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Quang Bao Le

Roman Seidl

Roland W. Scholz

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Quang Bao Le, Roman Seidl, Roland W. Scholz
Natural and Social Science Interface (NSSI), ETH Zurich, Universitaetstrasse 22, CH-8092 Zurich, Switzerland
E-mails: {quang.le, roman.seidl, roland.scholz}@env.ethz.ch

Abstract: A key challenge of land-use modeling for supporting sustainable land management is to understand how environmental feedbacks emerged from land-use actions can reshape land-use decisions in the long-term. To investigate that issue, we use an agent-based land-use change model (LUDAS) developed by Le et al. [2008] based on a case study that was carried out in Hongha watershed (Vietnam). In LUDAS, goal-directed land-use decisions by household agents are explicitly modeled (i.e. agents calculate utilities for all land-use and location alternatives and likely select the alternative with highest utility). The model is run for two mechanisms of adaptation in land-use decisions to environmental changes that emerged from land-use actions. The first mechanism includes only a primary feedback loop learning, in which households adapt to the changing socio-ecological conditions by choosing the best land-use in the best location. The second mechanism builds on the first one but adds a secondary feedback loop learning, in which households can change their behavioural model in response to changing socio-ecological conditions. Patterns of land-use and interrelated community income changes driven from the two feedback mechanisms are compared to evaluate the added value of the inclusion of the secondary feedback loop learning. The results demonstrate that spatio-temporal signatures of the added feedback loops depend on domain type, time scale, and aggregation level of impact variables.
Keywords: human-environment interaction; agent-based modeling; land-use change; adaptive decision-making; feedback loop learning

1. INTRODUCTION

Modeling of land-use changes faces the complexity of coupled human-environmental systems that involves feedback loops between environmental dynamics and human decision-making processes [Scholz, in prep]. Land-use change emerges from the interactions among various components of the coupled human-landscape system, which then feeds back to the subsequent development of those interactions [Le, 2005; Le et al., 2008]. Changes in land allocation occur at the level of land plots, resulting from decisions made by individual actors situated in diverse socio-ecological settings. Accrual of short-term changes over time and aggregation of localized changes over space generate larger-scale emergent patterns of land-use change and economic performance. In turn, changes on the macro level such as climate or policy regimes affect the behavior of the individuals that produce changes at the micro-level [Lambin et al., 2003]. Understanding how such human-nature and cross-scale feedback mechanisms affect the dynamics of environmental and human systems at different spatial and temporal scales is still one of the major challenges in land-use change modeling [Verburg, 2006; Turner et al., 2007].

During the last decade, there has been a rapid growth of agent-based models (ABM) for simulating land-use changes [Matthews et al., 2007]. These models consist of a number of human agents which interact with each other and with their environment. This environment can also be represented as autonomous land units, i.e. "land agents" (e.g. Le et al. [2008, 2010]). Human agents make decisions influenced by socio-ecological interactions and change their behavior as a result of these interactions, thus offering the opportunity to take into account the adaptation of human decision-making to land-use at different levels of landscape and human organizations.

However, most of ABM for land-use changes have incorporated different feedbacks mechanisms without carefully testing the new insights added by the inclusions of the feedback mechanisms. Adding unnecessary feedbacks may lead to a dramatic increase in the model's complexity, in which the model would become too sophisticated (i.e. parsimony principle is not respected). 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 the model and an increase in confidence.

In this paper, we test a simple methodology for modeling the adaptation of farmer's decision-making in coping with long-term changes in socio-ecological conditions in a case study area in central Vietnam. We use an agent-based land-use change model (LUDAS) developed by Le et al. [2008] to examine the effects of a secondary feedback in land-use decision making with respect to different system performance indicators at different levels of aggregation.

