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Method Article

A Combined method to model policy interventions for local communities based on people knowledge

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ABSTRACT

Policy interventions to promote innovative industries in peripheral regions are often hampered by lack of information on the functioning of the local socio-economic systems, due to their complexity. This might result in mismatches between policy objectives and the actual needs and capability of local communities. To overcome this drawback, it is crucial to obtain appropriate knowledge on the local system, which nevertheless is typically embedded in local actors' minds in uncodified and tacit form. Fuzzy Cognitive Maps (FCMs) have been employed to decode this kind of knowledge in a reproducible manner. However, some problems remain as to how to integrate the necessary vagueness of local actors' heuristic with experts' knowledge into a rational framework.

The following methodology customization is proposed:

• Combine the FCMs with the Discourse Analysis to obtain relevant narratives (i.e. concepts, visions, insights, etc.) needed to define system boundaries and variables.

• Employ individual interviews – rather than a participatory approach – to define the causal relations among system variables.

• Integrate tacit and uncodified knowledge embedded in local actors within experts' scientific knowledge.

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Method details

The FCMs approach [8, 14] is a technique which allows: (i) gathering information on variables and interactions forming a complex system; (ii) representing the system as a computational model; (iii) analyzing future evolution of the system by means of fuzzy inference. This approach has been applied to a variety of problems such as climate change, drought forecast, landscape change, sustainable transition, rural development planning – to cite only some recent works see: [2, 4, 5, 10–13]. The principal output of the FCM is a map representing the causal relations among the system components as perceived by the actors forming the system itself. The underlying idea of this method is that the knowledge relevant to the structure and functioning of a social complex system is embedded into the minds of its members. This knowledge is framed into three main elements forming the FCMs: (1) a set of concepts or variables forming the system under investigation; (2) a set of causal relationships among these variables; and (3) a set of fuzzy weights, measuring the intensity of these causal relationships. Applying Fuzzy inference, the cognitive map is in turn used to simulate possible scenarios under two different conditions (i.e. without external interference, with external intervention).

In what follows, we present a customization of the protocol presented in Ozesmi and Ozesmi [14] to build and analyze an FCM. The proposed protocol is articulated in three phases:

1. Identification of system boundaries and variables;
2. Identification of causal relations among variables;
3. Fuzzy inference.

Each phase, in turn, is articulated in several steps, which will be discussed in the following subsections.

Phase 1 - Identification of system boundaries and variables

The identification of the system boundaries and relevant variables (x_i) is done by employing the Discourse Analysis technique. This technique allows to frame narratives in a certain context, taking into consideration ideas, opinions and facts through which *"actors try to convince others of their positions, suggest certain practices, and criticize alternatives"* ([7]: 71). Following Rosenbloom et al. [16], the authors propose the following three interrelated traits for the selection and inclusion of documents in the study and for an accurate understanding of relevant visions surrounding the investigated topic (i.e. narratives): first, the text should have a clear reference to the phenomenon under investigation; subsequently, the manuscript should include a well-defined idea or value judgement with regard to the area of investigation; finally, there should be an adequate narratives' extension to enable qualitative analysis .

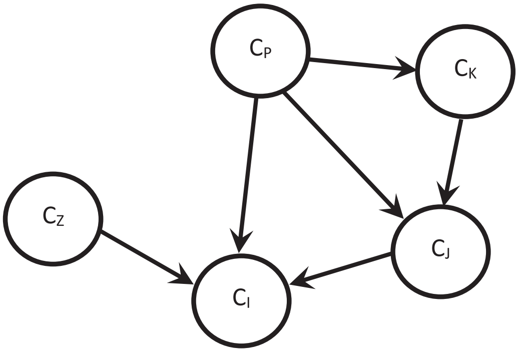


Fig. 1. System variables relationships

Selected articles are then qualitatively examined through the QDA Miner 5.0 software package [15] in order to identify and code relevant text segments that, in turn, would lead to the characterisation of related narratives [5]. System variables are obtained by carefully examining the semantic perspective in which the narratives are used, in each scrutinized article [1].

As this phase aims at identifying system variables able to grasp and integrate in the next phase (i.e. fuzzy mapping) the tacit knowledge pertaining to the experts, the description of variables is purposely simple and vague so as to enable the emergence of respondents' opinions, avoiding any influence or external bias [6]. Identified variables are divided into three main groups (Figure 1), according to their role played within the system: (i) senders (e.g. $c_{p,}$ c_z), whose role is to send stimuli to the rest of the system; (ii) transmitters (e.g. $c_{k,}$ c_j), who can both send and receive inputs being the connecting fabric of the system [9]; and (iii) receivers (e.g. c_i), who only receive inputs from other variables but not send them [3].

Therefore, a cognitive map is characterized by two main components: (1) a bundle of system variables, and (2) their cause-effect relationships – to be discussed in the next subsection.

Phase 2 - Identification of causal relations among variables

To complete the representation of the system structure, after the identification of its variables it is necessary to trace the cause-effect relationships among them. Usually, this is done by using a participatory approach that implies the organisation of interaction events among people, such as focus groups and workshops. Although this approach is useful to analyze group dynamics, it is expansive in terms of both time and money. In what follows an alternative method, relying on individual interview, is proposed as a viable way to get the same information. In this approach, interviews are directed to a set of actors composing the system under investigation. This phase requires the following steps:

1. Respondents recruitment;
2. Respondents interviews;
3. Numerical codification of verbal responses;
4. Aggregation of the individual cognitive maps into a social map;
5. Normalization of the social map.

1. Respondents recruitment - This operation is done based on the recognition of the various categories of stakeholders according to Fig. 2. All the relevant stakeholders belonging to these categories are identified and recruited, via email to be sent from the research institution in charge of the research. Personal contacts and relationship established in conferences are also used.

