A Fuzzy Cognitive Map for México City's Water Availability System

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Abstract: In the present work a fuzzy cognitive map was used to analyze México city's water system, to study the water availability and the system's response under different possible scenarios of climate change. The map includes the water sources and their availability, as well as climatic and social factors that affect the system. The map was built based on the analysis of the previous study *"Vulnerabilidad de las fuentes de abastecimiento de agua potable de la Ciudad de México en el contexto de cambio climático."* ("Vulnerability of fresh water sources in Mexico city in the context of climate change") by Escolero (2009). Once the map was built, it was analyzed using the technique of vector state and adjacent matrix. First, the values of $\{0,1\}$ were used to find the "hidden patterns". Then, different weights were considered for the edges to analyze the system's sensibility to changes in the strength of the processes. Finally, to investigate the importance of different nodes over the water availability, the *min - max* criteria was used to propose implementations for possible solutions. In the analysis, considerations were made between climatic and social drivers, in order to assign the corresponding attributions for each kind.

1 INTRODUCTION

1.1 Fuzzy Cognitive Maps (FCMs)

FCMs use graph structures to represent the flux of cause and effect relationships among predefined variable concepts; these are depicted as nodes $(C_1, C_2, ..., C_n)$ in an interconnected network, each one representing a concept, and the edges e_{ij} which connect two nodes (denoted as $C_i \rightarrow C_j$) are causal connections and they express how much C_i causes C_j. These edges can be negative or positive. A positive relation $C_i \rightarrow {}^{+}C_j$ states that if C_i grows also does C_j, and a negative relation $C_i \overset{-}{\rightarrow} C_j$ indicates that as C_i grows, C_j decreases. The edges among the network nodes can be represented in a an adjacent matrix, and the state of each node at an specific time can be represented in a row vector state. The value of the vector for each iteration is calculated by multiplying the vector by the adjacent matrix.

$$v_t = v_{t-1} * M \quad (1)$$

FCMs can be used to model the causal relationships of a system. To accurately capture the system's dynamic, the maps are usually built considering experts opinions (Kosko 1986). Once they are built, they can be analyzed with different techniques that give information about the system's properties. We consider a map fuzzy when we have used linguistic quantifiers as weights for its edges (Kosko 1992).

1.2 Fuzzy Sets

The fuzzy sets are classes of objects, taken from a universe, with a continuum of grades of membership to a particular set (Zadeh, 1965). These grades of membership are specified by a membership function which assigns a degree of membership to each fuzzy subset for each object. The fuzzy sets are a useful tool to work in universes where we have imprecision in the class membership criteria, i.e. when it is not well defined whether or not an element belongs to an specific set. In our study, we will use fuzzy sets to model causality when it is referred by experts as linguistic quantifiers, such as low or high.

1.3 Indirect and Total Effect (min - max criteria)

As the cognitive maps represent the causal flux among the nodes of the network, one thing that is important to know is how much causality a node imparts over another. To know this, we use the indirect and total

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causal effects when we work with linguistic edges. A causal path from some concept C_i to concept C_j comprises the sequence $C_i \to C_{k_1} \ldots \to C_{k_n} \to C_j$. The indirect effect of C_i on C_j is the causality C_i imparts to C_j via the path $(i, k_1 \ldots k_n,\ j)$. The total effect of C_i on C_j is the composite of all the possible indirect effects that C_i imparts over C_j. The indirect effect of an specific branch or path is defined as the minimum value of all the edges in the path. And the total effect is defined as the maximum of all the indirect effects (Kosko, 1986).

As the causality can be positive or negative, we used the following rules in order to know the sign of the causality of one node over another. The indirect effect of a path is negative if the number of negative edges in the path is odd, and is positive if the number is even. The total effect of C_i on C_j is negative if all the indirect effects of C_i on C_j are negatives, and is positive if they are all positive, in any other case the total effect is undetermined. The indeterminacy can be removed using a weighted scheme. If we assign weights to the edges (this weights can be positive or negative real numbers) w_{ij} then the indirect effect in a path $(i, k_1 \ldots k_n,\ j)$ is the product $w_{i,k_1} * w_{i,k_2} * \ldots * w_{i,k_1}$ and the total effect is the sum of all path products (Peláez 1996).

