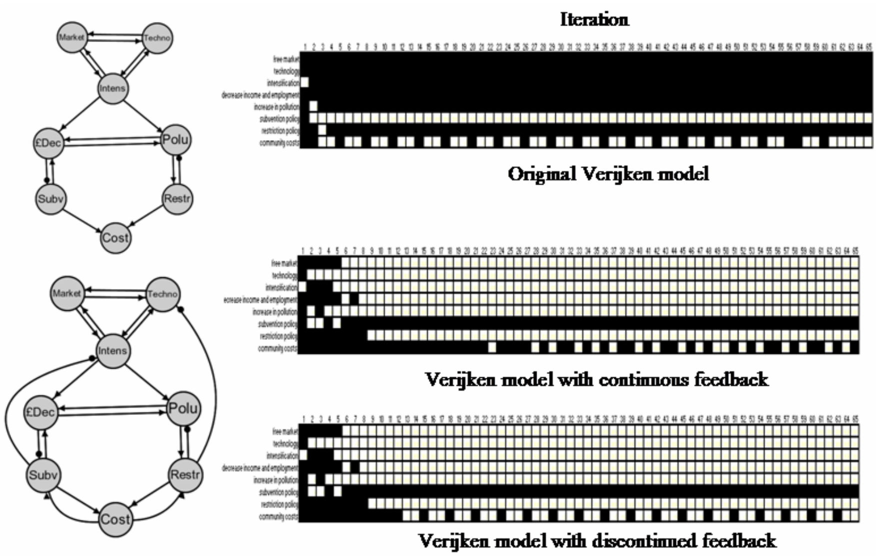

Fig. 1 Simulation of a cognitive map concerned with the relationship between intensive agriculture and negative externalities. The nodes in the map are: Market, free market trade; Techno, technological development in agriculture; Intens, intensification in agriculture; £Dec, decrease in income and employment; Pollu, increase in pollution; Subv, subvention policy; Restr, restrction policy; Cost, community (or social) cost. Filled cells in the projection output indicate active states, empty cells indicate inactive states

The process followed in Figure 1, and described in the preceding paragraph, is essentially one of examining the consequences of internalising the external costs of intensive agriculture. The analysis suggests that given suitable feedbacks these externalities can be controlled, but of course the analysis is conducted at a very broad scale and leaves open the question of how the necessary feedback would be enacted in reality. Answering that question moves us from the broad scale analysis of the previous example, to one concerned with linking actions by individual farmers to policy objectives; this is the FCM analogue of the problem structure (although not the specific detail) which is required for an ABM to explore the issue of agri-environment measures and their uptake by farmers. To begin to explore this issue we examine an hierarchical FCM model of weed control in which domains representing farmers' behavior and policy implementation either do or do not interact.

1.2.1 An Example of FCM Analysis Applied to an Hierarchical Problem Structure

Weeds are an important component of agricultural biodiversity. Plants are the primary mechanism by which energy enters the ecosystem, so much of healthy ecosystem function, and maintenance of biodiversity, depends on sufficient functional plant biodiversity. One of the main impacts of agricultural intensification has been a reduction in both the number and diversity of weeds in agricultural ecosystems (Doyle *et al.*, 2000; Heard *et al.*, 2003). Given the functional importance of weeds in biodiversity and their potentially damaging effects on farmers' financial livelihoods, it is not surprising that the issue of whether weeds can be managed in such a way as to satisfy both farmers and ecosystem service requirements has received a great deal of attention.

The issue can be framed in economic terms by considering the leaving weeds in a crop represents an opportunity cost to farmers, who could utilise the resources captured by the weeds to increase crop yield and thereby increase their income. In contrast, for policy makers, acting to maintain ecological goods and servies for the public, weeds have positive utility. We see in this simple example, then, a specific case of the hierarchical optimisation problem that was mentioned very early in this introduction. The problem has been partially analysed previously by McRoberts & Hughes (2001) using a FCM to illustrate the potential dependence of farmers' willingness to adopt evidence-based weed control measures on a financially-based inducement, expressed in terms of the utility of weeds to the farmers. As with the previous example, we expand here on the original analysis conducted by McRoberts & Hughes (2001).

McRoberts & Hughes (2001) used the implicit assumption that agri-environment payments made from the policy level down to individual farmers could be used by society to buy ecological services from farmers. Here we extend that analysis by making the implicit hierarchical problem structure explicit.

Figure 2, shows an hierarchical FCM which describes the structure of the problem. The problem is seen to comprise two levels. The lower or inner level contains the decision-makers' FCM and is labelled DM-FCM. This is the level at which farmers make decisions about weed control. These decisions depend on the degree to which farmers have a positive perception of weeds. The weed population comprises two parts; the weed plants themselves and a seed bank. The upper or outer level of the model contains the policy-makers' FCM and is labeled PM-FCM. This level contains factors which interact in forming the policy-makers' utility evaluation of weeds and consequently whether or not an agri-environment measure (AEM) to protect weed biodiversity is enacted. Factors such as public pressure and policy cost are present at this level.

The upper set of projection data in Fig. 2 illustrate the behaviour of the system when there is no connection between the upper and lower levels in the hierarchy. It can be seen that the dynamics of the two sub-FCMs are independent and quite different. A real world interpretation of this output is that the policy debate operates in a vacuum because it is not connected to farming or to indicators of the impact of farming on the ecosystem. At the same time, the intrinsic dynamics of farming operate without reference to the policy debate.

