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ARTICLE

Quantifying local ecosystem service outcomes by modelling their supply, demand and flow in Myanmar's forest frontier landscape

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ABSTRACT
In complex tropical forest frontier landscapes, ecosystem service (ES) models are essential tools to test impacts of different land schemes on people. Considering several factors of supply, demand and flow and focusing on local stakeholders, we developed nine ES models using Bayesian networks and applied them in different land scenarios in Myanmar's Tanintharyi Region. We found land use and tenure as well as demand for specific products to be the key factors determining final ES outcomes. While forested lands have high regulating and overall balanced ES bundles, mixed agricultural lands provide subsistence and commercial products as well as better environmental education opportunities. By contrast, commercial agricultural concessions strongly limit ES outcomes for local communities. As our models reveal more distinct impacts of land policy scenarios in a homogeneous setting, where demand is better accounted for, we recommend their use for spatially explicit analyses of forest frontier landscapes.

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Ecosystem services; Bayesian network; scenarios; land policy; frontier landscape; Tanintharyi

Introduction

Nature, as part of both natural and anthropogenic landscapes, contributes to people's lives in various forms. The impacts of its changing use are particularly evident in tropical forest frontiers, where remaining forests face pressure from agricultural development. While intact forest landscapes provide a disproportionately high amount of ecosystem functions including carbon sequestration and water regulation (Potapov et al., 2017), commercial agriculture increases income in areas with good market access, and multifunctional land uses enhance livelihoods and adaptive capacity of rural communities (van Vliet et al., 2012). In a multifunctional tropical forest landscape, mixed policies supporting both land sparing and land sharing were suggested as most effective for achieving multiple ecosystem services (Law et al., 2017). However, as valuation of and comparison between these services remain challenging, they are often neglected in policymaking (Pandeya et al., 2016).

In this context, the conceptualization of ecosystem services (ES) has gained attention in research and policy (MEA, 2005). The ES framework describes how ecological structures and processes lead to benefits and values for human well-being (Groot et al., 2002). ES *supply* thus refers to the goods and services provided by a landscape, whereas ES *demand* refers to people's use and perceived value

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thereof. Services can be supplied both by natural ecosystems or man-made landscapes (Potschin et al., 2016) and therefore both must be considered. *Demand* is defined as 'the amount of a service required or desired by society' (Villamagna et al., 2013). In addition, ES *flows* determine whether services can be accessed and thus used by society. Flows can be seen as the spatial movements of ecosystem-derived materials and other services from a providing to a benefiting area or actor (Schröter et al., 2018), leading to actual service production and use (Schirpke et al., 2019; Vallecillo et al., 2019; Villamagna et al., 2013). In this study, ES flows are understood as people's access to services based on various enabling conditions including biophysical, spatial, social and political factors.

Modelling approaches to ES emerged around ten years ago but face several challenges, including high complexity and poor measurability (Landuyt et al., 2013). While most ES assessments use one indicator for each service, modelling approaches usually contain a variety of factors and indicators. ES research has strongly benefited from emerging frameworks at landscape scale such as the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) (Sharp et al., 2020) or the Artificial Intelligence for Ecosystem Services (ARIES) (Villa et al., 2014), which aim to standardize assessments. While InVEST uses biophysical data and provides output maps in biophysical or economic terms, ARIES uses several underlying process models to produce benefit flow maps showing sources and beneficiaries of ES. Even though both frameworks are valuable for standardized land use planning, disadvantages include the pre-determined services with few cultural services included, moderate transparency, weaknesses in incorporating spatial demand and limited overall ability to account for qualitative data (Bagstad et al., 2013; Sharps et al., 2017; Vigerstol & Aukema, 2011). A promising approach to ES modelling is the use of Bayesian networks (BN) with underlying conditional probabilities as described by Aguilera et al. (2011). A key feature is that they operate with probabilities, which is expedient especially for models where results are expressed in values. A further advantage is the possibility of integrating different types of knowledge sources such as biophysical data, expert and local knowledge and earth observation data, particularly in data-scarce regions. BN have thus become a popular technique to model ES and predict supply within a landscape (Burkhard & Maes, 2017). With regard to indicators, different BN studies used water availability, farming practices (Dang et al., 2019), land cover (McVittie et al., 2015) or topography (Grêt-Regamey et al., 2013) for supply; presence of people (Stritih et al., 2018), rural population (Kleemann et al., 2018) or available substitutes (McVittie et al., 2015) for demand; and distance to road (Grêt-Regamey et al., 2013) or government permissions (Smith et al., 2018) for flow. But, until now, most models have remained limited either in terms of scale (small study area or focus on one ecosystem), ES types (provisioning, regulating, cultural), dimensions for ES outcomes (supply, demand, flow) or number of indicators thereof, due to the complexity of socio-ecological systems as well as limited data availability (Schirpke et al., 2019). Nevertheless, developing complex models with several input factors influencing ES supply, demand and flow are necessary for examining underlying mechanisms. Subsequently, demonstrating potential model applications to identify options for enhanced ES bundles in a landscape is just as important in view of policy development.

The identification of key factors that have a positive leverage effect on multiple ES is particularly important in forest frontier contexts with competing claims on land and its products and services. In Myanmar's Tanintharyi Region, cropland expansion into primary and secondary forests is driven by private rubber plantations and oil palm concessions (de Alban et al., 2019; Zaehringer et al., 2020), which often conflict with traditional land rights or the boundaries of the permanent forest estate (Woods, 2016). Only few people benefit commercially from such agricultural expansion. Furthermore, conservation efforts in the same region aim to maintain biodiversity and other globally important ES (Pollard et al., 2014). As shown by Feurer et al. (2019), because of these land use changes in Tanintharyi, landless people and smallholders have lost access to locally important products and services and gained only few economic opportunities. Impacts were especially negative where these land use changes were connected to tenure insecurities and disputes limiting their access to land and corresponding ES. Nevertheless, people were often able to adapt to diminishing ES supplies by substituting certain products, lowering their demand for a certain service and reducing their dependence on nature. These dynamics underline the necessity of analysing multiple factors to predict ES outcomes and identify promising scenarios for local communities to benefit from natural and human-made landscapes, both at local and at regional scale.

The present study addresses these issues by developing comprehensive models for supply, demand and flow of nine ES in Tanintharyi Region. We identified key factors with a leverage effect in forest frontier landscapes and tested them in scenarios at a regional scale (Tanintharyi Region) with a highly heterogeneous landscape and at a local scale with a homogenous forest landscape. The study was guided by the following research questions:

(1) What are the key factors that influence the supply, demand and flow of nine ES?
(2) Based on the models, what are the ES outcomes for local stakeholders across Tanintharyi Region?
(3) How do the ES outcomes change according to agricultural and forest-based scenarios at regional and at local scale?

To conclude, we discuss the potential of the developed models to inform policymakers of optimized ES outcomes considering supply, demand and flow at different spatial scales.

Materials and methods

Study area

Tanintharyi Region in southern Myanmar is a long stretch of land located between the Andaman Sea and Thailand (Figure 1). It extends over a total area of approximately 4.3 million ha and is a forest frontier landscape including intact dipterocarp forests with high biodiversity value in remote hilly areas, degraded primary and secondary forests, and an increasing number of agricultural plantations in the more populated areas (Bhagwat et al., 2017). Some of the forest lands are used for shifting cultivation by local communities, whereas others are protected areas. The predominant perennial crops are rubber, betel nut and cashew. In addition, almost 800 000 ha of oil palm concessions have been allocated to companies in the past 20 years (Woods, 2016). A second important landscape context in Tanintharyi is the coastal stretch including archipelagos in the Andaman Sea. This area is mostly covered with mangroves and people's main livelihood is related to fishery. Between the two landscapes there is a stretch of flat land mainly used for paddy rice production.

Spatial zoning is an important regulating element in terms of land use and land tenure in Myanmar. Zoning broadly distinguishes between areas under the responsibility of either the General Administration Department (GAD) or the Forestry Department (FD). Under both departments, there are several land uses and tenure systems. In Tanintharyi, spatially explicit data are available for the following zones: (forest) protected areas, community forests (CF), oil palm concessions, mining concessions and the special economic zone (SEZ), which is reserved for infrastructure development and a planned deep sea port. The remaining area is under the control of either the FD or the GAD. If under the FD, it can be managed forest (permanent forest estate) or agricultural land where farmers pay annual taxes to the FD. If under GAD regulations, it can be settlements or croplands, which are either under customary land tenure or registered with land use certificates. Tanintharyi has three urban centres and a total population of 1.4 million people (DOP, 2014), with most of the villages concentrated along the main road. The forested hills near the Thai border are only sparsely populated.

Major challenges for sustainable development in Tanintharyi Region are posed by the different claims on natural resources from various actors. While private investors and companies are engaged in timber exploitation, large-scale agricultural plantations, mining or aquaculture, local communities use the land for planting perennial crops, vegetable gardens or rice. On agricultural land, the number of smallholder land use certificates has strongly increased in recent years (Lundsgaard-Hansen et al., 2018). In some forest areas, including mangroves, CF have been established to give formal user rights to communities for 30 years (Feurer et al., 2019). These contrasting developments influence the provision of ES and rural communities' access to them. At the same time, infrastructure improvements after the civil war have increased job opportunities, facilitated market development and improved access to imported foods,