2 THE MODEL

2.1 State of the Art

Soft computing models oriented to systems analysis and decision making have gained popularity in different areas. The utility of these kind of models in comparison with hard computing models relies on their tolerance for imprecision and their ability to make decisions under uncertainty (Nguyen et al. 2003). Fuzzy cognitive maps were introduced by Kosko (1986) and since then, they have been used to model complex systems (Stylios 2004), distributed systems (Stylos et al. 1997), as a system model for failure modes and effects analysis (Peláez 1996), and to model virtual worlds (Kosko 1994). In environmental sciences, they have been recently used for environmental decision making and management (Elpiniki 2012), and to evaluate cases of study, like the future of water in the Seyhan Basin (Cakmak 2013) and the description of current system dynamics together with the development of land cover scenarios in the Brazilian Amazon (Soler et al. 2010).

The water availability problem is one of the many fields where we need to work under great uncertainty. The climate models have different outputs. Models should deal with social, climatic and political variables, and many of these processes are not precisely quantified. Then, the FCMs are a useful tool to explore, assess and make strategic decisions.

2.2 The Fuzzy Cognitive Map

The FCM was built throughout a detailed analysis of the study *"Vulnerabilidad de las fuentes de abastecimiento de agua potable de la Ciudad de México en el contexto de cambio climático."* ("Vulnerability of fresh water sources in Mexico city in the context of climate change") by Escolero (2009). First, the concepts that describe the dynamics of the system were identified, and these were related in terms of causes and consequences. When the map was finished, Dr. Escolero was consulted to validate the map, and to add relations and nodes that were missed. The concepts identified in the study were divided in climatic and social variables. This classification allowed us to have a more detailed analysis of the system. The following concepts were identified:

• Climatic concepts: Temperature increase, which refers to the increase in mean temperature and in the extreme values; Precipitation (PCP) decrease, which refers to the decrease in mean precipitation; and Extreme events increase, that refers to the rise of the frequency and intensity of extreme events (IPCC 2007). These three concepts belong to climatic variables, and so, they represented the climate drivers on the map.

• Social identified concepts are: Population growth, describes the increase of inhabitants in the city; Agriculture development, due to land use change and increases the water demand; Urbanization, refers to the development and growth of the city; and Industry growth, that refers to the development of the industries and its possible development tendencies.

As consequences of the drivers mentioned above, the result concepts are: Waste water discharge increase, Degradation in the water quality, Vegetal cover loss, Social water demand increase, Erosion increase, Non-planned extraction, Evapotranspiration increase, Aquifers degradation referring to basins, Basins degradation in the case of dams, Decrease in dams levels, Decrease in water availability (which is the concept we wanted to analyze), and finally, Social and administrative conflicts increase. The fuzzy cognitive map for México's city water availability system is shown in Figure 1.

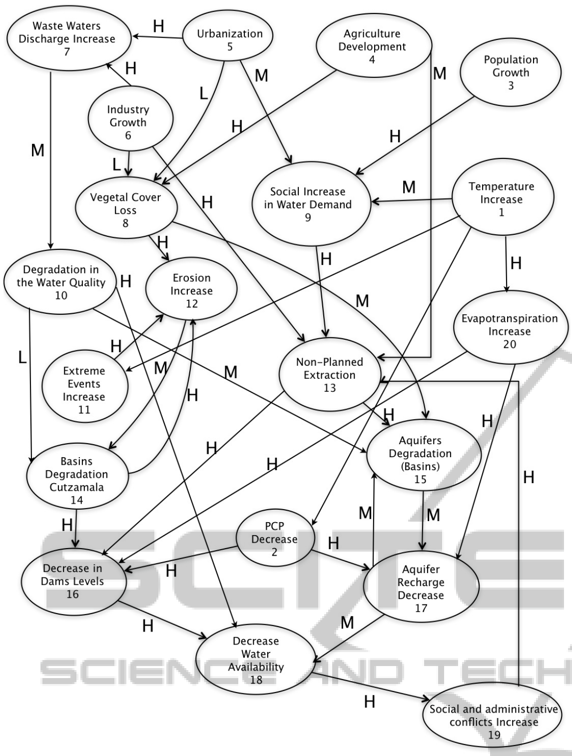


Figure 1: Fuzzy Cognitive map for México city's water availability system.

