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# Minimisation of uncertainty in decision-making processes using optimised probabilistic Fuzzy Cognitive Maps: A case study for a rural sector

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ABSTRACT

Several studies have focused on methods of increasing system and uncertainty knowledge for socio-economic and environmental policies; however, the nonlinearity and dynamism of real world increase the gap between uncertainty depiction and its evaluation in policy strategies. This work attempts to implement a methodology that is able to minimise uncertainty in decision support tools related to rural planning and management. Fuzzy Cognitive Maps, the Dempster–Shafer theory and nonlinear optimisation were applied to achieve the above-mentioned goal. The method was tested to describe suitable policies and intervention strategies to address the effects of the recent economic crisis in the agricultural sector.



## 1. Introduction

Rural systems, both natural and manmade, are examples of complex structures characterised by interactions among many socio-economic and ecological variables. These interactions can be represented by a high degree of nonlinearity due to the presence of feedback and loops expressed by reciprocal connections among the biotic and abiotic components of natural systems and anthropogenic issues. In addition, the temporal and spatial dynamism of the parameters characterising these systems, i.e., the qualitative/quantitative variation of environmental elements in time and from a geographical point of view, make framework analysis a difficult task.

For socio-economic and environmental assessment and management, these aspects are particularly relevant when Decision Support Systems (DSSs) are implemented to put policies and strategies into practice. The intrinsic uncertainty related to modelling (uncertainty that can address one or more of the following definitions) and current rapid changes in such systems must be introduced and estimated in the DSS results [4,6]. A detailed literature analysis on the identification and categorisation of uncertainty in models was developed by Ref. [51]. The authors stated that, despite the importance of the introduction of uncertainty in DSS results, this rarely occurs in a consistent manner. The sources and classification of uncertainty are often reported in the literature with a lack of unambiguous terminological statements and categorisation among different authors. For example [17], classified the sources of uncertainty as linguistic uncertainty, epistemic uncertainty, variability and decision uncertainty. According to [10]; uncertainty can be classified as aleatory or epistemic. A similar categorisation could be depicted in the assertion that uncertainty concerns both people's knowledge about a particular environmental system (epistemic uncertainty) and its presence in all bio-geophysical and socio-economic processes (stochastic uncertainty) [51].

As expressed by Ref. [19]; there is a need to strengthen the role of science to maintain and enhance the rigour and formality of the information that informs decision making to incorporate uncertainty in expert elicitation modelling [43] stated that the currently dominant approaches to addressing and classifying uncertainty tend to advance scientific knowledge in a specific sector or topic and to acquire, evaluate and transfer information in participated approaches involving researchers, policymakers and other stakeholders. The main objectives of uncertainty analysis in science and environmental policy interfaces can be described as follows: i) increased precision and ability to identify knowledge gaps, ii) an increase in decision-maker confidence and in the robustness of scientific results, iii) an improvement in stakeholder and public confidence in science, iv) increased stakeholder confidence in

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decision making, v) improving the quality of decisions, and vi) highlighting the influence of science communication patterns on decision making [25].

Different methods can be used in uncertainty assessment and management. A review by Ref. [38] analysed fourteen methodologies for uncertainty characterisation. As examples [52], described and identified uncertainties in a structured matrix modified from Ref. [51] to present a set of more specific and mutually exclusive definitions to be used in uncertainty identification. A risk and uncertainty assessment of complex operational systems was developed by Ref. [3] using the integrative approach in an holistic framework. A spatial definition of uncertainty in environmental management was defined in Ref. [16]. Uncertainty in decision making and strategic assessment related to the rural sector was addressed by the application of the Pastoral Properties Futures Simulator (PPFS), a dynamic participatory-based model developed by Ref. [14,15] incorporated structural and observational uncertainty into a model based on the Adaptive Management (AM) and Partially Observable Markov Decision Processes (POMDP) approaches.

The results from the above-mentioned studies suggest that extending knowledge and the sharing of information in complex systems could be interpreted as an integrated evaluation of the real world. Under these terms, despite the possibility of including more knowledge (e.g., more processes) into models, the increase in understanding of real systems could lead to the further modelling (simplification) of processes and inevitably to the introduction of additional uncertainty components. To address this negative loop, enhanced quantitative and/or qualitative descriptions and evaluations of the systems in socio-economic and environmental models are insufficient. On this subject, certain authors have recommended the use of different methodologies that are able to not only analyse and classify uncertainty but also mitigate and act on this component. The scheme proposed by Ref. [43] for minimising uncertainty in environmental decision making is based on the reconstruction of the main objective in sub-problems by moving backwards from the desired environment towards the present state of the ecosystem. A similar approach is suggested in different studies in several fields such as informatics, mechanics and aerodynamics (see, e.g., [12,36,42,47]).

