Report on Investment Priority Mapping

An activity of the project:

Promoting and accelerating responsible social forestry investment in ASEAN, a component of "Climate change mitigation through social forestry actions in ASEAN countries (Switzerland contribution to UN-REDD Asia Technical Assistance)"

Contents

1. Context and Objectives

This context for this effort is an opportunity to address the pressing challenges facing ASEAN countries in mitigating the impacts of climate change while bolstering social forestry (SF) initiatives. As Southeast Asia grapples with increasing vulnerability to climate change, member states within ASEAN have taken proactive measures, engaging in international dialogues like the Paris Agreement and outlining national strategies.

Despite these efforts, persistent challenges, from slow policy implementation to limited monitoring systems, hinder comprehensive assessments of social forestry's contributions. This initiative aims to fortify the evidence base for social forestry's climate mitigation contributions and identify priorities for forest commodity investment in the region that can increase benefits to people and forests.

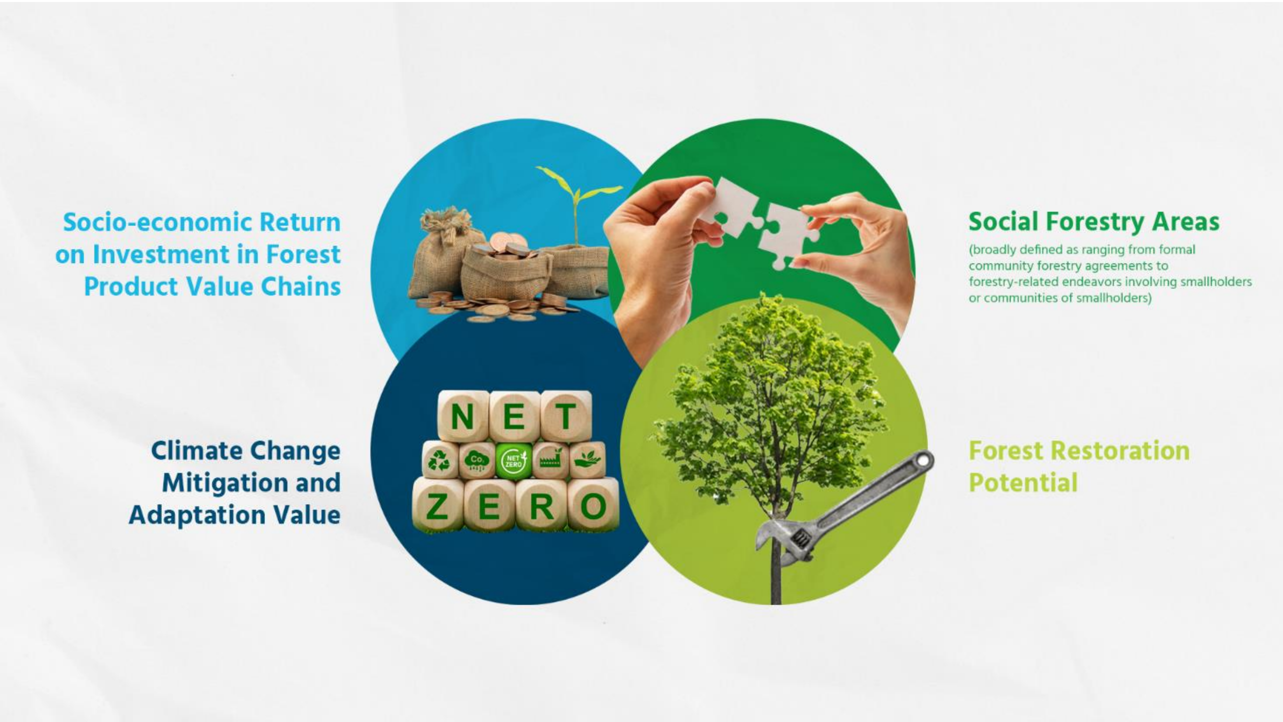
This aspect of the project leveraged se.plan, a spatial prioritization tool built on the System for Earth Observation Data Access, Processing and Analysis for Land Monitoring (SEPAL), an open-source platform that facilitates efficient access to and analysis of Earth observation data. Designed to map and assess social forestry programs and business models, our use of se.plan aids in delineating investment-worthy areas within the social forestry landscape. Its geospatial analysis considers biogeophysical aspects, market infrastructure proximity, and accessibility to market intermediaries, aligning with the initiative's goal of identifying priority areas for social forestry investment in some ASEAN countries. Results provide actionable insights to help guide the sustainable commercialization and scaling up of social forestry-based enterprises in the region.

In this analysis, we have customized se.plan's standard model structure to include current and likely future social forestry areas not adequately represented in available data. Using a predictive model based on available spatial data on social forest areas, we identified high-probability areas for social forestry, extending se.plan's standard output.

2. Objective

The objective of this work is to identify areas in Cambodia, Lao PDR, and Indonesia where investment in forest commodity enterprises will 1) have a high socio-economic return on investment, 2) have the potential to be integrated in social forestry management and governance structures, 3) have relatively high climate change mitigation and adaptation value, and 4) support the restoration of tree cover. This intersection of economic benefits and forest-positive outcomes is illustrated in Figure 1 below.

Figure 1. Graphic showing the combination of characteristics of areas ranking highest in this analysis.



3. Methods

The methodology employed in this analysis comprises two distinct steps. In the first step, we used a machine learning approach to produce continuous spatial data layers in Laos, Cambodia, and Indonesia representing the likelihood of a given location either already being under social forestry (SF) or being under SF in the future. In the second step, we used the se.plan tool with these and other data layers as input to produce another set of continuous surfaces covering Laos, Cambodia and Indonesia that represent relative suitability of a location in terms of both likely economic viability of forest enterprises associated with commodities underlying key value chains (identified in the complementary work under this project) *and* strong potential for social forestry development.

SF Modeling

In this first step, we compiled data that our team and experts consulted within and outside of RECOFTC deemed likely relevant to accurately mapping where SF areas currently occur and where they are likely to be established in the future. Table 1 is a list of these data layers that we used to train the machine learning models for identifying the likelihood of current and future SF occurrence.

Table 1: Data layers used in mapping probability of social forestry.

Dataset		Description	Source
Dynamic Forest Fragmentation Index (FFI)	Global	This dataset represents the differences, from 2000 to 2020, in characteristics of forest fragmentation, including edge, isolation, and patch size effects.	Link
Forest-Proximate People (FPP)	Global	This dataset provides an estimate of the number of people living in or within 5 kilometers of forests for 2019.	Link
SRTM Landforms	Global	This dataset provides landform classes created by combining the Continuous Heat-Insulation Load Index (SRTM CHILI) and the multi-scale Topographic Position Index (SRTM mTPI) datasets for 2006 to 2011.	Link
Oxford Map Friction Surface	Global	This dataset contains land-based travel speed for all land pixels between 85 degrees north and 60 degrees south for the year 2019. It also includes "walking-only" travel speed, using non-motorized means of transportation.	Link
NASA SRTM Digital Elevation 30m	Global	This dataset provides global elevation data and was used to derive other topographic variables such as slope, aspect, eastness, and northness	Link
ESA WorldCover 10m v200	Global	This dataset provides 11 land cover classes as a global map for the year 2021 on Sentinel-1 and Sentinel-2 data.	Link
Land cover	Cambodia	This dataset provides 14 land cover classes as a map for the year 2020. It was derived from the Biophysical M&E Dashboard tool, being used by USAID/Cambodia to track performance and report on landscape-scale efforts and biophysical conditions on the ground in accordance with quantifying areas of biological improvement and improved natural resource management.	Link

For Cambodia, RECOFTC provided current data detailing established social forestry areas, forming the foundation for our analysis. However, in the case of Indonesia and Laos, comprehensive or high-quality data on established social forestry areas was either unavailable or insufficient. We therefore adopted a transfer learning approach, leveraging the social forestry area data from Cambodia and global-coverage input data layers to construct a training dataset and model for Cambodia that can be easily applied in Indonesia and Laos. This method aims to transfer knowledge across regions, optimizing the model's accuracy despite varying data availability across the ASEAN countries.

