Environmental Modelling & Software

\[ y_k = \frac{d_1 \rho_1}{dt} \phi_1 y_k \]
\[ \phi_0 x_k + d_1 a_{k-1} + \]

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Feedback loops and types of adaptation in the modelling of land-use decisions in an agent-based simulation

Quang Bao Le*, Roman Seidl, Roland W. Scholz

Swiss Federal Institute of Technology (ETH) Zurich, Natural and Social Science Interface (NSSI), Universitaetstrasse 22, CH-8092 Zurich, Switzerland

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A B S T R A C T

A key challenge of land-use modelling for supporting sustainable land management is to understand how environmental feedback that emerges from land-use actions can reshape land-use decisions in the long term. To investigate this issue, we apply the Human–Environment System framework formulated by Scholz (2011) as a conceptual guide to read typical feedback loops in land-use systems. We use an agent-based land-use change model (LUDAS) developed by Le et al. (2008, 2010) to test the sensitivity of long-term land-use dynamics to the inclusion of secondary feedback loop learning with respect to different system performance indicators at different levels of aggregation. Simulation experiments were based on a case study that was carried out in the Hong Ha watershed (Vietnam). We specified two model versions that represent two mechanisms of human adaptation in land-use decisions to environmental changes that emerged from land-use actions. The first mechanism includes only primary feedback loop learning, i.e. households adapt to the annual change in socio-ecological conditions and direct environmental response to land-use activities. The second mechanism includes the first one and secondary feedback loop learning, in which households can change their behavioural model in response to changes in socio-ecological conditions at the landscape-community level in the longer term. Spatial-temporal patterns of land-use and interrelated community income changes driven from the two feedback mechanisms are compared in order to evaluate the added value of the inclusion of secondary feedback loop learning. The results demonstrate that the effect of the added secondary feedback loop learning on land-use dynamics depends on domain type, time scale, and aggregation level of the impact indicators.

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Software availability

For non-commercial uses, the LUDAS model (including its complete codes) and example input data presented in this paper, together with a short user’s guide are offered free of charge from the corresponding author.

Email: quang.le@env.ethz.ch, blequan@uni-bonn.de

1. Introduction

A major challenge of modelling land-use changes is to represent the complexity of coupled human–environmental systems and particularly the feedback loops between environmental dynamics and human decision-making processes (Scholz et al., 2011). The concept of ‘feedback loop’ means that at least two unidirectional

cause–effect relationships link two or more system components, thus representing circular causalities. Consideration of feedback loops in a system is a basis for understanding system regulation, adaptation and resilience, as well as system vulnerability and collapsing (Morrison, 1991; Scholz and Binder, 2004; Chapin et al., 2009; Folke et al., 2009). Land-use change emerges from the interactions among various components of the coupled human–landscape system, which then feeds back to the change of those interactions (Lambin et al., 2003). Understanding how such human–nature and cross-scale feedback mechanisms affect the dynamics of environmental and human systems on different spatial and temporal scales is crucial, but is still one of the major challenges in land-use change modelling (Kates et al., 2001; Verburg, 2006; Turner et al., 2007; Parker et al., 2008a, b).

The last decade has seen rapid growth in the number of agent-based models (ABMs) for simulating land-use changes (Matthews et al., 2007; Robinson et al., 2007). These models consist of a number of human agents that interact with each other and with their environment (Berger, 2001; Parker et al., 2003; Bithell et al., 2008; Bithell and Braisington, 2009). This environment can be
represented by autonomous land units, i.e. ‘landscape agents’ (Le et al., 2008, 2010). Landscape agents represent land units hosting natural processes, such as crop/forest growth and vegetation succession, which are naturally self-controlled and can change in response to interventions by human agents (such as fertilizer use or logging). Decisions of human agents affect the socio-ecological environment and the agents change their behaviour as a result of these environmental changes, thus forming numerous and variable feedback loops between and within sub-systems on different scales. ABMs offer the opportunity to take into account the adaptation of human decision-making with regard to land-use at different environmental (landscape) and human (social organization) levels (Scholz et al., 2011).

Although adaptation has been regarded as one of the key capabilities in ABMs (Parker et al., 2003; Grimm et al., 2006), the realization of the concept in an ABM for land-use change still has major shortcomings. First, given that feedback loops are inherently crucial for understanding adaptation, apart from very recent work (Scholz and Binder, 2004; Pahl-Wostl et al., 2007; Smajgl, 2007; Priess et al., 2010; Scholz et al., 2011), a systematic approach for classifying and analyzing feedback mechanisms in land-use systems that guides the modelling of coupled human—environment system is lacking (Liu et al., 2007; Parker et al., 2008a).

Second, the representation of human adaptation in current ABMs for land-use change is over-simplistic. In the context of human—environment system dynamics, adaptation of a human system (e.g. household, group, or community) usually refers to the development of structure or behaviour characteristics which enable the system to better cope with, manage, or adjust to environmental changes (O’Brien and Holland, 1992; Smit and Wander, 2006). In Piaget’s terminology, adaptation has two sides: assimilation (i.e. the modified usage of existing behavioural patterns to new situations) and accommodation (i.e. the development of new behavioural patterns to deal more efficiently with new situations; Smajgl, 2007; Scholz, 2011). However, except a few authors (for instance Manson, 2006; Gotts and Polhill, 2009), so far many ABMs for land-use change have assumed that human agents behave in a uniform mode, formulated in behaviour models that are fixed during the course of a simulation (Villamor et al., 2010).

