

# A framework for modeling payments for ecosystem services with agent-based models, Bayesian belief networks and opinion dynamics models<sup>☆</sup>



Zhanli Sun, Daniel Müller\*

Leibniz Institute of Agricultural Development in Central and Eastern Europe (IAMO), Theodor-Lieser-Str. 2, 06120 Halle (Saale), Germany

## ARTICLE INFO

### Article history:

Received 1 April 2011

Received in revised form

12 June 2012

Accepted 13 June 2012

Available online 20 July 2012

### Keywords:

Payments for environmental services

Land use change

Agent based modeling

Bayesian network

Social influence

Human–environment interaction

IAMO-LUC

China

## ABSTRACT

We present an integrated modeling framework for simulating land-use decision making under the influence of payments for ecosystem services. The model combines agent-based modeling (ABM) with Bayesian belief networks (BBNs) and opinion dynamics models (ODM). The model endows agents with the ability to make land-use decisions at the household and plot levels. The decision-making process is captured with the BBNs that were constructed and calibrated with both qualitative and quantitative information, i.e., knowledge gained from group discussions with stakeholders and empirical survey data. To represent interpersonal interactions within social networks, the decision process is further modulated by the opinion dynamics model. The goals of the model are to improve the ability of ABM to emulate land-use decision making and thus provide a better understanding of the potential impacts of payments for ecosystem services on land use and household livelihoods. Our approach provides three important innovations. First, decision making is represented in a causal directed graph. Second, the model provides a natural framework for combining knowledge from experts and stakeholders with quantitative data. Third, the modular architecture and the software implementation can be customized with modest efforts. The model is therefore a flexible, general platform that can be tailored to other studies by mounting the appropriate case-specific “brain” into the agents. The model was calibrated for the Sloping Land Conversion Program (SLCP) in Yunnan, China using data from participatory mapping, focus group interviews, and a survey of 509 farm households in 17 villages.

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## 1. Introduction

Land-use changes affect the long-term functioning of natural ecosystems that are crucial for human well-being (Foley et al., 2005; MA, 2005). A thorough understanding of spatial and temporal changes in the land system is therefore of paramount importance when designing management and policy strategies that promote sustainable land use and preserve the benefits humanity derives from ecosystems. Recently, market-oriented instruments, such as programs of payments for ecosystem services (PES), have been gaining importance as a policy tool for directing land use to sustainable pathways. Many PES schemes provide monetary incentives to motivate land users to alter their decision making to be in line with a desired conservation outcome (Ferraro and Kiss, 2002).

However, an effective evaluation of PES programs that target sustainable land-use change is challenging because of the

fundamental integration of social and ecological processes, the dynamic nature of the cause and effect chains, and the necessary consideration of feedback effects and nonlinearities. Conventional tools, such as statistical analysis, yield only part of the picture because they often fail to include longer-term perspectives and emerging system properties. Moreover, the consideration of temporal and spatial outcomes is crucial for several reasons, including the nonlinear responses of farm households to changes in external framework conditions or the evolution of new habitat structures in response to land-use incentives.

To address the complexities of such coupled systems, we propose a hybrid agent-based modeling approach to comprehensively simulate the effects of payment schemes on changes in land use and livelihoods. We include an empirical application for the Sloping Land Conversion Program (SLCP) in China, one of the world's largest PES programs, which compensates farmers for converting cropland to forest and grassland. Agent-based models (ABMs) are bottom-up approaches that provide a natural way of both conceptualizing and implementing complex, dynamic, and disaggregated models of human decision-making (Le et al., 2010;

<sup>☆</sup> Thematic Issue on Spatial Agent-Based Models for Socio-Ecological Systems.

\* Corresponding author. Tel.: +49 (0)345 2929328; fax: +49 (0)345 2929399.

E-mail address: [mueller@iamo.de](mailto:mueller@iamo.de) (D. Müller).

Valbuena et al., 2010). ABM are increasingly popular and can be effective in modeling coupled socioecological systems such as land-use change, which is a cumulative result of individual land users' decisions (Bonabeau, 2002; Parker et al., 2003; Valbuena et al., 2008). ABMs have also been applied to examine the impact of PES on land-use decisions (see, e.g., Chen et al., 2012; Deffuant et al., 2002b; Sengupta et al., 2005).

One of the major advantages of ABMs is their ability to model decision-making entities (Rindfuss et al., 2004; Turner II et al., 2007). Hence, the validity of ABMs depends on their ability to model individual behavior, which is a major challenge due to the complexity of human actions (Grimm et al., 2005; Parker et al., 2003; Smajgl et al., 2011). Many ABMs rely on heuristic rules or single-objective optimization models to describe the decision making of agents. Consequently, agents are often assumed to act in an economically rational way (Balmann, 1997; Filatova et al., 2009; Parker et al., 2008; Schreinemachers and Berger, 2011). Such models have substantial explanatory power, for instance, in describing the evolution of farms or entrepreneurs in competitive market settings (Happe et al., 2006). However, human behavior is often irrational and subjective due to limited knowledge and information or because of personal preferences and beliefs. Thus, humans employ a variety of strategies in land-use decisions that go beyond the maximization of profits or minimization of risk (Bonabeau, 2002; Parker et al., 2008). The optimization approaches based on microeconomic theory are therefore inadequate for capturing the complexity, uncertainty, heterogeneity, and bounded rationality of human behavior (Filatova et al., 2011; Parker et al., 2003; Simon, 1955).

As a result, empirical approaches derived from comprehensive data have gained increasing attention in ABM research. Examples include participatory approaches and sample surveys that serve to model decision making (Matthews et al., 2007; Parker et al., 2003; Robinson et al., 2007). Such approaches are particularly promising in settings where agents may not strictly follow the principles of economic rationality. This behavior is prevalent in developing countries where farmers often face a number of simultaneous objectives and constraints that go beyond profit maximization principles, such as minimizing risks, satisfying auto-consumption requirements, and balancing labor skills and availability. Moreover, culture and traditions may play more important roles in land-use decisions, and information asymmetry may limit knowledge about market developments and technological advances. Participatory approaches more effectively account for multifaceted objectives and constraints by including stakeholders in the development and calibration of the model, which will enhance the decision-making component of ABMs (Matthews et al., 2007; Parker et al., 2003). Prominent examples of participatory methods include role-playing games that allow the incorporation of the hypothetical decisions of and interactions between agents in an ABM model (Bousquet et al., 2002; Castella et al., 2005). Yet, how to formulate and parameterize the mathematical models based on qualitative knowledge gained during the group discussion and how to effectively communicate with stakeholders remain key challenges. Another approach is to use survey data and microeconomic theory to parameterize and calibrate agents' behavioral models with quantitative data from individuals and households (Robinson et al., 2007). However, the snapshot-type data collected through questionnaires and the lack of direct involvement of stakeholders (unlike the participatory approach) precludes a comprehensive description of the complex and dynamic decision-making process.

To tackle these challenges in ABMs, we adopted Bayesian belief networks (BBNs) to simulate land-use decision making under uncertainty. BBNs encode probabilistic relationships among variables of interest with a graphical interface that provides a natural and intuitive way to model causal reasoning with a solid

mathematical foundation (Heckerman et al., 1995; Jensen, 2002; Pearl, 2009). The advantages of using BBNs in land-use change simulations are multi-fold. First, the capability of knowledge representation and inference under conditions of uncertainty makes BBNs an appealing tool to represent individual reasoning in decision making. The probabilistic outcomes account for the variation inherent in parameter estimates and thus implicitly incorporate a risk component (Kinzig et al., 2003; Newton et al., 2007). The ability of BBNs to model causal connections between factors that shape land-use decisions is particularly valuable for our purposes because it allows us to draw inferences about the effects of land-use policies on local land-use outcomes. Second, BBNs can incorporate the qualitative beliefs and attitudes of stakeholders, so-called prior knowledge, along with quantitative data (Marcot et al., 2001; Newton et al., 2006). This feature allows modelers to parameterize and validate land-use decision making by combining qualitative information gained from participatory discussions and quantitative data collected, for example, in household surveys. BBNs can effectively facilitate focus group discussions via the graphical interface and the influence diagram, which support the active involvement of stakeholders in model calibration and validation. The influence diagrams are also relevant for decision makers because they are transparent, intuitive and easy to understand. Contrary to many other simulation models, stakeholders can be more readily involved in model and scenario development, which eases their skepticism towards the modeling exercise (Gilbert et al., 2002; Voinov and Bousquet, 2010). Compared to other graphical models, such as decision trees, BBNs have higher predictive performance and are better suited to capture the complexity of the underlying decision making (Janssens et al., 2004). In summary, the flexibility of BBNs in combining quantitative evidence with stakeholder information renders them an excellent extension to more rigid, rule-based expert systems that characterize an optimal production program.

