Using Fuzzy Cognitive Mapping and Nonlinear Hebbian Learning for Modeling, Simulation and Assessment of the Climate System, Based on a Planetary Boundaries Framework

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Abstract: In the present work a fuzzy cognitive map for the qualitative assessment of the Earth climate system is developed by considering subsystems on which the climate equilibrium depends. The cognitive map was developed as a collective map by aggregating different experts opinions. The resulting network was characterized by graph indexes and used for simulation and analysis of hidden pattens and model sensitivity. Linguistic variables were used to fuzzify the edges and were aggregated to produce an overall linguistic weight for each edge. The resulting linguistic weights were defuzzified using the "Center of Gravity", and the current state of the Earth climate system was simulated and discussed. Finally, a nonlinear Hebbian Learning algorithm was used for updating the edges of the map until a desired state. The overall results are discussed to explore possible policy implementation, environmental decision making and management.

1 INTRODUCTION

Nowadays, the widespread concerns over the climate stability and the resilience of natural ecosystems under pressure have pointed out the necessity of developing new tools to monitor present conditions, asses future scenarios and explore possible policy implementations oriented to environmental decision making and management.

Currently a strong tendency to explore the use of Fuzzy cognitive maps for the development of models in the environmental sciences is emerging. Examples include FCM as methodological framework for environmental decision making and management (Papageorgiou and Kontogianni 2012), to evaluate cases of study, like the future of water in the Seyhan Basin in Turkey (Cakmak et al. 2010), and the description of current system dynamics together with the development of land cover scenarios in the Brazilian Amazon (Soler et al. 2011).

This approach is useful by its capability for including quantifiable and non-quantifiable concepts in a model (Papageorgiou and Kontogianni 2012), but also due to the fact that it doesn't require neither large capacity of computation nor to have numeric equations of the analyzed phenomena. FCM are also a suitable framework for integrating information that is scattered in several places, as is the case in environmental systems in which, to built integrated models, the information must be taken in several disciplines (e.g atmospheric sciences, biology, and geophysics). Moreover, the latest models in cognitive mapping seek not only to simulate systems, but to control and thus to establish recommendations and explore possible policy implementation, environmental decision making and management. The training and tuning of FCM is performed by using Hebian learning algorithms (Papakostas et al, 2011). These algorithms aim to find appropriate weights between the concepts of the map so the model equilibrates to a desired state.

In the present work we used a FCM to analyze the dynamic of the climatic system based on a planetary boundaries framework, with Earth subsystems identified by Rockström et al. (2009) as those on which the Earth's climate equilibrium depends. The paper is structured as follows: In Section 2 we present the basis of the FCMs theory. Section 3 describes the planetary boundaries framework. Section 4 presents the FCM simulation and a comparison with the current state of the results versus the current state, Section 5 describes the implementation of a nonlinear Hebian

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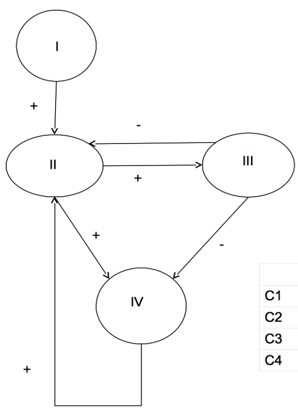
learning algorithm to adjust the weights of the map until the map reaches a desired state. And finally, Section 6 includes the conclusions and further work.

2 FUZZY COGNITIVE MAPS

Fuzzy cognitive maps are directed graph structures for representing causal reasoning between variable concepts (Kosko 1986). The concepts are represented as nodes $(C_1, C_2, ..., C_n)$ in an interconnected network. Each node C_i represents a variable concept, and the edges e_{ij} which connect C_i and C_j (denoted as $C_i \rightarrow C_j$) are causal connections and express how much C_i causes C_j. Edges can have either a numerical or a linguistic value. $w_{ij} > 0$ indicates a positive causality between concepts C_i and Cj, $w_{ij} < 0$ indicates a inverse (or negative) causality, and $w_{ij} = 0$ indicates no causality. Linguistic quantifiers (such as low, medium or high) are also used to represent the value of the weights, they indicate the qualitative relation among concepts.
Figure 1 shows a FCM containing four concepts (or nodes) numbered I, II, III, and IV. The table shows the assigned weights for the relationships between concepts.



	C1	C2	C3	C4
C1	0	0.5	0	0
C2	0	0	1	0.2
C3	0	-0.3	0	-1
C4	0	0.7	0	0

Figure 1: A FCM of four concepts (numbered I, II, III, IV). The table shows the weights for the edges associated with the relationships between concepts.

FCM are built using expert's opinion. They define, considering their expertise, the main components of the system as the concepts of the network. Once these are defined, the (causal) relations among them, as well as the weights for each relation, are established.

