Journal of Natural Resources and Environmental Management
http://dx.doi.org/10.29244/jpsl.14.3.438

RESEARCH ARTICLE

OPEN ACCESS

Check for updates

Environmental Dynamics in The Sumatran Coffee Landscapes: Opportunities and Challenges Through Spatial Perspectives

Intan Diani Fardinatri[a], Aryo Adhi Condro[a], Durrah Hayati[b], Ashabul Anhar[b]

[a] Rainforest Alliance, Denpasar, 80227, Indonesia
[b] Department of Forestry, Faculty of Agriculture, Syiah Kuala University, Banda Aceh, 23111, Indonesia

Article History
Received
10 December 2023
Revised 01 January 2024
Accepted
21 February 2024

Keywords
coffee, deforestation, EUDR, spatial analysis, suitability

ABSTRACT

The coffee industry in Indonesia, particularly in the Sumatran landscape, emerges as a vital contributor to the nation's economy, impacting regional growth. Nevertheless, this landscape faces ecological threats from rapid deforestation, resulting in a substantial loss of primary forest cover. This historical deforestation along with climate crisis presents challenges for coffee plantations. The study employs geospatial analysis to comprehensively outline challenges and opportunities for smallholder coffee farmers in Sumatra, particularly in the Arabica (Central Aceh) and Robusta (Tanggamus) landscapes. The study shows non-shade coffee plantations covered approximately 23,453 ha in Central Aceh and 43,991 ha in Tanggamus. Additionally, mixed agroforestry areas were prevalent, comprising about 132,569 ha in Tanggamus and 19,450 ha in Central Aceh. Tanggamus and Central Aceh have become favorable areas for Robusta coffee and Arabica coffee, respectively. One significant opportunity identified for coffee development in Central Aceh is that 86% of existing coffee farms already adhere to EUDR. Furthermore, 94% of existing coffee farms in Tanggamus meet EUDR standards, opening doors for more farmers to access the European market.

Introduction

Indonesia's coffee industry contributes significantly to the country's economy through foreign exchange, farmer livelihoods, industrial raw materials, employment, and regional growth [1]. Coffee is one of Indonesia's primary plantation crops, making Indonesia the fourth largest global coffee producer. The majority of coffee cultivation involves around 1.7 million smallholder farmers, predominantly Robusta coffee, accounting for 75.4% and providing livelihood to 1.23 million farmers. Arabica coffee accounts for 24.6% of coffee production, involving over 500 thousand farmers. Coffee cultivation spans most Indonesian provinces, but the primary coffee-producing areas are concentrated within Sumatra, notably in the Provinces of Aceh, North Sumatra, South Sumatra, Lampung, and Bengkulu [2].

Sumatra Island plays a significant role in the ecological landscape of Indonesia. It hosts a long mountain range housing three crucial national parks, acknowledged as the "Tropical Rainforest Heritage of Sumatra" by UNESCO [3]. These parks include Gunung Leuser National Park located in North Sumatra and Aceh, Kerinci Seblat National Park in West Sumatra, and Bukit Barisan Selatan National Park, stretching across Lampung, Bengkulu, and South Sumatra [4]. The diverse wet highland vegetation in Sumatra is currently under threat due to rapid deforestation, particularly in the Bukit Barisan Landscape [5]. Over the years, Sumatra has experienced substantial depletion of forests due to various factors, such as agricultural expansion, wood extraction, and forest fires, leading to the conversion of forests into plantation areas [6]. The historical trend of deforestation has resulted in a considerable loss of primary forest cover, with Sumatra witnessing a reduction of approximately 7.54 million hectares between 1990 and 2010, leaving only 30% of the original forest cover intact [7].

Corresponding Author: Aryo Adhi Condro acondro@ra.org Rainforest Alliance, Denpasar, Indonesia

Historical deforestation in Sumatra poses challenges and opportunities for coffee plantations. Challenges arise from the loss of available land due to deforestation, making it difficult to find appropriate areas for coffee cultivation. Opportunities, however, lie in reclaiming and restoring degraded land for coffee plantations. Therefore, deforestation in Sumatra has significantly reduced the availability of land suitable for coffee plantations, posing a challenge to the industry. Recent focus on global ecological changes has increased interest in studying human-driven and natural changes in land cover and landscapes. Historical land cover changes examine the outcomes of numerous temporal events to understand the cumulative sequence of changes and interpret the resulting spatial patterns [8].

In this case, by integrating factors such as forest cover change and agroclimatic conditions for coffee production, spatial analysis can provide valuable insights into understanding how past changes in the coffee landscape may influence its suitability for cultivation. This information is crucial for the future intervention and enhancement of coffee ecosystems. Here, we comprehensively provide challenges and opportunities for smallholder coffee farmers within two different Sumatran coffee landscapes in Central Aceh District, Aceh Province (to represent the Arabica coffee landscape) and Tanggamus District, Lampung Province (to represent the Robusta coffee landscape) using geospatial analysis. In this study, we assessed coffee agroclimatic suitability, historical deforestation, and detected coffee farms within the study areas to understand the challenges and opportunities for coffee plantations in the Sumatran Landscape.

Materials and Methods

Study Areas

The study areas were located in two districts on Sumatra Island: (i) Tanggamus District, Lampung Province, and (ii) Central Aceh District, Aceh Province. Both districts became prominent areas for coffee production in Sumatra; Tanggamus and Central Aceh were dominated by Robusta coffee and Arabica coffee, respectively. The total area of our locations was approximately 270,251.91 ha and 453,215.27 ha for Tanggamus and Central Aceh, respectively (Figure 1).

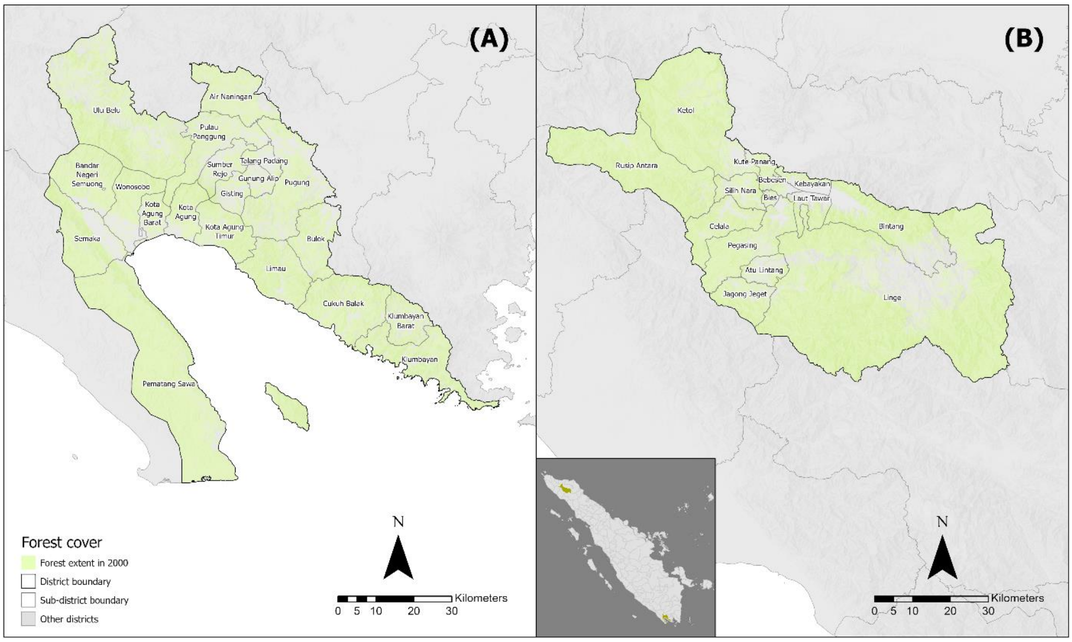

Figure 1. Map of the study areas in Tanggamus (A) and Central Aceh (B) Districts, Sumatra Landscape.