BBNs and ABMs are complementary in land-use simulations because ABMs provide a natural framework for accommodating multiple agents and compensate for the deficiency in the spatial and temporal dimensions of BBNs. However, due to the technical and computational challenges in coupling the two approaches, few attempts at integrating BBNs and ABMs have been reported thus far. One exception is the MABEL model, implemented in the C/C++ programming languages, which loosely coupled BBNs and ABMs with Swarm in a distributed client/server architecture and was successfully applied for land-use change simulations (Alexandridis and Pijanowski, 2007; Lei et al., 2005).

Farmers make land-use decisions not only based on their socioeconomic characteristics and physical traits of their land, but they also learn from and follow other farmers' actions. In other words, farmers show contingent behavior in the process of adopting a policy or technology (Weisbuch, 2000). Much empirical evidence supports such a "bandwagon effect" because farmers frequently base their adoption decisions on information conveyed to them by their peers (Berger, 2001; Deffuant et al., 2002b, 2000), make decisions under the influence of social norms (Chen et al., 2012, 2009a), and sometimes simply imitate the land-use practices adopted by their peers (Gotts and Polhill, 2009). Additionally, the spatial autocorrelation and agglomeration patterns exhibited in land-use change often go beyond the clustered distribution of biophysical features of landscapes and are also characterized by social interactions among land managers (Verburg et al., 2004). Unfortunately, many land-use-change models fail to explicitly incorporate social behavior and interactions among land users despite the importance of peer influences on decision making and the adoption of policies and technologies (Buttel et al., 1990). The "soft" nature of social variables and the difficulty of measuring the

associated parameters often discouraged the consideration of social interactions in ABMs (Bonabeau, 2002). In this paper, we capture social influence with an opinion dynamics model (ODM) that explicitly addresses social communication and interactions in human decision making.

In summary, we present a hybrid modeling framework that tightly integrates an ABM, BBNs and an ODM. Under an ABM framework, BBNs are mounted onto the agents to model each landowner's decision making on land use based on socioeconomic and ecological factors. The ODM accounts for the influences of land-use decisions by peer agents in a social network. Thus, the model replicates complex land-use decision-making processes and allows for the simulation of land-use responses to various policy scenarios. We called this model IAMO-LUC, which stands for the Integrated Agent-based MOdel of Land-Use Change. IAMO-LUC was developed to study the effect of the SLCP in the Yunnan province of southwestern China, where we collected rich qualitative and quantitative data. However, the model has a wide range of other possible applications for analyzing policy effects on local land-use trajectories.

## 2. Study area and data

### 2.1. Sloping land conversion program

This study evaluated China's Sloping Land Conversion Program (SLCP), also known as the "Grain-to-Green program". The SLCP is one of the world's largest PES programs and was designed to reduce soil erosion by compensating farmers for the conversion of cropland into forest or grassland (Bennett, 2008; Liu et al., 2008). The main targeting criterion for conversion is the slope (steepness) of the land in question. In northwestern China, land with a slope greater than 15° is eligible for conversion, and land with a slope over 25° qualifies elsewhere. The duration of the compensation depends on the post-conversion land-use type. Payments are made for five years for an economic forest and for eight years for an ecological forest (Liu et al., 2008; Yin et al., 2005). Although the major goal of the SLCP is the reduction of environmental degradation, the program also explicitly envisages the alleviation of poverty and promotion of local economies (Liu and Diamond, 2005; Liu et al., 2008; Yin et al., 2005). The dual goals of the SLCP render it an excellent example for investigating the outcomes of land-use incentives on socioecological dynamics.

The SLCP has generally been regarded as successful. However, many questions remain about its validity, efficiency and sustainability (Bennett, 2008; Uchida et al., 2005). Most program evaluations to date have relied on statistical *ex post facto* assessments of the socioeconomic impacts of the SLCP and, less frequently, on its effect on tree cover (Weyerhaeuser et al., 2005; Xu et al., 2006). While such evaluations are useful for detecting the impacts of the SLCP at one point in time, they lack the capability to simulate the dynamic processes that may better inform future policy design. Second, existing program evaluations have relied on empirical data but lack the ability to generalize the results and to explore "what-if" scenarios. Third, the majority of SLCP evaluations have been non-spatial in nature. The spatial distribution and the ecological impacts of the program are therefore largely unclear (Li et al., 2010). Finally, the results of existing program assessments are difficult to interpret due to their limited capacity to explore the underlying causal relationships because statistical program evaluations fail to adequately capture the decision-making processes of farm households. A better understanding of causality is of particular importance in settings that are characterized by dynamically changing external framework conditions, such as those in China.

The predominant lack of incorporation of decision-making processes in program evaluations calls into question the validity

of projections of the future effects of the SLCP. Understanding how local farmers adapt their land-use decision making in response to land-use incentives is vital to anticipating the effect of PES programs because the behavioral patterns of farmers have important ramifications that determine program success (Cao et al., 2009; Sengupta et al., 2005). Profound knowledge about local land-use outcomes is therefore crucial for informing future implementation strategies and for achieving the environmental and economic targets of the SLCP with the given budget constraints.

Our study area is in the Yunnan province in southwestern China (Fig. 1), where the SLCP has been implemented in 126 out of 128 counties since 2000 (Chen et al., 2009b). The complex topography, diversity of cultures and ethnicity, climate and vegetation, and the comparatively high level of poverty render Yunnan an excellent showcase for the investigation of the environmental and economic effects of the SLCP. We selected the Longyang District in Baoshan City and Yulong County in Lijiang City as our in-depth study sites (Fig. 1). The sites are located in the upstream areas of three of the largest river systems of Asia, the Yangtze (*Jinsha*), Mekong (*Lancang*), and Salween (*Nu Jiang*). The study area has suffered from extensive ecological degradation due to agricultural expansion and unsustainable forest management in the past decades (Weyerhaeuser et al., 2005; Xu et al., 2007).

### 2.2. Data

We selected 17 villages, seven from Baoshan and ten from Lijiang, and collected socioeconomic and behavioral data in a statistically representative household survey. Villages were stratified into two groups based on their distance to the district capitals, which are the major market centers. Households were selected randomly within the villages. We interviewed 509 households with a total of 1973 plots, including 417 SLCP participants and 92 nonparticipants. We collected data on demographics, income sources, the penetration of agricultural and forestry policies, and the various asset categories of the households. At the plot level, we requested data on the biophysical properties of each plot, on land use, and regarding whether plots were targeted by a policy program. The household survey was complemented by in-depth discussions with selected individuals.

In addition, we facilitated group discussions at the village level that concentrated on the disentanglement of land-use decisions, including decisions related to the participation in the SLCP, the conversion of cropland into forests, and investments in agricultural and forestry activities. The discussions allowed us to sketch village-level influence frameworks that included the key factors and connections surrounding the major land-use and livelihood changes of households. We also conducted participatory mapping together with villagers using very-high-resolution satellite imagery (Quickbird, Ikonos, and WorldView). We used the plotted images to discuss land-use changes in each village with key informants. Villagers were asked to indicate landmarks, demarcate village boundaries, and delineate current land use on transparencies that were later digitized and stored in a geographic information system (GIS). The resulting data corroborated our understanding of where, how and why land use has been changed. The qualitative information from the mapping and group discussions were used together with the quantitative survey data to help construct the causal influence networks and to train the parameters in the Bayesian belief networks.

## 3. Bayesian belief networks (BBNs)

### 3.1. Introduction to BBNs

A BBN consists of a directed acyclic graph (DAG) that encodes probabilistic relationships among the variables of interest (Jensen,

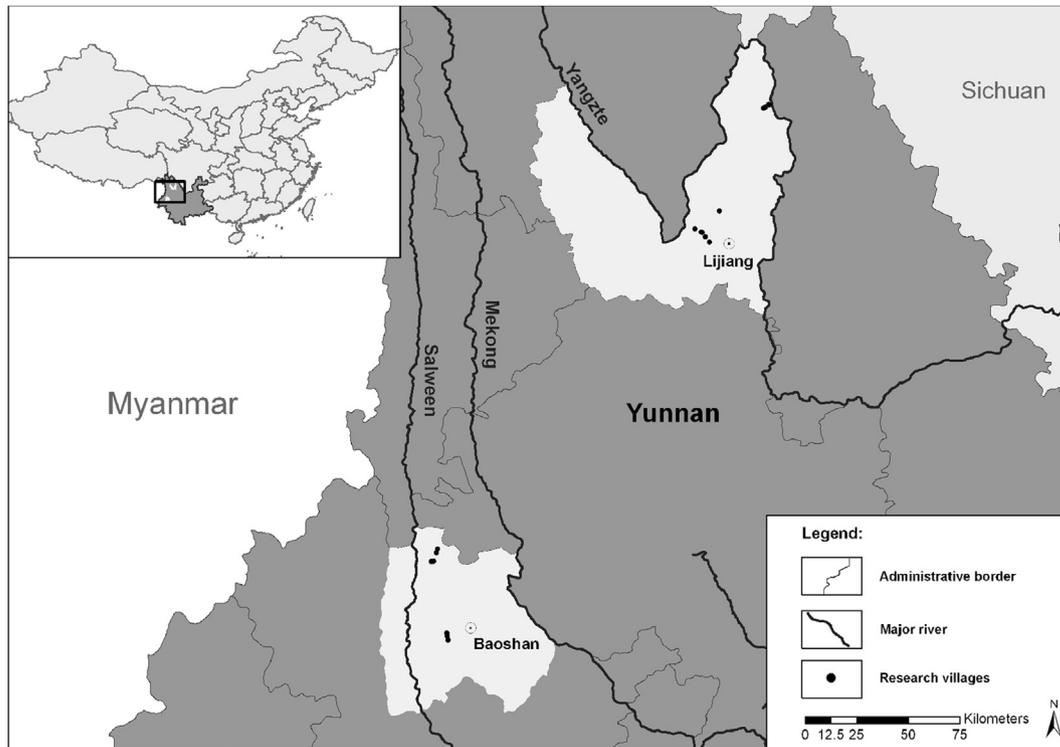


Fig. 1. Study area. Source: Authors.