2. METHODOLOGY

2.1 Concept of feedback loop learning in coupled human-environmental systems

We use the Human-Environmental System framework (hereafter referred as HES framework), developed by Scholz [in prep.], as the conceptual guide for the detailed investigation of feedback loops in land-use change. An important postulate of the HES framework states that there are different types of environmental feedback loops that represent perception, evaluations, and adaptation of human systems regarding environmental changes. Adaptation of human decision-making to environmental change is the actor'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 behavioral program).

In general, adaptive decision-making of human actors involves (i) a primary feedback loop and (ii) a secondary (higher-order) feedback loop learning. With the former, human agents perceive the environment status and react on it, and the human action transforms the environment, with a retroactive effect on the decision-making process of itself and of other agents in a short-term fashion. This first-order feedback learning does not alter the goal-related decision rules of agents. The later type of feedback loop learning is defined by human-driven cumulative changes in social/economic and environmental conditions at larger scales and in the longer term (possibly unintended), leading to the reframing of the actor's behavioral program. Because of involving multiple interactions and feedbacks among variables and subsystems across different scales, the secondary feedback loop learning can be delayed [Scholz, in prep.], and often causes a legacy impact on the performance of the whole coupled human-environmental system [Liu et al., 2007].

2.2 The LUDAS model

We apply the Land Use Dynamics Simulator (LUDAS) [Le, 2005; Le et al., 2008] to test the effect of the inclusion of a secondary feedback loop learning on land-use and income patterns in the long-term at different aggregation levels. LUDAS is a multi-agent system model for spatio-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. Goal-directed land-use decisions by household agents are explicitly modeled, i.e. the agents calculate utilities for all land-use and location alternatives and likely select the alternative with the highest utility. The decision model is specific for the livelihood typology of the household. The natural landscape was modeled as landscape agents, i.e., 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 neighborhood. Relevant ecological models (e.g. biomass productivity and vegetation succession models) have been integrated into the structure of the landscape agents (see Figure 1). A detailed specification of the LUDAS model is shown in Le et al. [2008].

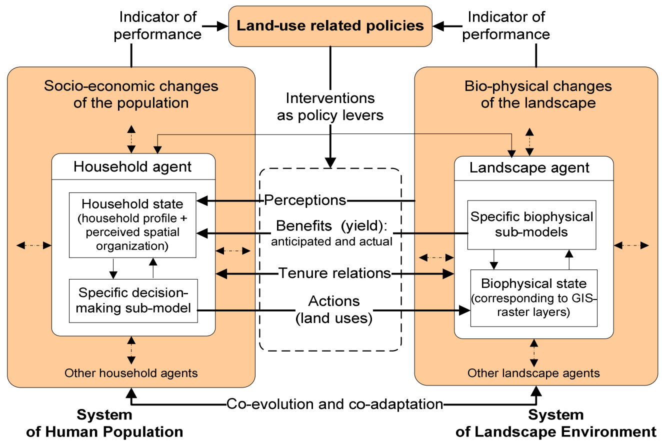

Figure 1. The conceptual framework of LUDAS model: multi-agent system for the coupled human-landscape system. Source: Le [2005] and Le et al. [2008].

2.3 Design of simulation experiments

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 the *primary feedback loop learning*. 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 the agent can derive in arriving at decisions. When household agents use land they receive some actual benefits (e.g. agricultural products) that can lead to changes in certain attributes of their profile, and thus the interaction means now become physical. Through land-use activities the household agents modify the structure of spatial organisation in their environments, which then constraint or support his/her decisions in the next few years (via updating variables of the internal decision model).

Mechanism II: *Household's behaviour with a secondary feedback loop learning.* This adapted decision mechanism builds on the first mechanism but adds a simple secondary feedback loop learning, in which households can change their behavioural model in response to changing socio-ecological conditions. Here, we assume that households can change their land-use behavior model by imitating the strategy of the livelihood group who is most similar to them. In the context of Vietnam uplands, the sustainable livelihood framework concept [Ashley and Carney, 1999] is a relevant basis to specify a land-use strategy, which is a core compoment of the total livelihood strategy.