Third, most ABMs for land-use change have incorporated feedback loops without assessing the value brought to human—environment system investigations, as revealed by what new insights are generated. Adding unnecessary feedback may lead to a dramatic increase in the model’s complexity, such as requiring more data or assumptions or introducing more degrees of freedom and uncertainties within the model (Priess et al., 2010). This may lead to unnecessarily sophisticated models (i.e. the parsimony principle is not respected) that have a high cost regarding implementation (e.g. high costs of data input, a lengthy cycle of model development, and difficulty in usage by the stakeholders). In contrast, if an added feedback mechanism is proven to trigger new insights in the model’s outcomes, it will offer a new quality of model and an increase in confidence for the model’s users (Verburg, 2006; Caessens et al., 2009).

In this paper, we test a simple methodology for modelling the adaptation of a farmer’s decision-making process when coping with long-term changes in socio-ecological conditions in a case study area in central Vietnam.

2. Methodology

2.1. Concept of feedback loop learning in coupled human—environmental systems

We use the Human—Environment System framework (hereafter referred to as the HES-Framework) developed by Scholz (2011; Fig. 1A) as a guide for the detailed investigation of feedback loops in land-use change (Fig. 1B). An important postulate of the HES-Framework illuminates different types of environmental feedback loops that represent perception, evaluation, and adaptation of human systems regarding environmental changes (Fig. 1B). Adaptation of human decision-making to environmental change is defined as the agent’s learning with respect to the adjustment of their decision rules, depending on their static internal model of the human—environmental interactions (i.e. a fixed behavioural program).

In general, adaptive decision-making of human agents involves (1) a primary feedback loop and (2) a secondary (higher-order) feedback loop learning. With the former, human agents perceive the status of the environment and react to it. The human action transforms the environment, with a retroactive effect on the decision-making process in itself and of other agents in a short-term fashion. This first-order feedback learning does not alter the goal-oriented decision rules of agents, and thus can be conceived as assimilation in Piaget’s terminology. In Fig. 1B, the primary learning feedback loop can be represented by the inner circle of the sequence of actions represented by the arrows forming the loop $F_1 = (1, 2, 3)$. The loop often occurs in the short term: human actions at time $t_0$ cause intended impacts at time $t_1 = t_0 + t$, where $t$ is, for instance, in the case of annual cropping, an annual time step. The secondary feedback loop learning is defined by human-driven cumulative changes in social/economic and environmental conditions on larger scales and in the longer term (possibly unintended), leading to the reframing of the agent’s behavioural program. This learning mechanism is relevant to the concept of accommodation in Piaget’s terms, as it may ask for new cognitive structures concerning how the environment works, and subsequently, for new behavioural programs (Scholz, 2011). In Fig. 1B, this feedback loop is represented by the arrows defining the loop $F_2 = (1, 4, 6, 9)$. Differing from the primary feedback loop, the secondary feedback loop often means a delayed, long-term environmental impact: human actions at time $t_0$ cause a substantial changes in the environment system at time $t_1 = t_0 + T$, where $T$ is about, for instance, some decades. Because secondary feedback loops involve change in the land-user’s cognitive structures (i.e. internal behaviour models), their functions may induce qualitative changes in human actions (e.g. triggering the adoption of new classes of farming technology or new farm types, or migration).

![Fig. 1.](image)
refers to slow variables in the theory of resilience in social-ecological systems (Chapin et al., 2009; Folke et al., 2009).

Furthermore, there is another secondary feedback loop that reflects environmental consciousness: human systems can fundamentally cope with critical environmental transition by changing their goal system and action programs. It means that the internal model of human–environment interaction reflects on policies and goals as well as its own program (Argyris, 1977). This feedback loop, sometimes called the third-order feedback loop or double loop learning, is represented by the dotted lines defining the loop \( F_3 = (8, 1, 7) \).

2.2. The LUDAS model

We applied the land-use dynamics simulator (LUDAS) (Le, 2005; Le et al., 2008, 2010) to test the effect of the inclusion of a secondary feedback loop learning on land-use and income patterns over the long term at different aggregation levels. LUDAS is a multi-agent system model for spatial-temporal simulation of a coupled human–landscape system. The model falls into the class of all agents, where the human population and the landscape environment are all self-organized interactive agents. The human community is represented by household agents that integrate household, environmental and policy information into land-use decisions. Bounded rational land-use decisions by household agents are explicitly modelled, which includes the risk that some household agents select a land-use type that may not be the optimal alternative, but the chance for choosing the optimal land-use is relatively high (Le et al., 2008; Fig. S2). The decision model is specific for the livelihood typology of the household. The natural landscape was modelled as landscape agents representing land units that host natural processes and change their nature in response to local conditions, exerting influence on each unit of land and its immediate neighbourhood. Relevant ecological models (e.g. biomass productivity and vegetation succession models) have been integrated into the structure of the landscape agents (see Fig. 2). A short description of the LUDAS model is shown in Supplementary text S1.

