Participatory Bayesian network modeling to understand driving factors of land-use change decisions: insights from two case studies in northeast Madagascar

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Forest frontiers worldwide reveal trade-offs that are key in mitigating global change. In the forest frontiers of northeast Madagascar, land-use changes result from decisions made by smallholder farmers. In the past, subsistence needs led to increasing shifting cultivation, resulting in forest degradation and deforestation. This study focuses on investigating the role of locally determined factors in land-use change decisions in the forest frontier context. Therefore, we developed a Bayesian network-based land-use decision model that represents the causalities between factors influencing land-use decisions and takes into account local decision-makers' knowledge. The approach is applied in two comparative case studies in northeast Madagascar. Results show that farmers mostly aim at extending the cultivation of cash crops. These results and the causal mechanisms disentangled for the forest frontier of northeast Madagascar help understand change mechanisms and hence, support decision-making to attain the Sustainable Development Goals.

Keywords: Bayesian networks; land-use decision modeling; drivers; land-use change; modeling.

1. Introduction

Land cover and land-use change are among the most important drivers of global change, impacting ecosystems and ultimately their capacity to supply ecosystem services (Lambin *et al.*, 2001; de Groot, Wilson, and Boumans, 2002; Turner, Lambin, and Reenberg, 2007). Several indicators that monitor progress toward achieving Sustainable Development Goal 15 (SDG 15) (United Nations, 2018) —protect, restore, and promote sustainable use of terrestrial ecosystems; sustainably manage forests; combat desertification; and halt and reverse land degradation and halt biodiversity loss—show an improvement in forest protection measures. However, the indicators also show a decline in forest area and its productivity (United Nations, 2018). Currently, deforestation remains the most significant land-use change in tropical countries, generally resulting from commercial agricultural, subsistence, and mining activities, but also from urban expansion and infrastructure construction (Geist and Lambin, 2001; Swenson *et al.*, 2011; Hosonuma *et al.*, 2012; Sonter *et al.*, 2015; Garrett *et al.*, 2018). In tropical regions, forests are converted into shifting cultivation and export-oriented crops, causing a loss of valuable forest goods, of support and regulation services, and of the provision of cultural and aesthetic benefits (Kull, 2000; Moser, 2008; Gibbs *et al.*, 2010). For the case of Madagascar, shifting cultivation is still an important land-use practice in forested areas (Styger *et al.*, 2007; Waeber *et al.*, 2015) that remains the main land-use change in rural areas. Land-use change research shows that shifting cultivation expanded in northeast Madagascar between 1990 and 2017, as this practice ensured rice production in the area (Llopis *et al.*, 2019).

A large body of research has addressed these land-use and land-cover changes and identified a wide array of drivers and determinants in the process of expanding or intensifying agriculture expansion to increase food production (e.g., Chowdhury, 2006; Mottet *et al.*, 2006; Levers *et al.*, 2016; Schulp *et al.*, 2019) or protecting forest for biodiversity conservation (e.g., Rindfuss *et al.*, 2007; Lambin and Meyfroidt, 2011). Although many studies have investigated the effects of socioeconomic opportunities and constraints created by markets, policies, and institutions on land-use and land-cover change (Lambin *et al.*, 2001; Lambin, Geist, and Lepers, 2003; Bürgi, Hersperger, and Schneeberger, 2005), the integrated consideration of biophysical, societal, and economic factors and their causal relationships at various scales of the landscape in the forest frontier context are still an important challenge, and highly needed to tackle sustainable land management for fulfilling the SDG 2030 targets (United Nations, 2018).

Land-use models are often used to better detangle the complexity of factors defining choices in land-use decisions (Rindfuss *et al.*, 2008; Noszczyk, 2018). Bayesian networks model represents causal relationships through their directed acyclic graph, combining empirical data from different sources (statistics, reports, other models, etc.) with expert knowledge (Aalders and Aitkenhead, 2006; Marcot *et al.*, 2006; Celio, Koellner, and Grêt-Regamey, 2014). As Bayesian networks are based on probability theory, they handle uncertainty, particularly when there is lack of data about the system (Cain, 2001; Kocabas and Dragicevic, 2007; Uusitalo, 2007). Bayesian networks have been used to understand causal relationships in water resources management (e.g., Bromley, 2005; Castelletti and Soncini-Sessa, 2007; Zorrilla *et al.*, 2010), wildfire expansion (e.g., Dlamini, 2010), ecosystem services assessment (e.g., Sun and Müller, 2013; Landuyt, Broekx, and Goethals, 2016; Shaw *et al.*, 2016), biodiversity conservation and management (e.g., Marcot *et al.*, 2001, 2006; Pollino *et al.*, 2007; Ticehurst *et al.*, 2007), and the agricultural sector (e.g., Pérez-Miñana, Krause, and Thornton, 2012). Aalders (2008) used Bayesian networks to model decisions and behavior of land managers as drivers of land-use change in mountain regions of Scotland. Bashari *et al.* (2009) developed decision support tools for rangeland management using Bayesian networks in Queensland, Australia. Celio *et al.* (2014) modeled effects of land-use decision-making in a spatially explicit manner using Bayesian networks in a pre-alpine area of Switzerland.

In this contribution, we investigate the influence of the combined effect of biophysical and socioeconomic factors driving land-use change decisions in the forest frontier context. To tackle the data-poor environment, we developed a spatially explicit Bayesian network of farmers' decision-making in a participatory process. In addition, we investigated whether the importance of the factors driving land-use change decisions varies across the case study sites. We focused on comparing the factors that trigger shifting cultivation in two sites located in northeast Madagascar, which have experienced strong expansion of subsistence rice production and cash crop cultivations in the last 20 years (Zaehringer, Eckert, and Messerli, 2015; Ministère de l'Environnement de l'Ecologie et des Forêts MEEF, 2017; Llopis *et al.*, 2019).

2. Methods

2.1. Conceptual framework and terminology

Land managers' decisions are at the center of land-use change. This is true for the conversion of natural landscapes to agricultural cultivation, or the change of a specific area of land from one use to one another, or a change in the management and practice on the land (Aalders, 2008; Malek *et al.*, 2019). These changes may generate environmental problems, both locally and globally (Foley *et al.*, 2005).

In a socio-ecological system, land-use change is a function of multiple factors that are called drivers or determinants interacting at different levels. For example, at the local level, institutions regulating the management of village plots are seen as drivers; at the regional level, accessibility can be a determinant of landscape layout (Turner and Meyer, 1993; Groeneveld *et al.*, 2017). These factors are differentiated in terms of their source, importance, and outcome. On the one hand, drivers or driving forces designate factors related to human, social, or land system forces that directly or indirectly cause land or environmental change for which knowledge is not necessarily sufficient to explain the causal mechanism (Turner, 1989; Millennium Ecosystem Assessment, 2003;

Meyfroidt, 2016). On the other hand, “determinant” or “spatial determinant” denotes “variables that are frequently used as location factors in land change models” or as “a series of biophysical and socio-economic factors [which] can explain the spatial distribution or other spatial characteristics (spatial pattern or structure) of land systems” (van Asselen and Verburg, 2012; Meyfroidt, 2016). Furthermore, a “predisposing factor” or “trigger” refers to a causal factor that is relatively unimportant in explaining land-use change, but which may be an important cause of the precise location or timing or realization of an event (Meyfroidt, 2016).

In this study, we developed the causal network based on local people’s perspective of causality. Hence, the network structure and therein contained nodes are drivers of land-use change. The drivers were selected because, e.g., farmers chose “slope” as a cause for their land-use decision.

2.2. Study sites

Madagascar is a “hotspot” of biodiversity because it is a tropical country where 5% of the world’s biodiversity resides, but also where natural resource degradation is increasing, including a rapid annual deforestation rate of 0.5% from 2000 to 2010 (Myers *et al.*, 2000; Lambin, Geist, and Lepers, 2003; Wilmé, Goodman, and Ganzhorn, 2006; Office National pour l’Environnement *et al.*, 2013). On the occasion of the Vth World Parks Congress in Durban, South Africa, in 2003, Madagascar committed to increase the total size of protected areas from 1.7 million hectares to 6 million hectares over the next five years to guarantee conservation of the unique biodiversity of the world’s fourth largest island (Terborgh, 2004; Ratsirarson, 2006). However, about 36,000 hectares of natural forests were lost each year in Madagascar between 2005 and 2010. The rate of annual deforestation within Protected Areas (PAs) managed by the

Madagascar National Parks has been 0.2%, which is half of the national rate (Harper *et al.*, 2007; Office National pour l'Environnement *et al.*, 2013).

Madagascar's forests are subject to major conversions, including mining, protected areas, commercial and subsistence agriculture, etc. Subsistence agriculture using fire is the primary factor of deforestation in Madagascar for households without access to irrigable land parcels (Kull, 1998, 2000; Zaehringer *et al.*, 2016). Slash-and-burn agriculture, also known as "tavy", "jinja" or "hatsake" remains the traditional and most common land use in Madagascar (Styger *et al.*, 2007).

This study was carried out in northeast Madagascar in two forest frontier sites. Each is composed of two villages within the District of Maroantsetra, Region of Analanjirofo. The northern study site included to the villages of Mahalevona and Fizono, and the southern one the villages of Morafeno and Beanana (Figure 1). The southern site (the Morafeno commune) is located on hilly land near Makira Natural Park, characterized by a steep and rugged relief, while the northern site (the Mahalevona commune) lies in a downstream plain with low hills further northeast toward the forest of Masoala National Park (Andriamanana, 2014; Rakotoarison, 2014).