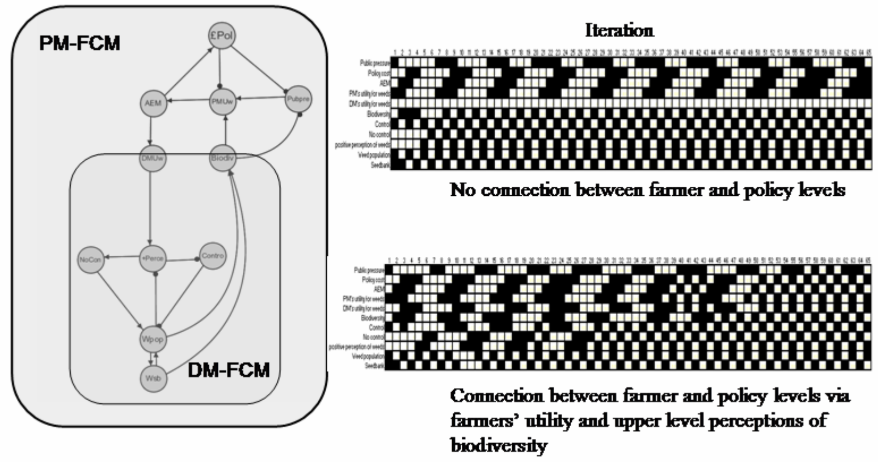

Fig. 2 An hierarchical FCM representing an agri-environment policy issue; in this case how to manage weed biodiversity. The inner or lower part of the FCM represents the farmer (decision-maker, DM) problem (i.e. weed control). The upper or outer level represents the policy-makers' problem (i.e. how to manage the environment). The two levels can be connected through the famers' utility evaluation of weeds, which is influenced from the upper level by agri-environment payments, and the level of biodiversity generated by farming, which influences public pressure on the policy-makers and directly the policy-makers themselves. The two sets of projection data show what happens when the upper and lower systems either are not (upper data set) or are (lower data set) connected

In the lower set of output a long feedback loop between the two levels of the system is activated. Information flows from the upper level into the lower level because the activation of AEM now increases weeds' utility to farmers, increasing the extent to which they are perceived positively and thus reducing the likelihood that they will be subject to control efforts. At the same time, information on the state of biodiversity flows out from the lower level to the upper level and influences public pressure and also policy-makers' utility assessments of agriculture. Although the dynamics of the two parts of the system are initially still somewhat different, eventually (after approximately 50 cycles) the dynamics of the whole system come to resemble those of the lower level. A real world interpretation of this result is that the policy making cycle comes to respond more directly to the dynamics of the system that it refers to. While it might be argued that this is a good thing[1], one might take a more pessimistic view and argue that short cycles imposed on the system would be difficult to deal with in practice; *i.e.* that the policy cycle would be over-responsive to short term effects, resulting in knee-jerk policy formulation. We do not attempt to resolve this issue here, but leave readers to consider it, and how to represent potential solutions, in more detail (in an FCM framework, of course) at their leisure.

The previous example illustrates how an FCM can represent behavioural rules for agents; in this case famers and policy-makers. In the example we invented the rules,

---

[1] Indeed, it is the basis of evidence-based policy formulation and a central justification for the effort expended on identification of indicators of system properties such as sustainability.

with reference to experience of the subject at hand, simply to illustrate the concept. However, for more realistic models, we have been interested to use FCMs as a means to represent empirical rules extracted from questionnaire/interview data provided by farmers. FCMs have some features which make them particularly attractive in this respect. Not the least of these is that, as will be apparent from other chapters of this book, FCM analysis is far more than simply a means to capture and organise information. Even without its use in developing rule bases for ABM, it can be used for policy analysis in its own right; essentially FCMs can provide a prediction of system behaviour against which the ABM can be evaluated, or they can be used as a precursor to ABM to describe behavioral rules. In the following case study, we describe how we have used FCMs to capture the causal relationships which Belgian farmers recognise among variables associated with environmental management, that reflect their perception of the specific policy options. The case study also provides an illustration of the way in which the structure of the FCMs can be used to provide information on similarities in the mental states of different farmers and on the quality of information collected with respect to the main focus of an interview.

2 Case Study: FCMs and Farmer Types with Respect to Agri-Environment Measures in Belgium

The FCMs analysed here were generated from a database of questionnaire responses and interview transcripts collected as part of a research project on agri-environment measures in Europe. The data allowed us to extract causal relationships between the general concept of agri-environment measures, specific agri-environment measures and a wide range of economic, social and biophysical variables from a group of 20 Belgian farmers. Because the data set was not originally intended to be used in this way, it was not possible reliably to extract causal strengths (i.e. fuzzy weights) of connections identified in the farmers' questionnaire responses; we were restricted to inferences as to whether causal relationships were positive or negative. Thus, our analysis of individual maps is restricted to three-valued maps in which the set of values of possible connections is the set {-1,0,1}. In fact, much of our analysis makes use of the adjacency matrix for the FCMs so only the values [0,1] are employed.

Static, graph theoretic properties of the 20 individual FCMs, based on three-valued weights for the connections, are summarised in Table 1. The number of nodes (N) identified by the farmers ranged from 17 to 37, while the number of causal connections (C) per map ranged from 19 to 51. In total the 20 farmers identified 183 concepts associated with implementation of agri-environment measures. Figure 3 shows three example FCMs from the analysis. In each case, the shaded node at the centre of the map is the node for agri-environment measures; the three maps were selected to illustrate the range in number of nodes across the sample of farmers.