2002; Pearl, 2009). The DAG, also known as the structure of the BBN, visualizes the variables (or nodes in BBN terminology) and interdependencies between the variables (arrows connecting nodes). The arrows represent directional influences that typically depict a cause–effect relationship. Each variable denotes an attribute, feature or hypothesis about an uncertain event with a set of state values, which are often discrete, mutually exclusive, and collectively exhaustive. For example, a variable for land use can have “cropland”, “forest” and “others” as its states. Additionally, each variable has a conditional probability table (CPT) to quantify the influence of the causal variables (parent nodes). A BBN thus consists of a qualitative part and a quantitative part, which are represented by the structure (the DAG) and a set of parameters (the CPTs), respectively. Mathematically, the influences in the network are defined by conditional dependencies that are derived using probabilistic inference based on Bayes’ theorem (Heckerman et al., 1995; Pearl, 2009). For instance, a variable  $x_i$  with the parents  $x_j, \dots, x_n$  has a CPT of the form  $P(x_i|x_j, \dots, x_n)$ . Following Bayes’ theorem, this becomes

$$P(x_i|x_j, \dots, x_n) = \frac{P(x_j, \dots, x_n|x_i)P(x_i)}{P(x_j, \dots, x_n)} \quad (1)$$

This is equivalent to the likelihood times the prior divided by the evidence (Pearl, 2009). Decomposing this with the chain rule of probability calculus yields

$$P(x_j, \dots, x_n) = \prod_{j=1}^n P(x_j|x_{j+1}, x_{j+2}, \dots, x_n) \quad (2)$$

The advantage of the directed acyclic graphs in BBNs is that the conditional probability of a variable  $x_i$  is not dependent on all other variables, but only on its specific predecessors in the network. This simplifies the inputs required and reduces the computing time for estimating the CPT because not all possible realizations need to be accounted for (Pearl, 2009). The DAG also relaxes the black-box

character of many other data mining methods with its intuitive graphical structure. This is particularly relevant for our purposes because it facilitates the participatory model development by including stakeholders in the design of the network (Aguilera et al., 2011; Bromley et al., 2005).

The capability of combining causal (expert) and evidence-based (empirical) information renders BBNs attractive for environmental analysis (Pollino et al., 2007; Varis, 1997). Applications include the analysis of complex socioecological interactions, such as those found in environmental management (Uusitalo, 2007), land-use change (Aalders, 2008; Aitkenhead and Aalders, 2009), water management (Bromley et al., 2005), forestry (Newton et al., 2006), and wildlife management (Smith et al., 2007). For a holistic review of the use of BBNs in environmental modeling, see Aguilera et al. (2011).

Building a BBN generally involves two tasks: the development of the network structure (the DAG), including the variables and their relationships (the nodes and how they are connected), and the estimation of the parameters (the CPTs). In the development of our model, we derived the structures of the BBNs with a data mining process using quantitative survey data and constraints predefined by experts, who enforced some links and disallowed others. The expert knowledge was derived from interviews with local officials, farm households, and scientists. We then estimated the CPTs for the variables in the network using our survey data. The final network structure illustrates the underlying factors that influence land-use decision-making and the interactions of the influences. We mounted the BBNs onto the agents to allow for their perceptual reasoning at the household and plot levels.

### 3.2. The BBNs for households and plots

We populated the BBN models with the quantitative data and qualitative evidence gathered in the villages. In the first step, we selected variables that have relevance for land-use decision making from the questionnaire and were based on expert knowledge and

group discussions. To simplify the models, we filtered several redundant variables. For example, we removed the number of livestock from the network, as we were primarily interested in the income from livestock, which was typically proportional to the number of livestock. Second, we added several variables that were not included in the questionnaire. For example, we created a proxy variable for labor availability that was calculated from survey data based on household demographics and off-farm labor usage. Third, we categorized continuous variables into discrete classes, as the learning processes in most BBN software rely on discrete data. For example, income from livestock was grouped into categories of high, medium and low income. Some discrete variables were reclassified into a smaller number of classes to reduce both the complexity of the CPT and the requirements to train the network because CPTs grow exponentially as the number of variable states increase. For example, we categorized ethnicity status into a binary layer of the Han majority as one ethnicity class and the remaining ethnic groups as the second ethnicity class.

We used the structural learning algorithm in Hugin, a commercial software for BBNs modeling, and augmented the results with our qualitative expert knowledge. The learning was performed by enforcing or impeding selected links and directions during the learning process, as many mathematically correct networks can be generated from a single data set. Expert knowledge thus plays a vital role in producing a meaningful influence network (Bromley et al., 2005), because the computer program is not reliably able to make a wise choice based on statistical relationships. For example, income from crops is a function of total cropland area; thus, a link from the variable “cropland area” to “crop income” makes more sense than the other way around. The structure of BBNs should be simple to remain both tractable and understandable to experts and stakeholders, and the structure should be reliable when BBNs are calibrated using limited empirical data modeling (Marcot et al.,

2006). We therefore adopted a pseudo tree-augmented naïve Bayesian (TAN) network, which outperforms the simple naïve Bayesian network while maintaining computational simplicity and robustness (Friedman et al., 1997).

The final household-level network is shown in Fig. 2, and the plot-level network is shown in Fig. 3. Both of the BBN models were originally constructed and calibrated in Hugin and were replicated in Netica (another commercial BBN software) to provide an improved visual presentation.

### 3.3. Validation of the BBNs

To validate the accuracy of the models, we randomly divided the 509 households and 1973 plots into training and test data sets. We used 80% of the cases as training data to conduct network learning, and we verified the model using the remaining 20% of the cases. The final model has high predictive power, with prediction accuracies of 85.3% and 84.6% at the plot and household levels, respectively (Table 1).

To test the robustness of these results, we repeated the random selection of the training and test data from the survey data four times for the household BBN. The results are relatively stable and consistent, with error rates of 15.4%, 17.7%, 15.1%, and 15.4%. In addition, we also split the training and test data of the household BBN by 70/30 and 50/50; unsurprisingly, the error rate increased to 18.7% and 19.4%, respectively, because fewer observations were used for training. Nonetheless, we consider these results acceptable and evidence of the advantage of using BBN, as a moderate number of training cases can still produce reliable and accurate results (Uusitalo, 2007).

We also calculated the area under the curve (AUC) of the receiver operating characteristics (ROC). A ROC curve is derived by plotting the rate of true positives (sensitivity) versus the rate of