Coffee Plantation Mapping

To predict the current coffee distribution in the study area, we used machine learning (Random Forest Algorithm) based on optical satellite imagery (Planet-NICFI data) and coffee farm points from field surveys. This study used the Planet-NICFI Tropical Basemap, a very high-resolution optical satellite imagery (~5 m), as a predictor for land classification. We performed filter medians in the image collections between 2022 and 2023 to acquire the best pixels to depict the current condition. We obtained Planet-NICFI data from Google Earth Engine Platform [9]. It provides four essential optical bands: blue, green, red, and near infrared.

We then calculated several vegetation indices to capture a better variation in the land surface: i) Normalized Difference Vegetation Index (NDVI) [10], ii) Normalized Difference Wetness Index (NDWI) [11], iii) Soil-Adjusted Vegetation Index (SAVI) [12], and iv) Enhanced Vegetation Index (EVI) [13]. In addition, we added topographic parameters (elevation, slope, and aspect) to the model to deal with hill-shading issues that frequently occur in the optical satellite retrieved from DEM Geospatial Information Agency of Indonesia (https://tanahair.indonesia.go.id/demnas/, accessed on 4 December 2023). In total, we elaborate 12 predictors in the model.

To conduct supervised classification, we collected training data of eight label classes of land categories in Central Aceh and Tanggamus Districts (Table 1). To obtain training data, we performed visual detection from various fine satellite sources (Planet-NICFI, Google Earth, etc.) for Land ID 1, 2, 3, 6, 7, and 8. We then conducted a field survey to collect coffee (four) and mixed agroforestry (five) categories. In total, we collected 150 training samples for each location for the coffee training data.

Table 1. Land categories for model classification in the study area.

Land ID	Description	Simplified class for coffee mapping
1	Forests	Non-Coffee
2	Degraded forests	Non-Coffee
3	Shrubs	Non-Coffee
4	Coffee	Coffee
5	Mixed agroforestry	Coffee
6	Other cultivation areas	Non-Coffee
7	Non-vegetation and built-up areas	Non-Coffee
8	Waterbodies	Non-Coffee

All predictors were used for Simple Non-Iterative Clustering (SNIC) segmentation and segmented into a series of superpixels [14]. The features of each superpixel are obtained from the images of each image combination. The value of each feature of each superpixel was calculated by averaging the values of all pixels contained in the superpixel. Random forest was used as the classifier [15]. The rule set for this identification is shown in Figure 2.

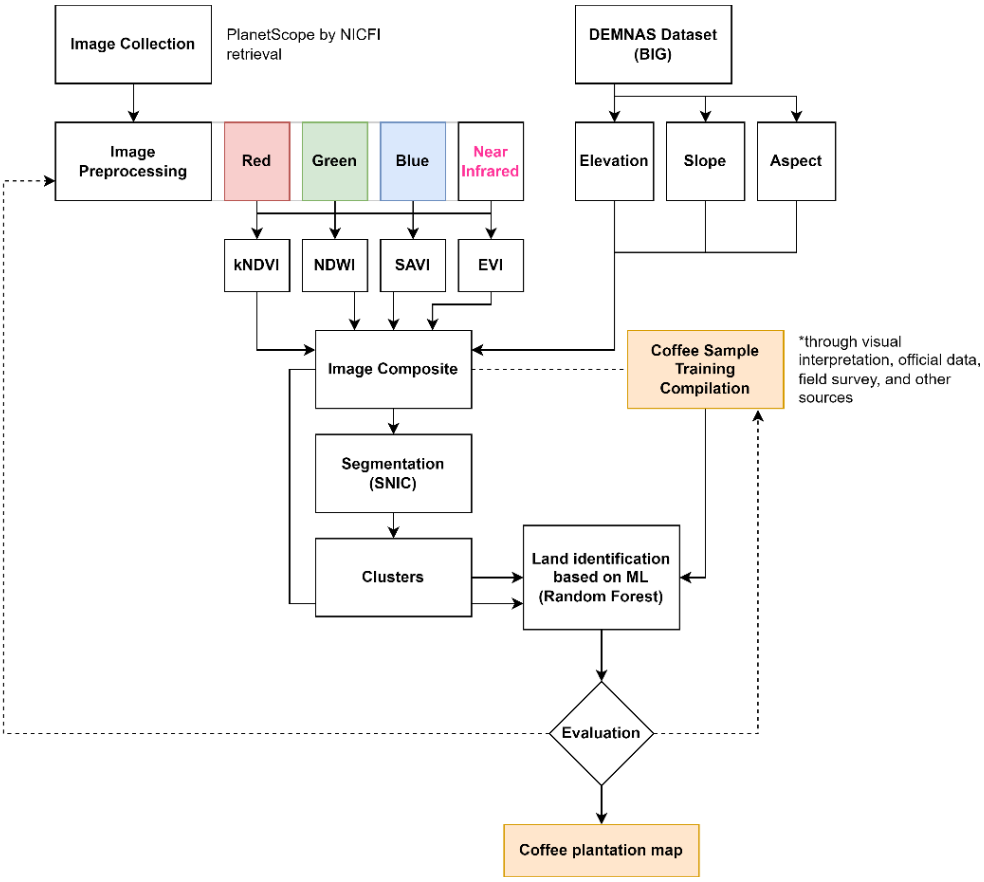

Figure 2. Flowchart for coffee and land cover identification in Central Aceh and Tanggamus Districts.

This study calculated the overall accuracy (OA; [16]; Equation 1) and Kappa coefficient (κ; [17]; Equation 2) to evaluate the land classification model. We used 30% of the training data to identify the model performance by creating random sampling. The formula for calculating the evaluation metrics is as follows:

$$OA = \frac{TP}{N} \tag{1}$$

$$\kappa = \frac{p_o - p_e}{1 - p_e} \tag{2}$$

where TP is the number of true positives of the testing samples, which is the total number of hits between the model and training data; N is the total number of testing samples; p_o refers to the percentage of agreement observed; and p_e refers to the percentage of agreement expected by chance alone.

Cocoa Agroclimatic Suitability

In this study, we conducted land suitability analysis for coffee plantation based on soil and agroclimatic parameters, following the technical guidance of land evaluation for agricultural commodities, issued by the Indonesian Center for Agricultural Land Resources Research and Development (ICALRRD), Ministry of Agriculture-Indonesia [18] (Table 2). The data used in this analysis are listed in Table 3.

Table 2. Suitability criteria for coffee commodities based on ICALRRD reference.