2.3. The study site

The LUDAS model was empirically calibrated for the Hong Ha watershed in central Vietnam. The watershed lies about 70 km west of Hue City, at 16°15′04″–16°20′17″ N latitude, 107°15′01″–107°23′06″ E longitude, and covers an area of about 90 km² (Fig. 3). The area is home to three ethnic groups (K’tu, Ta-Oi, and Khinh), and is relatively representative of the ethnic distribution in the greater region. In 2003, the population totalled about 1200 inhabitants in 240 households. The mean of annual population growth has been about 4.5% for the period 1974–2003. Agricultural production and collection of forest products (e.g. biomass productivity and vegetation succession models) have been integrated into the structure of the landscape agents (see Fig. 2). A short description of the LUDAS model is shown in Supplementary text S1.

2.4. Design of simulation experiments

2.4.1. Mechanism I: household's behaviour without any secondary feedback loop learning (baseline)

In this design, human–environment interrelations are mainly characterised by tenure rules and primary feedback loop learning (i.e. feedback loop \( F_1 = (1, 2, 3) \) in Fig. 1). Tenure rules, possibly de facto and/or de jure, explicitly regulate the household's access to and the usage of land resources. The primary feedback loop involves direct information/physical flows between household agents and their landscape environments. Household agents perceive the spatial status of the biophysical conditions around them and anticipate benefits that are used for their decision-making about land-use. The land environment responds directly to land-use activities in term of agricultural and forest yields. When household agents use land they receive some tangible benefits, such as agricultural products, that can lead to changes in certain attributes of their profile, such as increased income, and thus the interaction means now become physical. Through land-use activities, such as converting brush land to crop field and growing different crops, the household agents modify the spatial organisation of their environments, which then constrain or support their decisions over the next few years (via updating variables of the internal decision model).

2.4.2. Mechanism II: household's behaviour with secondary feedback loop learning

This adapted decision mechanism includes the first mechanism but adds a simple secondary feedback loop learning mechanism, in which households can change their behavioural model in response to changing socio-ecological conditions (i.e. feedback loop \( F_2 = (1, 4, 6, 9) \) in Fig. 1). Major assumptions and algorithms of the tested secondary feedback loop are justified and described in the following.

2.4.2.1. Imitation ("Learning by observing models") as a major cognitive process of social-ecological learning in rural land-use. A major assumption of social psychology is that people often become aware of new behaviours by using information about the attractive behaviour of others – so-called social processing (Kenny, 1978; Janssen and Jager, 1999; Jager et al., 2000; Bandura, 2001; Pahl-Wostl et al., 2007; Smajgl, 2007). When people are uncertain about their decision outcomes (assessed by comparing expected and actual recent outcomes) they tend to engage

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**Fig. 2.** The conceptual framework of the LUDAS model: multi-agent system for the coupled human–landscape system. Source: Le (2005) and Le et al. (2008).
in social learning (Festinger, 1954). Given a high degree of uncertainty, dependent on the level of need satisfaction (i.e. seeking for a good enough solution, but not further to avoid further search cost (Simon, 1955), social learning can be either social comparison or imitation behaviour. Social comparison behaviour means that the human agent will compare its own behaviour with the behaviour of those with somewhat similar abilities, and then choose the behaviour that gives the highest need satisfaction. Here is a clear link to the concept of aspiration level: what one wants to achieve and when one is satisfied may be inter-individually different (Schulz, 1980). Given high uncertainty, human agents with a high degree of need satisfaction tend to imitate the behaviour of others having similar characteristics. Modellers represent this as a typology to economize cognitive efforts and minimize risks of failures with the changed strategy (Jager et al., 2000; Gotts and Polhill, 2009). Imitation is an automatic social process, which can be explained by social learning theory (Vygotsky, 1978; Bandura, 1986, 2001) and the theory of normative conduct (Cialdini et al., 1991).

Empirical evidence for imitation in the adoption of agricultural innovations goes back to Ryan and Gross (1943), with a case of hybrid corn varieties. During the last two decades, several studies have provided evidence showing that farmers' adoption of a land-use/farming solutions between various options are influenced by the example of other farmers somewhat similar to them (Warriner and Moul, 1992; Feder and Umali, 1993; Pomp and Burger, 1995; Leteneyi, 2001; Chiffoleau, 2005).

Because of the genuine uncertainty of agricultural productivity and high need satisfaction of rural uplanders, it is reasonable to assume that imitation is the dominant cognitive process of social-ecological learning behaviour (regarding land-use) of peasant farmers in rural mountains. In tropical mountains such as the Hong Ha commune, agricultural production has a high degree of uncertainty because there is a high risk of soil erosion, pests and diseases for crops (Le, 2005). Moreover, because of the high complexity of land conditions (e.g. complex topography and soil mosaics) and the absence of farmer knowledge for yield prediction, farmers are uncertain in anticipating and comparing different future outcomes of land-use choices. Poor agricultural dependents with high risk aversion are often willing to utilize all their available labour for farming to survive, but quickly revert to more leisure once they become slightly better-off (Kaimowitz and Angelsen, 1998). Thus, given this context social comparison is unlikely and imitation can be understood as a common cognitively efficient strategy (Gotts et al., 2003; Schmit and Rounsevell, 2006; Gotts and Polhill, 2009).