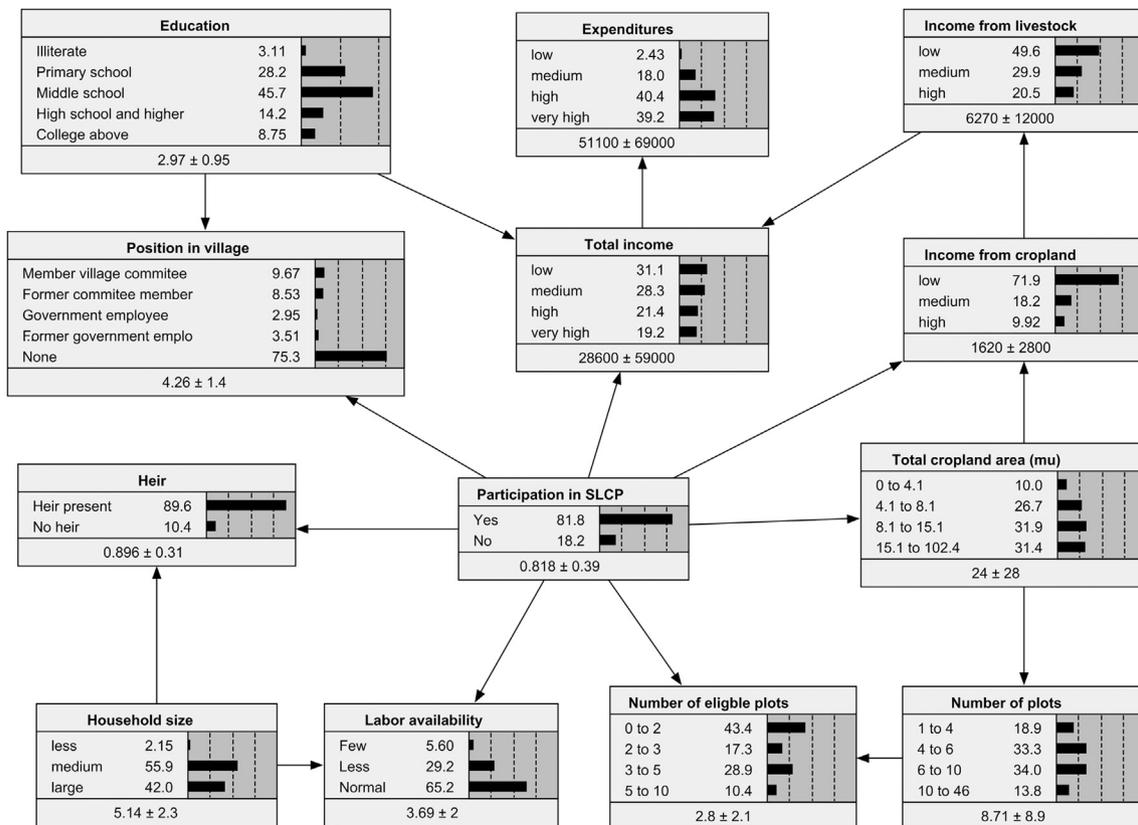


Fig. 2. Household-level Bayesian belief network. Source: Authors.

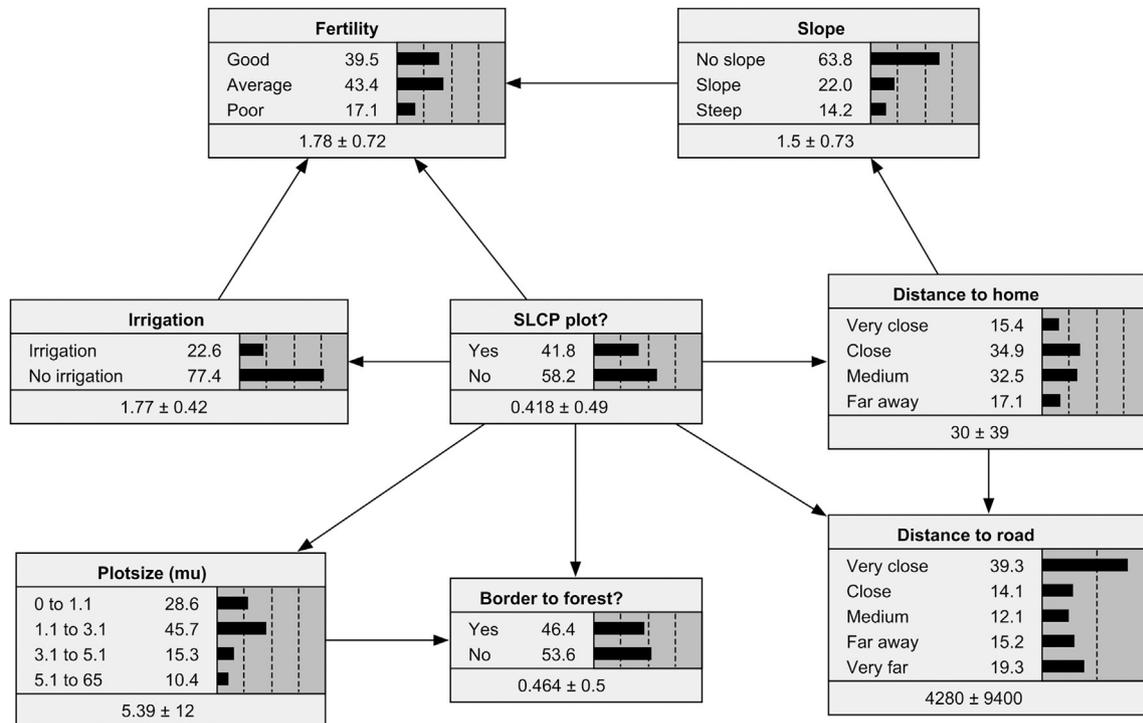


Fig. 3. Plot-level Bayesian belief network. Source: Authors.

false positives (1 – specificity; Metz, 1978). The AUC is a commonly used measure of goodness-of-fit in classification problems. For our BBNs, the AUC at the household level is 0.79 and 0.86 at the plot level (Fig. 4).

However, the evaluation of models should extend beyond a purely quantitative “validation” that is based solely on model accuracy and should also incorporate subjective criteria, such as fitness, for the purpose and transparency of the modeling process (Jakeman et al., 2006). We therefore invited other experts to conduct a qualitative peer review of the models to augment the quantitative evaluation, which further strengthened the credibility of the relevance and reliability of the BBN results.

### 3.4. Sensitivity analysis of the BBNs

A sensitivity analysis of BBNs can gauge how sensitive is the belief of a target variable to fluctuations in the values of other variables. This analysis not only helps to further verify the validity of the model but also reveals the most influential and informative variables with respect to the target variable of interest. We performed sensitivity analyses at both the household and plot BBNs using “SLCP participation” and “SLCP plot”, respectively, as the target variables. Based on the variable reduction value, which is an index that reflects the contribution of particular variables, we

**Table 1**  
Prediction matrices for BBNs at plot and household level.

Households	Predicted		Plots	Predicted	
	Negative	Positive		Negative	Positive
Negative	2	13	Negative	202	37
Positive	3	86	Positive	23	146
	Error rate	15.4%		Error rate	14.7%

Source: Authors.

ranked the influencing factors to SLCP enrollment at the household (Table 2) and plot (Table 3) levels.

For the variables that influence household enrollment (Table 2), the area of cropland and the number of plots that a farm household owns have the largest influence, which are followed by whether the farmer has a son (heir) and the labor availability of the household. These findings are in agreement with what we observed empirically: when a farmer owns more cropland, he is more likely to set aside some of their cropland. Farmers with heirs are more likely to opt to plant trees on a part of their plots to benefit from the relatively longer-term financial returns compared with the returns from croplands. Finally, farmers who lack farming labor, either due to demographic reasons or because family members pursue off-farm work in distant localities, tend to convert land to forests because of the lower labor requirements in forestry activities compared with crop farming. Our simulations further show that the program enrollment level would increase to 90% (from the current level of 81.3%) if the average number of farm laborers per household would drop by half (from 3.6 to 1.8). In view of the aging Chinese society and the continuous flow of migrant workers to urban centers, Chinese farm households are likely to become increasingly willing to participate in the SLCP or in similar environmental programs.

Crucial influences on plot-level land-use decisions (Table 3) are affected by the spatial neighborhood of a land plot. Under the SLCP program, a plot that is adjacent to either a natural forest or planted forest is more likely to be converted. Evidence obtained from participatory mapping and group discussions support this finding. The agglomeration effect is due to land-use planning that encourages the conversion of contiguous plots. Neighboring plots with tree cover can also have a negative effect on the adjacent cropland plots due to both their shading effect and crop damage from animals living in the forest. Contrary to our *a priori* expectations, both slope and distance to home have extremely marginal influences. Although this finding seems both counter-intuitive and

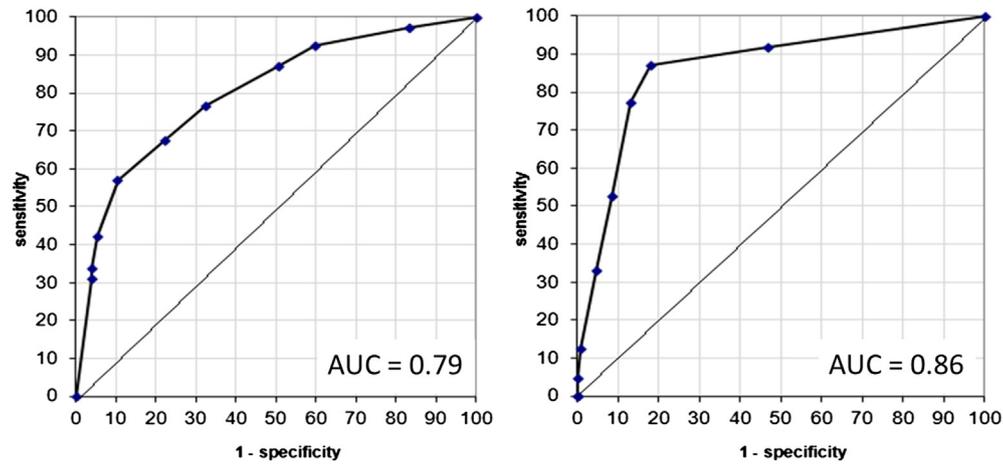


Fig. 4. Receiver operating characteristics (ROC) curves. Source: Authors.

inconsistent with the judgments of experts, it reflects the reality on the ground. Namely, the importance of slope on the SLCP program was repeatedly downplayed or ignored by local officials, although the steepness of the farmland is the decisive criterion in the selection of plots according to the SLCP regulation policy (note that plots with a slope that is greater than  $25^\circ$  qualify for the SLCP in Yunnan province; see also Section 2.1). This mistargeting of SLCP funds also calls into question the desired ecological effects of the program.

