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Analyzing the drivers of tree planting in Yunnan, China, with Bayesian networks

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ABSTRACT

Strict enforcement of forest protection and massive afforestation campaigns have contributed to a significant increase in China's forest cover during the last 20 years. At the same time, demographic changes in rural areas due to changes in reproduction patterns and the emigration of younger population segments have affected land-use strategies. We identified proximate causes and underlying drivers that influence the decisions of farm households to plant trees on former cropland with Bayesian networks (BNs). BNs allow the incorporation of causal relationships in data analysis and can combine qualitative stakeholder knowledge with quantitative data. We defined the structure of the network with expert knowledge and in-depth discussions with land users. The network was calibrated and validated with data from a survey of 509 rural households in two upland areas of Yunnan Province in Southwest China. The results substantiate the influence of land endowments, labor availability and forest policies for switching from cropland to tree planting. State forest policies have constituted the main underlying driver to the forest transition in the past, but private afforestation activities increasingly dominate the expansion of tree cover. Farmers plant trees on private incentives mainly to cash in on the improved economic opportunities provided by tree crops, but tree planting also constitutes an important strategy to adjust to growing labor scarcities.

Introduction

The change from net deforestation to net reforestation is known as the forest transition (Mather, 1992). This aggregate change may result from a cascading set of processes. For example, industrialization might pull people from rural to urban areas leading to a decline in the rural labor force. Consequently, resulting rural labor shortages may spur land-use changes as marginal agricultural land is left uncultivated, possibly leading to forest regeneration (Rudel et al., 2005). Prior research into forest transitions has highlighted the diversity of contexts that exhibit significant forest return, either through natural regeneration or active afforestation (Lambin and Meyfroidt, 2010). The ecological significance of such "regreening" may be highly variable, as the regenerated forest may differ in species composition or quality from the original forest cover (Xu, 2011).

The pathways framework (Lambin and Meyfroidt, 2010; Rudel et al., 2005) is one conceptual approach used to understand the relative role of socioeconomic dynamics and socioecological feedbacks leading to forest transitions. When changes in off-farm opportunities, such as employment in urban areas, are the primary mechanism underlying land-use changes that lead to forest regrowth, such cases are said to follow an "economic development pathway". On the other hand, when land-use change in rural areas corresponds with a shift away from labor-intensive toward capital-intensive agricultural production, such as the cultivation of tree products, a "smallholder intensification pathway" is at work (Rudel, 2009). When observed negative environmental impacts from past degradation lead to policies encouraging forest recovery, the "forest scarcity pathway" is said to be dominant (Hyde et al., 1996). The various pathways to forest transition are not expected to be mutually exclusive, but nevertheless, these ideas are most often used to emphasize the most salient set of drivers in a given case, in order to make comparisons across cases (Lambin et al., 2003; Lambin and Meyfroidt, 2010; Rudel et al., 2005).

We argue that existing forest transition pathway frameworks to date are not sufficiently flexible to understand how forest

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transitions evolve over time and space. A study of forest change in Yunnan Province, China, is used to demonstrate two key findings that we feel have broader relevance to other contexts. First, though particular processes, such as off-farm employment opportunities, may be the most important initial catalysts of change, rural systems will likely continue to evolve over time, and long-term implications for forests will vary according to such ongoing change. Secondly, rural households may be differentially positioned to take advantage of new economic opportunities. For example, household age structure, population growth rates or dependence on forest products could vary at both a household and community level, and the ability to initiate and sustain forest protection efforts will depend on such differences.

We examine recent afforestation programs in China and their specific effects within 17 villages in Yunnan Province. We focus specifically on households as major actors of rural change who to date have received less conceptual and empirical attention in studies of forest change in China. Decades of prior deforestation in China led to severe floods and major droughts, triggering the introduction of large-scale forest programs. We focus here on the impacts of the Sloping Land Conversion Program (SLCP) implemented in 1999. The SLCP encouraged afforestation through the conversion of steeply sloped land to forest or grassland with monetary or in-kind compensation. In addition to new national policies, many regional programs also encouraged farmers to plant trees, implemented by local governments often with support from private companies (Bennett, 2008; Yin and Yin, 2010). Thus, both the SLCP and regional programs have led to increased tree planting on cropland, with multiple local social and environmental impacts (Ediger and Chen, 2006). Evidence suggests that household engagement with tree planting has been highly variable. Greater knowledge of which factors have been most important in shaping land-use adaptations that result in tree planting is necessary to understand the longer-term social and environmental effects of Chinese forest policy. Yunnan is particularly interesting for a study of the relative contribution of forest policies versus the reactions of land users to changing external conditions (Barbier et al., 2010). The province still has abundant forest resources, an ethnically diverse population and is intersected by two globally valuable biodiversity hotspots (Conservation International, 2007).

In order to understand how multiple processes interact over space and time, we employ a distinct methodological approach. Prior analyses of forest transitions that have relied on regression analysis have been limited in their ability to detect causality among multiple, related factors. Other statistical techniques that allow for causal inference in non-experimental settings, such as structural equation modeling, Bayesian analysis and matching techniques have been increasingly used in applied land-change analysis (Alix-Garcia et al., 2012; Andam et al., 2008; Arhonditsis et al., 2006). In this paper, we use Bayesian networks (BNs) to analyze the decision to plant trees on former cropland at the household level. BNs are particularly suited to analyze decision-making in land use because they allow the inclusion of causal and hierarchical dependencies. This includes interactions between variables, accounting for nonlinearity in relationships and permitting the integration of stakeholders in model building and validation (Sun and Müller, 2013). We populate the networks with qualitative information attained from expert interviews and village-level group discussions and with data from a large household survey.

We are interested in how much of the increase in tree cover on former cropland can be attributed to government policies, and to what extent the voluntary tree planting by farmers, with little government support, is responsible. We focus on the household level where land-use decisions are made and analyze the factors that stimulate or hamper the change in household-level land use from cropland to trees. Our overall research questions are twofold:

(1) What are the main drivers that influence the *decision* of farmers to plant trees on former cropland?
(2) Which drivers are the most influential in explaining the *area* planted with trees?

We hypothesize that returns to rural land use are rapidly changing in response to changing economic conditions, which increasingly influence household-level decisions and result in more tree planting on former cropland. We formally assess the relative effects of household labor constraints due to emigration versus the importance of state afforestation programs on tree planting decisions. In addition, private tree planting efforts, outside of formal policies, also represent a rational response to changes in economic conditions. A better understanding of the main drivers of the decision to plant trees and the main drivers influencing the area of tree planting helps improve our knowledge of the distinct forest transition pathways at work in Yunnan.