2.1 The FCM Inference Process

The dynamic of a fuzzy cognitive map can be simulated analytically through a specific inference process (Papageorgiou and Kontogianni 2012). For this process, we considered FCM concepts having values in a specific numerical interval (e.g $[0, 1]$). The value of each C_i at time t is called the "activation level", and is interpreted as the state of activation (or quantity) of this concept.

The values of the concepts $C_i^{(t)}$ at each time t are represented in a row state vector $A^{(t)} = [C_1^{(t)}, ..., C_n^{(t)}]$ which describes the state of the system at each time step or iteration t (Kosko, 1991). Given a particular input $A^{(0)}$, the state of the system during the iterations can converge into an equilibrium point, into a limit cycle or diverge. The inference process is calculated using the following equation:

$$A_i^{t+1} = f\left(\sum_{i=1, i\neq j}^{N} W_{ij} A_j^{(t)}\right) \quad (1)$$

2.2 FCM Graph Indexes

The structural properties of cognitive maps can be analyzed by using graph theory indexes. Through this analysis we gain intuition of the general structure and quality of the network. This is important since cognitive maps are a subjective representation of the real system, hardly dependent on the expert's opinion. Graph indices allow us to analyze how experts are regarding and structuring the system. Those include, among others, the number of concepts, connections, the ratio concepts/connections, and the density, defined as the ratio of the number of connections in the map and the square value of concepts.

The complexity of the concepts is analyzed through structural measures like the conceptual centrality index for a particular node C_i defined by Kosko (1986) as:

$$CEN(C_i) = IN(C_i) + OUT(C_i) \quad (2)$$

where:

$$IN(C_i) = \sum_{k=1}^{n} \overline{w}_{ik} \quad (3)$$

$$OUT(C_i) = \sum_{k=1}^{n} \overline{w}_{ki} \quad (4)$$

$IN(C_i)$ represents the number of concepts that causally act on concept C_i. Similarly, the row sum $OUT(C_i)$ is the number of concepts in which C_i causally acts (Kosko 1986). Then the conceptual centrality represents the importance of C_i to the causal

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flow on the map. When fuzzy weights values are used, the causal amount counts, i.e, a node can be connected to fewer nodes than another and still have greater conceptual centrality (Kosko 1986).

The density index (D) shows how connected the network is. It is defined as the number of existing connections divided by the maximum number of possible connections among all nodes (given by N^2). A map with high density will have a large number of causal relations.

The structure analysis of a cognitive map also includes the transmitter, receiver and ordinary variables. These are defined by their associate values of $IN(C_i)$ and $OUT(C_i)$, called indegree and outdegree, respectively. Nodes whose outdegree is positive and their indegree is 0 are defined as transmitter variables. Receiver variables, on the contrary, are those nodes whose outdegree is 0 and their indegree is positive. Variables with non zero outdegree and indegree are called ordinary variables. (Eden et al. 1992, Ozesmi & Ozesmi, 2004). Receiver and transmitter variables show the structure of the map, for example, transmitter variables can be seen as forcing functions, which influence the system but cannot be controlled by other system's variables. The complexity of the system, or sometimes the degree of elaboration, can be analyzed by considering the number of receiver and transmitter variables. A great number of receiver or transmitter variables could be interpreted as the map is not being well elaborated or the relationships among its variables are not well known, which means that the causal relations among components are not clear for the experts (Eden, 1992, Papageorgiou and Kontogianni 2012).

Collective maps are used to integrate different perspectives of a particular system. When collective cognitive maps are developed each expert creates a map and then the different versions are condensed either by grouping subgraphs in a single node, or by maintaining the nodes when several experts coincide. The centrality is used to decide which concepts will be represented in the collective map.

3 SUBSYSTEMS OF THE CLIMATE SYSTEM: A PLANETARY BOUNDARIES FRAMEWORK

The stability analysis of the Earth climate system is based on the planetary boundaries framework proposed by a group of scientist heading by Rockstöm (2009), and later discussed by Foley (2010). They established a planetary boundaries frame by identifying and quantifying the boundaries associated with the planet's biophysical subsystems that must not be transgressed in order to prevent an unacceptable environmental change. Based on the review of those reports we created an expert's opinion knowledge base for the construction of the fuzzy cognitive map. To do this, we grouped in a single map the concepts and relations identified in each article by its authors. They mentioned nine processes suggested as those in which is necessary to define planetary boundaries: climate change; rate of biodiversity loss (terrestrial and marine); interference with the nitrogen and phosphorus cycles; stratospheric ozone depletion; ocean acidification; global freshwater use; change in land use; chemical pollution; and atmospheric aerosol loading. These concepts and their relationships are briefly described below.

