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Policy Evaluation and Monitoring of Agricultural Expansion in Forests in Myanmar: An Integrated Approach of Remote Sensing Techniques and Social Surveys

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Abstract: Agricultural expansion is the main driver of deforestation in Myanmar. We analyzed the effectiveness of a national policy intervention on agricultural encroachment in state forests in Taungoo District in Myanmar from 2010 to 2020. The policy aims to stop agricultural encroachment and reforest encroached areas through farmers' participation in an agroforestry community forestry. We applied an integrated approach that involved a land cover change analysis together with a household survey about encroachment behavior. The remote sensing analysis for the years 2010, 2015 and 2020 showed the land cover change pattern and an increase in agricultural encroachment from 9.5% to 18.5%, while forests declined from 62.8% to 51.9%. The survey showed that most farmers (91%) believed that the policy intervention did not lead to a change in their encroachment behavior or farm size. The main reasons that incentivized encroachment were stated to be livelihood needs, immigration due to marriage and increased accessibility due to road construction. The main reason for reducing encroachment was plantation establishment, leading to a loss of land for encroaching farmers. In conclusion, the integrated approach showed that the policy intervention did not decrease encroachment, whereas other factors influenced encroachment behavior. We recommend solving interministerial conflicts of interest related to encroachment in Myanmar and using an integrated approach for future studies.

Keywords: deforestation; encroachment; perception; land cover change; forest policy

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1. Introduction

Deforestation and forest degradation are among the major global challenges contributing to biodiversity loss and climate change. At the same time, forests are relevant for human well-being, particularly in many countries of the Global South, where local communities are directly dependent on the benefits of forest ecosystems, including the provisioning of timber and non-timber products, as well as many regulating services, such as flood protection and climate regulation. Addressing deforestation is therefore not only relevant to Sustainable Development Goals (SDGs) 15 (Life on land) and 13 (Climate Action) but to the sustainability agenda overall. The drivers of deforestation and forest degradation can be diverse and variable in different local contexts [1,2]. However, one of the main drivers of deforestation in many parts of the world, in particular in forests with high biodiversity value in the Global South, is agricultural expansion [2,3]. In the context of agricultural expansion, commercial agriculture stands out as the main driver of deforestation in the Americas, while both subsistence and commercial agriculture are the main drivers of deforestation in Africa and tropical Asia [2,3].

Similar to other tropical countries, deforestation in Myanmar has been driven by agricultural expansion due to commercial commodity production (e.g., rubber and oil

palm), as well as subsistence agriculture (i.e., shifting cultivation and small-scale agricultural encroachment by farmers) [4–6]. According to the existing Myanmar Forest Law (2018), forests may only be used for non-timber collection, and the establishment of new settlements and farming are strictly prohibited in state forests [7]. The Forest Department, under the Ministry of Natural Resources and Environmental Conservation (MoNREC), is responsible for enforcing and monitoring this law [7], but poor governance, an unstable political situation, corruption, poverty and population growth have limited the effectiveness of this law, leading to continued high levels of deforestation due to agriculture, even in state-managed forests [4,6]. Furthermore, conflicting interests between the Ministry of Agriculture, Livestock and Irrigation (MoALI), which supports an increase in arable land, and the MoNREC, which aims to reduce deforestation and expand forest lands, undermine coherent intervention efforts. Once a forest land title is converted into an agricultural land title and subsequently managed under the MoALI, the land title change becomes practically irreversible, and the Forest Department loses the right to intervene, e.g., through reforestation. Therefore, agricultural expansion in state forests has been a serious threat to the forests of Myanmar, causing permanent deforestation.

While the Myanmar Forest Department is dedicating intensive efforts to expand state forests to meet the target of 30% of the country's area as mentioned in the nationally determined contributions submitted to the UNFCCC, many conflicts between the land use rights of farmers and the interests of forest conservation have become apparent, leading to intensive debates in parliament between 2010 and 2013 [8]. To resolve this conflict, the government issued a policy intervention in 2013 that includes instructions to survey encroached areas in state forests, degazette established paddy fields from forest to agriculture and reforest rainfed agricultural areas through agroforestry community forests [9].

Despite the promotion of agroforestry community forests for reforestation on agricultural land, these efforts have fallen short of expectations, as highlighted by San et al. (2023) [10], who conducted the only study reported to date on the effectiveness of the policy on agricultural encroachment of forests in Myanmar. The importance of monitoring and evaluating policy implementation for effective forest management has been highlighted in many previous studies [11,12]. However, given the limited availability of financial and human resources, monitoring agricultural encroachment in forests and evaluating the effect of forest policies pose significant challenges [13–15]. To overcome the challenges associated with the need for substantial investment of manpower and money for effective monitoring, remote sensing has been proposed as a cost- and time-effective tool for sustainable forest management [16]. Blackman (2013) also suggested remote sensing as a low-cost method to conduct ex post analysis of forest policies [12].

However, its limitations lie in its ability to capture context-specific explanations and social issues crucial for refining policies and their implications [17]. To address this shortcoming, Ishtiaque et al. suggested the integration of remote sensing techniques with social science methodologies as a promising approach to deal with social challenges in forest management [18]. In order to evaluate the effectiveness of the policy intervention in changing the behavior of farmers, social data including the reasons for increasing or decreasing encroachment activities and farmers' perceptions are therefore necessary to provide a deeper comprehension. The usefulness of the integrated approach in forestry research has also been demonstrated in previous studies [19,20].