3 ANALYSIS

3.1 Analysis of Feedback Processes, Social and Climate Drivers

Our first analysis identified the feedback processes in the map. The feedbacks are important because they are the parts of the network that once they are initiated, the nodes constituting them will continue interacting, even though the drivers are turned off. We identified four feedbacks in the map:

• The first one is between the nodes 12 and 14, and it represents the process between erosion increase and the basins degradation (in the Cutzamala). A similar structure is between nodes Aquifers degradation (Basins, 15) and Aquifer recharge decrease (17).

• The third process is constituted by nodes 13 (non planned extraction), 15 (aquifers degradation basins), 17 (aquifer recharge decrease), 18 (decrease in water availability), and 19 (social and administrative conflicts increase).

• The fourth one is among concepts 13, 16, 18, 19, and 13.

When any node in a feedback is activated, the presence of the signal remains in the map, and only disappear if it is damped by fractionary weights at the edges.

We analyzed the map using the technique of the adjacent matrix and the vector state described section 1. We iterate using equation 1. We will denote de *t-th* iteration by v_t

In order to check the feedback processes we started climate and social drivers separately. In the first case, starting climate drivers i.e. Temperature increase and PCP decrease (the initial vector had a 1 in its first and second entrances), without considering in this case extreme events, the system reached the final vector in five iterations:

$$v_5 = [\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,1\,0\,1\,1\,1\,1\,1\,0\,]$$

Which means that together the increase of temperature and the PCP decrease, will trigger nodes 13 (non-planned extraction), 15 (aquifers degradation, basins), 16 (decrease in dams levels), 17 (aquifer recharge decrease), 18 (decrease of water availability), and 19 (social and administrative conflicts increase).

When nodes 3 (population growth), 4 (agriculture development), 5 (urbanization), and 6 (industry growth) were activated, the system converged in five iterations to the vector:

$$v_5 = [\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,1\,1\,1\,1\,1\,1\,1\,1\,0\,]$$

Which differs from our last result only by the nodes 12 (erosion increase) and 14 (basins degradation, Cutzamala). When we considered $C_1 \rightarrow C_{11}$ the resulting vectors were equals.

In both cases, we turned on the forcers only in the initial vector (v_0) and we let the system evolve. As expected, the nodes with feedback remained ON even though the driver was turned OFF.

We observed that the resulting vectors, forcing climate or social nodes, differ only by two nodes. This indicates that nodes 13 (non-planned extraction), 15 (aquifers degradation basins), 16 (decrease in dams levels), 17 (aquifer recharge decrease), 18 (decrease of water availability), and 19 (social and administrative conflicts increase) are driven by climate and social factors.

3.2 Hidden Patterns

Once we identified the feedback processes, we analyzed the map in the cases where we kept the forcing after each iteration. These cases showed the final states, when the forcer remained in the system. For this analysis we considered the state vector and the

adjacent matrix with values in the set $\{0,1\}$. Forcing the system to different configurations showed how the system responds to various initial conditions. We used the three following configurations:
a. First we turned ON the Temperature increase and PCP decrease and turned OFF the concepts 3, 4, 5 and 6. This showed how the system responds to persistent climate forcing.
b. Turned OFF the Temperature increase and the PCP decrease, and turned ON the concepts 3, 4, 5 and 6. Which considers only the social forcing of the system.
c. We turned the Temperature increase and PCP decrease ON, as well as concepts 3, 4, 5, and 6. Which showed the system's behavior having both climate and social forcing.

