

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

Andriatsitohaina Ravosaina Ntsiva Nirinimanitra ^a (*Corresponding author*)

ntsiva_intel@yahoo.fr

Celio Enrico ^b

ecelio@ethz.ch

Llopis Jorge Claudio ^c

jorge.llopis@cde.unibe.ch

Rabemananjara Zo Hasina ^a

zorabema@hotmail.com

Ramamonjisoa Bruno Salomon ^a

bruno.ramamonjisoa@gmail.com

Grêt-Regamey Adrienne ^b

gret@ethz.ch

^a *Mention Foresterie et Environnement, Ecole Supérieure des Sciences Agronomiques, Université d'Antananarivo, BP 175, Antananarivo 101, Madagascar*

^b *Planning of Landscape and Urban Systems (PLUS) - Institut für Raum- und Landschaftsentwicklung (IRL), ETH Zürich, HIL H 51.3, Stefano-Frascini-Platz 5, CH-8093 Zürich, Switzerland*

^c *Centre for Development and Environment (CDE), University of Bern, Mittelstrasse 43 CH-3012 Bern, Switzerland*

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1 **Participatory Bayesian network modeling to understand driving**
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3 **northeast Madagascar**

4

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

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

21 **1. Introduction**

22 Land cover and land-use change are among the most important drivers of global change,
23 impacting ecosystems and ultimately their capacity to supply ecosystem services
24 (Lambin *et al.*, 2001; de Groot, Wilson, and Boumans, 2002; Turner, Lambin, and
25 Reenberg, 2007). Several indicators that monitor progress toward achieving Sustainable
26 Development Goal 15 (SDG 15) (United Nations, 2018) —protect, restore, and promote
27 sustainable use of terrestrial ecosystems; sustainably manage forests; combat
28 desertification; and halt and reverse land degradation and halt biodiversity loss—show

1 an improvement in forest protection measures. However, the indicators also show a
2 decline in forest area and its productivity (United Nations, 2018). Currently,
3 deforestation remains the most significant land-use change in tropical countries,
4 generally resulting from commercial agricultural, subsistence, and mining activities, but
5 also from urban expansion and infrastructure construction (Geist and Lambin, 2001;
6 Swenson *et al.*, 2011; Hosonuma *et al.*, 2012; Sontter *et al.*, 2015; Garrett *et al.*, 2018).
7 In tropical regions, forests are converted into shifting cultivation and export-oriented
8 crops, causing a loss of valuable forest goods, of support and regulation services, and of
9 the provision of cultural and aesthetic benefits (Kull, 2000; Moser, 2008; Gibbs *et al.*,
10 2010). For the case of Madagascar, shifting cultivation is still an important land-use
11 practice in forested areas (Styger *et al.*, 2007; Waeber *et al.*, 2015) that remains the
12 main land-use change in rural areas. Land-use change research shows that shifting
13 cultivation expanded in northeast Madagascar between 1990 and 2017, as this practice
14 ensured rice production in the area (Llopis *et al.*, 2019).

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

1 sustainable land management for fulfilling the SDG 2030 targets (United Nations,
2 2018).

3 Land-use models are often used to better detangle the complexity of factors defining
4 choices in land-use decisions (Rindfuss *et al.*, 2008; Noszczyk, 2018). Bayesian
5 networks model represents causal relationships through their directed acyclic graph,
6 combining empirical data from different sources (statistics, reports, other models, etc.)
7 with expert knowledge (Aalders and Aitkenhead, 2006; Marcot *et al.*, 2006; Celio,
8 Koellner, and Grêt-Regamey, 2014). As Bayesian networks are based on probability
9 theory, they handle uncertainty, particularly when there is lack of data about the system
10 (Cain, 2001; Kocabas and Dragicevic, 2007; Uusitalo, 2007). Bayesian networks have
11 been used to understand causal relationships in water resources management (e.g.,
12 Bromley, 2005; Castelletti and Soncini-Sessa, 2007; Zorrilla *et al.*, 2010), wildfire
13 expansion (e.g., Dlamini, 2010), ecosystem services assessment (e.g., Sun and Müller,
14 2013; Landuyt, Broekx, and Goethals, 2016; Shaw *et al.*, 2016), biodiversity
15 conservation and management (e.g., Marcot *et al.*, 2001, 2006; Pollino *et al.*, 2007;
16 Ticehurst *et al.*, 2007), and the agricultural sector (e.g., Pérez-Miñana, Krause, and
17 Thornton, 2012). Aalders (2008) used Bayesian networks to model decisions and
18 behavior of land managers as drivers of land-use change in mountain regions of
19 Scotland. Bashari *et al.* (2009) developed decision support tools for rangeland
20 management using Bayesian networks in Queensland, Australia. Celio *et al.* (2014)
21 modeled effects of land-use decision-making in a spatially explicit manner using
22 Bayesian networks in a pre-alpine area of Switzerland.

23 In this contribution, we investigate the influence of the combined effect of biophysical
24 and socioeconomic factors driving land-use change decisions in the forest frontier

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

9 **2. Methods**

10 ***2.1. Conceptual framework and terminology***

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

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

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

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

13 **2.2. Study sites**

14 Madagascar is a “hotspot” of biodiversity because it is a tropical country where
15 5% of the world’s biodiversity resides, but also where natural resource degradation is
16 increasing, including a rapid annual deforestation rate of 0.5% from 2000 to 2010
17 (Myers *et al.*, 2000; Lambin, Geist, and Lepers, 2003; Wilmé, Goodman, and Ganzhorn,
18 2006; Office National pour l’Environnement *et al.*, 2013). On the occasion of the Vth
19 World Parks Congress in Durban, South Africa, in 2003, Madagascar committed to
20 increase the total size of protected areas from 1.7 million hectares to 6 million hectares
21 over the next five years to guarantee conservation of the unique biodiversity of the
22 world’s fourth largest island (Terborgh, 2004; Ratsirarson, 2006). However, about
23 36,000 hectares of natural forests were lost each year in Madagascar between 2005 and
24 2010. The rate of annual deforestation within Protected Areas (PAs) managed by the