Hence, in this study, we intend to analyze land cover change and agricultural encroachment dynamics before and after the policy intervention to evaluate its effectiveness at the landscape level. The study provides a holistic and thorough evaluation of the policy related to agricultural encroachment in the state forests of Myanmar at the landscape scale. We apply an integrated approach using a land cover change analysis based on remote sensing techniques together with social data analysis, including a survey of local farmers. The results of the study have the potential to contribute to the effective monitoring and management of agricultural encroachment in Myanmar, as well as other tropical countries facing similar challenges and constraints.

2. Materials and Methods

2.1. Study Site

The study area, Taungoo District, is located in the Bago Mountain Range (known as Bago-Yoma in the Bago Region), where naturally regenerated valuable timber species, especially teak (*Tectona grandis*. L), are abundant [21]. It is located between 18°8′ and 19°20′ N and 95°50′ and 96°45′ E (see Figure 1) in the central part of Myanmar. The minimum temperature is 21 °C, and the maximum temperature is 32 °C [22]. The average annual precipitation ranges between 2500 mm and 3000 mm [21]. The elevation of the study area ranges from 5 to 1884 m above sea level. The total area of the district is 10,677 km^2, and state forests occupy 52.4%. This study area was selected due to its ecological significance and high rate of forest degradation caused by legal and illegal logging and agricultural expansion [10,23,24]. Field data collection was conducted in July and August 2020.

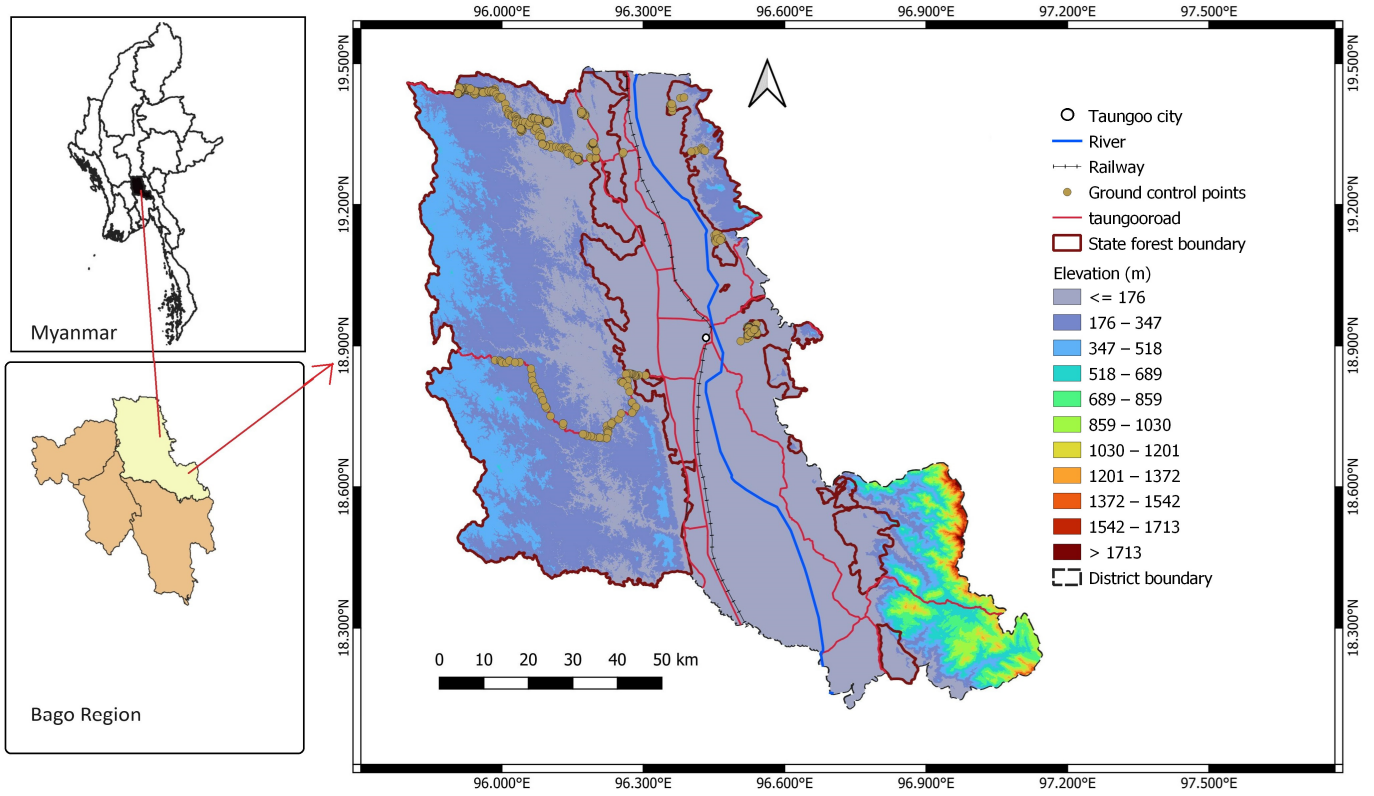


Figure 1. Location of the Taungoo District and the study area (State Forests) (Source: adapted from San et al., 2023 [10]; Forest Department, 2020, [25]).