2. Respondents interviews - Each respondent is asked to recognize the cause-effect relationships among the system variables identified in phase 1. This task requires that, per each ordinated couple of variables (x_i, x_j) in the system, the respondent ascertains whether a cause-effect relation ($v_{i,j}$) exists, that is, according to its knowledge, whether x_i affects the state of x_j, and whether this effect is positive

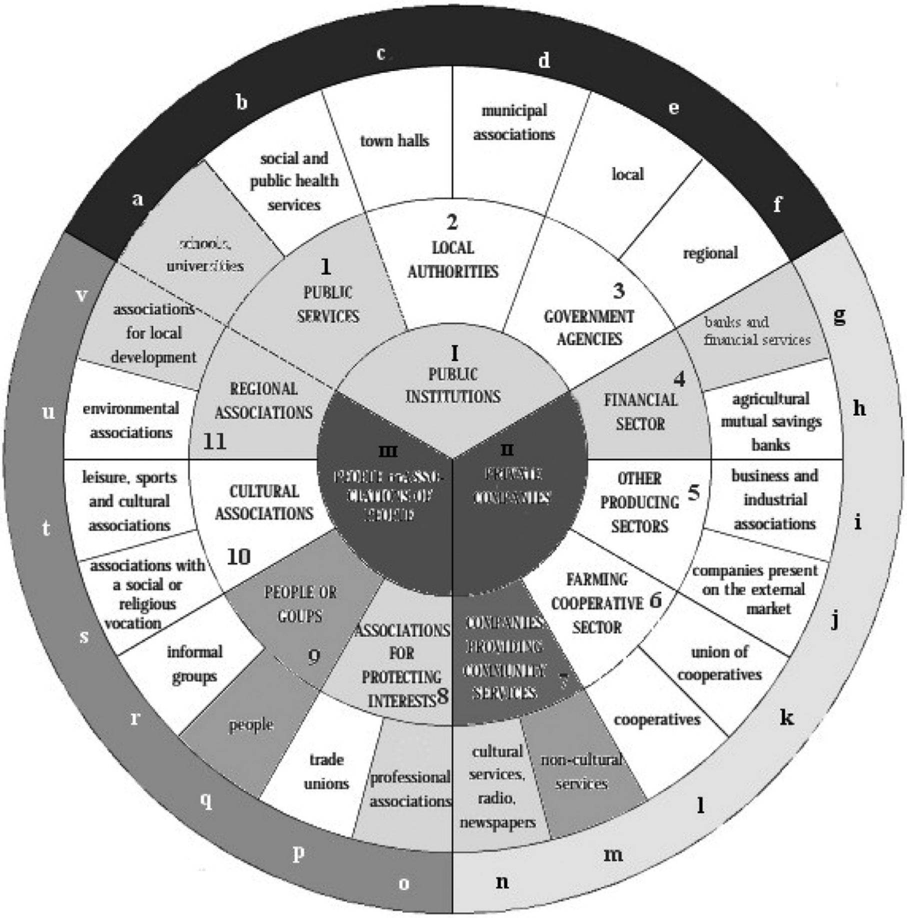


Fig. 2. The categories of stakeholders
Source: Source: Leader European Observatory, 1997

(negative), that is if x_j status augments (diminishes) the operation of x_i. The respondent identifies also the force of the relationship in a verbal form, quantifying it according to three qualitative judgment levels - i.e. strong, medium and weak. Operatively, this enquiry can be carried out by means of a square table of paired comparisons (Fig. 3) reporting on rows and columns the n system variables.

Setting, for instance, $n=30$, a thirty-variables table would contain ($30 \times 29=$) 870 relationships, which would represent a heavy workload for any respondent. To lighten this potential exhausting task (which might lead to loss of concentration and rationality), variables can be visually grouped in different categories (see section 1.1) by means of coloured cards (Fig. 4), each group forming a sort of meso-variable. This allows respondents to exclude the existence of relations among variables based on their nature or logical functioning - e.g. system drivers are typically not influenceable by other variables, that is they do not receive any causal relation – reducing *a priori* the number of couples to investigate.

3. Numerical codification of verbal responses – To make the gathered data tractable within a computational process, the individual verbal evaluation of the causative relations $v_{i,j}$ made by the respondent is transformed into numerical form recurring to a simple onto function g, which associates

	Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6	.	.	.	Variable n
Variable 1										
Variable 2										
Variable 3										
Variable 4										
Variable 5										
Variable 6										
.										
.										
.										
Variable n										

Fig. 3. The comparison table.