In the context of secondary feedback loop learning, we assume that households can change their land-use behaviour model by imitating the behavioural model (i.e. the way of using information to decide how to select a land-use type) of the livelihood group that is most similar to their own, rather than imitating directly activity options (i.e. concrete land-use type) performed by a similar group.

2.4.2.2. Livelihood similarity. A fundamental principle of imitation is that the process is facilitated by favouring some similarity between the imitator and the group to be imitated. This similarity is often viewed in terms of (1) social profile such as attributes, beliefs, education, social status (Rogers, 1983), and (2) abilities of owned resources or of access to resources (Le, 2005). Applied to agricultural land-use, Schmit and Rounsevell (2006) assumed the highest probability of imitation being between farmers of a similar typology. For instance, a farmer specialized in field cropping is more likely to imitate a farmer with the same typology rather than someone specialized in livestock grazing. It is possible that a potentially imitating farmer would assess the extent to which a ‘model’ farmer’s situation is similar to his own in order to determine how valuable the imitation would be (Polhill et al., 2001; Gotts and Polhill, 2009).

We used the sustainable livelihood framework (SLF) concept (Ashley and Carney, 1999; Farrington et al., 1999) for selecting criteria that represent the livelihood typology of households and incorporating a livelihood similarity comparison component in the model. The SLF includes five core asset categories: human, social,
finanical, natural, and physical capital. This spectrum of livelihood assets is the basis of people’s capacity to engage in new activities in response to needs and opportunities in ways that utilize all asset types and minimize risk (Farrington et al., 1999). The concept forms a theoretical basis for deriving indicators for multi-dimensional assessment of the livelihood performance and similarity, helping to avoid bias selection of indicators from one particular discipline (Campbell et al., 2001).

2.4.2.3. AgentCategorizer algorithm: imitative vs. repeating strategy. In LUDAS, there is an automatic classification algorithm, called AgentCategorizer, to annually update the livelihood typology of household agents by evaluating the temporal cumulative changes in variables of the five main household capitals, namely natural, physical, social, human, and financial capitals. These variables – such as land-use structure of household land, agricultural income and so on (see Table 1) – are the results of cumulative impacts caused by land-use actions of the considered households and his/her neighbour. AgentCategorizer annually compares and ranks dissimilarities between the considered household and all livelihood groups in the population, and then assigns each household into the most similar livelihood group. Details of the algorithm are shown in the following.

The algorithm is similar to the K-mean clustering procedure, except that the group centroids here were predefined outside the simulation model by descriptive statistics of household groups, and thus fixed during the simulation runs. The categorizing process consists of the following steps:

(i) A given household h measures dissimilarities in livelihood typology, based on grouping criteria. It compares itself and all defined household groups in the population:

\[
D_{h} = \sum_{i=1}^{c} w_i \cdot \frac{(H_{hi} - \bar{H}_{i})^2}{\bar{H}_{i} + \bar{H}_{i}}
\]

where \(D_{h}\) is the squared Chi-squared livelihood distance from household \(h\) to the centroids of group \(g\) \((g = 1, 2, \ldots, C)\). \(H_{hi}\) is the instant value of criterion \(c\) \((-1, 2, \ldots, C)\) of household \(h\). Criteria \(H_{hi}\) are household livelihood variables, many of which change as the results of micro household–land interactions during the simulation (e.g. Table 1). \(\bar{H}_{i}\) is the mean value of criterion of the group \(g\). Parameter \(w_i\) is the weight coefficient of the criteria explaining the discrimination of household groups. The default value of \(w_i\) is \(1/C\).

(ii) Household \(h\) assigns itself into the most similar livelihood group \(g\):

\[
g = \arg \min \{D_{h1}, D_{h2}, \ldots, D_{hC}\}
\]

where \(g\) is the most similar group to household \(h\). \(D_{h1}, D_{h2}, \ldots, D_{hC}\) are livelihood distances from household \(h\) to groups 1, 2, \ldots, \(K\), respectively.

(iii) If the livelihood group of a household has changed, it will ask to delete the old land-use decision model and to adopt the decision model of the new group (imitative strategy). Otherwise, the household will repeat its former land-use decision-making model (repeating strategy). When adopting a new land-use decision model, there are not only changes in parameter values but possibly also in the behaviour structure: some decision variables and production components are added or deleted.

Because livelihood distances \(D_{h}\) are computed (see equation (1)) based on the group means of livelihood variables \(\bar{H}_{i}\), the evaluation of the highest livelihood similarity as in equation (1) relies on the consideration of the entire population and related agricultural landscape. A household follows its previous behaviour as long as it perceives itself as similar (enough) to other households of its group compared to other household groups. If the accumulative changes in a household’s livelihood variables are large enough and really make the household belong to another livelihood cluster

Table 1

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
</tr>
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<tbody>
<tr>
<td>(H_{labour})</td>
<td>Availability of household labour (number of workers)</td>
</tr>
<tr>
<td>(H_{pend})</td>
<td>Dependency ratio (number of dependents/(H_{labour}))</td>
</tr>
<tr>
<td>(H_{land})</td>
<td>Landholding per capita (m²/person)</td>
</tr>
<tr>
<td>(H_{income})</td>
<td>Gross income per capita of a household (1000 VND person⁻¹ year⁻¹)</td>
</tr>
<tr>
<td>(H_{paddy})</td>
<td>Percentage income from paddy rice (%)</td>
</tr>
</tbody>
</table>