We used a random forest model, known for its effectiveness in capturing intricate and non-linear relationships within datasets, to predict the likelihood of social forestry establishment within each country. To generate a training dataset and model for Cambodia, we utilized all predictive data layers except the global land cover dataset, substituting it for the Cambodia-specific land cover dataset (Table 1). Using the labeled SF area data, we randomly sampled 1000 point locations each from within and outside the SF areas, extracting the predictor datasets' values and their SF area label (1 or 0) at each location. These 2000 points were then subsampled following a randomized split, creating a training dataset comprising approximately 70% of all samples, and a validation dataset containing the remaining 30%. We set the model development complexity at 50 'trees' (the random forest model term for decision trees built from a bootstrap subsample of the training data) to balance model effectiveness and complexity. Given that available data did not facilitate creating independent models in Indonesia and Laos, for these two countries, we re-ran the training data generation and model training steps, keeping model hyperparameters constant, but using the se.plan's global land cover dataset instead of the Cambodia-specific dataset used in the development of the Cambodia model.

The results of these modeling exercises are probability surfaces (Figures 2a and 2b) where continuous values represent the relative likelihood of social forestry establishment.

Because our development of this SF area likelihood map was to be used to mask out areas of each focal country from the eventual se.plan prioritization model, we needed to set a threshold probability value below which social forestry is impossible or very unlikely to be implemented . In Cambodia, the government's objective to designate 2 million hectares to social forestry areas by 2029 aligns with a $p > 0.7$ threshold, representing 2.2 million hectares of high-probability regions. However, this threshold setting significantly constrains the analysis to a small area of the country when the environmental constraints for robust target species propagation were applied. Therefore, to allow for a larger area of investment priorities, we opted for a threshold of $p > 0.5$, translating into something like "areas where social forestry establishment is "more likely than not."

Figures 2b-1-3 highlight areas of higher relative probability of occurrence of SF governance and/or management arrangements in each of three countries for which likelihood of SF occurrence was modeled. In Figure 2b-1, yellow points show where environmental predictor variables were sampled for fitting the random forest model.

Figure 2a. Relative likelihood of social forestry management/governance arrangements in Laos PDR (upper left panel), Cambodia (upper right panel), and Indonesia (lower panel).

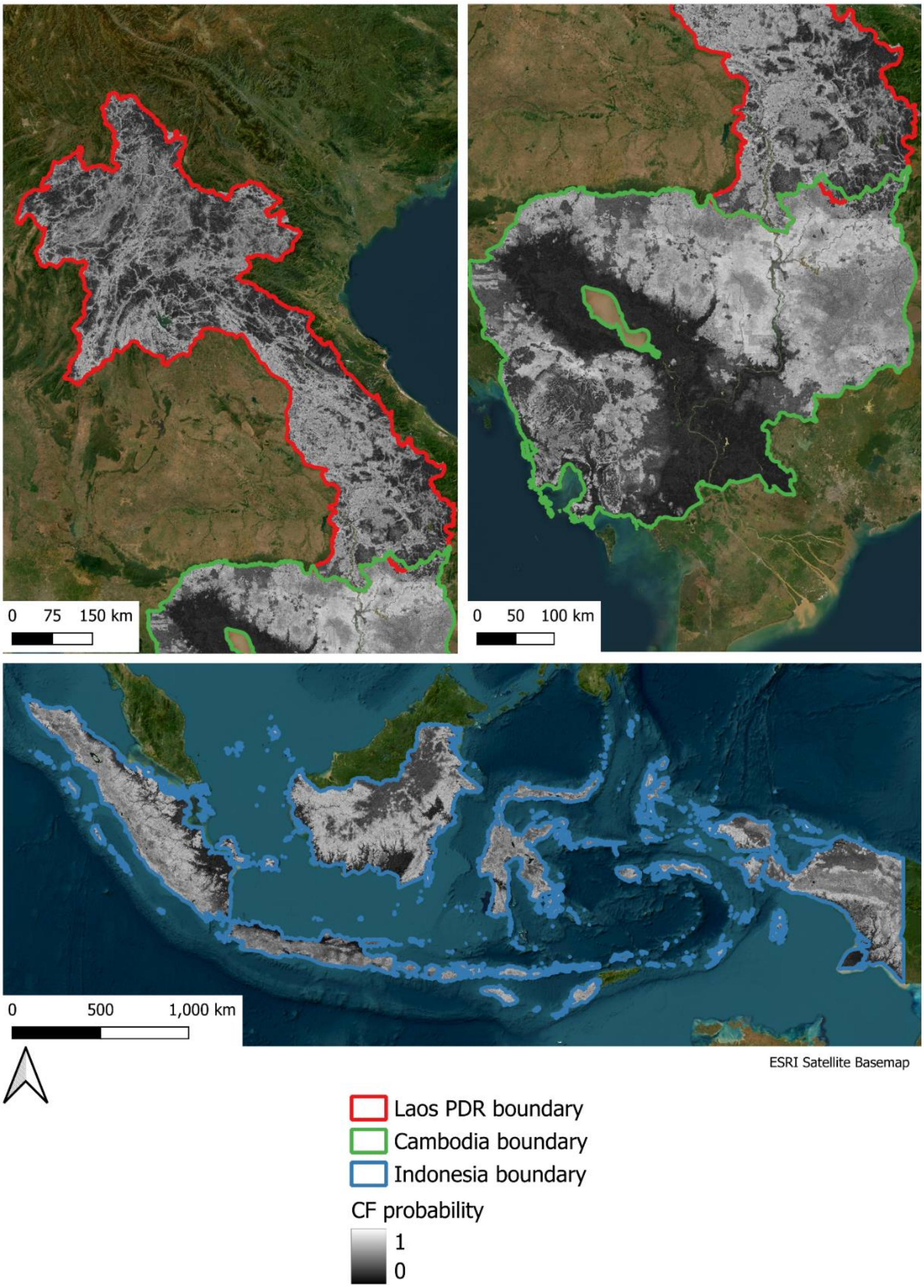


Figure 2b-1. Areas of higher relative likelihood (p > 0.5) of social forestry management/governance arrangements in Cambodia. Point locations in yellow are where environmental predictor variables were sampled for fitting the random forest model.

