ASSESSING THE INFLUENCE OF INCENTIVES NETWORKS ON LAND USE/COVER CHANGES: A SOCIAL AND SPATIAL AGENT-BASED SIMULATION APPROACH

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1. Introduction

Land-use/cover changes (LUCC) are the result of the interaction between humans and their environment. The impact of agriculture is unparalleled in its combination of spatial extent and intensity of influence (Lambin & al. 2001). Agriculture development has induced dramatic consequences on habitats, water degradation, and biodiversity (Butler & al. 2007; Gordon & al. 2008) by modifying landscape patterns (i.e. its composition and structure). LUCC come from the actions and interactions of different stakeholders operating at different levels who are continuously influencing the structure and composition of the landscape (Valbuena & al. 2010). Agricultural landscape patterns are driven by multi-scale driving forces – from the global economy, international policies, and regional soils' properties, to local social choices and individual practices (Veldkamp & al. 2001). Increasing number of agricultural products are now embedded in global commodity chains, i.e. " a network, or rather a set of networks, and processes that result in an end-product or commodity and linking labor, production, households, states, and enterprises to one another within the global economy" (Gereffi et Korzeniewicz 1994). Such global network provokes production and practices changes in response to social, environmental and economic demands from different stakeholders at different scales. At contrary, local factors, such as the "neighborhood" are still influential and deemed to explain the diffusion by contagion of farming innovations (Daudé 2004). Intermediaries scale factors –regional or national–, such as the union membership, may influence also the decision of farmers concerning their land uses. Farming decisions results from the internal representations and beliefs of the farmers which may evolve with information given and diffused by other farmers, institutions, associations and others networks (Wauters & al. 2010). Thus, most land use and land cover changes occur at the farm scale where these driving forces are integrated (Kristensen & al. 2001; Baudry and Thenail 2004). Such continuous changes results from top-down and bottom-up interactions.

Landscape change models are particularly appropriate for testing and assessing the influence of social, economic and ecological processes, their dynamics and interactions that modify landscape spatial patterns (Baker 1989; Gaucherel and Houet 2009; Zimmerman, 2008). A common approach to simulate LUCC as the consequence of collective or individual decisions and actions is the use of agent-based modelling (ABM) (Matthews & al. 2007; Parker & al. 2003, 2008; Robinson & al. 2007; Treuil & al. 2008). ABM are particularly adapted to model different type of networks which can lead to the emergence of new spatial patterns (Bretagnolle & al 2000; Gimblett 2001; Urbani 2006). They show great performances to assess influence of land use policies on socio-ecological systems based on scenarios (Le & al 2010). Because the driving forces of LUCC in agricultural landscapes are numerous and multi-scaled (Bürgi & al. 2004), the assessment of their respective / combined influence still remain a challenge. Indeed, landscape exhibits a hierarchical structure (Burel & Baudry 2003), the modelling of involved processes has not always lead to the simulation of realistic landscapes. Thus, land-use systems are characterized by complex interactions between human decision-makers and their biophysical environment. LUCC/ABM models are particularly well suited for representing complex spatial interactions under heterogeneous conditions and for modeling decentralized, autonomous decision making (Parker & al, 2003). Furthermore, the use of neutral landscape models is interesting to better understand interactions between several driving forces and helpful to tackle the complexity of the processes involved (Gardner 1987; O'neill 1992; McAllister & al. 2005; Gaucherel & al. 2006; Houet & al. 2010-a).

The aim of this paper was to implement a simple theoretical – neutral – model for exploring the influence of different and multi-scaled incentives networks on the landscape pattern through the farmer decision. In our model, three scaled networks are considered: a global 'policy' network promoting specific land uses through incentives to farmers, an intermediate 'social' network where land use practices are shared and promoted collectively, and a local 'neighborhood' network where the land use practices are influenced by those of their neighbors. Except few studies (Berger 2001; IMAGES 2004) such a multi layered networks approach is quite original in the field of LUCC/landscape modelling. In this study, the main question is how the combination of networks influences landscape pattern dynamics?

2. Methodology: model description and experiments

The NetLogo platform (version 4.1 – Wilensly 1999) has been used and the model description follows the ODD protocol (Grimm et al. 2006, Grimm et al., 2010).

2.1 Overview

Purpose

The purpose is to explore and assess the impact of different and multi-scaled incentives networks on farmers' land use decision and consequently on landscape pattern.

Entities

The model includes various entities:

- 'farmers' (agents/individuals). Agent have limited cognitive capacities and are rational. Their main restriction is to follow agronomic constraints (crop succession). After receiving incentives of land use types from networks, they prioritize them and choose the most recommended. In case of diverging incentives, they can make random choices.
- 'farm' (spatial units). Each farm belongs to a farmer. The overall landscape is composed by the amount of all spatial units. Each spatial unit has two state variables: land use type and age. A numerical code 1, 2 or 3 is initially randomly attributed to each spatial entity according to its 'land use type'. Land use types change over time according to farmer decisions and agronomic constraints such as crop successions. Such constraints define the maximum duration of each land use type (*'age'*). When the maximum value of the age is reached, current land use type should change to one of the two other possible land-use types.
- 'global network' (environment). This entity simulates a public policy encouraging farmers to adopt specific land use practices according to a global land use assessment made at the landscape scale.
- 'local network' (collective). These entities, different for every farmers, intends to simulate the influence of land use practices of neighbors. Based on the observed surrounding land use practices, each farmer tends to imitate them.
- 'social network' (collective). This entity simulates voluntary membership in formal or informal associations (e.g. farmers' association, lobbies, etc.) that influences farmers' practices in order to incite most common practices. All farmers are part of one of the 5 user-defined social groups and every social group encompasses 20% of farmers.