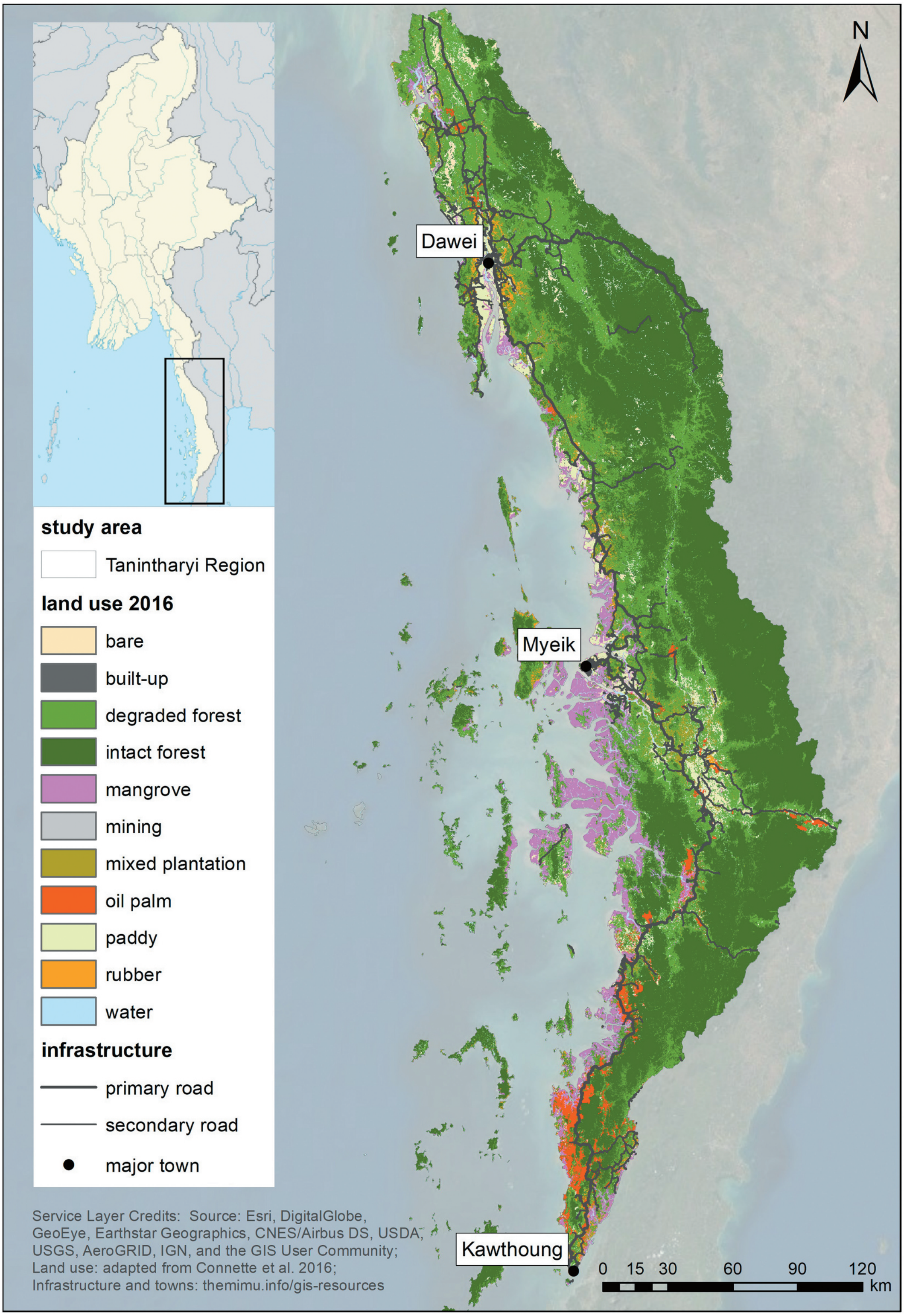

Figure 1. Overview of the study area and land use (Connette et al., 2016) in Tanintharyi Region, Myanmar, in 2016.

modern medicine and other goods, thus reducing people's dependence on nature and changing their demand for ES.

Theoretical framework

This study used a framework touching on different prevalent concepts in ES research. It is based on the common notion that ES are only achieved when (i) there is a potential 'supply' from the ecosystem or land use and its underlying processes and functions, and (ii) there is a 'demand' and people benefit directly or indirectly (Burkhard & Maes, 2017; Groot et al., 2010; Mouchet et al., 2014). Taking into account the difference between potential and actual supply and demand, we added 'flow' as a precondition for final outcome (Schirpke et al., 2019; Schröter et al., 2018; Villa et al., 2014; Villamagna et al., 2013). We use the term 'outcome' similarly to 'ES benefit' in Villa et al. (2014) and analogous to other studies (Dade et al., 2019; Mace et al., 2012; Olander et al., 2018) to describe final ES that are not only potentially provided (supply) but also enabled (flow), desired and used (demand). We thus assume that for assessing final ES outcomes, models need to include three aspects: ES supply, ES demand, and ES flow (Figure 2). In this study, all ES models followed this principle. On the supply side, our starting point was land use under consideration of local management practices. Our focus was specifically on local stakeholders.

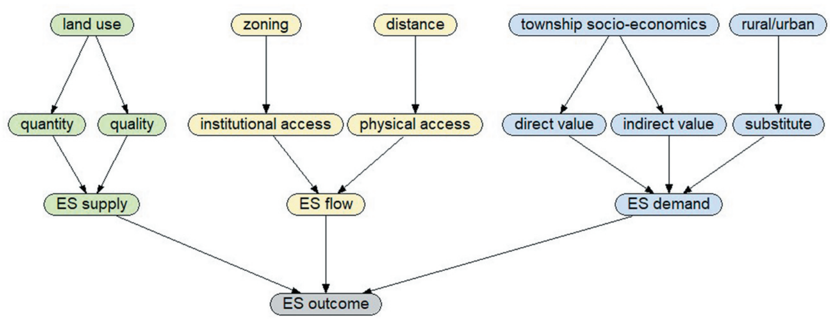

Figure 2. Theoretical framework and basic structure for ecosystem service (ES) model development; diagram produced using Netica (version 6.05).

ES classification and selection

Aiming to cover all ES types (provisioning, regulating, cultural), we selected ES based on classes from the Common International Classification of Ecosystem Services (CICES) (Haines-Young & Potschin, 2018), adapting them to the local context. Selection was done in several steps including a literature review and focus group discussions with local land users in three villages in northern Tanintharyi that together cover all relevant land uses, zones as well as three ethnic groups (Burmese, Karen, Mon). Finally, we chose nine ES (Table 1) according to the following criteria (in this order): link to dominant land uses, relevance for rural communities (based on a ranking exercise in three villages with 20 community members each), suitability (including secondary data availability) for modelling, and relevance for policymakers (literature-based). In this study, biodiversity – sometimes conceptualized as underpinning other services, as conflicting with them or as a service itself (Mace et al., 2012; Schröter et al., 2016) – was considered a regulating service and defined accordingly (Table 1).

Table 1. List of nine selected ecosystem services and description.

Ecosystem service		Description
Provisioning	Subsistence foods	All crops, wild foods, meat and fish used for consumption in the household, for guests or for religious ceremonies
	Commercial products	All products from nature used for income generation (including timber, non-wood forest products, cash crops, meat and fish)
	Fuelwood	All plant parts which are used for cooking fuel, either as fuelwood or as charcoal
	Medicinal plants	All wild plants with known medicinal properties
Regulating	Biodiversity	The diversity of animals, plant species and varieties including agrobiodiversity, related products and pollination services
	Climate regulation	Regulation of microclimate and global climate including carbon sequestration
	Water regulation	Regulation of water flow including associated services such as clean water supply
Cultural	Environmental education	The contribution of nature to education, environmental and agricultural knowledge generation and exchange
	Cultural identity	The contribution of nature to cultural identity, including cultural products supplied by different land uses

Bayesian (belief) networks and software

Bayesian (belief) networks (BN) as probabilistic models based on causal dependencies (Kjærulff & Madsen, 2008) were chosen for their ability to include different knowledge types and demand factors in data-scarce regions (Burkhard & Maes, 2017). This seemed relevant as we focus on locally relevant ES. Our BNs include root nodes (input variables without parent nodes), several levels of intermediary nodes (structuring the BN) and end nodes (output variables). All nodes possess discrete states (possible values) and are linked to other nodes with arrows showing causalities. A child node has causal dependency on its parent node(s). Relationships are defined by conditional probability tables (CPTs). ES models in this study were implemented using the commercial software Netica (version 6.05) for constructing and analysing BNs.

Model development

We developed nine ES models following an iterative process using several steps (Pollino et al., 2007) in three main phases: (a) defining model structures with nodes and states, (b) populating and parameterizing CPTs, (c) validating final models. An overview of these phases in model development is given in the next three paragraphs. Appendix I describes all steps in detail.

For each model, the first step was to develop the structure, including root, intermediary and end nodes as structuring elements and following the theoretical framework (Figure 2) using the Delphi-method (Okoli & Pawlowski, 2004). We first did a literature review and subsequent individual interviews with 15 experts from various institutions (including non-governmental organizations, civil society organizations, research institutions and governmental bodies) active in the study area. After findings were consolidated into draft structures, a set of discrete states was defined for each node based on recognized classifications or combined information from literature and expert interviews. In the end, all nodes and states were verified through follow-up interviews discussing the printed model structures with the above-mentioned experts and village representatives (final model structures in Appendix II, Figures A2–A10).

After finalizing the structure, we parameterized each model by populating and calibrating the CPTs differently according to the type of node using both secondary data (GIS layers, census data, literature review) and primary data (interviews, survey, field observations). Specifically, we used spatial data for the root nodes and population census data for twenty nodes connected to the ‘township’ root node. For intermediary nodes, we elicited rules (Appendix III, Table A2) based on triangulated data from field observations during a total of three months between 2017 and 2020, the 15 expert interviews taking place over three weeks in 2019, as well as reflections stemming from a comprehensive literature review. Thirteen nodes were subjected to a household survey (n = 40) using a standardized questionnaire (Appendix IV), asking, e.g., 'Do you trust in herbal medicine?' The distribution of responses (e.g., 93% 'yes', 7% 'no') was set as conditional probability for the respective node. For the nine continuous end nodes ('ES outcome') discretized into five states, we elicited rule-based CPTs under consideration of existing ES concepts (Groot et al., 2002; Schirpke et al., 2019; Villamagna et al., 2013) and a standardized survey with 12 additional experts using values of supply, demand and flow of ES. These experts had a scientific background and were familiar with ES and natural resource use in the Southeast Asian context. Resulting from this, the final 'outcome' was defined as the average score of its parent nodes 'supply', 'demand' and 'flow', with uncertainties accounted for through additional probabilities within the range of the minimum and maximum values of each of parent node.

Finally, we administered two validation approaches. As suggested and described by Kleemann et al. (2018), we applied first an extreme-condition test to confirm the operational validity of each parameterized model checking model outputs given most extreme inputs. Secondly, we conducted a face validity test with the 12 scientific experts. Based on a standardized survey including illustrations of the model structures, the experts had to rate the conditional score for supply, demand and flow of each ES based on the direct parent nodes or, where needed for contextual reasons, the parent nodes to those. On average, expert ratings were 5.2% lower than model values across all ES (Appendix V). The highest differences were found for medicinal plants (−14.7%), climate (−11%) and water regulation (−10.4%). Generally, experts gave lower values for supply (−8.8%) and demand (−8.7) and slightly higher values for flow (+1.9%).

Sensitivity analysis for ES indicators

After model development and evaluation, we did a second sensitivity analysis using the Sensitivity to Findings function in Netica for the 'ES outcome' node for the nine parameterized models. For each model, the nodes were then ranked from highest to lowest mutual information (MI). We considered all nodes with MI > 0.01 under the supply, demand and flow paths, subsequently identifying the key factors with MI ≥ 0.1, to answer the first research question.

ES outcomes

Nine ES outcomes predicted on a discrete scale from 1 (no outcome) to 5 (very high outcome), were computed in Netica with the most recent geodata available for Tanintharyi Region for the root nodes (Appendix VI, Table A4), (a) using the actual distribution of land uses in 2016 across the region as soft evidence (50% intact forest, 28% secondary forest, 6% mangrove, 2% mixed plantation, 2% rubber, 3% oil palm, 4% paddy, 5% other) and (b) using hard evidence for each individual land use. In addition to the resulting probability distributions, weighted averages were calculated and used as ES outcome scores.