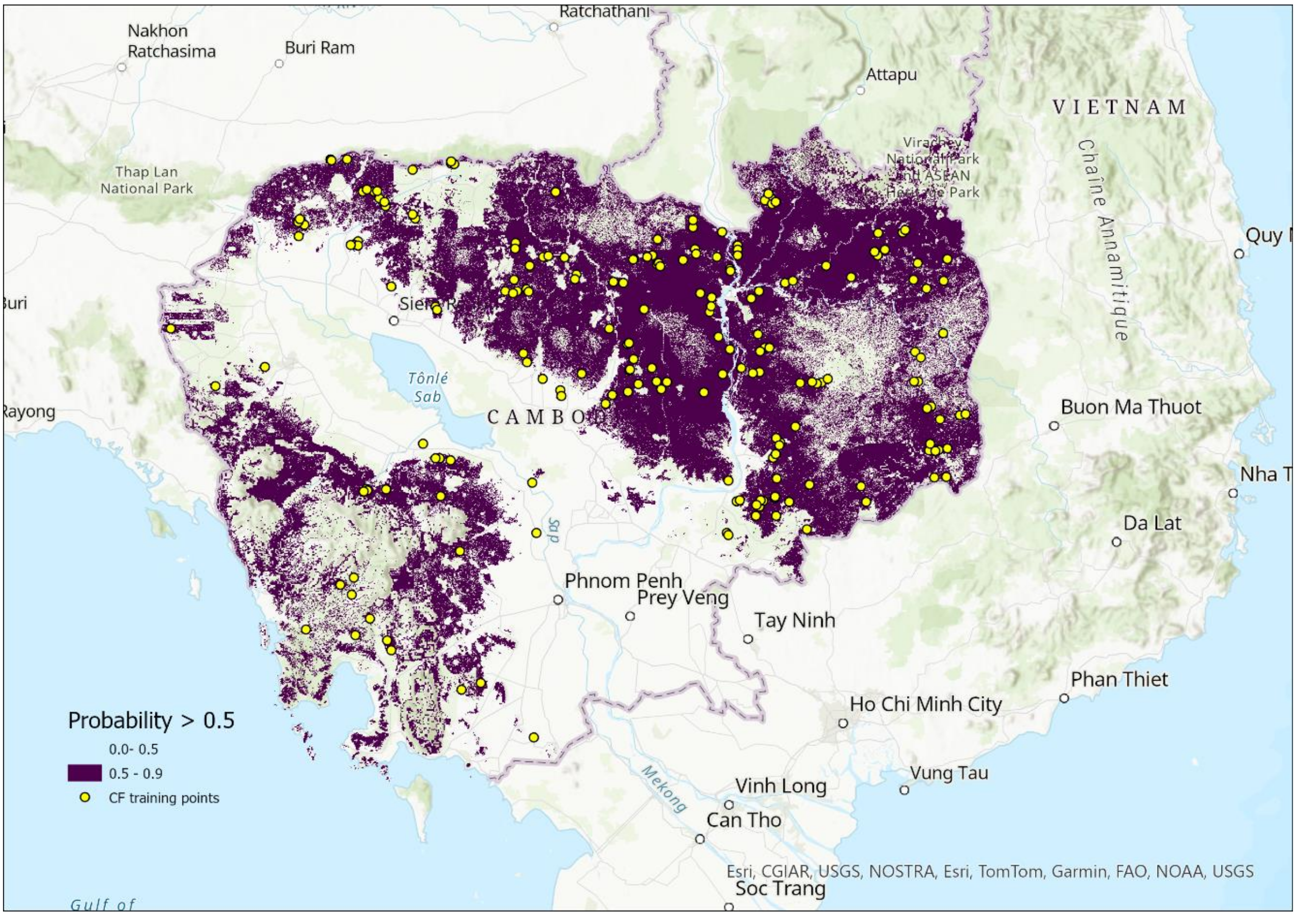


Figure 2b-2. Areas of higher relative likelihood (p > 0.5) of social forestry management/governance arrangements in Lao PDR.

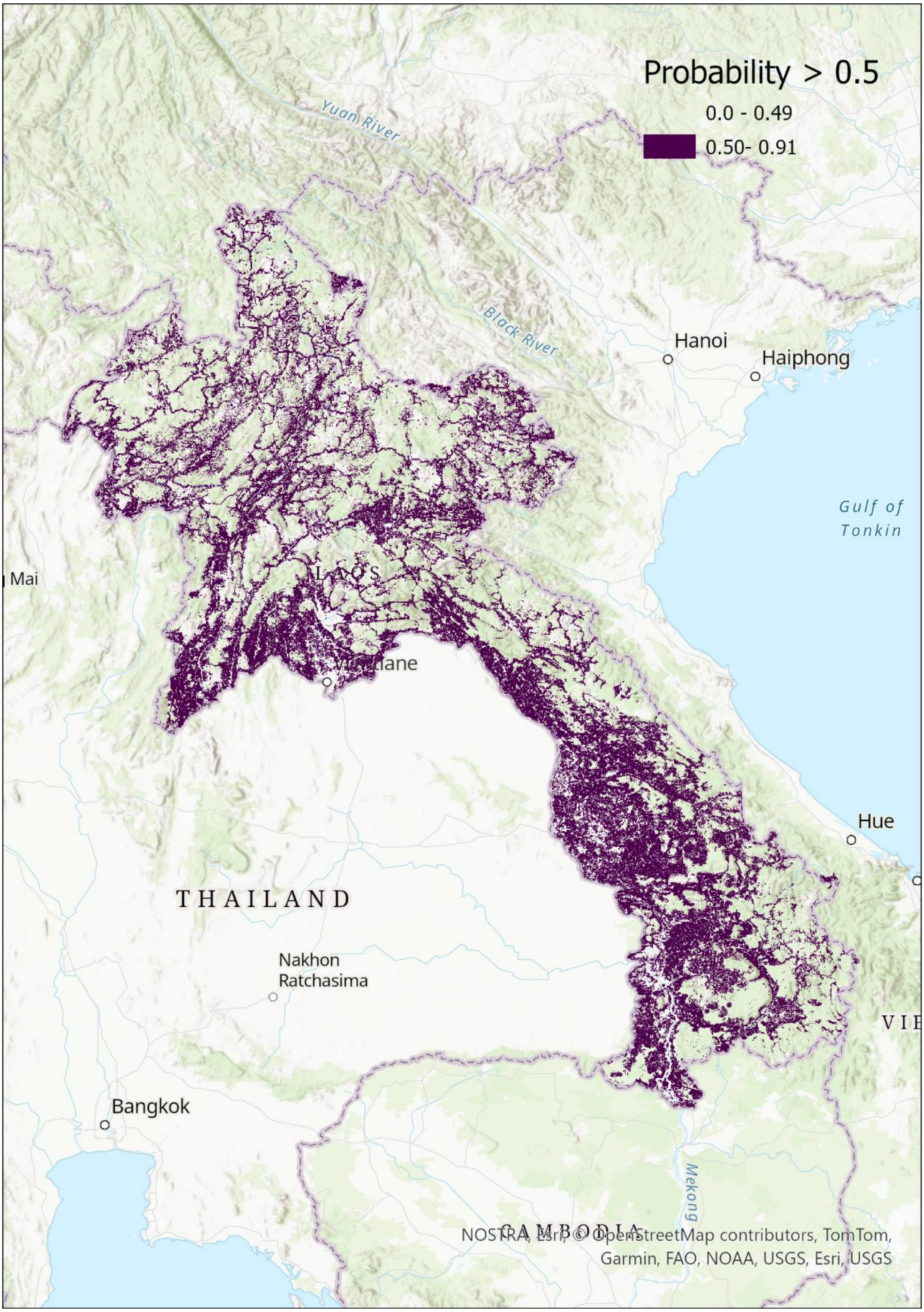
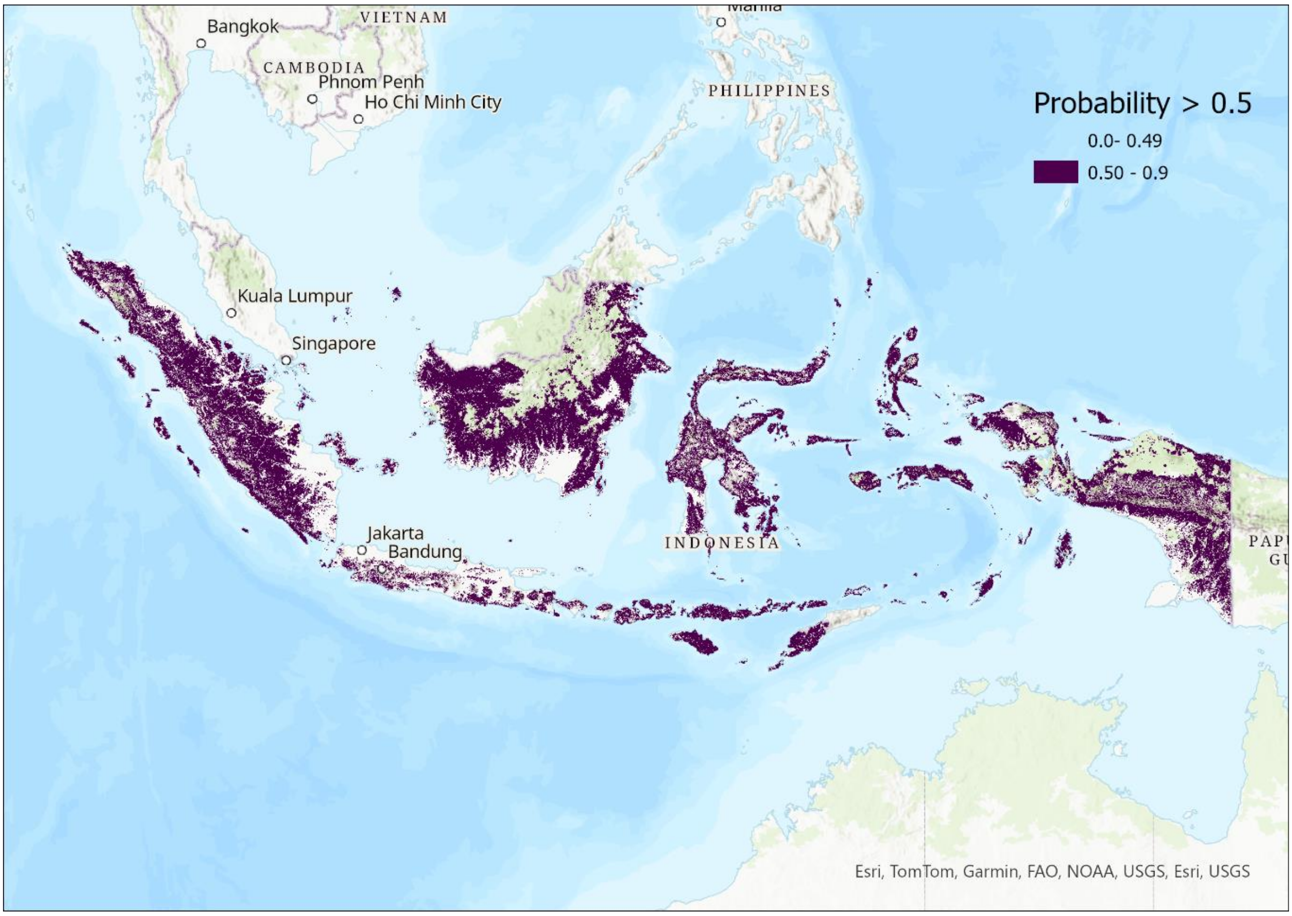