#### 4. Social influence model

Social agents rarely make isolated decisions because decisions directly and indirectly influence and are influenced by other agents in the community (Fig. 5). Indirect influences are transmitted through changes in the agents' shared environment, which in turn alter the agents' perceptions of their environment and thus influence their decisions and actions. For example, the land-use decisions of upstream farmers can impact the land-use decisions of downstream farmers. When facing the decision to adopt an innovation, a new practice or a product, agents often mutually influence each other's beliefs for informational and normative reasons (Chen et al., 2009a; Martins et al., 2009). Social influences also play an important role in decision problems related to environmental management, such as land-use decisions, that go beyond purely economic decisions and encompass a plethora of biophysical and social contexts (Turner II et al., 2007). To simulate social interactions among farmers in a social network, we developed an opinion dynamics model with a small-world social network.

Table 2

Sensitivity analysis for household-level BBN.

Variables	Variance reduction (%)
Total cropland area	6.22
Number of plots	0.85
Heir	0.51
Labor availability	0.34
Income from cropland	0.34
Position in village	0.28
Number of eligible plots	0.11
Total income	0.01
Income from livestock	0.01
Expenditure	<0.01
Education	<0.01
Household size	<0.01

#### 4.1. Continuous opinion dynamics models

Due to the potential applications in social and political science, research on public opinion formation has recently gained favor, and numerous mathematical opinion dynamics models have been developed (Deffuant et al., 2002a, 2005; Kurmyshev et al., 2011; Lorenz, 2010; Martins, 2009; Weisbuch et al., 2002). Opinion dynamics models can be classified as discrete or continuous, depending on the representation of opinions with either discrete or continuous values. Well-known discrete models include the voter model (Clifford and Sudbury, 1973; Holley and Liggett, 1975), the Sznajd model (Stauffer, 2002; Sznajd-Weron and Sznajd, 2000), the social impact model (Nowak et al., 1990), the Axelrod culture model (Axelrod, 1997), and the Rumors model (Galam, 2002, 2003). Examples of continuous opinion dynamics models include the Deffuant model (Deffuant et al., 2000; Weisbuch et al., 2002), the Hegselmann-Krause model (Hegselmann and Krause, 2002), and the CODA model (Martins, 2008, 2009). The first two models are bounded-confidence models (Lorenz, 2010) with similar opinion representation (i.e., a continuous variable) and opinion exchange (i.e., agents only influence each other when their opinions are close enough). They differ in the opinion update rule that characterizes whether agents interact with compatible neighbors one-by-one or all at once (Castellano et al., 2009). The CODA model is a hybrid approach where agents hold continuous opinions as in the bounded-confidence model but make binary decisions. Agents update their opinions based on the observed actions of their peers following Bayesian rules (Martins, 2009). These classic models and their modified versions have been widely applied in exploring public opinion formation and social contagious behavior.

In the IAMO-LUC model, the Deffuant model was selected to simulate the social influence among farmers because it is simple and intuitive. The Deffuant model was initially conceived to model farmers' adoption of agro-environmental measures in exchange for financial support, which perfectly matches our research questions. In the original Deffuant model (Deffuant et al., 2000) agents are connected on a square lattice. Each agent is initially given an opinion  $x_i$ , represented by a continuous number between 0 and 1. At each time step an agent randomly chooses one of its peers, e.g., agent  $j$ , to meet and potentially update their opinions according to:

$$x_i(t+1) = x_i(t) + \mu [x_j(t) - x_i(t)]$$

$$x_j(t+1) = x_j(t) + \mu [x_i(t) - x_j(t)]$$

**Table 3**  
Sensitivity analysis for plot-level BBN.

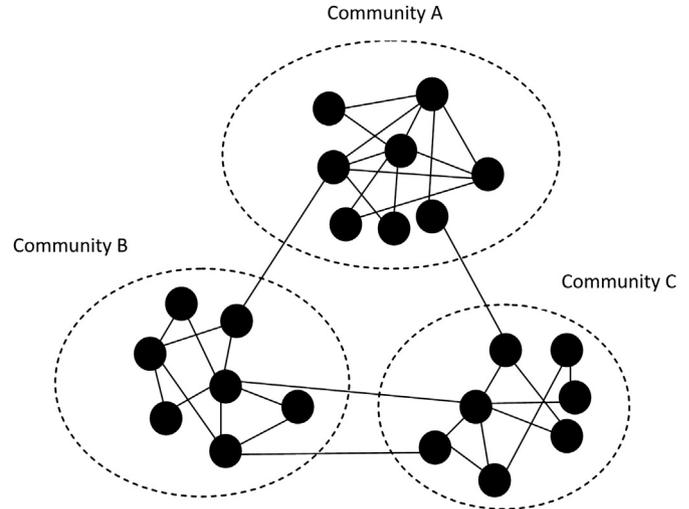
Variables	Variance reduction (%)
Adjacent to forest	49.90
Plot size	7.30
Soil fertility	1.61
Distance to home	1.34
Distance to road	0.88
Irrigation	0.55
Slope	0.01

If  $|x_j(t) - x_i(t)| < d$ , where  $d \in [0, 1]$  is a threshold reflecting an agent's openness or uncertainty, then  $\mu \in [0, 0.5]$  is the convergence parameter.

The opinion dynamics models, including the Deffuant model, were criticized for a lack of connection to the real world because the models were often only tested on oversimplified social networks such as nearest neighbor interactions on a square lattice. A small-world network has thus been advocated because it can better replicate the actual relationships between people and groups (Sobkowicz, 2009).

4.2. A small-world network with a community structure

Social networks exhibit the so-called small-world property, where most nodes can be reached through a small number of edges (Costa et al., 2006). Small-world networks have been widely applied in agent-based social modeling and, more recently, in opinion dynamics (Stauffer and Meyer-Ortmanns, 2004; Suo and Chen, 2008). Examples of small-world networks include the well-known Watts–Strogatz network (Watts and Strogatz, 1998) and the scale-free network (Barabási and Albert, 1999). Different networks are suitable for different systems and may also lead to different dynamics and simulation results (Amblard and Deffuant, 2004; Suo and Chen, 2008). In IAMO-LUC, we adopted a community structure for our small-world network (Girvan and Newman, 2002) to account for the multilevel nature of our data with villages and households (Fig. 6). In the network, farmers are naturally grouped into several communities (villages), and farmers within the same community are randomly linked with a probability  $p_{in}$ . Farmers are connected with the probability  $p_{out}$  to farmers from other communities. The probability value controls the number of connections within and among communities. The condition  $p_{in} > p_{out}$  always holds to assure the maintenance of community structure in the network. In other words, farmers have more connections to their peers within their community than to outsiders.



**Fig. 6.** Small-world network with community structure. Source: Adapted from Girvan and Newman (2002).

4.3. Adapted Deffuant model

In addition to using a more realistic social network, we modified the Deffuant model to account for the empirical evidence we observed on the ground regarding the SLCP adoption and also to better integrate the opinion dynamics model under the IAMO-LUC framework. We set a continuous opinion  $x_i$  for each agent  $i$  that quantifies its belief level. A threshold  $d_i$  reflects the openness or uncertainty of agent  $i$ . Both the opinion  $x$  and the threshold  $d$  take values between 0 and 1. Agents for which  $x = 1$  have the highest positive belief towards the SLCP, and agents for which  $x = 0$  have the lowest belief. Both agents with  $x = 0$  or  $x = 1$  have extreme opinions and either completely endorse or completely reject the SLCP. The agents with a threshold  $d = 0$  are fully confident and do not discuss their opinions with anyone, whereas agents with  $d = 1$  have maximum uncertainty and discuss matters with everyone, irrespective of how different their opinions are. We assume that  $d$  is related to  $x$  as follows:

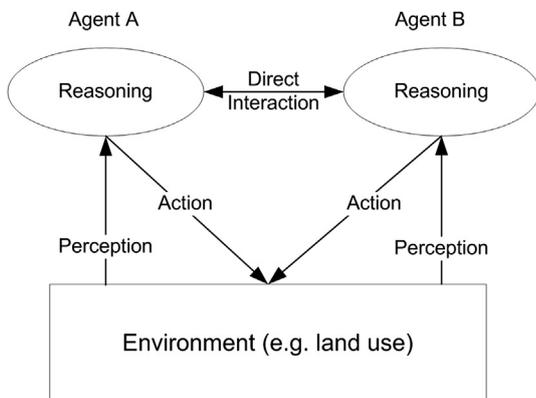
$$d = 1 - 2 * |x - 0.5| \tag{3}$$

The rationale behind Equation (3) is that agents with extreme opinions ( $x$ -values close to 0 or close to 1) are less open to discussion ( $d \rightarrow 0$ ). Agents with neutral opinions ( $x$ -values near 0.5) tend to have large uncertainties and are therefore open to discussion ( $d \rightarrow 1$ ). This assumption is based on what we observed in the field: farmers tend not to discuss with their peers when they are very confident about and have strong opinions towards the SLCP.