Regional and local scenarios

Two regional and three local scenarios were constructed and applied in Netica, based on hypothetical but likely scenarios according to common developments in forest frontier landscapes. The regional scenarios were established by the authors, based on triangulated information from literature, field observations and the 15 regional expert interviews, while the local scenarios correspond to actual developments experienced and documented in three focus groups in northern Tanintharyi on land use changes in the past 20 years. These scenarios are representative of similar developments across Tanintharyi at the forest frontier (Bhagwat et al., 2017). At regional scale, the baseline (R0) was the most recent spatially explicit land use data for Tanintharyi Region (Connette et al., 2016). Two hypothetical scenarios were decided on based on most likely developments according to experts

Table 2. Characteristics of regional and local scenarios

		Regional			Local			
Values based on		literature, field observation, expert interviews			case study, focus group discussions, field observation			
Scenario		R0	R1	R2	L0	L1	L2	L3
		Current situation	Agricultural expansion	Forest conservation	Forested landscape	Community forestry (CF)	Small-scale agriculture	Oil palm concession
Description		current land uses and zoning in Tanintharyi Region	concessions for oil palm and rubber, expansion of smallholder agriculture	forest conservation and restoration with protected areas and CF	mostly intact forest landscape, partly used for shifting cultivation	CF certificate, restored degraded areas, some agroforestry plots	forest conversion to mixed plan-tations and rubber, no land tenure	agricultural concession, conversion to oil palm and processing plant
Land use (%)	**Intact forest**	50	40	70	80	85	10	5
	Secondary forest	28	0	10	15	10	5	5
	Mangrove	6	4	8	0	0	0	0
	Mixed plantation	2	6	4	0	5	70	0
	Rubber	2	20	2	0	0	10	0
	Oil palm	3	6	2	0	0	0	80
	Paddy	4	16	3	0	0	0	0
	Bare	5	5	0	5	0	5	5
	Mining	0	1	0	0	0	0	0
	Built-up	1	2	1	0	0	0	5
Zoning (%)	**Protected area**	5	5	40	0	0	0	0
	Oil palm concession	7	22	2	0	0	0	100
	Mining concession	0	1	0	0	0	0	0
	SEZ	0	1	0	0	0	0	0
	Community forestry	0	1	17	0	100	0	0
	Other	87	70	41	100	0	100	0
Other variables		existing datasets (Appendix VI)	population density ↑, distance to village ↓	distance to forest ↓	existing datasets, low population density (hard evidence)			

* All percentages were rounded so that sums may not always be 100%. In R0, no value is 0 but rather < 0.5

and our own field observations: agricultural expansion and intensification (R1) and forest conservation and restoration (R2). R1 includes more agricultural areas (particularly rubber) and concession land. R2 includes the restoration of degraded secondary forests and conservation in increasing numbers of protected areas and community forests. At local scale, the baseline (L0) consisted of an exemplary rural forest landscape without formal land tenure and low population density. The three scenarios defined by previous land use changes in northern Tanintharyi were community forestry (L1), expansion of small-scale agriculture (L2), and conversion to an oil palm concession (L3). Table 2 gives an overview of all scenarios and specific model updates giving soft evidence for land use and zoning.

Results

Key factors for ES outcomes

Our nine ES models include up to 30 factors (nodes) each. The relevance of each node, represented through its mutual information (MI) with the respective ES outcome, is depicted in Table 3 for the

Table 3. Main nodes and their relevance for the outcomes of nine ecosystem services based on mutual information (sensitivity analysis carried out in Netica, MI = mutual information).

Ecosystem service		Supply			Flow			Demand		
		Node	MI	mean	Node	MI	mean	Node	MI	mean
Provisioning	Subsistence foods	food amount	0.38	0.42	distance to village	0.13	0.13	consumption frequency	0.23	0.32
		land use	0.32					price of food	0.06	
		food type	0.25					population density	0.04	
		subsistence value	0.13					township	0.04	
	Commercial products	type of product	0.28	0.28	market access	0.02	0.04	access to food	0.02	0.51
		revenue	0.26					type of product	0.45	
		selling price	0.25					expected revenue	0.44	
		land use	0.17							
		land use intensity	0.05							
		price stability	0.05							
		input costs	0.04							
	Fuelwood	fuelwood quantity	0.32	0.34	physical access	0.06	0.09	use of fuelwood	0.12	0.18
		land use	0.31					use in cooking	0.08	
		fuelwood quality	0.26					township	0.04	
								population density	0.04	
	Medicinal plants	land use	0.06	0.07	plant knowledge	0.26	0.26	current use	0.26	0.38
								use frequency	0.23	
								future value	0.12	
Regulating	Biodiversity	species diversity	0.13	0.13	access to products	0.11	0.17	planted crop	0.11	0.15
		land use	0.11		distance to village	0.07		ntfps	0.10	
		agrobiodiversity	0.04					use of products	0.10	
	Climate regulation	air quality	0.13	0.16	distance to village	0.04	0.10	air quality value	0.13	0.19
		tree cover	0.11							
		land use	0.11							
		carbon storage	0.11							
		net ghg emissions	0.10							
		climate mitigation	0.10							
		non ghg emissions	0.05							
	Water regulation	water quality	0.09	0.24	water source	0.07	0.13	household use	0.10	0.17
		water pollution	0.08		township	0.07		population density	0.07	
		water quantity	0.08					type of product	0.06	
		land use	0.07					agricultural use	0.03	
		water purification	0.05					crop requirements	0.03	
		water retention	0.04							
		precipitation	0.03							
Cultural	Environmental education	vocational trainings	0.48	0.86	zoning	0.04	0.06	livelihood knowledge	0.03	0.04
		land use	0.09							
		community groups	0.03							
		local knowledge	0.02							
	Cultural identity	land use	0.14	0.16	products access	0.03	0.06	cultural product use	0.33	0.44
		cultural value	0.13		ancestral land	0.02		annual product use	0.27	
		old cultural value	0.13		zoning	0.02		cultural products	0.17	
		traditional products	0.13					nature in culture	0.02	
		traditional land use	0.10							

most important nodes (MI > 0.01). Comparing the respective contributions of supply, demand and flow to ES outcomes across nine models, we found supply overall to be the most important (mean = 0.30), closely followed by demand (mean = 0.26). Specifically, supply is particularly defining for the outcome of subsistence foods, fuelwood, climate, water and environmental education, which varies widely in different areas of Tanintharyi. In contrast, demand highly influences the outcome of cultural identity, commercial products and medicinal plants, most of which are found on many land use types but used only selectively. The influence of flow factors is highest for medicinal plants, as knowledge is a crucial requirement for using them. Overall, flow has comparably low MI (mean = 0.12), which can be partly explained by the lower number of states (three) as against supply and flow (five).

Considering key factors, land use stands out as the single most important node. It is represented in all models and is particularly relevant (MI ≥ 0.1) for subsistence crops, commercial products, fuelwood, biodiversity, climate and cultural identity (Table 3). In addition, several other factors are directly linked to land use. The vital role of land use for ES outcomes is not surprising, given that it represents the natural and human-made ecosystem and its functions. In terms of demand, there is no single key factor, but some patterns emerge. One key node pattern reflects actual use of specific products (e.g., consumption frequency of subsistence foods or use of cultural products). Other patterns, such as the availability of alternatives (e.g., imported food, alternative cooking stoves, modern medicine) or intrinsic values have lower impacts on outcomes. In terms of flow, physical access appears to have slightly more influence on outcomes than institutional access for subsistence foods and fuelwood, though institutional factors are also relevant (MI > 0.01) for commercial products, fuelwood, water regulation and cultural identity. This is rather surprising, as zoning and corresponding rules and regulations have been reported by local communities as highly affecting their livelihoods and well-being. It can be assumed that, due to a combination of weak law enforcement and high uncertainties related to land tenure, the models do not sufficiently account for this. Thus, rural communities have access to land and its products but only informally. As this might change in the future, zoning should still be considered an important factor for ES outcome.

ES outcomes for Tanintharyi region and individual land uses

Currently, the most probable outcomes for all nine services are between low and high levels (Figure 3). We found the highest outcome scores for water regulation (3.6) and biodiversity (3.5). The lowest outcome by far is for commercial products (2.3). No clear pattern appears between provisioning, regulating and cultural ES types. When comparing individual land uses, two clusters can be distinguished. The first cluster includes forest-related land uses (intact forest, secondary forest, mangrove) and smallholders' mixed plantations, which are extensively managed and often quite diverse. This cluster provides a broad and well-balanced set of ES with most at medium to high levels but some deficiencies in commercial and educational services. Mangroves are an exception with fisheries contributing greatly to commercial outcomes and frequent mangrove conservation trainings enhancing environmental education, leading to an overall balanced ES bundle. The second cluster involves intensively managed agricultural land uses (rubber, oil palm, paddy) with more heterogeneous ES outcomes. Both rubber and oil palm plantations have limited cultural value and provide few subsistence foods. On the other hand, they offer opportunities for agricultural training from companies aiming for high-quality products and from NGOs aiming to enhance rural livelihoods. Since perennial crops dominate agricultural lands, these still provide relatively high levels of regulating services such as climate regulation and biodiversity, especially where farmers manage them extensively and with few chemical inputs. In comparison, paddy fields provide very low levels of regulating services but are important for subsistence and cultural identity, as rice is both a staple food and a product donated in religious ceremonies. Considering that for commercial products demand is highly relevant for outcome, agricultural land uses are expected to be more important in highly populated areas of Tanintharyi.

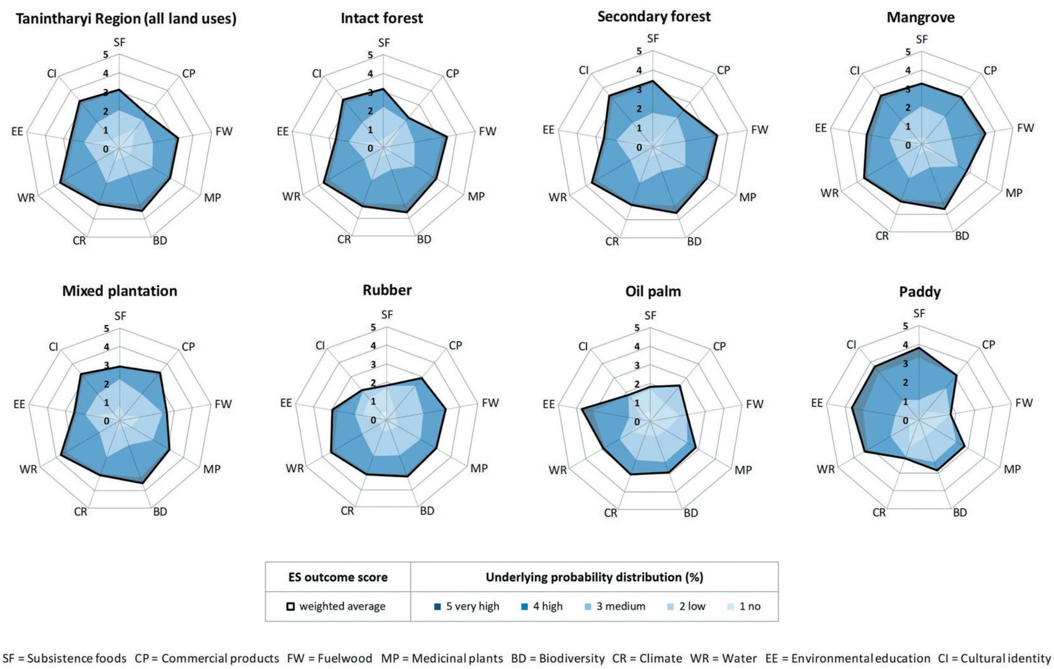

Figure 3. Ecosystem service outcome scores based on weighted average and underlying conditional probability distributions from Bayesian networks for Tanintharyi Region (land use distribution according to Connette et al. (2016) and for each land use separately.

The underlying probability distributions (Figure 3) provide an indication of the extent to which individual ES can be influenced within a certain land use. For example, if good agricultural practices are promoted for rubber, it will be possible to achieve high regulating ES as there are high probabilities of scoring 4. However, there will still be a limited supply of subsistence foods, which has zero probability of a score higher than 3 and thus can only be achieved with other land uses, namely paddy or upland rice fields. On the other hand, for all land uses and ES there is always a risk of low outcomes, as demand may be low. Therefore, policies trying to optimize ES outcomes would need to consider spatial distributions of supply, demand and flow to make sure that the rural communities can indeed benefit from the relevant ES.