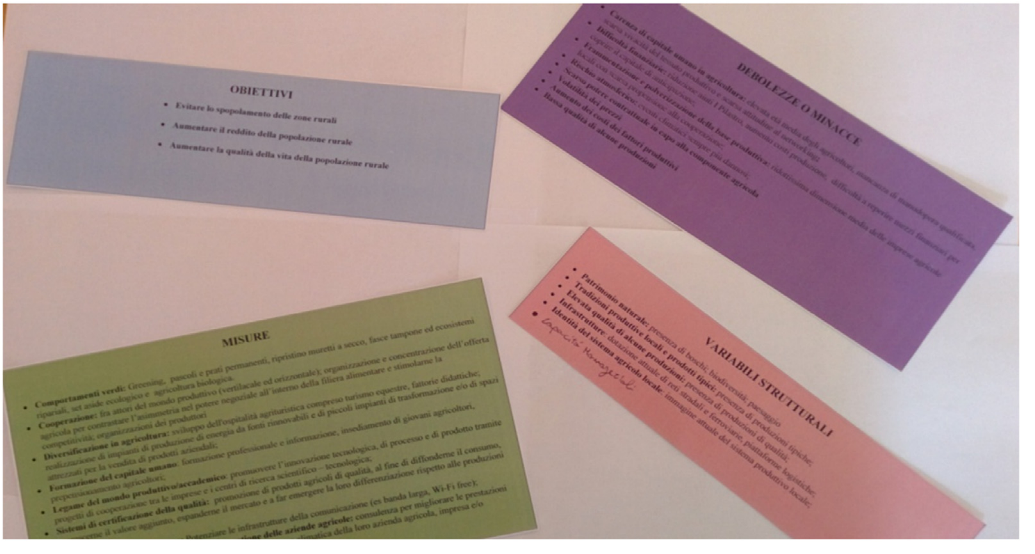


Fig. 4. Variables-categories cards

to each verbal evaluation $r \in L$, with $L=\{weak, medium, strong\}$, a numerical index $k \in K$, with $K=\{1, 2, 3\}$, as specified in Fig. 5.

Then, the index $(R_l)_{l \in K}$ associated to each relation $v_{i,j}$ is multiplied by the sign of the relation declared by the respondent, to derive the individual weight $iw_{i,j}$ of $v_{i,j}$ as specified in [1]:

$$iw_{i,j} = \begin{cases} (R_l)_{l \in K} \; if \;\; positive \\ (R_l)_{l \in K}(-1) \; if \;\; negative \end{cases} \quad (1)$$

This operation allows transforming the comparison table of each respondent into a numerical matrix containing individual weights associated to each causal relation among variables. This represents the basis from which a social map can be obtained.

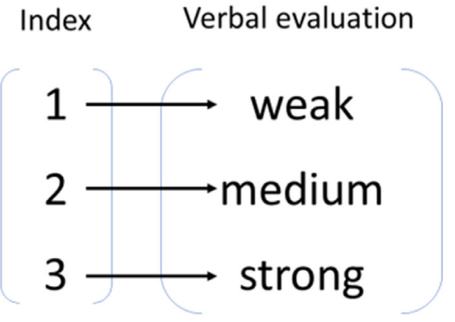


Fig. 5. Indexing function

4. Aggregation of the individual cognitive maps into a social map – The social map is a combination of individual weight matrixes. This operation is directed at obtaining a single weight per each relation representing a summary of the single M (= number of respondents) evaluations. It is denoted as $w_{i,j}$ and calculated as:

$$w_{i,j} = \sum_{m=1}^{M} iw_{i,j} \tag{2}$$

This procedure aims at providing a reliable depiction of the complex system under scrutiny, considering that the summation of individual weights amplifies the power of the relations on which respondents share a similar vision, while it weakens relations with different signs – reproducing a conflicting vision [14].

5. Normalization of the social map – Values obtained with step 4 can vary significantly, presenting calculation and comparison problems. In order to avoid these issues, a normalization step is added. This is done by dividing each $w_{i,j}$ by the absolute value reached to obtain a normalized weight $\hat{w}_{i,j}$:

$$\hat{w}_{i,j} = \frac{w_{i,j}}{max\left|w_{i,j}\right|} \tag{3}$$

The purpose of this normalization is to narrow the relations weight in the range [-1, 1] making the calculations easily tractable. Indeed, $\hat{w}_{i,j}$ is the element of the connection matrix W of the system variables which represents, in turn, a numerical depiction of the social cognitive map and, at the same time, the basis of the fuzzy inference.

Phase 3 - Fuzzy inference

This final phase of the proposed methodology is carried out by using the artificial neural network approach. The neural network used is a back-forward type, which has proven particularly suitable to analyse the dynamic of complex systems, due to its capacity to represent the typical causative loops and feedbacks interconnecting the variables of an FCM by means of its back-forward logic.

Phases 1 and 2 provide the fundamental elements to perform the neural network calculations, that are: (i) the variables forming the system; and (ii) the set of cause-effect relationship connecting them. These data are operationalised respectively by means of a state vector $S = (a_1,\dots, a_i,\dots a_n)$ containing the activation values of the variables a_i (with $a_1 = \dots a_i \dots = a_n = 1$), and the connection matrix $W = (w_{i,j})$. To simulate the dynamic of the system, S and W are multiplied and transformed (see sub-section below) at the activation time-step t_0 to calculate the new state vector $S_{new} = (s_1, \dots, s_i, \dots, s_n)$. In the subsequent model time-steps t, S_{new} is reiteratively calculated by multiplying S_{new} at t_{-1} by W.

This calculation is repeated through the running period $T = (t_1, \dots, t_n)$ needed to reach the system steady state, represented by the final state vector S_s (i.e. the vector of variable values which do not vary anymore, that is the state value is the same at t_{n-1} and at t_n).

Two specific steps can be identified to model policy interventions, (1) the natural dynamic simulation; and (2) the policy intervention simulation.

(1) The natural dynamic simulation – With this step the researcher uses the model to predict the way the system will evolve, according to peoples' knowledge, without external influence. To calculate the single variable value s_i at time t, the algorithm used is:

$$s_{i,t} = f\left(s_{i,t-1} + \sum_{j=1}^{n-1} s_{j,t-1} w_{i,j}\right) \tag{4}$$

where f is the logistic function in the form:

$$\frac{1}{1 + e^{-x}} \tag{5}$$

This transformation allows to maintain the variables values in the interval [0, 1]. It provides non- negative values that are easy to compare and allows to reach a steady state equilibrium. The steady state value assumed by the variable x_i under the natural simulation scenario (${s^n}_{j,tn}$) reflects its importance within the system according to peoples' knowledge and provides an idea of the evolution of the system in an autarchic context.