In LUDAS, there is an automatic classification algorithm, called *AgentCategorizer*, to annually update the livelihood typology of household agents by evaluating the temporal *cummulative changes* in variables of 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 – are subject of cumulative impacts caused by land-use actions of the considered households and his/her neighbor. *AgentCategorizer* is annually comparing and ranking dissimilarities between the considered household and all livelihood groups in the population, then assigning the household into the most similar livelihood group. Thus, an imitative learning behavior is assumed. Details of the algorithm are shown in the Appendix.

The Study Site. The LUDAS model was empirically calibrated for the Hongha watershed in central Vietnam. The watershed lies about 70 kilometers 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 km^2. The area is home of three ethnic groups (K'tu, Ta-Oi, and Kinh), fairly representing the population in the region. By 2003, the population is of about 1200 inhabitants in 240 households. The average population growth is about 4.5%. Agricultural production and collection of forest products (e.g. firewood, timber, rattan, trapped wild animals) are the main livelihoods of most villagers.

As in many areas in the uplands along the Central Coast of Vietnam, three types of agricultural land use most commonly found in the study area are upland crops, paddy rice, and fruit-based agroforestry. The upland crop system, practiced traditionally by the ethnic minorities (K'tu and Ta-Oi groups) is a type of shifting cultivation. Main upland crops are local dry rice, casava and maize. The cultivation of upland crop is rain-fed with almost no or very low input of chemical fertilizers. Paddy rice is widely practiced by most households. Most of the paddy rice fields have two crops a year. Chemical fertilizers (mostly NPK) and pesticides have been increasingly used in the paddy rice system since 1998, along with agricultural extension programs. Fruit-based agroforestry, widely practiced in Hongha since the 1990s, include bananas, pineapples, jackfruits, lemon, longan trees and black pepper, which are usually planted in association. NPK fertilizer is sometimes applied when fruit crops are first planted.

Data Inputs, Impact Indicators and Uncertainty Quantification. Data inputs include landscape and household attributes. Landscape data were obtained by remote sensing (land use/cover), soil-landscape (terrain indices), accessibility (proximities to rivers/streams and roads) analyses, as well as social mapping (holdings, village territory, protection zoning class). Household data, covering socio-economic attributes (educational status, size, labour, land endowment, income) and household's access to policies or developmental programs, were gathered through surveys using a structured questionnaire. Detailed input data and calibrated parameters for the model were described and explained in Le [2005].

We assess the effect of the inclusion of the secondary feedback loop learning by estimating the divergences and bounds of impact indicators between the two adaptive mechanisms described above. The impact variables/indicators are as follows:

- Global coverage of a land-use/cover type (%) = (area of such a land-use/cover type / total area of the landscape) × 100%
- Coverage of dense/rich forest within a buffer zone of the main road (%) = (area covered by dense forest within the buffer zone / total area of the buffer zone) × 100%. By calculating this localized coverage of dense forest for different extent of the buffer zone, we expect to measure a spatial pattern of deforestation or forest degradation in relation to road development.
- Total area of different farm types (ha)
- Average farm size (ha $household^{-1}$)
- Average yield of different farm types (ton rice ha^{-1} $year^{-1}$)
- Average household gross income (1000 VND $household^{-1}$ $year^{-1}$) and its partial components (from different income sources)
- Gini index of household income (varying between 0 and 1; 0 - perfect equality in income distribution across population, 1- completely inequality).

Because LUDAS is a stochastic model, it is not recommended to draw any conclusions from the outputs of a single simulation run. The outputs represent only one realization of a stochastic process. To quantify the uncertainty in the model outputs induced by the uncertainties in its inputs, the method of independent replications [Goldsman, 1992; Nguyen and de Kok, 2007] is used. In its application in this paper, we independently replicated the simulation 12 times for each mechanism and computed the mean values of the impact indicators and their confidence intervals at 95% reliability.