Forest transition in China

The falling and rising of each Chinese dynasty was always accompanied with environmental change, particularly deforestation and forest recovery. Based on China's long recorded history, China has few, if any, 'pristine' forests. Chinese forests are human-manipulated ecosystems, which have been cut, used, managed and regenerated over time again and again. The latest round of deforestation occurred during the Great Leap Forward from 1958 to 1961 and the Cultural Revolution from 1966 to 1976 (Song and Zhang, 2010; Zhang, 2000). The first forest protection efforts were implemented by the government in the 1980s when forest-use rights were devolved to local communities via the "Three Fixes Policy", which aimed to increase private sector participation by transferring responsibility and benefits of forest management to rural households (Xu and Jiang, 2009). As a result, deforestation rates slowed down and China experienced a change from net deforestation to net reforestation. According to data from national forest inventories, conducted every 5 years in China, forest cover was at a low point of 12% in 1981 (Song and Zhang, 2010). However, the actual transition may have happened later than the data revealed because measurement methods, and even the definition of "forest", were inconsistent across the seven national inventories. For example, in 1994 the definition of "forest" in China was adjusted from a minimum of 30% canopy cover to 20% (Zhang and Song, 2006). Thus, reported forest cover artificially increased in later inventories (Wilson, 2006; Zhang, 2000). In 2010, forest cover in China reached 20.4% according to official statistics (China Statistical Bureau, 2010), and a further increase in forest cover continues to be a policy priority. The goals of the Chinese government aim to achieve a forest cover of 23% in 2020 and 26% in 2050 (SFA, 2009).

Despite the reported rapid increase in forest area, the ecological quality of the Chinese forest transition is questionable. Afforestation efforts were not overly successful in recovering the ecological functions of natural forest cover, resulting in a continuation of soil erosion and flooding (Xu, 2011; Xu and Ribot, 2004). Severe floods and major droughts in the late 1990s triggered the introduction of two vast forest programs: the Natural Forest Protection Program (NFPP) in 1998 and the Sloping Land Conversion Program (SLCP) in 1999. The NFPP aimed to protect and recover natural forests with a logging ban and afforestation schemes (Liu et al., 2008). The SLCP focused on reforestation by encouraging the conversion of cropland on steeply sloped land to forest or grassland with monetary and in-kind compensation (Yin and Yin, 2010). In addition to national afforestation programs, many regional programs that encouraged farmers to voluntarily plant trees on cropland were initiated by local governments (Ediger and Chen, 2006) and were sometimes supported by private companies. For example, local governments and private walnut processing companies in northwestern Yunnan provided support, such as free seedlings, for farmers to grow walnut trees on their cropland.

State and private initiatives, either through (a) regulatory forest protection or; (b) incentive-based afforestation programs or; (c) spontaneous plantation, are undoubtedly important drivers of the forest transition in China. In particular, the SLCP, which covered 19.9 million hectares by 2009 (China Statistical Bureau, 2010), contributed significantly to a national forest cover increase. Yet, privately initiated tree planting on cropland has become more common in recent years. Recently the implementation of the collective forest tenure reform has increased the incentives for private tree planting. As a result of state and private initiatives, forest area increased on former cropland, with multiple impacts on household economies and the environment (Ediger and Chen, 2006).

Materials and methods

Study area

The area of Yunnan Province in Southwest China is the source of headwater and major tributaries that influence the lives of more than 600 million people (Xu et al., 2007). East of where the Asia-Pacific plate meets the Indo-European plate to form the Himalayan range, a number of smaller ranges run almost parallel to each other from Northern Yunnan through the Southwest portion of the province. The headwaters of the Yangtze, Pearl, Salween, Irrawaddy, Mekong and Red Rivers are located within those montane regions. The Yangtze and Pearl Rivers flow through China; the other four rivers flow through the mainland Southeast Asia countries of Myanmar, Laos, Thailand, Cambodia and Vietnam. The complex topography results in a wide range of different landscapes and climatic conditions, with tropical forest in the southwest to permanent glaciers on the high mountain peaks in the north. Yunnan has one of the highest poverty rates in China and hosts a large variety of ethnic groups. The variety of both culture and environment leads to diverse land-use systems. Yunnan is particularly interesting from a forest transition perspective because the province has implemented the incentive-based SLCP and the regulatory NFPP across almost its entire area while its population is still highly dependent on agriculture (Chen et al., 2009).

According to Yunnan forest inventories, forest cover increased from 26% in 1978 to 34% in 1997 and to 50% by 2006 (Xu et al., 2007). In general, Yunnan's forest cover followed national trends and went through similar cycles of afforestation and deforestation. During the late 1960s and early 1970s local farmers increased grain production to meet state requirements for self-sufficiency by expanding cropland, resulting in rapid deforestation (Xu and Ribot, 2004). The implementation of the Household Responsibility System (HRS) in the early 1980s amplified this trend and further lead to an increase in animal husbandry (Wilson, 2006; Xu and Ribot, 2004) and an over-harvesting of forest resources (Xu et al., 2005). In 1981 the state implemented the "Three Fixes Policy" to stop the exploitation of forest resources resulting from unclear forest use rights (Xu and Jiang, 2009). In 1994 the provincial government leased degraded forestland to farmers through "wasteland auctions" for a period of 30–70 years. But these attempts to secure user rights and to decentralize forest management as well as aerial seeding in 1991 did not succeed in regenerating the forests and were unable to stop the forest degradation. Not until the logging ban of the NFPP was there a reversal of this general trend (Xu et al., 2005).

The driving forces underlying forest cover increase varied spatially within Yunnan. In the headwaters of the major rivers, including the Yangtze, Salween and Mekong in the northern part of the province, the NFPP and the SLCP were most directly related to the increase in forest cover (Ediger, 2006; Xu et al., 2007). In the subtropical southern regions however, the expansion of rubber plantations is arguably the main cause for the increase in reported forest cover (Ziegler et al., 2009) since all tree crops are counted as forest cover. Since 2003, a new round of forest tenure reform has been undertaken that aims to devolve rights to collective forestlands to individual households (Yin et al., 2013).

Within Yunnan, we selected two study regions: Yulong County and Longyang District.[1] These regions were selected because of their comparable agroecological context and because both were prioritized for the implementation of the NFPP and the SLCP. Yulong County and Longyang District are located in northwestern Yunnan and are 350 km (Longyang) and 320 km (Yulong) from the provincial capital of Kunming (Fig. 1). Both study regions share similar topographic and land-use characteristics and both implemented the SLCP, the NFPP and the other small-scale afforestation programs. Within each region, we chose one township close to and one township far from the county and district capital (Fig. 1) to represent the effect of market access on afforestation outcomes. From the four townships, we selected a total of 17 villages.