\(\text{The variable list corresponds to vector } H_{g}, \text{ in equation (1). See Section 2.5.2 for more detailed information.}\)
3. Results

3.1. Landscape responses

The time series of simulated forest cover types for the two tested adaptive mechanisms are shown in Fig. 4. The inclusion of the secondary feedback loop learning likely leads to a significant conversion of dense natural forest to open natural forest (degradation of dense forest in the area) (Fig. 4A) and grassland to crop-land (Figs. 4A and 5A) after 21–23 years. Moreover, the simulation result reveals that such an impact happens mainly within a buffer zone of 2–4 km distance from the main road, suggesting a location-specific impact on forest degradation.

The pattern shown in Fig. 4B is in relative accordance with the observed reality. Apparently, the land strip within 1 km of the main road has no more rich forest for logging. Whereas, the further land from the road (distance to road >4 km) is covered by dense forests but is not easily accessible due to complex mountain terrain and labour constraints of households. With the added secondary feedback loop, it is likely that there is a temporal progressive shift of household behaviour from the strategy of “poor” groups to those of the “better-off”. A closer look at the empirical data reveals that allocation of slightly more labour to logging and other off-farm activities (e.g. trading and technical work) is characteristic of the livelihood strategy of the “better-off”.

The adding of secondary feedback learning likely leads to a significant decrease in the area of upland crops, and the increase of paddy and agro-forestry areas, compared to the baseline (Mechanism I) (see Fig. 5A and B). The overall decline in the average farm size (i.e. total farmland/total household) (Fig. 5B) indicates that the population growth exceeds the expansion rate of farmland, thus likely being an underlying cause for land pressure in the area.

The delayed impacts of the added secondary feedback loops on forest cover (Fig. 4A and B), agricultural area, and farm size (Fig. 5A and B) are observed. This clearly confirms a common awareness that time lags (legacy effects) follow profound non-linear dynamics when considering secondary feedback (Liu et al., 2007; Scholz, 2011).

3.2. Income responses

The inclusion of secondary feedback loop learning has no significant impacts on overall household income patterns (Fig. 6). However, this stable behaviour is no surprise. The fact that the “poor” would like to imitate the strategy of the “better-off” does not necessarily include that all poor farmers will be successful regarding their income generation after changing their behaviour. The mechanism of changing the livelihood typology of the household might not count for all important conditions that support the realization of the new adapted livelihood strategy (i.e. imitative learning can be based on a “wrong” reflection of keys for the successful adoption of a new strategy). This could be the limitation of the current model algorithm that potentially misses important variables for a household’s behaviour program adjustment. However, the phenomenon can also reconcile with the genuinely incomplete evaluation of the situation in the adoption of new strategies by poor farmers in the real world. For example, poor farmers may not be aware of some “hidden” constraints they face whereas the “similar” neighbours indeed do not have. These constraints can be resource limitations, such as lack of sufficient financial capacity, knowledge, health and land quality, or cultural barriers which would make poor farmers not successful with the options imitated from the better-off.

3.3. Global and local responses

The simulation results shown in Fig. 7A and B show that the productivity of main farm types in Hong Ha commune are relatively non-responsive between the two tested adapted mechanisms. Moreover, agro-forestry farms in general increase over time from small initial values. This agrees with the fact that in 2002 (the initial year) fruit-based agro-forestry was still new in Hong Ha commune. At the beginning of the farm’s establishment, pineapple and banana crops will be harvested for the first time two or three years after planting. Subsequently, the auto-vegetative propagation of bananas and pineapples increases the density of these crops and subsequently returns higher yields. In later years, fruit-trees (e.g. lemon and jackfruit trees) and black peppers will probably increase overall annual yields, while some banana and pineapple crops will be replaced due to declining yields. Thus the annual yield will still increase steadily following a concave upward pattern.

At the level of group aggregation, the patterns shown in Fig. 7B–D indicate that different household livelihood groups have different responses to the inclusion of the secondary feedback loop in terms of the temporal pattern of agro-forestry productivity. Taking into account a second feedback loop (Mechanism II), the productivity of agro-forestry farms under the management of “paddy-rice based and poor” and “upland crop-based and poor” farmers is considerably higher than that of the baseline (Mechanism I). With the “off-farm and better-off” farmers, the phenomenon is reversed. It is given that the empirical productivity function for agro-forestry farms used by the LUDAS model is (positively) responsive only to labour inputs and cropping time length (Le, 2005). Because the setting of cropping time length is the same between the two tested mechanisms, the observed differences would only be caused by the change in labour allocation of households for agro-forestry farms. Thus, it becomes clear that the adding of the secondary feedback learning triggers poor farmers to invest more time for agro-forestry farming, which can return the benefit in the long run. This is an insightful adaptation of poor farmers to meet their long-term food demands in a difficult context. That is: (1) productivity of farms on hill slopes (i.e. upland crops) is already marginal to inputs and faces a high risk of lost yield (Le, 2005), and (2) the potential access to suitable land for paddy fields in the narrow mountain valley will be very limited in future decades.