(2) The policy intervention simulation – This simulation is performed to answer the question "how would the system evolve, if subject to external interventions?". To this purpose, the first thing is to select those variables that are likely to be used as policy drivers (these drivers are identified from among senders or transmitters). The simulation is performed by applying the same procedure described above with the only difference that, at each time-step t, variables representing the policy drivers are clamped at their maximum value (normally set equal to 1). The effect of the policy measure analyzed can be evaluated by calculating the difference of the steady-state of variables representing the policy objectives (e.g. some of the receivers or system ends), with and without the policy intervention. This is done by applying the followings:

$$p_{i,j=} s^n_{j,tn} - s^p_{j,tn} \tag{6}$$

Where $p_{i,j}$ is the effect of policy intervention i on the objective represented by the variable j, and ${s^n}_{j,tn}$ has the same meaning above, and ${s^p}_{j,tn}$ represents the steady state of variable j in the policy simulation scenario.

Method validation

In this section, we present an exemplificative application of phase 3 of the method explained above. Data are drawn from a case study, using an online available resource targeted at performing FCMs simulation, that is an excel macro implementing the procedure described in paragraphs 1.2 and 1.3 and the calculation algorithm presented in eq. [4] (FCMapper, see next section). The variables and the connection matrix used are a subset of data concerning a study on rural development interventions. Tables 1 and 2 report, respectively, the list of variables used and the connection matrix.

The connection matrix is copied and pasted into the matrix sheet of the FCMapper tool (available at http://www.fcmappers.net/joomla/ under open license) to run the model. The GUI interface of the FCMapper excel tool is reported in Fig. 6. The check matrix button performs a check of the general characteristics of the matrix and applies to the value entered eq. [3] to normalise values in the range [-1,1]. Then, the connection matrix appears as in Fig. 7.

The FCM_Scenarios sheet shown in Fig. 8 is used to run the simulations. Cells B6:B23 represent the activation vector S and the "calculation selected scenario" button performs the scenario corresponding to the one reported in cell B3. Scene 1 runs the natural dynamic simulation (step 1, phase 3) and applies eq. [4] to the data. Cells E6:E23 contain the ${s^n}_{j,tn}$ values that are the steady states of the variables under the natural dynamic scenario.

Scenes 2 and 3 allow to simulate different policy intervention scenarios (Fig. 9). In our example, as emerges from Fig. 9, in Scene 2 we simulated the enforcement of an "agri-environmental-climate" payments by clamping the relate value at 1 (see the value in cell C9). Scene 3 simulates a policy

Table 1
The list of variables.

N.	Name	Category
1	Population	Policy objective
2	Income	Policy objective
3	Quality of Life	Policy objective
4	Agri-environment-climate	Policy driver
5	Producer groups and organisations	Policy driver
6	Farm and business development	Policy driver
7	Knowledge transfer	Policy driver
8	Co-operation	Policy driver
9	Quality schemes	Policy driver
10	Information technology	Policy driver
11	Input costs	Context variable
12	Low quality products	Context variable
13	Lacking human Capital	Context variable
14	Credit crunch	Context variable
15	Fragmentation	Context variable
16	Environmental risks	Context variable
17	Bargaining power	Context variable
18	Price volatility	Context variable

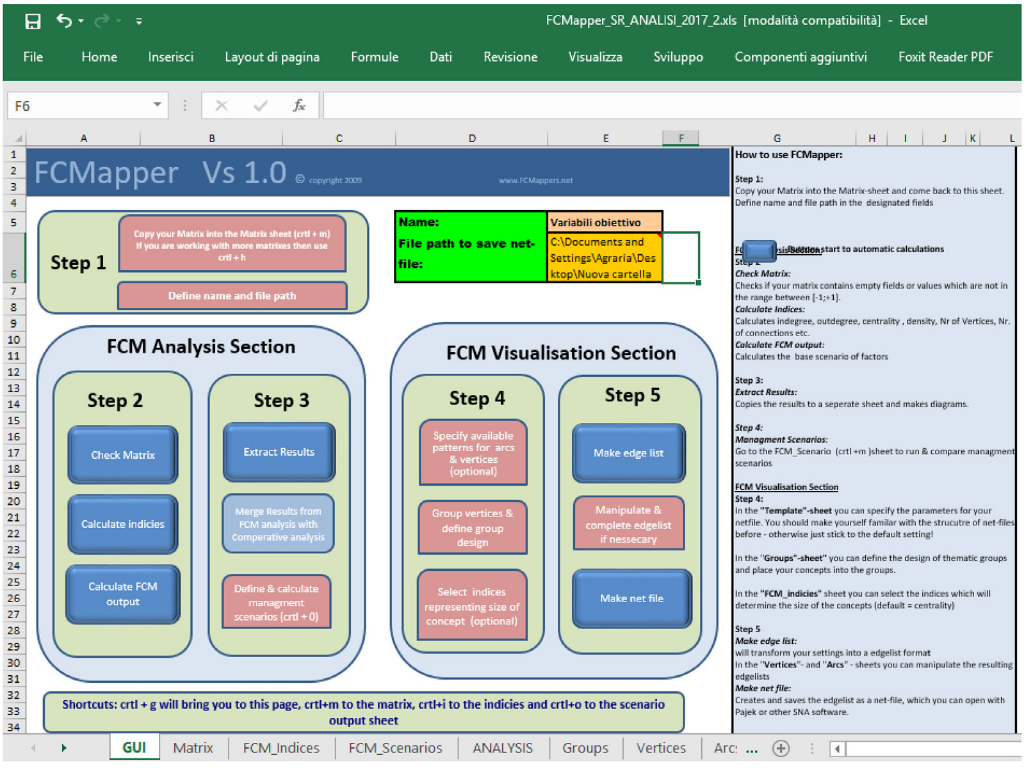
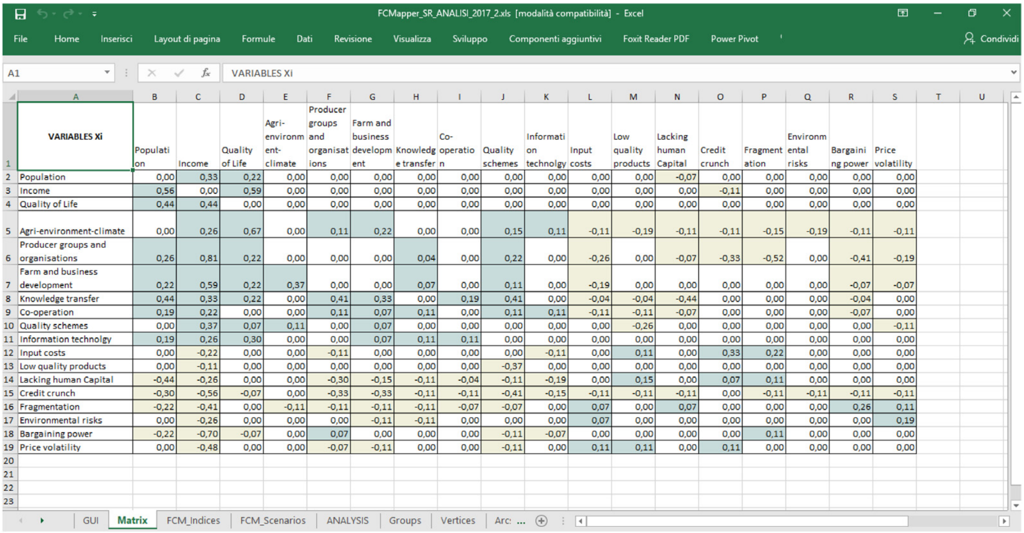