Longyang District

Longyang District is located in the center of Baoshan Prefecture. The elevation ranges from 640 m at the Nujiang River (Salween River) up to 3655 m at Mount Daoren. In 2005, the total population was 853,800 (170 persons per km^2), of which, 13% were ethnic minorities. Overall, 86% of the population were registered as rural residents. In Longyang, agriculture is the main source of local livelihoods. The most important food crops include corn and potatoes and paddy rice in the river valleys, which are mainly produced for subsistence needs. Cash crops include grain, tobacco and sugarcane, and the most important tree crops are coffee, walnuts and chestnuts. Only a small number of households own machinery such as a tractor or rice thrasher (Baoshan Statistical Bureau, 2005).

Yulong County

Yulong County is located in Lijiang City (prefecture-level) in northwestern Yunnan, where the Yunnan-Guizhou Plateau meets the Qinghai-Tibet Plateau. The highest elevation is the Yulong Mountain (5596 m), and the lowest elevation is the valley of the Shilong River (1015 m). The county had a population of 1.137 million (54 persons per km^2) in 2005, most of whom registered as rural residents. Lijiang is the home of more than 12 minorities, the most important being the Naxi, Yi and Lisu (Lijiang Statistical Bureau, 2005). Corn, rice and potatoes are the most important crops.

Both study areas are characterized by mountainous landscapes and annual crop production concentrates in the valley bottoms. Most villages suffer from adverse market access that elevates transportation costs and decreases marketing options and farm profits from agriculture. Poverty incidence in the study villages is high for Chinese standards, 60% of the population of Lijiang lived 2012 below the poverty line, compared to 20% in Yunnan Province or 13.4% in China (Central Intelligence Agency, 2013; Hu, 2012; Yunnan Government, 2012), and the major source of cash income are occasional off-farm work opportunities. The study areas exhibit large diversity of ethnic groups and the most important

[1] Counties or districts are the same administrative level in China. They are part of a prefecture, which in turn is a subunit of a province. Counties and districts consist of several townships, which are the lowest formal administrative unit. Each township contains a number of villages.

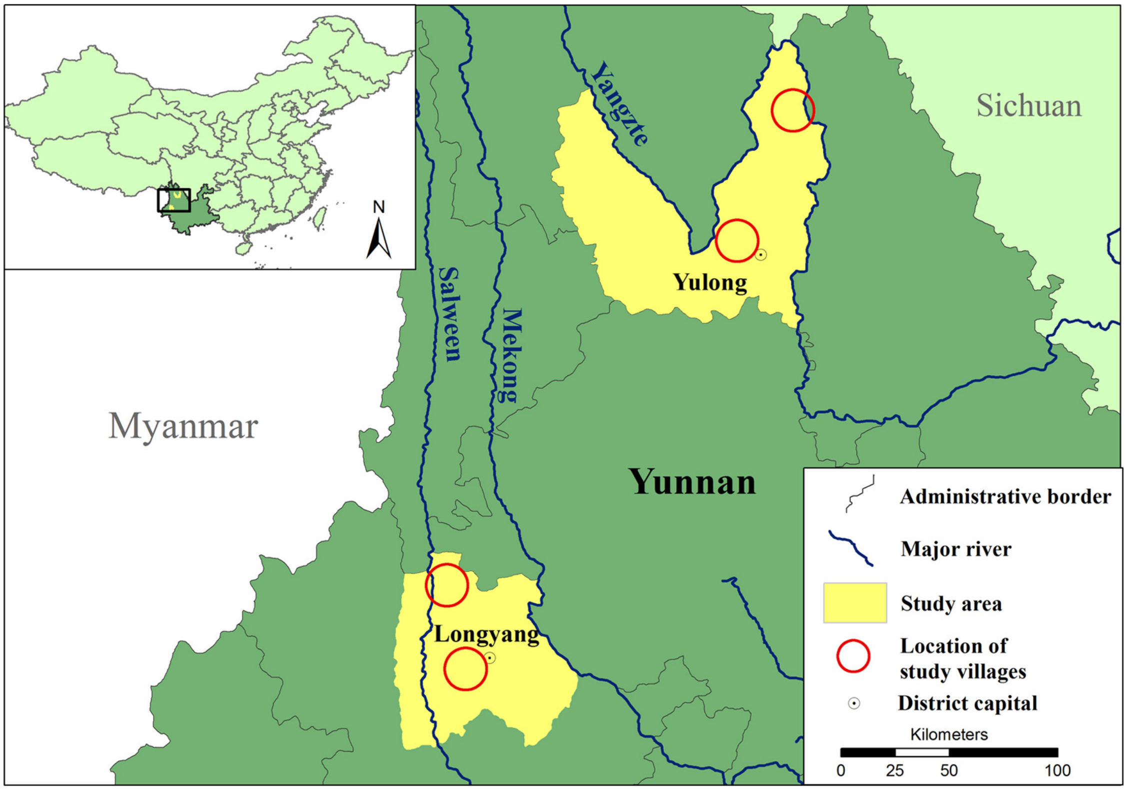

Fig. 1. Study area.

farm income sources are crop production, animal husbandry and, more recently, the marketing of tree crops.

Data collection

We conducted a household survey in the 17 villages in September and October 2009 using a structured questionnaire. The questionnaire encompassed questions about the current (2009) state of physical and financial endowments, demography and educational background, land use, land-use changes and farmers' perceptions of the environmental changes of the last decade. For most of the socioeconomic variables, we also inquired about the situation in the year 2000 using recall techniques in order to understand the magnitude of recent changes and to obtain information on the conditions prior to the implementation of the SLCP. We followed a stratified random sampling approach to obtain representative strata by participation in forestry programs and estimated wealth. In total, we interviewed 509 households, including 417 participants and 92 non-participants in the SLCP.

We also carried out participatory group discussions in ten villages with between five and 15 key informants per village. The key informants included farmers of diverse ages, gender and social background as well as village committee members and successful entrepreneurs. The group discussions provided information on land-use decision making within the village and on the various connections between proximate causes and underlying drivers of land-use change.

To facilitate group discussions, we also mapped land use from very-high resolution satellite imagery (QuickBird, IKONOS, or WorldView 1) that were printed on large paper sheets to cover the entire village territory. The maps enhanced the group discussions with spatial insights of land-use decisions and their implications in terms of land-use change. Thus, we obtained a quantitative and qualitative understanding of the extent of land-use transitions in each village, including afforestation activities, expansions and contractions of farmland and other land-use changes.