4. Discussions

Three following questions are discussed in this section in comparison with previous related studies.

4.1. How is the study placed in the context of most relevant studies on feedback loop systems in land-use changes (human—environment dynamics)? What are sensible strategies to investigate the neglected feedback loops?

Besides some general similarity with the feedback loop systems described by Folkie et al. (2009), Pahl-Wostl (2009), Rotmans and Loorbach (2008), the HES-Framework used in this study also showed important differences. While other approaches do not specify which actors on what temporal and spatial scales show learning that causes changes in framing, the HES-Framework specifies social-ecological learning processes for human systems also at the individual level and postulates relationships and interferences between micro and macro levels (Scholz and Brand, 2011). This explicit representation of the HES-Framework enables modellers to engineer the complex feedback loops in land-use systems easier. The secondary feedback loop learning considered here


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involves the multi-scale and coupled human–environmental
structure of the land-use system (Fig. S1, Supplementary data),
which have not yet been commonly included or tested in current
ABM models for land-use change. In an ABM applied to rural land-
use in southern Vietnam, Dung et al., (2005), using the ‘Consumat’
approach (Janssen and Jager, 1999; Jager et al., 2000) to model the
switching between four different ways of decision-making (i.e.
repetition, deliberation, imitation, and social comparison), the
evaluation of need satisfaction and uncertainty is based on thresh-
olds that are randomly given, with no relation to changes either in

Fig. 4. Time series graphs of simulated land-use/cover for feedback mechanisms I and II. (A): area coverage (%) of 3 main land cover types calculated for the whole study area, (B): area coverage (%) of dense (rich) forest calculated within different buffer areas of the main road. Note: vertical bar indicates the confidence interval (CI) of the mean values (confidence level at 95%, number of independent replications n = 12).
land environment or population or in the underlying socio-ecological drivers. Thus, such a modelled shift of decision behaviour seems not to be relevant to the secondary feedback loop learning discussed here. The study reported here is one of a few recent efforts to fill the gap, including the work within the FEARLUS project (Polhill et al., 2001, 2010; Gotts et al., 2003; Gotts and Polhill, 2009).

The feedback loops between framing actors at higher levels (e.g. policy-making bodies) and basic actors (e.g. households and household groups) as well as the landscape environment (Pahl-Wostl et al., 2007; Pahl-Wostl, 2009) have not been endogenously captured in the LUDAS simulation. However, the importance of the feedback loop is acknowledged. Alternatively, the feedback loop can be formed by using LUDAS-like models, after being validated at an acceptable level, for supporting mutual science-practice learning towards sustainable land uses. Indeed, although ABMs have been or are being used for policy related research in a range of topic areas, there is no evidence for their application as decision support systems (Matthews et al., 2007). Related reasons are: (1) model users expected a ‘predictive’ model. However, in reality social-ecological features of future land-use are complex and not accurately predictable. (2) The construction of land-use change ABM, yet sophisticated, has been isolated from, thus less accessible for resource-users and policy-makers (Matthews et al., 2007; Zellner, 2008). To cause an appropriate science-practice feedback loop learning with the ABM instrument, firstly the model

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**Fig. 5.** Time series graphs of simulated cropland area (A), and average farm size (B) for the feedback mechanisms I and II. Note: vertical bar indicates the confidence interval of the mean values (95%, n = 12).
utilization needs to expand beyond the predictive thought, towards a ‘metaphorical’ thinking that is well-suited for understanding complexity and deep uncertainty in HES (O’Brien and Holland, 1992; Zellner, 2008). ABMs can be seen as metaphorical representations of land-use change complexity that highlight the common organizing principles/processes of the underlying HES, hence suggest ways in which to maintain them. At the same time, ABMs should be used as a vehicle for on-going collective analysis and learning through which a range of stakeholders and their knowledge are incorporated, rather than an isolated analytical exercise informing the stakeholders (Becu et al., 2003; Zellner, 2008; Barreteau et al., 2010; Smajgl, 2010; Voinov and Bousquet, 2010). One alternative strategy is validating an ABM in a first round of stakeholder interaction and using it as a test bed for cyclically iterating between framing and basic actors to test different what-if questions. This formulates a higher-order feedback loop learning

Fig. 6. Time series graphs of simulated (A) household gross income and (B) income inequality (Gini index) for feedback mechanisms I and II. Note: vertical bar indicates the confidence interval of the mean values (95%, n = 12).
between the three domains: scientists/modelled system — basic actors — framing actors. The pertinent role of scientists would be in providing scientific reasoning and coordinating, yet with a neutral (non-bias) sense, the feedback loops between actors and the land environment by analyzing and synthesizing feedback from actors based on the model’s assumptions and outputs, and consequently adapting their model to help enhancing environmental literacy and cope with sustainability (Arnette et al., 2010; Gaddis et al., 2010) (see Fig. S2, Supplementary data).