Figure 2b-3. Areas of higher relative likelihood (p > 0.5) of social forestry management/governance arrangements in Indonesia.



Social forestry likelihood of occurrence for all countries analyzed was predominantly influenced by a combination of the Forest-proximate people and elevation data layers. For example, in Cambodia (Figure 2b-1), likely areas for social forestry occurrence are the northern edge of the Cardamom Mountains (southwestern part of the country) and selected areas in the northeast part of the country—particularly areas in Ratanakiri province—where large numbers of people live in proximity to standing forests but where elevation is generally lower.

SE.PLAN

The se.plan tool and underlying methodology "aims to identify locations where the benefits of forest restoration are high relative to restoration costs, subject to biophysical and socioeconomic constraints that users impose to define the areas where restoration is allowable." (https://docs.sepal.io/en/latest/modules/dwn/seplan.html) To do this, se.plan combines two key components: cost layers and normalized benefit layers. These elements combine to compute a detailed cost-benefit ratio, which in turn is categorized into a 0-5 priority score or index value. In the context of this study, a higher score can be interpreted as a more promising geographic area for investing in the commodity species and associated value chain(s) identified in the companion analysis. Areas deemed completely unworthy of investment are masked from the solution set.

Our approach was to run a se.plan analysis for priority forest commodity species identified for each country (identified in the complementary work under this project) – with each run integrating national ecosystem and demographic contexts. To maintain consistency and comparability, all scenarios across species and countries adhered to the same default cost layers provided by the se.plan tool. Notably, we allocated the maximum weight to benefits associated with local livelihood enhancement and wood production.

Our methodology relied on environmental constraints derived from data on optimal environmental niches for each species based on published references (Table 2).

Table 2. Environmental niche information for species analyzed.

Species	**Tectona grandis** (Laos, Indonesia)	**Cratoxylum formosum** (Laos)	**Paraserianthes falcataria** (Indonesia)	**Sindora siamensis** (Sindora cochinchinensis) (Cambodia)	**Vatica astrotricha** (Cambodia)	**Shorea obtusa** (Cambodia)	**Xylia xylocarpa** (Xylia dolabriformus) (Cambodia)
Annual rainfall range (min and max)	1,000-3,800 mm	1000 to 3000 mm	800 to 3,500 mm	1,000 - 4,000	800 to 4,000 mm	1,250 - 4,000 mm	500 - 5,000 mm
Temperature range (min and max)	20-40°C	20°C to 35°C	15-35°C	15°C-35°C	15°C-35°C	20°C-35°C	16 - 35°C
Altitude range (min and max)	0-1500 m	0-1500 m	0-2,000 m	0-1,500 m	0 -1,500 m	0- 1,500 m	0-1,500 m
Slope	<20%				> 5%		

* Note that taxonomic synonyms are frequently used for two of the species above (Sindora siamensis and Xylia xylocarpa) so the synonyms are provided here for clarity to all readers.

A detailed description of the se.plan tool including standard datasets can be found at: https://docs.sepal.io/en/latest/modules/dwn/seplan.html.

4. SE.PLAN Map Results

The results obtained from the se.plan analysis provide insight into the suitability of social forestry-focused investment in expanding areas of commodity species underlying selected value chains in Cambodia, Laos, and Indonesia. Below is a description of the results for each country.

Cambodia

The most influential factors in the se.plan outputs for Cambodia were areas where tree cover had already reached its maximum, designated protected areas, and varying elevation requirements–all of which clearly defined lower priority scores. Temperature and precipitation were not significant factors as the ranges for all species exceeded the conditions present in Cambodia at the global dataset's resolution. Results are similar for Sindora siamensis, Shorea obtusa, and Xylia xylocarpa (Figures 3a and 3b-1-3). In the case of Vatica astrotricha, specific slope requirements resulted in a distinctively different pattern (Figure 3b-4).

These patterns signify the most favorable regions for potential social forestry-related forest enterprise investment in Cambodia for the commodity species considered.

Figure 3a. se.plan map outputs for focal commodity species in Cambodia.

