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Modelling Interactions and Feedback Mechanisms in Land Use Systems

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Abstract — Land use change (LUC) is often a complex process. In such a process land use systems can show non-linear behaviours caused by mechanisms such as interactions between agents and feedbacks from higher system level. Land use systems might be very sensitive to such non-linearity, for instance in the form of tipping points, which lead them to a different land use regime. Many models deal with the causes and consequences of LUC but few focus on the non-linear process in land use systems. Thus there is a need for an explicit treatment of interactions and feedback mechanisms in LUC models to better understand the behaviour of land use systems. Two primary mechanisms are implemented with an agent-based model (ABM) to capture 1) the social interaction between land use decision makers (farmers) and 2) the positive feedback mechanism in agricultural production, with each applied to a case study showing how such mechanism can give rise to non-linear changes in land use systems. Due to a lack of focus on feedbacks in LUC-ABMs, we propose a framework to approach feedback mechanisms in land use systems in a structured way.

1. Need for modelling of non-linear process in Land Use Systems

Land use (and land cover) changes marked one of the most prominent changes of the Anthropocene (Crutzen, 2002; Ellis et al., 2013; Goldewijk, 2001; Zalasiewicz et al., 2011). Descriptive land use change models seek to understand the dynamics of coupled human and environmental systems. Land use change is often a complex process, in which complexity arises from the multiplicity of interlinked driving forces (Lambin et al., 2003), the interaction between land use system and the driving forces, the interaction between land use decision makers, the spatial and temporal dimensions, and the cross-scale dynamics due to the feedbacks from higher system level (Rindfuss et al., 2004; Veldkamp & Lambin, 2001; Verburg et al., 2004). Such a complex process may result in non-linear behaviour in land use systems. It thus requires models to not only analyse the causes and consequences of the land use change (Verburg et al., 2004), but also capture these non-linear characteristics. Land use systems might be very sensitive to such non-linearity, for instance in the form of tipping points (Scheffer et al., 2009), that lead to a different land use regime. A model which is able to approximate the non-linear development of land use change is valuable for policymakers, for whom it is essential to know how a land use system will respond to an external trigger or policy.

2. A focus on interactions and feedbacks

Depending on the goal of research, a model should include part of the complexity typical for land use systems (Veldkamp & Lambin, 2001). As research on tipping points and regime shifts of land use system is still at its infant stage, a solid step forward can be the modelling of non-linear land use change, which needs to incorporate, amongst others, 1) the interactions between system components and 2) feedbacks from higher levels. Bousquet and Le Page (2004) summarized three types of interactions that Agent-Based Models (ABMs) applied to ecology need to capture, namely (i) direct interactions (communication and exchange of information between agents), (ii) physical interactions (e.g. one exerting physical action such as pull, push, or predation on the other), and (iii) interactions mediated by the environment. This classification can help to clarify interactions and communication between modellers and audience. We propose that land use change researchers not limit interactions to the widely studied relationship between aggregated driving forces and land use system properties (i.e. type ii) but to incorporate explicitly social interactions between individuals and groups (i.e. type i and the combination of type i and type ii), which usually take place over a specific space or via a network. We hypothesize that these social interactions contribute to the non-linearity of land use systems. The second aspect is the explicit treatment of feedback mechanisms. In our framework, Bousquet and Le Page's (2004) type iii interactions are considered as feedback mechanisms. Feedbacks from high system levels either accelerate (positive feedback) or mitigate (negative feedback) the land use change process. This way, they give rise to the non-linearity of land use system. Different types of feedbacks in land change models are discussed by Verburg (2006).

3. Complex Adaptive Systems and Agent-Based Modelling as theoretical and methodological guide

Non-linear changes caused by interactions and feedbacks as well as the co-evolving drivers and system states, classify land use systems as Complex Adaptive Systems (CAS) (Brownlee, 2007; Holland, 1992; Holland, 2002; Lansing, 2003; Levin, 1998). Land use change, in particular land use transitions or regime shifts, can be understood as an emergent property of CAS (Lambin et al., 2003). Following the CAS perspective of investigating land use systems, one would be interested in how micro level behaviour among a (heterogeneous) set of interacting agents leads to macro level phenomena, i.e. the emergent properties (Holland, 1992; Janssen, 2005) such as observed land use transitions and regime shifts. Agent-based modelling (ABM), is well suited to facilitate our requirements of capturing interactions and feedbacks (Gilbert, 2008; Janssen, 2005). As a process-based modelling approach, ABM is also ideal for modelling non-linear land use changes. Bousquet and Le Page (2004) discussed the strength of ABM on linking spatial and social aspects and the potential of application to land use change. Parker et al., (2003) reviewed the applications of ABM in land use and cover change and summarized the challenges that researchers face. Another review of ABM applications to Coupled Human and Natural Systems (CHANS) can be found in the work of An (2012). The author summarized nine types of decision models based on complexity of behavioural theories, spatial interactions, social interactions, learning and adaptability of agents, each contributes to the generation of agent's decision making rules.

Though many LUC-ABMs have explored interactions in land use systems, they lack a focus on feedbacks from higher levels. This is probably because of the small scale of the cases in which aggregated effect is hardly considered to result in such change that it could feed back to the lower level.