Bayesian networks

We use Bayesian networks (BNs) for the analysis of household-level tree planting behavior. BN are non-parametric statistical tools that rely on Bayesian inference to deduce the influence of explanatory variables on the outcomes of interest. A BN consists of two parts: First, a directed acyclic graph (DAG), also known as the structure of a BN, depicts interdependence among variables with directed arrows connecting nodes (corresponding to variables). The second component are conditional probability tables (CPTs), also known as parameters of a BN, which define the probability distributions of nodes conditioned upon the values of their parent nodes (where an arrow originates). The CPT of a child node (where an arrow ends) hence contains the conditional probability of being in a specific state, given the states of its parent node. When a node has no parent, the CPT is simply its prior probability distribution (Jensen, 2002; Pearl, 2009). The conditional probability of a variable is also known as the belief for this state of the variable (Charniak, 1991).

Probabilistic inference following Bayes' theorem is used to quantify influences in the network with conditional dependencies (Heckerman et al., 1995b; Pearl, 2009). Given observations of some variables (i.e., evidence), BNs can—in principal, regardless of the directions of arrows connecting them—deduce the posterior probabilities of any other variables. Thus, BNs can support not only forward inference or predictive analysis (from causes to effects), but also backward inference or diagnostic analysis (from effects to causes) (Pearl, 2009). Unlike regression models, BNs do not require explicit specification of the dependent variables in the model structure. Despite the fact that some variables are conceived by modelers as the key dependent variables based on the model objectives, in theory, any variable can be used as the target or inquiry variable during inference analysis and sensitivity analysis.

One important advantage of BNs is their ability to incorporate qualitative stakeholder knowledge, and quantitative and spatially explicit data (Marcot et al., 2001; Newton et al., 2006; Ticehurst et al., 2011). This flexibility can account for subjective decision-making and qualitative reasoning. Moreover, the representation of effects as probability distributions implicitly incorporates an uncertainty component by going beyond a mere point estimate, such as in traditional regression analysis (Kinzig and Starrett, 2003; Newton et al., 2007). The capability of BNs to combine causal stakeholder knowledge and empirical, evidence-based data explains their growing importance in environmental analysis (Ticehurst et al., 2011). Recent applications include environmental management (Uusitalo, 2007), water management (Bromley et al., 2005), forestry (Newton et al., 2006), wildlife management (Smith et al., 2007) and land-use change (Aalders, 2008; Aitkenhead and Aalders, 2009).

BNs also enable the assessment of different scenarios on the outcome variable. Scenarios can be implemented either by incorporating new variables into the network or by changing the probability distributions, which are the CPTs of existing variables. The resulting variation in the target variable's probability distribution then corresponds to the potential developments under the scenario conditions. Altering the CPT of a node to examine corresponding changes in outcome probabilities also facilitates insights into the sensitivity of individual variables.

Construction of the Bayesian network

The construction of a BN entails two steps: building the structure (the DAG) and learning the CPTs. We developed the DAG by structural learning from the survey data. Structural learning is conducted via data mining that automatically searches for statistical relationships among variables. However, purely statistical interdependence may not reflect realistic cause–effect relationships among variables because the direction of the influences between variables cannot be determined by machine learning. Given these limitations, we opted for a supervised learning strategy that draws on our prior knowledge derived from domain experts and our qualitative interviews with villagers and local officials. During supervised learning, we imposed constraints that prohibit some links while enforcing others. For example, we prohibited a directed link from education level to ethnicity to reflect prior knowledge that education does not affect ethnicity.

Relationships in BNs do not have to be causal but can also assert non-causal statistical association (Heckerman et al., 1995a; Nadkarni and Shenoy, 2001). For that reason, based on Bayes' theorem, arrows can be reversed in order to, for example, reduce the number of parent nodes while maintaining a mathematically equivalent network (Pearl, 2009). This may help improve the clarity of the network and keep the CPT of the target variable simpler and tractable and hence facilitates parameterization when sample sizes are small (Marcot et al., 2006).

After the structure of the BN was defined, the CPTs for each node were learned from questionnaire data using the expectation-maximization (EM) algorithm implemented in Netica software (Norsys Software Cooperation, 2008). The EM algorithm was selected due to its robustness. In sum, the CPT learning process can be viewed as a probabilistic classification to estimate the conditional probabilities between a node and its parent nodes (Heckerman, 1996).

Following the law of parsimony, the BN was designed with a topology as simple as possible, but without losing considerable predictive accuracy (Marcot et al., 2006). Variables were kept in the model, if their inclusion improved the predictive accuracy in form of a reduced ratio of incorrectly predicted cases to the total number of cases (lower error rate) of the target variable. The influence of an input variable on the target variable is measured by the magnitude of probabilities changes of the target variable when the input variable is altered. This essentially resembles a sensitivity analysis (Pollino et al., 2007). The influence of a variable corresponds to how much explanatory information a variable imposes on the target variable. Consequently, a number of variables, which were a priori hypothesized to being important, were excluded because they carried redundant information and had relatively low explanatory power. Variables were kept in the model if the error rate stayed stable or decreased and the influence on the other variables was above 0.05%. After removing eight variables with low influence from the network the desired compromise between simplicity and high model accuracy, measured by the error rate, was achieved (Marcot, 2012; Marcot et al., 2006). The resulting model was updated with prior and conditional probabilities that represent the distribution in the sample population (Marcot, 2006). The final BN (the DAG and the CPTs) illustrates the variables that influence land-use decision-making (i.e., the target variable) and the interactions between variables. This final network was used to calculate the effects of each variable on the target variable.

Variable description and discretization

All variables included in the BN were derived from the survey data and refer to the situation in 2000 before the analyzed period of change. This year was after the NFPP but before the SLCP was implemented in the study areas. The target variable *total area planted with trees* (italics indicate variable names) shows the area on which trees are planted after the year 2000. We calculated the area of marginal cropland per household from the plot level questions of the survey data. We define *marginal land* as plots that are more than a 1-h walk away from the household homestay, with poor or medium soil fertility, not irrigated and on slopes above 15 degrees. The variable *cropland* measures the cropland area of each household. Available household labor was approximated with the *labor force*, measured as the number of household members between 15 and 65 years of age. We used two variables to describe household income: First, *total income* (from all cash-generating activities) and, second, *crop income* (from crop sales only). This separation helped distinguish the land-use behavior of households between those that primarily rely on income from crop production and those that derive most of their income from animal production or off-farm jobs. We also requested the most important cash *income sources* of households and approximated the value of key *household assets* with the net present value of any tractor, TV set and mobile phone owned by a household. According to local villagers, these consumables best distinguished the wealth status between households. We asked households for the costs at the purchase date and the age of these items and discounted them to current prices with price indices from the Statistical Yearbook (China Statistical Bureau, 2010). We accounted for *ethnicity* to proxy for land-use traditions, and for the highest attained *education level* to capture human capital effects on land use. Finally, we included the area enrolled in the *SLCP*, the area enrolled in the *walnut program* and the area planted with trees without monetary or in-kind incentives from external sources (*private afforestation*). The income-related and area-related variables are continuous variables, whereas the participation in a state-run program, ethnicity, education, political position and income source are discrete (Table 1). The descriptive statistics of all variables included in the final network are depicted in Table A1 in Appendix.