At each time step, an agent randomly chooses one of its peers (an agent to whom he/she is directly linked in the social network), say agent  $j$ , with whom to exchange information and from whom to seek an external opinion, if their opinions differ less than the threshold  $d_i$ . The external influence  $\Delta x$  is calculated for agent  $i$  as follows:

$$\Delta x_i = \mu_i * (x_j - x_i) \quad \text{if } |x_j - x_i| < d_i \tag{4}$$

where  $\mu$  is a convergence factor ranging between 0 and 1 that reflects the persistence or stubbornness of an agent. In other words,  $\mu$  is perceived as the personality of a farmer: A farmer with  $\mu = 0$  never changes its opinions in response to social interactions, and a farmer with  $\mu = 1$  always follows the opinions of its peers. Ideally,



**Fig. 5.** Direct and indirect interactions among agents. Source: Adapted from Janssen and Ostrom (2006).

the convergence factor for each agent is assigned based on his/her personality gained from interview or questionnaire. However, it is extremely difficult, if possible at all, to measure the personality with a number in reality. Hence the convergence factor  $\mu$  can be simply assigned, for example, as a random number between 0 and 1, drawn from a truncated normal distribution  $N(0.5, 0.2)$ . In general, the convergence factor  $\mu$  has limited effects on the statistics of global dynamics, but controls the speed of convergence (Castellano et al., 2009).

The external influences are accumulated over time (assuming that agents remember past influences) and are added to the internal belief  $x_{i,t}^I$ , which is quantified by the BBN at time step  $t$ . The result is the adjusted belief  $x_{i,t}^A$ :

$$\dot{x}_{i,t}^A = x_{i,t}^I + \sum_{t-M}^t \Delta x_{i,t} \quad (5)$$

$M$  is a parameter controlling the duration of the external influence. When  $M = 0$ , Equation (5) becomes

$$\dot{x}_{i,t}^A = x_{i,t}^I + \Delta x_{i,t} \quad (6)$$

The adjusted belief  $x_{i,t}^A$  is the decisive parameter in the decision-making process for participation in the SLCP. It also serves as the base value for the opinion dynamics in the next time step,  $t + 1$ .

In sum, we substantially modified the Deffuant model in order to represent the empirically observed heterogeneities. Yet we maintain the model's simplicity as well as its intuitive interpretations. Such simple modifications of the Deffuant model can yield rich dynamics, which are not analytically solvable and often difficult to systematically evaluate (Lorenz, 2010). The adapted model differs from the Deffuant model in three aspects. First, the adapted model assigns heterogeneous threshold values to agents, which are endogenously estimated based on opinion values. This enables modeling of situations of extreme opinions, whereas the Deffuant model tends to produce agents with converging opinions. Compared to other modifications (e.g., Deffuant, 2006; Deffuant et al., 2004), this simplified the model instead of introducing more variables because the threshold values are very difficult to be calibrated from empirical data. Second, our adaptation randomly assigns heterogeneous convergence factors to agents, which allows for asymmetric interactions. Third, the adapted model quantifies opinions as two parts, namely the internal beliefs that are estimated using a BBN and the external social influence; this allows for a seamless integration with the BBN.

#### 4.4. An experiment on social influence

Interesting spatial and temporal patterns of participation in the SLCP emerged in our study area. While the opinions of villagers within a village tended to converge, neighboring villages with similar biophysical and socioeconomic characteristics frequently showed very different participation behavior, which was unrelated to the top-down implementation scheme of the SLCP. Moreover, many households experienced a shift in opinions, mainly from skepticism regarding the SLCP to persuasion. The spatial disparities and shifting opinions are partially caused by social influences, which lead to opinion clusters that can be revealed with an opinion dynamics model.

To demonstrate how the adapted Deffuant model can generate such patterns, we designed a simulation experiment in the following hypothetical setting: The farmers are organized into four villages containing 100 farmers each. The characteristics of the farmers between villages are identical, and the beliefs of the farmers in each village were randomly initialized between 0 and 1

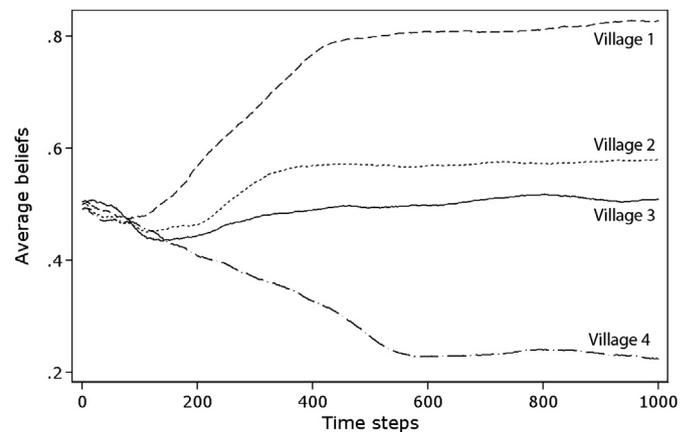


Fig. 7. Path dependence on beliefs. Source: Authors.

with uniform distribution and a mean value of 0.5 to avoid excessive complexity. We then connected farmers randomly to approximately four peers in the same village through a small-world network. There were no connections among farmers in different villages, and social influences are allowed only within a village. The simulation results after 1000 time steps clearly show the diverging beliefs of farmers across villages (Fig. 7).<sup>1</sup> Thus, even under identical starting conditions, villages can evolve into different regimes in terms of beliefs towards the SLCP: some tend to have more positive beliefs, whereas others tend to oppose the program, and this difference is due exclusively to the social interactions among the farmers. This hypothetical experimental highlights the effect of social influence on the participation in the SLCP.

In the full version of IAMO-LUC the initial beliefs of farmers are quantified with BBN based on their socioeconomic and biophysical endowments. In contrast to the results of Chen et al. (2012), the inclusion of social influences in IAMO-LUC can either foster or hinder a farmer's participation in the SLCP in unpredictable ways, thus leading to path dependencies. These patterns demonstrate that farmers in segregated communities, albeit with similar livelihood strategies and biophysical settings, exhibit contrasting attitudes towards the SLCP. Thus, improved consultation and information dissemination in the early stages of the SLCP implementation may have greatly increased the acceptance level of the program among farmers.

## 5. Model integration and results

### 5.1. Model framework

Under the agent-based modeling framework, IAMO-LUC integrates the BBN models and the adapted Deffuant model to simulate farmers' land-use decision-making in rural areas. Farm households are modeled as autonomous agents endowed with socioeconomic attributes such as ethnicity, education, family size, and income. Farmers manage one or many plots, which are conceived as square patches in a cellular space. The patch attributes include plot characteristics such as plot size, soil quality, slope, and land-use type. Farmers make land-use decisions based on their beliefs, consisting of internal beliefs and external influences, and on whether or not to

<sup>1</sup> We ran the simulation model several times to account for the stochastic nature of the model. We show only one run here for the sake of brevity; however, the other results were qualitatively similar.

participate in the SLCP program, i.e., to convert one or more of their cropland plots to forest.

Internal beliefs reflect the tendency of a farmer to participate in the SLCP based on endogenous factors (e.g., income, number of plots, and land quality), exogenous factors (such as food price and agriculture subsidies) and the SLCP policy arrangement (Fig. 8). The internal beliefs are quantified by the household-level BBNs, which are analogous to the brain or the major decision engine of the agents. The influencing factors may vary over time and, therefore, the internal beliefs are updated dynamically (Fig. 9).

External influences modulate the internal beliefs due to a farmer's bounded confidence. This belief adjustment is the result of social influences, including persuasion, peer pressure, conformity, and imitation. Thus, a farmer adjusts his/her beliefs based on the beliefs of peers within the social network, represented by a small-world network (Watts and Strogatz, 1998). In the network, farmers are socially connected to their peers and can reach most farmers on the network via friendship relations. This dynamically evolving process is modeled with the adapted Deffuant model presented above.