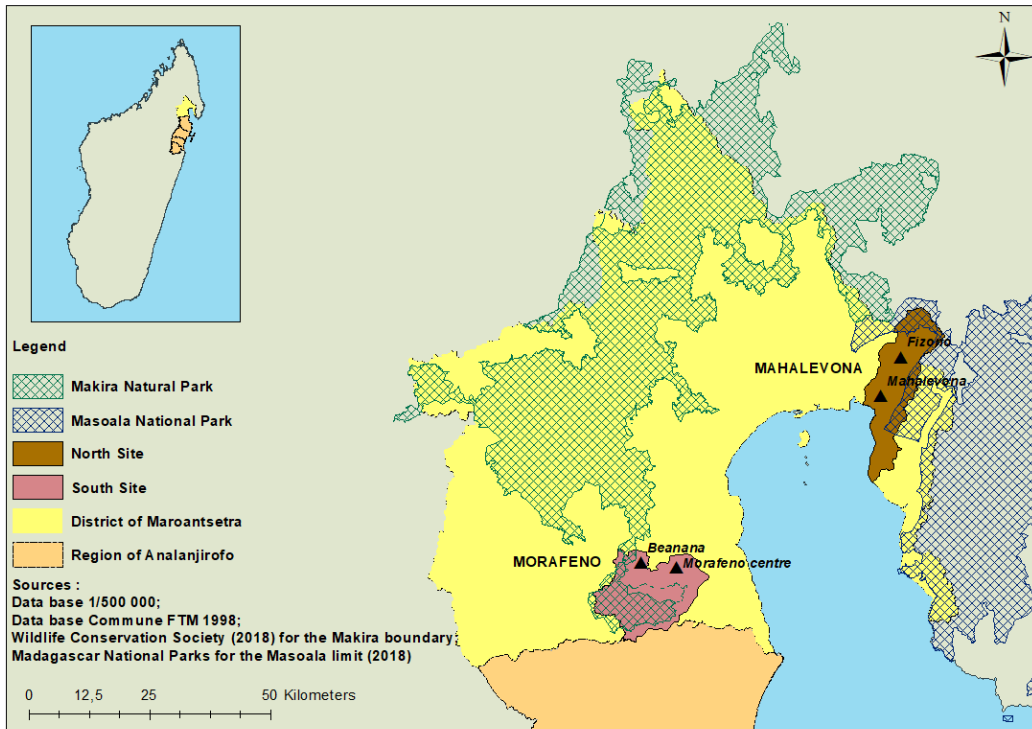
1 Madagascar National Parks has been 0.2%, which is half of the national rate (Harper *et*
2 *al.*, 2007; Office National pour l'Environnement *et al.*, 2013).

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

9 This study was carried out in northeast Madagascar in two forest frontier sites. Each is
10 composed of two villages within the District of Maroantsetra, Region of Analanjirofo.

11 The northern study site included the villages of Mahalevona and Fizono, and the
12 southern one the villages of Morafeno and Beanana (Figure 1). The southern site (the
13 Morafeno commune) is located on hilly land near Makira Natural Park, characterized by
14 a steep and rugged relief, while the northern site (the Mahalevona commune) lies in a
15 downstream plain with low hills further northeast toward the forest of Masoala National
16 Park (Andriamanana, 2014; Rakotoarison, 2014).

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



1
2 Figure 1: Case study area: northeast Madagascar.
3

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

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

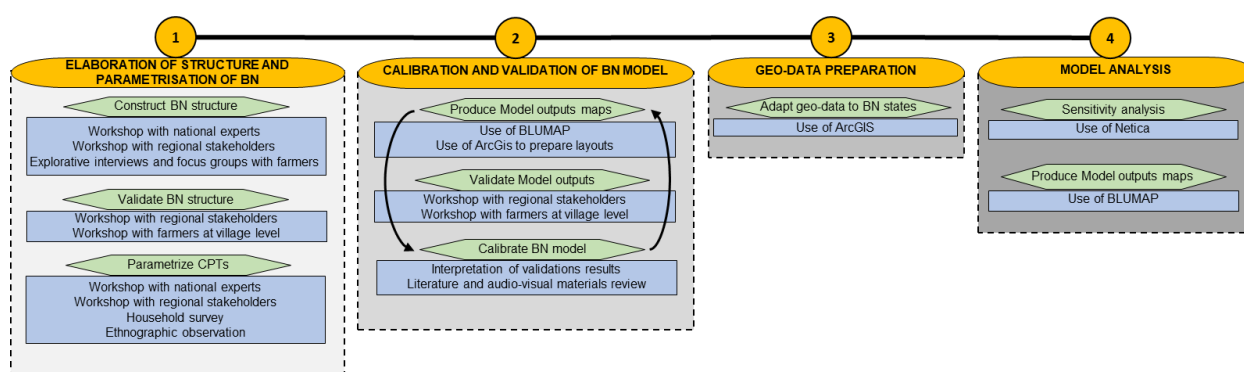
1 Compared to the central highlands of Madagascar, where economic and demographic
2 factors such as population growth, state policies, market incentives, and access to land
3 and water resources have been identified as important factors for the conversion of
4 forest into cultivated area (Kull, 1998,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

11 ***2.3. Bayesian network-based land-use decision modeling approach***

12 A Bayesian network consists of three elements: nodes as variables, arrows, which
13 represent causal links between the nodes, and conditional probability tables (CPTs),
14 quantifying the strength of two or more nodes' connection (Neapolitan, 2003; Kjærulff
15 and Madsen, 2008; Korb and Nicholson, 2010). In the present study, we used the
16 available participatory Bayesian network-based Land-Use Modeling Approach
17 (BLUMAP), which was developed to help conceptualize and parameterize the model in
18 collaboration with concerned actors and stakeholders. Celio, Koellner, and Grêt-
19 Regamey (2014) used this approach to take into account biophysical factors and local
20 actors' decisions influencing land-use change and to represent uncertainties of land-use
21 changes in a spatially explicit manner. A spatially explicit model refers to a model that
22 combines a model with land-use maps and other related ecological and socioeconomic
23 geodata related to land-use decision-making (Dunning *et al.*, 1995; Noszczyk, 2018).
24 The network is used to calculate posterior probabilities for each land-use category on

1 each raster cell. Thus, the Bayesian network is updated by our current state of
 2 knowledge (e.g., the slope of a location or the status of a regulation for the site), and the
 3 posterior probabilities determine future land use. Biophysical factors such as slope will
 4 remain constant. However, comparing their importance to other factors driving land-use
 5 change and including their effect for each location separately help analyze land-use
 6 change decision-making.

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



13
 14 Figure 2: Participatory Bayesian network-based Land-Use Modelling Approach
 15 (BLUMAP) adapted for the case study context.