Climate change refers to the increase in the mean temperature of the earth. More precisely, to changes in climate variability in terms of the extreme and mean values (IPCC, 2007, 2014). Specifically we refer to antropogenic climate change, which is a consequence of the human activity. Climate change causes changes in vegetation distribution, and so threat the ecological live-support systems as well as human activities. The climate change is described in terms of two variables having critical thresholds that qualitatively separate different climate system states (Rockstöm et al., 2009), these are the atmospheric CO_2 concentration and the radiative forcing.

Changes in atmospheric CO_2 concentration
Defined as the increase in the parts per million of CO_2 molecules in the atmosphere (IPCC, 2007, 2014). Most models suggest that, as atmospheric CO_2 increases also does global temperature. For example, doubling atmospheric CO_2 will lead to a rise about 3C (with a probable uncertainty of 2-4.5C).

Changes in radiative forcing
The radiative forcing is the rate of energy change per unit area of the globe as measured at the top of the atmosphere.

Rate of biodiversity Loss
Refers to the extinction rate, the number of species loss per million per year. Mace and collaborators (2005), define biodiversity as the variability of living organisms, included terrestrial and marine ecosystems, other aquatic ecosystems and the ecological systems in which they reside. It comprises the diversity within species, among species and within ecosystems. Mace emphasizes three levels of biodiversity: genes, species, and ecosystems. Biodiversity loss during the industrial period has grown notably. The species extinction rate is estimated against the fos-

sil record. The extinction rates per million per year varies for marine life between 0.1 and 1 and for mammals between 0.2 and 0.5. Today, the rate of extinction of species is estimated to be 100 to 1,000 times more than what could be considered natural (Rockström, 2009).

Ocean Acidification
Defined as the ocean pH increase, mainly in the surface layer. The acidification process is closely related with the CO_2 emission level. When the atmosphere CO_2 concentration increases, the amount of carbon dioxide dissolved in water as carbonic acid increases, which in turn, modifies the surface pH. Normally, the ocean surface is basic with a pH of approximately 8.2. Nevertheless, the observations show a decline in pH to around a value of 8. These estimations are made using the levels of aragonite (a form of calcium carbonate) that is created in the surface layer. This concept has an important relation with biodiversity loss as many organisms (like corals and phytoplankton), basic for the food chain, use aragonite to produce their skeletons or shells. As the aragonite value decreases, the ocean ecosystems weaken. (Foley *et al.,* 2010).

Phosphorus and Nitrogen Cycles
The human activity at the planetary scale is perturbing the global cycles of phosphorus (P) and nitrogen (N). The agriculture activity convert around 120 million tones of N_2 from the atmosphere per year into reactive forms (Rockström, 2009). The pressure that this changes exerted over the environment threats the balance of natural equilibrium. For example the nitrous oxide is one of the most important greenhouse gases and its grown directly increases the radiative forcing. In the case of phosphorus around 20 million tonnes are mined every year and around 8.5 million - 9.5 million tonnes flow into the oceans perturbing the marine ecosystems. To establish boundaries, the changes in P and N cycles are estimated with the quantity of P going to the oceans, measured in million tones per year, and with the amount of N_2 removed from the atmosphere for human use, also in million tones per year.

Change in land use (Urban Growth and Agriculture Use)
The IPCC defines the change in land use as the percentage of global land converted into cropland. A general definition of land use change includes any type of human use. This transformation, either to cropland or urban, increases the biodiversity loss, which is associated with the destruction of ecosystems. In order to establish the difference in land use between urban growth and agriculture use, and their different consequences, we include both concepts as nodes in the map.

Chemical pollution
It refers to the emitted quantity, persistence, or concentration of organics pollutants, plastics, heavy metals, chemical and nuclear residues, etc., which affect the dynamic of ecosystems.

Global Freshwater use
Defined as the increase in its current use. Today, the annual use of freshwater from rivers, lakes and groundwater aquifers is of 2,600 km^3. From that, 70% is destined for irrigation, 20% for industry, and 10% for domestic use. This extraction causes the drying and reduction of body waters. (IPCC, 2007, 2014).

Atmospheric aerosol loading
Referred as the concentration of particles in the atmosphere. These can be lead, copper, magnesium, iron, traces of fire, ashes, etc.

Stratospheric Ozone Depletion
O_3 depletion is estimated according to the ozone concentration in the atmosphere in Dobson Units. [1]

With the previous subsystems and the highlighted relations among them we built the cognitive map. Even though FCM are a subjective representation of the reality, this representation is not arbitrarily because its constructions is reviewed and processed carefully to extract the system knowledge of the experts.