Type	Parameter	Suitability classes			
		Highly suitable	Suitable	Marginally suitable	Non-suitable
Arabica coffee					
Climatic	Annual precipitation (mm)	1,200–1,800	1,000–1,200	2,000–3,000	> 3,000
			1800–2000	800–1,000	< 800
	Annual temperature (°C)	16–20	15–16	14–15	< 14
			20–22	22–24	> 24
	Relative Humidity (%)	40–70	30–40	20–30	< 20
			70–80	80–90	> 90
Topographic	Slope (%)	< 8	8–15	15–30	> 30
	Elevation (m)	1,000–1,500	1,500–1,700	1,700–2,000	> 2,000
			700–1,000	500–700	< 500
Soil properties (chemical)	Cation exchange capacity	> 16	5–16	< 5	-
	pH water	5.6–6.6	6.6–7.3	< 5.5	-
				> 7.4	-
	C-organic content (%)	> 2.0	0.8–2.0	< 0.8	
	Nitrogen content (%)	medium	low	very Low	-
Soil properties (physical)	Soil texture	fine	medium	slightly coarse	coarse, very fine
Robusta coffee					
Climatic	Annual Precipitation (mm)	2,000–3,000	1,750–2,000	1,500–1,750	< 1,500
			3,000–3,500	3,500–4,000	> 4,000
	Annual Temperature (°C)	20–24	24–28	18–20	< 18
				28–32	> 32
	Relative Humidity (%)	45–80	80–90	> 90	< 30
			35–45	30–35	
Topographic	Slope (%)	< 8	8–15	15–30	> 30
Soil properties (chemical)	Cation exchange capacity	> 16	5–16	< 5	-
	pH water	5.3–6.0	6.0–6.5	> 6.5	-
			5.0–5.3	< 5.0	-
	C-organic content (%)	> 1.2	0.8–1.2	< 0.8	
	Nitrogen content (%)	medium	low	very Low	-
Soil properties (physical)	Soil texture	fine	medium	slightly coarse	coarse, very fine

Table 2. Land categories for model classification in the study area.

Type	Data	Unit	Source
Climatic	Annual precipitation	mm	CHELSA
	Annual temperature	°C	CHELSA
	Relative humidity	%	CHELSA

Type	Data	Unit	Source
Topographic	Slope	%	SRTM
	Elevation	meter asl	SRTM
Soil properties (chemical)	Cation exchange capacity	cmol	SoilGrids
	pH water	-	SoilGrids
	C-organic content	dg kg^{-1}	SoilGrids
	Nitrogen content	cg kg^{-1}	
Soil properties (physical)	Soil texture	-	SoilGrids

CHELSA = Climatologies at high resolution for the earth's land surface areas, SRTM = Shuttle Radar Topography Mission.

Historical Deforestation and Its Drivers

We analyzed historical deforestation within the study area based on the Global Forest Change dataset (GFC) v1.9, which captures forest loss between 2001 and 2021 with a 30 m resolution [19]. We defined 'deforestation' as detected forest loss from GFC data that occurred within the forest cover. In this study, we performed GFC forest loss data verification by visual interpretation of deforested areas using very high-resolution data (i.e., Planet-NICFI satellite imageries) with a spatial resolution of approximately 5 m based on discrimination metrics [20]. Furthermore, we calculated the total deforestation in each subdistrict using zonal statistics in geospatial analysis. This study also explored the drivers of deforestation based on correlative modeling. A previous study showed that the main drivers of deforestation consist of: i) poverty-driven, defined by permanent conversion of forest to agriculture, mining, or energy infrastructure; ii) shifting agriculture, defined as small-to medium-scale forest conversion to agriculture; iii) timber logging activities; iv) wildfire; and v) urbanization [6].

We examined deforestation probability in three periods using the Random Forest algorithm [15]. Deforestation from GFC v1.9 was used to capture the dependent variable, and various other variables were used to capture the model predictors (Table 4). We divided the predictors into two aspects: bio-geophysical (seven variables) and anthropogenic (four variables). The bio-geophysical aspect captures topographic, climatic, watershed, and forest ecosystems, and the anthropogenic aspect depicts spatial plans, land zoning/designation, and current human intervention. Several discrimination metrics were used to evaluate the model. We extracted the mean Gini coefficient decrease from the model to identify the variable importance for each predictor. In addition, we evaluated the relationship between each variable and the probability of deforestation by using Pearson's correlation.

Table 3. Predictors used in the deforestation probability model.

Aspect	Variable	Unit	Source
Natural & Biogeophysics	Elevation	m	SRTM
	Slope	%	SRTM
	Vegetation index	unitless	Landsat
	Distance to protected areas	km	WDPA
Anthropogenic	Access to forest plantation	minutes	MoEF
	Distance to road	meter	OSM
	Access to plantation	minutes	MoEF
	Access to logging concession	minutes	MoEF

WDPA = World database on protected areas, MoEF = Ministry of environment and forestry, OSM = Open street map.

RESULTS AND DISCUSSION

Coffee Plantation Mapping

Our remote sensing-based data showed that land cover classification had a relatively high performance in both areas. The OA and κ values in Central Aceh District were greater than 90% (OA = 0.882 ± 0.007 and κ = 0.878 ± 0.007, respectively). We also found that coffee plantations had excellent user accuracy (UA) and producer accuracy (PA), that is, UA_{coffee} = 0.780 and PA_{coffee} = 0.896 in the Central Aceh District. In addition, the overall accuracy (OA) and kappa coefficient (κ) values in Tanggamus District were greater than 90% (OA = 0.956 ± 0.004 and κ = 0.925 ± 0.002, respectively). We also found that coffee plantations have excellent user accuracy (UA) and producer accuracy (PA), that is, UA_{coffee} = 0.970 and PA_{coffee} = 0.986 in the Tanggamus District. Our results outperformed those of previous studies on the user and producer accuracies of coffee plantations [21,22] (Figure 3).