16 2.3.1. Elaboration process of the BN

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

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

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

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

21 We parametrized the Bayesian network CPTs using different sources of data. (a) To
22 include the diversity of the decisions made by individual farmers, we conducted a
23 household survey from November to December 2016 at both sites (Table 2). We
24 interviewed 35 household heads at the northern site and 36 at the southern site. Then,

1 we designed case files using 173 cases at the plot level obtained from the household
2 survey and used the expectation-maximization (EM) learning algorithm provided by
3 Netica to populate the CPTs. This algorithm is a robust method for performing
4 maximum likelihood estimation on the parameters from incomplete data sets (Zou and
5 Yue, 2017). (b) During a stakeholder workshop at the regional level, we conducted a
6 scenario exercise we called an “imagine exercise” that used little stories, which aimed
7 to obtain data to populate complicated nodes with more than two parent nodes (Cain,
8 2001). (c) We observed the farmers’ daily activities and behavior during our fieldwork
9 to verify the rationale behind decision of change. (d) We conducted semi-structured
10 interviews with experts in soil sciences and hydrology from ESSA-Forêts (University of
11 Antananarivo), which helped fill the CPTs of the intermediary nodes “soil fertility” and
12 “water”. (e) Finally, we conducted a review of the literature and audiovisual materials
13 (see Appendix B) to get insights into the change from forest to other land-use categories
14 and the importance of the driving factors of this particular process.

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

24

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

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

2 2.3.2. *Iterative process for calibrating and validating the model*

3 Using preliminary land-use change scenarios, we conducted a qualitative validation

4 process during workshops, where stakeholders informed us about the relevance of the

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

14 The results gained we source from the target node LU_{t1} that shows the probability of
15 occurrence of each land-use category after a decision period. To represent path
16 dependency, one determining factor of LU_{t1} is LU_{t0} that represents the land-use at
17 the beginning of the decision period (see Appendix A, Figure. A.1). Results showed that
18 the developed Bayesian network model represented a group view of farmers. At the
19 plot-specific level, (see Appendix C, Figure. C.1) and from the individual farmers’
20 perspectives (allocation measure), local actors agreed only partly with the proposed
21 land-use changes. However, on a generic level, with group consensus at the village level
22 (dynamic measure), the local actors widely agreed with proposed land-use changes
23 pathways (see Appendix C, Figure. C.2), and similarly at the regional level (see
24 Appendix C, Figure. C.3).

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

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

16 *2.3.3. Geodata preparation*

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

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

10 2.3.4. Sensitivity analysis

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

$$18 \quad I(X, Y) = H(X) - H(X|Y) \quad (1)$$

$$19 \quad I(X, Y) = \sum_{n=0}^x \sum_{n=0}^y P(x, y) \log\left[\frac{P(x, y)}{P(x)P(y)}\right] \quad (2)$$

20 where $H(X)$ is the entropy, and $H(X|Y)$ is the entropy of X given an observation on Y .
21 Lowercase indicates the actual instantiation, and $P(x, y)$ reflects the joint probability of
22 finding X and Y (Kjærulff and Madsen, 2008; Norsys, 2011). It has values between 0
23 and 1, where 1 denotes a uniform distribution between all possible states (maximum

1 uncertainty), and 0 denotes complete certainty about the state of the target node.

2 2.3.5. Production of Bayesian network model output maps

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

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

15

1 **3. Results**

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

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

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

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

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

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

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

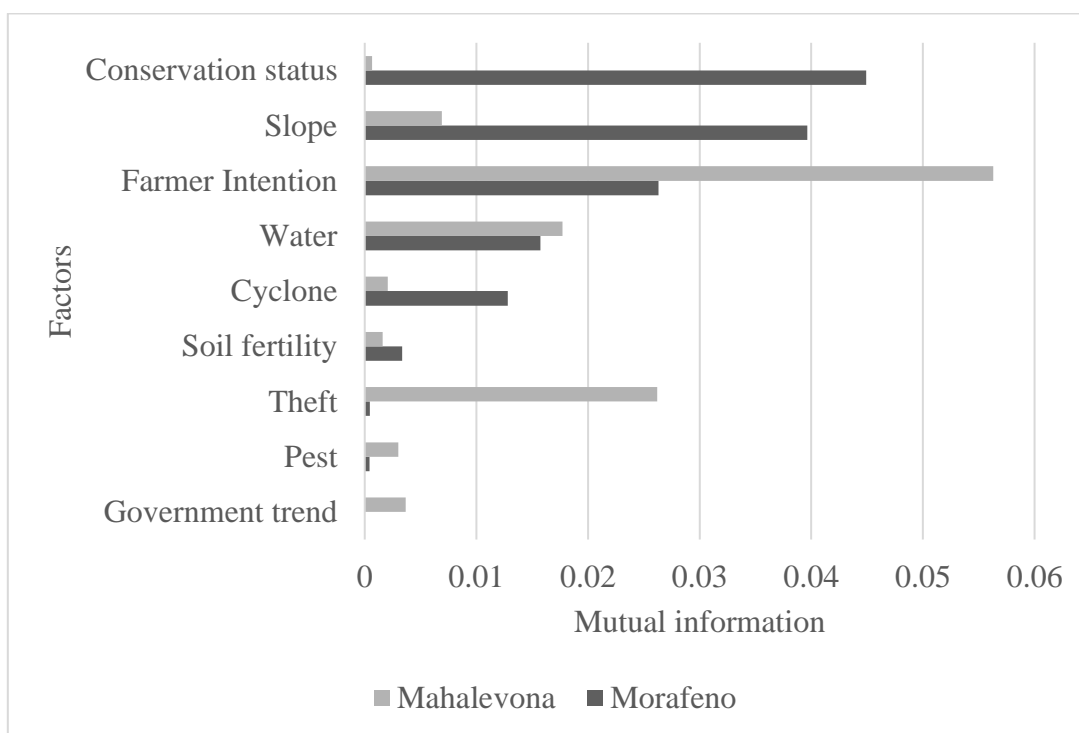
16 ***3.1. Relative importance of factors driving land-use change decisions***

17 Based on the two developed Bayesian networks (see Appendix A, Figure. A.1 and
18 Table A.1), we identified the importance of biophysical and socioeconomic factors in
19 the farmers' decision-making. While the farmers' intention (Mutual Information, $I =$
20 0.06) is driving land-use change at the northern site (Mahalevona), land-use change at
21 the southern site (Morafeno) is most sensitive to the presence of the conservation area
22 (Mutual Information, $I = 0.04$; Figure 3). Contextually, the northern site (Mahalevona)
23 provides important opportunities for cash crop cultivation, as the terrain is flatter than at

1 the southern site (Morafeno) where features hilly and upland areas. In contrast, at the
2 southern site (Morafeno), the protected area forces farmers to optimize their remaining
3 cultivated area to cover minimal needs. Theft is also an important driver of land-use
4 change in northeast Madagascar, and even more important at the northern site
5 (Mahalevona; $I = 0.02621$) than at the southern site (Morafeno; $I = 0.00040$) (Figure 3).
6 According to the farmers living in the northern site (Mahalevona), despite thefts on their
7 plots, the farmers keep planting cash crops and even expand the mixed agroforestry
8 systems to compensate for their losses. The process is also spurred by the soaring
9 vanilla prices.