4 A COGNITIVE MAP OF THE EARTH CLIMATE SYSTEM

The FMC constructed was based on four different cognitive maps. Two of them based on the analysis of Rockström et al, (2009) and Foley (2010), and others proposed by Paz-Ortiz (2011), and Gay-García (2012). Then, we analyzed the maps separately and a collective cognitive map was created. For maps based on Rockström et al, (2009) and Foley (2010) we extracted the concepts mentioned by the authors as those who described the Earth climate stability system, as well as the relations among the concepts. For each relation, we assigned a value of 1 or -1 (according to the positive or negative causality described by the author) to be the weight of the arc representing it. If an author did not mentioned a concept, it was included in its map's matrix without relation (writing 0 in the adjacent matrix) with other concepts. So all the matrices had the same dimensions. The adjacent

[1]Dobson unit is a measure of the ozone layer thickness, equal to 0,01 mm of thickness in normal conditions of pressure and temperature (1 atm and 0 C respectively), expressed as the molecule number. DU represents the existence of 2.69 x 10^{16} molecules per square centimeter.

matrix of the collective map was defined as the sum of all adjacent matrices of the individual maps. Figure 2 and 3 show the cognitive maps derived from Rockström (2009), and Foley (2010). Cognitive maps Paz-Ortiz (2011) and Gay-García & Paz-Ortiz (2012) are not shown. Figure 4 shows the collective cognitive map created considering the four cognitive maps. Figures were developed in pajek software [http://vlado.fmf.uni-lj.si/pub/networks/pajek/]).
Table 1. shows the average ($\pm$SD) graph theoretical indices (Papageorgiou & Kontogianni 2012) of the individual FCMs and the indices of the collective FCM. The indices allowed us to evaluate the descriptive strength of the model.

Table 1: Cognitive map index.

Indices	Individual Maps	Collective CM
Maps	4	1
Variables (N)	11.5 ± 0.5	14
Number of connections (W)	18.5 ± 6.42	40
No. of transmitter variables (T)	2 ± 1.22	1
No. of receiver variables (R)	1.25 ± 0.43	0
Connection/Variable (W/N)	1.84 ± 0.26	2.85
Density ($D = W/N^2$)	0.13 ± 0.04	0.20

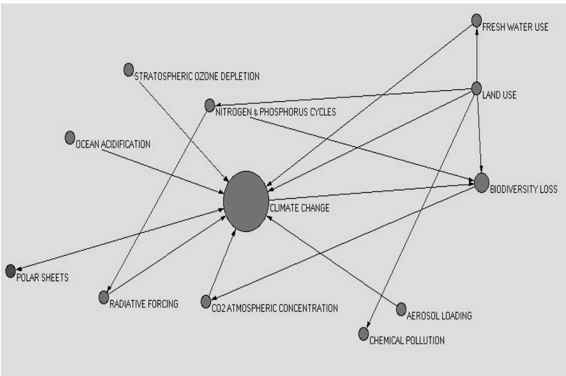

Figure 2: Rockström et al, (2009) Cognitive map of the Earth climate system.

In Table 1 the index for the number of connections (W) shows values of 40 for the collective map and 18.5 for the individual ones. Also the number of variables (N) is 11.5 for the individual and 14 for the collective. This illustrate how experts have different perspectives respecting to nodes and relations. The integration of these different perspectives in one model is another powerful characteristic of FCMs.

As said, a measure of how a cognitive map is connected or sparse, is the *density*, expressed as the number of connections divided by the maximum number of connections possible (N^2). The collective cognitive map is highly connected compared with individual maps.

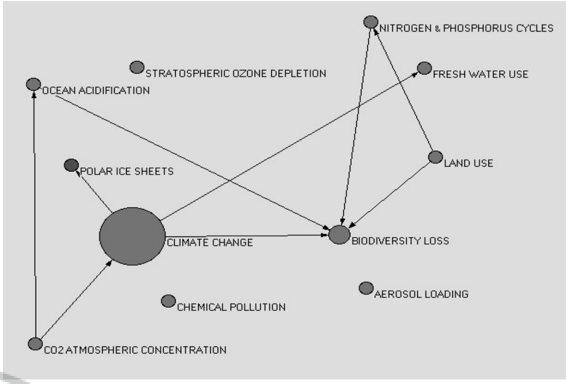

Figure 3: Foley, (2010) Cognitive map of the Earth climate system.

The transmitter and receiver variables indicate how the experts structured causal relations in a cognitive map. As referred by Papageorgiou & Kontogianni (2012), cognitive maps containing a larger number of receiver variables consider many outcomes that are a result of the system, while maps containing many transmitter nodes show the "flatness" of a cognitive map where causal arguments are not well elaborated.

The number of transmitter and receiver variables diminish in the collective map in comparison with individual maps. The indices ratio Connection/Variable (W/N) and Density also show that the collective map provides a strongest model in comparison with individual ones.