An alternative strategy is the ComMod (companion modelling) approach (Barreteau et al., 2003; Bousquet et al., 2005). This approach triggers stakeholder participation during the steps of model development in an iterative and cyclic way, thus ensuring that models are continuously confronted with knowledge feedback from stakeholders and the land environment (Barnaud et al., 2008; Naivinit et al., 2010; Simon and Etienne, 2010; Souchère et al., 2010). However, so far, the ComMod approach has been implemented with local stakeholders only (e.g. farmers and local administrators), and
not yet with policy-making bodies. Another approach comprises the representation of framing actors as endogenous agents of the modelled system. However, with this route modellers face a great challenge in the anticipation of the behaviours of policy decision-makers. Moreover, if policy-makers represented in the model are at the same time model users, one has to deal with a possible role conflict.

4.2. Is the main assumption for designing the secondary feedback loop learning plausible? Especially, what are the assumed restrictions that should be relaxed in further development of this study?

The key assumption of the secondary feedback loop learning discussed here (somewhat corresponding with accommodation in Piaget’s terms) is farmers’ imitation to adopt a behaviour strategy experienced by the most similar livelihood typology group. In agrarian societies, the imitation strategy is common and popular as it is an efficient way to economize limited cognitive resources, as well as to minimize risk, in the absence of knowledge for anticipating decision outcomes. Imitation popularity has been evidenced by several previous studies (see Section 4.2.2). As acknowledged by many studies, we also assume that imitation of a new behavioural strategy requires multi-dimensional conditions covering social, human, financial, natural and physical assets of household livelihood system. Thus, the assumption we used is generally plausible. It holds even truer under the condition of high uncertainty about differences in the outcomes from choices and the high-level of need satisfaction, which is currently realized in Hong Ha commune. Moreover, the social-ecological learning phenomenon we dealt with is the copying of others’ high-level decisions (i.e. behaviour schema/program), rather than specific farming activities, as demonstrated in many other related studies. Such a high-level imitation is relevant to the context of secondary (and often longer term) feedback loop learning.

One limitation of the presented model is that it assumes all household agents are equally aware of all land-use options, which are limited to alternatives currently observable in the study area. In reality, the space of options perceived by higher-educated household holds can be wider and more diverse than those recognized by less-educated ones. The set of land-use alternatives can change in the future with the adoption of new land-use types practiced in other regions, or introduced by agricultural extension agencies, or even invented by some households in the community. Overcoming these limitations would mean the improvement of the model mechanism to present more reasoned and deliberative forms of social-ecological learning.

The imitation strategy introduced so far has not been explicitly investigated with respect to the expected outcomes of land-use or innovation choices. In a long-term perspective, forms of more reasoned social learning, such as social comparison and deliberation decision-making (Janssen and Jager, 1999; Jager et al., 2000), occur along with changing driving factors of the uncertainty of outcomes and satisfaction of the actor’s needs. A more intense linkage of the local agrarian community with regional, national, and international markets would result in a transition of the agricultural system from mainly subsistence to more market orientation. Higher engagement of farmers in the market system would likely increase the visibility of economic benefits of farming choices (i.e. uncertainty about economic outcomes decreases), and increase the expectation of the farmers (i.e. reduce need satisfaction) regarding agronomic benefits. This can trigger deliberative behaviour of the better-off farmers, e.g. more households tend to follow the strategy with maximal economic outputs. They may even become motivated to adopt new farming technologies beyond those that are common in their community. Better access to education, in both formal and informal modes, would improve the knowledge of farmers that is needed for reasoning about human needs and rational land-use choices. Thus, improving the simulation algorithm to capture that process would be an interesting task in the future development of this work.

The model assumption that the predefined household types do not change during the simulation period makes sense in terms of utilizing empirical data in the present time, tracking and interpreting dynamics of characterized livelihoods. However, currently it is not possible that new household types occur. Efforts to relax this assumption will potentially spur novel outcomes, but create the challenge for presenting and tracking the group dynamics over time as well as validating them.

4.3. What is the methodological contribution of the study in the research field and what are its limitations?

Due to cultural, social, economic, and natural resource constraints, social-ecological learning can occur but will not necessarily lead to actual changes in an actor’s decisions. Thus, modelling of imitation and/or social comparison strategies requires the evaluation of similarity between the considered actor and their peers. And the similarity should be multi-dimensional according to the multiple constraints the actor faces in its shift from learning to actual behavioural change. So far, this study appears to be the only one using variables representing the five capital types of the sustainable livelihood framework (Ashley and Carney, 1999) to assess livelihood similarity between actors and their neighbours. With that, we tried to avoid a biased use of indicators from only one particular discipline. Schmit and Rounsevell (2006) used only parcel and farm location data for the geographic information system calculation of a similarity index, and for the subsequent analysis of imitation patterns. Their result calls into question the imitation assumption in several ABMs for rural land-use changes. However, one should be cautious with the results as the authors admit limitations in the method of similarity measurement (Schmit and Rounsevell, 2006; Gotts and Polhill, 2009). Most related social studies analyzed the phenomenon based on the evaluation of social and cultural relations (Stockdale, 2002; Chiffoleau, 2005; Lindsay et al., 2005). Although these studies deepened our understanding of social-ecological learning in the adoption of agricultural innovation, they did not (explicitly) connect the social learning to the environmental resource dynamics. Thus, the social learning in these studies should not be regarded as a secondary feedback loop learning that reflects adaptations of human actors within the context of human–environment systems.