The main issue facing the policy modeller is how to translate the information captured in the FCMs into something useful for modelling agents' behaviour. Recall that the aim of the modeller is to represent the behaviour of the farmers so that it can be used as part of a policy analysis model.

One approach would be to populate the ABM with as many types of agent as there are FCMs in the empirical data. However, since every FCM is unique, this approach would result in as many types of agent as there are farmers and thus no reduction in the complexity of the real world in constructing the model world. If the model world is not a simplification (or perhaps better put, a generalisation) of the real world it will not be informative as a policy analysis tool; the policy analyst may as well study the real world and dispense with models, but would have to accept that *ex ante* analysis would be very limited in such a situation.

Table 1 Graph theoretic variables calculated from adjacency matrices for cognitive maps elicited from 20 Belgian farmers

Farmer	N[1]	C[2]	T[3]	R[4]	D[5]	h[6]	Deg[7]	[8]var_{in}	[9]var_{out}
1	33	37	12	8	0.03	0.01	1.12	2.42	0.98
2	26	29	9	5	0.04	0.02	1.12	3.79	0.83
3	17	20	8	6	0.07	0.05	1.18	2.78	1.40
4	20	24	10	3	0.06	0.04	1.20	7.01	0.59
5	25	27	6	10	0.04	0.02	1.08	1.83	1.99
6	26	27	11	9	0.04	0.01	1.04	3.40	1.08
7	30	31	8	11	0.03	0.01	1.08	1.69	1.27
8	37	51	23	6	0.04	0.02	1.38	7.74	1.13
9	24	25	6	10	0.04	0.02	1.04.	0.65	1.87
10	22	19	9	9	0.04	0.00	0.86	0.79	0.69
11	21	20	10	6	0.05	0.02	0.95	4.55	0.85
12	20	23	6	4	0.06	0.03	1.15	2.34	0.66
13	18	19	7	4	0.06	0.04	1.06	2.06	0.88
14	28	29	11	9	0.04	0.01	1.04	2.48	1.44
15	23	25	17	14	0.05	0.02	1.09	2.90	0.72
16	25	25	10	8	0.04	0.02	1.00	2.58	0.92
17	31	35	12	9	0.04	0.01	1.13	2.98	1.45
18	25	24	11	10	0.04	0.02	0.96	4.62	2.04
19	17	22	4	6	0.08	0.06	1.29	1.35	2.22
20	20	20	13	14	0.05	0.03	1.00	1.26	1.37

[1]Number of nodes; [2]Number of connections; [3]Number of transmitter nodes; [4]Number of receiver nodes; [5]Map density; [6]Map hierarchy index; [7]mean in (and out) degree – mean indegree and outdegree are equal when calculated on binary matrices; [8]variance of indegree values over nodes; [9]variance in outdegree values over nodes.

FCMs offer two ways of considering agents. In one approach we can look at the *structure* of the FCMs which have been elicited from the farmers. This approach will capture properties of the rule bases which agents can use and, in this way, on the type of information that the farmers give to the interviewer. In the alternative approach, we could analyse the specific cause and effect relationships which are encoded in the FCMs and use these in constructing the agents' rule bases. Following this approach we will be likely to end up with rule bases that deal specifically with the problem posed in the information elicitation phase.

In order to extract this type of information from a set of FCMs the analyst can use a range of multivariate statistical methods which are readily available in most statistical analysis software. In our own research to date we have made use of two different types of methods; hierarchical cluster analysis and principal components analysis. A detailed description of these techniques is beyond the scope of this chapter, but Krzanowski (1988) gives a unified and very clear introdution to this entire field of statistical analysis.

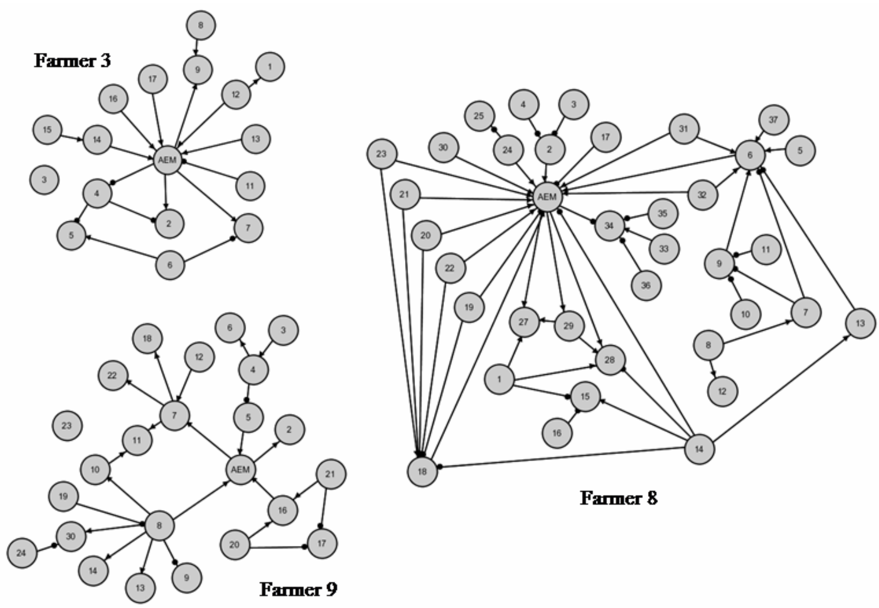

Fig. 3 Three cognitive maps repres0065nting the range of map size recovered from questionnaires and interviews with 20 Belgian farmers on the subject of agri-environment measures. Causal effects are indicated as either • = negative, or ▸ = positive. Note that the similarly numbered nodes in different maps do not necessarily correspond to the same concept