10 Slope is a much more important factor of land-use change at the southern site
11 (Morafeno) than at the northern site (Mahalevona) (Figure 3). The flatter topography at
12 the northern site (Mahalevona) allows farmers to establish irrigated paddy rice fields or
13 to cultivate other crops, such as vegetables. Due to hilly land constraints, at the southern
14 site (Morafeno) farmers keep producing rice in shifting cultivation systems. Although
15 both sites are located in forest frontier contexts, the large flat areas at the northern site
16 (Mahalevona) allow farmers to cultivate irrigated paddy rice fields in addition to
17 shifting cultivation (Figure 3). This is not the case at the southern site (Morafeno),
18 which has a more rugged terrain, and only a few farmers own small-scale paddy rice
19 fields. Thus, rice is produced mostly through shifting cultivation. This reason explains
20 why the value of probability of shifting cultivation in the Bayesian network target node
21 LU_{t1} (see Appendix A, Figure. A.1 a and b) at the southern site (Morafeno) is higher
22 (prior probability $P=38.6\%$) than at the northern site (Mahalevona) (prior probability
23 $P=23.2\%$).

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

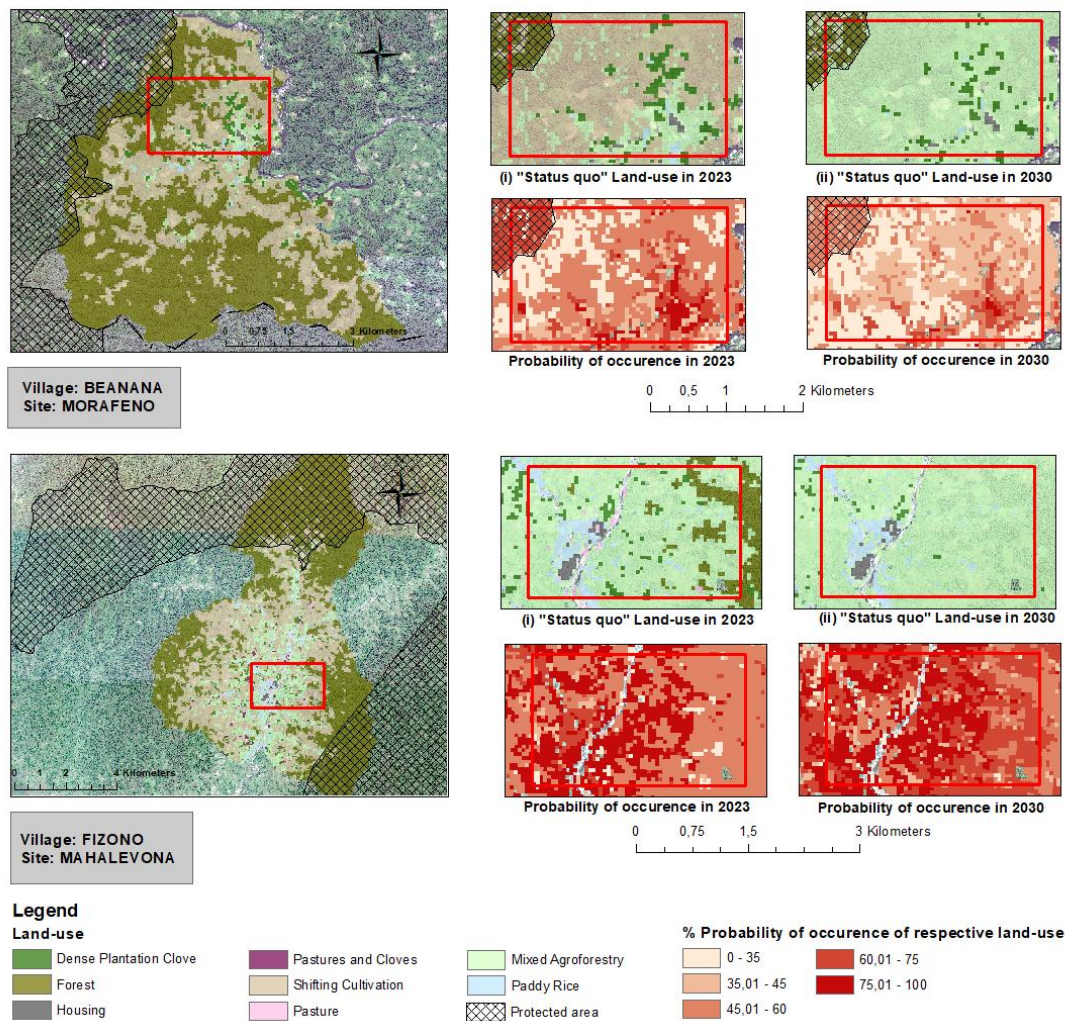


12
 13 Figure 3: Sensitivity of land-use change to various societal, economic, and biophysical
 14 factors. LU_tI is the target node. Values are given in terms of Mutual Information (I).
 15 Only factors whose difference of (I) values between the two sites are higher than 0.001
 16 are shown.

1 **3.2. Dynamics of shifting cultivation**

2 Focusing on factors driving changes from the land-use category shifting cultivation to
3 other categories, Farmer intention was the most important factor at the northern site
4 (Mahalevona). In contrast, the factor Slope outweighed the others at the southern
5 (Morafeno) (see Appendix E, Figure. E.1 a, and b). In addition, we found that the
6 dynamics of shifting cultivation differs between the sites. That is, shifting cultivation is
7 more persistent at the southern site (Morafeno) than at the northern site (Mahalevona).
8 In technical terms, we put hard evidence on “Shifting cultivation” of LU_{t0} to
9 determine the probability of occurrence of LU_{t1} . While at the southern site (Morafeno)
10 after a time step of five to seven years, shifting cultivation remains shifting cultivation
11 ($P = 56.28\%$), at the northern site (Mahalevona), the land use with the highest
12 probability is the mixed agroforestry system ($P = 51.33\%$). Shifting cultivation is
13 converted into mixed agroforestry systems for planting mainly vanilla and cloves (see
14 Appendix E, Table E.1). The change of shifting cultivation, thus, is slower at the
15 southern site (Morafeno) than at the northern site (Mahalevona). At the southern site
16 (Morafeno), the change of shifting cultivation into mixed agroforestry takes ten years,
17 while it takes only four years at the northern site (Mahalevona).