4. Interactions and Feedback mechanisms implemented in two cases

Land use change models are considered in this research as learning tools that help researchers and policy makers understand different components and functionalities of land use systems. Two primary mechanisms are presented here: 1) the competitive behaviour of farmers captured as a type of social interaction, which can lead a non-linear growth of farm size, as observed in 20th century U.S.; and 2) the positive feedback between local land users, supporting companies, and policy regulations leading to the rapid growth of soybean production in Sorriso, Brazil and rapid decline of sugar beet production in Ireland.

4.1 Farmers' social interaction and non-linear farm size growth in the U.S.

Non-linear farm size growth remains a puzzle

Farms in the U.S. underwent tremendous transformation in the 20th century. Average farm size increased from around 40 hectares on average to around 180 hectares (Dimitri et al., 2005). Even though decreasing margins and the development of technology have been identified to contribute to the growth of average farm size, the s-shaped curve of farm size development remains a puzzle. Traditional approaches may have predicted continuous growth (Gardner, 2002) while stabilization is observed (see Figure 1). The levelling off of farm size after the rapid growth has not been formally explained. Our research objective is to explore and generate hypothesis of the non-linear (s-shaped) growth curve of U.S. farm size in the 20th century by a stylized agent-based model. Figure 2 shows the social interaction of farmers operationalized in our ABM.

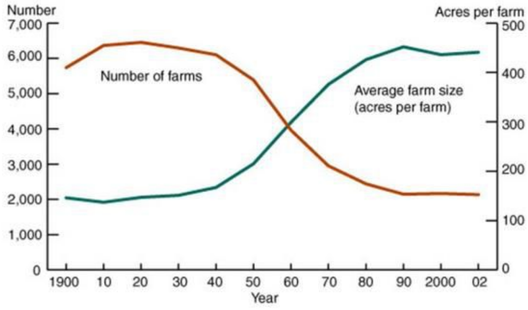

Figure 1. The S-shaped curve of U.S. farm size growth. Source: Dimitri et al. (2005)

Storyline of the model

The gradual decline of margins made farmers poorer and poorer. For a while they could cope, but once all economic buffer capacity was exceeded, some farmers (or banks) decided to grow by confiscating land from those who had to quit. This caused anxiety among remaining farmers, who sensed it as "eat or be eaten". A positive feedback was initiated of farmers trying to grow or having to quit. Farmers continually compared to their neighbours to check if they were lagging behind. This process slowed down once the system ran out of small shrinking farms.

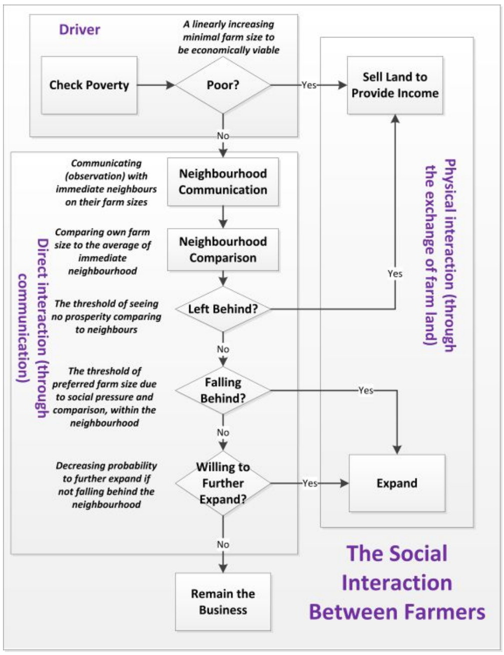

Figure 2. Farmers' social interaction as implemented in an ABM

Model assumptions

The model implements a number of principal social interactions. As farmers constantly communicate within their reference group (in this case their neighbourhood) to maintain social coherence, recognition and identity, peer pressure from such social interaction makes them compete—a satisfactory income (based on neighbourhood comparison), safeguarding for the future competitiveness (by keeping up with the growth of neighbourhood), and gaining recognition and identity to the farming community (Gasson, 1973). In order to investigate the role of social interactions between farmers, the following assumptions are made:

- Because of decreasing margins and increasing need of income, farmers need more land to be economically viable (Hurt, 2002). We assume a linear, positive relationship between prosperity and farm size.
- Farmers as social agents compare with neighbours (Festinger, 1954; Manski, 1993, 2000) and are motivated to expand if they fall behind. They are less motivated to grow once they are satisfied.
- Land transactions are made spatially continuous — farmers can only buy the land neighbouring their current farmland — to avoid land segmentation.
- When investigating the effect of farmers' interaction along a considerably long time span, succession is assumed constant.