The starting point for both types of method we have used is a two-way array of data, arranged with the individual farmers as the rows and the FCM attributes as the columns. In the similarity analysis, the columns of data are considered to be coordinates for the farmers in a multidimensional data space. The aim of the analysis is, then, simply to calculate the similarities among all the farmers in that space and render an overall summary of the information in a format that can be easily understood. In many applications the usual format is to represent the similarities as lengths in a rooted tree, commonly referred to as a dendrogram (Krzanowski, 1988).

In the second approach, the starting motivation is again to view the data table as giving information about similarities among the farmers in a multidimensional space, but in principal components analysis the aim is to construct a lower dimensional sub-space from linear combinations of the original variables which best represents the distance relationships contained in the initial data. This process reveals not only which FCMs are similar to each other overall (by inspecting which ones end up close to each other in the constructed sub-space), but also provides information on the correlation or co-variance structure among the variables extracted from the FCMS. Both types of information can be inspected together in a graphcial device known as a biplot (Kraznowski, 1988).

2.1 Clustering Based on Map Structure

Graph theoretic variables derived from the FCMs were used to perform an hierarchical cluster analysis of the similarity among the 20 farmers. The variables were all continuous in nature and the similarity matrix among farmers was constructed using a Euclidean distance metric; clustering was performed with a furthest neighbour algorithm implemented in Genstat (Release 11.1, VSN International,. Figure 4 shows the dendrogram generated from the analysis, with an insert showing the relationship between the value of ln(D) against ln(N) for each farmer's FCM (see below).

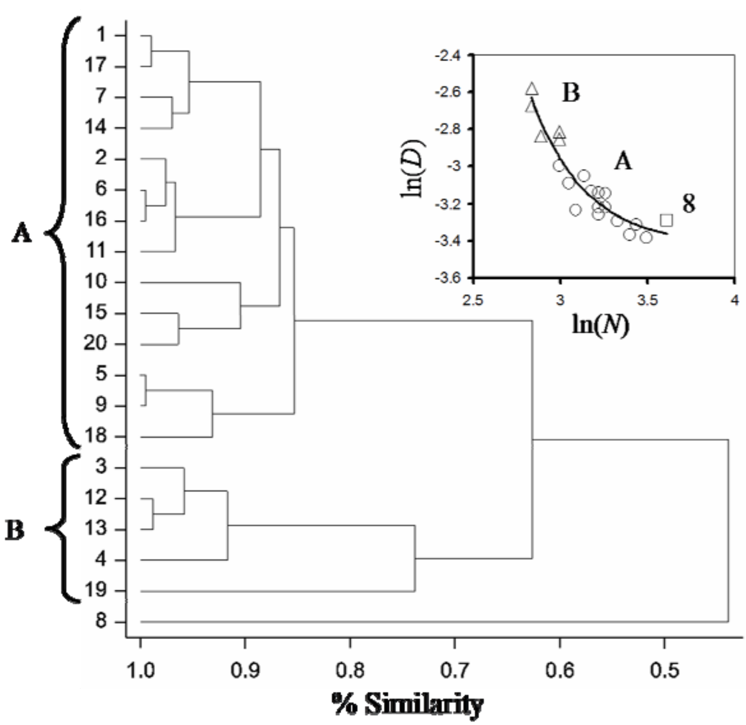

Fig. 4 Main figure: Furthest neighbour dendrogram derived from graph theory variables for 20 cognitive maps elicited from Belgian farmers. Clusters A and B and the unique individual (Farmer 8) are apparent at 75% similarity. Insert: the relationship between the natural logarithm of node number, N, and map density, D, for the same data. Note that cluster B comprises individuals with relatively high density maps

The cluster analysis of map structure suggested that there were two main types of agent, with a third type represented by a single individual. The smaller cluster (B) comprised the 5 individuals with highest map density values. As is well known, map density (*D*) is the proportion of all possible connections which are actually present in a map. Since connections are causal relationships between concepts, higher densities indicate agents whose behavioural response to changes in the world is potentially more variable than those with relatively low *D* values (Özesmi & Özesmi, 2004) For the modeller, the analysis suggests the need to generate rule bases for three different types of agent who will differ in the potential variability of their behaviour in response to changes in the ABM world.

The insert in Figure 4 shows empirical relationship between ln(*N*) and ln(*D*) estimated over the sample of farmers. The statistical relationship in the data is an emergent property of the sample of farmers. In this case a negative exponential relationship between ln(*D*) and ln(*N*) is apparent, with the individuals in cluster B at one end, the unique individual Farmer 8, at the other, and the remaining individuals (comprising cluster A) between these extremes. The emergent relationship can be described mathematically as indicated in equation 1.

$$\ln(D) = \alpha + \beta \cdot r^{\ln(N)} \tag{1}$$

The fitted relationship between ln(*D*) and ln(*N*) was obtained by non-linear regression analysis using maximum likelihood to obtain the parameter estimates. The fitted relationship explained 89% of the variance in ln(*D*); the parameter estimates (s.e. in parentheses) were, α = -3.4 (0.09), β = 6933 (16667), r = 0.041 (0.0357).