The area is characterized by a peri-humid tropical climate with an average of 234 rainy days per year and experiences cyclones regularly (Ranoarisoa, 2012). The majority of the households in the region belong to the Betsimisaraka ethnic group (Rasolofomanana, 2009). Most of the households' activity is related to agriculture. Of particular importance is the cultivation of cash crops, such as cloves, vanilla, and coffee. Rice is cultivated in irrigated paddy rice fields and in upland shifting rice fields, called "jinja" or "tavy" locally (Rasolofomanana, 2009). Table 1 provides an overview of the current shares of land uses in the two case study sites.

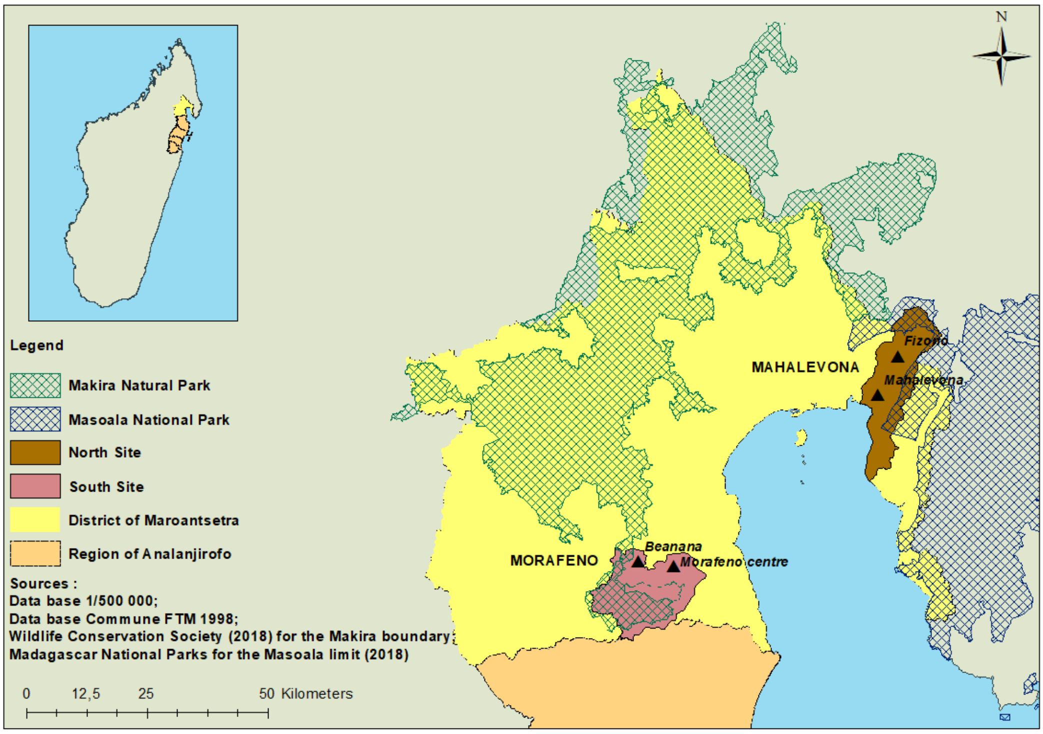

Figure 1: Case study area: northeast Madagascar.

Sites	Northern site (Mahalevona)		Southern site (Morafeno)	
Population characteristics				
Village	Mahalevona	Fizono	Morafeno	Beanana
Number of inhabitants	9834	3851	1889	721
Main categories of land use (percentage)				
Forest	30.92	50.07	8.92	56.77
Shifting cultivation	17.08	33.54	45.70	36.59
Mixed agroforestry	27.94	10.29	34.26	2.30
Irrigated paddy rice	8.05	1.93	2.12	0.49
Pastures and cloves	3.44	0.48	0.30	0.05
Pastures	4.24	1.15	0.10	0.04
Dense plantation of cloves	3.18	1.40	4.83	2.06
Housing	0.55	0.11	0.57	0.15
Others (river stream, not cultivated, bare soil and sand)	4.60	1.03	3.20	1.55

Table 1 : Population and main land use of the study area (source: Recensement 2015 Service de la population District de Maroantsetra).

Compared to the central highlands of Madagascar, where economic and demographic factors such as population growth, state policies, market incentives, and access to land and water resources have been identified as important factors for the conversion of forest into cultivated area (Kull, 1998, 2000; Moser, 2008; Gibbs *et al.*, 2010), northeast Madagascar is characterized by important upland rice cultivation leading to conversions of forest into shifting cultivation areas. In this region, biophysical characteristics of the plots condition the choice of land use (van Vliet *et al.*, 2012; Zaehringer, Eckert, and Messerli, 2015; Ramboatiana *et al.*, 2018), and shifting cultivation was the most prominent land use replacing forest between 1995 and 2011 (Zaehringer, Eckert and Messerli, 2015; Llopis *et al.*, 2019).

2.3. Bayesian network-based land-use decision modeling approach

A Bayesian network consists of three elements: nodes as variables, arrows, which represent causal links between the nodes, and conditional probability tables (CPTs), quantifying the strength of two or more nodes' connection (Neapolitan, 2003; Kjærulff and Madsen, 2008; Korb and Nicholson, 2010). In the present study, we used the available participatory Bayesian network-based Land-Use Modeling APproach (BLUMAP), which was developed to help conceptualize and parameterize the model in collaboration with concerned actors and stakeholders. Celio, Koellner, and Grêt-Regamey (2014) used this approach to take into account biophysical factors and local actors' decisions influencing land-use change and to represent uncertainties of land-use changes in a spatially explicit manner. A spatially explicit model refers to a model that combines a model with land-use maps and other related ecological and socioeconomic geodata related to land-use decision-making (Dunning *et al.*, 1995; Noszczyk, 2018). The network is used to calculate posterior probabilities for each land-use category on each raster cell. Thus, the Bayesian network is updated by our current state of knowledge (e.g., the slope of a location or the status of a regulation for the site), and the posterior probabilities determine future land use. Biophysical factors such as slope will remain constant. However, comparing their importance to other factors driving land-use change and including their effect for each location separately help analyze land-use change decision-making.

The setup procedure of the model followed several existing guidelines (Cain, 2001; Bromley, 2005; Marcot *et al.*, 2006; Carmona and Varela-Ortega, 2007; Chen and Pollino, 2012; Barreteau *et al.*, 2014) and connected the elaborated Bayesian network with spatial data. In three concerted field visits, data was collected, processed, and fed back to the participating group of local farmers and regional experts. In the following, we elaborate on the different steps (Figure 2).

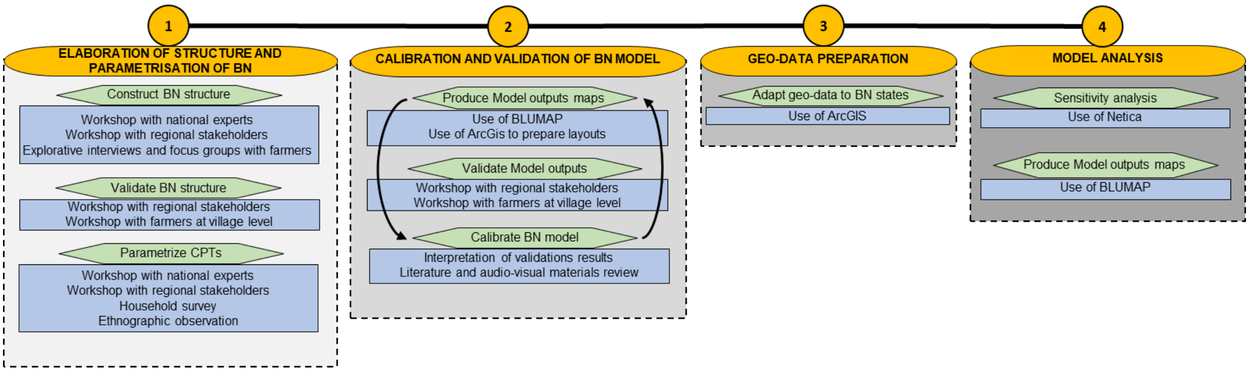

Figure 2: Participatory Bayesian network-based Land-Use Modelling APproach (BLUMAP) adapted for the case study context.

2.3.1. Elaboration process of the BN

To elaborate the Bayesian network structure, we conducted explorative interviews with the four village heads and 17 farmers, who were informed by the village heads and had agreed to participate, using a questionnaire which covered four aspects (land-use change, causes, related actors, and ecosystem services), and a workshop in each village.

During the workshop, a cause and effect network was constructed. Through content analysis inspired by Mayring (2000), we analyzed the interviews and workshop transcripts to identify additional important factors driving land-use change and their inter-relations. This content analysis allowed us to gather all factors through all texts from fieldwork. We used an inductive analysis of all transcripts and established categories while reading.

We validated the causal-effect network structure of the Bayesian network in four workshops, each conducted in one of the villages. As the Bayesian network is composed of different causal chains, we presented a series of causal chains to workshop participants and asked them if we should remove or modify the names of the variables, and if they would like to add more factors and information.

The network is motivated by the theory of planned behavior (Ajzen, 1991). Thus, we used the distinction between intention and behavior as a structuring element. We considered decisions of land-use change as the behavior. Land-use *LU_t1* is influenced by diverse factors related to institutions, events, biophysical context, and the farmer's intention. Intention, in turn, is influenced by factors related to the household situation and the economic context; more concretely, the node Farmer intention is influenced by factors related to household situation, such as Annual incomes, Savings, Farm trained, etc. The final Bayesian network structure is shown in Figure. A.1 a, and b, in Appendix A; and Table A.1 shows the descriptions of nodes.