4.1 Simulation

To simulate the dynamic of the map, the inference process described in Equation 1 was used. For the simulation, we represented the earth process in a state vector ordering the nodes as follows: 1 Climate Change, 2 Ocean acidification, 3 Stratospheric ozone depletion, 4 Nitrogen and Phosphorus cycles, 5 Fresh water use, 6 Land use, 7 Biodiversity loss, 8 Aerosil loading, 9 Chemical pollution, 10 CO_2 atmospheric concentration, 11 Radiative forcing, 12 Polar sheets, 13 Agriculture, 14 Industrialization. For the basic simulation process, in order to analyze the general behavior of the network, we considered three cases. These will give us information about hidden patterns (when forcing the network), and the net sensitivity when we use random values. Knowing the hidden patterns (or feedback process) allows policy makers to pay attention in the processes that can be irreversible. While network sensitivity shows how much the output of the network depends on the initial values, and

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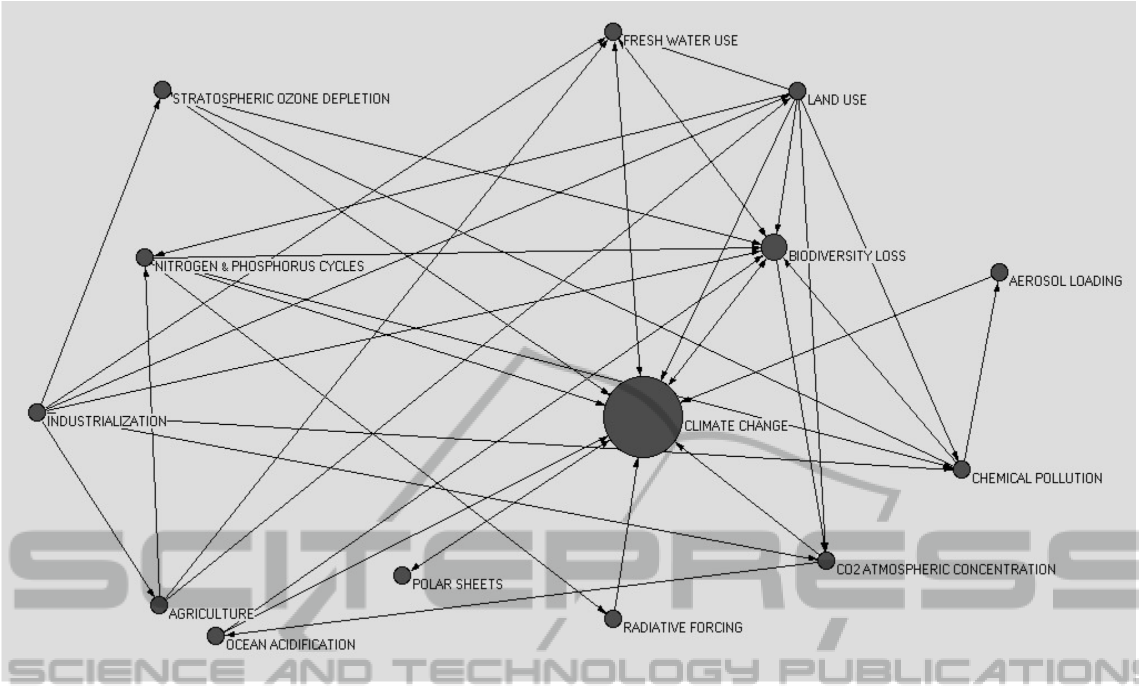

Figure 4: Collective cognitive map.

therefore how much our approximations for the edges values will influence the results. This allow the stakeholders to consider the model taking this perspective into account.

Case 1: Initializing the network with random values in the interval [0,1] for nodes and in the interval (0,1] for edges. This, since we assumed that the links established by the experts cannot have a value of zero, in which case there would be no such link. In the process, all randomly generated values were generated independently.

Case 2: Initializing the network with the same random values used in Case 1 for nodes and edges. And forcing Industrialization (Node 14) by giving a value of 1 to this node after each iteration.

Case 3: Forcing the Industrialization (Node 14), by inducing a recurrent value of 1 in this node after each iteration, and considering an initial value of 0 for all nodes.

Table 2, summarizes the three cases: Initial values of the nodes, initial weights used, the resulting vector, and the number of the iterations where the convergence is reached.

Case 1: Cycles and feedback processes.
The resulting vector in the first simulation shows the feedback processes of the network. Nodes that appear with non zero values. We can see that Climate change (Node 1), Ocean acidification (2), Fresh water use (5), Biodiversity loss (7), and CO_2 atmospheric concentration (10) converge into a value of 1. While node polar sheets (12), only activated in the map by node Climate change (and that got an edge random value of 0.3), remain "ON" with this value. All these nodes are inside feedback processes in the network, for this reason they remain "ON" even when the driver has gone out. These nodes are key to the design of policies, since disturbances in these systems could trigger irreversible processes. In this type of simulation, i.e initializing some nodes without forcing the network, the resulting values will depend on the values of the nodes and weights (Gay-García & Paz-Ortiz, 2012). In some cases, where the weights are small enough, the value of the concepts is damped until zero as the system is iterated.