In the first case (a), turning ON the nodes 1 and 2 (Temperature increase and PCP decrease), the system converged in three iterations to the vector:

$$v_3 = [\,1\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 1\ 1\,]$$

This last result means that keeping nodes 1 and 2 forced increases the concepts: water social demand, non-planned extraction, aquifers degradation (in basins), decrease in dams levels, aquifer recharge decrease, decrease in water availability, and social and economic conflicts.

When node 11 was turned ON (extreme events increase) together with nodes 1 and 2, the system converged in three iterations to:

$$v_3 = [\,1\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\,]$$

With this configuration, nodes 12 (erosion increase), and 14 (basin degradation, Cutzamala) were turned ON.

In the case (b), when we turned OFF the nodes 1, 2, and 11, but instead we turned ON the nodes 3, 4, 5, and 6, the system converged in four iterations to:

$$v_4 = [\,0\ 0\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 0\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 0\,]$$

Nodes 7 (waste waters discharge increase), 8 (vegetal cover loss), were turned ON and node 10 (degradation in water quality), and node 20 (evapotranspiration increase) were turned OFF.

Case (c), we turned ON the concepts 1, 2, 3, 4, 5, 6, and 11. The system converged in three iterations to the vector:

$$v_3 = [\,1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\,]$$

The difference between only considering temperature increase (1) and PCP decrease (2) in comparison of turning ON the nodes population growth (3), agriculture development (4), urbanization (5), and industry growth (6), both keeping the forcer, are basically the nodes: waste waters discharge increase (7), vegetal cover loss (8), degradation in the water quality (10), erosion increase (12) and basins degradation, Cutzamala (14). Notice that this nodes were turned on when social forcers were ON.

3.3 Considering Climate Predictions of Models

Although the climate drivers on México city do not completely depend on the processes developed there (over the city), we know how they change and interact by following the predictions given by the climate models (Oglesby et al. 2010). Different predictions allowed us to use the model we created to explore different scenarios. The climate forcers in the model are: temperature increase, PCP decrease, and extreme events increase. The relations among these three concepts, considering the scenarios of precipitation decrease, and its opposite, precipitation increase, are shown in the next image (Figure 2).

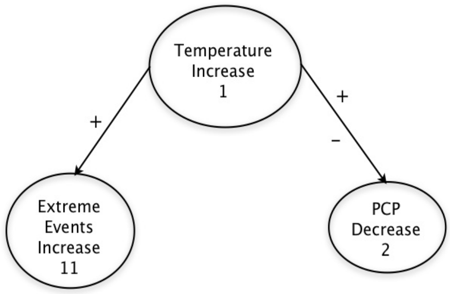


Figure 2: Interaction among climate forcers considering the scenarios of precipitation decrease and increase.

As we said, the scenarios stated by the models suggest different relations between the nodes temperature increase and PCP decrease. Some models suggest that if the temperature increases, the amount of precipitation will decrease, while other models suggest the opposite (Oglesby et al 2010). So, in the map we considered positive and negative causality separately for different scenarios. On the other hand, all the models predicted an increase in extreme events, but they ranged in their predictions among intensity and frequency of the events. So the edge from temperature increase to extreme events increase is considered to be positive. If we assume that an increase in temperature causes an increase in the PCP decrease and an increase in extreme events, and running the model with these characteristics, i.e. connecting node 1 with nodes 2 and 11, and restarting node 1 after each iteration we have in four iterations the following vector:

$v_4^* = [\ 1\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1]$

Which in comparison with the vector v_3 obtained in the case (a) in section 3.2, when nodes 1 and 2 were forced, differs in nodes 11, 12 and 14.

$v_3 = [\ 1\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 0\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 1\ 1\ ]$

Considering that an increase in temperature causes a decrease in PCP decrease (i.e. an increase in PCP), in five iterations we have:

$v_5 = [1\ \text{-}1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 1\ 0\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1]$

As seen, the only difference with respect to v_4^* is the -1 in the node 2. Which means that even though we considered an increase in PCP, the structured interactions in the map have kept the tendency. This is due to the fact that many nodes have more than one node which is activating them, therefore, the sum of the interactions is more than one, before the threshold function.