3. RESULTS AND DISCUSSIONS

3.1 Landscape responses

Time-series of simulated land-use/cover for the two tested adaptive mechanisms are shown in Fig. 2. 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/rich forest in the area) after 21-23 years (Figure 2A). Moreover, the simulation result reveals that such an impact likely happens mainly within a buffer zone of 2-4 km distance from the main road, suggesting a spatial scale-dependent impact on forest degradation.

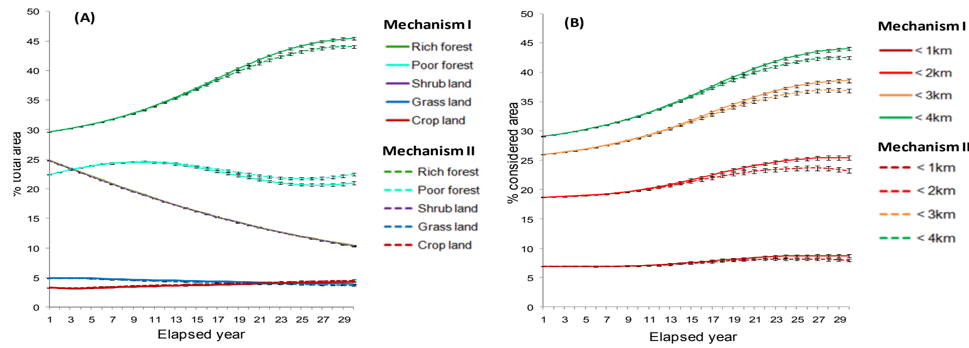

Figure 2. Time series graphs of simulated land use/cover for feedback mechanisms I and II. (A): area coverage (%) of 5 main land cover types calculated for the whole study area, (B): area coverage (%) of dense/rich forest calculated within different buffer areas of the main road. *Note: Vertical bar indicates the confidence interval of the mean values (95%).*

The pattern shown in Figure 2 B is in relatively accordance with the observed reality. Apparently, the land trip with 1km from the main road has no more rich forest for logging. Whereas the further land from the road (distance to road > 4km) are covered by dense forests but are not easily accessible due to complex mountain terrain and labor constraint of households. With the added secondary feedback loop, it is likely that there is a temporally progressive shift of household behavior from the strategy of "poor" groups to those of the "better-off". A closer look at empirical data reveals that allocation of a bit more labor to logging and other off-farm activities (e.g. trading and technical work) is characteristics of the livelihood strategy of the "better-off".

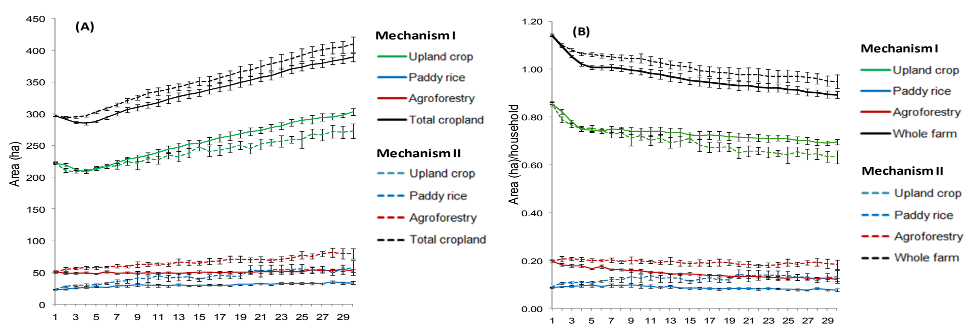

Figure 3. Time series graphs of simulated cropland area (A), and average farm size (B) for the feedback mechanisms I and II. *Note: Vertical bar indicates the confidence interval of the mean values (95%).*

The delayed impacts on forest cover in this case study clearly confirms a common awareness that time lags (legacy effects) follow profound non-linear dynamics when considering secondary feedback [Liu et al., 2007; Scholz, in prep.]. The adding of secondary feedback learning likely leads to a significant decrease in the area of upland crop, and the increase of paddy and agro-forestry areas, compared to the baseline (Mechanism I) (see Figure 3 A, B). The overall decline in the average farm size (i.e. total farmland /total household) (Figure 3 B) against the background of increasing cropping area

(Fig. 5C) indicates that the population growth exceeds the expansion rate of farmland, thus likely being an underlying cause for land pressure in the area.