2.2. Methodology

In evaluating the effects of the forest policies, Blackman (2013) reviewed different approaches applied in previous studies [12]. A common approach is a "before-versus-after comparison" that compares the status of the forest in two cross-sectional periods before and after policy implementation. In this study, we applied this approach to assess the effect of the policy on agricultural expansion in the study area (see Section 2.3.1). In this approach, considering spillover is an important aspect; therefore, we selected a large extent of state forests as the study area to cover spillover or leakage effects. In comparing the two study periods, we employed an integrated approach including land cover change analysis using remote sensing techniques and social data analysis through a questionnaire survey with closed and open-ended questions covering both quantitative and qualitative aspects related to monitoring and management of agricultural encroachment in forests at the landscape level.

2.3. Land Cover Change Analysis

2.3.1. Selected Time Frames

As the policy intervention was introduced at the national level in 2013 and the implementation in the study area started in the governmental fiscal year of 2014–2015, we selected the years 2010, 2015 and 2020 for the land cover change analysis.

To evaluate the impact of the policy intervention, these years were divided into two periods. The first period of 2010 to 2015 shows the general encroachment dynamics before the policy intervention showed any impacts. It therefore functions as a baseline for comparison.

The period of 2015 to 2020 shows the general encroachment dynamics after the policy intervention was established to analyze the impact of the policy intervention on the land cover changes compared to the previous period.

2.3.2. Data acquisition

In the first step, the Landsat-7 Enhanced Thematic Mapper Plus (ETM+) images for 2010, Landsat-8 Operational Land Imager (OLI) images for 2015 and 2020 with 30 m resolutions and the digital elevation model for the study area were downloaded for free from the website of US Earth Explorer [26] (Step 1, Figure 2; Appendix A, Table A1). We selected images with a cloud cover percentage of less than 10% in November and December, when deciduous trees have full canopies. It is also the harvesting time for most farmers and provides clearer differentiation between agriculture and forested land. The steps of land cover classification and land cover change analysis are illustrated in Figure 2.

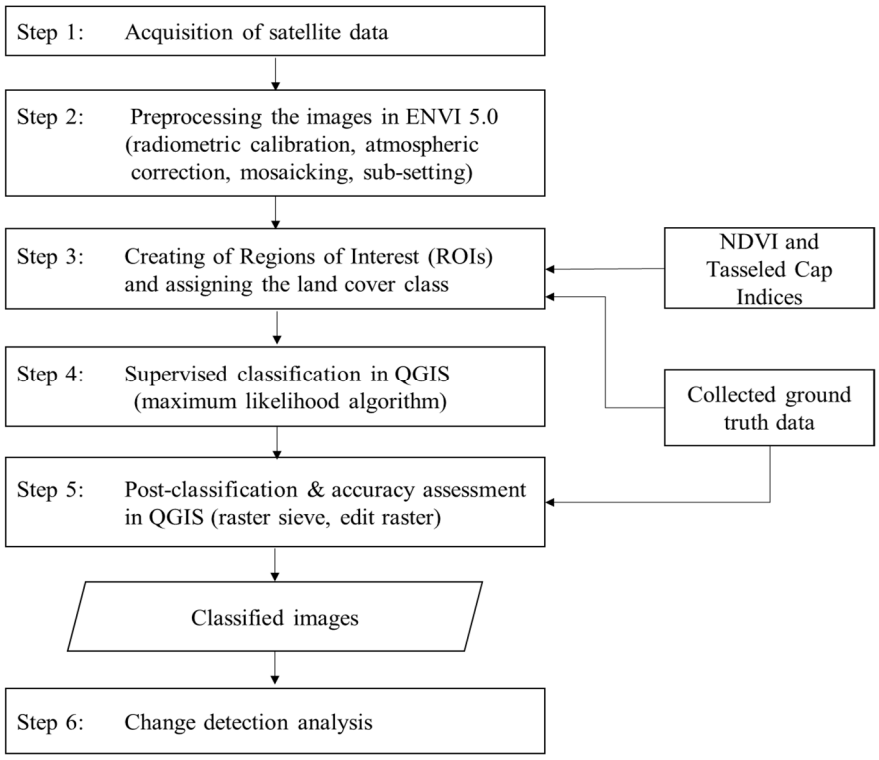


Figure 2. Processing steps of land cover classification and land cover change analysis in ENVI 5.0 and QGIS 3.28.6.

2.3.3. Preprocessing

Downloaded satellite images were preprocessed using ENVI 5.1. software (Step 2, Figure 2). Image preprocessing included atmospheric correction, radiometric calibration, dark subtraction, mosaicking of the images using the nearest neighbor algorithm and subtraction of the study area from the mosaicked image.

2.3.4. Land Cover Classification and Indices for Land Cover Classification

We employed supervised classification using the semi-automatic plug-in with QGIS 3.28.6.software. The semi-automatic plug-in is an open-source tool [27] that is widely used for land cover classification, as well as land use planning and monitoring. It enables users to achieve reliable image processing and land cover classification by creating regions of interest (ROIs) with their spectral signatures as training samples and applying a relevant algorithm with the collected samples containing the respective spectral signatures [28].