Spatial and temporal Scales

One time step corresponds to a cropping season (several months), and the model is run for 250 time steps. The landscape is made of 25x25 spatial units, i.e. 625 farms. To avoid border effects, local network is defined by the Moore neighborhood of each cell within a torus space.

Process overview and scheduling
At each time step, farmers receive information from each network that encourages them to produce a specific land use type. According to the agronomic constraints of the current land use, each farmer lists the possible land use types he would be able to produce. From these informations, a decision rule-set allows farmers to choose a land use type for the next time step. The landscape is updated with new land uses implemented within each cell. Finally, respective and combined influence of network is assessed throughout 8 scenarios for which sensitivity analysis was made based on 40 simulations for each scenario.

2.2 Design concepts
Basic principles
The aim of this model was to implement a simple theoretical – neutral – model for exploring the influence of different and multi-scaled incentives networks on the landscape pattern through the farmer decision. The interest of this study lies in its simplicity that nevertheless allows testing all possible combinations of simulated networks. Moreover, it focuses on their influence on landscape spatial pattern which is quite common in most of LUCC modeling studies, but also on the characterization of the behaviors of landscape dynamics which is more innovative.
Emergence
We assume that for various combinations of networks, different landscape pattern (heterogeneity, fragmentation) and/or dynamics would emerge from individual-based decisions.
Adaptation
Farmers do not have wide range of possible decisions. They adopt the land use type suggested by the majority of the three networks. Any individual initiative in the choice of land use type is avoided.
Objectives
Networks incite farmers to adopt the land use type they recommend. 'Local' and 'social' networks encourage farmers to adopt the land use type used by the majority of their respective members (e.g. in order to maximize agricultural production). The 'global' network analyses which the land use type is less represented at the landscape scale and incite all farmers to adopt it (e.g. to improve landscape heterogeneity at an aggregated level to favor biodiversity preservation) (Poiani & al 2000; Lindenmayer & al 2006).
Learning
Neither farmers nor networks change their behavior according to their experience.
Prediction
No prediction activity is realized by any kind of agent or entity in the model.
Sensing
Farmers directly receive from 'social' and the 'global' networks the recommendation for a specific land-use type. They calculate themselves which is the major land use type in their neighborhood, and use the result as a recommendation from the 'local' network to adopt this land use.
Interaction
Farmers indirectly interact each other by sharing the same information incite by 'global' and 'social' networks whereas farmers have direct (neighboring) interactions within their local network.
Stochasticity
We assume that landscape configuration at the initial step doesn't strongly affect landscape dynamics. Thus randomness occurs at the initialization, the modeler can only specify land use ratios. The land use attribute and age of each cell are randomly allocated. The social group for which each farmer belongs to is also randomly chosen. Randomness also occurs while running the model: a 'blank' land use recommendation may be sent (e.g. none land use type is favored). In such case, farmers would randomly choose a land use type among the possible land use type list. This case occurs for example when the three networks send the same information (e.g. 2 – 2 – 2), similar to the current land use of the farmer (e.g. 2) which as reached is maximum age and must be changed.

In order to assess model sensitivity to initial landscape configuration we design an experiment consisting in estimating the influence of initial land use and age patterns. Based on scenario 8, the experiment crosses two archetypal initial configurations of land use spatial distribution (a scattered distribution and a perfectly aggregated one[1]) and two configurations for the initial age distribution (a random one and all spatial units set to one year old). The influence of the initial spatial distribution for the social groups is not assessed as it does not evolve during the simulation and can thus be consider as a static variable. We therefore use a same random spatial distribution of the social groups during the whole analysis.

Observation

Assessing the influence of networks on landscape dynamics (Gustafson, 1998) is carried out using landscape fragmentation and heterogeneity – Shannon – indices (O'neill & al. 1988; Burel and Baudry, 2003). Landscape pattern is considered here under the point of view of the combined evolution of landscape fragmentation and heterogeneity. A mean value of landscape heterogeneity and fragmentation is computed for each scenario from the 40 simulations of sensitivity analysis. To assess and characterize the influence of each and combined networks on landscape pattern (heterogeneity and fragmentation), we used standardized value of these landscape indices. Thus, these values of landscape heterogeneity and fragmentation make all scenarios comparables.

2.3 Details

Initialization

All the simulations run with an equal ratio of land use types. The number of social groups is user-defined, but was fixed to five in this study. Farmers are randomly affected to one of the social groups which finally show equal number (125 farmers here). The maximum 'age' for each land use can be selected from two possible values (5 or 10). Finally, user can activate (or not) the influence of one or several networks.

Input data

The model does not use input from external sources such as data files or other models

Submodels

Creation, diffusion and processing (decision) of information are the main operators of the existing submodels. At every time step, farmers receive incentive from the networks into a single list, called '*recommendation list*'. Then, a new list of information is created according to current land use age, called '*list of possibilities*'. Figure 1 resume submodels implementation.