3.2 Income responses

The inclusion of secondary feedback loop learning has no significant impacts on overall household income pattern (Figure 4). However, this stable behavior 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 behavior. The mechanism of changing 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 successful adoption of new strategy). This can be the limitation of the current model algorithm that potentially misses important variables for household's behavior program adjustment. However, the phenomenon can also reconcile with the genuinely incomplete evaluation of the situation in 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" ones indeed do not have, or vice versa with some opportunities.

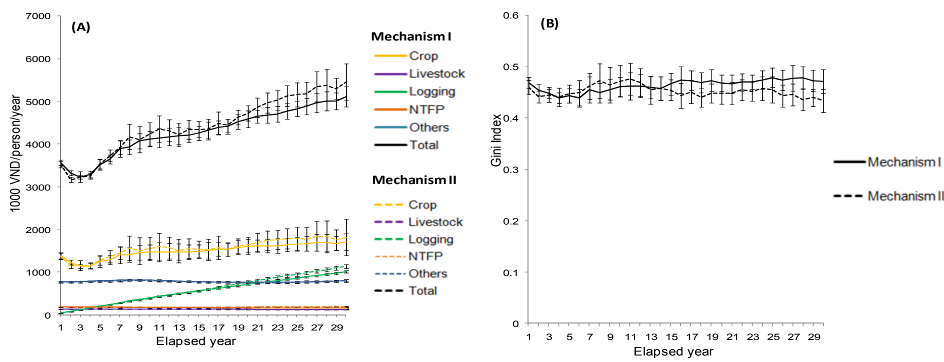

Figure 4. Time series graphs of simulated (A) household gross income and (B) income inequality (Gini index) for feedback mechanisms I and II. *Note: Vertical bar indicates the confidence interval of the mean values (95%).*

3.3 Global and local responses

The simulation results shown in Figure 5 A, B show that productivities of main farm types in Hongha 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 agroforestry was still new in Hongha commune. At the beginning of the farm 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 return 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 up pattern.

At the level of group aggregation, the patterns shown in Figure 5 B 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 the vice versa. It is given that the empirical productivity function for agro-forestry farms used by the LUDAS model is (positively) responsive to only 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 be only 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 farm, which can return the benefit the in long run. This is an insightful adaptation of poor farmers to meet their long-term food demand in a difficult context. That is: (i) productivity of farms on hill slope (i.e. upland crop) is already marginal to inputs and facing a high risk of lost yield (Le, 2005), and (ii) the potential access to suitable land for paddy in the narrow mountain valley will be very limited in the future decades.