We parametrized the Bayesian network CPTs using different sources of data. (a) To include the diversity of the decisions made by individual farmers, we conducted a household survey from November to December 2016 at both sites (Table 2). We interviewed 35 household heads at the northern site and 36 at the southern site. Then, we designed case files using 173 cases at the plot level obtained from the household survey and used the expectation-maximization (EM) learning algorithm provided by Netica to populate the CPTs. This algorithm is a robust method for performing maximum likelihood estimation on the parameters from incomplete data sets (Zou and Yue, 2017). (b) During a stakeholder workshop at the regional level, we conducted a scenario exercise we called an “imagine exercise” that used little stories, which aimed to obtain data to populate complicated nodes with more than two parent nodes (Cain, 2001). (c) We observed the farmers’ daily activities and behavior during our fieldwork to verify the rationale behind decision of change. (d) We conducted semi-structured interviews with experts in soil sciences and hydrology from ESSA-Forêts (University of Antananarivo), which helped fill the CPTs of the intermediary nodes “soil fertility” and “water”. (e) Finally, we conducted a review of the literature and audiovisual materials (see Appendix B) to get insights into the change from forest to other land-use categories and the importance of the driving factors of this particular process.

Using steps (a) and (b), we established a basic parameterization of key conditional probabilities. Next, we used steps (c) and (d) to apply trends starting from the key conditional probabilities to deduct the missing CPTs values (Cain, 2001). For the final parametrization of the node LU_t1, we applied the trends and compiled all data from the different sources in Microsoft Excel. Cases of CPTs for which we could not elaborate information were parametrized with a uniform probability distribution. For CPT cases that had values from one source (e.g., a workshop), those values were considered, and for those that had values from multiple sources, the means were calculated. This allowed us to parameterize CPTs with high numbers of conditional probabilities.

STEP	ACTIVITY	NO. OF PARTICIPANTS		TIME
		Northern site (Mahalevona)	Southern site (Morafeno)	
1: Set up and parameterize BN Model	*Workshop with national experts (Antananarivo)*	4		November 2016
	Workshop with regional experts (Maroantsetra)	12		Field visit 1 : 11 April - 28 April 2016
	Explorative interviews	6	11	
	Focus group with farmers	6	13	
	Workshop with regional stakeholders (Maroantsetra)	11		Field visit 2 : 10 November – 20 December 2016
	Workshop with farmers at village level	Mahalevona: 9 Fizono: 21	Morafeno: 4 Beanana: 10	
	Workshop with national experts (Antananarivo)	7		June 2017
	Workshop with regional stakeholders (Maroantsetra)	11		Field visit 2 : 10 November – 20 December 2016
	Household survey	35 88 plots	36 85 plots	
	Ethnographic observation	-		
3: Validate and Re-parameterize BN Model	*Workshop with regional stakeholders (Maroantsetra)*	12		Field visit 3: 30 January-15 February 2018
	Workshop with farmers at village level	Mahalevona: 14 Fizono: 11	Morafeno: 10 Beanana: 19	

Table 2: Number of participants during each activity and field visit duration.

2.3.2. Iterative process for calibrating and validating the model

Using preliminary land-use change scenarios, we conducted a qualitative validation process during workshops, where stakeholders informed us about the relevance of the variables for triggering land-use change and assessed the model outputs based on first parametrization for accuracy (Celio, Brunner and Grêt-Regamey, 2012). We conducted five two-hour workshops with farmers, economic operators in cash crops sector, state representatives, and representatives of nongovernment organizations (NGOs) at the village and regional levels, considering the three dimensions of change motivated by Pontius and Millones (2011): quantity, dynamics, and allocation. During the quantity exercise, stakeholders were asked if the quantity of land-use change matched their beliefs. For the dynamics dimension, we conducted 30-minute exercises, during which we presented land-use change pathways from an established initial condition of a given land use. For the allocation criteria, we presented land-use change trajectories in two time steps, 2016–2023 and 2023–2030, and asked groups of three to five participants to comment on the proposed patterns of change. Each group reported separately according to the specific characteristic of the plot and the information they had about it.

The results gained we source from the target node *LU_t1* that shows the probability of occurrence of each land-use category after a decision period. To represent path dependency, one determining factor of *LU_t1* is *LU_t0* that represents the land-use at the beginning of the decision period (see Appendix A, Figure. A.1). Results showed that the developed Bayesian network model represented a group view of farmers. At the plot-specific level, (see Appendix C, Figure. C.1) and from the individual farmers' perspectives (allocation measure), local actors agreed only partly with the proposed land-use changes. However, on a generic level, with group consensus at the village level (dynamic measure), the local actors widely agreed with proposed land-use changes pathways (see Appendix C, Figure. C.2), and similarly at the regional level (see Appendix C, Figure. C.3).

To produce the model output for the dynamic validation exercise, we used five-to seven-year time steps, i.e., t_1 and t_2 corresponding to 2023 and 2030, respectively. However, most of the land-use change rates evoked by farmers were faster than the proposed time steps, except the change from shifting cultivation to the mixed agroforestry system (SC-MAFS) for the southern site (Morafeno). Farmers, at first, did not take into account the time lags due to the removal of one crop and its replacement by another, meaning the time until a change is perceived in the landscape. In summary, the interval of five to seven years was widely accepted once participants agreed on the aspects that should be covered by this time interval.

Based on stakeholders' remarks during the validation step, we recalibrated the Bayesian network by adding nodes and then adjusting CPTs. As we obtained group results from the validation exercises, we translated the answers into probabilities. Focusing on an identical starting land-use category in two time steps, we calculated the ratio of groups indicating the same land-use change pathway to the total number of participating groups and fed it into the CPTs.

2.3.3. Geodata preparation

To prepare base maps for modeling, we used ArcGIS 10.2.2. We reclassified the initial land-use categories of Llopis *et al.* (2019) produced by a participatory and remote sensing-based approach (Zaehringer *et al.*, 2018) into aggregated categories (see Appendix D) including Dense Plantation of cloves (DP), Shifting Cultivation (SC), Mixed AgroForeStry (MAFS), irrigated Paddy Rice (PR), Pastures and Cloves (PC), Pastures (P), Forest (F), Housing (H), and Artisanal Mining (AM). These land-use categories follow the terminology of local actors by separating the broad categories in their land-use.

Slope was created by processing digital elevation model data of the area provided by DLR/Airbus, using the slope tool in Spatial Analyst Extension of ArcGIS. Boundaries of protected areas were provided by the Wildlife Conservation Society and the Madagascar National Parks, which are the institutional managers of Makira Natural Park and Masoala National Park, respectively. We obtained water availability maps using a participatory approach. Local stakeholders mapped the water-scarce areas during the validation workshops. Based on the land-use map, participants drew polygons of water availability areas, and we digitalized these polygons using ArcMap. Subsequently, we converted all model input maps (vector) into a 50×50 m raster.

2.3.4. Sensitivity analysis

In Netica, we ran a sensitivity analysis on all factors to understand the relative importance of land-use change drivers on the model output maps using the Shannon measure of mutual information (Pearl, 1988). Mutual information *I(X, Y)* is also known as "cross entropy", and "is a measure of the information shared by *X* and *Y* (i.e., the reduction in entropy from observing *Y*)" (Kjærulff and Madsen, 2008). If *X* is the variable of interest, then *I(X, Y)* is a measure of the value of observing *Y* (Kjærulff and Madsen, 2008). It is calculated as follows:

$$I\,(X,Y) = H(X) - H(X|Y) \qquad (1)$$

$$I(X,Y) = \sum_{n=0}^{x}\sum_{n=0}^{y} P(x,y)\log[\frac{P(x,y)}{P(x)P(y)}] \qquad (2)$$

where *H(X)* is the entropy, and *H(X|Y)* is the entropy of X given an observation on Y. Lowercase indicates the actual instantiation, and *P(x,y)* reflects the joint probability of finding *X* and *Y* (Kjærulff and Madsen, 2008; Norsys, 2011). It has values between 0 and 1, where 1 denotes a uniform distribution between all possible states (maximum uncertainty), and 0 denotes complete certainty about the state of the target node.

2.3.5. Production of Bayesian network model output maps

To produce maps of future land-use change according to different scenarios, we used a C-programmed platform that can combine a Bayesian network with geospatial data (Stritih *et al.*, 2020). The platform provided outputs for the target node of the Bayesian network at each iteration.

For the production of model outputs, we used the Bayesian network feature of providing evidence for nodes. Farmer characteristics of were kept constant at each iteration (updated with soft evidence). In addition, we used slope and water availability maps to update the respective nodes (with hard evidence). For the “status quo” scenario, we used soft evidence, which means that we were uncertain about a specific state but certain about its distribution (Peng, Zhang, and Pan, 2010). Outputs were spatially explicit probabilities of each state of the target nodes, that is, the probability of occurrence for each land use in target node *LU_t1*.

3. Results

After the iterative setup process, we distinguished six groups of factors driving land-use decisions:

(a) Household situation and its objectives: Farmer intention, Rice production, Rice sufficiency months, Savings, Annual incomes, Farm trained, Need of land, Mouths to feed.

(b) Economic factors related to markets: International and local Prices of cash crops.

(c) Societal factors that reflect the situation within the community: State of the irrigation system, Clearing of forest, and Theft.

(d) Biophysical factors: Number of shifting cycle, Soil fertility, Water sufficiency, and Slope.

(e) Institutional factors: Conservation status, Acceptance of conventions on conservation and trade by the government of Madagascar.