Based on their adjusted beliefs, farmers make decisions on whether or not to plant trees in the SLCP program. Higher belief scores indicate a higher likelihood of program participation. The model offers three ways to decide on participation: based on an assigned quota, voluntarily, or a combination of the two. The three modes correspond to the three policy mechanisms of the SLCP currently in effect. In the quota-based mode, an overall quota, i.e., the area of cropland to be converted, is set at each time step. This quota is distributed across households based on their belief scores. Farmers with higher belief values have a higher likelihood of being selected for participation. This mode corresponds to the actual implementation mechanism, in which a regional quota is set that must be fulfilled. In other words, the degree of participation in the SLCP is dictated by the magnitude of the quota. Two contrasting outcomes may result: either many farmers with low belief scores may be forced into the program when the quota is high or many farmers with high belief scores may be left out of the program when the quota is low. In the voluntary mode, a single overall belief threshold is set during the model run. Farmers with higher beliefs than the threshold value are selected to participate. This corresponds to purely voluntary participation because farmers willing to participate have sufficiently high scores to be selected by the program. The results may range from very low participation rates caused by low overall willingness to near-universal participation when the program's anticipated benefits lead to universally high belief scores. In the combined mode, both an external quota and

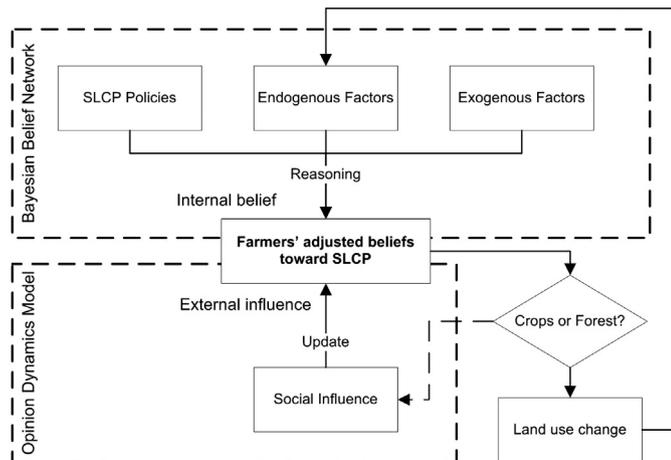


Fig. 8. The agent-based model framework of farm household participation in the SLCP. Source: Authors.

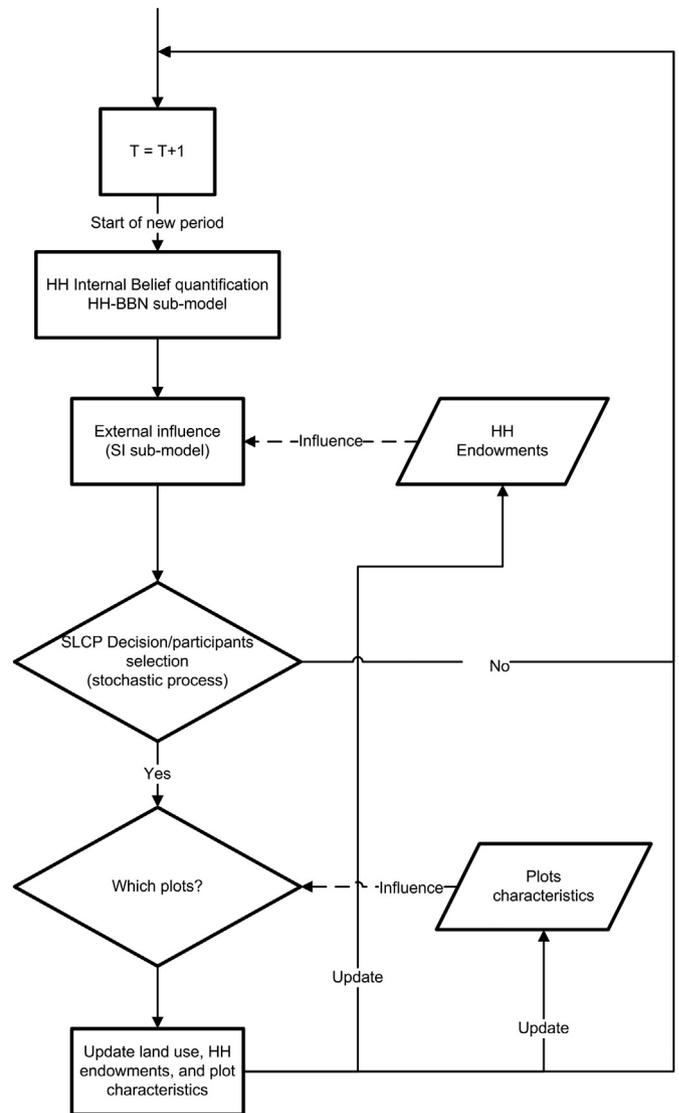


Fig. 9. Flowchart of IAMO-LUC. Source: Authors.

a threshold value are set. The quota has an upper limit but does not have to be fulfilled. When the quota is large enough, all farmers with beliefs higher than the threshold will participate. When demand for participation exceeds the quota, participants with higher belief scores are more likely to be selected for participation.

In the next step, the selected participants decide which plots to set aside for tree planting. This decision is again emulated with the plot-level BBNs, which quantified the conversion likelihoods based on the plot characteristics. The plot with the highest likelihood score will be converted to forest. For the sake of simplicity, a participant is allowed to convert only one plot at each time step in the model.

In sum, IAMO-LUC dynamically mimics the land-use decision process in response to the SLCP. Farmers first decide whether to enroll in the SLCP. If they do, they select the plot to be set aside. Both decisions follow a stochastic process that is based on their adjusted beliefs, which are composed of internal beliefs and external influences. Internal beliefs are retrieved from one BBN at the household level and another at the plot level, and the external influences stem from the ODM. Participation in the SLCP program changes the factor endowments of farmers, feeding forward into their future decision-making process (Fig. 8).

## 5.2. Model implementation and software

We selected NetLogo for our agent-based modeling environment. NetLogo is a multi-agent modeling platform for simulating complex phenomena and has a built-in programming language (Tisue and Wilensky, 2004). We chose NetLogo because it is a high-level platform and provides a simple but intuitive and powerful programming language and because it is equipped with a graphical user interface (Railsback et al., 2006). NetLogo's programming style is similar to natural programming languages and is therefore both easy to understand and transparent. These features facilitate both a straightforward review process and the sharing and exchange of models. Finally, NetLogo provides a Java-based application programming interface (API) that allows the user to add new functions in the form of extensions.

IAMO-LUC models farmers as “turtles” (i.e., as movable agents in NetLogo) and models plots as “patches” (square cells with attributes that are immovable). The social network is modeled as “links” that connect the “turtles”. The social influence sub-model is coded using NetLogo's built-in language. We constructed and analyzed the BBN at the household and plot levels using Hugin by creating a fusion of data and expert knowledge (Madsen et al., 2003). Hugin is the leading—and one of the first—software packages that is dedicated to the use of BBN. Compared with Netica, Hugin offers additional advanced functions. In particular, Hugin's capability to obtain structure from data is relevant to our modeling framework, and the Hugin API libraries provide the necessary Java interface.

The BBN and ABM models were integrated using the NetLogo and Hugin Java APIs (Fig. 10). BBN is embedded into the NetLogo platform as an extension. Agents in the ABM can therefore exchange attribute values with node variables in the BBN. This structure also allows the BBN to vary both among agents and over time within a single ABM framework. Therefore, the integration between BBN and ABM is open, flexible and seamless.<sup>2</sup>

The IAMO-LUC framework consists of the following two spaces: a social space and a biophysical space. The social space is the social network (i.e., the small-world network) in which agents interact with each other. The biophysical space is represented by a square lattice that can be populated with spatial data layer, such as land-use raster data. In this manner, IAMO-LUC provides a comprehensive modeling environment and can be used as an exploratory platform (Fig. 11).<sup>3</sup> IAMO-LUC enables modelers to visualize and examine the dynamics of innovation diffusion within the social network. Moreover, IAMO-LUC allows the exploration of multiple policy scenarios and the effect of these scenarios on land-use changes.

## 5.3. Land use scenario

IAMO-LUC provides a comprehensive simulation laboratory for land-use change in response to payments for ecosystem services in general, and the SLCP in particular. The spatially explicit simulation results are particularly valuable for assessing the potential environmental and ecological impacts of certain policy scenarios. The resulting spatial data can also be fed into environmental models (e.g., habitat fragmentation models or water run-off models) for subsequent analysis. To illustrate this application, we constructed

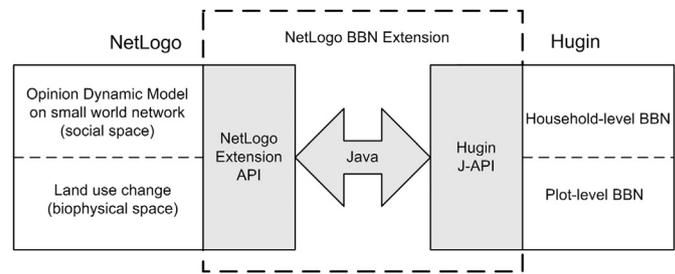


Fig. 10. Software integration framework in IAMO-LUC. Source: Authors.

a scenario in which we altered the conditional probability distribution of the variable “adjacent to forest” in the plot-level BBN (Fig. 3) to diminish its influence on the likelihood of a plot being converted from cropland to forest. As expected, the simulation results show an increase in fragmented SLCP plots with considerably less spatial clustering than in the business-as-usual scenario (Fig. 12). This finding demonstrates that the simulation results can illustrate the impact of a potential policy and can facilitate discussions among stakeholders and policy makers.

## 6. Summary and conclusions

We presented the framework for the Integrated Agent-based Model of Land-Use Change (IAMO-LUC). IAMO-LUC is a hybrid model that incorporates an innovative decision-making module in which land-use decisions are driven by Bayesian belief networks and in which social dynamics are modulated with an opinion dynamics model in a small-world network. This model is designed to assist in the analysis of the effects of land-use incentive payments on socioecological systems and was used to analyze the Sloping Land Conversion Program in Yunnan, China. The model is driven by quantitative survey data, qualitative information, and high-resolution land-use maps.