Briefly, a lack of models able to minimise uncertainty from a quantitative point of view is found in the literature on rural-focused DSSs. An in-depth qualitative analysis of such systems is the main approach used to reduce uncertainty. However, the idea developed in the present work is that uncertainty can be reduced through the best application of the policy and intervention strategies of decision makers in a particular system. In these terms, the system can be described as a nonlinear model where policy and intervention strategies serve as input variables. Therefore, the uncertainty related to a particular scenario can be managed by the application of nonlinear optimisation models where the input parameters (such as policy and intervention strategies) represent the constrained variables needed to modify or solve an objective function (e.g., minimisation of uncertainty).

With these premises, the objective of this work was to introduce a new methodology capable of optimising a system and depicting and minimising uncertainty in rural-focused DSSs. Therefore, this technique must address three main issues: i) The analysis of complex systems. As reported in Ref. [8], there is no agreed upon definition of complexity; however, among the definitions, the presence of nonlinear interactions (when a change in one variable does not cause a proportionate constant change in a dependent variable) could be considered as one of the most common. In addition, Chapman states that “the single parameters of a system have a cognitive model of their role and position in the system, but because these cognitive models cannot claim complete knowledge either of themselves or of the system, the partiality of knowledge is the reason that the characteristic behaviour of the whole is seen to be emergent” ([8], pp.1). For those reasons, nonlinearity and emergency were here considered peculiar characteristics of complex systems. ii) The quantification of uncertainty. Due to the need to introduce uncertainty evaluation to DSSs and due to the different definitions of this term in scientific contexts, we have to analyse a specific uncertainty that is easily quantifiable from the decision makers' assertion and communicable and interpretable to them. iii) The optimisation of the system and/or minimisation of uncertainty through a nonlinear optimisation procedure.

As a consequence, the developed method, called Optimised Probabilistic Fuzzy Cognitive Maps (OPFCM), combines three different techniques. The first technique is Fuzzy Cognitive Maps (FCMs), which permit the analysis of nonlinear and dynamic systems in a comprehensive manner [21]. Next, a statistical and quantitative computation of uncertainty is introduced into the FCMs via the application of the Dempster–Shafer (DS) theory of evidence [41]. Finally, both optimisation of the system and minimisation of uncertainty are implemented through the application of the Differential Evolution and Particle Swarm (DEPS) optimisation algorithm [33]. Additional insights into the above methods and why they were chosen are specified in the methodological section. The OPFCM were tested against the definition of potential intervention strategies and policies (P) that can be applied to overcome the recent economic crisis effects highlighted in the agricultural sector. The case study involves medium–small brand name capital wine farms located in a specific area of the Chianti region (Tuscany, central Italy).

An introduction and a brief explanation of the use related to both FCMs and DS theory are defined in sections 2.1 and 2.2, respectively. The OPFCM are described in section 2.3. A case study is presented in chapter 3; thereafter, the main results and discussion are presented in chapters 4 and 5. A comparison among OPFCM and other FCM-based methods is reported in section 6. Finally, the primary findings, limits and potential improvements to the method are outlined in the Conclusions section.

## 2. Methodology

### *2.1. Analysis of the system: the Fuzzy Cognitive Maps*

Fuzzy Cognitive Maps (FCMs) are considered here as a suitable approach to describing a complex framework such as the socio-economic and environmental behaviour of wine industries in the event of an economic crisis. The description of the evolution of nonlinear and dynamic systems and the influences on management policies have been frequently applied using this technique in the rural sector (see, e.g., [7,22,31,50,53]).

FCMs are a graphical, semi-quantitative and dynamic system composed of $n$ concepts – or nodes – (indicated as $C_i$ where $i = 1, \ldots, n$) and their relations represented by arrows (Ref. [21] – Fig. 1).

The link between two concepts – indicated as $w_{j,i}$ with $j \in i$ – is weighted. The value $w_{j,i}$ shows the influence that a concept $C_j$ (defined as transmitter) exercises on another concept $C_i$ (indicated as receiver). Nonlinear behaviour of FCMs is due to the presence of feedbacks among concepts (see e.g. concepts $C_1$ and $C_4$ in Fig. 1) and loops in a same node (see e.g. concept $C_5$ in Fig. 1). The value of concepts as well as the weight of relations are normalised or, in other terms, constrained in a specific range (usually 0–1) to facilitate the interpretation of FCMs [31]. This aspect clarifies why FCMs are defined as “semi-quantitative” systems.

FCMs can be implemented through interviews of one or more stakeholders of a particular sector via focus groups or literature