(f) Events triggering land-use change: Cyclones and Pests.

3.1. Relative importance of factors driving land-use change decisions

Based on the two developed Bayesian networks (see Appendix A, Figure. A.1 and Table A.1), we identified the importance of biophysical and socioeconomic factors in the farmers' decision-making. While the farmers' intention (Mutual Information, I = 0.06) is driving land-use change at the northern site (Mahalevona), land-use change at the southern site (Morafeno) is most sensitive to the presence of the conservation area (Mutual Information, I = 0.04; Figure 3). Contextually, the northern site (Mahalevona) provides important opportunities for cash crop cultivation, as the terrain is flatter than at the southern site (Morafeno) where features hilly and upland areas. In contrast, at the southern site (Morafeno), the protected area forces farmers to optimize their remaining cultivated area to cover minimal needs. Theft is also an important driver of land-use change in northeast Madagascar, and even more important at the northern site (Mahalevona; I = 0.02621) than at the southern site (Morafeno; I = 0.00040) (Figure 3). According to the farmers living in the northern site (Mahalevona), despite thefts on their plots, the farmers keep planting cash crops and even expand the mixed agroforestry systems to compensate for their losses. The process is also spurred by the soaring vanilla prices.

Slope is a much more important factor of land-use change at the southern site (Morafeno) than at the northern site (Mahalevona) (Figure 3). The flatter topography at the northern site (Mahalevona) allows farmers to establish irrigated paddy rice fields or to cultivate other crops, such as vegetables. Due to hilly land constraints, at the southern site (Morafeno) farmers keep producing rice in shifting cultivation systems. Although both sites are located in forest frontier contexts, the large flat areas at the northern site (Mahalevona) allow farmers to cultivate irrigated paddy rice fields in addition to shifting cultivation (Figure 3). This is not the case at the southern site (Morafeno), which has a more rugged terrain, and only a few farmers own small-scale paddy rice fields. Thus, rice is produced mostly through shifting cultivation. This reason explains why the value of probability of shifting cultivation in the Bayesian network target node *LU_t1* (see Appendix A, Figure. A.1 a and b) at the southern site (Morafeno) is higher (prior probability P=38.6%) than at the northern site (Mahalevona) (prior probability P=23.2%).

Changes from any types of land -use into pastures or pastures and cloves are rarely found at the southern site, because farmers do not need pasture land as they neither have nor need zebus for upland rice farming (see Appendix E, Figure. E.1 b). Factors related to water availability are similar at both sites, although northeast Madagascar is the rainiest region of Madagascar (Figure 3). Water system management, however, differs between the two sites. At the northern site (Mahalevona), there are dams and canals to irrigate the paddy rice fields although some are dysfunctional because of damages, leading to the drying up of some paddy rice fields. At the southern site (Morafeno), in addition to the scarcity of flat land for paddy rice fields, irrigation infrastructure is nonexistent. Farmers rely on traditional canals to irrigate the few paddy rice fields they own.

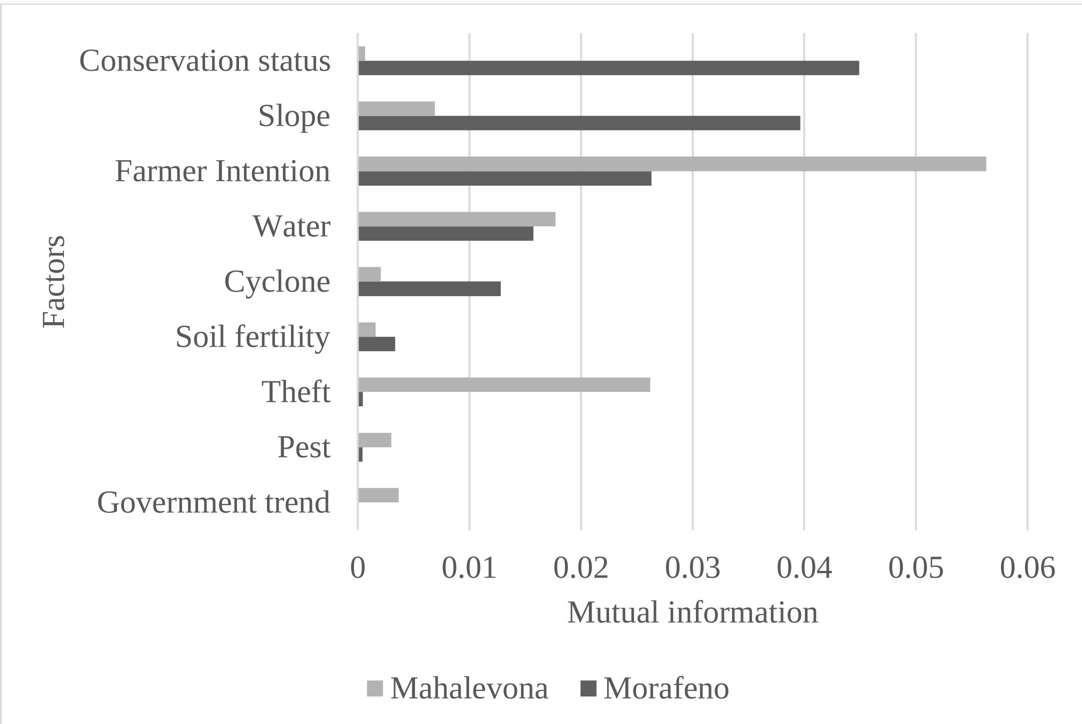

Figure 3: Sensitivity of land-use change to various societal, economic, and biophysical factors. *LU_t1* is the target node. Values are given in terms of Mutual Information *(I)*. Only factors whose difference of (I) values between the two sites are higher than 0.001 are shown.

3.2. Dynamics of shifting cultivation

Focusing on factors driving changes from the land-use category shifting cultivation to other categories, Farmer intention was the most important factor at the northern site (Mahalevona). In contrast, the factor Slope outweighed the others at the southern (Morafeno) (see Appendix E, Figure. E.1 a, and b). In addition, we found that the dynamics of shifting cultivation differs between the sites. That is, shifting cultivation is more persistent at the southern site (Morafeno) than at the northern site (Mahalevona). In technical terms, we put hard evidence on “Shifting cultivation” of *LU_t0* to determine the probability of occurrence of *LU_t1*. While at the southern site (Morafeno) after a time step of five to seven years, shifting cultivation remains shifting cultivation (P = 56.28%), at the northern site (Mahalevona), the land use with the highest probability is the mixed agroforestry system (P = 51.33%). Shifting cultivation is converted into mixed agroforestry systems for planting mainly vanilla and cloves (see Appendix E, Table E.1). The change of shifting cultivation, thus, is slower at the southern site (Morafeno) than at the northern site (Mahalevona). At the southern site (Morafeno), the change of shifting cultivation into mixed agroforestry takes ten years, while it takes only four years at the northern site (Mahalevona).

Figure 4 demonstrates that the high probability of occurrence of mixed agroforestry is clustered at the northern site (Mahalevona). This land-use type is more spatially extended than at the southern site (Morafeno). In addition, at the southern site (Morafeno), the probability of occurrence of land -uses, namely, shifting cultivation and mixed agroforestry, is low for plots near the protected area (Figure 4).

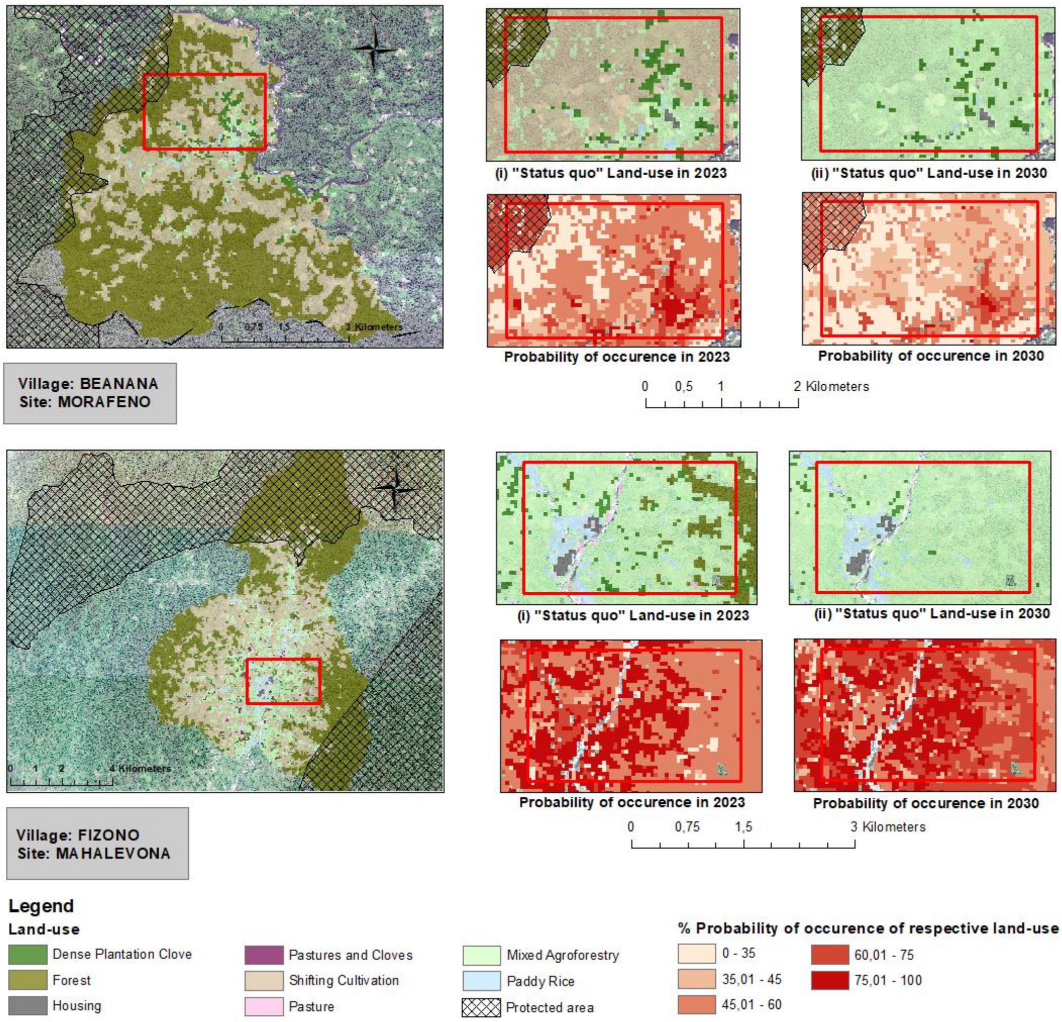

Figure 4: As the model is spatially explicit, these maps show various land-uses with respect to their probability of occurrence in 2023 and 2030 for the village Beanana (part of the southern site Morafeno) and the village Fizono (part of the northern site Mahalevona).