ABMs are more of a mindset than a technology (Bonabeau, 2002). ABMs provide a framework and strategy to model the dynamics of complex socioecological systems. However, the strength and quality of ABMs depend on how well they embody agent behavior. The decision-making module is therefore critical to the value of an ABM for understanding land-use changes (Parker et al., 2003), particularly in developing countries (Schreinemachers and Berger, 2006). Nonetheless, ABMs have been impeded and continually challenged because they frequently lack tractable rules and credible arguments for the decision-making modules (Bankes, 2002). We overcame this deficiency by employing BBNs, which are powerful analytical tools that are grounded in statistical theory. In IAMO-LUC, BBNs are the decision engine and endow agents with an empirical “brain” that performs perceptual reasoning. The synapses of the brain are shaped by various sources of qualitative information. The brain's capacity to draw inferences can be learned and trained with quantitative data. BBNs exploit and represent expert knowledge, explicitly address uncertainty, deal with missing data, and feature an intuitive graphical structure. These capabilities make BBNs ideal decision-making modules for ABMs.

Although social influences on land-use decisions are well recognized and are supported by a wealth of evidence, few land-use change models have included social influence factors because of the “soft” nature of social models that render data collection challenging and complicate the calibration of interpersonal interactions. An adapted opinion dynamics model is seamlessly integrated under the IAMO-LUC framework to account for social influences. A

<sup>2</sup> A description of IAMO-LUC and the code for our NetLogo extensions (the dashed rectangle in Fig. 10) can be found at [www.iamo.de/iamo-luc](http://www.iamo.de/iamo-luc). We welcome comments on the improvement of the code and invite other modelers to use and comment on the code, as we believe that this integration is of general interest to other modelers.

<sup>3</sup> Although the social agents share the same display window with land use, the agent's location and links show only social topological relations.

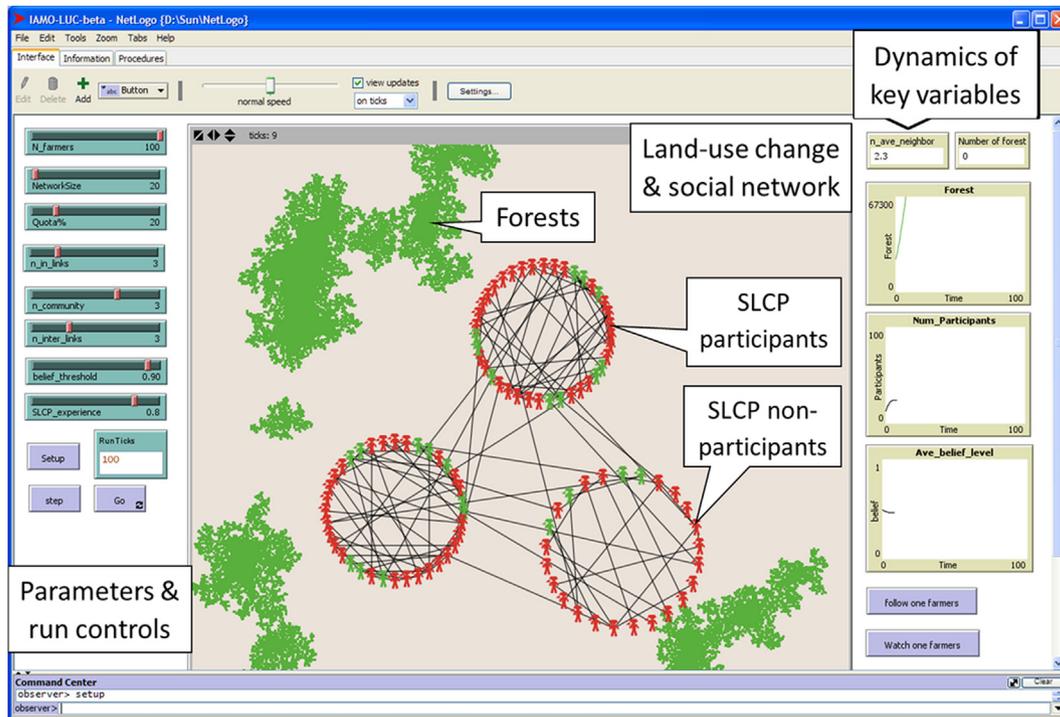


Fig. 11. IAMO-LUC model interface. Source: Authors.

farmer's decision to enroll in SLCP is both determined by the socioeconomic and physical endowments and influenced by his peers. The application example presented here reveals that social influences can lead to diverging opinions towards SLCP and to the formation of social regimes, even among farmers with similar profiles and similar initial conditions. Therefore, timely consultation with farmers and efficient information dissemination can ease uncertainty and are recommended to ensure the success of such agro-environmental programs.

Overall, our approach provides three important innovations. First, the modeling approach in IAMO-LUC provides a representation of decision making in a causal, directed graph. The brain of each agent deals with uncertainty, bounded rationality, heterogeneity, and social behavior in a comparatively simple and reproducible modeling structure. Second, the model provides a framework for combining knowledge from experts and stakeholders, as the model can be calibrated using both qualitative and

quantitative data. Third, the modular architecture and software implementation of IAMO-LUC can be customized with modest effort. The model is therefore a flexible general platform that can be tailored to other studies by mounting the appropriate case-specific "brain" into the agents. Although we selected the software packages NetLogo and Hugin, we do not envision problems with other software packages, such as RePast and MASON for ABM or Netica for BBN, all of which either use Java as the native modeling language (e.g., RePast) or provide Java APIs.

IAMO-LUC is designed to be an exploratory tool to help scientists and decision makers in land-use management and policy to understand better the dynamics of coupled socioecological systems under the influence of payments for ecosystem services. Although the model is capable of producing both historic and future land-use maps, it is not intended for use as a predictive tool. The central application domain of IAMO-LUC is the simulation of land-use policy scenarios to generate a range of spatial and non-spatial

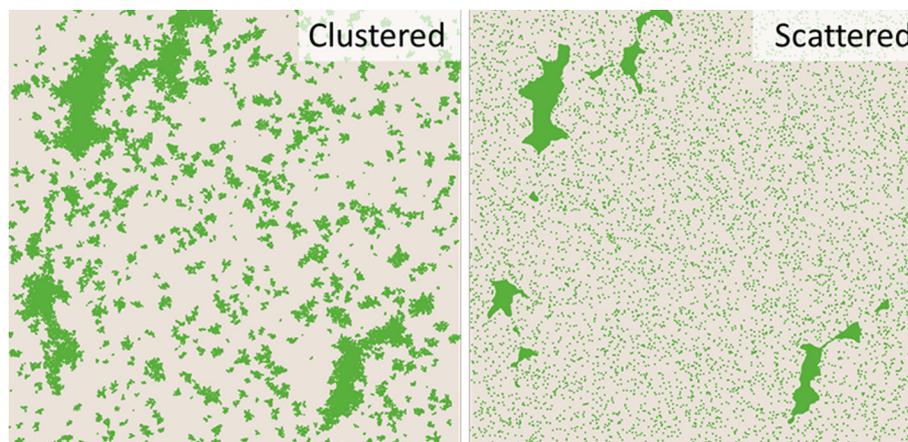


Fig. 12. Scenario-based patterns of land-use outcomes. Source: Authors.

outcomes. These outcomes can improve the *ex-ante* understanding of the likely consequences of policies and can therefore assist to better formulate and target land-use policies that are based on direct incentives. Thus, the model has a wide range of potential applications, most notably, the assessment of the implications of carbon-based payments on forest cover and rural livelihoods in the framework of REDD+ (Reducing Emissions from Deforestation and Forest Degradation plus enhancement of forest carbon stocks). For example, IAMO-LUC can help project-level (Tier 3) activities to formulate crediting baselines and monitor the effects of REDD+ payments on the carbon content of forested landscapes.

## Acknowledgments

This research was conducted within the IAMO International Research Group “Economic Dynamics and Social Equilibrium in Rural China”. We gratefully acknowledge financial support from the Joint Science Conference (GWK) under the “Pakt für Forschung und Innovation” (PAKT). We also acknowledge support from the research project entitled Impacts of Reducing Emissions from Deforestation and Forest Degradation and Enhancing Carbon Stocks (I-REDD+). I-REDD+ is funded by the European Community’s Seventh Framework Research Programme. More information can be found on the following website: <http://www.i-redd.eu>. Special thanks go to Prof. Jianchu Xu, Dr. Caizhen Lu, and Yufang Su at ICRAF Kunming and to Jens Frayer for facilitating the data collection and for numerous helpful discussions. The development of the model benefited greatly from input from Alfons Balmann, Omar Baqueiro, Jens Frayer, and Christoph Sahrbacher. We also thank the editors of this special issue and three anonymous reviewers for their valuable comments on earlier versions of this manuscript.

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