As the analysis was mainly focused on agricultural encroachment dynamics and forest cover status, five land cover classes were categorized: 'forest', 'other wooded lands', 'agriculture', 'water bodies' and 'other'. Given the objective of the study, categorization was achieved during the field survey using field observations with reference to forest land categorization from FAO (2014) [29]. We categorized forest plantations depending on their canopy coverage and height. Forest plantations in Myanmar are established through Taung-ya practice, in which agricultural crops are planted in between newly planted trees by farmers during the first 2–3 years of plantation establishment. Therefore, young forest plantations were categorized through remote sensing as agriculture, as they are dominated by crops. After cropping stopped in the tree plantations, forest plantations were categorized as 'other wooded lands' until the trees were mature enough to meet the definition of the 'forest' category. A detailed description for each land cover class is provided below in Table 1.

Table 1. Categories and definitions of land cover classes (adapted from FAO 2014) [29].

Land Cover Class	Definition
Forest:	Forest land including mature forest plantations spanning more than 0.5 hectares, with trees higher than 5 m and a canopy cover of more than 10 percent or trees able to reach these thresholds in situ.
Other wooded lands	Land not classified as "forest" spanning more than 0.5 hectares, with trees higher than 5 m and a canopy cover of 5–10 percent or trees able to reach these thresholds; or with a combined cover of shrubs, bushes and trees above 10 percent. This category also includes immature forest plantations after Taung-ya cropping has stopped but before they meet the criteria for "forest".
Agriculture:	Cropping areas, grazing land and agricultural fallow land which predominantly occupied by grasses or shrubs. This category also includes the first 2–3 years of Taungya forest plantations during which crops are planted between trees until the trees' canopies are closed.
Water bodies:	Inland water bodies, generally including major rivers, lakes and water reservoirs.
Other:	All land that is not classified as any of the above categories. It mainly includes built-up areas, such as villages, buildings, and paved roads, and barren lands, such as sand and current and abandoned stone extraction areas without any vegetation.

We employed stratified sampling based on the land cover types and collected respective land cover information from 458 ground control points covering all land cover classes (see in Figure 1), including forests (50), for other wooded lands (207), agriculture (172), water bodies (14) and other land (15). Although around 75–100 ground-truthing sites per class were suggested, the number and location of ground control points varies depending on the homogeneity, total extent of coverage and accessibility of each land cover class to fulfil the objective of the study [30]. Therefore, we collected more ground-truthing sites in other wooded lands and agriculture areas, where heterogeneity is high, and fewer sites in forests, water bodies and other areas. Collected field data were split into training (80%) and validation (20%) sets for accuracy assessment.

Before performing supervised land cover classification, a training dataset with land cover information was built by creating the ROIs (Step 3, Figure 2). In addition to ground truth data, values of other indices (normalized difference vegetation index (NDVI) and Tasseled cap indices or Tesseled cap transformations) were also applied.

The NDVI is an index indicating vegetation greenness, which correlates with vegetation density and distribution and is widely used in forest-related studies [31–33]. NDVI can be calculated using the following formula:

$$\text{NDVI} = (\text{NIR} - \text{RED})/(\text{NIR} + \text{RED}) \quad (1)$$

where NDVI is the Normalized Difference Vegetation Index, NIR is the spectral reflectance of the near-infrared band and RED is the spectral reflectance of the red band of the image. The NDVI value can range between −1 and 1; higher NDVI values correspond to healthier vegetation. The value of the NDVI for each pixel was calculated using QGIS software 3.28.6. and can directly be applied during the process of determining the respective land cover of each training ROI.

Tasseled cap indices or Tesseled cap transformations were also additionally employed during land classification to identify bare soil and wet paddy fields in the study area. Among the indices, the brightness index (BI) and wetness index (WI) were used due to their effectiveness in indicating the biophysical characteristics of land [34]. Different maps for each tasseled cap index were separately produced and overlaid on the original satellite images. The respective value and visualization of each pixel from the produced maps helped in determining different land cover classes.

Overall, to determine the land cover class of each ROI, land cover information from ground truth data, reference data from Google Earth, visual interpretation of different band combinations and values of the NDVI index and tasseled cap indices were cross-checked and validated. After creating the training input dataset, we applied supervised classification with a maximum likelihood algorithm that is widely used in land cover classification and considered one of the most reliable approaches, producing high levels of accuracy relative to other supervised land classification techniques [35,36] (Step 4, Figure 2).

2.3.5. Post Classification and Accuracy Assessment

After classification, we used the classification sieve and edit raster tools of the SCP plug-in to eliminate isolated pixels and misclassified areas (Step 5, Figure 2). Consequently, an accuracy assessment for each land classification was carried out, as this is an important step in land cover classification that reveals the usefulness of the classified map [37]. We determined the required sample size for validation using the following equation proposed by Olofsson et al. (2014) [38].

$$N = \left(\sum_{i=1} (W_i S_i) \Big/ S_o \right)^2 \quad (2)$$

where N is the desired number of samples for accuracy assessment, while W_i is the mapped proportion of the area of class 'i', S_i is the standard deviation of stratum 'i' and S_o is the expected standard deviation of overall accuracy. The accuracy values explain the reliability of classification. In previous literature, an accuracy value greater than 70% was considered acceptable by Congalton (1991) [39], while Anderson (1976) mentioned accuracy values between 85% and 90% as satisfactory [40]. The acceptable accuracy level can be varied depending on the users, nature of applications, land cover types and the classification scheme [41,42].