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



1
 2 Figure 4: As the model is spatially explicit, these maps show various land-uses with
 3 respect to their probability of occurrence in 2023 and 2030 for the village Beanana (part
 4 of the southern site Morafeno) and the village Fizono (part of the northern site
 5 Mahalevona).

6

7 **4. Discussion**

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

1 of this land-use change.

2 Farmers' decisions are highly dependent on their households' economic situations. At
3 the two case study sites, slope and water availability are among the most important
4 factors for land-use change, which match the current understanding that these
5 biophysical factors highly influence the type of crops farmers adopt (Ramboatiana *et*
6 *al.*, 2018). Delineation of a protected area can ultimately determine farmers' decisions,
7 which supports the concept that rules and institutions regulating land -use influence
8 land-use change (Irwin and Geoghegan, 2001; Ramboatiana *et al.*, 2018; Llopis *et al.*,
9 2019).

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

23 Farmer intention is less important than conservation status of the area in the southern

1 site (Morafeno). The farmers' intention can, also be overruled by institutional decisions,
2 when agricultural land is placed under conservation, as shown by other authors (Lambin
3 and Meyfroidt, 2011). The implementation of such protected areas is often driven by
4 distant decisions at the national government level, even internationally (Andriamihaja *et*
5 *al.*, 2019) through a top-down process (Scales, 2014), often ignoring the socio-
6 ecological context (Gardner *et al.*, 2018). The Masoala National Park was created in
7 1997, but the expansion of protected areas in Morafeno is the result of the Malagasy
8 government's policy since the Vth World Parks Congress in Durban, South Africa in
9 2003, during which the government committed to triple the surface of protected areas.
10 The influence of conservation status are apparent not only in the land-use management
11 at the boundaries of the parks but also in the agricultural training of farmers, which
12 encourages them to adopt alternatives in exchange for their commitment to stop "tavy"
13 (Brimont *et al.*, 2015). As a result, farmers act and adapt their use of land according to
14 the situation. Constraints due to the protected area boundaries at the southern site
15 (Morafeno) influence farmers to reuse the land. This last observation confirms the idea
16 that farmers might intensify their shifting cultivation (Brimont *et al.*, 2015) and convert
17 the remaining non-protected forests not only to increase their rice production but also
18 out of fear of losing the legitimate property of the land, because traditionally whoever
19 clears the land owns it (Andrianirina-Ratsialonana and Burnod, 2012).

20 The rate of change to shifting cultivation is dependent on the biophysical factors and
21 household situation of a site. At the southern site (Morafeno), expansion of shifting
22 cultivation is observed, and previous shifting cultivation is still maintained for one more
23 time step (2023), which is not occurring at the northern site (Mahalevona) where
24 shifting cultivation becomes very rare after one time step. The spatially explicit model

1 outputs showed differences in terms of timing of land-use change between the sites
2 while expansion of the mixed-agroforestry system is generalized at the two sites. This
3 last observation may partially distort the idea that shifting cultivation would remain the
4 main use of land in northeast Madagascar (Heinimann *et al.*, 2017). We hypothesize
5 that conservation regulations influence not only decision-making (see above), but also
6 the dynamics. Due to the implementation of conservation restrictions for the Makira
7 Protected Area, farmers at the southern site have difficulty finding new plots to cultivate
8 because they are not allowed to clear new fields. This might slow the speed of land-use
9 change and lead the farmers to maintain the same land-use, here shifting cultivation, on
10 the same plots until soil fertility decreases which is still consistent with the results that
11 conservation restrictions may shorten the fallow periods for “jinja” resulting in
12 decreased fertility (Brimont *et al.*, 2015).

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

1 Thus, to secure sustainable land in forest frontiers, land management strategies should
2 consider biophysical, societal, institutional factors and household intention. The results
3 of this study can support rural territory planning and management by providing
4 information about key factors of local decision-making and future development of the
5 landscape of Maroantsetra. The participatory setup process and the resulting maps are
6 means to the end to support participatory land-use planning processes. Tools for
7 supporting such processes using, for example, visualizations help rationalize strategic
8 planning such as the national project “Projet Agriculture Durable par une Approche
9 Paysage (PADAP)”. This project, a national cross-sectoral project underway since 2018,
10 aims to increase agricultural productivity while sustainably managing natural resources
11 in five landscapes in northwest and east of Madagascar by designing development and
12 management plans for these landscapes as a the first step. It did not include the
13 landscape of Maroantsetra (Ministère de l’Agriculture de l’Elevage et de la Pêche,
14 2018), however, future similar project in the northeast Madagascar could rely on results
15 of this study.

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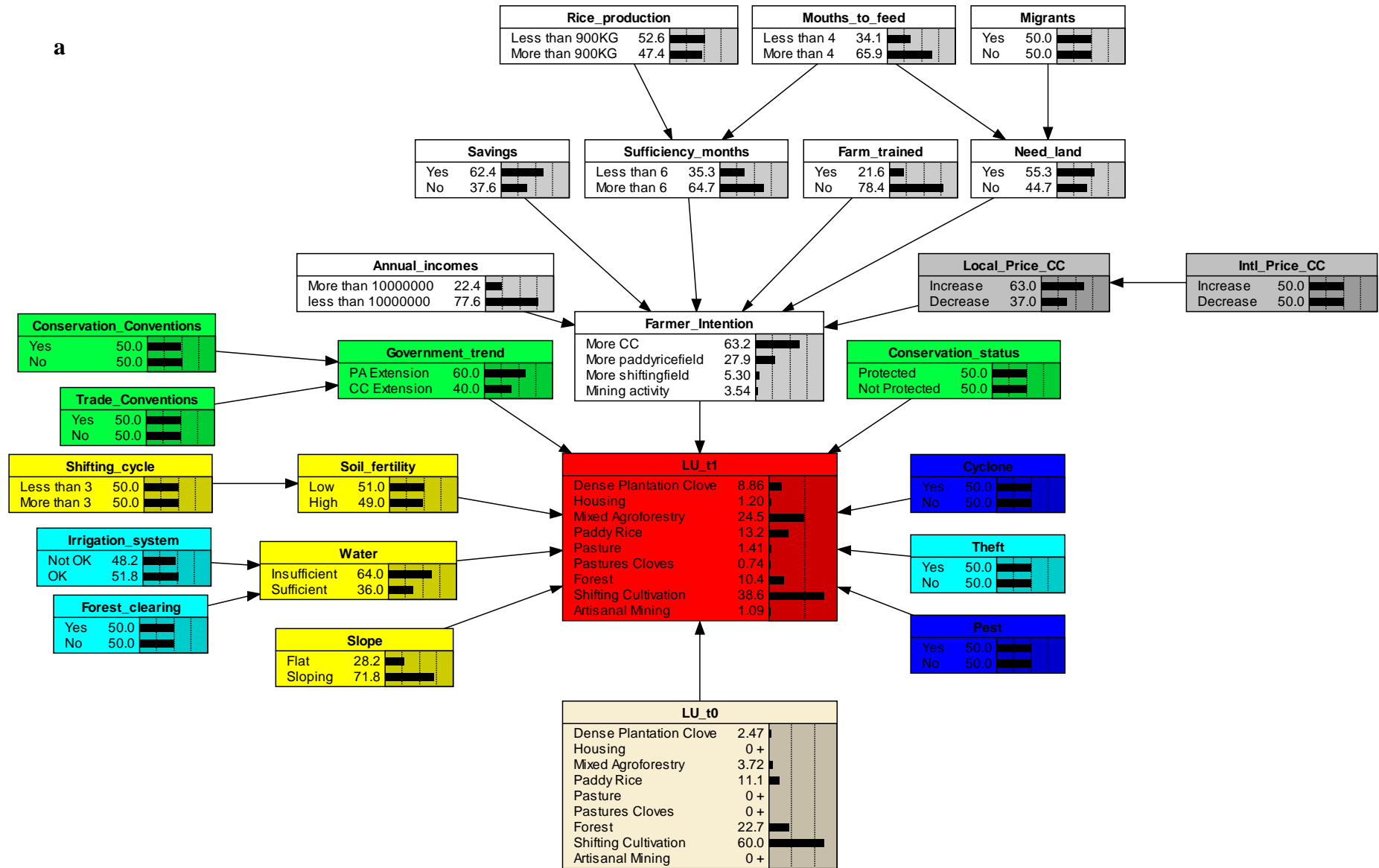
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Appendices