4. Discussion

We used a Bayesian network-based land-use decision modeling approach to better understand drivers of land-use change in the forest frontier context of Madagascar. The spatially explicit model outputs showed differences in terms of the importance of shifting cultivation between two sites, which induce differences in terms of trajectories of this land-use change.

Farmers' decisions are highly dependent on their households' economic situations. At the two case study sites, slope and water availability are among the most important factors for land-use change, which match the current understanding that these biophysical factors highly influence the type of crops farmers adopt (Ramboatiana *et al.*, 2018). Delineation of a protected area can ultimately determine farmers' decisions, which supports the concept that rules and institutions regulating land -use influence land-use change (Irwin and Geoghegan, 2001; Ramboatiana *et al.*, 2018; Llopis *et al.*, 2019).

At the northern site (Mahalevona), whether there is enough land available for farming or not, the farmers' intention is a key driver of land-use change. The farmers' objective is to cultivate more cash crops, triggering changes from shifting cultivation to mixed agroforestry, or to keep their mixed agroforestry cultivated parcel. The farmers' intention to focus on cash crops results from several factors: First, this part of Madagascar has been subject to the production of cash crops, namely, cloves, coffee, and vanilla, since colonization, and it became a tradition of each household to cultivate cash crops; in addition, the region's climate supported this development. Second, the farmers' income depends mostly on selling cash crops, which allows them to buy the extra -quantity of rice that they need as their own rice production is insufficient. Third, as clove crops are a perennial crop and require several years to reach maturity, the farmers might not be able to adapt their crop choices quickly and easily in response to price volatility (Llopis *et al.*, 2020).

Farmer intention is less important than conservation status of the area in the southern site (Morafeno). The farmers' intention can, also be overruled by institutional decisions, when agricultural land is placed under conservation, as shown by other authors (Lambin and Meyfroidt, 2011). The implementation of such protected areas is often driven by distant decisions at the national government level, even internationally (Andriamihaja *et al.*, 2019) through a top-down process (Scales, 2014), often ignoring the socio-ecological context (Gardner *et al.*, 2018). The Masoala National Park was created in 1997, but the expansion of protected areas in Morafeno is the result of the Malagasy government's policy since the Vth World Parks Congress in Durban, South Africa in 2003, during which the government committed to triple the surface of protected areas. The influence of conservation status are apparent not only in the land-use management at the boundaries of the parks but also in the agricultural training of farmers, which encourages them to adopt alternatives in exchange for their commitment to stop "tavy" (Brimont *et al.*, 2015). As a result, farmers act and adapt their use of land according to the situation. Constraints due to the protected area boundaries at the southern site (Morafeno) influence farmers to reuse the land. This last observation confirms the idea that farmers might intensify their shifting cultivation (Brimont *et al.*, 2015) and convert the remaining non-protected forests not only to increase their rice production but also out of fear of losing the legitimate property of the land, because traditionally whoever clears the land owns it (Andrianirina-Ratsialonana and Burnod, 2012).

The rate of change to shifting cultivation is dependent on the biophysical factors and household situation of a site. At the southern site (Morafeno), expansion of shifting cultivation is observed, and previous shifting cultivation is still maintained for one more time step (2023), which is not occurring at the northern site (Mahalevona) where shifting cultivation becomes very rare after one time step. The spatially explicit model outputs showed differences in terms of timing of land-use change between the sites while expansion of the mixed-agroforestry system is generalized at the two sites. This last observation may partially distort the idea that shifting cultivation would remain the main use of land in northeast Madagascar (Heinimann *et al.*, 2017). We hypothesize that conservation regulations influence not only decision-making (see above), but also the dynamics. Due to the implementation of conservation restrictions for the Makira Protected Area, farmers at the southern site have difficulty finding new plots to cultivate because they are not allowed to clear new fields. This might slow the speed of land-use change and lead the farmers to maintain the same land-use, here shifting cultivation, on the same plots until soil fertility decreases which is still consistent with the results that conservation restrictions may shorten the fallow periods for "jinja" resulting in decreased fertility (Brimont *et al.*, 2015).

Similar to Celio, Koellner, and Grêt-Regamey's finding, in 2014, the Bayesian network-based land-use decision modeling approach can identify the combined effect of locally-determined factors driving land-use change and their causalities in a data-poor environment. In addition, the participatory approach made it possible to investigate and understand the farmers' decision-making context (Bromley, 2005) and causalities in the decision-making. The stakeholders involved in our participatory approach considered better understanding of the drivers of land-use change highly useful. Nevertheless, compared to methods of BN parametrization used by, e.g., Celio, Koellner, and Grêt-Regamey (2014), we chose to use methods more adapted to the local context, such as the imagine exercise. Although understanding conditional probabilities is difficult for all persons, we tried to reduce this barrier as much as possible while taking into account the low rate of literacy in the study sites.

Thus, to secure sustainable land in forest frontiers, land management strategies should consider biophysical, societal, institutional factors and household intention. The results of this study can support rural territory planning and management by providing information about key factors of local decision-making and future development of the landscape of Maroantsetra. The participatory setup process and the resulting maps are means to the end to support participatory land-use planning processes. Tools for supporting such processes using, for example, visualizations help rationalize strategic planning such as the national project “Projet Agriculture Durable par une Approche Paysage (PADAP)”. This project, a national cross-sectoral project underway since 2018, aims to increase agricultural productivity while sustainably managing natural resources in five landscapes in northwest and east of Madagascar by designing development and management plans for these landscapes as a the first step. It did not include the landscape of Maroantsetra (Ministère de l’Agriculture de l’Elevage et de la Pêche, 2018), however, future similar project in the northeast Madagascar could rely on results of this study.

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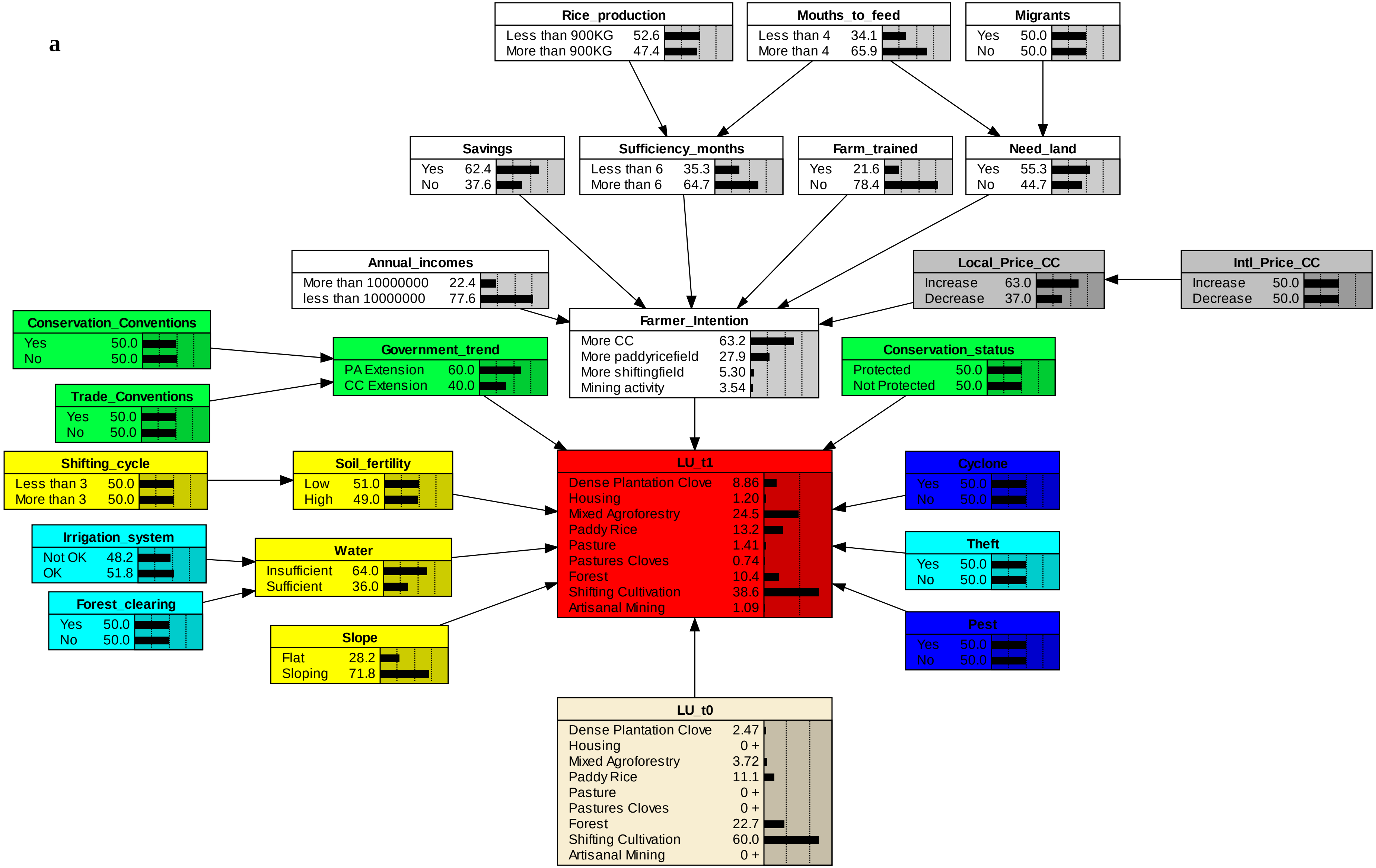
Appendices