One might ask whether the observed trade off between ln(*D*) and ln(*N*) is a particular example arising from a general (and theoretically justified) phenomenon, or is simply an artifact of these data? One potential theoretical justification is as follows.

Since both the number of nodes and the number of connections are components of the complexity of an agent's cognitive model, one might hypothesise that some combination of *N* and *C* will set a limit on the overall complexity which a cognitive model can have. Here we are taking a view of cognitive processing capacity in keeping with the ideas proposed Halford *et al*. (1998), such that "*limits are best defined in terms of the complexity of relations that can be processed in parallel. Complexity is defined as the number of related dimensions or sources of variation*". That is, if there is an upper limit of complexity on the representational models an agent can form, and complexity depends on both *N* and *C*, then one might hypothesise that agents will be able to maximise *N* or *C* in forming a model, but not both. However, other things being equal, we would expect larger maps to have more connections[2], so a complexity limit might be expected to affect not the number of possible connections, C_{max}, but the proportion of possible connections which is filled; this is the map density, *D*. This hypothesis leads to an expectation of a negative correlation between *N* and *D*, as observed.

---

[2] The number of possible causal relationships in a FCM, C_{max}, increases with the square of N: $C_{max} = N^2$ if self loops are possible, or $C_{max} = N(N\text{-}1) = (N^2\text{-}N) \cong N^2$ for large N if self loops are not possible.

Generalising, we can say that the trade off between $\ln(D)$ and $\ln(N)$ suggests that people lie somewhere on a continuum between "*cataloguers*" (who maximise N) and "*connectors*" (who maximise D). The trade off means that the number of concepts which a map contains can increase as long as the number of causal connections among concepts decreases. However, without causal connections among its nodes a FCM model will be limited in its usefulness for inferential analysis; tending to be simply a catalogue of potentially relevant concepts.

2.2 Clustering Based on Map Content

The clustering exercise described in the previous section was intended to identify potential types of agent based on the structure of the FCMs elicited from the Farmers. For a specific application to policy questions concerning agri-environment measures it would clearly be useful to know not only broadly what types of individual comprise the population, but also something about the specific concepts and causal relationships they consider. To examine this issue we employed a different approach to detect clustering within the FCMs.

Recall that our context for this analysis is a bi-level problem structure in which the farmers will be represented by model agents at the lower level whose aggregate behaviour will result in outcomes (for example environmental quality) against which policy objectives will be assessed at the upper level. The question for the policy analyst is two-fold: What are the drivers of behaviour which can be affected by pulling policy levers? What are the outcomes that the farmers view as important and against which policy success can be measured?

We examined the FCMs and identified six driving variables and three outcome variables. The drivers were: (*i*) subsidies; (*ii*) presence of less productive land; (*iii*) cereal prices; (*iv*) exterior constraints; (*v*) fixed dates (associated with implementation of particular agri-environment measures); (*vi*) inflexible regulation. The three outcomes were: (*a*) soil erosion; (*b*) public image of farming; (*c*) environmental quality.

To examine relationships among farmers with respect to these drivers and outcomes we constructed a 20×9 binary data matrix by recording whether each driver or outcome was present in the FCM for each farmer. A principal components analysis was used to examine the relationships between the farmers and the driver and output variables by analysing the correlation matrix for the data. Figure 5 summarises the results of this analysis.

For the policy modeller the pattern of vectors and points in Figure 5 suggests (as might be expected) that there are varying degrees of association among the drivers of behaviour and policy outcomes for the set of farmers. Avoiding becoming too engrossed in methodological detail, the analysis suggests that three broad types of agent should be included in the ABM world: a first type who respond most strongly to drivers concerned with commodity market prices and regulatory constraints; a second type who are interested in land productivity and subsidies and who connect these drivers to soil erosion, and a third type who are not strongly concerned with any particular driver but are motivated by the public's

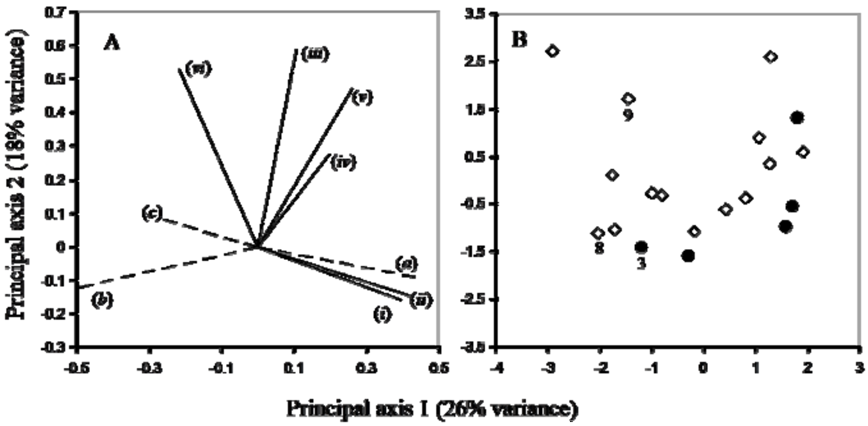

Fig. 5 Ordination diagram showing the output from a principal component analysis of FCM concepts identified as drivers and policy outputs for a set of Belgian farmers. A: vectors representing the drivers (i) – (iv) and outputs (a) – (c) as in the main text. B: Clustering of the farmers in the principal component space. The open symbols are farmers from cluster A in Fig 1., the closed symbols are farmers from cluster B. Farmers 3, 8, and 9 whose FCMs are shown in Fig.1 are identified by numbers

image of farming. The distribution of farmers from the previous clustering exercise in the principal components space suggested that each of the three types just identified should contain a small number of agents whose rule bases are based on relatively high density maps, and a larger number of agents with rule bases reflecting lower density maps.