After land cover classification, we calculated the annual rate of change for each land class using the following equation (Equation (3)) proposed by Puyravaud, 2003 [43], which has been widely used for land cover change studies.

$$r = \left(\frac{1}{t_2 - t_1} \ln \frac{A_2}{A_1} \right) 100, \quad (3)$$

where r is the standardized annual rate of land cover change in percentage, and A_1 and A_2 are the areas of land cover at times t_1 and t_2, respectively, in years. We obtained the values of A_1 and A_2 from the land cover classification analysis conducted using QGIS software 3.28.6. for different study periods.

2.3.6. Change Detection Analysis

As the final step, we compared and analyzed the outputs of classification from different studied years using a change detection tool of the SCP plug-in (Step 6, Figure 2). It generates the land cover conversion matrices among land cover classes, the extent of the unchanged and changed areas among different land cover classes and a map showing the locations where changes occur among different studied years. The land cover conversion matrices help users to understand which land cover classes have shifted to which other land cover classes and the extent of the shifted area for each class.

2.4. Questionnaire Survey

2.4.1. Data Collection

We carried out a questionnaire survey to understand the household and socioeconomic situation of encroaching farmers, as well as the impact of policy intervention on their encroachment behavior related to the policy intervention. We collected data from a total of 291 sample households. These were selected out of a total of 2409 households registered by the Forest Department using a stratified random sampling method covering different locations (see also San et al., 2023 [10]). Of the interviewed participants, 75% were male, and 25% were female. Although we aimed to interview the same proportion of male and female participants, the gender of the interviewees varied depending on their availability and willingness to participate. In the field survey, we collected quantitative data related to the socioeconomic characteristics of the households, such as household size, income and farm size, as well as qualitative data, using open-ended questions to explore the influence of the policy intervention, as well as other factors affecting their encroachment behavior (see questionnaires in Appendix C).

2.4.2. Data Analysis

We employed descriptive statistical analysis to explain the household characteristics and livelihoods of farmers, previous land cover of the encroached areas and the extent of their farm size dynamics. We coded and analyzed the qualitative responses, which were the reasons affecting the dynamics of encroachment in the study area, using ATLAS. ti software version 23 and visualized the results using Sankey diagrams.

3. Results

3.1. Land Cover Classification and Accuracy Assessment

The land cover classification results for 2010, 2015 and 2020 can be seen in Table 2 and Appendix B. Figure A1a–c. The accuracy assessment of classified land cover reveals high overall accuracy values of 95.0, 95.5 and 93.4 for 2010, 2015 and 2020, respectively. The average producer and user accuracy for each land cover class for each year and their standard error can be seen in Table 2.

According to the land cover classification results, most of the study area was covered by forests, other wooded lands and agriculture land, while water bodies and other land cover occupied only a small proportion of the study area. The area of water bodies slightly increased between 2010 and 2015 due to the construction of a new dam (see Figure A1a,b).

Apart from that, water bodies did not show significant changes between 2015 and 2020. Other land cover classes, including settlements, roads and bare land, covered only a small area, ranging between 0.3% and 0.4% throughout the entire ten-year (2010–2020) study period. Therefore, only land cover changes among forests, other wooded lands and agriculture are highlighted in Section 3.2.

Table 2. Detailed accuracy assessment results of land cover classification.

	Forest	Other Wooded Lands	Agriculture	Water	Other
2010					
Area (km^2)	3509	1430	529	107	15
(% of the total area)	(62.8%)	(25.6%)	(9.5%)	(1.9%)	(0.3%)
Standard Error	0.007	0.0078	0.0047	0.0026	0.0002
Producer Accuracy (%)	97.294	93.888	86.476	85.367	100
User Accuracy (%)	97.403	88.333	98.361	92.857	91.304
2015					
Area (km^2)	3254	1308	812	201	20
(% of the total area)	(58.2%)	(23.4%)	(14.5%)	(3.6%)	(0.3%)
Standard Error	0.0066	0.0075	0.005	0.0036	0
Producer Accuracy (%)	100	89.185	92.679	84.325	100
User Accuracy (%)	95.069	95.946	96.591	95.652	100
2020					
Area (km^2)	2903	1406	1037	224	23
(% of the total area)	(51.9%)	(25.1%)	(18.5%)	(4.0%)	(0.4%)
Standard Error	0.0075	0.0081	0.0059	0.0031	0.0007
Producer Accuracy (%)	94.093	92.128	92.824	94.438	100
User Accuracy (%)	98.101	86.441	92.667	81.250	83.333

3.2. Comparison of Land Cover Changes before and after the Policy Intervention

The total forest area in 2010 was 62.8%, and it declined continuously throughout the whole study period: down to 58.2% and 51.9% in 2015 and 2020, respectively (Figure 3). Before the policy intervention, the annual rate of forest loss was −1.5% and, afterwards, increased to −2.28% per year. If we analyze the net forest loss by different land covers before the policy intervention, the major net forest loss was caused by a shift to agriculture rather than a shift to the other wooded lands. Contrarily, after the policy intervention, the amount of forest loss to other wooded lands was considerably higher than forest loss to agriculture (Figures 4 and 5).