Appendix A

Figure. A.1. Bayesian Networks of land-use decisions at the two case study sites: a) southern site (Morafeno), b) northern site (Mahalevona). The target node is the land-use after one time-step (LU t1), whose states represent the modeled land-use categories (cf. Appendix D). In our Bayesian network four broad categories of drivers influence the target node LU t1 (red), biophysical factors (yellow), societal factors (light blue),economic factors (grey), household's situation (white), institutions (green) and events (blue). Value of CPTs 50:50 means there was no data available.

a



Rice_production
Less than 900KG 52.6
More than 900KG 47.4
Mouths_to_feed
Less than 4 34.1
More than 4 65.9
Migrants
Yes 50.0
No 50.0
Savings
Yes 62.4
No 37.6
Sufficiency_months
Less than 6 35.3
More than 6 64.7
Farm_trained
Yes 21.6
No 78.4
Need_land
Yes 55.3
No 44.7
Annual_incomes
More than 10000000 22.4
less than 10000000 77.6
Local_Price_CC
Increase 63.0
Decrease 37.0
Intl_Price_CC
Increase 50.0
Decrease 50.0
Farmer_Intention
More CC 63.2
More paddyricefield 27.9
More shiftingfield 5.30
Mining activity 3.54
Conservation_Conventions
Yes 50.0
No 50.0
Government_trend
PA Extension 60.0
CC Extension 40.0
Conservation_status
Protected 50.0
Not Protected 50.0
Trade_Conventions
Yes 50.0
No 50.0
Shifting_cycle
Less than 3 50.0
More than 3 50.0
Soil_fertility
Low 51.0
High 49.0
LU_t1
Dense Plantation Clove 8.86
Housing 1.20
Mixed Agroforestry 24.5
Paddy Rice 13.2
Pasture 1.41
Pastures Cloves 0.74
Forest 10.4
Shifting Cultivation 38.6
Artisanal Mining 1.09
Cyclone
Yes 50.0
No 50.0
Irrigation_system
Not OK 48.2
OK 51.8
Water
Insufficient 64.0
Sufficient 36.0
Theft
Yes 50.0
No 50.0
Forest_clearing
Yes 50.0
No 50.0
Slope
Flat 28.2
Sloping 71.8
Pest
Yes 50.0
No 50.0
LU_t0
Dense Plantation Clove 2.47
Housing 0 +
Mixed Agroforestry 3.72
Paddy Rice 11.1
Pasture 0 +
Pastures Cloves 0 +
Forest 22.7
Shifting Cultivation 60.0
Artisanal Mining 0 +

b

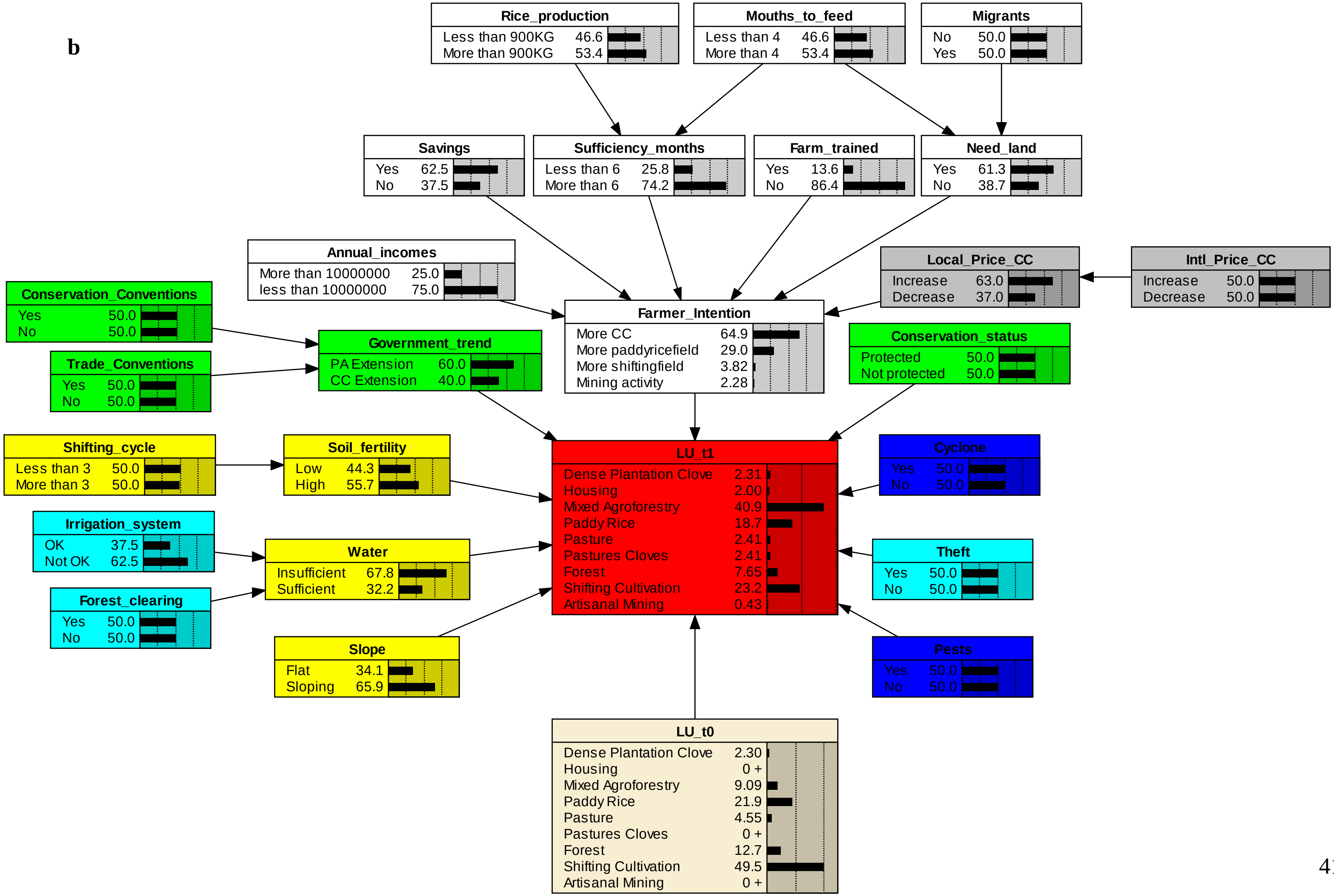

Rice_production
Less than 900KG 46.6
More than 900KG 53.4
Mouths_to_feed
Less than 4 46.6
More than 4 53.4
Migrants
No 50.0
Yes 50.0
Savings
Yes 62.5
No 37.5
Sufficiency_months
Less than 6 25.8
More than 6 74.2
Farm_trained
Yes 13.6
No 86.4
Need_land
Yes 61.3
No 38.7
Annual_incomes
More than 10000000 25.0
less than 10000000 75.0
Local_Price_CC
Increase 63.0
Decrease 37.0
Intl_Price_CC
Increase 50.0
Decrease 50.0
Conservation_Conventions
Yes 50.0
No 50.0
Farmer_Intention
More CC 64.9
More paddyricefield 29.0
More shiftingfield 3.82
Mining activity 2.28
Government_trend
PA Extension 60.0
CC Extension 40.0
Trade_Conventions
Yes 50.0
No 50.0
Conservation_status
Protected 50.0
Not protected 50.0
Shifting_cycle
Less than 3 50.0
More than 3 50.0
Soil_fertility
Low 44.3
High 55.7
LU_t1
Dense Plantation Clove 2.31
Housing 2.00
Mixed Agroforestry 40.9
Paddy Rice 18.7
Pasture 2.41
Pastures Cloves 2.41
Forest 7.65
Shifting Cultivation 23.2
Artisanal Mining 0.43
Cyclone
Yes 50.0
No 50.0
Irrigation_system
OK 37.5
Not OK 62.5
Water
Insufficient 67.8
Sufficient 32.2
Theft
Yes 50.0
No 50.0
Forest_clearing
Yes 50.0
No 50.0
Slope
Flat 34.1
Sloping 65.9
Pests
Yes 50.0
No 50.0
LU_t0
Dense Plantation Clove 2.30
Housing 0 +
Mixed Agroforestry 9.09
Paddy Rice 21.9
Pasture 4.55
Pastures Cloves 0 +
Forest 12.7
Shifting Cultivation 49.5
Artisanal Mining 0 +