With our approach of 0 and 1 for edges and values, this is as far as we can go. But is very intuitive that different processes have different amounts of causality, e.g. we know that temperature increase causes social water demand increase, as well as evapotranspiration increase, but the strength of causality could be different. It is convenient at this point to assign pondered weights for each process in the map.

It is important to emphasize that we are evaluating the map in a qualitative way, and assigning weighted values only indicates a degree of causality among concepts. We are not assuring, by indicating 0.5 for a specific edge, that one concept causes exactly 0.5 the other. But, pondering the edges we gain intuition about the map's importance and sensitivity to each process. These weighted values can be assigned by expert's opinion or proposed assuming specific conditions we want to analyze.

3.4 Considering weighted Edges for Sensitivity Analysis

In the previous analysis, we only considered positive or negative causality in order to figure out the general behavior of the system. However, this assumption requires each edge to be either positive or negative, but with the same causality value. Nevertheless, we know that different processes have different amounts of causality, for example, it could be intuitive that the temperature increase will have different impacts in social water demand increase and in evaporation increase, and this is an interesting thing to analyze. As the next example will show, these changes in the value of interactions will lead different final states for different edges values. Then, when we consider weighted edges, the map's behavior is qualitatively different. In this case, some processes occur slowly and some times their values will stabilize in a different point.
For example, the following vector shows the state vector resulting from considering a value of 0.5 for each edge after 10 iterations, when the system converges into an equilibrium state given by:

$v_{10} = [\ 1\ 0.5\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0.5\ 0\ 0.5\ 0.33\ 0.44\ 0.16\ 0.61\ 0.80\ 0.80\ 0.79\ 0.39\ 0.5]$

We can see how different nodes reached different values in a new equilibrium state of the system. As we said, we have considered all edges with value of 0.5 and we have restarted $v[1] = 1$ after each iteration. In the Figure 3, the upper graph shows the evolution of the concepts: erosion increase(12), non-planned extraction (13), basins degradation (Cutzamala) (14), aquifers degradation (basins) (15), decrease in dams levels (16), aquifer recharge decrease (17), decrease water availability (18), and social and administrative conflicts increase (19). Concepts 3, 4, 5, 6, and 7 (which correspond with social forcers) were turned off. Concepts 8 and 10 were not activated, because they depend on the social forcers. Finally, the value of C_1 (1), remained equal to 1, and the concepts 2, 9, 11 and 20 were not shown, because as they are only activated by the concept C_1, they remained with value of 0.5. When upper and bottom graphs are compared, it can be observed how dependent is the final value of the concepts with the value of the edges. In the left graph we used the same configuration but we changed the sign in the edge $C_1 \rightarrow C_2$ which is taken as -0.5. In this case the state vector after 10 iterations is:

$v_{10} = [\ 1\ \text{-}0.5\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0.5\ 0\ 0.5\ 0.33\ 0.28\ 0.16\ 0.18\ 0.22\ 0.09\ 0.15\ 0.07\ 0.5]$

These results show that the model is highly sensible to changes in the edge values, sings, and initial conditions, however we can see that the concept's values tendency to growth remains.