Model application using scenarios at regional and local scale

Applying the models through scenarios based on different land use and zoning settings, we found that at the regional level, the models predict few differences for either scenario (Figure 4), with agricultural expansion and intensification (R1) having slightly lower mean outcomes (3.08) than forest conservation and restoration (R2) (3.20). It can be noted that the outcome of R2 is very similar to the current situation, but it includes also larger areas of community forestry, which is always accompanied by training from the FD and NGOs and thus increases environmental education. Turning to the local perspective and a specific, rather homogenous, forest landscape, differences between the scenarios are much more accentuated. In a forested landscape, ES outcomes increase if CF is introduced (L1) (3.36) and decrease if forest is converted to croplands. While small-scale agriculture including rubber and mixed plantations (L2) still provides relatively high outcomes (3.14), the conversion to oil palm (L3) is more detrimental (2.37), especially in terms of cultural identity. Additionally, the comparison of all five scenarios shows that commercial products remain low except for L2, which indicates that especially at regional level, income for rural communities

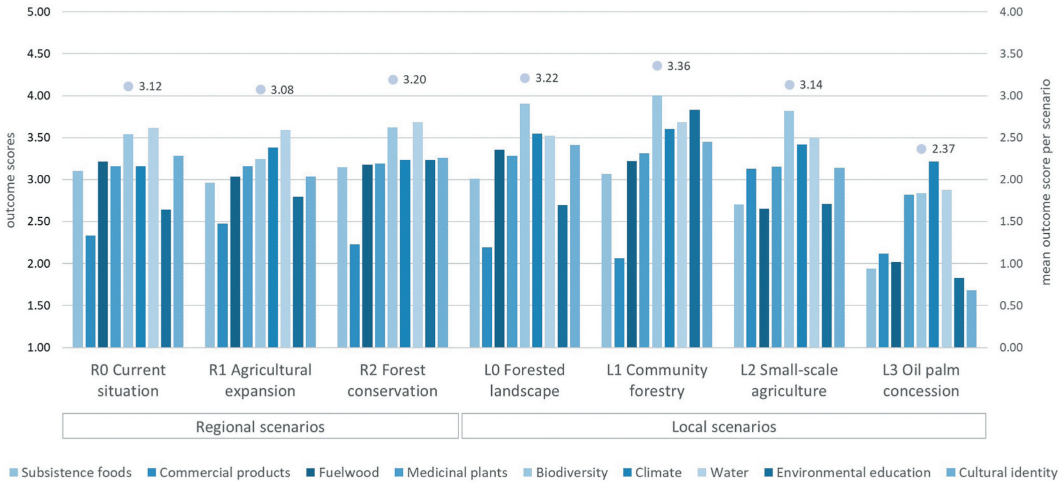

Figure 4. Modelled ecosystem service outcome scores based on supply, demand and flow in two regional and three local scenarios in Tanintharyi Region.

cannot be improved by steering land use and tenure alone. It is thus possible that investigating additional factors such as intensity of land use management or quality of processing practices would have a higher effect specifically for commercial outcomes.

These findings suggest that the models, as an approximation of the complex reality on the ground, can predict the impact of certain land use and zoning policies on ES outcomes more effectively at the local scale, which is less heterogeneous than the entire region. Demand, which has a high influence on outcomes, is difficult to account for at regional scale. The regional scenarios thus cannot respond to the question of whether supply meets demand. On the contrary, while regional-level land use decisions may have negligible effects on overall ES outcomes, local communities in specific areas may be highly impacted in terms of their livelihoods and well-being.

Discussion

In line with a previous review (Landuyt et al., 2013), we found the use of Bayesian networks highly suitable for modelling ES, particularly as our study is located in a data-scarce region (ibid) and involves different types of ES (Shaw et al., 2016). BN's probability distributions indicate to what extent certain ES can be enhanced, which can be a useful basis for designing targeted intervention strategies. Compared to existing ES models (InVEST, ARIES), our models include a broad set of ES, which had been defined together with local stakeholders, and diverse (in particular many qualitative) factors contributing to ES outcomes. They thus provide a more detailed representation of local circumstances, actual demand and benefits for local communities. As the perspective was on these communities, our results did not account for the global relevance of some ES. But based on different actors' contested objectives, scenarios can be defined in a participatory way and used to discuss different ES outcomes from potential policies and interventions. In Myanmar, such an application is a promising opportunity due to ongoing land reforms and the existence of a multi-stakeholder land platform (Bächtold et al., 2020).

According to Norton et al. (2016), larger-scale studies are useful for targeting action, especially when assessing several ES. However, when zooming in to smaller-scale landscapes, our models were able to predict ES outcomes in a more differentiated way. More extreme but rather unrealistic scenarios, such as the conversion of the entire forest complex into rubber plantations, may have led to more compelling results of ES impacts at regional level. Nonetheless, our findings suggest that at regional level it is difficult to optimize ES outcomes based on land use and tenure factors alone, and demand cannot easily be steered with one single factor in our models. A spatially explicit representation of ES supply, demand and flow should thus come as a next step for applying the models. As suggested by Landuyt et al. (2013) and implemented in various studies, e.g., recently in Stritih et al. (2020), spatially explicit modelling through the combination of BN and geographic information systems also presents an opportunity for Tanintharyi Region for more targeted policy and interventions. As BNs can be updated and adjusted as soon as new information becomes available, it is possible to adjust the models to other areas of Myanmar or the wider region either by modifying relevant nodes and states or by updating CPTs. The expert model validation (Appendix V) serves as a reference for potential differences in other areas of Southeast Asia. Generally, the high conformity rate between BN and expert responses implies that the models are applicable in the wider region with slight adjustments. For example, experts with experience outside of Myanmar rated ES outcomes of oil palm slightly higher, which may result from better growing conditions (Saxon & Sheppard, 2014) or better inclusion of local communities. Further, some of the experts rated physical access as more relevant compared to the models, as infrastructure and road access are known to encourage the use of forest products and conversion from forest to croplands (Barber et al., 2014). Improved physical access may have various more long-term impacts on supply, demand and flow ES. In the sparsely populated Tanintharyi Region, this is yet to be seen.

Overall, our study suggests that to optimize ES outcomes, several aspects of supply, demand and flow should be considered. Land use and actual product use being key factors that correspond to similar findings on ES indicators (Meacham et al., 2016; Schirpke et al., 2019). In contrast, these studies also point to zoning aspects as key indicator, which did not show in our results and implies a need for further investigation. Our models show that a large-scale conversion of forests to agriculture would not necessarily increase local revenues from commercial products. Instead, sustainable intensification to increase crop yields or measures to improve quality could be preferred options (Pretty & Bharucha, 2014). This would at the same time allow remaining forests to keep providing valuable ES bundles (Ahammad et al., 2019; Emerton & Aung, 2013). But while rubber, oil palm and paddy generally had more diverging ES outcomes than forests or mixed plantations, different types of agricultural practices need to be investigated more deeply to make a clear statement on their relevance for ES. Shifting cultivation as an integral part of secondary forest areas has not yet been sufficiently considered in other ES assessments. Complementary to studies documenting the role of shifting cultivation in rural livelihoods in Southeast Asia (Cairns, 2017; Dressler et al., 2017; Fox et al., 2014), our results show that these secondary forest landscapes provide nearly the same amount of regulating services of intact forests and additionally contribute to subsistence foods. At the same time, shifting cultivation plots are often transformed by local land users into mixed plantations, which include betel nut, cashew, a variety of fruit trees and annual crops. They provide the commonly known benefits of agroforestry systems (such as improved agrobiodiversity, carbon sequestration or income diversification) and are crucial for rural people's subsistence and income generation. Indeed, because it provides more subsistence and commercial products while retaining reasonable levels of regulating services, local people see agroforestry as a complementary or even better source of ES than forests (Feurer et al., 2019; Muhamad et al., 2014).

If the aim is to enhance ES outcomes for local communities, it seems crucial to consider land tenure and zoning. The apparent low sensitivity of the 'institutional access' factor stands in contrast to several studies documenting local communities' constrained access to natural resources in protected areas (Pollard et al., 2014; TRIP NET, 2016) or agricultural concessions (Feurer et al., 2019; Thein et al., 2018; Woods, 2016) and the fact that improved land tenure security encourages sustainable management practices (Higgins et al., 2018). Although our ES models did not sufficiently account for that at regional scale, the local scenarios revealed that establishing CF may enhance overall ES outcomes, whereas transferring land to a company negatively affects rural communities' benefits from these lands. Recognizing the administrative hurdles and multiple stakeholder claims on land (Lundsgaard-Hansen et al., 2018), it seems nonetheless a viable option to improve land registration processes, issue more land certificates to local land users and allocate additional CF.

As we found demand factors to be highly relevant for ES outcomes, efforts to enhance supply need to consider demand in the respective locations. Spatially explicit modelling can help to identify supply/demand (mis)matches and devise targeted intervention strategies. For the forestry sector, this effectively means that strict forest conservation measures should be complemented with local forest use where feasible. For example, near villages CF may be the best option, whereas in remote areas nature reserves can protect primary forests from agricultural conversion and ensure regulating ES for downstream users. Alternatively, promoting valorisation of selected forest products may be crucial for long-term ES outcomes where forest-dependent communities are present (Gritten et al., 2015). In Tanintharyi's coastal area, clear policies need to be established and enforced to protect remaining mangroves and support rehabilitation in selected sites in order to secure the valuable ES bundles provided by them, as shown in our results. For the agricultural sector, investments should consider areas with high population density and good access to markets to ensure flow and demand. While our scenarios support other studies in the assumption that any form of concession will reduce ES outcomes for local stakeholders (Baird & Fox, 2015; Kenney-Lazar, 2012), it should be mentioned that oil palm production in Tanintharyi is currently not even profitable for investors (Saxon & Sheppard, 2014) and more diverse landscape trajectories should be considered.

Conclusions

This study presented an ecosystem service modelling approach using Bayesian networks and considering multiple supply, demand and flow factors. We determined that land use has the highest impact on multiple ES and suggests that further decisive factors are land tenure and demand for natural resources, in particular for local stakeholders. Using scenarios, we found that differences in ES outcomes from changes in land use and land tenure are much more pronounced in a homogenous (local) landscape than at regional scale in the present context of Tanintharyi Region. In a forest landscape, overall ES outcomes increased with the introduction of community forestry but decreased with the expansion of small-scale agriculture. The 'oil palm concession' scenario, on the other hand, had particularly negative effects on local communities' livelihoods and cultural identity. Thus, while forests are important sources of ES, agricultural land uses, especially mixed tree crop plantations, can be equally or more beneficial where rural communities depend on those products for income generation. In existing croplands, sustainable intensification and product quality improvements could improve livelihoods further. We conclude by suggesting that the new ES models are land use science tools with considerable potential to inform policymaking. In view of the ongoing land reform processes in Myanmar, such models could play a critical role in multi-stakeholder platforms by facilitating discussions on contested issues and different scenario outcomes. Overall, the consideration of spatial scales is crucial when applying the models. In a next step we recommend applying the models in a spatially explicit manner, which will allow the identification of supply/demand mismatches at the regional level. This – and considering access factors – would enable more targeted policies and interventions to be designed for enhanced ES outcomes and, finally, the sustainable development of a forest frontier landscape.