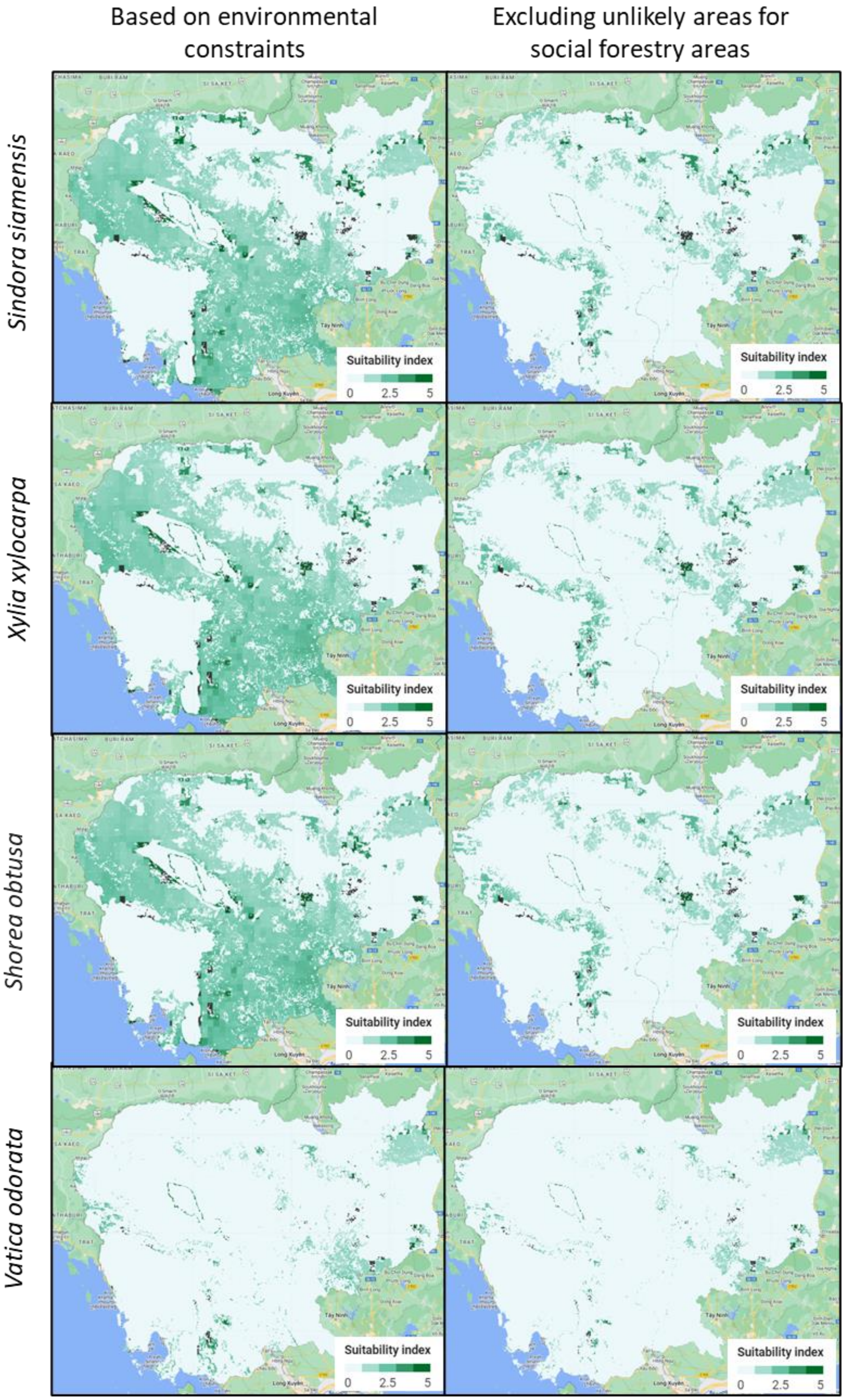


Figure 3b-1. Aggregate area of each of five se.plan index scores for Sindora siamensis in Cambodia. Note: In this and all subsequent histograms, "Count" is equivalent to square kilometers since final outputs of se.plan are at a 1 sq. km resolution.

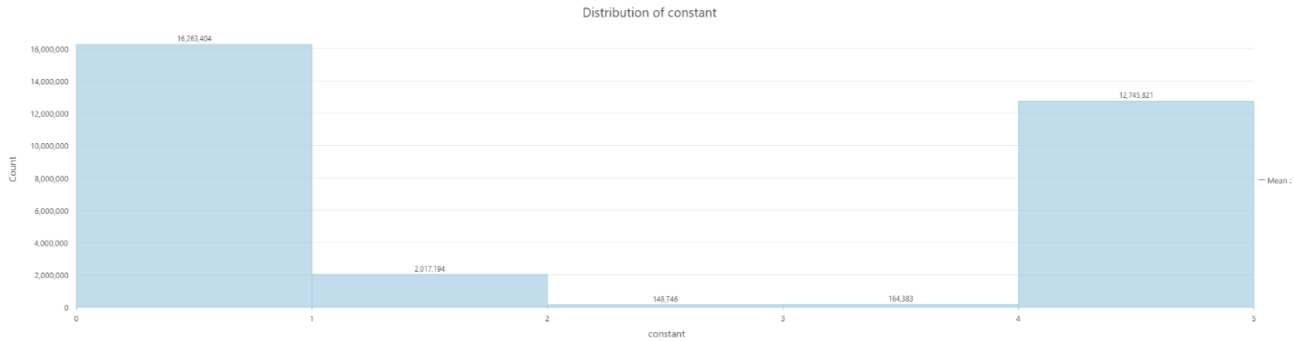


Figure 3b-2. Aggregate area of each of five se.plan index scores for Xylia xylocarpa in Cambodia.

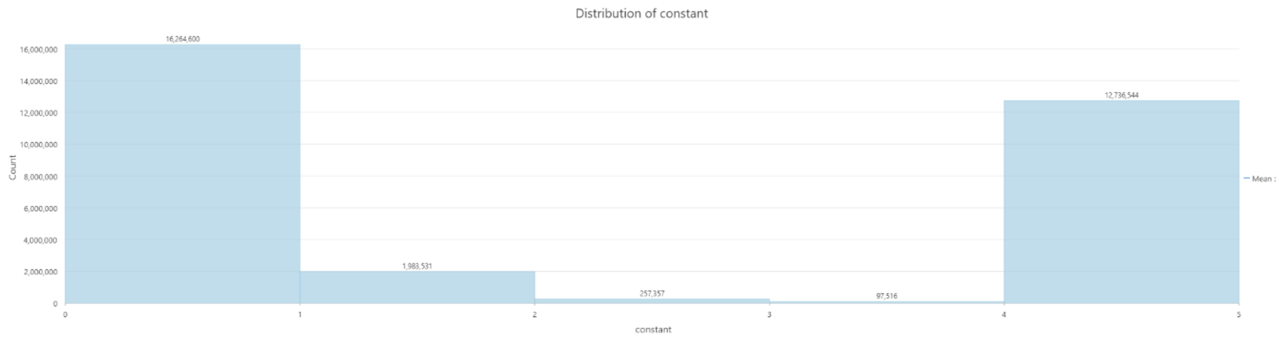


Figure 3b-3. Aggregate area of each of five se.plan index scores for Shorea obtusa in Cambodia.

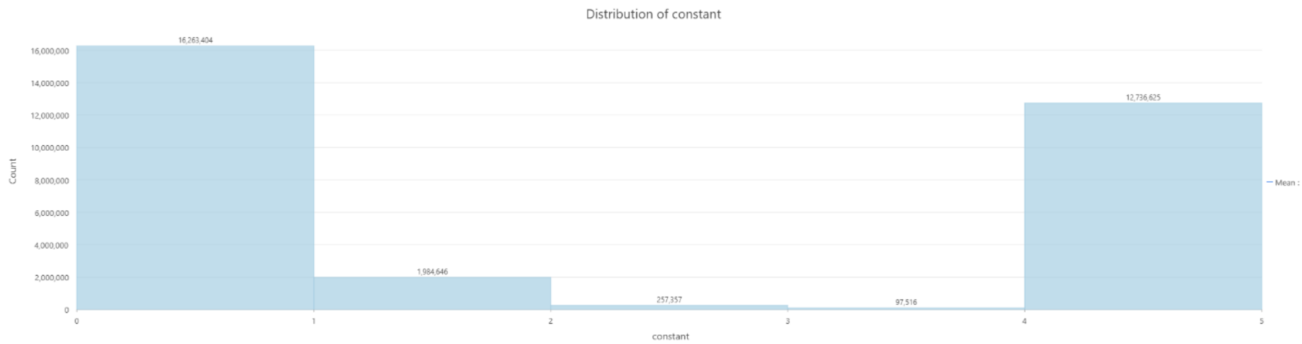


Figure 3b-4. Aggregate area of each of five se.plan index scores for Vatica odorata in Cambodia.