- The global network intends to favor the minor land use at the landscape scale in order to maximize landscape diversity according to Deke (2008). Land use proportions are calculated for each time step. If two minor land uses equal, this network doesn't recommend any land use.
- The local network is reproducing a common farmer behavior that consists in copying dominant agricultural practices in its neighborhood (Deffuant, 2002; Kaufmann & al 2009). For each farmer, land use ratios are computed and the dominant land use is recommended. If two land uses are dominant, this network doesn't recommend any land use.
- The social network is promoting a common land use practice which is illustrated here through the dominant land use of its members. It somewhat replicates the impact of innovative land use practices diffusion (Saltiel & al, 1994). For each group, land use ratios are calculated and the dominant land use is recommended. If, for a group, two land uses are dominant, this group of the network doesn't recommend any land use.
- Farmer's decision rule is extensively described in figure 1 and performs as follow: If the "recommendation list" contains a dominant land use type, and if this type is in the "list of possibilities", the farmer chooses this type of land cover. If the "recommendation list" doesn't provide any land use recommendation (all null), a land use type from the list of possibilities is randomly chosen by the farmer. If the "recommendation list" does not contain a dominant land use type, it is randomly chosen from land use types listed in the list of possibilities.

[1] For the scattered distribution, the landscape is generated randomly, yet respecting equal distribution of each land use. For the aggregated one, the landscape is split into three large stripes, one for each land use.

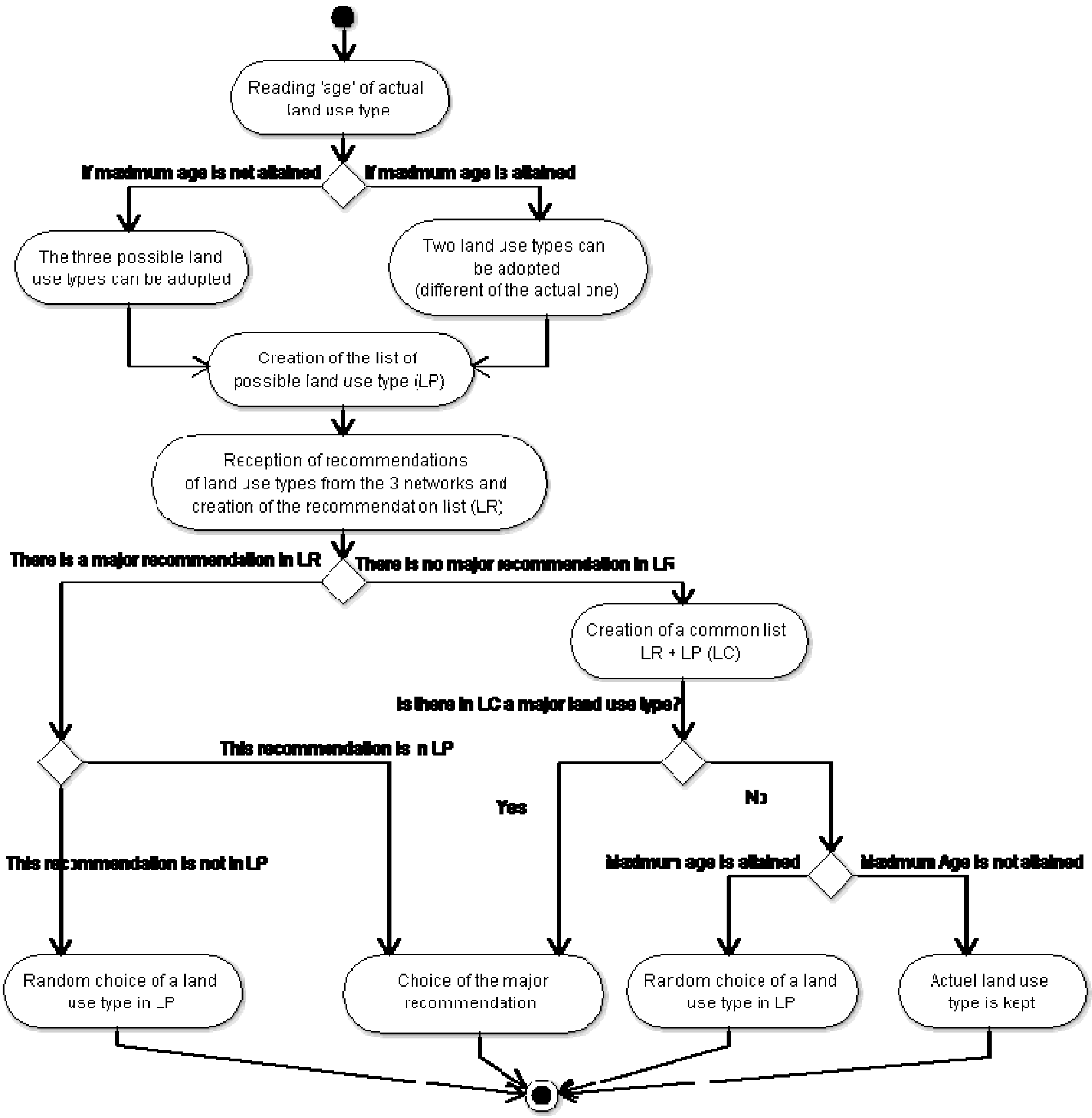


Figure 1. Activity diagram summarizing land use type decision rules made by each farmer

2.4. Experiments

Respective and combined influence of networks on landscape pattern is assessed through the simulation of eight defined scenarios (table 1).

	Networks (Activated = x / Inactivated = o)		
Scenario	Local	Social	Global
1	o	o	o
2	x	o	o
3	o	o	x
4	o	x	o
5	x	o	x
6	x	x	o
7	o	x	x
8	x	x	x

Table 1: Summary of the simulated scenarios

3. Results

3.1. Behaviors of landscape heterogeneity induced by networks

Sensitivity analysis and simulated scenarios permitted to extract six main ‘behaviors’ of landscape heterogeneity based on the normalized mean value of Shannon Index (SI). All these behaviors are summarized in table 2 and figure 2.