Fig. 6. The GUI interface of the FCMapper excel tool (http://www.fcmappers.net/joomla/)

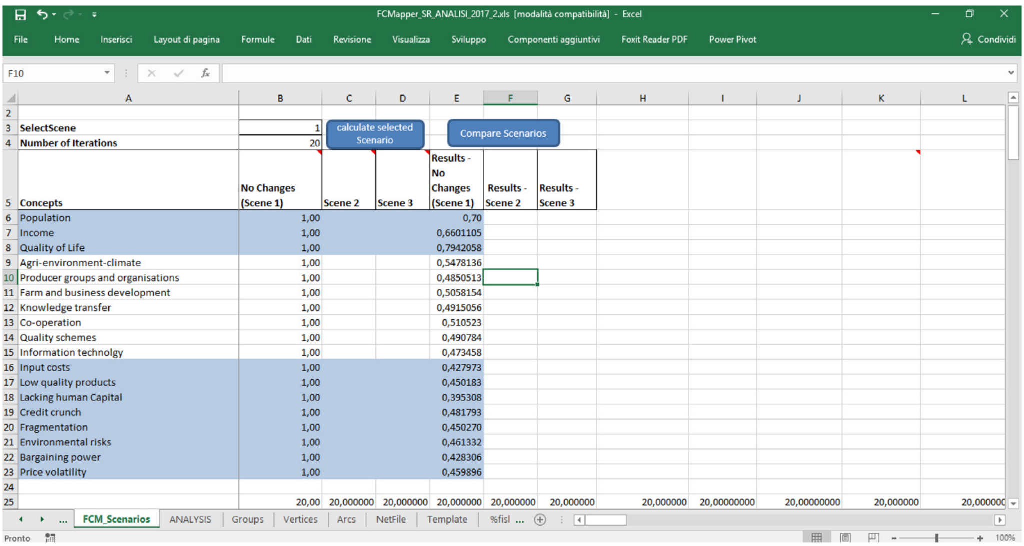
Table 2
The connection matrix

Variables	Pop.	Inc.	Qual.	Agri-e.	Prod.	Farm	Know.	Coop.	Qual.	Inf.	Inp.	Low	Lack.	Credit	Fragm.	Envir.	Barg.	Price
Population	0,00	0,33	0,22	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	-0,07	0,00	0,00	0,00	0,00	0,00
Income	0,56	0,00	0,59	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	-0,11	0,00	0,00	0,00	0,00
Quality of Life	0,44	0,44	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Agri-environment-climate	0,00	0,26	0,67	0,00	0,11	0,22	0,00	0,00	0,15	0,11	-0,11	-0,19	-0,11	-0,11	-0,15	-0,19	-0,11	-0,11
Producer groups and organisations	0,26	0,81	0,22	0,00	0,00	0,00	0,04	0,00	0,22	0,00	-0,26	0,00	-0,07	-0,33	-0,52	0,00	-0,41	-0,19
Farm and business development	0,22	0,59	0,22	0,37	0,00	0,00	0,07	0,00	0,11	0,00	-0,19	0,00	0,00	0,00	0,00	0,00	-0,07	-0,07
Knowledge transfer	0,44	0,33	0,22	0,00	0,41	0,33	0,00	0,19	0,41	0,00	-0,04	-0,04	-0,44	0,00	0,00	0,00	-0,04	0,00
Co-operation	0,19	0,22	0,00	0,00	0,11	0,07	0,11	0,00	0,11	0,11	-0,11	-0,11	-0,07	0,00	0,00	0,00	-0,07	0,00
Quality schemes	0,00	0,37	0,07	0,11	0,00	0,07	0,00	0,00	0,00	0,00	0,00	-0,26	0,00	0,00	0,00	0,00	0,00	-0,11
Information technolgy	0,19	0,26	0,30	0,00	0,00	0,07	0,11	0,11	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Input costs	0,00	-0,22	0,00	0,00	-0,11	0,00	0,00	0,00	0,00	-0,11	0,00	0,11	0,00	0,33	0,22	0,00	0,00	0,00
Low quality products	0,00	-0,11	0,00	0,00	0,00	0,00	0,00	0,00	-0,37	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Lacking human Capital	-0,44	-0,26	0,00	0,00	-0,30	-0,15	-0,11	-0,04	-0,11	-0,19	0,00	0,15	0,00	0,07	0,11	0,00	0,00	0,00
Credit crunch	-0,30	-0,56	-0,07	0,00	-0,33	-0,33	-0,11	-0,11	-0,41	-0,15	-0,11	-0,11	-0,11	0,00	-0,11	-0,11	-0,11	-0,11
Fragmentation	-0,22	-0,41	0,00	-0,11	-0,11	-0,11	-0,11	-0,07	-0,07	0,00	0,07	0,00	0,07	0,00	0,00	0,00	0,26	0,11
Environmental risks	0,00	-0,26	0,00	0,00	0,00	-0,11	-0,11	0,00	0,00	0,00	0,07	0,00	0,00	0,00	0,00	0,00	0,00	0,19
Bargaining power	-0,22	-0,70	-0,07	0,00	0,07	0,00	0,00	0,00	-0,11	-0,07	0,00	0,00	0,00	0,00	0,11	0,00	0,00	0,00
Price volatility	0,00	-0,48	0,00	0,00	-0,07	-0,11	0,00	0,00	-0,11	0,00	0,11	0,11	0,00	0,11	0,00	0,00	0,00	0,00