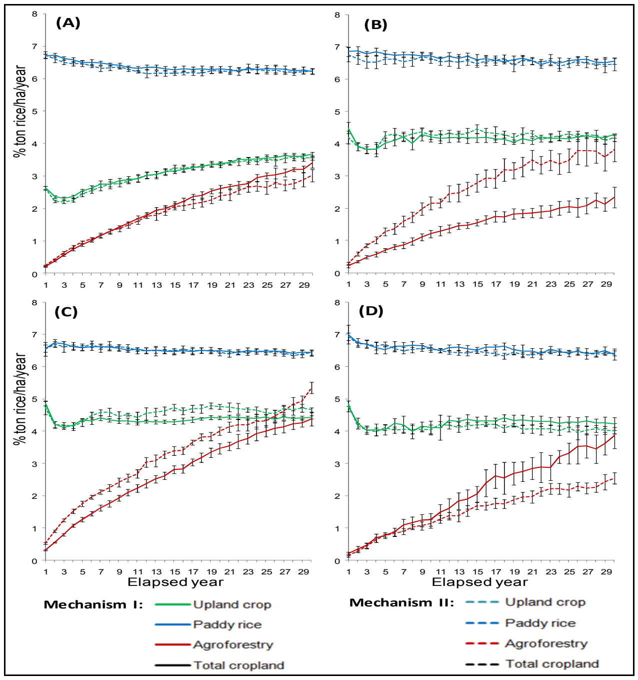

Figure 5. Time series graphs of simulated crop productivity for different levels of farm's aggregations.
(A) whole population,
(B) "paddy-based and poor" farmers,
(C) "upland crop and poor" farmers, and
(D) "off-farm and better-off" farmers.
Note: Vertical bar indicates the confidence interval of the mean values (95%).

5. CONCLUSIONS

Understanding how environmental feedbacks emerged from land-use actions can reshape land-use decisions in the long-term is important for integrated system models of land-use change to support sustainable land management. To investigate that issue, we use an agent-based land-use change model (LUDAS) based on a case study that was carried out in Hongha watershed (Vietnam). The model was run for two mechanisms of adaptation in land-use decisions to environmental changes that emerged from land-use actions. The first mechanism includes only a primary feedback loop learning (Mechanism I), in which households adapt to the changing socio-ecological conditions by choosing the best land-use in the best location. The second mechanism builds on the first one but adds a secondary feedback loop learning (Mechanism II), in which households can change their behavioural model in response to changing socio-ecological conditions. Patterns of land-use and interrelated income changes driven from the two feedback mechanisms are compared to evaluate the added value of the inclusion of the secondary feedback loop learning.

The results demonstrate that spatio-temporal signatures of the added feedback loops depend on domain type, time scale, and aggregation level of impact indicators. The inclusion of very simple secondary feedback loop learning can cause long-term delayed effect in forest cover transition, significant change in agricultural area and farm size, and different responses of farming productivity managed by different farmer groups. The interpretation of the change patterns helps to improve our understanding of the co-adaptation between humans and the natural landscape that suggests new insights for alternative land management strategies. However, it also raises a new requirement of validating for the potential added values of the inclusion of more complex feedback loops.

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Appendix. *AgentCategorizer* algorithm

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 categorising process consists of the following steps:

- A given household *h* measures dissimilarities in livelihood typology, based on grouping criteria, between himself and all defined household groups in the population:

$$D_{hg} = \sum_{c=1}^{C} w_c \left[\frac{(H_{h,c} - \overline{H}_{g,c})^2}{\left| H_{h,c} + \overline{H}_{g,c} \right|} \right]$$

  where D_{hg} is the Squared Chi-squared Distance from household *h* to the centroids of the group *g* (g = 1, 2, …, K), $H_{h,c}$ is the instant value of criterion *c* (c = 1, 2, ...,C) of household *h*, $\overline{H}_{g,c}$ is the mean value of criterion *c* of the group *g*, w_c is the weight coefficient of the criteria explaining the discrimination of household groups. The default value of w_c is $1/C$.
- Household *h* assigns himself into the most similar livelihood group ($g*$):
  $g* = arg\ min\{D_{h1},D_{h2},D_{h3}, \ldots,D_{hK}\}$ where $g*$ is the most similar group to household *h*; D_{h1}, D_{h2}, D_{h3}, …, D_{hK} are distances from household *h* to groups *1*, *2*, …, *K*, respectively.
- Once the livelihood group of a household has changed, he/she will ask to delete the old land-use decision model and to adopt the decision model of the new group. When adopting a new land-use decision model, there are not only changes in parameter values but possibly also in the behavior structure: some decision variables and production components are added or deleted.