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



b

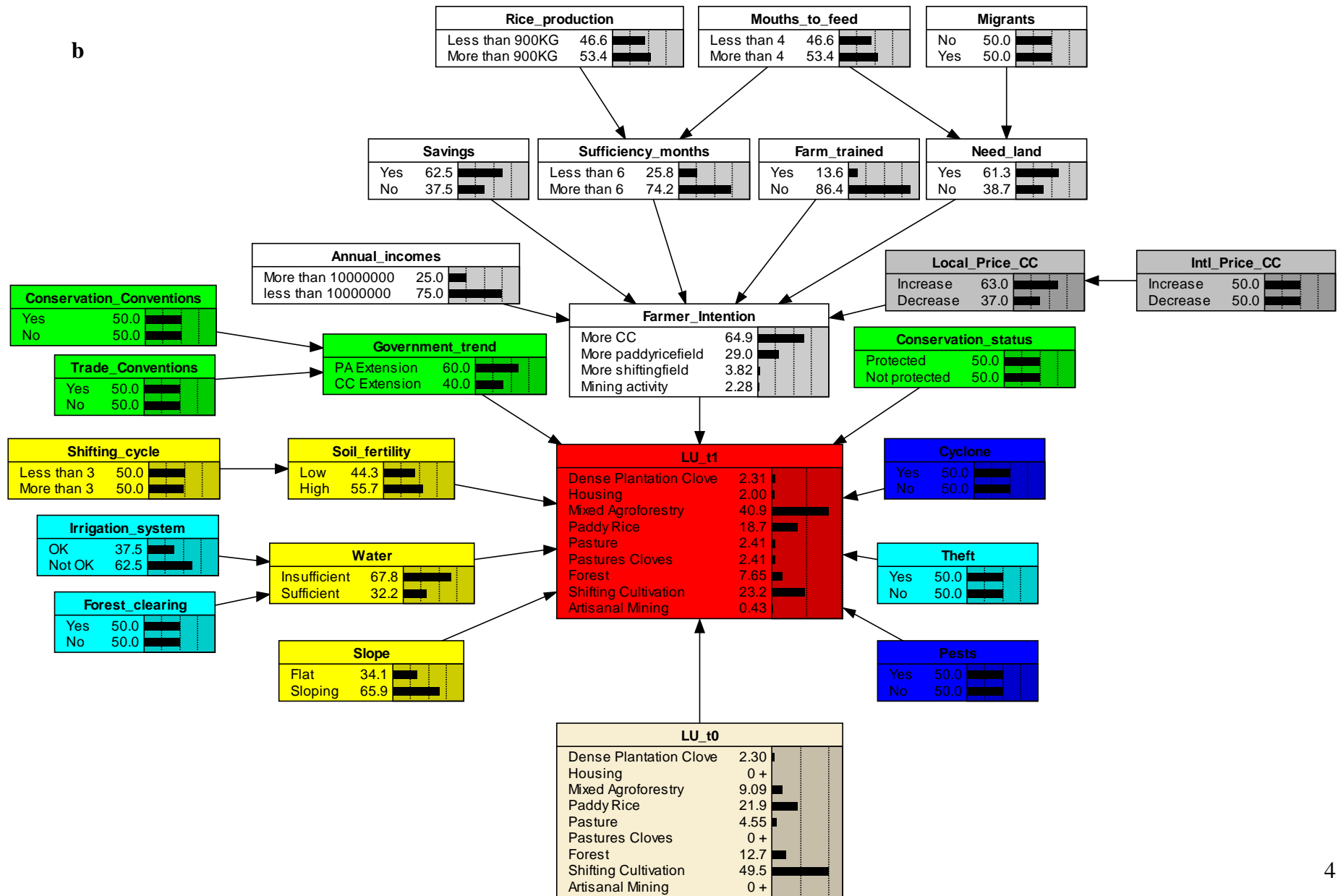


Table A.1. Description of the Bayesian networks variables

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

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

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