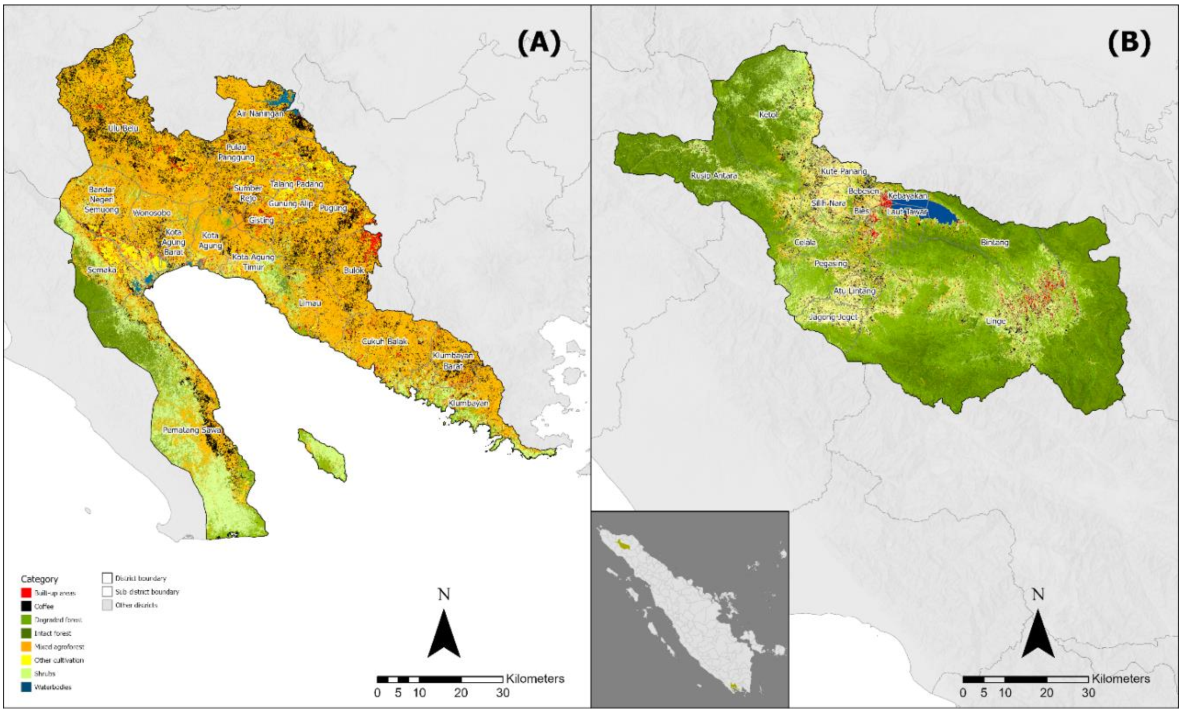

Figure 3. The current land cover conditions in Tanggamus (A) and Central Aceh (B) are coffee producers.

This study found that the total area of coffee plantations (non-shade grown coffee plantations) in Central Aceh and Tanggamus Districts were about 23,453 ha and 43,991 ha, respectively (Figure 4). Tanggamus District landscape has a relatively low to medium terrain and slope, so the accessibility of the local community to cultivate coffee or other commodities is easier than in the Central Aceh Ditrict landscape, which has hilly and steep slope areas. These conditions also contributed to the difficulties in coffee plantation identification in Central Aceh District. In addition, we also predicted mixed agroforestry areas that correspond to coffee plantation existence in our study areas. We incorporated the canopy height model; other cultivations with an average canopy height greater than 10 m were identified as mixed agroforestry, including shaded-grown coffee. This study found that mixed agroforestry areas are relatively high, around 132,569 ha and 19,450 ha in the Tanggamus District and Central Aceh, respectively.

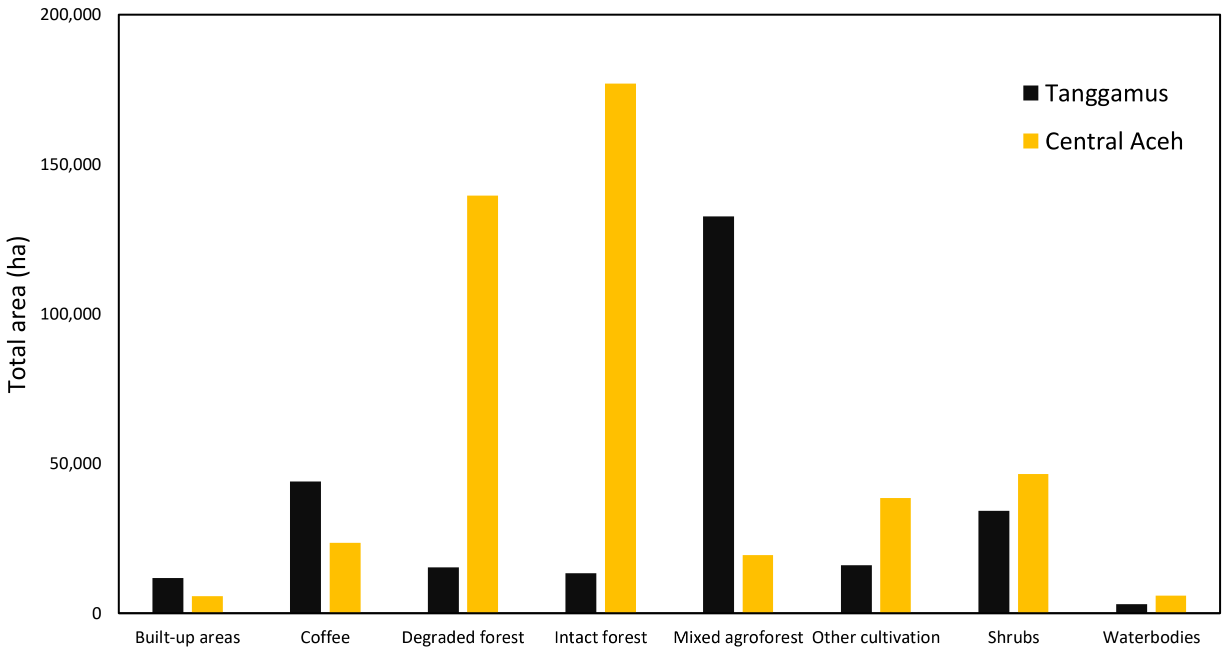

Figure 4. Statistics of the current land cover categories in the study area.

The study showed that the majority of coffee plantations can be found in other designated areas (APL) based on forest state data from the MoEF in both areas. In addition, the total area of coffee plantations within other land designations was 16,364 ha and 27,443 ha in Central Aceh and Tanggamus, respectively. The second-largest coffee plantation occurred in the protection forest, with a total area of approximately 3,406 ha and 14,938 ha in Central Aceh and Tanggamus, respectively. We also found coffee plantations within protected areas (e.g., national parks, nature reserves, and hunting parks) in both areas.

Coffee Agroclimatic Suitability

This study assessed agroclimatic suitability based on climate, topography, and soil property parameters for arabica coffee in Central Aceh District and robusta coffee in Tanggamus District (Figure 5). Two approaches were used to determine coffee suitability: i) the order approach (i.e., the landscape will be divided into binary classes: suitable and non-suitable) and ii) the class approach (i.e., the landscape will be divided into ordinal classes: N (non-suitable), S3 (marginally suitable), S2 (suitable), and S1 (very suitable) based on the ICALRRD reference). Based on the order approach, the results showed that the total suitable areas for coffee were 440,881 ha (97.27%) and 263,013 ha (98.67%) for Central Aceh's arabica and Tanggamus robusta, respectively.

Based on the order approach, the suitable areas for Arabica coffee production in Central Aceh at the sub-district level ranged from 68% to 100%. In addition, we found a very high coverage of suitable areas for Robusta coffee in Tanggamus, approximately 93% to 100%. Linge, Ketol, Rusip Antara, and Bintang sub-district had a vas suitable area for Arabica Coffee in Central Aceh while Pematang Sawa, Ulu Belu, Pugung, and Cukuh Badak Sub-districts had a high suitable area for Robusta Coffee in Tanggamus. Most areas in Central Aceh were classified as suitable to very suitable for Arabica coffee based on agroclimatic analysis at the class level. In addition, the majority of Tanggamus areas were classified as marginally suitable to moderately suitable for Robusta coffee. Thus, Tanggamus and Central Aceh Districts have become favorable areas for Robusta and Arabica coffee, respectively.