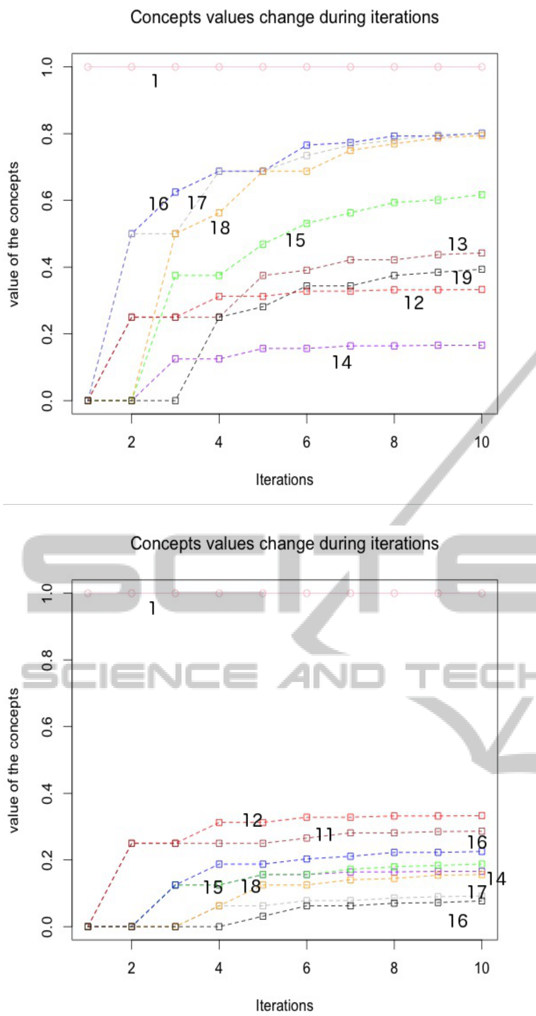


Figure 3: Upper graph: evolution of the concepts erosion increase(12), non-planned extraction (13), basins degradation (Cutzamala) (14), aquifers degradation (basins) (15), decrease in dams levels (16), aquifer recharge decrease (17), decrease water availability (18), and social and administrative conflicts increase (19) after 10 iterations with all the edges having a value of 0.5. Bottom: the same configuration, but changing edge $C_1 \rightarrow C_2$ which is taken as -0.5. In both graphs concept C_1 is in pink color.

3.5 Using weighted Edges

As we just discussed, the behavior of the model is completely different depending on the value of the edges. Nevertheless, sometimes is difficult to ponder processes of different nature, like the increase in social and administrative conflicts and the temperature increase. For this reason, this process involves the experts opinion. We assigned the value of the edges by consulting Dr. Escolero. We asked him to assign "how much one node causes another" using linguistic quantities. In this case, we chose as linguistic quantities: low (L), medium (M), and high (H). These linguistic values are shown in Figure 1.

This map contains the expert opinion, which is based on the knowledge of the system. Now, in order to analyze it using the technique of the adjacent matrix and the vector sate, we divided the interval [0,1] in three subsets, each one of them representing one set of strength of causality. Then, we chose a representative value for each set which was used as its corresponding entrance in the matrix. In this case we chose the values of 0.3 for low, 0.6 for medium, and 0.9 for high. And we selected medium causality for the edge $C_1 \rightarrow C_2$ and low for $C_1 \rightarrow C_{11}$.

Then, we ran the model using these values, starting only C_1 with value of 1 and keeping the forcing. The state vector after six iterations is:

v_6 = [1 0.9 0 0 0 0 0 0 0.6 0 0.3 0.16 1 0.08 1 1 1 1 0.9 0.9]

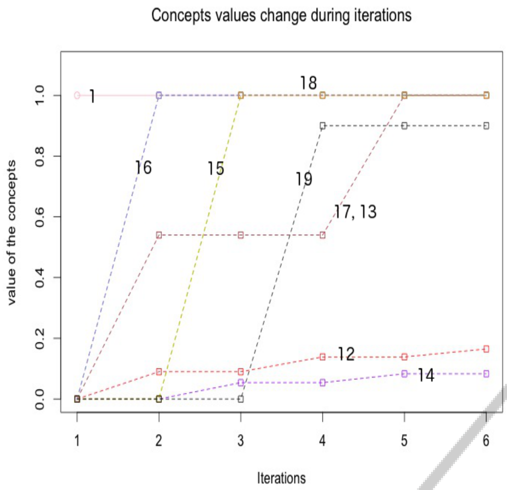
Concepts 2 (0.9 PCP decrease), 9 (0.6 social increase in water demand), 11 (0.3 extreme event increase), and 20 (0.9 evapotranspiration increase) remained constant, as they were activated by C_1. Concepts 3, 4, 5, and 6 (social forcers) were not activated. Concepts 7, 8, and 10 depended on the social forcers. In figure 6, we represented concepts erosion increase(12), non-planned extraction (13), basins degradation (Cutzamala) (14), aquifers degradation (Basins) (15), decrease in dams levels (16), aquifer recharge decrease (17), decrease water availability (18), and social and administrative conflicts increase (19) after 6 iterations.