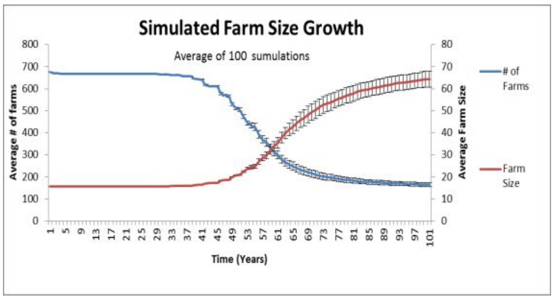

Figure 3. The s-shaped curve of farm size growth--model results, based on 100 simulations

Discussion based on the farm size growth model

- Compared to traditional economic reasoning (technological development (Gardner, 2002), economies of scale (MacDonald, 2011) and relative factor price (Kislev & Peterson, 1982), etc.) which only explained the growth of farm size, our model captures a more complete picture (Figure 3), including both the rapid growth and the subsequent levelling off of farm size.
- In our model, farm size responds to the driver non-linearly, whereby complexity arises from famers' interaction. Such social interaction implemented in the ABM contains the direct interaction and physical interaction (see Figure 2) described by Bousquet and Le page (2004).
- As farmers compare within their immediate neighbourhood to remain competitive, their individual behaviours lead to the increase of average farm size in the neighbourhood. As time progresses, this feeds back to each individual, pushing them to further expand their farms. This seems to be a feedback, but from the same level.
- This model captures the decision making behaviour of farmers as social agents, whose decisions are dependent on the behaviour of their reference group (in this case their immediate neighbours). There are other types of social behaviours (homo socialis and homo psychologicus) which might play important roles in socio-ecological systems and contribute to the explanation of observed land use changes.

4.2 Feedback mechanism in the production of soybean (Sorriso, Brazil) and sugar beet (Ireland) (work in progress)

From narrative description to modelling

Despite the fact that feedback mechanisms are well recognized in land use systems, the way they are treated is mostly at a narrative level. For example, Garrett et al., (2013) explained the rapid conversion of land to soybean production in Sorriso, Brazil with a positive feedback loop resulting from agglomeration economies, which create a concentrated and diverse supply chain allowing for technology innovation, and wider access to information. Such agglomeration economies concern easier access to credit and fewer environmental regulations whereas in the comparing case of Santarem producers are challenged by difficulties to credits (due to land tenure) and strong environmental regulations and supervision, which prevent such agglomeration economies, even though it has a relative advantage of cheap transportation costs.

A framework of modelling feedback mechanisms

Feedback mechanisms in land use systems, such as the positive feedback of agglomeration economies, can take place across different scales — spatially, temporally, and organizationally — linking different dimensions of the system such as biophysical conditions, market conditions, policy regulations, etc. We propose a systematic approach to the description of feedbacks in land use system by providing a framework (work in progress) which may help to clarify the system process and better facilitate modelling. By answering the following questions, one can have a clear description of the feedback mechanism under study and can better approach it at the model designing phase.

(1) Who/what is the sender of the feedback?
(2) What is the nature of the feedback signal? (e.g. economic, psychological, biophysical, informative, and legislative)
(3) Is there a time lag or a spatial lag between the sending the reception of feedback?
(4) Is the feedback positive or negative?

(5) Is the initiation of termination of the feedback subject to excess of thresholds or tipping points?

The cases of soybean and sugar beet production

We present an agent-based model in which feedback mechanisms are explicitly treated and apply it to the narrative cases of Brazilian soy production case (Garrett et al., 2013) and the sugar beet production in Ireland (Busse & Jerosch, 2006). The feedback mechanism of these two cases is composed of multiple individual local producers (land users) and several firms (processing, seed company, R&D, etc.) whose existence depend on the amount of the individual producers and whose function can influence the decisions of producers. The feedback mechanism functions by changing the market dimension (supply, demand, price, and cost) as well as biophysical conditions, which might be under the adjustment of policy regulations.

Model in progress

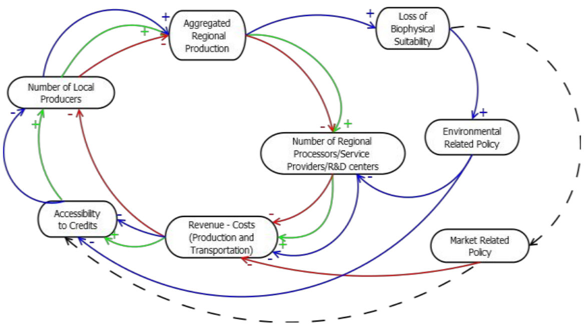

Figure 4. A conceptual framework of feedbacks in three cases. (Green: positive feedback leading to the rapid conversion of land use to soybean production in Sorriso; Red: positive feedback of the breaking down of sugar beet production in Ireland; and Blue: feedbacks (both positive and negative) in the production of soybean in Santerem.)

5. Conclusions and recommendations

With the explicit treatment of the interaction between individual decision makers and the feedback mechanisms in land use systems, we demonstrate how these can lead to the non-linear behaviour of land use systems with an agent-based approach. That land use systems might be very sensitive to such mechanisms to come across some tipping points and move to a different land use regime opens the research arena in which different approaches can contribute to the knowledge pool. The challenge of applying an agent-based approach to the modelling of regime shifts in land use systems lies in the identification of interactions and feedback mechanisms. In doing so one has to strike a balance between realistic representation of agent behaviours (micro level validation) and the modelling of emergent properties (macro level validation).

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