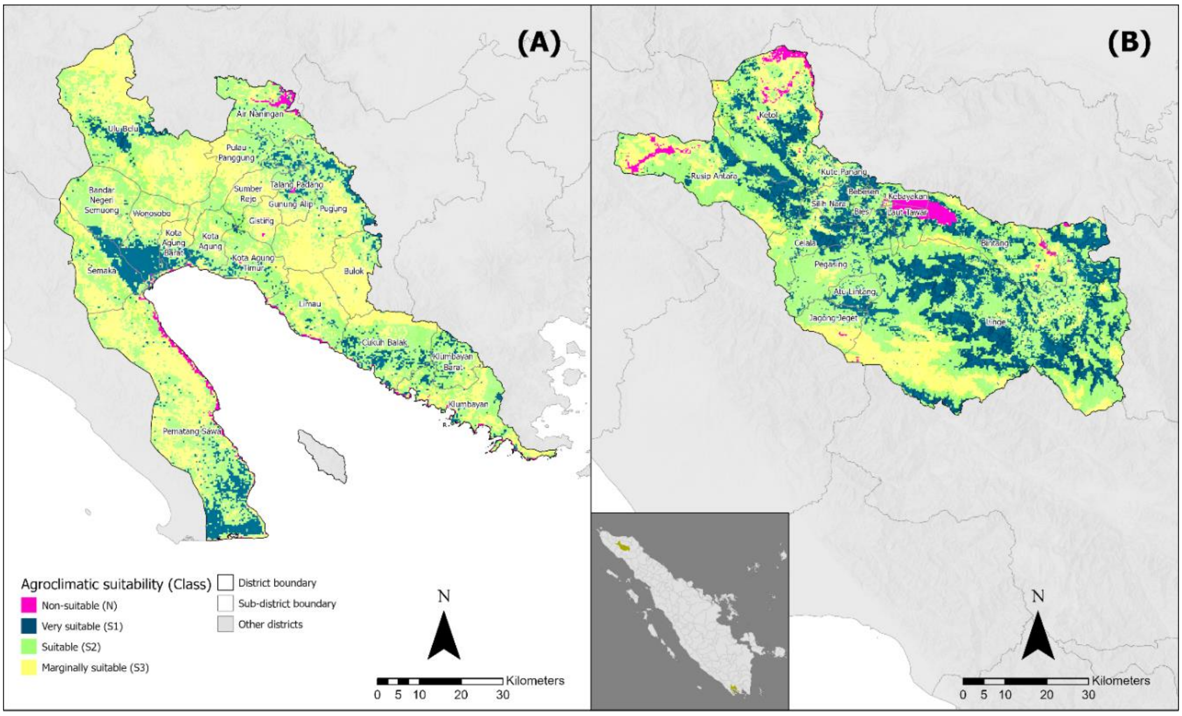

Figure 5. Agroclimatic suitability for robusta coffee in Tanggamus (A) and arabica coffee in Central Aceh (B) at the class level.

Historical Deforestation

Field observations from a very high resolution (2015–2020) revealed that GFC data can greatly depict deforestation within the time with an overall accuracy of more than 80%. Thus, the GFC data were reliable for historical deforestation analyses within our study areas. This study showed that the historical deforestation rates (2001–2021) were 1,468.31 ha year^{-1} and 904.53 ha year^{-1} in Central Aceh and Tanggamus

Districts, respectively. The highest deforestation occurred in 2016 and 2017 in the Central Aceh and Tanggamus Districts, respectively. We found a significant increase in forest loss from 2011 to 2017 in Central Aceh. Although deforestation has continued to decrease since 2017, the total number of deforested areas in 2017–2021 remains quite high. This study found a bimodal pattern of deforestation in the Tanggamus District, with peaks in 2004 and 2017 (Figure 6).

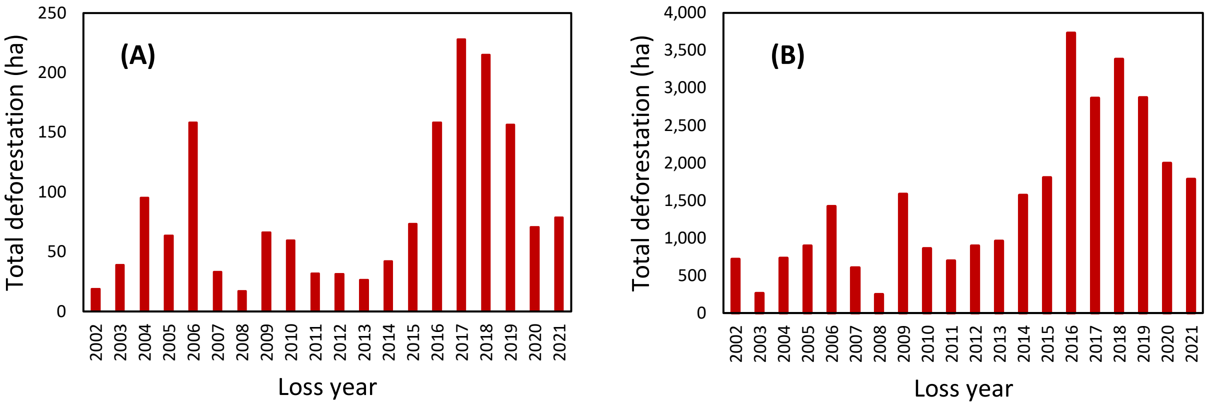

Figure 6. Historical Forest loss in Central Aceh (A) and Tanggamus (B) districts based on GFC data.

The results found that the highest deforested areas in Central Aceh within the 2001–2021 period occurred in Linge (deforestation rate: 333.25 ha year^{-1}), Pegasing (deforestation rate: 246.69 ha year^{-1}), and Ketol (deforestation rate: 234.76 ha year^{-1}). Besides, the highest deforestation in Tanggamus within 2001–2021 period occurred in Pematang Sawa (deforestation rate: 228.15 ha year^{-1}), Ulu Belu (deforestation rate: 137.84 ha year^{-1}), and Pugung (deforestation rate: 70.95 ha year^{-1}) Sub-districts (Figure 7).