The ability of BN to deal with continuous data is limited and continuous variables are therefore usually discretized (Jensen, 2002). The discretization of continuous variables requires a decision on the number of discrete bins, and the corresponding cut-off values.

Table 1
Description of variables.

Variable (node)	Type	Description	States (range)
Total area planted with trees	Continuous	Total area planted with trees after the year 2000	0 mu; 0–3 mu; >3 mu
SLCP	Continuous	Area in SLCP	0 mu; 0–3 mu; >3 mu
Walnut program	Continuous	Area in walnut program	0 mu; 0–3 mu; >3 mu
Private afforestation	Continuous	Area afforested without compensation	0 mu; 0–3 mu; >3 mu
Cropland	Continuous	Cropland area in the year 2000	<6 mu; 6–15 mu; >15 mu
Marginal land	Continuous	Area of marginal land per household	0 mu; 0–3 mu; >3 mu
Participation in forestry program	Discrete	Participation in forestry program	Yes/no
Ethnicity	Discrete	Ethnicity of household	Han; Yi; Naxi; other
Education	Discrete	Highest education level attained by any household member	Illiterate; primary school; middle school; high school; college and above
Asset value	Continuous	Value of assets in 2000	¥0; ¥1–1000; >¥1000
Crop income	Continuous	Income from selling crops	<¥100; ¥100–500; >¥500
Total income	Continuous	Total income	<¥1500; ¥1000–5000; >¥5000
Major income source	Discrete	Major source of cash income	Agriculture; animal husbandry; forest & NFTP; off-farm work; other
Labor force	Continuous	Number of family members with full labor capacity	< 3; 3–4; >4

Note: 1 mu = 0.07 ha; ¥100 = €10 in 2010; NTFP, non-timber forest products.

Thus, there are infinite ways to discretize continuous variables. A good discretization method should minimize information loss and maintain or maximize the interdependence among variables. However, no optimization method has been identified and the searching process has proved to be computationally very intensive and time consuming (Kotsiantis and Kanellopoulos, 2006). Heuristic methods such as equal width (or equal interval), equal frequency methods and entropy minimization are widely used (Aguilera et al., 2011). An increasing number of intervals or bins tends to improve the precision but not necessarily the accuracy, and it certainly increases the complexity of BNs. Marcot (2006) suggested using the least possible number of intervals to find a balance between parsimony and precision. In addition, when deciding on cut-off values, model objectives and domain knowledge on certain variables should be considered in order to make the binning more sensible and logical (Chen and Pollino, 2012). For example, we set the cut-off value for cropland area to 15 mu, which is equivalent to exactly 1 ha. Following these principals, we binned the area-related and the income-related variables into same intervals to facilitate comparison, reduced household size to three categories and kept the remaining categorical variables in the original measurement scale (Table 2).

Table 2
Discretization methods for continuous variables.

Variables	States	Discretization methodology
Walnut program; private afforestation; total area planted with trees; marginal land	None (0 mu)	Equal width and frequency
	A little (0–3 mu) A lot (>3 mu)	
SLCP	None (0 mu) Little (0–3 mu) Medium (3–6 mu) A lot (>6 mu)	Entropy reduction
Labor force	Low (<3)	Logical, Equal frequency
	Medium (3–4) High (>4)	
Cropland	Little (0–6 mu)	Expert knowledge, equal width
	Medium (6–15 mu) A lot (>15 mu)	
Crop income	Low (¥0–100) Medium (¥100–500) High (>¥500)	Equal frequency
Total income	Low (¥0–1000) Medium (¥1000–5000) High (>¥5000)	Equal frequency
Asset value	Low (¥0) Medium (¥1–1000) High (>¥1000)	Logical

Results

The resulting Bayesian network

The final network (Fig. 2) contains 14 variables and captures the directional relationships among these variables. The two target variables in the network are the participation in forestry programs and the total area planted with trees. The network shows that the area of cropland, household size, area of marginal land, education level, and ethnicity all directly affect the participation in a forestry program (Fig. 2). The total area of tree planting on former cropland is directly influenced by the participation in forestry programs, including the SLCP and the Walnut program, by the extent of private afforestation and by the amount of cropland available to a household. The three different strategies of tree planting and the area of cropland determine the total area that a household converts from cropland to trees. Moreover, the total area planted with trees is influenced by the major income sources and asset values of households (both for the year 2000 before the implementation of the SLCP), although they are connected as child nodes (see "Construction of the Bayesian network" section).

The network shows the initial probability distribution for all variables (Fig. 2). More than 60% of the households had more than three household members, and 71% of the farmers had no marginal land (Fig. 2, see also Table A1). 69% of the households had members who had a middle school or higher education, and 79% of the households participated in at least one of the forestry programs. 72% of the households converted cropland due to participation in the SLCP, but only 15% planted walnut trees with support from the walnut program. Interestingly, 54% of the farmers afforested voluntarily without any compensation. Only 8% of the households did not plant trees at all, but 76% of households planted more than 3 mu with trees. The distribution of asset values demonstrates the high inequality at the household level. The majority of farmers do not own household assets with a significant net present value. 12% own items with a net present value up to 1000 yuan, while 11% have assets worth more than 1000 yuan. Finally, more than half of the households received less than 100 yuan from selling crops in the preceding year and hence rely on other sources for cash