In ABM simulations, endogenous judgement as to when the human agent should change their behaviour in coping with a changing socio-ecological situation is a challenge. In the ABMs of Dung et al. (2005), Polhill et al. (2001) and Gotts et al. (2003), the change in agent behaviour is based on the comparison of the agent’s satisfaction and/or uncertainty (regarding the outcomes of behaviour) with thresholds that are given or randomly generated. However, the feedback loop between the functions of the agent’s satisfaction/uncertainty and the past change in the socio-ecological conditions (driven from agent actions) were not clearly explained. The study presented here models the switching between repetition and imitation strategies (regarding the adoption of a behaviour program that guides the selection of specific land-use activities) based on the comparison of livelihood distance. The distance is a function of multiple variables that reflect agent-induced changes in socio-ecological conditions in the past. In that way, environmental secondary feedback loop learning is clearly formed.
4.4. Model validation: towards a multi-criteria approach

Because of inherent complexity, path-dependency, deep uncertainty of the coupled HES underlying land-use change, validation of an ABM for HES must be expanded beyond the straightforward evaluation of numerical fits between simulated and observed patterns in time and space (Becu et al., 2003; Nguyen and de Kok, 2007; Zellner, 2008; Le et al., 2010; Naivinit et al., 2010). With a metaphorical thought about meaningful uses of the complex system models, the validity of this model type lies within the continuous review/evaluation with multiple criteria to inform users about the model’s usefulness, its limitations and development needs (Messina et al., 2008; Zellner, 2008; Naivinit et al., 2010). The multiple criteria should include (1) the fitting of the model to the questions it is meant to answer, (2) the plausibility of the assumptions and theories forming the model (construct validity), (3) the validity of elementary causal relations used for constructing the model (e.g. behavioural rules and sub-models) (internal validity), (4) the validity of input data, and (5) the validity of model outputs (Scholz and Tietje, 2002; North and Macal, 2007).

Because the basic psychological concept of this study is genuinely process-based and the model used (LUDAS) is a generative model, construct validity should be the umbrella criterion to assess the validity of the approach. The model assumptions are based on validated psychological theories, as justified in Section 2.4.2.

As the tested concept is applied for a real case, case-specific validities of model’s internal mechanisms, input and output are important. The land-use decision sub-model of LUDAS was calibrated and validated using standard inferential statistics that use data from household-survey, farm terrain and accessibility analyses (Le, 2005, Section 4). The behavioural rule set that governs household level activities was empirically extracted from surveys as well as participatory exercises. Calibrations and tests for crop yield response and forest growth sub-models were reported in Le (2005, Section 5). Data for initializing the modelled HES include GIS data that were collected through soil-landscape analysis, remote-sensing analyses of land-use and a field survey along typical transects. Data on the household population were derived from a dataset of 30% of the population. All data used by LUDAS were evaluated and processed in separate studies to adequately represent the coupled HES (Le, 2005, Sections 4 and 5).

Using an exploratory modelling output validity of the model firstly focuses on the robustness in comparison of outcomes driven by different feedback mechanisms (Lempert, 2002). The statistically significant differences between many impact indicators such as forest area, farm size and crop yields (Figs. 4, 5, and 7) indicate the robustness of the designed model in generating consistent land-use change scenarios in the face of uncertainties. The overall declining trend of farm size in the area corresponds to a trend extrapolated from local statistics reported by Le (2002). The fact that secondary feedback loop learning likely leads to better agro-forestry productivity of “paddy-rice based and poor” farmers (Fig. 7B) (compared to the case of Mechanism I) reflects the willingness of these farmers (79%) to invest more fertilizers, manures and time on their fruit-based farms in the future when asked in a survey in 2002. The results also fit to some important properties of complex human-environment systems, such as the delayed effects of secondary feedback loops, theoretically anticipated (Scholz, 2011) or empirically found in many places in the world (Liu et al., 2007). However, more comparing the simulated results to empirical patterns is still important and a subject of our on-going research. Related efforts certainly require new socio-ecological data at both micro and macro levels within the simulation period.

5. Conclusions

Understanding how environmental feedback has emerged from land-use actions can reshape land-use decisions in the long term, and is important for integrated system models of land-use change to support sustainable land management. Conceptually, we differentiate two types of human adaptation following feedback loops in the coupled human–environmental system. The objective of this study is to examine the effects of a secondary feedback loop in land-use decision-making in coping with socio-ecological changes, with respect to different system performance indicators at different levels of aggregation.

To investigate that issue, we use an agent-based land-use change model (LUDAS) based on a case study that was carried out in the Hong Ha watershed (Vietnam). Based on the HES-framework we identified two different types of adaptation following different types of feedback loops between the human and the environmental system. We compared the patterns of land-use and associated income changes driven by the two adaptation mechanisms to evaluate the added value of the inclusion of secondary feedback loop learning. We conclude from the results that spatial-temporal signatures of the added feedback loops depend on domain type, time scale, and aggregation level of the impact indicators. The inclusion of a simple secondary feedback loop learning can cause long-term delayed effects in forest cover transition, significant changes in agricultural area and farm size, and different responses in farming productivity managed by different farmer groups.

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Supplementary data

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