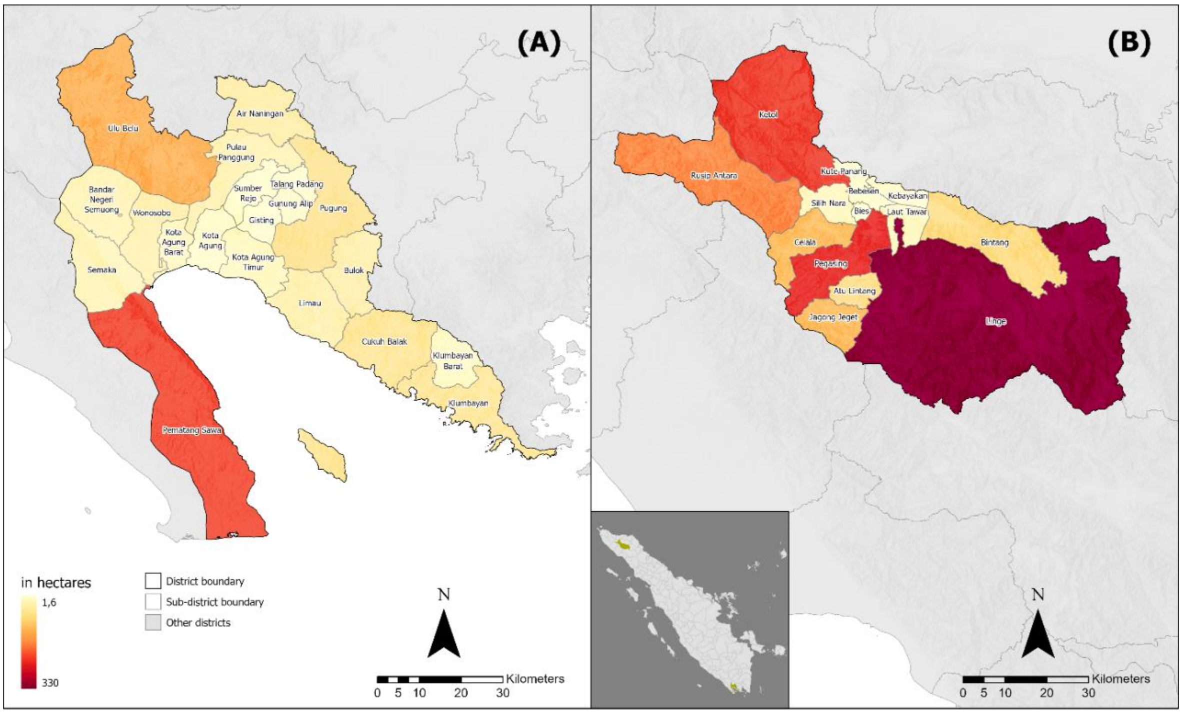

Figure 7. Spatial pattern of historical deforestation in Central Aceh (A) and Tanggamus (B) districts zoned by sub-districts.

This study found that the deforestation rate after 2014 in the two study areas was two times higher than that in the previous period (2 times higher). The deforestation rate after 2014 was relatively higher by about 3 times than before 2014 in Central Aceh. In Tanggamus, we observed a contrasting pattern related to the historical deforestation rate. We indicated a higher deforestation rate before 2014 in Air Naningan, Bulok, West Klumbayan, Pematang Sawa, and Ulu Belu sub-districts. Our findings revealed that forest loss mostly occurred in protected forest designation areas, with a total rate of approximately 644.94 ha year^{-1} (43.92%) in Central Aceh. In addition, we found relatively high-deforested areas within other designated areas/*areal penggunaan lain* (APL) and production forests, with percentages of approximately 43.06% and 8.07%, respectively. Meanwhile, APL has the most significant deforestation in the Tanggamus district, with a total rate of approximately 483.83 ha year^{-1} (53.49%). We also found that massive deforestation occurred in protected forests (27.99%) and national parks (18.52%).

Our study also investigated the drivers of deforestation after 2014 based on the rainforest certification deforestation risk cutoff date (Figure 8). We performed correlative modeling by analyzing the spatial patterns of deforestation points using several explanatory variables that included natural and anthropogenic parameters in the two districts. The results showed that road accessibility (distance to road variable) plays a critical role in deforestation activities in both areas, with a percent contribution of approximately 26.78% and 17.28% for Central Aceh and Tanggamus, respectively. Access to logging concessions also had a high contribution to deforestation, with a percentage of approximately 21% in Central Aceh. In addition, we found that access to forest plantations played a relatively prominent role in deforestation, with a percentage contribution of approximately 17.18% in Tanggamus. Field observations in Central Aceh also showed that wildfires triggered deforestation.

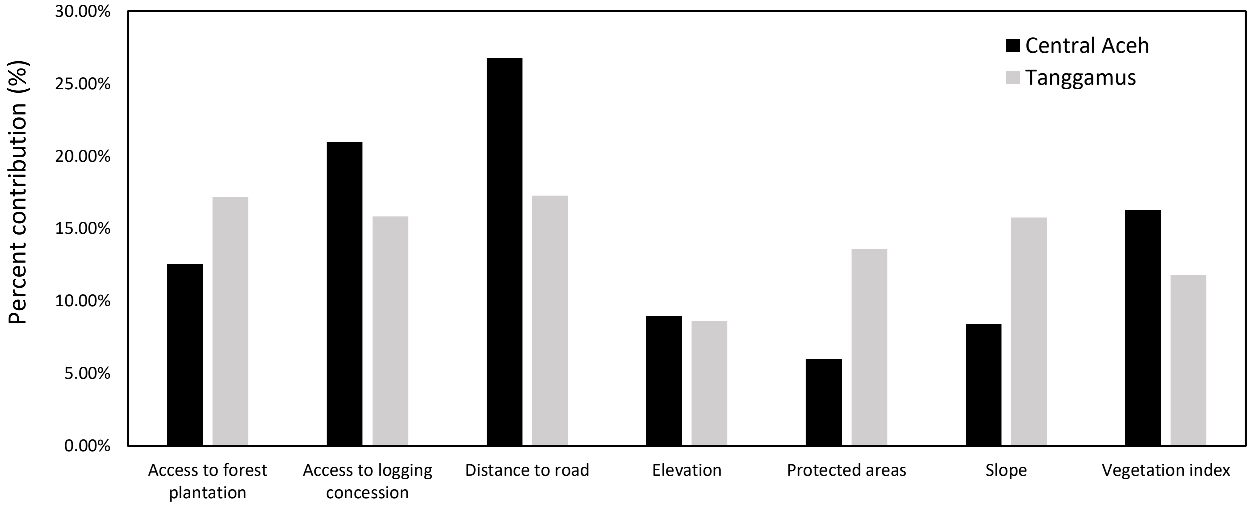

Figure 8. Explanatory variable importance for deforestation after 2014 in Central Aceh and Tanggamus.

This study also investigated the motif of deforestation by overlaying historical deforestation data (after 2014) with current land cover data (Table 5). Remote sensing analysis found that more than 50% of deforestation in Central Aceh and Tanggamus was caused by the agricultural sectors (i.e., coffee, mixed agroforest, and other cultivations).

Table 4. Historical deforested areas within the current land cover types in the study area.

Land categories	Cumulative deforestation in 2014–2020 period (ha)	
	Tanggamus	Central Aceh
Built-up areas	394.33	4,759.64
Coffee	5,355.39	3,821.08
Mixed agroforestry	175.00	2,540.48
Other cultivation	267.19	2,343.95
Shrubs	674.92	48.93
Grand total	6,866.83	13,514.07

Coffee Sustainability Outlook

Coffee cultivation in the Sumatran landscape faces significant challenges owing to climate change and deforestation. Climate change poses a threat to coffee cultivation by altering weather patterns, increasing temperature extremes, and disrupting ecological balances [1,23]. This can result in a reduction in suitable areas for coffee cultivation and a decrease in production, affecting smallholders who rely on coffee farming for their livelihoods [24]. However, there are opportunities for coffee cultivation to address these issues. Agroforestry systems, such as planting shaded trees alongside coffee crops, can help mitigate the effects of climate change by providing lower temperatures, increasing soil moisture, and promoting biodiversity [25–28].