In all, then, the cluster analyses of FCM structure and content suggested a set of six types of agent for the ABM world. These static analyses give us some idea of what will constitute the agents' behavioural rules, but say nothing about how a world populated by these agents will evolve over time. Some clues as to that issue are available by using the FCMs to iterate any initial set of states over some notional time scale. We illustrate this concept briefly in the next section by examining the responses of three farmers' conceptual models to a policy decision to maintain support for agri-environment measures via two drivers: support for maintaining farming's image with the public and subsidies to farming.

2.3 Anticipating Isolated Agent's Behaviour

Figure 6 shows the output from iterating the FCMs shown in Figure 1 for 20 cycles. In each case the left hand diagram shows the pattern of concept activations when inputs to the map are made at the initiation cycle (cycle 0) and then the FCMs are left to equilibrate without further input. Open cells in the output correspond to inactive concepts, filled cells correspond to active concepts. The right hand diagrams show the pattern of concept activations when inputs to the nodes for "farming's public image" and "subsidies" are made at every cycle. The row in each output corresponding to agri-environment measures (AEM) is indicated.

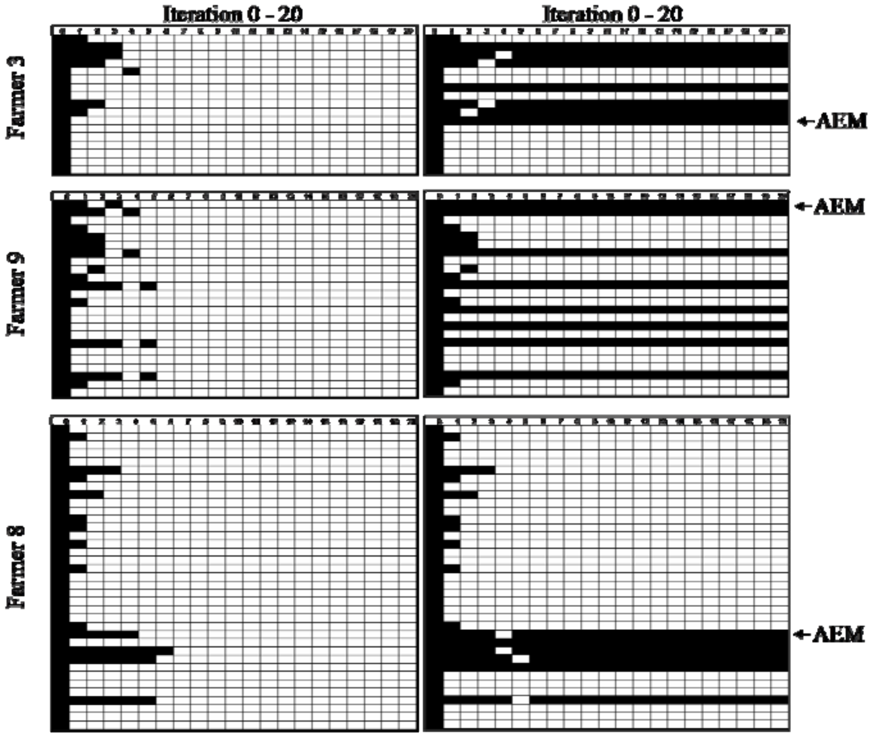

Fig. 6 Iterated output from three FCMs (see Figure 1) elicited from Belgian farmers on the subject of agri-environment measures (AEM). In each case the left-hand diagram shows the output when activations are made only to the initial cycle, while the right-hand diagram shows the output when input to two driving variables is maintained at each cycle

Several points are worth making about the output from the analysis. First, irrespective of the complexity of the FCM, if no input to driving variables is maintained the systems conceived by all three farmers quickly reach a state with no active concepts. Secondly, in all three cases, maintaining input to support the public image of farming and to subsidies leads to continuous (or near continuous) activation of the AEM node. Thirdly, when input is maintained, we can see that the relative number of *active* nodes per map decreases from the map with highest density (farmer 3, 7/19 concepts active) to the map with the lowest density (farmer 8, 6/37 concepts), with the intermediate density map (farmer 9) between these (8/24 concepts active). A final point of interest, although not one readily apparent from Figure 4, is that while all three FCMs imply that AEM can be maintained in an active state by continuous input to driving variables, none of the specific measures (for example, installing refuges for beneficial insects) was maintained in an active state. This analysis suggests an intriguing disconnection in the minds farmers between the general concept of AEM and the specific mechanisms for delivering environmental goods from farming. Such a disconnection may or may not be important to policy analysis (and hence to the efforts in constructing an ABM) depending on the level of detail at which the policy makers wish to analyse their problem.