Before the policy intervention, other wooded lands decreased from 25.6% to 23.4% of the study area, with an annual rate of decrease of −1.78%. In contrast, after the policy intervention, other wooded lands increased considerably to 25.1% of the study area, with an annual increase rate of 1.46%. As previously mentioned, the major increase in other wooded lands areas was due to a large area of forest land cover loss to other wooded lands.

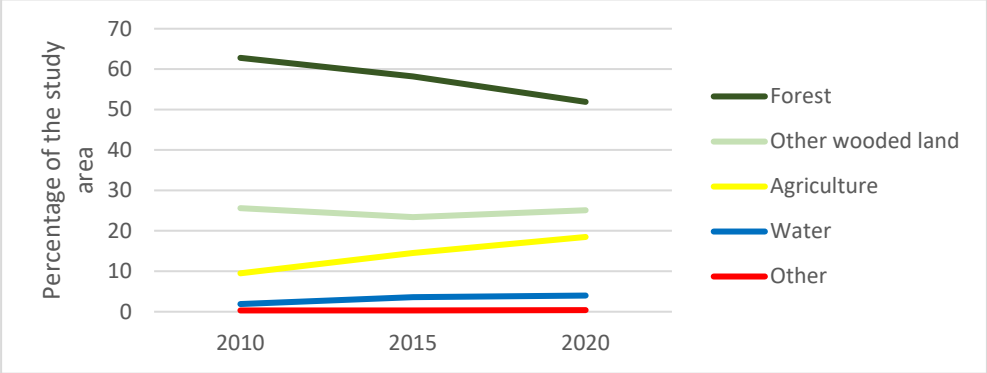


Figure 3. The extent of different land covers in 2010, 2015 and 2020.

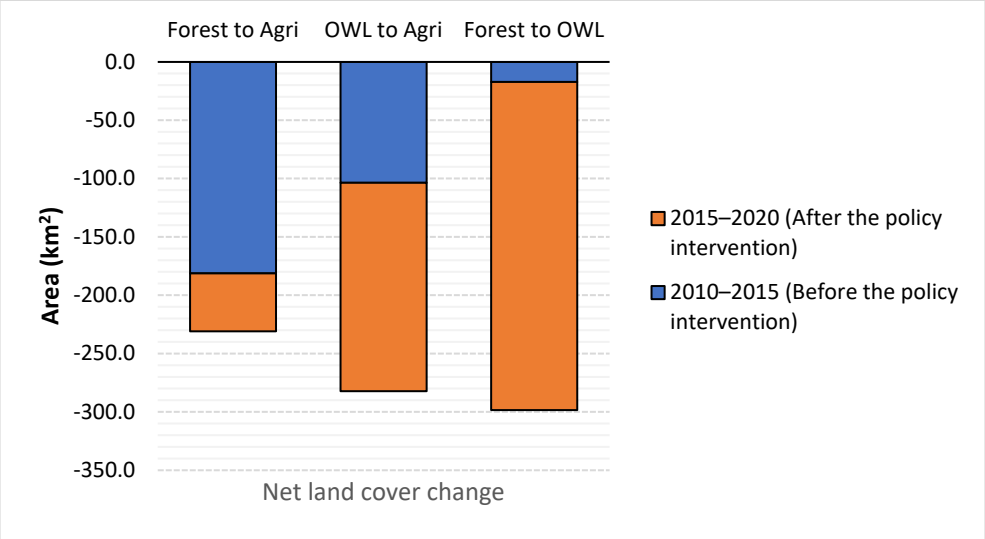


Figure 4. Net land cover changes among forests, agriculture (Agri) and other wooded lands (OWL) during the period of 2010–2020.