<table>
<tr><th>Behavior</th><th>Description</th><th>Initial SI value</th><th>Final SI value</th><th>Oscillations amplitude</th></tr>
<tr><td>A

A-bis</td><td>Simulations show low amplitudes of the SI value. Landscape heterogeneity remains high over the time.
A-bis behavior is similar to A but with a slightly lower SI value.</td><td rowspan="7">1</td><td>1

0.8</td><td>0.1

0.1</td></tr>
<tr><td>B

B-bis</td><td>Simulations show intermediate amplitudes of the SI value. Landscape heterogeneity remains quite high over the time.
B-bis behavior is similar to A but with a slightly lower SI value.</td><td>0.8

0.6</td><td>0.4

0.4</td></tr>
<tr><td>C</td><td>Simulations show low amplitudes of the SI value but with iterative strong decreasing of SI value for 10 to 20 time steps.</td><td>1</td><td>0.1 to 0.8</td></tr>
<tr><td>D</td><td>Simulations start with high SI values (1) and then slowly converge to low value (0.2). Oscillations remain low at the beginning and show intermediate values (0.4) at the end.</td><td>1 to 0.2</td><td>0.1 to 0.4</td></tr>
<tr><td>E</td><td>Simulations show a quick decreasing of SI value to 0.4 that initially equals to 1. Oscillations are low at first and then remain around 0.4.</td><td>1 to 0.4</td><td>0.1 to 0.4</td></tr>
<tr><td>F</td><td>SI value strongly decreases to 0 and then remains stable. Landscape is homogenous over time.</td><td>0</td><td>0</td></tr>
</table>

Table 2: Summary of landscape heterogeneity behaviors observed for all simulations.

Figure 2 show the results of sensitivity analysis expressed in terms of proportions of repetitions of a same initial configuration for each landscape heterogeneity behavior (in scenario 8 these are A, D or E). One hundred repetitions were simulated for each initial configuration. In order to test the influence of different initial scattered landscape (which were generated randomly) we first compared two different randomly generated initial landscapes (version 1 and 2 as shown on the left side of Figure2). Differences are in a range of 2 to 4 percents[2]. We find a similar margin when comparing configurations with ages all set to one to configurations with random ages. This indicates that the initial distribution of ages have no influence on the final simulation outputs. A deeper analysis showed that after 10 to 15 time steps (which is the very beginning of a simulation run) we can't differentiate anymore between configurations having different initial age patterns. On the opposite, output differences between scattered and aggregated initial land uses are significant. An aggregated initial landscape leads in approximately 77% of the case to an homogeneous final landscape while it happens approximately 67% of the cases with a scattered initial landscape. Hence, if the initial landscape heterogeneity has a slight influence on the final result (a weight of approximately 10% if we consider the mean Shannon index) the final simulation outputs are mainly influenced by the dynamic of interactions during the course of the simulation. In this model, this dynamic is defined by the activation or not of various incentive networks and their influence is assessed in the following scenario analysis.

[2] The same range of differences is found when comparing with scenario 8 results (looking at behavior A on one side and behaviors D and E on the other side).