Table A.1. Description of the Bayesian networks variables

Nodes	Categories	Definition	States
Land-Use t0	-	Current land-use	Dense Plantation Clove, Housing, Mixed Agroforestry, Paddy Rice, Pasture, Pastures Cloves, Forest, Shifting Cultivation, Artisanal Mining
Land-Use t1	-	Land-use after one time-step	
Farmer intention	Household's situation	Intention of farmer or household concerning his farm	More CC, More paddy rice field, More shifting field, Mining activity
Annual incomes	Household's situation	Household annual incomes agricultural or others, unity is Ariary	More than 10 000 000/ Less than 10 000 000

Savings	Household's situation	Whether households have savings during the year	Yes/ No
Sufficiency months	Household's situation	Number of months household finish its rice production	Less than 6/ More than 6
Rice production	Household's situation	Household annual production of rice	Less than 900 Kg/ More than 900 Kg
Mouths to feed	Household's situation	Number of household member to feed	Less than 4/More than 4
Farm trained	Household's situation	Whether household receive training or not on agriculture	Yes/ No
Need of land	Household's situation	Whether household need more arable land or not	Yes/ No
Migrants	Household's situation	Whether the household is migrant meaning not from the region	Yes/ No
Local price of cash crops	Economic	Local price of cash crops (vanilla, cloves)	Increase/Decrease

International price of cash crops	Economic	International price of cash crops	Increase/Decrease
Soil fertility	Biophysical situation	Fertility of soil	Low/High
Shifting cycle	Biophysical situation	Number of times successive shifting cultivation household did on the parcel	More than 3/Less than 3
Water	Biophysical situation	Availability of water on the plot	Insufficient/Sufficient
Irrigation system	Societal situation	State of irrigation system	OK/Not OK
Forest clearing	Societal situation	Existence of forest clearing upstream of the plot	Yes/No
Slope	Biophysical situation	Gradient state of the plot	Flat/ Sloping
Conservation status	Institution	Conservative status of the area	Protected/Not protected
Theft	Societal situation	Whether there is theft in the plot or not	Yes/No
Cyclone	Events	Whether the plot is hit by the cyclon	Yes/No
Pests	Events	Whether cultivation is ravaged by pests	Yes/No

Government trend	Institution	Current decision trend of the government	PA extension/ CC extension
Conservation conventions	Institution	Whether the government accept and sign conservation convention or not	Yes/No
Trade conventions	Institution	Whether the government accept and signed trade convention or not	Yes/No

Appendix B

List of references of literature and audio-visual material reviewed:

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Appendix C

Actors validated outputs following scenarios on price of cash crops (Increase and Decrease) and water availability (Sufficient or Insufficient). The following charts show validation results considering views of actors on three levels: Plot, Village, and Region levels. t1: corresponds to 2023 and t2 to 2030; n=number of validation participants.

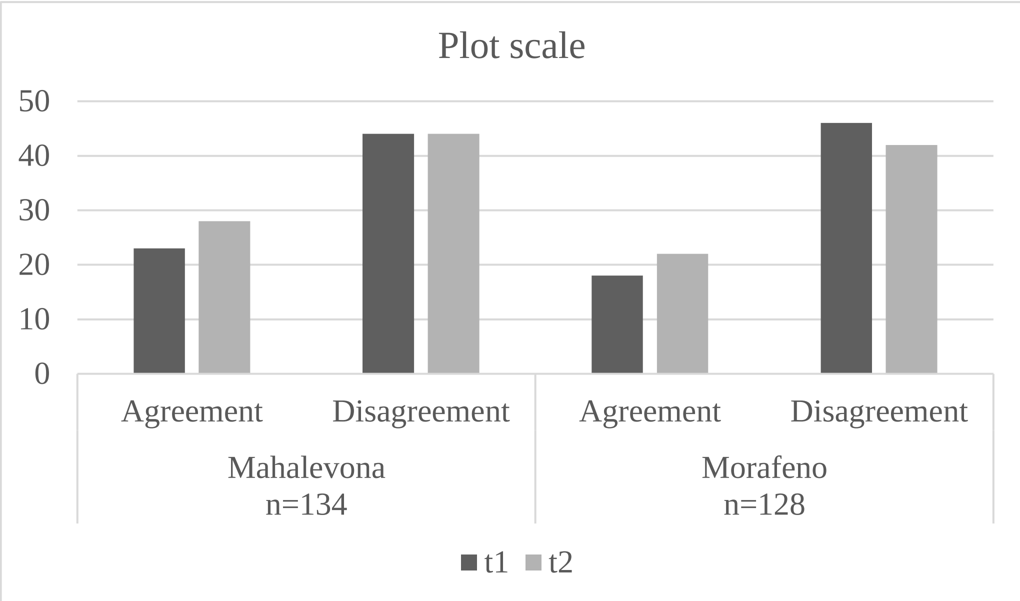

Figure. C.1. Plot level

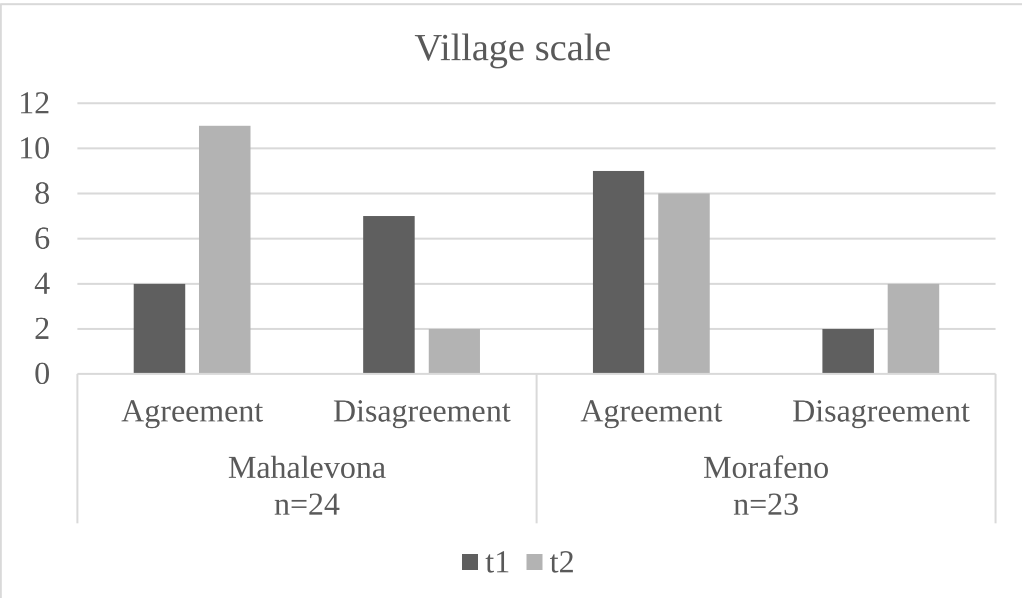

Figure. C.2. Village level

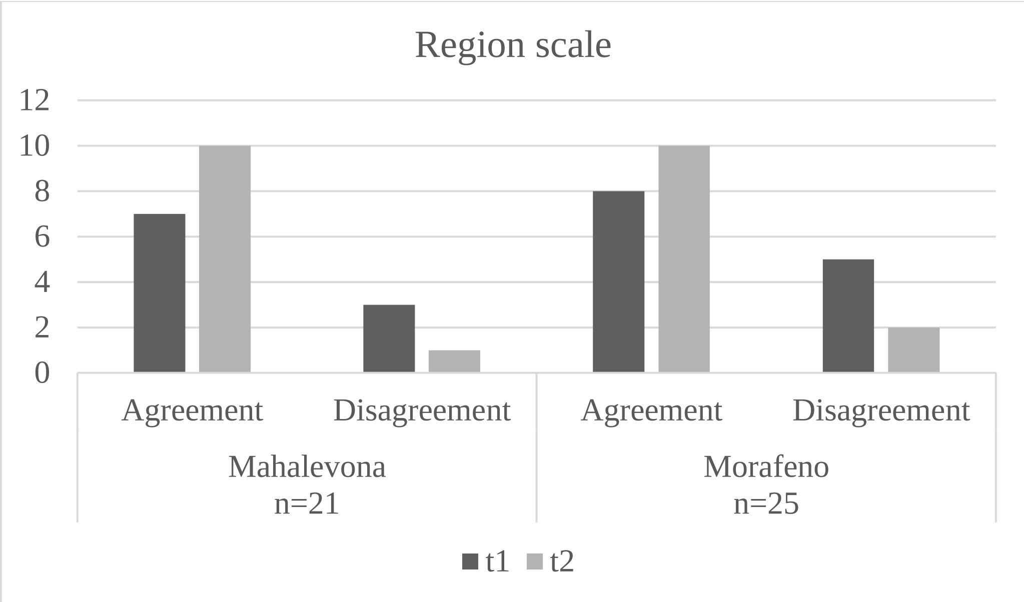

Figure. C.3. Region level

Appendix D

Reclassification of initial land-use categories for modeling (adapted from Llopis, J. *et al*., 2019)

Initial land-use categories	Modeled land-use categories
Clove plantation young **Clove from fallow** **Clove plantation dense**	Dense plantation of cloves (DP)
Shifting cultivation shrub-grass fallow **Forest degraded burned** **Shifting cultivation shrub fallow** **Shifting cultivation tree fallow** **Shifting cultivation, cultivated 2016** **Shifting cultivation grass fallow** **Shifting cultivation shrub-grass fallow**	Shifting cultivation (SC)
Clove plantation sparse, unmaintained **Multitree agroforest, open** **Multitree agroforest, close** **Clove-dominated agroforest** **Bamboo forest, separation between fields**	Mixed AgroForeStry (MAFS)
Dried irrigated rice fields **Irrigated rice fields**	irrigated paddy rice (PR)
Clove and pasture land	Pastures and cloves (PC)
Pasture with no trees **Pasture with trees (others than clove)**	Pastures (P)
Forest	Forest (F)
Population center, hamlet, isolated building	Housing (H)
-	Artisanal mining (AM)