Case 2: Dependency of initial conditions (values of nodes and edges).
The resulting vector in Case 2 shows the effect of the weights of the edges in the resulting vector. Even though the vector converges, the values to which each node converge will depend on the strength of the causal connections between them. This hypothesis is supported by Case 3. In which we have forced Industrialization (14) but considering a value of 1 for all connections. Cases 2 and 3 show the sensitivity of the network.

4.2 Fuzzy Weights

In order to have more information form the model, we considered fuzzy weights for the edges. These are

Table 2: Basic simulation of the cognitive map.

Initial values of nodes	Initial weights	Resulting vector	Number of iterations
Case 1 random values ∈ [0,1]	random values ∈ (0,1]	1, 1, 0, 0, 1, 0, 1, 0, 0, 1, 0, 0.3, 0, 0	6
Case 2 Same random values of Case 1 ∈ [0,1] Industrialization =1 for all t	random values (Case 1) ∈ (0,1]	1, 1, 1, 0.83, 1, 0.81, 1, 0.6, 1, 1, 0.08, 0.3, 0.3, 1	5
Case 3 Industrialization = 1 for all t	1 for all edges	1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1	3

fuzzy linguistic variables associated with the relationship between two concepts that determine the grade of causality between them. We created and associated these variables as proposed by the Papageorgiou and Kontogianni (2012) methodology. We used thirteen fuzzy quantities taken from the strength suggested for each relation by each one of the expert in its original map. The quantities used were T{influence}= {negatively very very strong, negatively very strong, negatively strong, negatively medium, negatively weak, negatively very weak, zero, positively very weak, positively weak, positively medium, positively strong, positively very strong, positively very very strong}. Then, the results were aggregated by using the SUM method (Papageorgiou & Stylios, 2008) to produce an overall linguistic weight for each edge. The resulting linguistic weights were defuzzified using the Center of Gravity (CoG) (Zadeh, 1986) that takes all the linguistic weights and creates numerical values within the interval [-1, 1]. The overall linguistic values are shown in Table 4.

To obtain initial values for the edges we considered the current state of the earth system processes referred by Rockström et al (2009) (shown in Table 3). We can see that subsystems: Climate change, Rate of biodiversity loss and Nitrogen cycle (i.e three of nine interlinked planetary boundaries), have already transgressed their proposed limits. Stratospheric ozone depletion and Ocean acidification are just above. Phosphorus cycle, Global fresh water use, and Change in land use are close to the boundary. While Atmospheric aerosol loading and Chemical pollution systems have not yet an established boundary. We assigned for each concept a fuzzy weight by considering its current position with respect to the proposed boundary. For the Industrialization, Agriculture, and Polar sheets processes, which are not considered in this frame, we used the description given by Rockström et al (2009) and Gay-Garca & Paz-Ortiz (2012) to set the initial values. Again, the overall fuzzy quantifiers were defuzzified by using the CoG method into a numerical values for the system's simulation. The initial defuzzified numerical values for the concepts are shown in the Initial Vector at the top of Table 4. For this simulation the map was iterated while keeping the forcing in node Industrialization (14) with its initial value of 0.4. The resulting vector converged after 10 iterations to:
0.69, 0.21, 0.25, 0.27, 0.62, 0.32, 0.90, 0.17, 0.56, 0.43, 0.08, 0.42, 0.24, 0.4 (button Table 4).
It can be seen that nodes Climate change (1) and Biodiversity loss (7) referred as concepts who have already crossed the boundary appeared with the highest values of 0.69 and 0.90, respectively. However, the node representing Nitrogen and Phosphorous cycles (4) exhibited a value of 0.27. This can be a consequence that although the threshold is established considering both processes, the distance of each process in respect to its proposed boundary is slightly different, so when the concepts were defuzzified the model could have lost accuracy. Also nodes Fresh water use (5), and Chemical pollution (9) exhibited high values of 0.62 and 0.56 respectively. In the first case, it is possible that the established edges, as well as the relations, are overestimating the state of the system. In the second case, since there are no data on the system state, this simulation is interesting since it allows us to estimate the state of this node.

4.3 Training the Fuzzy Cognitive Map by using Nonlinear Hebbian Learning

Up to this point, the simulation qualitatively describes the state of the climate system. However, in order to establish action strategies that allow for planning and support decision processes in terms of environmental policy, it is necessary to know what might be the changes of the weights in order to obtain a desired state for the system. To do this, we used the Nonlinear Hebbian Learning (NHL) algorithm proposed by Papageorgiou et al, (2006) to adjust the weights of the

Table 3: Planetary Boundaries.