3 Conclusions

3.1 General Comments

It is widely recognised that successful, formalised policy analysis must combine elements of objective methodology with realism based on input from relevant stakeholders (Parker *et al.*, 2003). Furthermore, many policy problems are at least bi-level (Candler *et al.*, 1981) so it is necessary for the policy analyst to construct models that take account of objectives at least two scales of resolution. It is clear that ABM has the potential to meet these criteria but that theory and practice are still some distance apart (Schmit & Rounsevell, 2006). Part of the difficulty in successfully applying the ABM approach to policy problems is to obtain sufficient data to construct the models. Because FCM construction focuses on the cause and effect relationships entailed in either qualitative or quantitative data, we believe that it offers a useful methodology for eliciting rule bases from data. Indeed, FCMs have proved useful in studying a wide range of complex problem types (e.g. Glikas & Xirogiannis, 2004; Chytas et al., 2006; Xirogiannis et al., 2008). While the analyses we have presented here are for a single case study and relate to only one type of problem, we believe that the approach of combining FCMs with ABMs will prove to be useful in many analogous arenas.

3.2 Statistical Analysis

Applying statistical analyses to the elicited FCMs from the farmers leads to two general results. First, straightforward listing of the causal relationships captured in the maps provides a catalogue of potential behavioural rules to include in the ABM. Secondly, analysis of the graph-theoretic statistics for the farmers gives us some idea of the types of cognitive agent who are present in the sample; i.e. it gives some guidance to the levels of rule-base complexity to include in the ABM. Finally, analysis of how the pattern of causal relationships among concepts is distributed over the set of FCMs gives some indication of which variables in the ABM should be used to connect the modelled agents with one another and with the larger scale features of the ABM world.

Esssentially the same concepts were suggested by Dickerson & Kosko (1994) when they suggested using FCMs as a means to construct virtual worlds. In their example, rule bases describing elements of the behaviour of predators and prey were linked together in an overall FCM. This optimistic view notwithstanding there are many issues to be overcome in developing the methodology we propose. Not the least of these is how one should handle the philosophical question of what the output of an FCM *means* in relation to other model representations of the same system and indeed the real world.

3.3 Identification of FCM Models with Reality: Lessons from Other Types of Model

A case study chapter may not seem like an obvious place to discuss such a point; one might be tempted to say that such things would be better dealt with in a chapter on theory or methodology. However, we suggest that it is in practical application that such questions become critical and thus ought to be discussed. After all, it matters less if purely abstract entities have physically impossible characteristics in a model than it does if the same is true of model analogues for real entities. This is particularly true when, as in our case, we wish to compare one type of model (FCM) with another (ABM) and use both types to inform decision-makers about potential properties of complex systems embeded in the real world.

If the nodes in an FCM represent real quantities, it is not clear how the process of thresholding and normalisation applied to the iteration outputs should be interpreted. Standard results from the analysis of the eigenvalue structure of constant matrices (May, 1974; Caswell, 2001) mean that the quantities being projected will either grow or shrink exponentially with the number of iterations depending on whether the value of the largest eigenvalue (λ_1) is >1 or <1; in the rare case that $\lambda_1 = 1$, the output will be constant. In a physical system, the eigenvalue results can be interpreted as implying that there either is ($\lambda_1 < 1$) or is not ($\lambda_1 > 1$) a local stable equilibrium in the dynamics. In the analysis of such systems the exponential growth over iterations implied by $\lambda_1 > 1$ is accepted as a limitation of the model structure; the same acceptance does not appear to be a feature of FCM analysis, leaving this potentially useful technique open to the question of what the outputs from FCM models mean. Of course the FCM community is not alone in being open to the criticism of constructing meaningless models. Few books on modelling attempt any sort of philosophical discussion of models. Doucet & Sloep (1992), however, discuss such issues at length (in their Chapter 13 in particular) and provide the invaluable advice that all models should have an identification statement explicitly associated with them. The role of the identification statement is to formally connect the model with the real world by stating of which part(s) of the world it is a model. As Doucet & Sloep (1992) point out without such a statement, the model remains an abstract entity and the logical entailments within it remain un-testable. It is particularly important in real world application, where models are used to inform decision making, that they are clearly identified with the systems they are supposed to represent.

3.4 Future Research

We are actively pursuing the issue of model identification with the real world in our research in FCMs and ABMs. In addition as the FCM and ABM approaches can be used either in conjunction or separately one potential area of future research will be in formal comparison of the quality of model inferences arising from each type of model applied to the same policy problem. Finally, a more practical future objective will be to continue the use of FCMs as a component of participatory research in agriculture.

Acknowledgments. Support for this research was provided by the European Union and the Scottish Government.

References

Axelrod, R.: Structure of Decisions: The Cognitive Maps of Political Elites. Princeton University Press, Princeton (1976)

Bousquet, F., Le Page, C.: Multi-agent simulations and ecosystem management. Ecol. Mod. 176, 313–332 (2004)

Burks, A.W.: Theory of Self-Reproducing Automata, by John von Neumann. University of Illinois Press, Urbana (1966)

Candler, W., Fortunyamat, J., McCarl, B.: The potential role of multi-level programming in agricultural economics. Amer. J. Ag. Econ. 63, 521–531 (1981)

Chytas, P., Glykas, M., Staikouras, C., Valiris, G.: Performance Measurement in a Greek Financial Institute Using the Balanced Scorecard. J. Meas. Bus Ex. 10(2) (2006)

Caswell, H.: Matrix Population Models: Construction, Interpretation and Analysis, 2nd edn. Sinauer Associates, Sunderland (2001)

Dickerson, J., Kosko, B.: Virtual worlds as fuzzy cognitive maps. AI Expert, 25–31 (July 1994)