VARIABLES Xi	Population	Income	Quality of Life	Agri-environment-climate	Producer groups and organisations	Farm and business development	Knowledge transfer	Co-operation	Quality schemes	Information technolgy	Input costs	Low quality products	Lacking human Capital	Credit crunch	Fragmentation	Environmental risks	Bargaining power	Price volatility
Population	0,00	0,33	0,22	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	-0,07	0,00	0,00	0,00	0,00	0,00
Income	0,56	0,00	0,59	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	-0,11	0,00	0,00	0,00	0,00
Quality of Life	0,44	0,44	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Agri-environment-climate	0,00	0,26	0,67	0,00	0,11	0,22	0,00	0,00	0,15	0,11	-0,11	-0,19	-0,11	-0,11	-0,15	-0,19	-0,11	-0,11
Producer groups and organisations	0,26	0,81	0,22	0,00	0,00	0,00	0,04	0,00	0,22	0,00	-0,26	0,00	-0,07	-0,33	-0,52	0,00	-0,41	-0,19
Farm and business development	0,22	0,59	0,22	0,37	0,00	0,00	0,07	0,00	0,11	0,00	-0,19	0,00	0,00	0,00	0,00	0,00	-0,07	-0,07
Knowledge transfer	0,44	0,33	0,22	0,00	0,41	0,33	0,00	0,19	0,41	0,00	-0,04	-0,04	-0,44	0,00	0,00	0,00	-0,04	0,00
Co-operation	0,19	0,22	0,00	0,00	0,11	0,07	0,11	0,00	0,11	0,11	-0,11	-0,11	-0,07	0,00	0,00	0,00	-0,07	0,00
Quality schemes	0,00	0,37	0,07	0,11	0,00	0,07	0,00	0,00	0,00	0,00	0,00	-0,26	0,00	0,00	0,00	0,00	0,00	-0,11
Information technolgy	0,19	0,26	0,30	0,00	0,00	0,07	0,11	0,11	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Input costs	0,00	-0,22	0,00	0,00	-0,11	0,00	0,00	0,00	0,00	-0,11	0,00	0,11	0,00	0,33	0,22	0,00	0,00	0,00
Low quality products	0,00	-0,11	0,00	0,00	0,00	0,00	0,00	0,00	-0,37	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
Lacking human Capital	-0,44	-0,26	0,00	0,00	-0,30	-0,15	-0,11	-0,04	-0,11	-0,19	0,00	0,15	0,00	0,07	0,11	0,00	0,00	0,00
Credit crunch	-0,30	-0,56	-0,07	0,00	-0,33	-0,33	-0,11	-0,11	-0,41	-0,15	-0,11	-0,11	-0,11	0,00	-0,11	-0,11	-0,11	-0,11
Fragmentation	-0,22	-0,41	0,00	-0,11	-0,11	-0,11	-0,11	-0,07	-0,07	0,00	0,07	0,00	0,07	0,00	0,00	0,00	0,26	0,11
Environmental risks	0,00	-0,26	0,00	0,00	0,00	-0,11	-0,11	0,00	0,00	0,00	0,07	0,00	0,00	0,00	0,00	0,00	0,00	0,19
Bargaining power	-0,22	-0,70	-0,07	0,00	0,07	0,00	0,00	0,00	-0,11	-0,07	0,00	0,00	0,00	0,00	0,11	0,00	0,00	0,00
Price volatility	0,00	-0,48	0,00	0,00	-0,07	-0,11	0,00	0,00	-0,11	0,00	0,11	0,11	0,00	0,11	0,00	0,00	0,00	0,00