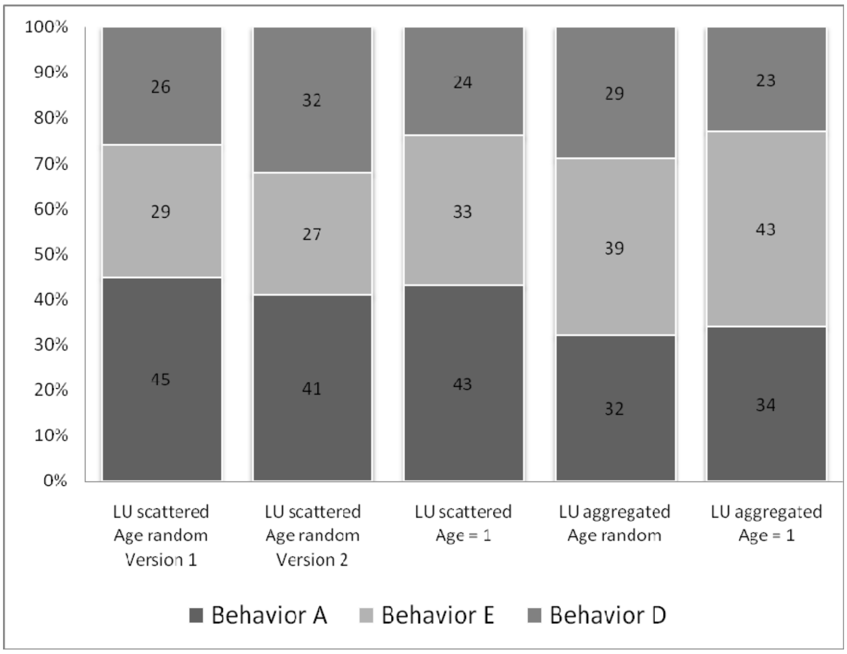


Figure 2. Proportions of behaviors for different initial configurations

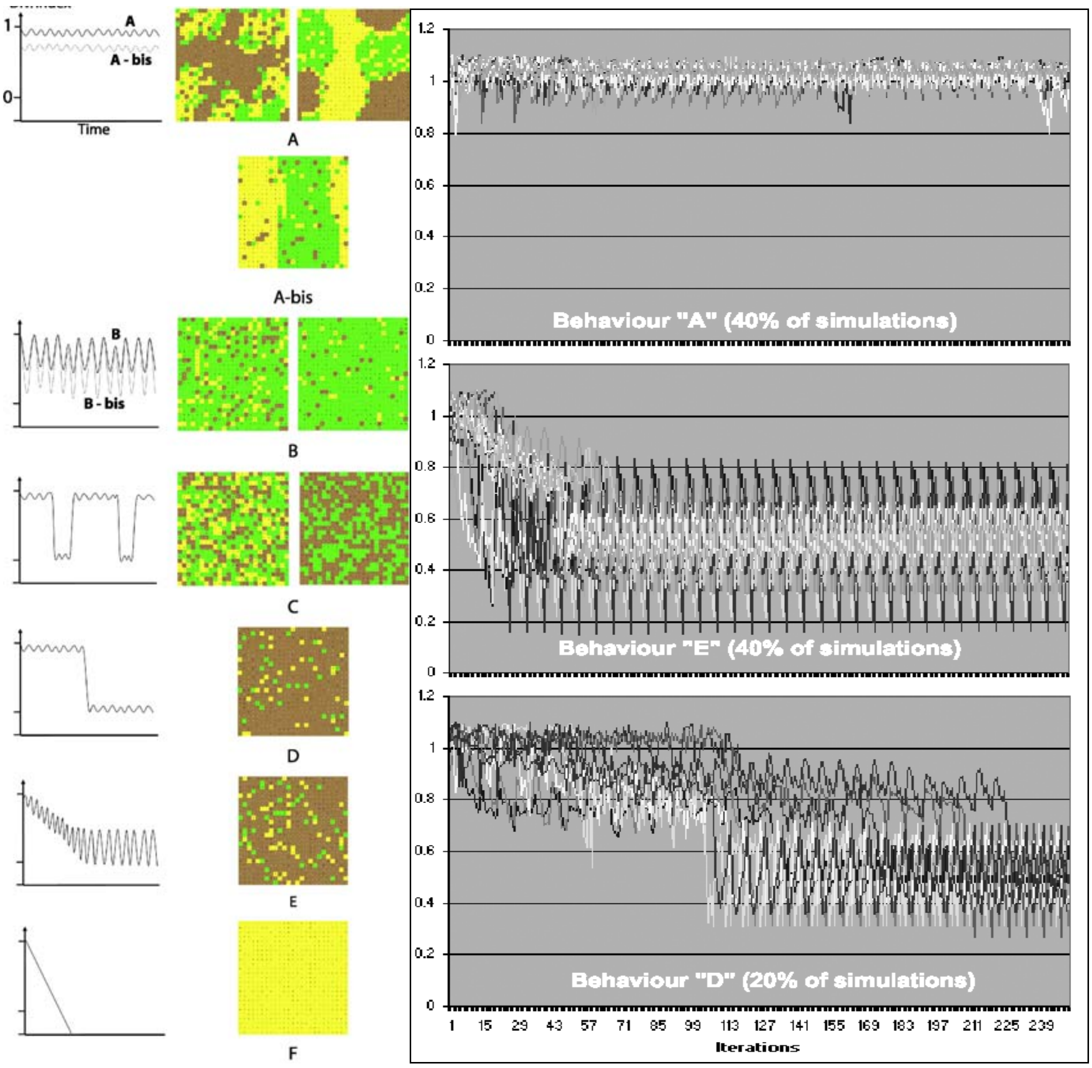
Scenarios are analyzed in the light of these behaviors to answer the question "does a scenario lie to a specific landscape heterogeneity behavior?" Proportions of behaviors for each scenario are estimated from sensitivity analysis (table 3).

Scenario	'age' value	A	A-bis	B	B-bis	C	D	E	F
1	5 / 10	100%							
2	5		15%					85%	
	10		18%					83%	
3	5 / 10								100%
4	5 / 10					100%			
5	5 / 10	100%							
6	5	38%	5%		58%				
	10	38%	13%		50%				
7	5			100%					
	10			78%	23%				
8	5	42%					19%	39%	
	10	75%						25%	

Table 3. Proportions of behaviors for each scenario

Figure 3 shows that when none network is taken into account (Sc1), landscape always remains heterogeneous. Global network (Sc3) always involves a homogeneous landscape (behavior F). Social network (Sc4) always produce a landscape exhibiting most of the time a high heterogeneity with iterative phases of homogeneity (behavior C). Combining local and global networks (Sc 5) always exhibit a heterogeneous landscape (behavior A).
But main scenarios provide contrasting outputs. Social network (Sc2) can provide either (15%) an heterogeneous landscape (behavior A-bis), or (85%) a less heterogeneous landscape (behavior E). Combining global and social (Sc 7) networks exhibit most of the time (78 to 100%) an heterogeneous landscape (behavior B/B-bis). Combination of local and social networks leads to more complex results. Landscape heterogeneity varies from 0.6 (50% to 58% of behavior B-bis), 0.8 (5 to 13% of behavior A-bis) to 1 (38% of behavior A). Thus, combination of two undifferentiated networks always improves landscapes heterogeneity over the time. When all networks are influencing farmers' decision, two opposite types of landscape patterns inherit from differentiated behaviors. Simulated landscapes can be either heterogeneous (40% of behaviors A) or quite homogeneous (40% of behavior E, 20% of behaviors D). Combining all networks doesn't

have cumulated effects. Even more they could imply controversial effects leading to diverging landscape heterogeneity. Final results show that the greater is the ‘age’ value, the more heterogeneous landscape is *a priori* simulated.