Diassanayake, M., AbouRizk, S.M.: Qualitative simulation of consrtuction performance using fuzzy cognitive maps. In: Proc. 2007 Winter Sim. Conf., pp. 2134–2140 (2007), `http://www.informs-sim.org/wsc07papers/266.pdf`

Doucet, P., Sloep, P.: Mathematical Modelling for theLife Sciences. Ellis Horwood, New York (1992)

Doyle, C.J., McRoberts, N., Kirkwood, R., Marshall, G.: Ecological Management of Crop-Weed Interactions. In: Masae, S., Hiroshi, K. (eds.) Structure and Function in Agroecosystem Function and Design. CRC Press, Boca Raton (2000)

Ettinger, M.: The complexity of comparing reactions. Bioinform. 18, 465–469 (2002)

Froelich, W., Wakuliicz-Deja, A.: Associational cognitive maps for medical diagnosis supoprt. Intel. Inf. Syst., 387–396 (2008), `http://iis.ipipan.waw.pl/2008/proceedings/iis08-38.pdf`

Giampietro, M.: Multiscale Integrated Analysis of Agroecosystems. CRC Press, Boca Raton (2004)

Glykas, M., Xirogiannis, G.: A soft knowledge modeling approach for geographically dispersed financial organizations. Soft Comp. 9, 579–593 (2004)

Gunderson, L.H., Holling, C.S.: Panarchy: Understanding Transformations in Natural Systems. Island Press, Washington (2002)

Halford, G.S., Wilson, W.H., Phillips, S.: Processing capacity defined by relational complexity: Implications for comparative, developmental and cognitive psychology. Beh. Brain. Sci. 21, 803–831 (1998)

Heard, M.S., Hawes, C., Champion, G.T., Clark, S.J., Firbacnk, L.G., Haughton, A.J., Parish, A.M., Perry, J.N., Rothery, P., Roy, D.B., Scott, R.J., Skellern, M.P., Squire, G.R., Hill, M.O.: Weeds in fields with contrasting conventional and genertically modified herbicide-tolerant crops II. Effects on individual species. Phil. Trans. R. Soc. Lond. B 358, 1833–1846 (2003)

Kosko, B.: Fuzzy cognitive maps. Int. J. Man-Mach. Stud. 24, 63–75 (1986)

Kosko, B.: Adaptive, bidirectional associative memories. Appl. Optics 26, 4947–4960 (1987)

Kosko, B.: Fuzzy Thinking. Harper Collins, London (1993)

Krzanowski, W.J.: Principles of Multivariate Analysis: A User's Perspective. Oxford University Press, Oxford (1988)

Matthews, R., Gilbert, N., Roach, A., Polhil, J.G., Gotts, N.M.: Agent-based land-use models: a review of applications. Lands. Ecol. 22, 1447–1459 (2007)

May, R.M.: Stability and Complexity in Model Ecosystems. Princeton University Press, Princeton (1974)

McRoberts, N., Foster, G.N., Davies, D.H.K., Evans, K.A., McKinlay, R.D., Wale, S.: The role of synoptic models in the development of crop protection for sustainable crop produiction systems. In: BCPC Proceedings 63. Intgrated Crop Protection: Towards Sustainability? BCPC, Farnham, UK, pp. 439–446 (1995)

McRoberts, N., Hughes, G.: Killing or culling? Is it possible to manage weeds as a resource. In: Proceedings BCPC Annual Conference, BCPC, Farnham, UK, pp. 383–390 (2001)

Meyn, S.P., Tweedie, R.L.: Markov Chains and Stochastic Stability. Springer, London (1993)

Özesmi, U., Özesmi, S.: Ecological models based on peoples' knowledge: a mult-step fuzzy cognitive mapping approach. Ecol. Mod. 176, 43–64 (2004)

Parker, D.C., Manson, S.M., Janssen, M.A., Hoffman, M.J., Deadman, P.: Multi-agent systems for the simulation of land-use and land cover change: a review. Ann. Assoc. Amer. Geog. 93, 316–340 (2003)

Pelaez, C.E., Bowles, J.B.: Using fuzzy cognitive maps as a system model for failure modes and effects analysis. Intell. Syst. 88, 177–199 (1996)

Schelling, T.: What Is Game Theory? In: Charlesworth, J.C. (ed.) Contemporary Political Analysis. The Free Press, New York (1967)

Schmit, C., Rounsevell, M.D.A.: Are agriclutural land use patterns influenced by farmer imitation? Agr. Ecosyst. Env. 115, 113–127 (2006)

Stylios, C.D., Groumpos, P.P.: Fuzzy Cognitive Maps in Modeling Supervisory Control Systems. J. Intel. & Fuzzy Syst. Appl. Engi. 8, 83–98 (2000)

Stylios, C.D., Georgopoulos, V.C., Malandraki, G.A., Chouliara: Fuzzy cognitive map architectures for medical decision support systems. Appl. Soft Comp. 8, 1243–1251 (2008)

Taber, R.: Knowledge processing with fuzzy cognitive maps. Exp. Syst. Appl. 2, 83–87 (1981)

Verijken, P.: A methodic way towards more sustainable farming systems. Neth. J. Ag Sci. 40, 209–233 (1992)

Xirogiannis, G., Chytas, P., Glykas, M., Valiris, G.: Intelligent impact assessment of HRM to the shareholder value. Exp. Sys. App. 35, 2017–2031 (2008)