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Appendix

Appendix I. Steps in model development

Phase (a) Defining model structures with nodes and states

For each model, the first step was to develop the structure, following the basic structure of the theoretical framework and using the Delphi-method (Okoli & Pawlowski, 2004). We first did a literature review and subsequent individual interviews with 15 experts from various institutions (including non-governmental organizations, civil society organizations, research institutions and governmental bodies) active in the study area. All selection criteria are detailed in Table A1.

After findings were consolidated into draft structures, a set of discrete states were defined for each node aiming for as many states as needed but as few as possible. For the parent nodes to 'ES outcome' we used an ordinary scale consisting of a scale from 1 to 5 for the nodes 'ES supply' and 'ES demand' and a scale from 1 to 3 for 'ES flow', which involves fewer options due to a lower number of input nodes. This allows for consistency across the nine models and makes them comparable at the level of supply, demand and flow. For nodes with available spatial data, states were defined according to the respective datasets after having prepared the geodata so that categories fit the desired content. For the other nodes, states were either defined by using recognized classifications (e.g., soil types) or combining information from literature and expert interviews.

In the end, all nodes and states were verified in a second round of interviews with the above-mentioned experts as well as with representatives from two villages in the study area using the printed consolidated draft model structures as discussion material.

Phase (b) Populating and parameterizing CPTs

As a fourth step, we parameterized each model by filling in the CPTs and calibrating them in several rounds, using a variety of both secondary data (GIS layers, population census data, literature review) and primary data (interviews, survey, field observations) collected during a total of three months in the field between 2017 and 2020. For a total of 54 root nodes (some repeating), available spatial data were compiled and processed into raster datasets with relevant states for the respective nodes using ArcGIS. For each dataset, the states' distribution across Tanintharyi Region was calculated and inserted as probability distribution for the corresponding root nodes. For intermediary nodes, three types were distinguished depending on the availability and quality of secondary data. The first type (n = 20) was based on township-level census data and CPTs were populated according to the distribution in the corresponding parent node 'township', which is spatially explicit. The second type (n = 27) had good literature information which determined the probability distributions. For the third type (n = 105) we used triangulated information from field observations, key informant interviews and reflections stemming from a comprehensive literature review as a basis to elicit rules for populating CPTs. Key informants included the same 15 experts from local institutions who were interviewed regarding the model structure. The interviews took place during three weeks in 2019. The elicited rules included shifts between classes of either 10%, 25% or 50% depending on the parent nodes. These were found to be most suitable for handling uncertainties according to experts. All rules are found in Appendix III. After the first parameterization, all intermediary

Table A1. Selection criteria for interviews with local stakeholders (n = 15).

Selection criteria	Number of interviewees
Institutional diversity	3 government representatives: Forest Department (FD), Environmental Conservation Department (ECD), Tanintharyi Nature Reserve Project (TNRP) 1 Karen National Union (KNU) 4 non-governmental and civil society organizations: 3x Worldwide Fund for Nature (WWF), 2x The Center for People and Forests (RECOFTC), Wildlife Conservation Society (WCS), Flora & Fauna International (FFI), 3 research institutions: 2x Onemap Myanmar (OMM), Dawei Research Association (DRA), Environmental Care and Community Security Institute (ECCSi)
Tanintharyi Region knowledge	11 interviewees based in Dawei 1 interviewee based in Yebyu 1 interviewee based in Myeik 2 interviewees based in Yangon with working experience in Tanintharyi
Position with good institutional overview and close to communities	5 heads or assistant heads of (local) institution 7 project leaders 3 field assistants
Cultural knowledge	13 Burmese 1 Foreign national with > 5 years working experience in Myanmar 1 Foreign national with < 2 years working experience in Myanmar

nodes were assessed according to the authors' confidence in them and they were subjected to a first sensitivity analysis in Netica. Nodes with a high sensitivity to ES outcome (mutual information ≥ 0.01) and a low authors' confidence were selected for calibration to improve the soundness of the CPTs and, consequently, the predictive accuracy of the models. Calibration was done through a household survey (n = 40) with a standardized questionnaire to ask about the most probable states for the respective nodes. An example question was 'Do you trust in herbal medicine?' A total of 40 household heads from seven different villages in three townships participated in the survey. The distribution of responses (in the example 93% yes and 7% no) was set as conditional probability for the respective node. For the nine end nodes ('ES outcome'), rules were compiled to populate the CPTs based on triangulation between existing ES concepts and a standardized survey with 12 additional scientific ES experts. The experts were asked 'What is the most likely ES outcome on a scale from 1 (lowest) to 5 (highest) if ES supply has state X, ES flow state Y and ES demand state Z?' The updated 'outcome' rules, valid for all ES, are:

- Range of outcome = Range of the values of 'supply', 'flow', 'demand' (min – max)
- ES outcome = mean of 'supply', 'demand' and 'flow'
- Accounting for uncertainty: 25% higher (if.00 or.75) and 25% lower (if.00 or.25)
- Accounting for 'no' values: 10% lower if no 'supply', 'demand' or 'flow'
- Accounting for expert estimations: 10% lower (all)

Figure A1 describes the process of populating CPTs for different types of nodes.

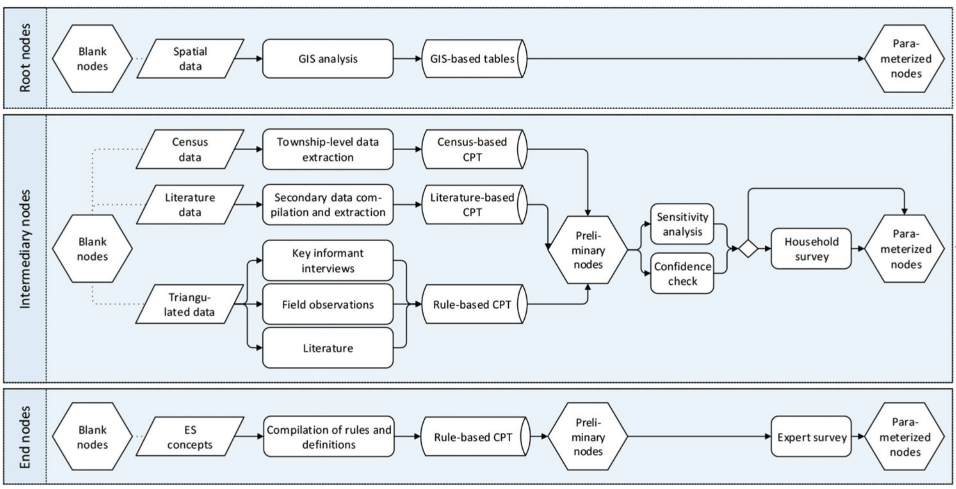

Figure A1. Flow chart of processes involved in populating probability tables for root nodes and CPTs for intermediary and end nodes

CPT = Conditional probability table; ES = Ecosystem services; GIS = Geographic information systems

Phase (c) Validating final models

As a final step, we used two validation approaches. As suggested and described by Kleemann et al. (2018), we applied the extreme-condition test checking model outputs given most extreme inputs to confirm the operational validity of each parameterized model. Then the models underwent a face validity test (Kleemann et al., 2018) with the 12 ES experts who are also familiar with natural resource use in the Southeast Asian context. Based on a standardized survey including pictures of the model structures, the experts had to rate the supply, demand and flow for each ES based on the direct parent nodes or, where needed for contextual reasons, the parent nodes to those. Combining all expert responses, probabilities and means for the states of supply, demand and flow were calculated for each ES and compared to the probabilities and weighted averages calculated from the models. Results are depicted in Appendix V.

Appendix II. Model structures

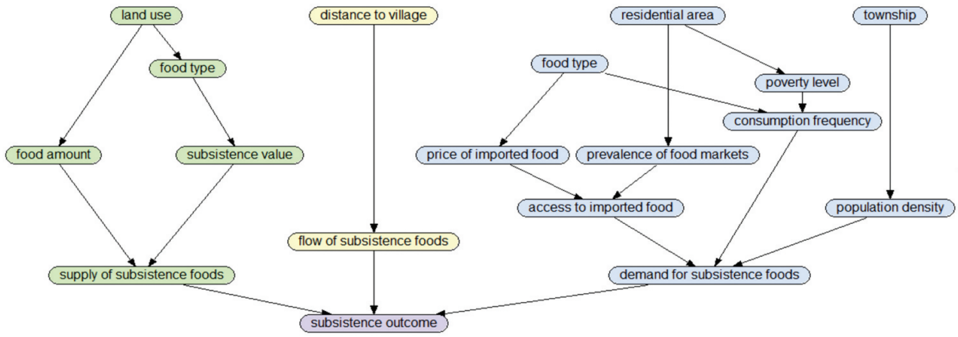

Figure A2. Model structure for ES 'subsistence foods' (green = supply nodes, yellow = flow nodes, blue = demand nodes; prepared in Netica).

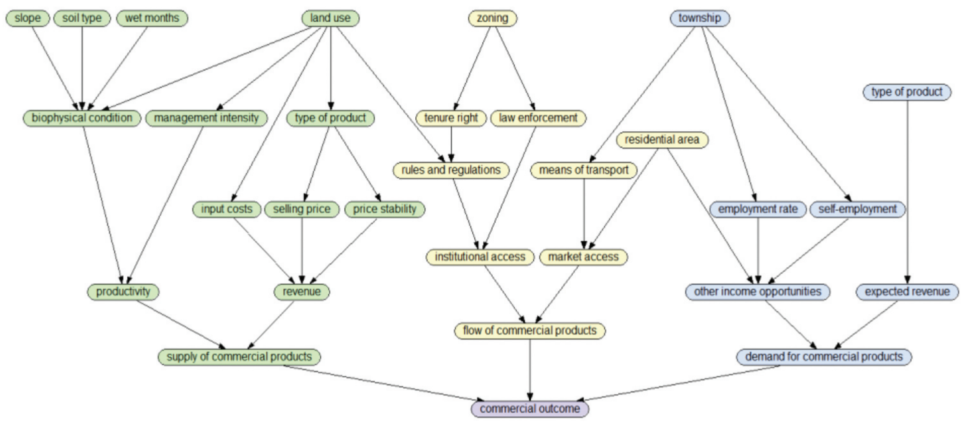

Figure A3. Model structure for ES 'commercial products' (green = supply nodes, yellow = flow nodes, blue = demand nodes; prepared in Netica).

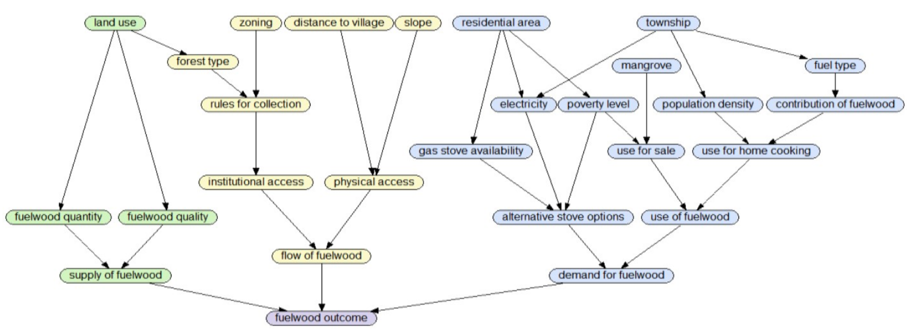

Figure A4. Model structure for ES 'fuelwood' (green = supply nodes, yellow = flow nodes, blue = demand nodes; prepared in Netica).