(a) (b)

Figure 3. Examples of landscape heterogeneity behaviors: (a) summary of all synthesized types of behaviors, (b) Illustration of the three behaviors inherited from scenario 8 (SI variations [Y-axis] over 250 time steps [X-Axis]).

3.2. Influence of networks on landscape pattern

Landscape pattern is considered here under the point of view of the combined evolution of landscape fragmentation and heterogeneity. Figure 4 presents the distribution of the values of the different synthesized indices for each scenario.

First results concern the influence of the user-defined ‘age’ threshold values. This parameter doesn’t strongly affect landscape pattern. It shows that whatever the number of possible successive land use occurrences, mean values of landscape heterogeneity and fragmentation are close or similar for each scenario. However, a greater age value seems to slightly reduce landscape fragmentation independently from scenarios (Fig. 4).

Scenario 1 (1_5/10 in Fig. 4) characterized by random land use changes and none activated network exhibits the highest landscape heterogeneity and fragmentation. This may inherit from randomly set up initial landscape configuration. Global network (Sc3, i.e. 3_5 and 3_10 in Fig. 4) produces the lowest heterogeneous and fragmented landscapes. If both landscape indices are quite strongly correlated, the combination of global and local networks illustrates the interest of using both of them. Indeed, if the fragmentation remains with low values in both scenarios 2 and 5, heterogeneity dramatically increases in scenario 5 with an original landscape pattern (behaviour A). Another example of results concerns scenario 6 (social and local networks). Values of landscape heterogeneity are similar to those of scenario 2 but exhibit higher fragmentation values.

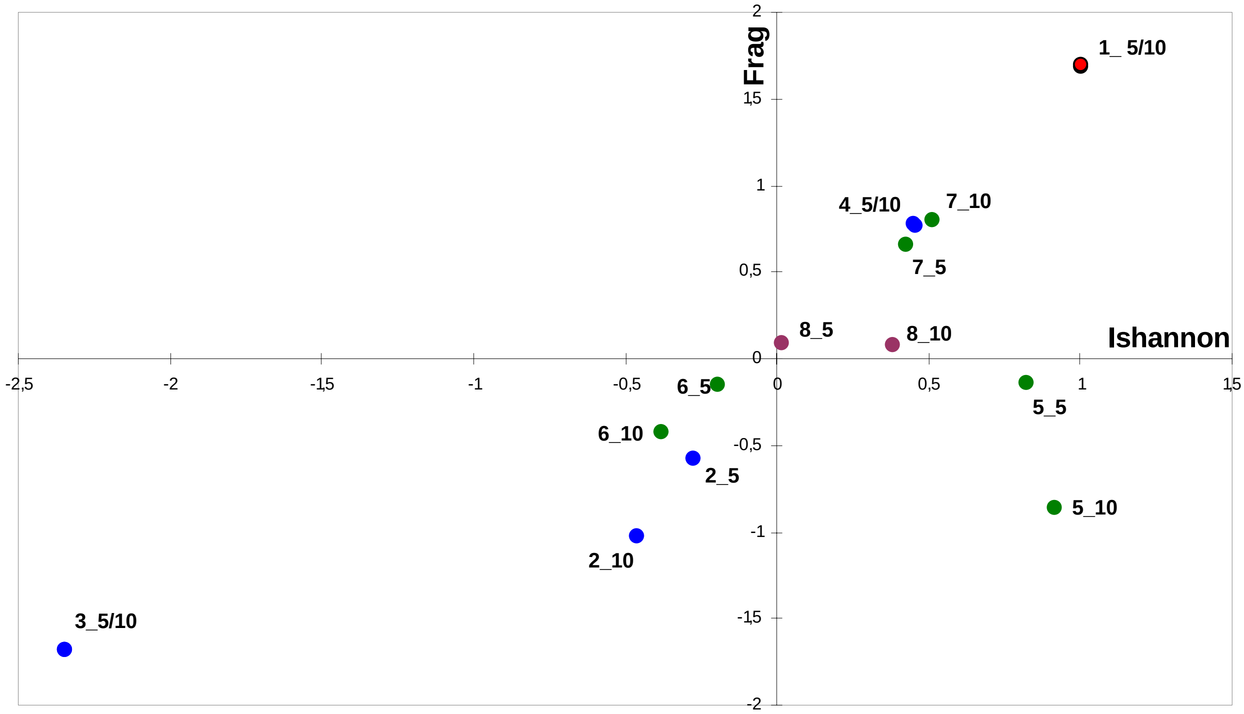


Figure 4. Landscape heterogeneity and fragmentation normalized values for each scenario with threshold values of 5 and 10 for the 'age' value, i.e. the maximum land use duration (e.g. scenario 2 with 5 and 10 threshold values is annotated 2_5 and 2_10).

Figure 5 helps to understand the combined influence of networks. For example, comparing scenario 2 (local network only) and 4 (social and local networks), their combination increases both fragmentation and heterogeneity of landscape pattern. On the other hand, combining global and local network only positively affects heterogeneity. Finally, it appears that the socio-economical network tends to improve heterogeneity of landscape. The global network has significant effect when it is combined with local network only. The local network has opposite effect on landscape pattern. Combined with the social network, it equally reduces fragmentation and heterogeneity. Combined with the global network, it severely improves landscape heterogeneity and slightly its fragmentation.