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

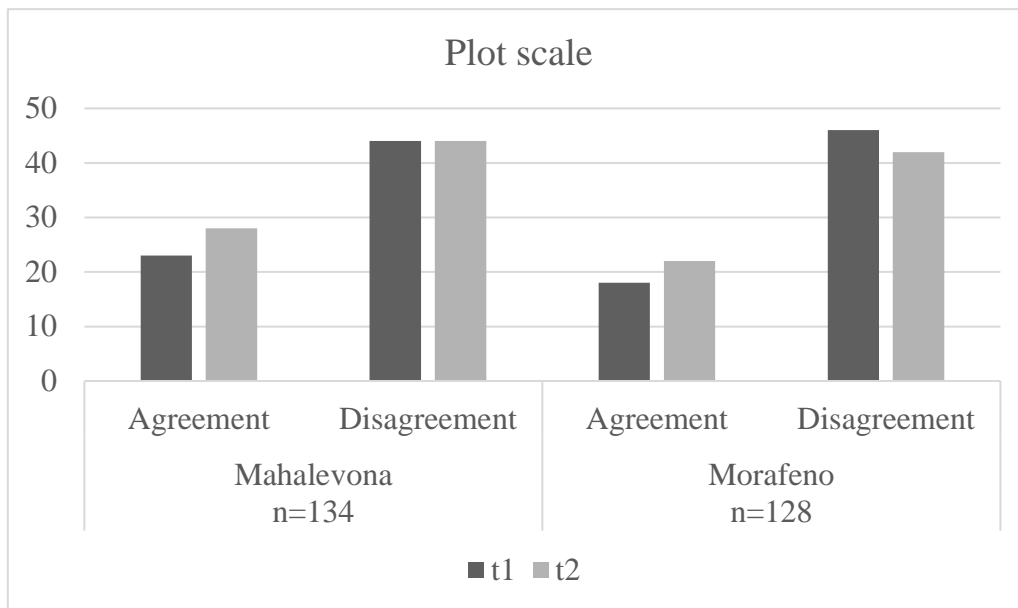


Figure. C.1. Plot level

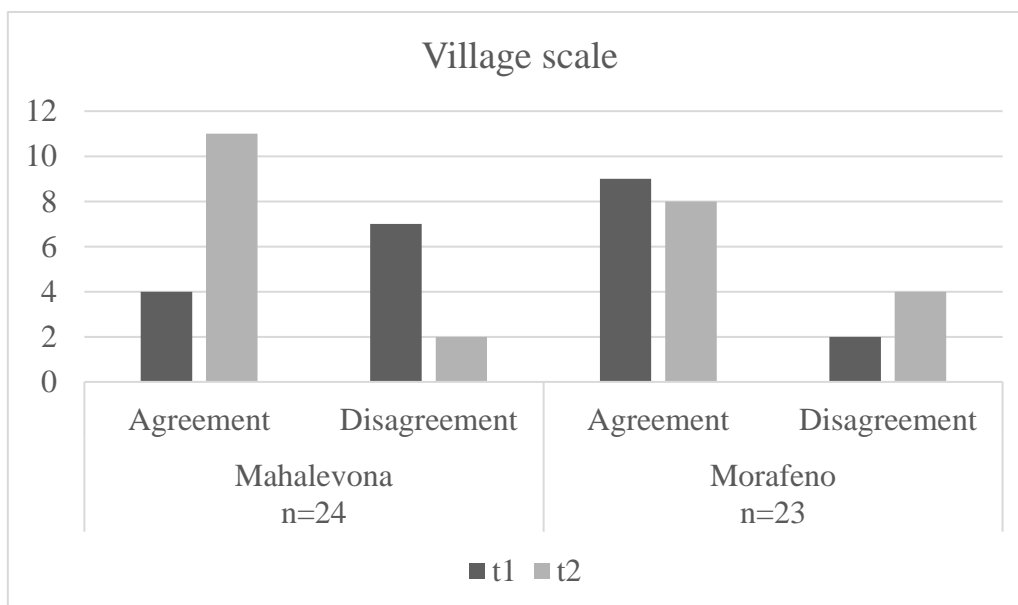


Figure. C.2. Village level

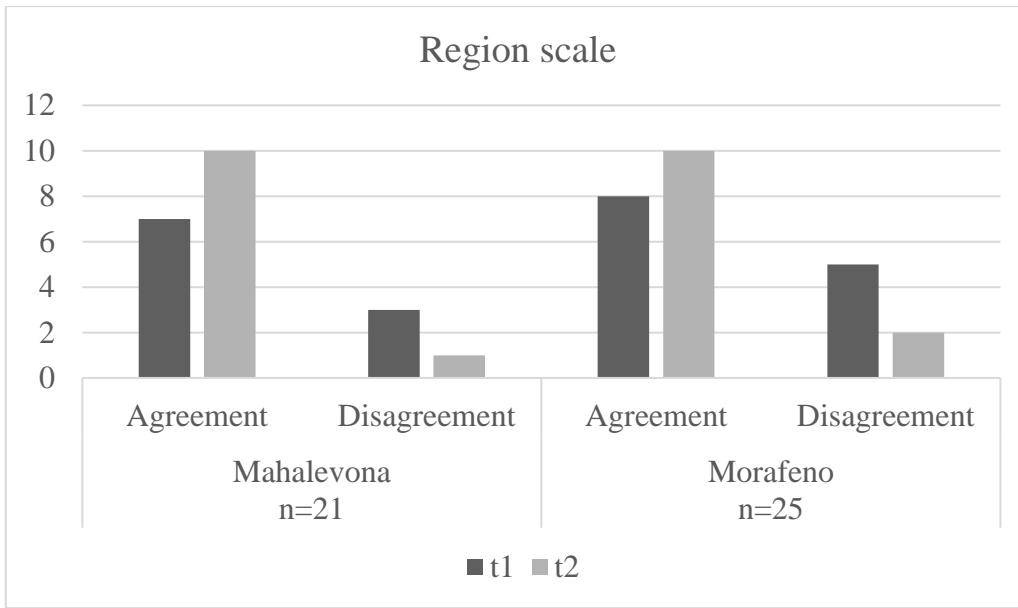


Figure. C.3. Region level