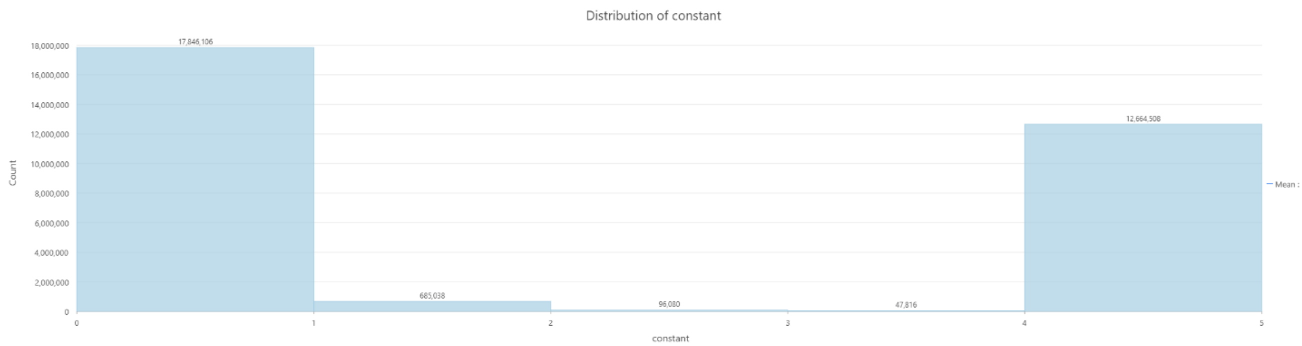
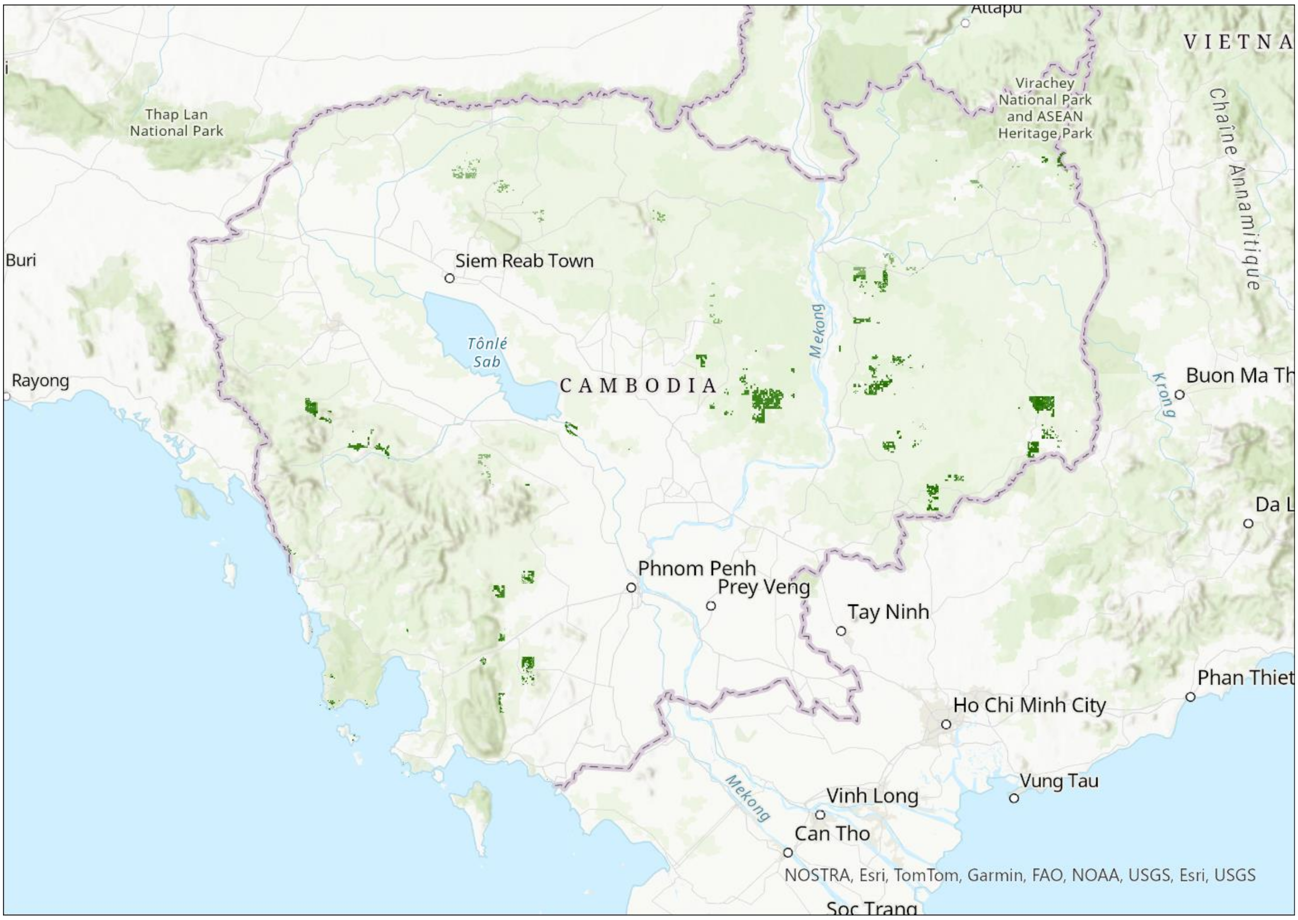


Figure 3c. Intersection of priority areas (se.plan indices 4 or 5) of four focal commodity species in Cambodia.



Laos

In Laos, the se.plan result maps for Tectona grandis (teak) and Cratoxylum formosum were similar with variability driven largely by topographical features (Figures 4a and 4b-1-2). The most influential layers shaping the suitability assessment were the se.plan “Forest Proximate to People within 5km (FPP 5km)” layer, elevation, and aspect. Notably, Tectona grandis’ aversion to higher slopes contrasts with the broader slope tolerance of Cratoxylum formosum.

The suitability of these two species overlaps particularly in areas where communities are within 5km of forests and that have elevation ranges preferred by these species.

Figure 4a. se.plan map outputs for focal commodity species in Lao PDR.