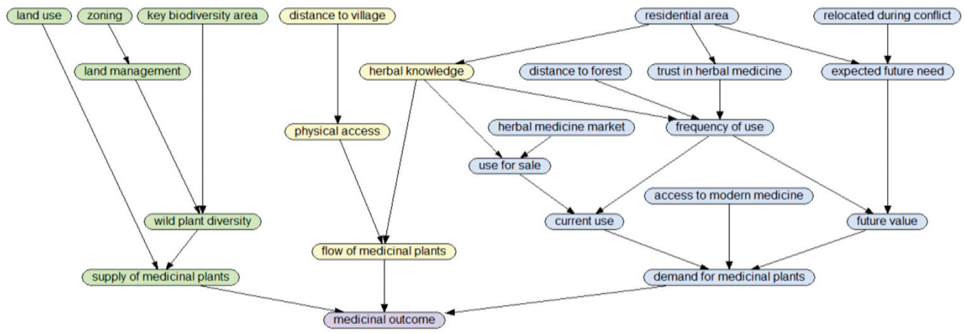

Figure A5. Model structure for ES 'medicinal plants' (green = supply nodes, yellow = flow nodes, blue = demand nodes; prepared in Netica).

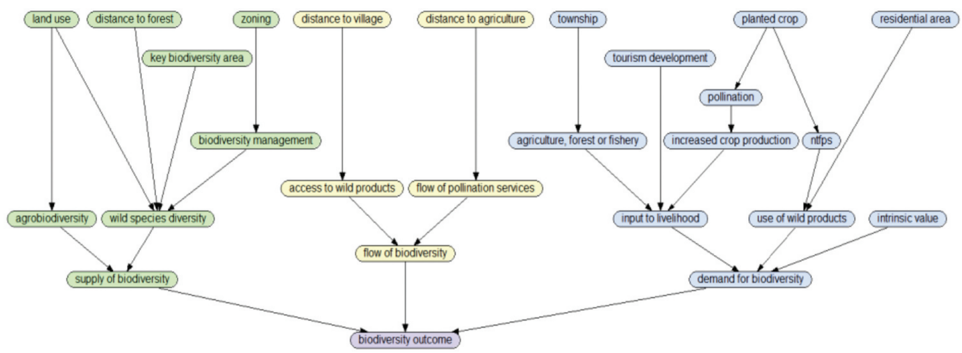

Figure A6. Model structure for ES 'biodiversity' (green = supply nodes, yellow = flow nodes, blue = demand nodes; prepared in Netica).

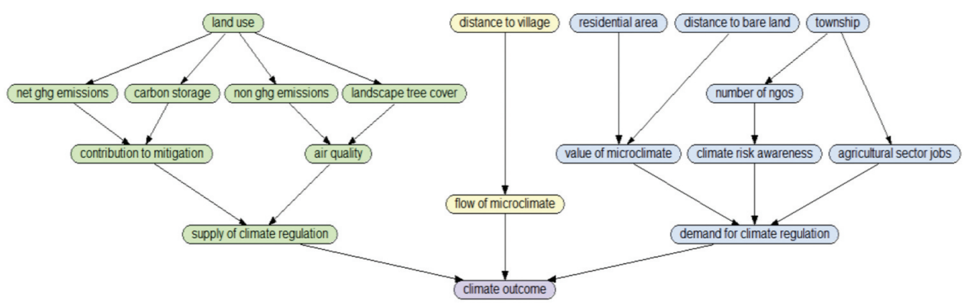

Figure A7. Model structure for ES 'climate regulation' (green = supply nodes, yellow = flow nodes, blue = demand nodes; prepared in Netica).

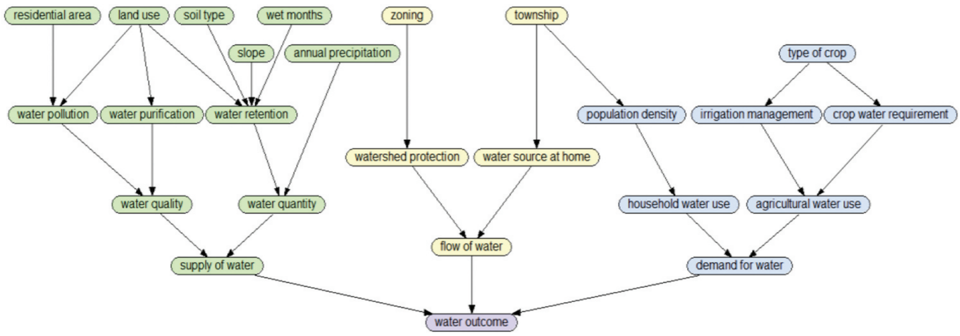

Figure A8. Model structure for ES 'water regulation' (green = supply nodes, yellow = flow nodes, blue = demand nodes; prepared in Netica).

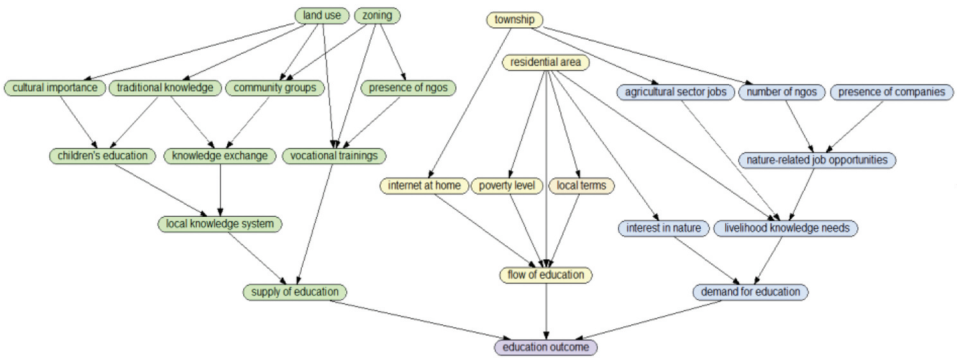

Figure A9. Model structure for ES 'environmental education' (green = supply nodes, yellow = flow nodes, blue = demand nodes; prepared in Netica).

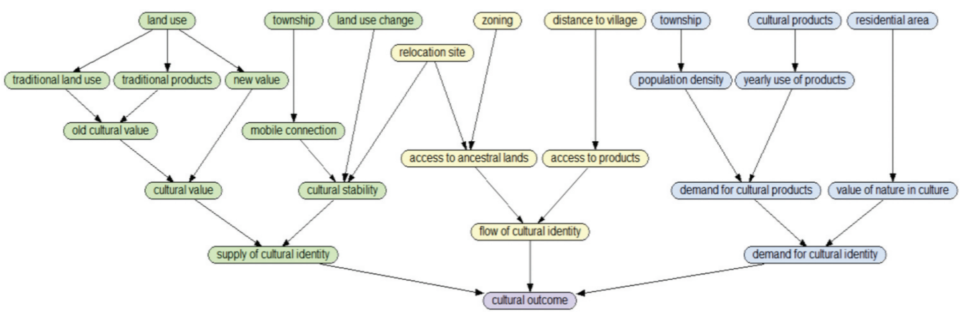

Figure A10. Model structure for ES 'cultural identity' (green = supply nodes, yellow = flow nodes, blue = demand nodes; prepared in Netica).

Appendix III. Nodes, data types and CPT rules

Table A2. Data types and rules for populating conditional probability tables for nine ecosystem service models using Bayesian networks (S = supply, F = flow, D = demand, O = outcome).

ES model	Node type	S/F/D/O	Code	Node	Type of data (spatial, census, literature, primary)	Additional information (rules or references) for filling conditional probability tables (CPT)
Subsistence foods	Root node	S	1a	land use	spatial	
		F	1b	distance to village	spatial	
		D	1 c	residential area	spatial	
			1d	township	spatial	
	Inter-mediary node	S	1e	food amount	household survey	based on 1a
			1 f	food type	triangulated	based on 1a
			1 g	subsistence value	triangulated	based on 1 f
			1 h	supply of subsistence foods	mixed	- based on 1e - 1 g: if very important *+50*, if important *+25*, if not important *−25*
		F	1i	flow of subsistence foods	mixed	*equals* 1b
		D	1 j	price of imported food	household survey	based on 1 f
			1 k	prevalence of food markets	triangulated	based on 1 c
			1 l	access to imported food	primary (mixed)	– 1 k: if always *yes*, if sometimes *75 yes* - 1 j: if high *−25*, if medium *−10*, if low *+10*
			1 m	poverty level	census	
			1 n	consumption frequency	household survey	based on 1 f
			1o	population density	census	
			1p	demand for subsistence foods	triangulated	- based on 1 n - 1 l: if yes *−50*, if no *-all*
	End node	O	1q	subsistence outcome	expert survey	- range of values supply, flow, demand - *mean*, (if.00 or.75 then *+25*, if.00 or 0.25 then *−25*) - *−10%* if no suppy, demand or flow - all: *−10%*

(*Continued*)

Table A2. (Continued).

ES model	Node type	S/F/D/O	Code	Node	Type of data (spatial, census, literature, primary)	Additional information (rules or references) for filling conditional probability tables (CPT)
Commercial products	Root node	S	2a	land use	spatial	
			2b	slope	spatial	
			2 c	soil type	spatial	
			2d	wet months	spatial	
		F	2e	zoning	spatial	
			2 f	residential area	spatial	
		D	2 g	township	spatial	
	Inter-mediary node	S	2 h	biophysical condition	triangulated	based on 2a – 2d
			2i	management intensity	triangulated	based on 2a
			2 j	productivity	mixed	- *equals* 2 h - 2i: if intensive *+25*, if extensive *−25*
			2 k	type of product	triangulated	based on 2a
			2 l	input costs	triangulated	based on 2a
			2 m	selling price	household survey	based on 2 k
			2 n	price stability	household survey	based on 2 k
			2o	revenue	mixed	- *equals* 2 m (if no sale *no change* later) - 2 l: if high *−50*, if low *+50* - 2 n: if fluctuating *+5* and *−20*
			2p	supply of commercial products	mixed	- *mean* of 2 j and 2o - for high *+50*, for low *−50*, for medium *+25* and *−25*
		F	2q	tenure right	triangulated	based on 2e
			2 r	rules and regulations	triangulated	based on 2a and 2q
			2s	law enforcement	triangulated	based on 2e
			2 t	institutional access	triangulated	based on 2 r and 2s
			2 u	means of transport	census	
			2 v	market access	triangulated	– 2 f: if urban *good*, if rural see below - 2 u: if car/tractor or boat *75 good*, if cart *50 good*, if motorbike *25 good*, if no *50 low*, rest *medium*
			2 w	flow of commercial products	mixed	- *equals* 2 v - 2 t: if no *75 low*
		D	2x	employment rate	census	
			2y	self-employment	census	
			2z	other income opportunities	mixed	– 2x and 2y: if 2x yes *high*, if 1x yes *medium*, if 2x no *low* - 2 f: if urban *+25*, if rural *−25*
			2aa	expected revenue	triangulated	equals 2o
			2ab	demand for commercial products	triangulated	- based on 2aa - 2z: if high *−25*, if low *+25*
	End node	O	2ac	commercial outcome	expert survey	see 1q

(*Continued*)

Table A2. (Continued).