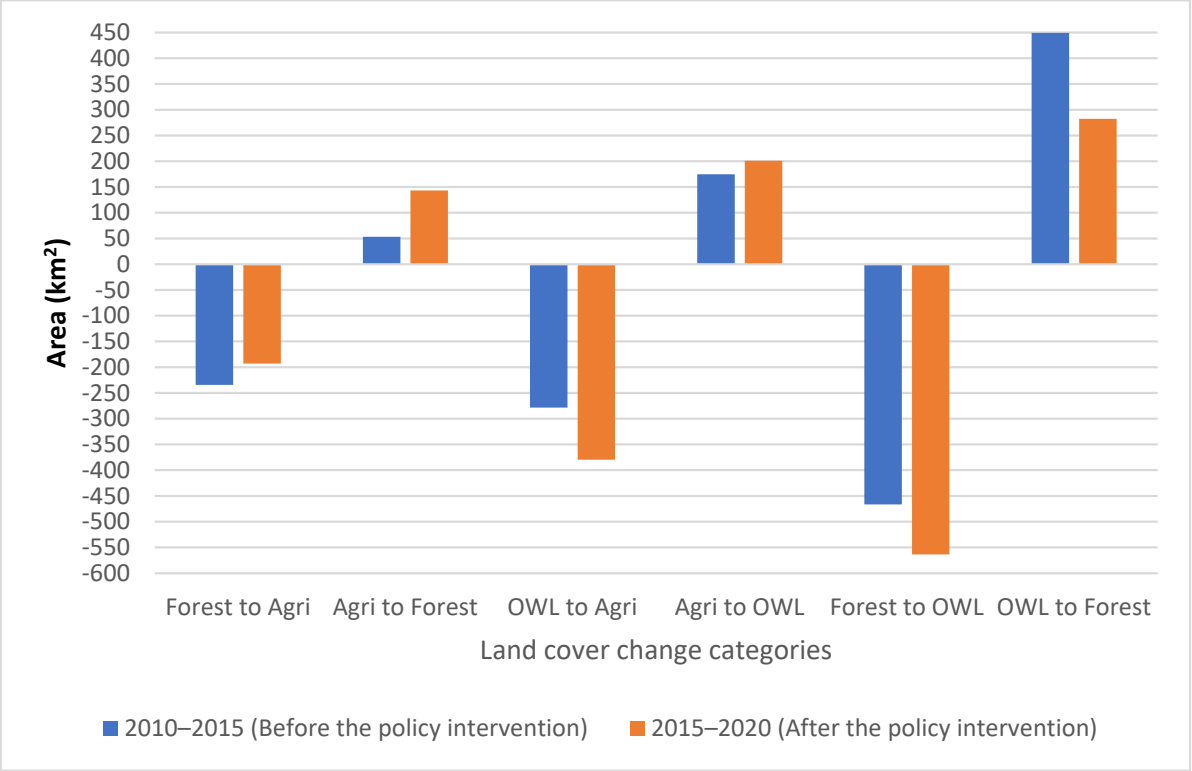


Figure 5. Comparison of land cover changes in the two study periods (before and after the policy intervention). Positive values represent an "increase/gain", and negative values represent a "decrease/loss" (Agri = agriculture, OWL = other wooded land).

In 2010, the total agricultural area covered 9.5% of the study area and increased in 2015 and 2020 to 14.5% and 18.5%, respectively. During the first five years (2010 to 2015), the annual rate of agricultural expansion was 8.58%. After the implementation of the policy in 2015, this expansion continued but at a lower annual rate of 4.9% until 2020.

Overall, we found that the net forest loss to agriculture reduced after the introduction of the policy compared to the period before the policy (Figures 4 and 5). We also found that a large area of other wooded lands was converted to agricultural land, resulting in a high net loss of other wooded lands to agriculture after the policy implementation. We found a comparable increase in agricultural land between the two study periods but with different dynamic land use change patterns (Tables A2 and A3). The net conversion of forest to other wooded land, which includes heavily degraded forest, immature forest plantations and fallow forests, increased up to 282 km^2 after the policy implementation and was significantly higher than before (Figure 4). An overview of the detailed land use changes between categories over the two time periods can be seen in Figures 4 and 5 and Tables A2 and A3.

Change detection analysis revealed that areas of forest other wooded lands gained from agriculture were partly from the areas cleared for Taung-ya forest plantation establishment, where farmers grow crops between newly planted trees for the first 2–3 years. Furthermore, the analysis detected areas of small-sized agricultural land that were reforested during both study periods.

Throughout the study periods, we found other wooded lands in buffer areas between forests and agriculture areas, and agricultural expansion occurred mainly in those areas according to change detection analysis. It seems that after establishing agricultural fields, encroaching farmers degraded the surrounding forests over time and changed the forests to other wooded lands. In both study periods, the expanded agricultural areas were mostly clustered in small, sparse patches (less than 15 ha) that are likely to be expanded by small-

scale encroaching farmers. We also observed a large clearance (greater than 60 ha) of forests and other wooded lands for forest plantation establishment.

3.3. Questionnaire Survey Responses

3.3.1. Household Characteristics, Livelihoods and Farming Practices

The average age of the interviewed farmers was 50 years, and the average agricultural area per household was 4.5 ha, indicating small-scale and subsistence farming. On average, a household consisted of five persons, out of which three were family workers. The average annual income was USD 2465. The main crops grown in the study area were sesame, rice and groundnuts in the rainfed upland areas and rice in the valley areas, which are often near streams among the hills. Out of the surveyed households, around 92% had been farmers since their first settlement in the forest. The occupations of the other 8% of respondents included government plantation workers, government staff, daily workers and bamboo harvesters, later changing their occupation to farmers.

During the field survey, it was found that 95.2% of total households (n = 291) practiced permanent agriculture, including bush fallow systems in their claimed farmland, while 3.1% practiced both permanent and shifting cultivation. No households were found to practice only shifting cultivation. The remaining 2% of households were no longer farmers and relied on off-farm income sources. Among the households practicing permanent agriculture during the field survey, 14% were originally shifting cultivators, and 2% were Taungya plantation farmers who switched to permanent agriculture and settled in villages within state forests between 2005 and 2020 while the rest practiced permanent agriculture since their first settlement. Shifting cultivators changed their practices for various reasons, such as a lack of areas for shifting cultivation because of occupation by private companies to establish plantations (32%) or due to population growth (16%); decisions to settle in a village instead of moving around for personal reasons such as marriage, getting old or limited labor capacity (29%); instruction from the Forest Department's to stop cutting down the forests (18%); and an informal demarcation of farmland in the surrounding areas (5%).