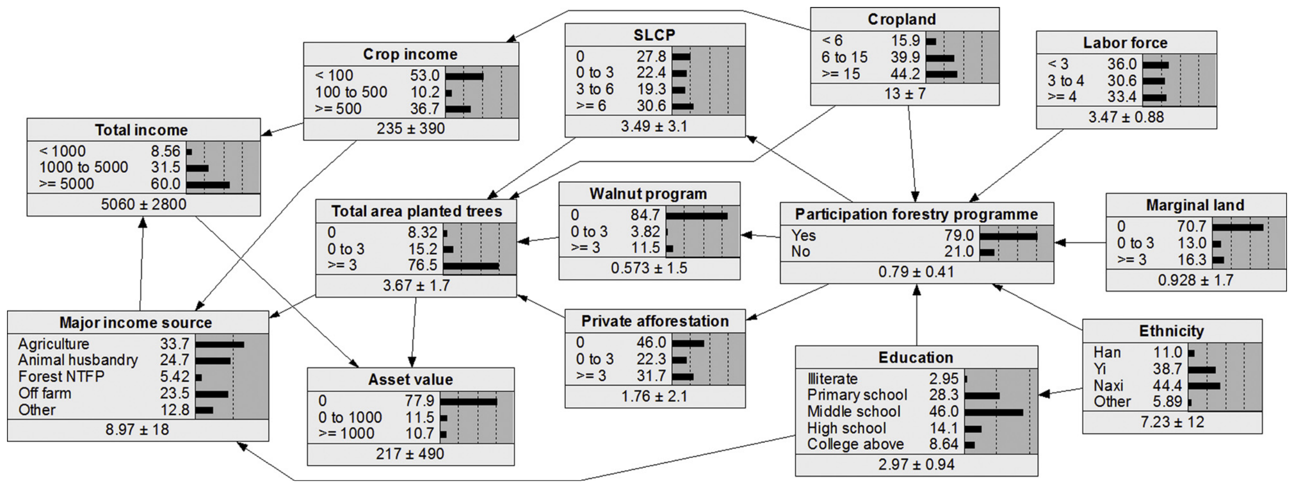

Fig. 2. The resulting Bayesian network.

income. Overall, the major income sources were agriculture, animal husbandry and off-farm jobs.

Model validation and sensitivity analysis

The quality assessment of the BN was performed in a two-stage process. First, the network structure was reviewed by experts and validated by villagers during our re-visit in the following year (2010). This helped to qualitatively verify that the model aligns with empirical knowledge on the ground. Second, model performance, or the accuracy of predictions, was evaluated with a cross-validation approach by splitting the data into training and test datasets (Dlamini, 2010; Fielding and Bell, 1997; Pollino et al., 2007). The use of training and test data is necessary to avoid over-fitting and to allow for testing with independent data. To obtain more robust results, ten rounds of cross-validation were performed using repeated random subsamples. In each round 80% of the data (407 out of 509 cases) was used for training the BN and the remaining 20% (102 households) was used for testing the performance of the BN. The overall evaluation of the BN was based on the average performance of all ten rounds of the cross-validation.

During the testing process, we compared the predictions based on the training data and test data in a confusion matrix and calculated the error rate. To test the performance of the model, we removed from the network the data on the area included in the three tree planting variables, the total area of tree planting, and on the participation in state-run afforestation program. The model correctly predicted the category of the area of tree plantings on average in 78 of the 102 test cases with a total average error rate of 0.23 (Dlamini, 2010).

In addition to the error rate, the classification accuracy was evaluated with the area under the curve (AUC) of the receiver operator characteristics (ROC). ROC analysis assesses how well an observer can assign cases to dichotomous outcome classes. To calculate the AUC of ROC, the true positive predictions are plotted against the true negative predictions across a continuum of prediction thresholds (Hanley and McNeil, 1982; Metz, 1978). The AUC therefore represents the probability that a positive outcome (the predicted variable matches the observed state) has a higher predicted probability than a negative outcome (the variable is not predicted correctly). The AUC can be used as a single measurement of overall accuracy and varies between 0.5 for a random guess and 1 for perfect performance; values below 0.5 indicate that the model predicted more cases wrong (Marcot, 2012). Because the

Variable	Variance reduction
Private afforestation	10.70%
SLCP	9.44%
Cropland	9.38%
Asset value	2.45%
Participation forestry program	1.14%
Major income	1.14%
Walnut program	0.74%

Fig. 3. Sensitivity to total area planted with trees. *Note*: The sensitivity reduction of participation in forestry program, ethnicity, marginal land, total income, education and labor force was below 0.5%

ROC curve assesses dichotomous variables, we calculated the AUC separately for each category of the target variable (0, 0–3 and >3 mu of the area planted with trees) and report the AUC for each category. The average AUC of 0.543 for the first category (albeit only for 3.4 observations on average), 0.596 for the second ($N = 15.8$ on average) and 0.608 for the third category ($N = 82.5$ on average) show the predictive performance of the model.

In a last step, we conducted a sensitivity analysis to quantify the influence of each independent variable on the dependent variable. We calculated the sensitivity of the two target variables (*total area planted trees* and *participation in forestry programs*) in relation to all other variables in the network. We relied on variance reduction, which measures the magnitude of how one variable alters the belief of another variable (Norsys Software Cooperation, 2008).

Factors influencing the area planted with trees

Fig. 3 shows the results of the sensitivity analysis for all influencing variables, ranked in descending order of influence on the respective target variable. The results suggest that the area of *private afforestation* is the most significant factor for a reduction of the sensitivity of *total area planted with trees*, with a variance reduction of 10.7%. The area enrolled in the *SLCP* and *cropland* area also have a strong influence on the *total area planted with trees* reducing the sensitivity by 9.4%. Additional influential variables include *asset values*, *participation in the forestry program*, *major income* and *walnut program*. The strong influence of the variables covering forestry programs is not surprising because these variables are the major proximate reasons for tree plantings. All remaining variables have minor effects on the *area planted with trees*, with variance reductions below 0.5%.

We further assess the strength of interactions between a target variable and the influencing variables with a diagnostic analysis

	Initial state	Change in absolute percentage		
		0 mu	0-3 mu	> 3 mu
Cropland				
< 6	15.9%	24.1%	14.3%	-5.5%
6 to 15	39.9%	-7.2%	9.3%	-1.1%
> 15	44.2%	-16.9%	-23.7%	6.5%
Asset value				
¥0	77.9%	-13.1%	2.6%	0.9%
¥0 to ¥1000	11.5%	-11.5%	-1.1%	1.5%
> ¥1000	10.7%	24.6%	-1.4%	-2.4%
Major income source				
Agriculture	33.7%	9.8%	1.5%	-1.4%
Animal husbandry	24.7%	-18.3%	0.4%	1.9%
Forest NTFP	5.4%	0.9%	-4.0%	0.7%
Off-farm	23.5%	2.3%	4.3%	-1.1%
Other	12.8%	5.2%	-2.2%	-0.1%
Private afforestation				
0 mu	46.0%	22.7%	-5.3%	-1.4%
0 to 3 mu	22.3%	-2.1%	30.9%	-5.9%
> 3 mu	31.7%	-20.6%	-25.6%	7.3%

Fig. 4. Probability change for different areas of tree planting.

that takes advantage of the two-way inference capability of BNs. The diagnostic analysis, in contrast to sensitivity analysis, gauges how the probabilities (beliefs) of influencing variables change given evidence in target variables (i.e., *total area planted trees* and *participation in forestry programs*). The diagnostic analysis considers all influencing variables with variance reductions above 0.5% but excluded variables directly related to the forestry programs. Fig. 4 shows the initial state of probability distributions (or prior probabilities in Bayesian terminology), taken from Fig. 2, for the three variables that have the highest statistical influence (*cropland*, *asset value*, and *income source*). Fig. 4 also reveals the changes in the probabilities of the influencing variables when the area planted with trees is hypothetically assumed to fall into a specific category. The magnitude of the probability changes then resembles the strength of the influence.