ES model	Node type	S/F/D/O	Code	Node	Type of data (spatial, census, literature, primary)	Additional information (rules or references) for filling conditional probability tables (CPT)
Fuelwood	Root node	S	3a	land use	spatial	
		F	3b	zoning	spatial	
			3 c	distance to village	spatial	
			3d	slope	spatial	
		D	3e	residential area	spatial	
			3 f	township	spatial	
			3 g	mangrove	spatial	
	Inter-mediary node	S	3 h	fuelwood quantity	triangulated	based on 3a
			3i	fuelwood quality	triangulated	based on 3a
			3 j	supply of fuelwood	triangulated	- equals 3 h (if no then *no change* later) - 3i: if high *+50*, if low *−50*
		F	3 k	forest type	literature	based on 3a
			3 l	rules for collection	triangulated	based on 3b and 3 k
			3 m	institutional access	triangulated	based on 3 l (if restricted *50/50*)
			3 n	physical access	triangulated	– 3 c: if low *100 good*, if medium *75/25*, if low *50/50* - 3d: if yes *−25*
			3o	flow of fuelwood	mixed	based on 3 m and 3 n
		D	3p	gas stove availability	triangulated	based on 3e
			3q	electricity	census	
			3 r	poverty level	census	
			3s	alternative stove options	triangulated	– 3 r: if non-poor *100 yes*, if poor *20 yes* - if no electricity and no gas then *100 no*
			3 t	use for sale	triangulated	based on 3 g and 3 r
			3 u	fuel type	census	
			3 v	population density	census	
			3 w	contribution of fuelwood	triangulated	based on 3 u
			3x	use for home cooking	triangulated	- *equals* 3 v - 3 w: if daily *+50*, if occasionally *−50*
			3y	use of fuelwood	mixed	- based on 3x - 3 t: if yes *25 to very high*, if no *−25*
			3z	demand for fuelwood	mixed	- *equals* 3y - 3s: if yes *−50*
	End node	O	3ab	fuelwood outcome	expert survey	see 1q

(*Continued*)

Table A2. (Continued).

ES model	Node type	S/F/D/O	Code	Node	Type of data (spatial, census, literature, primary)	Additional information (rules or references) for filling conditional probability tables (CPT)
Medicinal plants	Root node	S	4a	land use	spatial	
			4b	zoning	spatial	
			4 c	key biodiversity area	spatial	
		F	4d	distance to village	spatial	
		D	4e	residential area	spatial	
			4 f	distance to forest	spatial	
			4 g	relocated during conflict	literature	fixed CPT (UNHCR, 2015)
			4 h	herbal medicine market	primary	fixed CPT
			4i	access to modern medicine	primary	fixed CPT
	Inter-mediary node	S	4 j	land management	triangulated	based on 4b
			4 k	wild plant diversity	mixed	– 4 c: if yes *high*, if no *medium* - 4 j: if intensive −*25*, if extensive +*25*
			4 l	supply of medicinal plants	triangulated	- based on 4a - 4 k: if high +*50*, if medium −*25*
		F	4 m	physical access	household survey	
			4 n	herbal knowledge	household survey	
			4o	flow of medicinal plants	triangulated	– 4 n: if many *high*, if few *high/medium*, if no *low* and *no change* later - 4 m: if good +*25*, if low −*25*
		D	4p	use for sale	triangulated	based on 4 h and 4 n
			4q	trust in herbal medicine	household survey	
			4 r	frequency of use	household survey	
			4s	current use	mixed	- *equals* 4 r - 4p: if yes +*50*, if no −*25*
			4 t	expected future need	triangulated	based on 4e and 4 g
			4 u	future value	mixed	- *equals* 4 r - 4 t: if more +*50*, if less −*50*
			4 v	demand for medicinal plants	mixed	- *equals* 4s (if high +*50*) - 4 u: if high +*50*, if low −*25* - 4i: if yes −*25*, if no +*25*
	End node	O	4 w	medicinal outcome	expert survey	see 1q

(*Continued*)

Table A2. (Continued).

ES model	Node type	S/F/D/O	Code	Node	Type of data (spatial, census, literature, primary)	Additional information (rules or references) for filling conditional probability tables (CPT)
Biodiversity	Root node	S	5a	land use	spatial	
			5b	distance to forest	spatial	
			5 c	key biodiversity area	spatial	
			5d	zoning	spatial	
		F	5e	distance to village	spatial	
			5 f	distance to agriculture	spatial	
		D	5 g	township	spatial	
			5 h	tourism development	primary	fixed CPT
			5i	planted crop	spatial	
			5 j	residential area	spatial	
			5 k	intrinsic value	primary	fixed CPT
	Inter-mediary node	S	5 l	biodiversity management	triangulated	based on 5d
			5 m	wild species diversity	triangulated	- based on 5a - 5 l: if yes *+50*, if no *−50* - 5 c: if yes *+25*, if no *−25* - 5b: if low *100 very high*, if medium *+25*
			5 n	agrobiodiversity	triangulated	based on 5a
			5o	supply of biodiversity	mixed	- *equals* 5 m - 5 n: if >5 + 50, if 2–5 + *25*
		F	5p	access to wild products	household survey	
			5q	flow of pollination services	literature	FAO (1995)
			5 r	flow of biodiversity	mixed	- *equals* 5p - 5q: if good *+25*, if limited *−25*
		D	5s	agriculture, forest or fishery	census	
			5 t	pollination	literature	FAO (1995)
			5 u	increased crop production	literature	FAO (1995)
			5 v	input to livelihood	mixed	– 5 h, 5s, 5 u: if 3x yes *100 high*, if 2x *75*, if 1x *25*, if 3x *no*
			5 w	ntfps	triangulated	based on 5i
			5x	use of wild products	triangulated	- based on 5 w - 5 j: if rural *+25*, if urban *−25*
			5y	demand for biodiversity	mixed	- based on 5x - 5 v: if high *+50*, if low *−25* - 5 k: if high *+25*, if low *−25*
	End node	O	5z	biodiversity outcome	expert survey	see 1q

(*Continued*)

Table A2. (Continued).

ES model	Node type	S/F/D/O	Code	Node	Type of data (spatial, census, literature, primary)	Additional information (rules or references) for filling conditional probability tables (CPT)
Climate regulation	Root node	S	6a	land use	spatial	
		F	6b	distance to village	spatial	
		D	6 c	residential area	spatial	
			6d	distance to bare land	spatial	
			6e	township	spatial	
	Inter-mediary node	S	6 f	net ghg emissions	triangulated	based on 6a
			6 g	carbon storage	literature	Bhat et al. (2003), Donato et al. (2011), Kongsager et al. (2013)
			6 h	non ghg emissions	triangulated	based on 6a
			6i	landscape tree cover	literature	
			6 j	contribution to mitigation	triangulated	- *mean* of 6 f and 6 g
			6 k	air quality	triangulated	
			6 l	supply of climate regulation	mixed	– 6 k: if good *very h*igh, if medium *high/medium*, if low *low* - 6 j: if very high +*50*, if high +*25*, if low −*25*, if no −*50*
		F	6 m	flow of microclimate	mixed	based on 6b
		D	6 n	value of microclimate	triangulated	- *equals* 6d - 6 c: if urban +*50*, if rural −*50*
			6o	number of ngos	census	
			6p	climate risk awareness	mixed	based on 6o
			6q	agricultural sector jobs	census	
			6 r	demand for climate regulation	mixed	- based on 6 n - 6p: if aware +*50* - 6q: if yes +*50*, if no −*25*
	End node	O	6s	climate outcome	expert survey	see 1q

(*Continued*)

Table A2. (Continued).

ES model	Node type	S/F/D/O	Code	Node	Type of data (spatial, census, literature, primary)	Additional information (rules or references) for filling conditional probability tables (CPT)
Water regulation	Root node	S	7a	residential area	spatial	
			7b	land use	spatial	
			7 c	soil type	spatial	
			7d	slope	spatial	
			7e	wet months	spatial	
			7 f	annual precipitation	spatial	
		F	7 g	zoning	spatial	
			7 h	township	spatial	
		D	7i	type of crop	spatial	
	Inter-mediary node	S	7 j	water pollution	triangulated	- based on 7b (mining, built-up > oil palm > rubber, paddy, bare > rest) - 7a: if urban *+25*
			7 k	water purification	literature	Saad et al. (2013)
			7 l	water retention	triangulated	- based on 7b - 7e: if 1–3 − *50*, if 4–6 − *25* –7d: if slope −*25* - 7 c: if fluvisol/nitisol *+25*, if acrisol/gleysol −*25*
			7 m	water quality	mixed	– 7 j: if yes *polluted*, if no *good* - 7 k: if high *+50*, if medium *+25*
			7 n	water quantity	mixed	- based on 7 f - 7 l: if high *+50*, if low −*50*
			7o	supply of water	mixed	- *equals* 7 n - 7 m: if good *+25*, if polluted −*50*
		F	7p	watershed protection	triangulated	based on 7 g
			7q	water source at home	census	
			7 r	flow of water	mixed	- based on 7q - 7p: if yes *+25*, if no −*25*
		D	7s	population density	census	
			7 t	household water use	mixed	based on 7s
			7 u	irrigation management	triangulated	based on 7i
			7 v	crop water requirement	literature	calculated with Cropwat (FAO)
			7 w	agricultural water use	mixed	- *equals* 7 v - 7 u: if yes *+50* and *++50*
			7x	demand for water	triangulated	- *equals* 7 t - 7 w: if high *+all*, if medium *+50*, if low *+25* - potential additional demand (all): *+25*
	End node	O	7y	water outcome	expert survey	see 1q

(*Continued*)

Table A2. (Continued).

ES model	Node type	S/F/D/O	Code	Node	Type of data (spatial, census, literature, primary)	Additional information (rules or references) for filling conditional probability tables (CPT)
Environ-mental education	Root node	S	8a	land use	spatial	
			8b	zoning	spatial	
		F	8 c	township	spatial	
			8d	residential area	spatial	
		D	8e	presence of companies	primary	fixed CPT
	Inter-mediary node	S	8 f	cultural importance	household survey	
			8 g	traditional knowledge	triangulated	
			8 h	community groups	triangulated	based on 8a and 8b
			8i	presence of ngos	mixed	based on 8b
			8 j	children's education	triangulated	– 8 f: if high *yes*, if medium *50/50*, if low *no* - 8 g: if high *+25*, if low *−25*
			8 k	knowledge exchange	triangulated	– 8 h: if formal *regularly*, if informal *50/50*, if no *never* - 8 g: if high *+25*, if low *−25*
			8 l	local knowledge system	triangulated	- *equals* 8 k - 8 j: if part *+50*, if not part *−50*
			8 m	vocational trainings	triangulated	- based on 8a and 8b - 8i: if yes *+25*, if no *−25*
			8 n	supply of education	mixed	– 8 m: if yes *very high/high*, if no *no* - 8 l: if strong *+25* and *++25*, if medium *+25*
		F	8o	internet at home	census	
			8p	poverty level	census	
			8q	local terms	triangulated	based on 8d
			8 r	flow of education	triangulated	– 8d: urban *50/25/25*, rural *25/50/25* - 8p: if poor *−25*, if non-poor *+25* - 8q: if different *−25*
		D	8s	agricultural sector jobs	census	
			8 t	number of ngos	census	
			8 u	nature-related job opportunities	mixed	- based on 8 t and 8e
			8 v	livelihood knowledge needs	mixed	– 8s: if yes *yes*, if no change accordingly: - 8 u: if many *75 yes*, if some *50 yes*, if limited *25 yes* - 8d: if rural *+25*
			8 w	interest in nature	triangulated	based on 8d
			8x	demand for education	mixed	– 8 v: if yes *very high/high*, if no *low/no* - 8 w: if high *+50*, if medium *+25*
	End node	O	8y	education outcome	expert survey	see 1q

(*Continued*)

Table A2. (Continued).