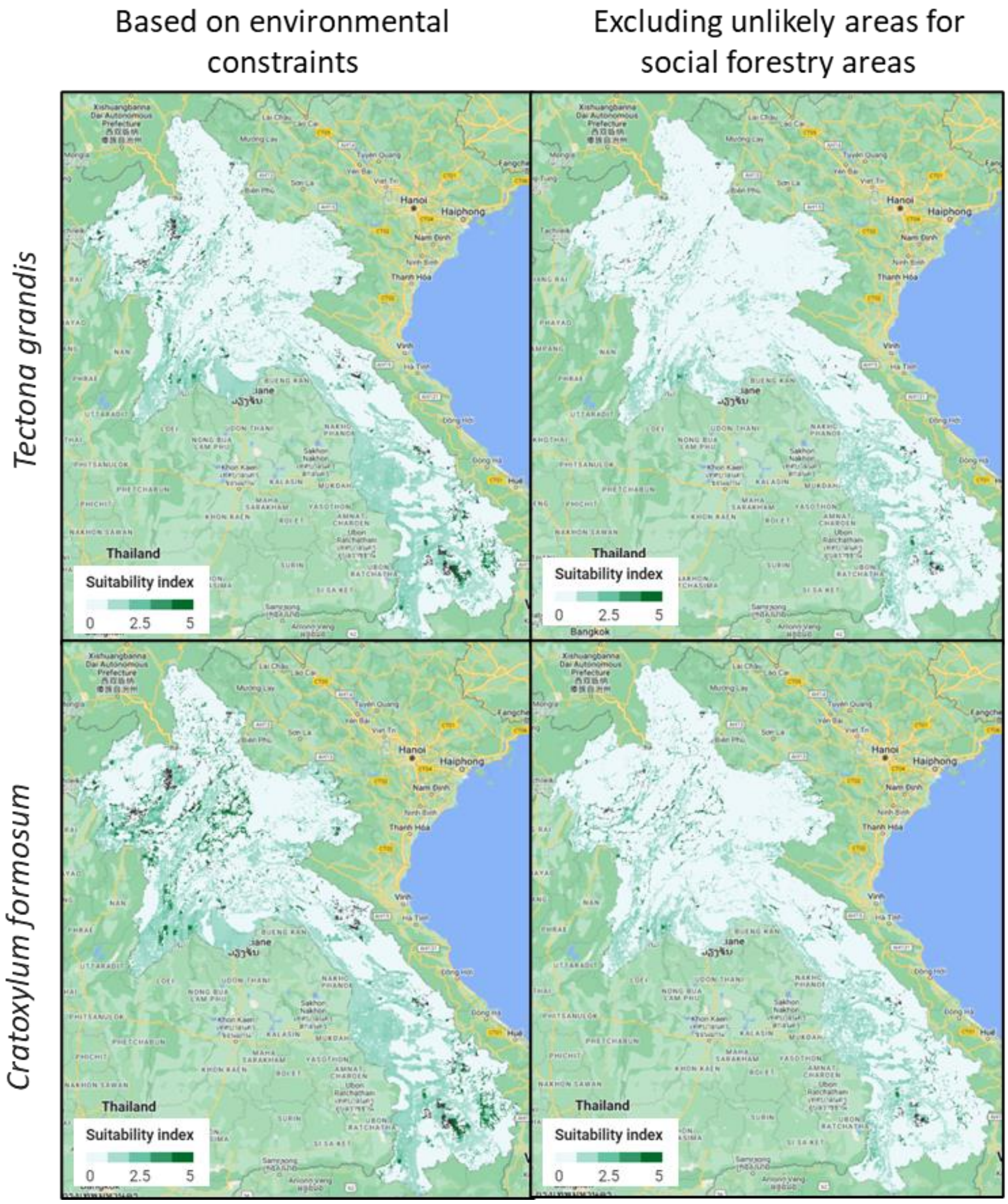


Figure 4b-1. Aggregate area of each of five se.plan index scores for Tectona grandis in Laos.

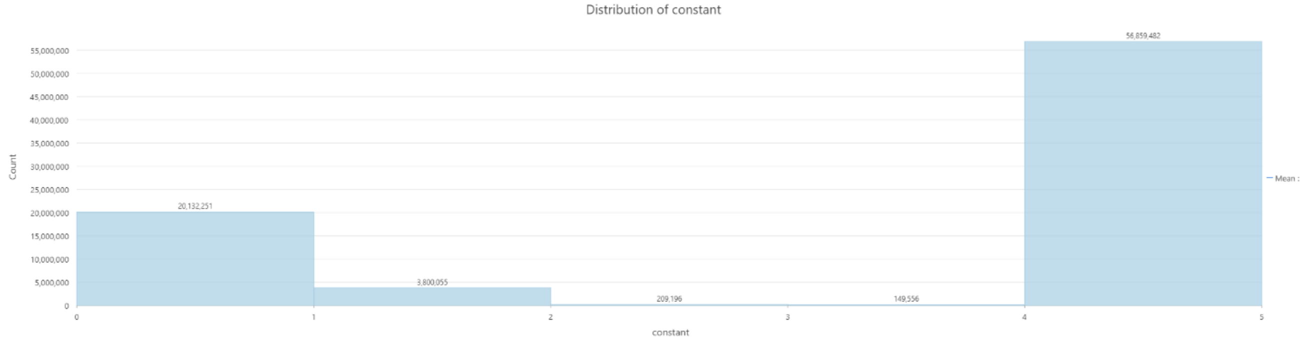


Figure 4b-2. Aggregate area of each of five se.plan index scores for Cratoxylum formosum in Laos.

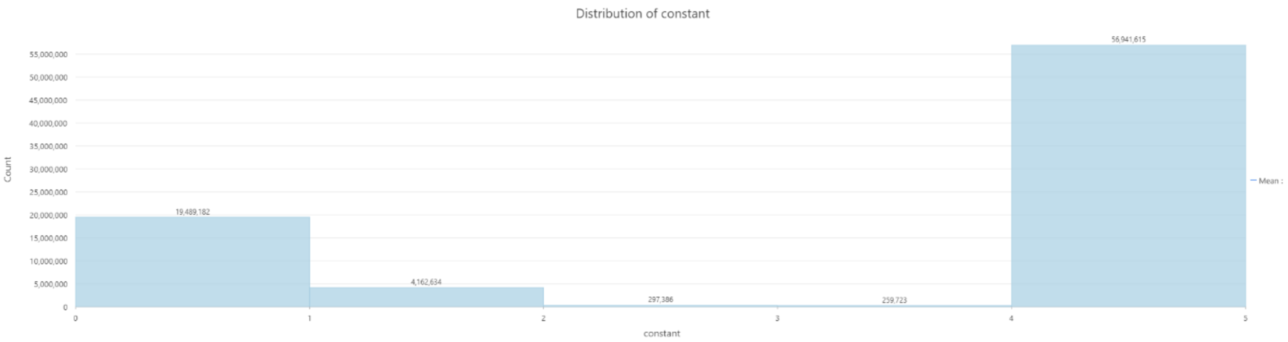


Figure 4c. Intersection of priority areas (se.plan indices 4 or 5) of two focal commodity species in Laos.

Indonesia

The se.plan priority area maps for two species in Indonesia are similar with the Tectona grandis' having less suitable areas due to its sensitivity to higher slopes (Figures 5a and 5b-1-2).

Figure 5a. se.plan map outputs for focal commodity species in Indonesia.

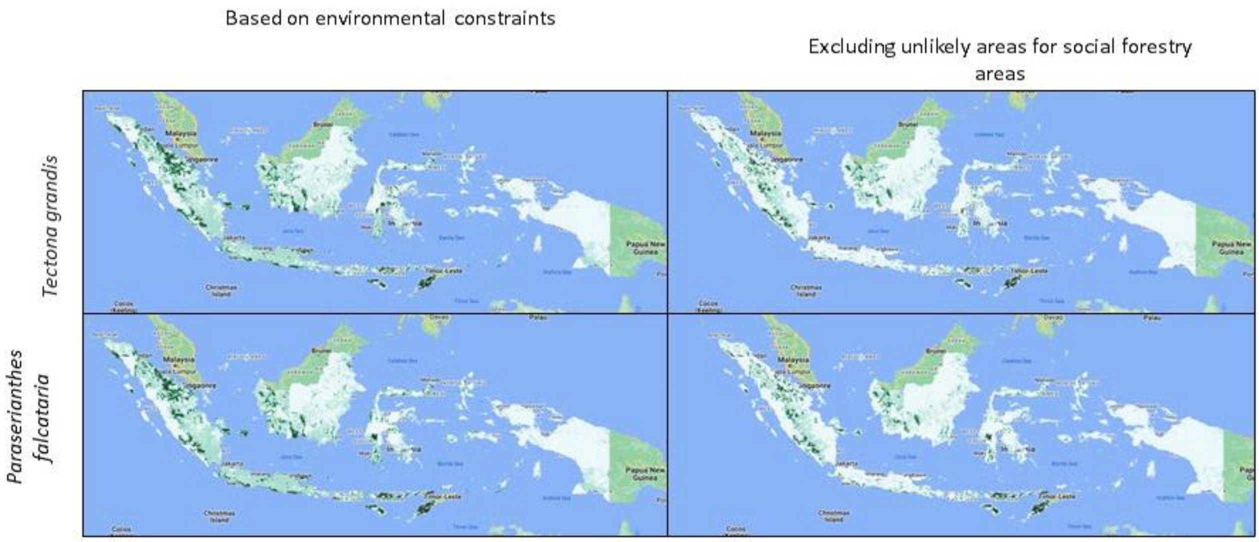


Figure 5b-1. Aggregate area of each of five se.plan index scores for Tectona grandis in Indonesia.