The availability of *cropland* has a strong influence on the *area of trees planted*. The assumption of zero tree plantings (area = 0 mu) increases the probability of a household to have less than 6 mu of cropland from 15.9% to 40% (15.9% plus 24.1%). Households that afforest more than 3 mu have a 50.7% probability (44.2% plus 6.5%) of managing more than 15 mu of cropland. Fig. 4 also reveals strong effects of the household's *asset value* on the *area of tree planting*. Without tree planting the probability for the lowest class without any valuable assets decreased by 13.1% and for asset values of up to 1000 yuan it decreased by 11.5%, whereas the probability for asset values above 1000 yuan increased by 24.6%. The probability distribution of the asset value is insensitive to the assumption of areas of tree planting above 3 mu. *Major income* source also reacted strongly to the assumption of zero tree planting: The probability of agriculture as main income source increased by 9.8% and the probability for animal husbandry reduced by 18.3%. In summary, the area of cropland available to a household has the largest bearing on the size of the area of tree planting.

Factors influencing the participation in forestry programs

Participation in government-sponsored forestry programs, the SLCP and the walnut program, is an important determinant of the total area of former cropland planted with trees (Fig. 3). Therefore, we tested the sensitivity of participation to its influencing variables. The sensitivity analysis revealed that the *ethnicity*, the area

Variable	Variance reduction
Ethnicity	2.25%
Cropland	2.08%
Education	1.53%
Marginal land	1.48%

Fig. 5. Sensitivity to participation in forestry program. *Note*: The sensitivity reduction of labor force, crop income, asset value, major income source, and total income was below 0.5%.

of *cropland*, *education*, and area of *marginal land* have substantial influences (Fig. 5).

The ethnicity of a household's is important for the decision to join an afforestation program. Especially the Yi ethnic group reacts sensitive to a change of no participation with a change by 9.3%. A comparison of probability distributions reveals that households with more *marginal land* are more likely to participate in forestry programs, as suggested by the formal goals of the SLCP (60% in case of no participation do not manage any marginal land compared to 71% in the initial situation, Fig. 6). In addition, participation

	Prior probability	Change in absolute percentage if	
		Participation	No participation
Ethnicity			
Han	11.0%	-0.7%	2.6%
Yi	38.7%	2.5%	-9.3%
Naxi	44.4%	-0.3%	1.0%
Other	5.9%	-1.5%	5.7%
Marginal land			
0 mu	70.7%	2.8%	-10.6%
0 to 3 mu	13.0%	-1.6%	5.8%
> 3 mu	16.3%	-1.3%	4.7%
Education			
Illiterate	2.9%	-0.7%	2.6%
Primary school	28.3%	0.6%	-2.4%
Middle school	46.0%	1.6%	-6.2%
High school	14.1%	-1.5%	5.8%
College above	8.6%	-0.1%	0.2%
Cropland			
< 6	15.9%	-2.7%	10.2%
6 to 15	39.9%	1.1%	-4.0%
> 15	44.2%	1.7%	-6.2%

Fig. 6. Probability change for participation in a forestry program.

in forestry programs is more likely for households that are in the medium education range; are from the Yi ethnic group, which traditionally inhabits higher elevation ranges and have more cropland. Overall, these results show that participants and non-participants have distinctive characteristics that determine participation and, hence, the amount of tree planting. In general, however, the variance reduction for explanatory variables is relatively low, which implies relative low explanatory power. In other words, the participation of SLCP is strongly influenced by other factors beyond the household characteristics included in our BN. This is in line with current literature and the reality that the SLCP in many places, including in some of our study sites, was implemented in a top-down manner without the prescribed voluntary participation (Uchida et al., 2009). Farmers were often forced to participate in the SLCP at early stages when few were effectively willing to participate. In later stages, several farmers told us in the interviews that the majority of households recognized the advantages of converting cropland and planting trees and enrolled voluntarily in the SLCP. The conversion from crops to trees even continued without governmental compensation because farmers frequently converted smaller plots and plots adjacent to roads (Meyfroidt, 2013).

The effects of participation in a forestry program on the amount of private afforestation are also noteworthy. Participants do not plant trees on private accounts in about half of the cases whereas more than 75% of the non-participants do so. Non-participants in forestry programs also tend to reforest areas larger than 3 mu while participants were more likely to reforest smaller plots of land. In reality, non-participants afforested on average 3.9 mu, and SLCP-participants 2.9 mu without compensation.

Discussion

In this paper, we investigated interesting patterns of tree planting across households, both in conjunction with forest policies and independent of them. Private afforestation activities and participation in the SLCP and the walnut program are important predictors for the total area of trees planted. However, differences in the sensitivities of the three variables reveal interesting insights. On the one hand, most households participated in the SLCP and thus afforested some land in response to financial incentives from the program. The large number of participants in the SLCP therefore contributed a significant share to the total afforested area. On the other hand, many households also converted cropland to plant trees without financial compensation or incentive schemes. Additional qualitative interviews with farmers revealed that such private tree planting activities were the response of farmers to the emerging labor scarcity that was the result of the high rates of rural emigration and the increase in off-farm work.

In our study sites, the SLCP arguably played an important role in facilitating private afforestation activities because it raised awareness of the economic potentials of tree crops and facilitated the introduction of planting techniques and tree seedlings. The qualitative interviews revealed that the positive benefits from commercial tree plantations of forest program participants also induced non-participants to convert cropland to trees by means of private investments. Increasing profit streams from tree crops also diminished the importance of compensation payments as the main driving factor for conversion. In summary, taking advantage of emerging economic opportunities from tree crops has become a viable and preferred strategy for the generation of cash income and for dealing with increasing on-farm labor shortages (cf. Perez et al., 2004).

The positive effects of the SLCP on household income has been established for Shaanxi province (Li et al., 2011; Liu et al., 2010) as well as for Hebei, Jiangxi and Sichuan provinces (Liu et al., 2010). Our results also demonstrate the sensitivity of the major income sources of households to the area planted with trees and, in addition, we illustrate the growing importance of private tree planting for household income in our study sites. This is corroborated by the strong relationship between income sources and the motivation to plant trees, because tree planting offers new promising opportunities to generate additional income in rural areas. Our survey data shows that the increasing returns from tree crops led to shifts in income composition (cf. Table A2). For example, the conversion of cropland to trees resulted in a loss of fodder and thus reduced opportunities for animal husbandry. Crop production decreased in its importance for income generation during the last decade, while off-farm jobs and income from forests and tree crops gained in importance. This proofs, in opposite to Li et al. (2011), that planting trees gives farmers the possibility to use new opportunities, as shifting labor to off-farm activities, to increase the household income. Farmers expect these trends to continue. The increasing importance of forestry and tree crops for income generation suggests that significant conversion of afforested areas back to cropland after compensation ends is an unlikely scenario (Groom and Palmer, 2012).