In Figure 4 Upper, concepts 12 (erosion increase) and 14 (basins degradation, Cutzamala), which form a feedback cycle, stabilize at 0.16 and 0.08 respectively, as well as concept 19 social and administrative conflicts increase with a value of 0.9. All other concepts exceeded the value of one, and thus they were limited to one. These are 13 (non-planned extraction), 15 (aquifers degradation (basins)), 16 (decrease in dams levels), 17 (aquifer recharge decrease), and finally 18 (decrease water availability) which is superposed with concept 13.

With the same map, we started and kept the social drivers 3 (population growth), 4 (agriculture development), 5 (urbanization), and 6 (industry growth) forced, and turned off C_1 (Figure 4 Bottom). After six iterations we obtained:

v_6 = [0 0 1 1 1 1 1 1 1 0.6 0 1 1 0.78 1 1 0.6 1 0.9 0]

Concepts that depend of C_1 remained off. Con-



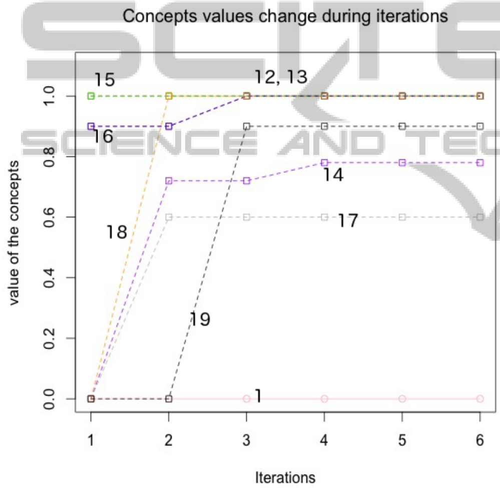


Figure 4: Upper: Evolution of the concepts erosion increase(12), non-planned extraction (13), basins degradation (Cutzamala) (14), aquifers degradation (basins) (15), decrease in dams levels (16), aquifer recharge decrease (17), decrease water availability (18), and social and administrative conflicts increase (19) after 6 iterations. Keeping forced C_1 denoted as 1. Bottom: Evolution of the concepts 12, 13, 14, 15, 16, 17, 18 and 19. Turning on the social forcers 3, 4, 5, and 6, and turning off C_1.

cepts 7, 8 and 9, which depend directly of activated concepts, went to one at the first iterations. Concept 10 was activated constantly by Concept 7. Concept 11 remained off. Concepts 12 (erosion increase) and 13 (non-planned extraction) went to one. Concept 14 (basins degradation Cutzamala) stabilized at 0.78. Concepts 15 (aquifers degradation (Basins)) and 16 (decrease in dams levels) went quickly to 1. Concept 17 (aquifer recharge decrease) stabilized in 0.6. While Concept 18 (decrease in water availability) went to 1 after 3 iterations. And finally, Concept 19 (social and administrative conflicts increase) remained as 0.9 because it is activated by Concept 18. The substantial difference between forcing the system with social or climatic factors is shown in nodes 12 (erosion Increase) and in 14 (basins degradation, Cutzamala).