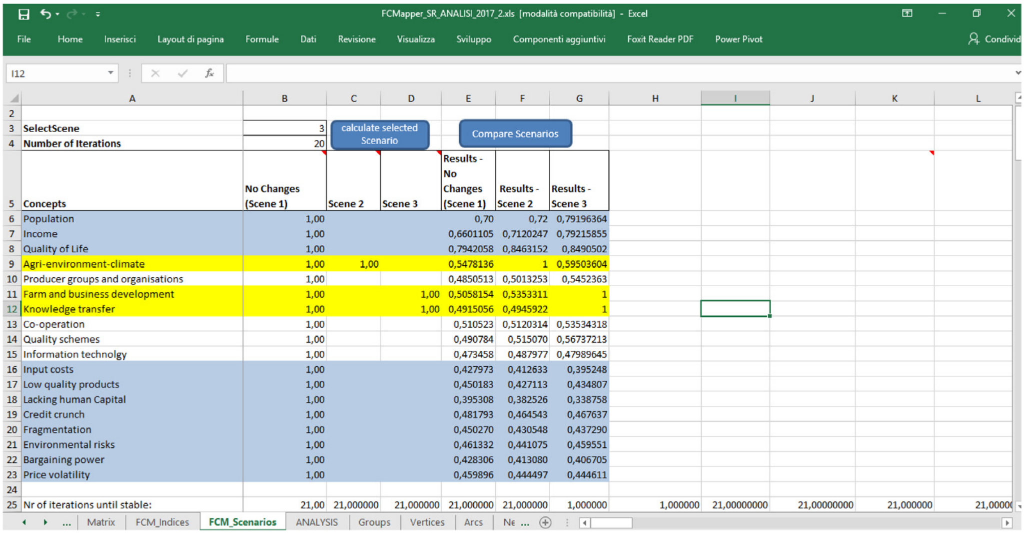
Fig. 7. The connection matrix as it appears in FCMapper (http://www.fcmappers.net/joomla/)



SelectScene	1										
Number of Iterations	20										
Concepts	No Changes (Scene 1)	Scene 2	Scene 3	Results - No Changes (Scene 1)	Results - Scene 2	Results - Scene 3					
Population	1,00			0,70							
Income	1,00			0,6601105							
Quality of Life	1,00			0,7942058							
Agri-environment-climate	1,00			0,5478136							
Producer groups and organisations	1,00			0,4850513							
Farm and business development	1,00			0,5058154							
Knowledge transfer	1,00			0,4915056							
Co-operation	1,00			0,510523							
Quality schemes	1,00			0,490784							
Information technolgy	1,00			0,473458							
Input costs	1,00			0,427973							
Low quality products	1,00			0,450183							
Lacking human Capital	1,00			0,395308							
Credit crunch	1,00			0,481793							
Fragmentation	1,00			0,450270							
Environmental risks	1,00			0,461332							
Bargaining power	1,00			0,428306							
Price volatility	1,00			0,459896							
	20,00	20,000000	20,000000	20,000000	20,000000	20,000000	20,000000	20,00000000	20,00000000	20,000000	20,00000C

Fig. 8. The natural dynamic simulation with FCMapper (http://www.fcmappers.net/joomla/)

intervention based on the combination of "farm development" and "knowledge transfer" measures. When Scene 2 or Scene 3 are selected, the "calculation selected scenario" button (corresponding to eq. [6]) is applied and $p_{i,j}$ – i.e. the effect of the policy i on the variable x_j - is calculated, where i and j are defined respectively by the row corresponding to the cell containing the value 1 in columns F or G, and the row corresponding to the policy objective under analysis. In our example, if i = "agri-environmental-climate" payments and j = "quality of life", the related $p_{i,j}$ is contained in cell F8 and is equal to 0.846.The method presented here eases the comparison between



	A	B	C	D	E	F	G	H	I	J	K	L
2												
3	SelectScene	3	calculate selected Scenario		Compare Scenarios							
4	Number of Iterations	20										
5	Concepts	No Changes (Scene 1)	Scene 2	Scene 3	Results - No Changes (Scene 1)	Results - Scene 2	Results - Scene 3					
6	Population	1,00			0,70	0,72	0,79196364					
7	Income	1,00			0,6601105	0,7120247	0,79215855					
8	Quality of Life	1,00			0,7942058	0,8463152	0,8490502					
9	Agri-environment-climate	1,00	1,00		0,5478136	1	0,59503604					
10	Producer groups and organisations	1,00			0,4850513	0,5013253	0,5452363					
11	Farm and business development	1,00		1,00	0,5058154	0,5353311	1					
12	Knowledge transfer	1,00		1,00	0,4915056	0,4945922	1					
13	Co-operation	1,00			0,510523	0,5120314	0,53534318					
14	Quality schemes	1,00			0,490784	0,515070	0,56737213					
15	Information technolgy	1,00			0,473458	0,487977	0,47989645					
16	Input costs	1,00			0,427973	0,412633	0,395248					
17	Low quality products	1,00			0,450183	0,427113	0,434807					
18	Lacking human Capital	1,00			0,395308	0,382526	0,338758					
19	Credit crunch	1,00			0,481793	0,464543	0,467637					
20	Fragmentation	1,00			0,450270	0,430548	0,437290					
21	Environmental risks	1,00			0,461332	0,441075	0,459551					
22	Bargaining power	1,00			0,428306	0,413080	0,406705					
23	Price volatility	1,00			0,459896	0,444497	0,444611					
24												
25	Nr of iterations until stable:	21,00	21,000000	21,000000	21,000000	21,000000	1,000000	1,000000	21,00000000	21,00000000	21,000000	21,0000(

Fig. 9. Policy interventions simulation with FCMapper (http://www.fcmappers.net/joomla/)