The cropland area of a household also has a strong influence on the area of afforestation and demonstrates the importance of land endowments for land-use decisions (Mullan and Kontoleon, 2009). Farmers with higher land availability tend to set aside more cropland for tree planting. Conversely, land-scarce households largely continue to rely on annual cropping coupled with pig production. They avoid the investments for seedlings and fertilizer as well as the production gap until the trees provide the first harvest. Legal regulations in China that require a farm household to maintain at least 1 mu of cropland reinforce this development. Only the remaining land is potentially available for afforestation activities.

Participation in state-run afforestation programs is a crucial determinant for the total area of former cropland that a household converts to trees. The sensitivity analysis revealed the strength of this connection, but the contribution of private afforestation activities is also remarkable. Both participants in a state-run program and non-participants afforested significant areas without compensation or incentive payments, but private afforestation initiatives were more likely to cover areas larger than 3 mu. This is likely because participants typically have less marginal cropland with land use certificates than non-participants. As a result, participants in state forest programs converted most of their larger marginal plots with government support while their smaller plots were planted with trees at a later stage without government support. Non-participants, in contrast, predominantly planted trees on large plots to increase labor efficiency, because less time is required for traveling to tree plots and for tree management.

Conclusion

The conversion of cropland to tree cover is an important land-use change in Yunnan Province due to both large-scale government afforestation programs and widespread private tree planting activities. We combined qualitative and quantitative data to analyze local land-use decisions in 17 villages of Yunnan Province. We developed a Bayesian network to combine information from group discussions with quantitative survey data from 509 households. BNs are highly flexible, nonparametric statistical models that allow us to integrate qualitative stakeholder knowledge and quantitative survey data. We used the BN to analyze the proximate causes and underlying drivers of the decision to plant of trees on former cropland.

The modeling results demonstrate the importance of government programs for the increase in the extent of tree planting on former farmland. Yet, we also illustrated the recent emergence of tree planting activities on private accounts with little external support in the study villages. Our qualitative information further reveal that the main causes for private afforestation activities were the expectations of high economic returns from trees, the household response to the reduced availability of farm labor and more secure forest tenure. In other words, the expectations of economic returns from planting trees and changes in production factor scarcities underpinned much of the changes in land-use decisions in rural Yunnan.

Multiple, interrelated causal chains are hence at play in the decision to plant trees on former cropland. The interplay of several causal explanatory frameworks suggests that the majority of households follow a mixture of forest transition pathways. The increase in the area of tree cover is mainly shaped by larger economic and institutional changes that led to local land-use responses, which can be subsumed in the smallholder intensification pathway (Lambin and Meyfroidt, 2010). The increase in smallholder afforestation activities in our case study area was driven by the response of land users to increasing labor shortages, higher capital availability, newly acquired knowledge in tree crop production and improved market access.

State forest programs were the initial trigger for the large-scale increase in tree cover beginning around the year 2000. Their impacts on local landscapes were modulated by local biophysical, cultural and socioeconomic conditions that defined plot selection and the area devoted to conversion. More recently, the increasing importance of economic development at the expense of the state-forest policy showed that the Chinese forest transition was not a linear process, driven by state policies and incentives. Instead, it has followed multiple trajectories over space and time.

Understanding this intermixed process of land-change trajectories is vital for informing land-use policy and for an efficient targeting of government afforestation programs. This understanding is important because the increasing amount of trees in the landscape support local development by providing considerable long-term income and by balancing household labor allocation. A better understanding of the underlying causes of the tree cover transition in Yunnan can thus help guide land-use policy. Nonetheless, the Chinese forest transition is deficient in its ecological quality (Xu, 2011), which is also the case for our study area where the vast part of the increases in tree cover are due to the planting of cash trees either for timber or, more often, for tree fruit. The lack of ecosystem value of the Chinese tree cover transition thus calls for improvements in land-use planning to improve ecological outcomes and restore ecological integrity.

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Appendix.

See Tables A1 and A2.

Table A1
Descriptive statistics of all variables.

Variable	States	Initial probability (%)	Mean	Standard deviation
Total area planted with trees	0 mu	8.22	3.67	1.7
	0–3 mu	15.3		
	More than 3 mu	76.4		
Participation in forestry program	Yes	81.6		
	No	18.4		
Asset value	¥0	77.9	217	490
	¥0–1000	11.5		
	More than ¥1000	10.6		
Crop income	Less than ¥100	53	235	390
	¥100–500	10.2		
	More than ¥500	36.5		
Cropland	Less than 6 mu	15.9	13	7
	6–15 mu	39.9		
	More than 15 mu	44.2		
Labor force	Less than 3	36.95	2.97	1.1
	3–4	30.65		
	More than 4	33.34		
Marginal land	0 mu	70.7	0.928	1.7
	0–3 mu	13		
	More than 3 mu	16.3		
Private afforestation	0 mu	46.7	1.72	2
	0–3 mu	22.4		
	More than 3 mu	30.8		
SLCP	0 mu	25.4	3.61	3.1
	0–3 mu	23.1		
	3–6 mu	19.9		
	More than 6 mu	31.6		
Total income	Less than ¥1000	8.56	5060	2800
	¥1000–5000	31.5		
	More than ¥5000	60.0		
Walnut program	0 mu	84.2	0.592	1.5
	0–3 mu	3.94		
	More than 3 mu	11.8		
Education	Illiterate	2.95		
	Primary school	28.3		
	Middle school	46.0		
	High school	14.1		
	College above	8.64		
Ethnicity	Han	11		
	Yi	38.7		
	Naxi	44.4		
	Other	5.89		
Major income source	Agriculture	33.6		
	Animal husbandry	24.7		
	Forest NTFP	5.41		
	Off farm	23.5		
	Other	12.8		

Table A2
Changing importance of income sources.

Income source	2000	2009	2015
Agriculture	34.1%	11.8%	9.7%
Livestock	26.4%	18.7%	15.9%
Off-farm work	24.3%	47.1%	42.5%
Forestry, NTFP	4.7%	16.4%	23.4%
Other	10.3%	5.9%	8.3%

Source: Own survey data including expectations from respondents for 2015; NTFP: Non-timber forest products.

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