3.6 Min - Max Criteria for the Analysis of Influences over the Decrease in Water Availability

As we said in the introduction, we can use the min - max criteria to analyze how much a node causes another. In this case, we wanted to compare the influence of climatic and social factors over the decrease in water availability. To estimate the total effect of temperature increase over decrease in water availability, we had to consider the effective paths: $I_1(1,9,13,16,18) = min\{M,H,H,H,H\} = M$, $I_2(1,9,13,15,17,18) = min\{M,H,H,M,M\} = M$, $I_3(1,20,16,18) = min\{H,H,H\} = H$, $I_4(1,20,17,18) = min\{H,H,M\} = M$, $I_5(1,2,16,18) = min\{M,H,H\} = M$, $I_6(1,2,17,18) = min\{M,H,H\} = M$, $I_7(1,11,12,14,16,18) = min\{L,H,M,H,H\} = L$. The total effect is the maximum of the indirect effects, in this case equal to H. But if we analyze closely the only path which has indirect effect H is $I_3(1,20,16,18) = min\{H,H,H\} = H$, so if we want to change the effect of the temperature increase over decrease in water availability we need to focus on the processes among: temperature increase $\rightarrow$ evaporation increase. evaporation increase $\rightarrow$ decrease in dams levels. decrease in dams levels $\rightarrow$ decrease water availability. These three edges are practically out of our control, but we can infer that if we want to counteract the influence of temperature increase over the system, we must probably focus on strategies to avoid the decrease in dam levels.

On the other hand, when we analyzed the social drivers (as a whole), we found that the total effect of all of them is High, but only one Indirect effect which is "High" is $I_{3\rightarrow 18}(3,9,13,16,18) = min\{H,H,H,H\}$. Like we just discussed, this observation can also help us for decision making and strategic planning.

4 CONCLUSIONS

We could observe, from the feedback processes form section 3.1, that both social and climatic drivers will lead the system to an undesirable state. The only difference between the two feedbacks of social and climatic drivers are nodes 12 (erosion increase) and 14 (basins degradation, Cutzamala). Both of them are turned on due to social drivers.

The results found in section 3.2 reconfirm that social drivers have a high influence over the network. By analyzing the hidden patterns obtained by keeping the different drivers ON, the difference were in the following nodes: waste waters discharge increase (7), vegetal cover loss (8), degradation in the water quality (10), erosion increase (12) and basins degradation, Cutzamala (14). That were activated by the social drivers and not by the climatic drivers.

In section 3.3 the system was forced under two different climate change scenarios. The considerations made were the decrease and the increase in PCP. The resulting vector in comparison with the vector v_3 obtained in the case (a) in section 3.2,(base scenario, that we obtained when nodes 1 and 2 were forced in section 3.2), differed only on the nodes 11, 12 and 14, and there was no difference when we considered a PCP decrease or increase. This is a consequence of the particular structure of the system.

When considering weighted edges for the whole system (section 3.5) we validated the results obtained in previous sections. Since the difference between social and climatic factors was in nodes 12 (erosion increase) and in 14 (basins degradation, Cuzamala) once again. In section 3.4 we could identify that, even though the system behavior was sensible to changes in the weights, it maintained the general tendency.

In section 3.6 we found that the "causality" that climate and social drivers (as a whole) imparted over the decrease in water availability was "high". But in both cases the "high" causality is centered on a particular processes.

From these results we can conclude, first of all, that the system is significantly affected by climatic an social drivers, i.e. both can trigger the system and lead it into an undesirable state. Moreover, it appears that the strength of social drivers are greater than those of the climatic drivers. Since the social drivers in Mexico city are currently on, climatic drivers will act as an accelerator for the degradation processes on the water system. Therefore both drivers should be taken into account for policies design.

The general recommendations after the analysis are focused on two branches:
Climatic drivers:
$I_{1\to18}(1,20,16,18) = min\{H,H,H\} = H$.
Social drivers:
$I_{3\to18}(3,9,13,16,18) = min\{H,H,H,H\}$.
Which have a "high" influence over water availability. Further investigation is needed for each node and edge on the two branches, to design policies and solutions.

A general conclusion based on this FCM for water availability in Mexico city, is that the degradation process will occur, given the present conditions, with climatic drivers or without them, as social drivers are more influential on the network. The social situation that operates over the water system is pushing the system into an undesirable state, and only with a more in depth study of the interactions among the nodes we will know whether or not the system can return to its equilibrium state.

It is remarkable that the system's dynamic did not change wether a consideration of an increase or a decrease in precipitation was made. It is also notable how the system is sensible to changes in the weight of the edges but without changing its general tendency.

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