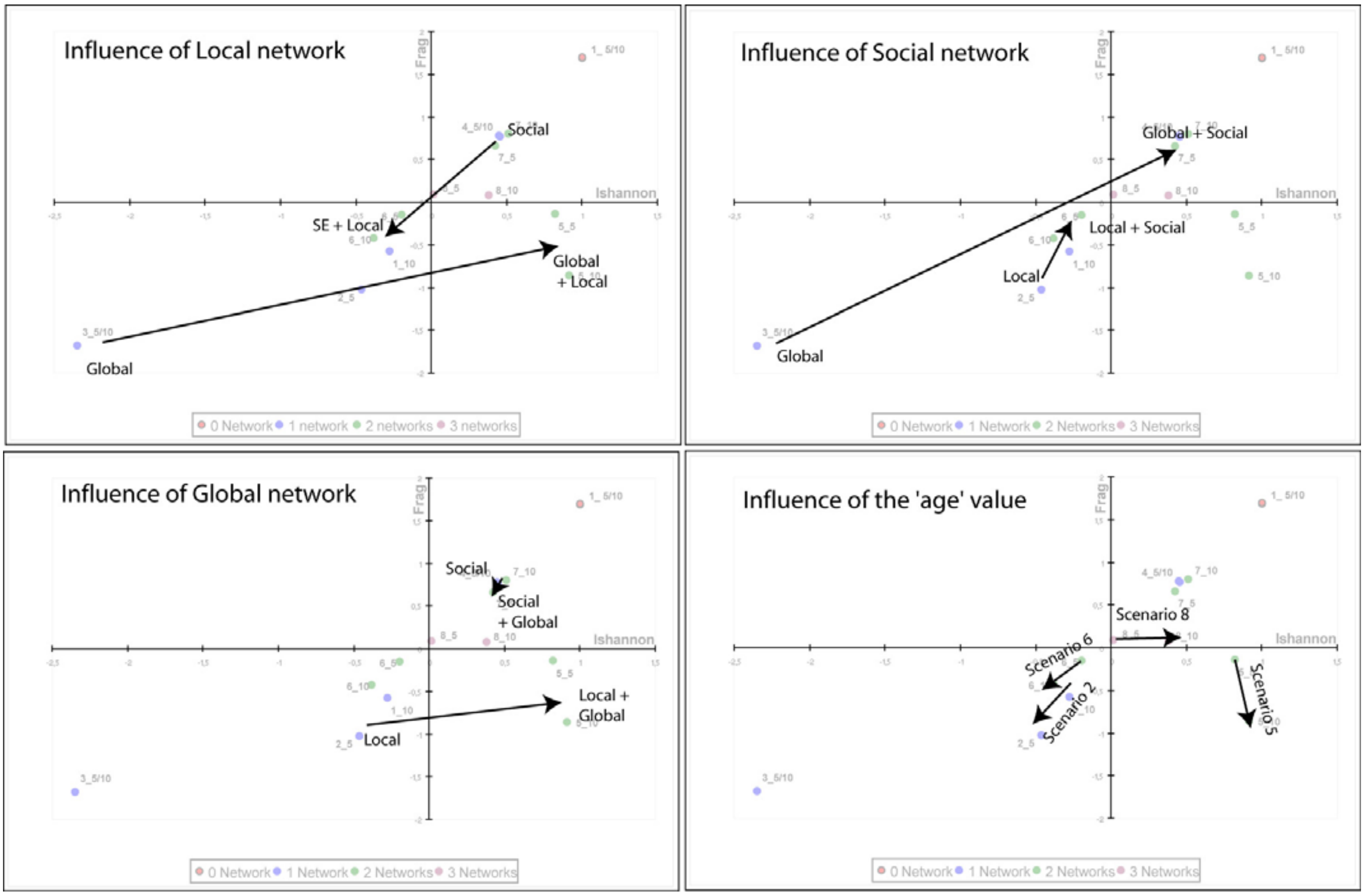


Figure 5. Influence of each network and of the maximum duration of successive land use types on landscape pattern

4. Discussion

4.1. Understanding landscape pattern complexity

This study illustrates how landscape may show complex patterns under the influence of different and multi-scaled networks. In the case of a global network favoring a unique land use, landscape is obviously characterized by a high homogeneity. Landscape pattern resulting from the influence of the social network (behavior C) is strongly dependent from the spatial distribution of social groups (visual interpretation). In these cases, landscape pattern reflect the spatial footprint of these two networks. In the case of the local network, even if it tends to standardized it, no clear landscape pattern can be extracted. The resulting patterns (behaviors A-bis and E) may inherit from the initial landscape configuration. Depending on its spatially explicit and dynamic properties, it can be assimilated as an alternative of the Schelling model with three (land use) classes (Daudé & Langlois 2006).

However, for a considered scenario and initial landscape configuration, simulated landscape pattern is not always similar. The diverging possible evolutions of landscape changes illustrate bifurcation in landscape dynamics. In the case of the influence of a unique -local- network (scenario 2), two behaviors can be distinguished (A-bis / E). Some “noise effect” affecting landscape pattern can be observed and explained by the modeled agronomic constrains (maximum duration for an identical land cover). Such results mean that local properties of landscape strongly influence possible future landscape pattern and lead to different trajectories and potential impacts of land use and land cover changes according to Houet & al (2010-b). In other words, bifurcation of land use and land cover changes signify that emergence phenomena are occurring as new landscape dynamics.