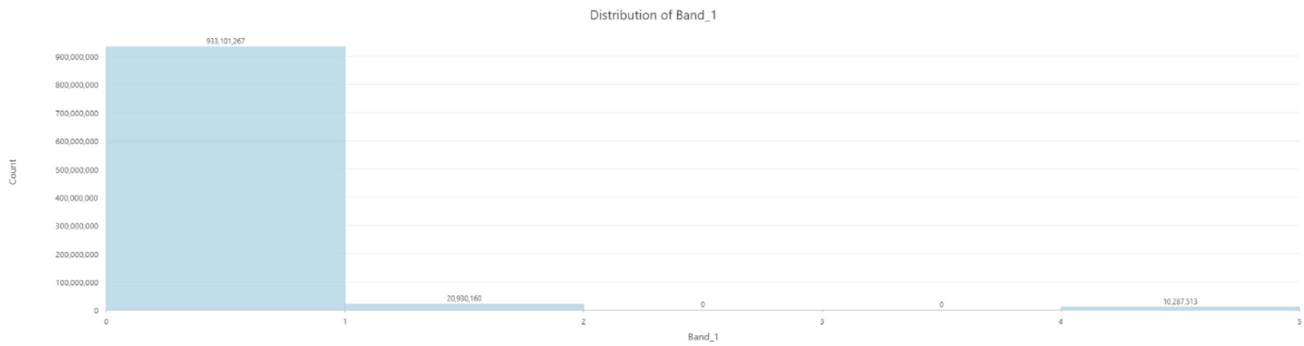


Figure 5b-2. Aggregate area of each of five se.plan index scores for Peraserianthes falcataria in Indonesia.

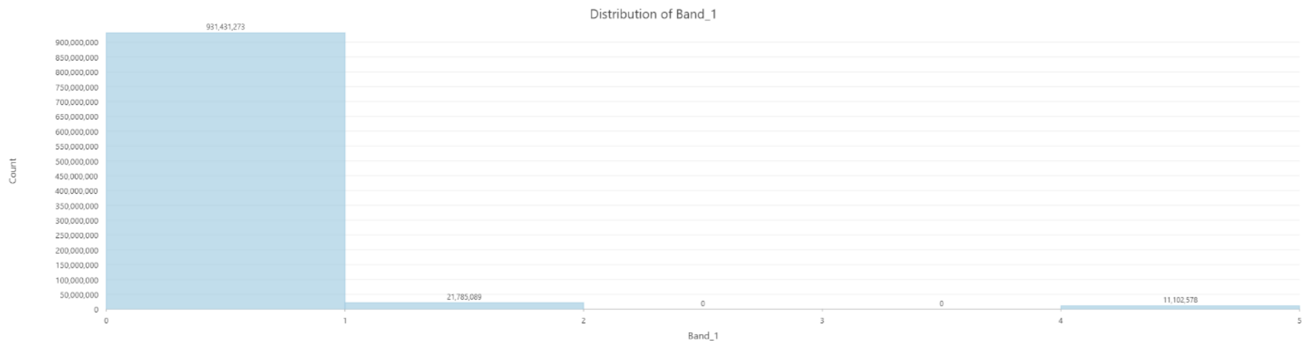
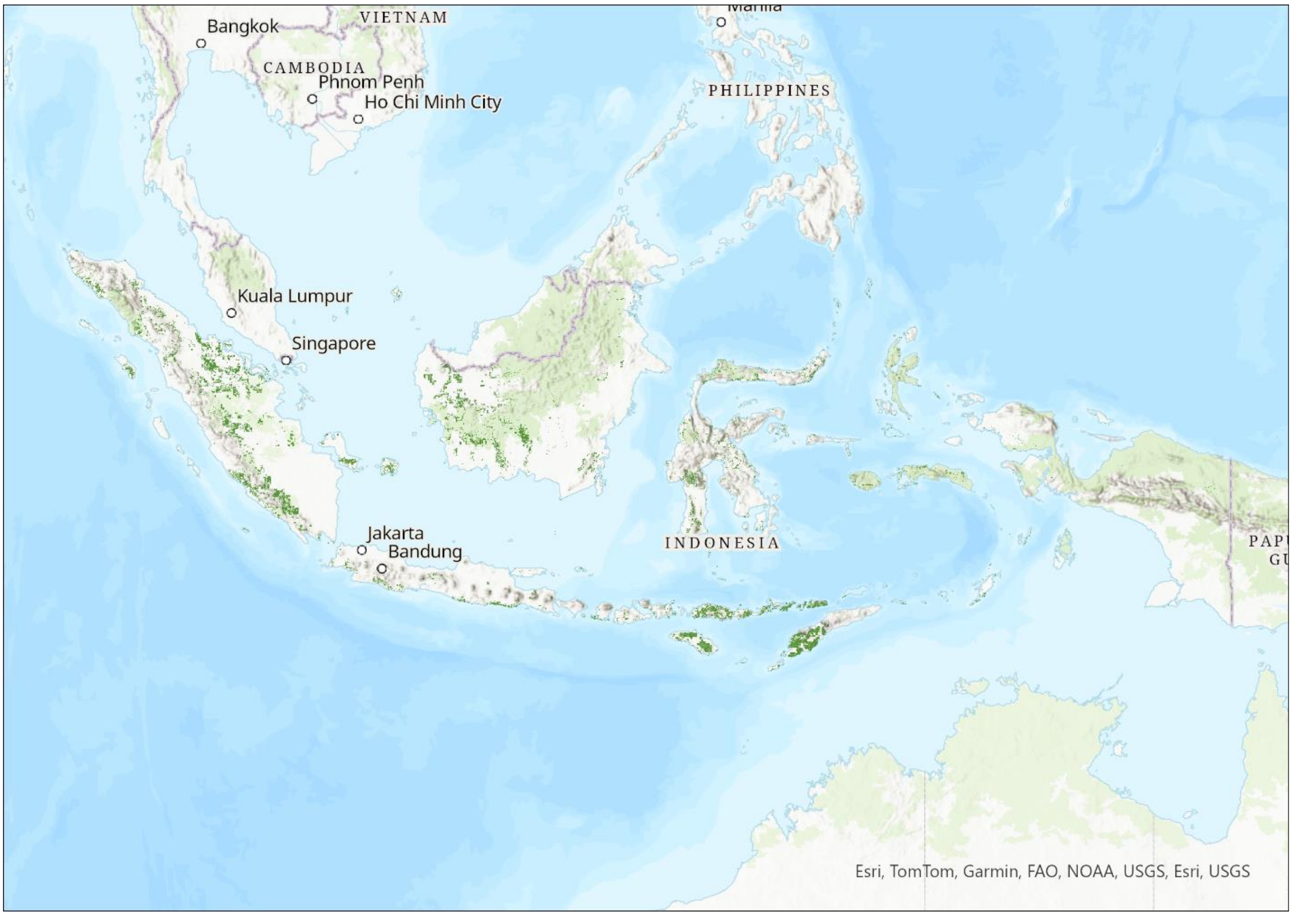


Figure 5c. Intersection of priority areas (se.plan indices 4 or 5) of two focal commodity species in Laos.



5. Conclusions

Our analysis provides insight into the potential for investment into the focal commodity species and associated value chains in a social forestry context.

In Cambodia, the evaluation highlighted significant potential north of the Cardamom Mountain region, areas north of the Tonle Sap, and in Ratanakiri province. The results in Laos displayed shared suitability across species, with variations primarily driven by slope preferences. In Indonesia, the distinct sensitivity of Tectona grandis to slopes stood out, impacting its suitability compared to other species. Despite these differences, the analysis consistently emphasized the significance of factors like forest proximity to communities, elevation, and forest fragmentation in determining suitability across these regions.

These maps are a significant step in prioritizing areas in these countries where investment, coupled with careful land use planning and the right supporting policies, can help secure economic benefits for communities and restoration of trees—likely with ecosystem conservation and climate change mitigation and adaptation benefits.