Additionally, promoting Good Agricultural Practices can aid in adapting to climate change and improving coffee production. By optimizing land use, conserving soil, and implementing proper fertilization, pruning, and pest control techniques, coffee farmers can increase the resilience of their coffee crops and ensure the sustainability of coffee production [29]. Furthermore, the adoption of technology and innovation in cultivation management, such as the use of improved coffee varieties adapted to heat and water stress, can also help farmers adapt to the changing climate and overcome the challenges they face [30]. Climate change and deforestation pose significant challenges to coffee cultivation in the Sumatran landscape, and there are opportunities for adaptation and mitigation through the implementation of agroforestry systems, promotion of Good Agricultural Practices, and adoption of innovative cultivation techniques [31,32].

Coffee farmers in Sumatra are grappling with the challenges posed by the European Union's deforestation regulation, which has imposed restrictions on land use and has the potential to limit the expansion of coffee production. These challenges include addressing environmental limitations, adapting to the impacts of climate change and deforestation on local weather patterns and water supplies, and the urgent need for coffee replantation to counter the diminishing yield and quality of existing coffee trees [33]. One of the main challenges faced by coffee cultivation in Sumatra under the European Union's deforestation regulation is the need to identify suitable areas for coffee cultivation and identify potential compliance farms under the EU deforestation regulation (EUDR). The EUDR stated that commodities shall not have been produced on land that has been subject to deforestation (or forest degradation) after December 31, 2020. Our analysis indicated that 94% and 86% of the current coffee farms comply with the main requirements of the EUDR (i.e., deforestation-free after 2020) in Tanggamus and Central Aceh, respectively. This study highlights the coffee's outlook for future sustainable management (Table 6).

Table 5. Highlights of challenges and opportunities for coffee cultivation in the study area.

District (Commodity)	Challenge	Opportunity
Central Aceh (Arabica coffee)	• Soil degradation due to poor soil conservation practices and excessive use of herbicides. • Land expansion to protected forest for coffee plantation. • Low productivity due to old coffee plants. • Some coffee plantations do not comply with sustainable certifications requirement. • We found 14% of existing coffee farms were indicatively deforested after December 2020, therefore they have risk of not complying with EUDR cutoff date.	• Implementation of regenerative farming practices like the use of legume cover crop planting to improve soil fertility, reduce erosion, and decrease herbicide use. • Promoting social forestry scheme and agroforestry practices in coffee plantations inside protected forest. • Revitalization of coffee plants and soil regeneration. • Assistance and facilitation for coffee farmers to acquire certifications. • There are 86% of existing coffee farms that do not contribute to deforestation after December 2020, therefore they might comply with EUDR cutoff date.
Tanggamus (Robusta coffee)	• Soil degradation due to poor soil conservation practices and excessive use of herbicides. • Land expansion to protected forest for coffee plantation. • Low productivity due to old coffee plants. • Some coffee plantations do not comply with sustainable agriculture practices. • We found 6% of existing coffee farms were indicatively deforested after December 2020, therefore they have risk of not complying with EUDR cutoff date.	• Implementation of regenerative farming practices like the use of legume cover crop planting to improve soil fertility, reduce erosion, and decrease herbicide use. • Promoting social forestry scheme and agroforestry practices in coffee plantations inside protected forest. • Revitalization of coffee plants and soil regeneration. • Training and socialization on Sustainable Agriculture Practices. • There are 94% of existing coffee farms that do not contribute to deforestation after December 2020, therefore they might comply with EUDR cutoff date.

Conclusion

This study comprehensively assessed the challenges and opportunities faced by smallholder coffee farmers in the Sumatran landscape of Indonesia, highlighting the distinct situation in the Arabica-producing region of Central Aceh and the Robusta-growing area of Tanggamus. Our geospatial analysis revealed extensive deforestation and prevalence of both non-shade and mixed agroforestry coffee systems. Despite the ecological threats posed by deforestation and climate change, several key opportunities for sustainable coffee production exist in both areas, particularly those related to the EUDR issue. Therefore, concerted efforts are necessary to address the challenges identified in this study. Continued deforestation necessitates aggressive afforestation and reforestation initiatives, whereas mitigating climate change impacts requires the adoption of climate-smart agricultural practices. Moreover, capacity building and market access facilitation remain crucial to empower smallholder farmers and ensure the long-term sustainability of Sumatra's coffee industry.

Author Contributions

IDF: Conceptualization, Writing - Review & Editing; **AAC**: Methodology, Writing - Review & Editing; **DH**: Writing - Review & Editing, Supervision, **AA**: Writing - Review & Editing, Supervision.

Conflicts of Interest

There are no conflicts to declare.

Acknowledgments

The authors would like to express their gratitude to The Netherlands Enterprise Agency (RVO) for supporting this research, as well as Azwar Sujaswara (Research Associate, ALGM Laboratory, IPB University) and the Rumah Peta Lampung Team for conducting field surveys and data collection.

References

1. Sujatmiko, T.; Ihsaniyati, H. Implication of climate change on coffee farmers' welfare in Indonesia. *IOP Conference Series: Earth and Environmental Science* **2018**, *200*, 012054, doi:10.1088/1755-1315/200/1/012054.
2. Sarvina, Y.; June, T.; Hadi Sutjahjo, S.; Nurmalina, R.; Surmaini, E. The impacts of climate variability on coffee yield in five Indonesian coffee production centers. *Coffee Science* **2021**, *16*, 1–9, doi:10.25186/.v16i.1917.
3. GOI (Government of Indonesia). State of Conservation Status of the World Heritage in Indonesia: World Heritage Property Tropical Rainforest Heritage of Sumatra (N 1167). Available online: https://whc.unesco.org/en/list/1167/ (accessed on 4 September 2020).
4. Claudino-Sales, V. Tropical Rainforest Heritage of Sumatra, Indonesia. In *Dictionary of Geotourism*; Springer Singapore: Singapore, 2020; pp. 646–647, ISBN 9789402415285.
5. Poor, E.E.; Frimpong, E.; Imron, M.A.; Kelly, M.J. Protected area effectiveness in a sea of palm oil: A Sumatran case study. *Biological Conservation* **2019**, *234*, 123–130, doi:10.1016/j.biocon.2019.03.018.
6. Curtis, P.G.; Slay, C.M.; Harris, N.L.; Tyukavina, A.; Hansen, M.C. Classifying drivers of global forest loss. *Science (1979)* **2018**, *361*, 1108–1111, doi:10.1126/science.aau3445.
7. Margono, B.A.; Turubanova, S.; Zhuravleva, I.; Potapov, P.; Tyukavina, A.; Baccini, A.; Goetz, S.; Hansen, M.C. Mapping and monitoring deforestation and forest degradation in Sumatra (Indonesia) using Landsat time series data sets from 1990 to 2010. *Environmental Research Letters* **2012**, *7*, 2000–2010, doi:10.1088/1748-9326/7/3/034010.
8. Etter, A.; McAlpine, C.; Possingham, H. Historical patterns and drivers of landscape change in Colombia since 1500: A regionalized spatial approach. *Annals of the Association of American Geographers* **2008**, *98*, 2–23, doi:10.1080/00045600701733911.