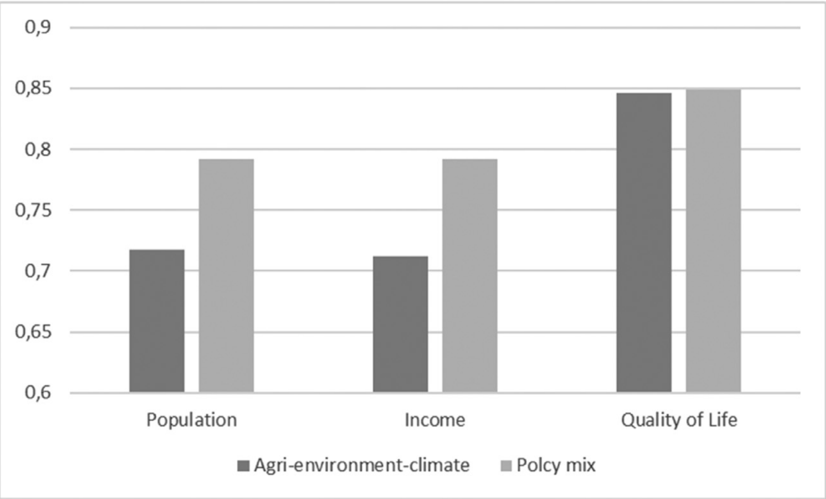


Fig. 10. Policy intervention effect: changes of policy objectives from steady state

policy interventions providing specific values comparison terms. In this example, the effect of "agri-environmental-climate" payments on the "quality of life" is similar to the one produced by "farm development" and "knowledge transfer" mix (0.846 and 0.849 respectively), while the latter policy is more effective as far as the other two policy objectives. When presenting results, $p_{i,j}$ values are typically represented by means of bar diagrams as in Fig. 10

Acknowledgements

We want to thank the colleague and friend Maurizio Prosperi (University of Foggia) for having introduced us to FCMs.

Additional information

The excel macro used in section 1.4 to perform the method validation is called “FCMapper” and has been developed by Michael Bachhofer and Martin Wildenberg. It is available upon request on the web portal: http://www.fcmappers.net/joomla/

References

[1] J.L. Anderson, L.D. Jolly, A.E. Fairhurst, Customer relationship management in retailing: A content analysis of retail trade journals, Journal of Retailing and Consumer Services 14 (2007) 394–399.
[2] A. Awasthi, H. Omrani, A scenario simulation approach for sustainable mobility project evaluation based on fuzzy cognitive maps, International Journal of Modelling and Simulation (2018) 1–11, doi:10.1080/02286203.2018.1451711.
[3] O. Çoban, G. Seçme, Prediction of socio-economical consequences of privatization at the firm level with fuzzy cognitive mapping, Inf. Sci. 169 (2005) 131–154.
[4] P.M. Falcone, A. Lopolito, E. Sica, Policy mixes towards sustainability transition in the italian biofuel sector: Dealing with alternative crisis scenarios, Energy Research and Social Science 33 (2017) 105–114, doi:10.1016/j.erss.2017.09.007.
[5] P.M. Falcone, A. Lopolito, E. Sica, The networking dynamics of the italian biofuel industry in time of crisis: Finding an effective instrument mix for fostering a sustainable energy transition, Energy Policy 112 (2018) 334–348, doi:10.1016/j.enpol.2017.10.036.
[6] P.M. Falcone, P. Morone, E. Sica, Greening of the financial system and fuelling a sustainability transition. A discursive approach to assess landscape pressures on the Italian financial system, Technological Forecasting & Social Change 127 (2018) (2018) 23–37.
[7] M.A. Hajer, Doing discourse analysis: coalitions, practices, meaning, in: M. van den Brink, T. Metze (Eds.), Words Matter in Policy and Planning: Discourse Theory and Method in the Social Sciences, Netherlands Geographical Studies, Utrecht, Netherlands, 2006.
[8] B. Kosko, Fuzzy cognitive maps, International Journal of Man-Machine Studies 24 (1) (1986) 65–75.
[9] A. Lopolito, P. Morone, R. Sisto, Innovation niches and socio-technical transition: a case study of bio-refinery production, Futures 43 (2011) 27–38.
[10] A. Lopolito, M. Prosperi, R. Sisto, E. De Meo, Translating local stakeholders' perception in rural development strategies under uncertainty conditions: An application to the case of the bio-based economy in the area of foggia (south italy), Journal of Rural Studies 37 (2015) 61–74, doi:10.1016/j.jrurstud.2014.12.005.
[11] M. Masinde, M. Mwagha, T. Tadesse, Downscaling africa's drought forecasts through integration of indigenous and scientific drought forecasts using fuzzy cognitive maps, Geosciences (Switzerland) 8 (4) (2018), doi:10.3390/geosciences8040135.
[12] M. Olazabal, A. Chiabai, S. Foudi, M.B. Neumann, Emergence of new knowledge for climate change adaptation, Environmental Science and Policy 83 (2018) 46–53, doi:10.1016/j.envsci.2018.01.017.
[13] T. van der Sluis, B. Arts, K. Kok, M. Bogers, A.G. Busck, K. Sepp, . . ., E. Crouzat, Drivers of european landscape change: Stakeholders' perspectives through fuzzy cognitive mapping, Landscape Research (2018) 1–19, doi:10.1080/01426397.2018.1446074.
[14] U. Özesmi, S.L. Özesmi, Ecological models based on people's knowledge: A multi-step fuzzy cognitive mapping approach, Ecological Modelling 176 (1-2) (2004) 43–64, doi:10.1016/j.ecolmodel.2003.10.027.
[15] , in: QDA Miner version 5.0 User Manual, Montreal, QC, Canada, 2011 Available on line at:.
[16] D. Rosenbloom, H. Berton, S. Meadowcroft, Framing the sun: a discursive approach to understanding multi-dimensional interactions within socio-technical transitions through the case of solar electricity in Ontario, Canada, Res. Policy 45 (6) (2016) 1275–1290.