Appendix E

Table E.1. Probability of change concerning shifting cultivation

LUt1	**Probability of LU in t=1**					
	Mahalevona			**Morafeno**		
Evidence	Lu t0 : Shifting cultivation	Lu t0 : Shifting cultivation Slope : flat	Lu t0 : Shifting cultivation Slope : Sloping	Lu t0 : Shifting cultivation	Lu t0 : Shifting cultivation Slope : flat	Lu t0 : Shifting cultivation Slope : Sloping
Dense Plantation of Clove	1.74	3.74	0.70	10.18	7.90	11.1
Housing	0.32	0.34	0.31	0.11	0.14	0.099
Mixed Agroforestry	***51.33***	***49.4***	***52.3***	26.02	34.4	22.7
Paddy Rice	1.87	4.88	0.31	5.85	16.3	1.74
Pasture	0.32	0.34	0.31	1.23	1.14	1.26
Pastures and Cloves	1.80	0.34	2.55	0.11	0.14	0.099
Forest	0.32	0.34	0.31	0.11	0.14	0.99
Shifting Cultivation	41.97	40.3	42.9	***56.28***	***39.7***	***62.8***
Artisanal Mining	0.32	0.34	0.31	0.11	0.14	0.099

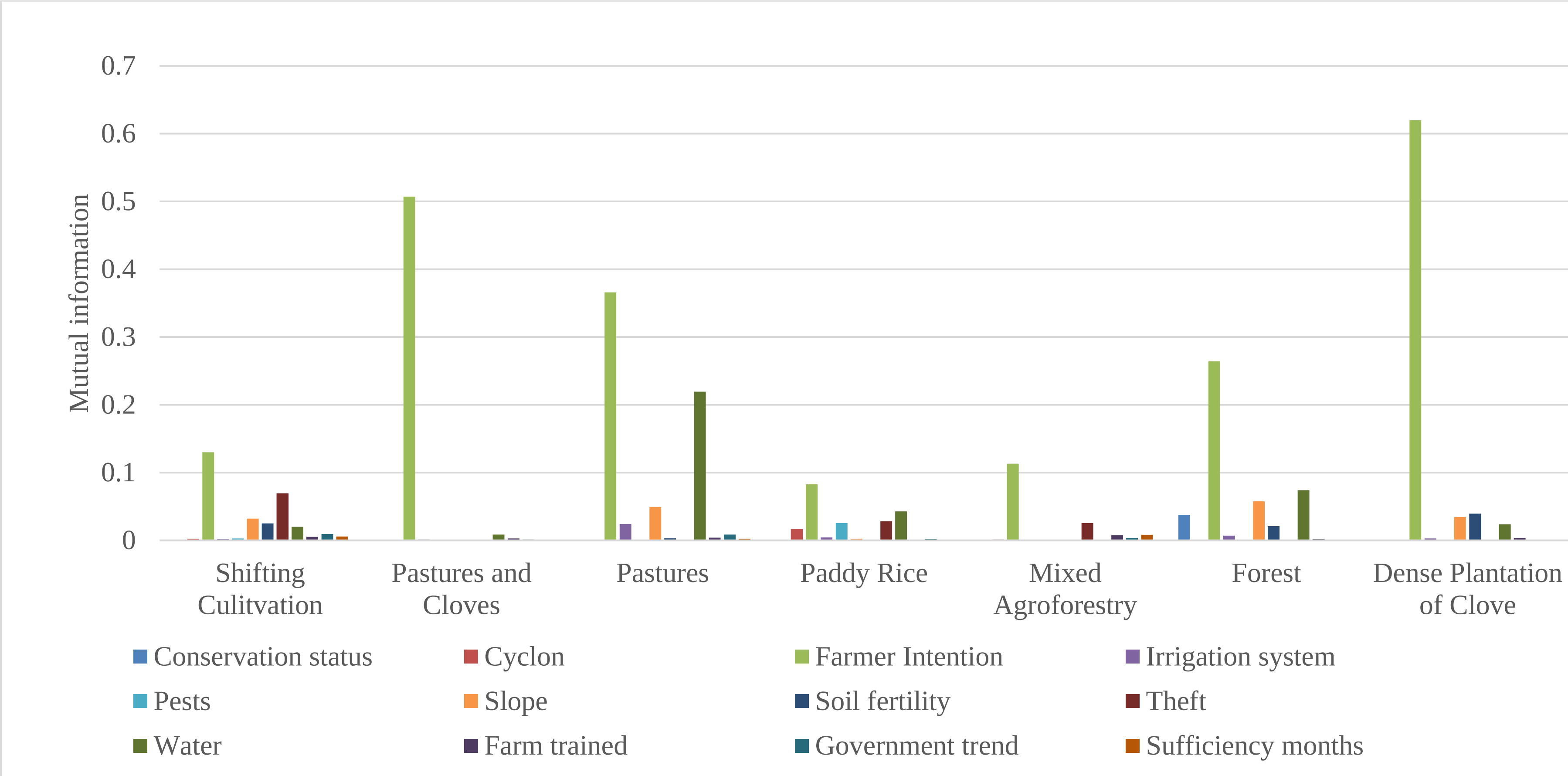

Figure. E.1.a. Importance of factors in terms of land-use at the northern site (Mahalevona)

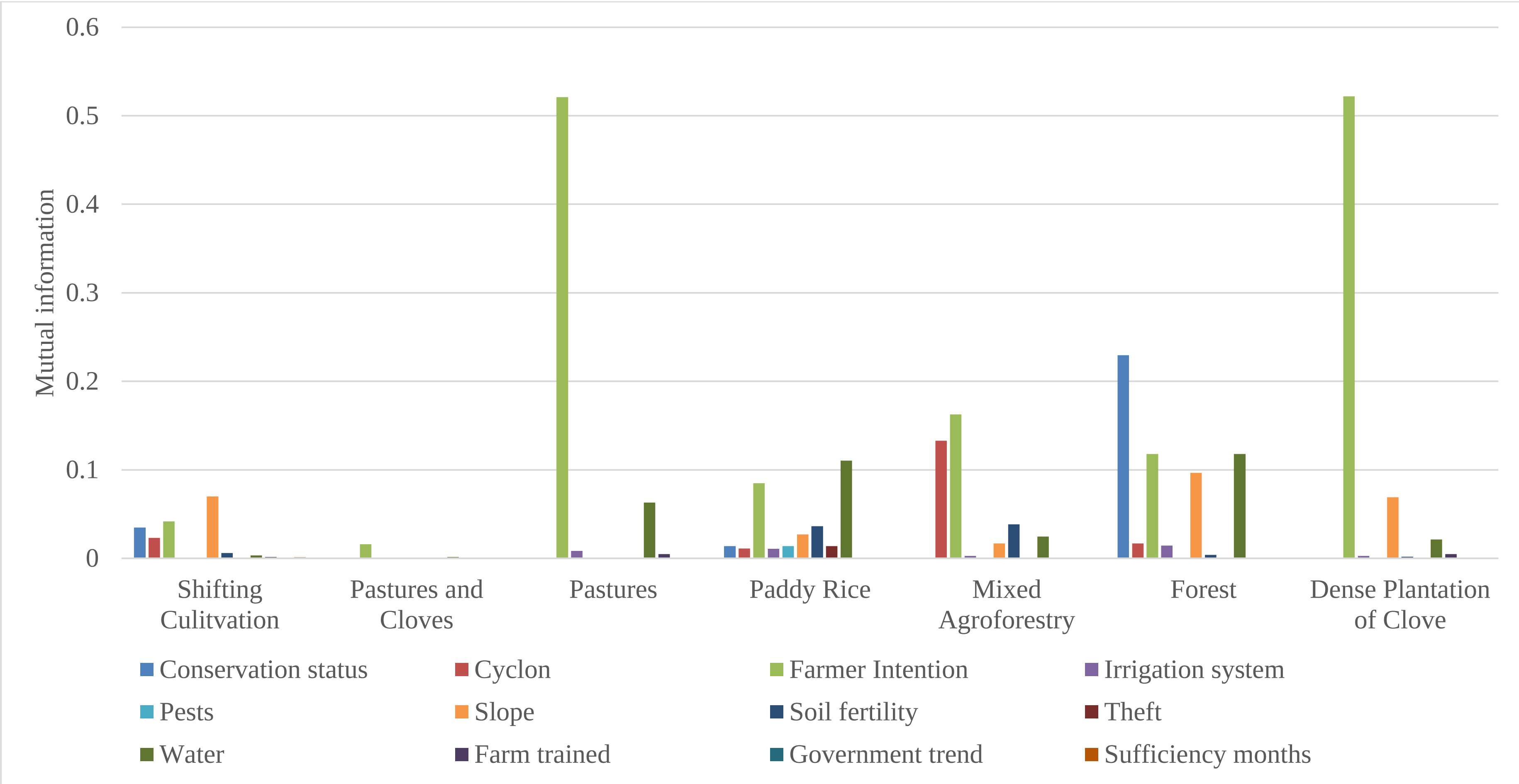

Figure. E.1.b. Importance of factors in terms of land-use at the southern site (Morafeno)