Earth-system processes	Parameters	Proposed boundary	Current status
Climate change	CO_2 concentration, changes in radiative forcing	350 ppm, $1W/m^2$	280 ppm, $1.5W/m^2$
Rate of biodiversity loss	Extinction rate	10	> 100
Nitrogen (with P cycle)	N_2 removed for human use	35	121
Phosphorus (with N cycle)	Quantity of P flowing into the oceans	11	8.5-9.5
Stratospheric ozone depletion	O_3 concentration	276	283
Ocean acidification	Global saturation of aragonite in surface sea	2.75	2.90
Global fresh water use	Consumption ($km^3/year$	4000	2600
Change in land use	Percentage of land cover converted to cropland	15	11.7
Atmospheric aerosol loading	Particulate concentration, on a regional basis	to be determined	-
Chemical pollution	Amount emitted to, or concentration	to be determined	-

map. This algorithm was used because it is referred by Papakostas et al, (2011) in a comparative study as the one which exhibits a satisfactory behavior in control systems, having at the same time a low algorithmic complexity when it is compared with similar algorithms (Papakostas et al, 2011).

Two restrictions for the algorithm were used. First: Don't change the edges values that describe relationships between concepts that operate over natural processes. For example, it cannot modify the dependency of climate change with respect to the increase in the atmospheric CO_2 concentration, since doing so it would modify a natural process. Therefore, the algorithm was restricted for to only change the weights of the edges starting from the node Industrialization. The values of the other edges were kept equal after each iteration. Second: the weight of these edges couldn't be less than zero, since the causal relations were positively established by experts. Therefore, the value of the concepts were kept >0.

The algorithm operates by using targets for the value of the concepts to be adjusted. For this, only targets over variables Climate change (1) and biodiversity loss (7) were used. This is because we were interested in reducing the concepts that are operating over the proposed boundary that were simulated by the model. The targets were established to perform a reduction in this two variables by 0.2 under its initial value. The values of the other concepts, in the state vector, were allowed to variate freely. Then, the algorithm operated as follows:
Step 1: Given the initial vector (A^0) and the initial adjacent matrix of weights W^0.
Step 2: For each iteration k.
Calculate A^k by using Eq (1).
Update W^k for edges coming out Industrialization by using the equation:

$$w_{ij}^{(t+1)} = w_{ij}^{(t)} + \eta A_j^{(t)} \left(A_i^{(t)} - sgn(w_{ij}^{(t)} A_j^{(t)} w_{ij}^{(t)}) \right) \quad (5)$$

Where η is the learning rate.
Calculate error associated with Climate change and Biodiversity loss, defined as the difference between the current value of each concept and its established target value.
Stop when error $\leq$ acceptable difference (0.05).
Step 3: Return the final weights.

The final weights of the concepts are shown in Table 4. The system converges into a final vector: 0.49, 0.14, 0.17, 0.20, 0.49, 0.22, 0.67, 0.13, 0.45, 0.29, 0.06, 0.29, 0.2, 0.4 after 24 iterations. We found the nodes Climate change and Biodiversity loss, 0.2 and 0.23 below its original values, respectively. This coincides with the established targets of 0.2 units below for each one.

A first remarkable result is that the greater reduction appears in the relation Industrialization - CO_2 atmospheric concentration, that goes from 0.7 to 0.45. This can be interpreted from the point of view of the possible action policies as the most important processes that must be taken into account.

In general we can arrange our results in four classes, depending on the reduction of the weights. Relations with minimal reduction (0.05), Industrialization - Fresh water use, Industrialization - Chemical pollution, and Industrialization - Biodiversity loss). Relations with reduction of 0.1,Industrialization - Stratospheric ozone depletion and Industrialization - agriculture. Relations with a reduction of 0.2, Industrialization - Land use, and concepts with weight reduction of 0.25 Industrialization - CO_2 atmospheric concentration. This results can be useful to establish different levels of action. It is important to say that declaring different levels of action does not neglect other processes while serving one. It is necessary to take into account that the systems are interrelated. However, these results allow us to establish hierarchies for a policy design.

Table 4: Comparison between initial and final vector (with initial and final weights). Nodes-relation and linguistic (initial and final) quantifiers and its respective associated numerical value.