ES model	Node type	S/F/D/O	Code	Node	Type of data (spatial, census, literature, primary)	Additional information (rules or references) for filling conditional probability tables (CPT)
Cultural identity	Root node	S	9a	land use	spatial	
			9b	township	spatial	
			9 c	land use change	spatial	
		F	9d	relocation site	literature	fixed CPT (UNHCR, 2015)
			9e	zoning	spatial	
			9 f	distance to village	spatial	
		D	9 g	township	spatial	
			9 h	cultural products	primary	based on land use
			9i	residential area	spatial	
	Inter-mediary node	S	9 j	traditional land use	triangulated	based on 9a
			9 k	traditional products	triangulated	based on 9a
			9 l	old cultural value	mixed	based on 9 j and 9 k
			9 m	new value	triangulated	based on 9a
			9 n	cultural value	mixed	- *equals* 9 l - 9 m: if yes *+50*
			9o	mobile connection	census	
			9p	cultural stability	triangulated	– 9 c: if yes *low*, if no *high* - 9d: if yes *−100*, if no *+50* - 9o: if yes *−50*, if no *+100*
			9q	supply of cultural identity	mixed	- *equals* 9 n - 9p: if high *+25*, if low *−25*, if very low *−50*
		F	9 r	access to ancestral lands	triangulated	based on 9e and 9d
			9s	access to products	household survey	
			9 t	flow of cultural identity	mixed	- if 2x yes *high*, if 1x yes *medium*, if 2x no *low* - 9s: if yes *+25* - 9 r: if no *−25*
		D	9 u	population density	census	
			9 v	yearly use of products	household survey	based on 9 h
			9 w	demand for cultural products	triangulated	- *equals* 9 v - 9 u: if > 100 + *25*, if < 50 − *25*
			9x	value of nature in culture	triangulated	based on 9i
			9y	demand for cultural identity	mixed	- *equals* 9 w - 9x: if high ++*25*, if low – *25*
	End node	O	9z	cultural outcome	expert survey	see 1q

Appendix IV. Questionnaire for household survey

Mélanie Feurer, 17/01/2020

ES-Survey Tanintharyi

Date: ____________________ Location: ________________ No: ___________________

Name: ___________________ Ethnic: ___________________ Gender: ________________

1. Which of the following types of lands do you have / use?

land use		tenure			distance	comments
		no	yes	area (ac)		
	Intact forest					
	Degraded forest					
	Mangrove					
	Betelnut					
	Cashew					
	Lime					
	Mixed plantation					
	Rubber					
	Oil palm					
	Paddy rice					
	Upland rice					

2. How do the following lands contribute to the food you consume in your household?

land use	a) contribution			b) seasonal		comments
	enough	additional	no food	yes	no	
Intact forest						
Degraded forest						
Mangrove						
Mixed plantation						
Rubber						
Oil palm						
Paddy rice						
Upland rice						

3. How is the price of the following foods to buy on the market?

i) Rice ☐ high ☐ medium ☐ low

ii) Vegetables ☐ high ☐ medium ☐ low

iii) Fruit ☐ high ☐ medium ☐ low

iv) Spices ☐ high ☐ medium ☐ low

v) Fish ☐ high ☐ medium ☐ low

vi) Meat ☐ high ☐ medium ☐ low

4. a) Which price do you currently get for selling the following products?

b) Compared to other products, do you think this price is high / medium / low?

c) Is the price stable or fluctuating?

product	a) current selling price	b) price range			c) stability	
		high	medium	low	yes	no
Timber						
NTFPs						
Rice						
Rubber						
Palm fruit						
Betelnut						
Cashew						
Lime						
Pepper						
Fruit						
Vegetables						
Fish						
Crab						

5. In your culture, how often do you use the following products?

i) NTFPs □ 1/w □ 1/m □ 3-4/y □ never
ii) Rice □ 1/w □ 1/m □ 3-4/y □ never
iii) Betelnut □ 1/w □ 1/m □ 3-4/y □ never
iv) Cashew □ 1/w □ 1/m □ 3-4/y □ never
v) Coconut □ 1/w □ 1/m □ 3-4/y □ never
vi) Toddy □ 1/w □ 1/m □ 3-4/y □ never
vii) Fruits □ 1/w □ 1/m □ 3-4/y □ never
viii) Snails □ 1/w □ 1/m □ 3-4/y □ never
other: ______________________________ □ 1/w □ 1/m □ 3-4/y □ never

6. How much fuelwood can you get from the following lands and how would you rate the quality?

land use	a) quantity (1=no, 5=very high)					b) quality		
	5	4	3	2	1	high	medium	low
Intact forest								
Degraded forest								
Mangrove								
Mixed plantation								
Rubber								
Oil palm								

7. a) How many medicinal plants do you know? □ > 10 □ 5 - 10 □ less than 5 □ none
b) Do you trust in herbal medicine? □ yes □ no
c) How often do you use herbal medicine? □ often □ sometimes □ never
d) How far is the closest forest? □ < 2 miles □ 2 miles or more
e) If you lived closer to a forest, would you use more medicinal plants? □ yes □ no

8. a) Do you participate in farmer / forest / environment groups within the community? ◻ yes ◻ no

b) group	c) formal	d) How often do you meet and exchange information?
	◻ yes ◻ no	
	◻ yes ◻ no	
	◻ yes ◻ no	

9. a) Are there NGOs present in your village / village tract? ◻ yes ◻ no
   b) Are there companies present in your village / village tract? ◻ yes ◻ no
   c) Did you ever have contact with staff from the FD or AD? ◻ yes ◻ no
   d) Did you ever have the opportunity to participate in a training on farming or forests? ◻ yes ◻ no
   If yes, please fill in this table:

a) trainer	b) institution			c) topic
	NGO	Company	FD/AD	

10. a) Are you interested in nature? ◻ yes ◻ no
    b) How do you rate the value of nature in your culture? ◻ very high ◻ high ◻ medium ◻ low

11. a) Do you get the following products from your lands or from the market?
    b) What is the maximum distance from your house that you would walk to collect them?

Rice a) ◻ own land ◻ market b)________________________________
Betelnut a) ◻ own land ◻ market b)________________________________
Fruit a) ◻ own land ◻ market b)________________________________
Fuelwood a) ◻ own land ◻ market b)________________________________
Vegetables a) ◻ own land ◻ market b)________________________________
Cashew a) ◻ own land ◻ market b)________________________________
NTFPs a) ◻ own land ◻ market b)________________________________
Medicine a) ◻ own land ◻ market b)________________________________

Appendix V. Validation process

Based on a standardized survey including pictures of the model structures, the twelve experts had to rate, on a scale from 1 to 5, the supply and demand and, on a scale from 2 to 4, the flow of each ES based on the direct parent nodes or, where needed for contextual reasons, the nodes above. Table A3 below is a summary of the differences (in %) found between the models and the expert responses. We calculated the differences by comparing the mean ratings of the experts with the weighted average of model output probabilities.

Appendix VI. Input variables and data sources

Table A3. Summary of validation results including the calculated differences in % between modelled supply, flow and demand values and expert estimations.

	Supply		Demand		Flow		
	mean	sd	mean	sd	mean	sd	Total (mean)
Subsistence foods	−0.7	16.0	−13.0	13.0	−0.7	4.1	**−4.8**
Commercial products	14.9	29.9	−9.7	26.7	8.4	12.1	**4.5**
Fuelwood	−4.4	27.4	−8.6	5.9	3.8	12.7	**−3.1**
Medicinal plants	−39.4	27.8	−2.4	21.2	−2.3	9.1	**−14.7**
Biodiversity	−19.0	10.8	−15.0	10.8	15.0	9.8	**−6.3**
Climate	−17.8	20.9	−17.0	18.3	1.7	1.7	**−11.0**
Water	−14.2	32.0	−12.4	16.5	−4.5	15.9	**−10.4**
Environmental education	17.0	42.1	−7.8	26.1	−2.2	12.2	**2.3**
Cultural identity	−15.2	26.5	7.4	43.1	−2.5	8.6	**−3.4**
Total (mean)	**−8.8**		**−8.7**		**1.9**		**−5.2**

Sd = standard deviation

Table A4. List of input variables (root nodes), states and data sources.

Variable (node)	Classes (states)	% in Tanintharyi (calculated in ArcGIS)	Integration in ES models	Sources	Processing (in ArcGIS)
Land use	Intact forest Degraded forest Mangrove Mixed plantation Rubber Oil palm Paddy Bare Mining Built-up	49.6 27.6 6.1 2.3 2.0 2.5 3.8 4.6 0.1 1.4	Subsistence foods (SF), Commercial products (CP), Fuelwood (FW), Medicinal plants (MP), Biodiversity (BD), Climate regulation (CR), Water regulation (WR), Environmental education (EE), Cultural identity (CI)	Connette et al. (2016) (16 land cover classes), Nomura et al. (2019) (oil palm), LaJeunesse Connette et al. (2016) (mining)	a) reclassify 16 land use classes into 9 by combining forest types (lowland, broadleaf, upland) and mangrove (intact, degraded) b) add updated oil palm data (multiply and reclassify) c) add mining data as additional class (multiply and reclassify)
Zoning	Protected area Oil palm concession Mining concession Special Economic Zone Community forestry Other	4.5 7.5 0.1 0.5 0.3 87.1	CP, FW, MP, BD, WR, EE, CI	WCS (Protected areas), Nomura et al. (2019) (oil palm concessions), OneMap Myanmar (2018) (CF) DOM (2015) (mining concessions), MIMU (2020) (SEZ)	- delete planned protected areas - merge all into a raster - no data = other
Key bio-diversity area	Yes No	48.7 51.3	MP, BD	BirdLife International (2010)	
Land use change	Yes No	52.5 47.5	CI	Schmid (2018)	
Slope	Flat Slope	57.0 43.0	CP, FW, WR	NASA (2001)	- classify flat/slope if < 30% >
Soil type	Acrisols Gleysols Fluvisols Nitisols	56.7 8.5 0.2 34.5	CP, WR	FAO (2007)	

(*Continued*)

Table A4. (Continued).

Variable (node)	Classes (states)	% in Tanintharyi (calculated in ArcGIS)	Integration in ES models	Sources	Processing (in ArcGIS)
Wet months	1–3	1.4	CP, WR	WorldClim (2012)	- count months with rainfall - classify
	4 – 6	84.7			
	> 6	13.9			
Annual precipitation	> 4000 mm	14.8	WR	WorldClim (2012)	- classify
	3000–3999 mm	48.9			
	2000–2999 mm	28.9			
	1000–1999 mm	7.2			
	< 1000 mm	0.2			
Township	Bokpyin	14.0	SF, CP, FW, BD, CR, WR, EE, CI	MIMU (2020) (townships) DOP (2014) (census)	
	Dawei	16.8			
	Kawthoung	6.1			
	Kyunsu	9.7			
	Launglon	1.9			
	Myeik	2.9			
	Palaw	5.9			
	Tanintharyi	27.5			
	Thayetchaung	5.1			
	Yebyu	10.1			
Residential area	Rural	96.8	SF, CP, FW, MP, BD, CR, WR, EE, CI	Worldpop (2013)	- classify rural/urban if < 4 pph >
	Urban	3.2			
Distance to village/forest/agriculture/bare land	low		SF, FW, MP, BD, CR, CI	Connette et al. (2016)	- Euclidean distance - classify according to ecosystem service
	medium				
	high				