The resulting question is “Does a specific network favor emergence of landscape dynamics”? The analysis of table 3 shows that diverging behaviors of landscape pattern appear for scenarios 2 (local network), 6 (local + social networks), 7 (social + global networks) and 8 (all networks). Thus none network is *a priori* leading to diverging landscape dynamics. But we could raise the assumption that the more combined networks, the more emergence occurring. Two scenarios (of the 3) combining two networks and scenario 8 combining all networks leads to at least two possible behaviors. Inversely, it doesn't mean that landscape is becoming more heterogeneous or homogeneous. Complexity is revealed by the multiplicity of pathways of landscape changes and not through the resulting spatial pattern of landscape.

This illustrates how complex it is to understand and explain landscape pattern. It is even more obvious when multiple networks are considered. But this study has also given some key elements to better understanding landscape pattern: (1) combination of incentives networks doesn't have linear influence on the direction and magnitude of landscape changes; (2) emergence phenomena are occurring and rely more to the temporal dimension of landscape pattern (bifurcation of landscape dynamics, multiple landscape trajectories) rather its spatial dimension (spatial design of land use and cover changes).

But it also highlights that to study and to understand real landscape pattern, it is essential to look backwards, i.e. to consider its dynamics. More generally, simulated landscape patterns inherit from previous landscape configuration. If reality is always more complex and if we do not consider unpredictable changes, we can assume that part of landscape dynamics is markovian.

4.2. Model limitations and future improvements

Concerning the limitations of the model they are threefold: the first one concerns the simplistic hypotheses taken, the lasting two with the study of the model's behavior, i.e. the difficulty imposed by the stochasticity of the model as well as the lack of deepened study of the model's behavior without the agronomic constraint. However, such limitations should be reduced according to the model aims and results. As a reminder, the model was built in order to tackle the simultaneous influence of networks farmers are involved in, and agronomic constraints they have to take into account. In most models in agent-based social simulation dealing with environment, those two aspects are rarely combined, either modelers include (mostly in abstract models on social influence) networks but then they do not include any constraint concerning the choice of the agent (the fact that the agent farmer has to change his culture regularly), or either the models are very detailed concerning the level of the farm management but do not take into account any external social influence. One of the main result of this model, however simplistic assumptions are made and could be relaxed in future works, is that both aspects played a key role in the landscape dynamics and both have to be taken into account.

Concerning the simplistic hypotheses taken that could be relaxed in subsequent work, on the first hand the limitation is that we considered an equal influence on farmers' decision for each kind of network. This is obviously not the case as social networks have a quite different weight in the decision than the family. An idea to be included that would enable to study such an evidence of the differentiated influence of the different network, keeping a reasonable parsimonious approach, would be to weight the different networks in the decision-making algorithm and to study different scenarios corresponding to different weights.

On the other hand, an important option would be to strengthen the link with the empirical approach by feeding the model with many different sources of data. Taking for instance a realistic landscape at initialization, using more finely the agronomical constraints by choosing the exact constraints corresponding to different types of culture on a given case study and including real social networks coming from sociological interviews would indeed improve the interest of such a model for decision makers.

Concerning the study of the model's behavior, one of the weak point to apply for instance classical sensitivity analysis techniques, concerns the stochasticity of the model dealing with the initialization of the landscape and on the randomized choice when the farmer faces with an equal influence of two networks. Both the use of realistic data to initialize the landscape and the weighting of social networks would enable to solve such problems. A last point we should have include in our work concerns the study of the model's behavior when relaxing the agronomic constraints in order to evaluate their importance in the network. We would have then a model where the farmers faces three different networks without the obligation to change his crop at given moments. Some theoretical works on discrete opinion dynamics on networks give us some insight about what could happen in such a case. As the three networks have an equal weight, they can be aggregated in a single network in which one central-agent (socio-economical world) always diffuse the same opinion and all the other agents apply a majority rule on the social neighborhood to determine their own choice. In such a situation, there is one attractor that is the opinion of the central agent as it remains constant in the simulation. Therefore, the simulations will have tendency to converge towards a homogeneous state in the population that corresponds to this opinion. Even if such theoretical results should be checked in experiments on this particular model, it gives us some arguments to state that agronomical constraints that obliges farmers to change their crops regularly is indeed an essential component in the dynamics described in the results section.

5. Conclusion

The simulation approach developed in this paper enabled answering a few questions about the respective and combined influence of different kind of networks on landscape pattern taking into account agronomic constraints (assimilated to crops successions). Only influence network of global ‘policy’ network favors landscape homogeneity (with various land use types for each time step), while local ‘neighborhood’ network induces an averaged landscape heterogeneity (SI = 0.4) with a non negligible variability. Social network favors a higher heterogeneity (SI = 0.8) but with strong variations of landscape heterogeneity for short but regular intervals. Combination of two networks generally improves landscape heterogeneity illustrating the non linear effect of networks interactions on landscape pattern. Behaviors of landscape pattern combining all networks lead to two main and opposite stable states: either a landscape with a strong heterogeneity or, either the emergence of a strongly dominant land-use and almost no landscape heterogeneity. A comparison of scenarios has also revealed that effects on landscape heterogeneity and fragmentation are complex: (1) social network tends to improve heterogeneity of landscape, (2) global network has a significant impact only when combined with local network and (3) local network has opposite effect on landscape pattern if combined with social network or global network. Finally, this study highlights landscape complexity has to be understand through the multiplicity of pathways of landscape changes and rather than through the resulting spatial pattern of landscape.

6. Acknowledgements

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