INITIAL VECTOR	0.6, 0.1, 0.3, 0.8, 0.1, 0.1, 0.7, 0.2, 0.3, 0.7, 0.8, 0.2, 0.3, 0.4 Iterations: 0
Nodes - Relation	Linguistic value - Initial weight - Final weight
1 - 5 Climate change - Fresh water use	positively very weak, 0.3 -
1 - 12 Climate change - Polar sheets	positively strong, 0.6, -
1 - 7 Climate change - Biodiversity loss	positively weak, 0.3, -
2 -1 Ocean acidification - Climate change	positively very weak, 0.1, -
2 - 7 Ocean acidification Biodiversity loss	positively very weak, 0.1, -
3 - 1 Stratospheric ozone depletion - Climate change	positively weak, 0.2, -
3 - 7 Stratospheric ozone depletion - Biodiversity loss	positively very weak, 0.1, -
4 - 9 N P cycles - Chemical pollution	positively medium, 0.5, -
4 - 7 N P cycles - Biodiversity loss	positively very weak, 0.1, -
4 - 1 N P cycles - Climate change	positively very weak, 0.1, -
4 - 11 N P cycles - Radiative forcing	positively weak, 0.3, -
5 - 7 Fresh water use - Biodiversity loss	positively very weak, 0.1, -
5 - 1 Fresh water use - Climate change	positively very weak, 0.1, -
6 - 9 Land use - Chemical pollution	positively strong, 0.6, -
6 - 4 Land use - N P cycles	positively medium, 0.4, -
6 - 7 Land use - Biodiversity loss	positively strong, 0.6, -
6 - 1 Land use - Climate change	positively weak, 0.2, -
6 - 5 Land use - Fresh water use	positively weak, 0.3, -
6 - 10 Land use - CO_2 concentration	positively weak, 0.2, -
7 - 10 Biodiversity loss - CO_2 concentration	positively very weak, 0.1, -
7 - 1 Biodiversity loss - Climate change	positively very weak, 0.05, -
8 - 1 Aerosol loading - Climate change	positively very weak, 0.05, -
9 - 8 Chemical pollution - Aerosol loading	positively weak, 0.3, -
9 - 7 Chemical pollution - Biodiversity loss	positively medium, 0.5, -
9 - 3 Chemical pollution - Stratospheric ozone depletion	positively weak, 0.3, -
10 - 2 CO_2 concentration - Ocean acidification	positively medium, 0.5, -
10 - 1 CO_2 concentration - Climate change	positively very strong, 0.7, -
11 - 1 Radiative forcing - Climate change	positively medium, 0.4, -
12 - 1 Polar sheets - Climate change	positively weak, 0.2, -
13 - 4 Agriculture - NP cycles	positively strong, 0.6, -
13 - 6 Agriculture - Land use	positively medium, 0.5, -
13- 5 Agriculture - Fresh water use	positively medium, 0.5, -
14 - 13 Industrialization - agriculture	positively strong, 0.6 , 0.5
14 - 6 Industrialization - Land use	positively medium, 0.5, 0.3
14 - 5 Industrialization - Fresh water use	positively medium, 0.5, 0.45
14 - 10 Industrialization - CO_2 concentration	positively very strong, 0.7, 0.45
14 - 9 Industrialization - Chemical pollution	positively strong, 0.6, 0.55
14 - 7 Industrialization - Biodiversity loss	positively weak, 0.2, 0.15
14- 3 Industrialization - Stratospheric ozone depletion	positively weak, 0.2, 0.1
FINAL VECTOR WITH INITIAL WEIGHTS	0.69, 0.21, 0.25, 0.27, 0.62, 0.32, 0.90, 0.17, 0.56, 0.43, 0.08, 0.42, 0.24, 0.4 Iterations: 10
FINAL VECTOR WITH FINAL WEIGHTS	0.49, 0.14, 0.17, 0.20, 0.49, 0.22, 0.67, 0.13, 0.45, 0.29, 0.06, 0.29, 0.2, 0.4 Iterations: 24

5 CONCLUSIONS AND FURTHER WORK

The methodology presented for evaluation and simulation of the climate system showed qualitatively consistent results, both with climate system state as well as with the expected scenarios. Moreover, the adjustments to the weights obtained through the implementation of the algorithm (where we clearly observed different levels of adjustment) allow the design and assessment of environmental policies, helping at the same time, to their planning.

Given that the system is highly sensitive to changes in the strength of interactions between subsystems, and considering the feedback processes (Section 4.1), it is clear that more research must be developed to increase the description accuracy of the model in the first case, and to analyze possible irreversible degradation processes within the feedback loops. However, since the system allows to asses and differentiate the importance between these relationships, further research can be prioritized. In that sense, this model can also help to the elaboration of the research agenda.

The methodological approach presented (based on Papageorgiou & Kontogianni, 2012) clearly allows the construction of stronger collective cognitive maps when compared with the capacity of descriptions of the individual ones. As cognitive maps highly depend

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on the expert's opinion, this methodology also allows us to evaluate the strength and descriptive capacity of the model. The performed simulation was capable to identify the feedback processes, and when linguistic variables were used and aggregated to produce an overall linguistic weight for each edge with the associated defuzzification by using Center of Gravity, the resulting model matched with the current description of the climate system referred by Rockström et al (2009). Although the algorithm for the adjustment of the weights was restricted, the adjustments where the principal reduction occurs in the relation Industrialization - CO_2 atmospheric concentration, were plausible in the context of the current reports on climate change. This, together with the results of the simulations, support the idea that the developed model can be used for the planning, implementation, and evaluation of policies. A possible further work, in order to analyze the adjustments performed, could implement migration or evolutionary algorithms to adjust the weights (Vaščák 2012) and evaluate the perform of each type from the point of view of the stakeholders.

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