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

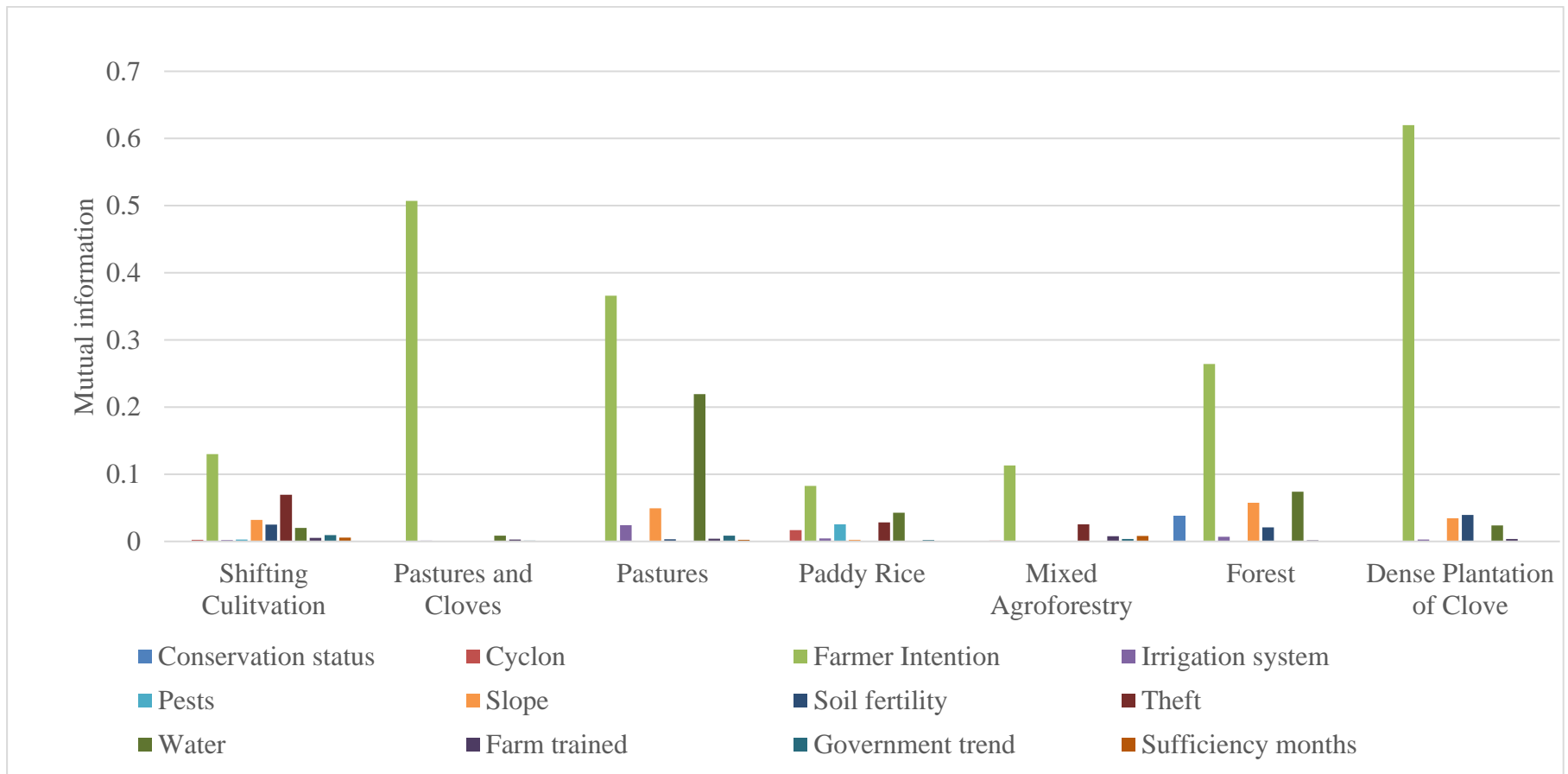


Figure. E.1.a. Importance of factors in terms of land-use at the northern site (Mahalevona)

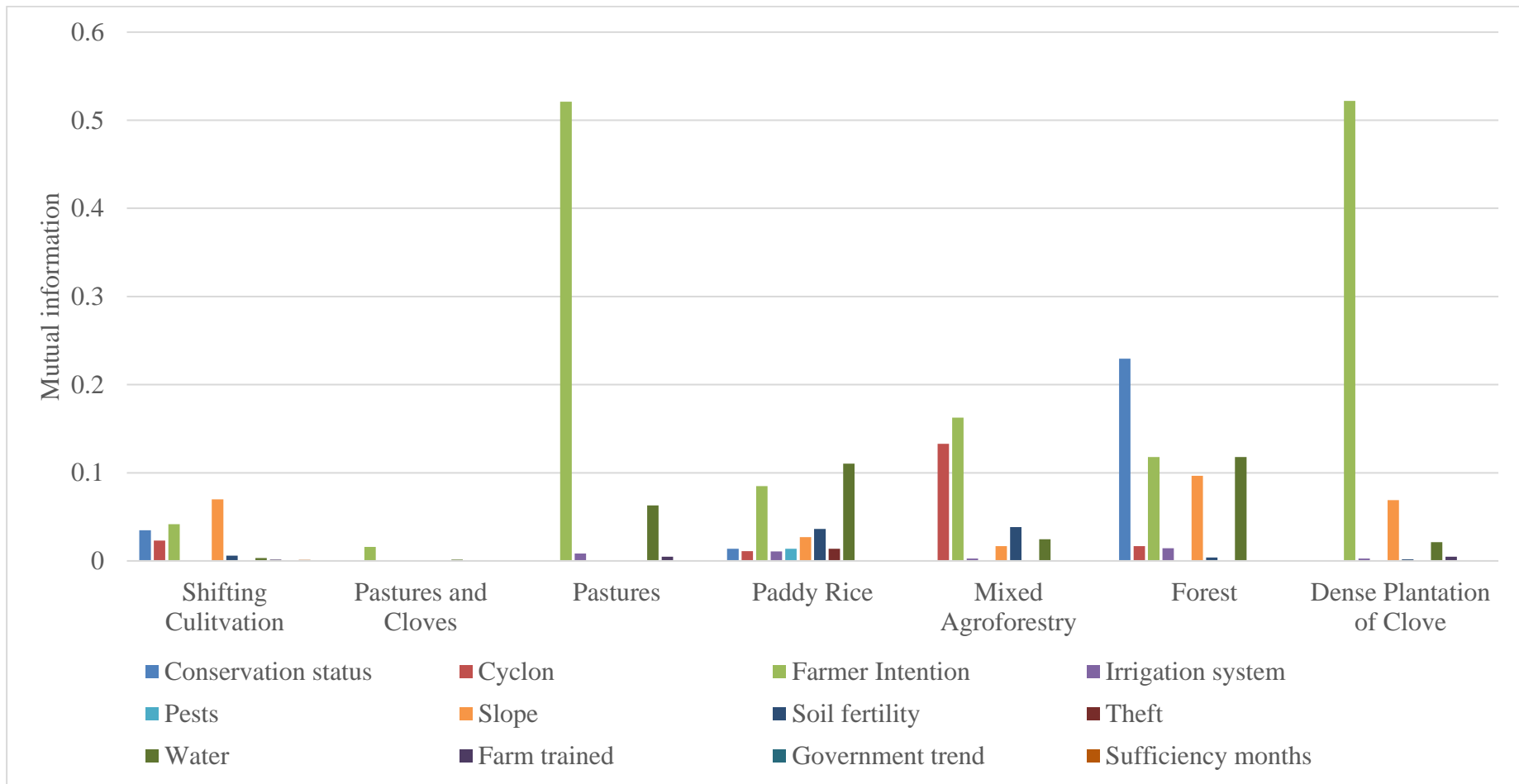


Figure. E.1.b. Importance of factors in terms of land-use at the southern site (Morafeno)