9. Gorelick, N.; Hancher, M.; Dixon, M.; Ilyushchenko, S.; Thau, D.; Moore, R. Google Earth Engine: Planetary-scale geospatial analysis for everyone. *Remote Sensing of Environment* **2017**, *202*, 18–27, doi:10.1016/j.rse.2017.06.031.
10. Camps-Valls, G.; Campos-Taberner, M.; Moreno-Martínez, Á.; Walther, S.; Duveiller, G.; Cescatti, A.; Mahecha, M.D.; Muñoz-Marí, J.; García-Haro, F.J.; Guanter, L.; et al. A Unified vegetation index for quantifying the terrestrial biosphere. *Science Advances* **2021**, *7*, 1–10, doi:10.1126/sciadv.abc7447.
11. Gao, B.-C. NDWI - A normalized difference water index for remote sensing of vegetation liquid water from space. *Remote Sensing of Environment* **1996**, *58*, 257–266, doi:10.1016/s0034-4257(96)00067-3.
12. Huete, A.R. A soil-adjusted vegetation index (SAVI). *Remote Sensing of Environment* **1988**, *25*, 295–309, doi:10.1016/0034-4257(88)90106-X.
13. Huete, A.; Didan, K.; Miura, T.; Rodriguez, E.P.; Gao, X.; Ferreira, L.G. Overview of the radiometric and biophysical performance of the MODIS vegetation indices. *Remote Sensing of Environment* **2002**, *83*, 195–213, doi:10.1016/S0034-4257(02)00096-2.
14. Yang, L.; Wang, L.; Abubakar, G.A.; Huang, J. High-resolution rice mapping based on SNIC segmentation and multi-source remote sensing images. *Remote Sensing* **2021**, *13*, 1–14, doi:10.3390/rs13061148.
15. Breiman, L. Random Forests. *Machine Learning* **2001**, *45*, 5–32, doi:10.1023/A:1010933404324.
16. Fielding, A.H.; Bell, J.F. A Review of methods for the assessment of prediction errors in conservation presence/absence models. *Environmental Conservation* **1997**, *24*, 38–49, doi:10.1017/S0376892997000088.
17. Cohen, J. A Coefficient of agreement for nominal scales. *Educational and Psychological Measurement* **1960**, *20*, 37–46, doi:10.1177/001316446002000104.
18. Ritung, S.; Wahyunto; Agus, F.; Hidayat, H. *Panduan Evaluasi Kesesuaian Lahan dengan Contoh Peta Arahan Penggunaan Lahan Kabupaten Aceh Barat*; Balai Penelitian Tanah dan World Agroforestry Centre (ICRAF): Bogor, ID, 2007;
19. Hansen, M.C.; Potapov, P.V.; Moore, R.; Hancher, M.; Turubanova, S.A.; Tyukavina, A.; Thau, D.; Stehman, S. V.; Goetz, S.J.; Loveland, T.R.; et al. High-resolution global maps of 21st-century forest cover change. *Science (1979)* **2013**, *342*, 850–853, doi:10.1126/science.1244693.
20. Leroy, B.; Delsol, R.; Hugueny, B.; Meynard, C.N.; Barhoumi, C.; Barbet-Massin, M.; Bellard, C. Without Quality presence–absence data, discrimination metrics such as TSS can be misleading measures of model performance. *Journal of Biogeography* **2018**, *45*, 1994–2002, doi:10.1111/jbi.13402.
21. Condro, A.A.; Setiawan, Y.; Prasetyo, L.B.; Pramulya, R.; Siahaan, L. Retrieving the national main commodity maps in Indonesia based on high-resolution remotely sensed data using cloud computing platform. *Land* **2020**, *9*, 1–15, doi:10.3390/land9100377.
22. Cordero-Sancho, S.; Sader, S.A. Spectral Analysis and Classification Accuracy of coffee crops using Landsat and a topographic-environmental model. *International Journal of Remote Sensing* **2007**, *28*, 1577–1593, doi:10.1080/01431160600887680.
23. Agrawal, A.; Wollenberg, E.; Persha, L. Governing agriculture-forest landscapes to achieve climate change mitigation. *Global Environmental Change* **2014**, *29*, 270–280, doi:10.1016/j.gloenvcha.2014.10.001.
24. Harvey, C.A.; Pritts, A.A.; Zwetsloot, M.J.; Jansen, K.; Pulleman, M.M.; Armbrecht, I.; Avelino, J.; Barrera, J.F.; Bunn, C.; García, J.H.; et al. Transformation of coffee-growing landscapes across Latin America, a review. *Agronomy for Sustainable Development* **2021**, *41*, 1–19, doi:10.1007/s13593-021-00712-0.
25. Nandakishor, T.M.; Gopi, G.; Champatan, V.; Sukesh, A.; Aravind, P.V. Agroforestry in shade coffee plantations as an emission reduction strategy for tropical regions: Public acceptance and the role of tree banking. *Frontiers in Energy Research* **2022**, *10*, 1–11, doi:10.3389/fenrg.2022.758372.
26. Garrity, D.P. Agroforestry and the Achievement of the Millennium Development Goals. *Agroforestry Systems* **2004**, *61*, 5–17, doi:10.1023/B:AGFO.0000028986.37502.7c.
27. van Noordwijk, M.; Duguma, L.A.; Dewi, S.; Leimona, B.; Catacutan, D.C.; Lusiana, B.; Öborn, I.; Hairiah, K.; Minang, P.A. SDG synergy between agriculture and forestry in the food, energy, water and income nexus: Reinventing agroforestry? *Current Opinion in Environmental Sustainability* **2018**, *34*, 33–42, doi:10.1016/j.cosust.2018.09.003.

28. Nyhus, P.; Tilson, R. Agroforestry, elephants, and tigers: Balancing conservation theory and practice in human-dominated landscapes of Southeast Asia. *Agriculture, Ecosystems & Environment* **2004**, *104*, 87–97, doi:10.1016/j.agee.2004.01.009.

29. Putri, A.; Syahni, R.; Hasnah; Miko, A. The Effect of arabica coffee farmers' innovation on good agriculture practice in Solok. *IOP Conference Series: Earth and Environmental Science* **2023**, *1160*, 1–7, doi:10.1088/1755-1315/1160/1/012064.

30. Le, Q.V.; Cowal, S.; Jovanovic, G.; Le, D.-T. A Study of regenerative farming practices and sustainable coffee of ethnic minorities farmers in the central highlands of Vietnam. *Frontiers in Sustainable Food Systems* **2021**, *5*, 1–14, doi:10.3389/fsufs.2021.712733.

31. Schoneveld, G.C.; van der Haar, S.; Ekowati, D.; Andrianto, A.; Komarudin, H.; Okarda, B.; Jelsma, I.; Pacheco, P. Certification, good agricultural practice and smallholder heterogeneity: Differentiated pathways for resolving compliance gaps in the Indonesian oil palm sector. *Global Environmental Change* **2019**, *57*, 1–18, doi:10.1016/j.gloenvcha.2019.101933.

32. Jelsma, I.; Woittiez, L.S.; Ollivier, J.; Dharmawan, A.H. Do wealthy farmers implement better agricultural practices? An assessment of implementation of good agricultural practices among different types of independent oil palm smallholders in Riau, Indonesia. *Agricultural Systems* **2019**, *170*, 63–76, doi:10.1016/j.agsy.2018.11.004.

33. Hung Anh, N.; Bokelmann, W.; Thi Nga, D.; Van Minh, N. Toward sustainability or efficiency: The case of smallholder coffee farmers in Vietnam. *Economies* **2019**, *7*, 1–25, doi:10.3390/ economies7030066.