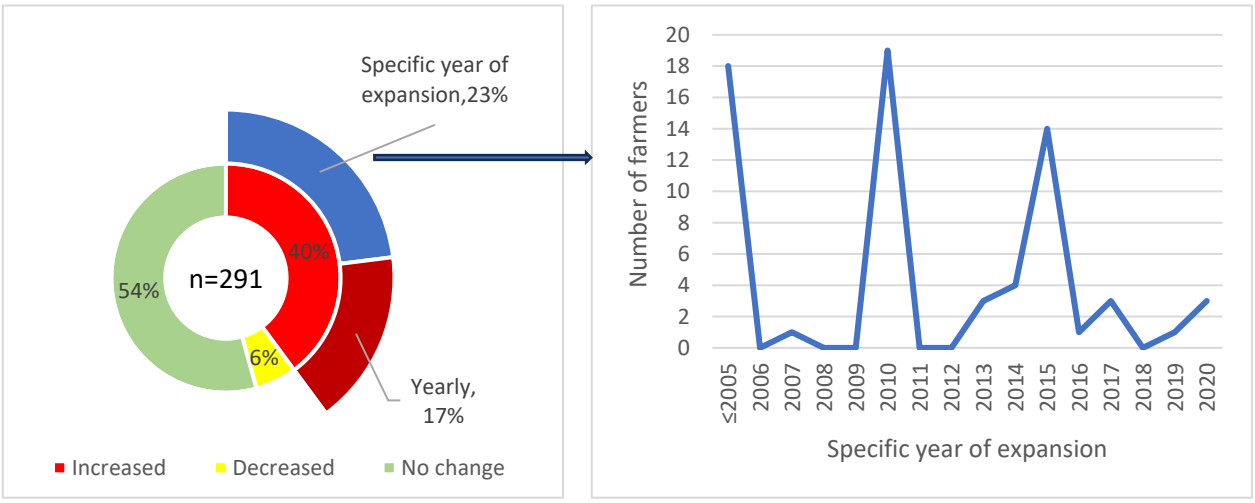
3.3.2. Previous Land Cover and Origin of Encroached Farms

The majority of farmers (45%) reported that they cleared already degraded forests to establish their agricultural fields. According to their general shared perception, a degraded forest is a forest that has been used for harvesting multiple times and consists of few and low-value tree species with a noticeably reduced density. Around 3% of farmers received land from the government as a special arrangement for old government plantation workers. Around 52% of the farmers either inherited or bought land from other farmers. Regardless of the illegal status of the encroached farms, the existence of an informal market for transfer land was observed. Around 25% of farmers expanded their agricultural land by cutting down the forest around their farms after buying or receiving the land as an inheritance.

3.3.3. Farm Size Dynamics and the Effect of the Policy Intervention

Among all households, for the majority of farmers (54%, n = 158), the farm size had not changed since their initial settlement. However, 40% (n = 116) of households expanded their agricultural area after settlement, while the other 6% (n = 17) had reduced their farm size in 2020 compared to their initial farm size.

Among the 40% of households that increased their farm size, 17% expanded their farms annually, while 23% expanded their farms only once in specific years (Figure 6a). Most farmers responded that expansion occurred between 2005 and 2020. Some farmers (n = 18) responded that they expanded a long time ago (before 2005) and could not remember the specific year. Therefore, they were categorized together as having expanded before 2005. The most frequent expansion years after 2005 were 2010 and 2015 (Figure 6b).



(**a**) (**b**)

Figure 6. (**a**) Percentage of farmers showing different farm size dynamics (n = 291); (**b**) number of farmers who expanded their farms in specific years.

Most farmers (91%, n = 265) responded that the policy intervention in 2013 did not affect their farm expansion behavior or farm size changes. A few farmers (5%, n = 14) said that they expanded their encroached agricultural land by clearing the nearby degraded forest to claim more areas as their land because of the policy intervention. The remaining 4%, (n = 12) mentioned that they started demarcating already encroached areas as their property after the policy intervention was initiated.

3.3.4. Factors Affecting Settlements and Agricultural Encroachment

We collected information related to the perception of interviewees on settlements and land use dynamics due to farmland encroachment in their surrounding areas between 2010 and 2020. As two farmers refused to respond, we were able to gather information about the perceptions of 289 farmers.

First, we asked farmers whether the policy intervention had the intended effect of decreasing the number of settlers and the encroachment area or if the policy intervention was instead working as an incentive for encroachment behavior and settlement. The majority (97%, n = 281) of farmers perceived that the policy did not reduce the amount of agricultural encroachment or the number of settlers in the study area. Only 3% (n = 8) indicated that some farmers had stopped farming in their surrounding areas as an effect of the policy intervention. The majority (93%, n = 270) of farmers said that the policy intervention, particularly the establishment of agroforestry community forests, did not incentivize or attract other farmers to move into the forests and did not cause more encroachment. The rest (around 7%, n = 19) of the interviewed farmers perceived a minor increase in new farmers in the area, who immigrated due to the policy intervention. In conclusion, the intervention was not seen as directly affecting encroachment.

Secondly, we asked the interviewees which other factors, apart from the policy intervention, might be affecting settlement and agricultural encroachment, starting with factors that increased the number of settlers and encroachment, followed by other factors that decreased settlement and encroachment. Among the total respondents, the majority (87%, n = 253) responded that they were not aware of other factors, while 12% (n = 36) named different factors causing increases in agricultural encroachment and the number of settlers between 2010 and 2020. These mainly included socioeconomic factors; like livelihood needs and poverty, the availability of marketable non-timber forest products and job opportunities; social factors entailing immigration due to marriage; and an increase due to improved accessibility because of road construction (Figure 7).

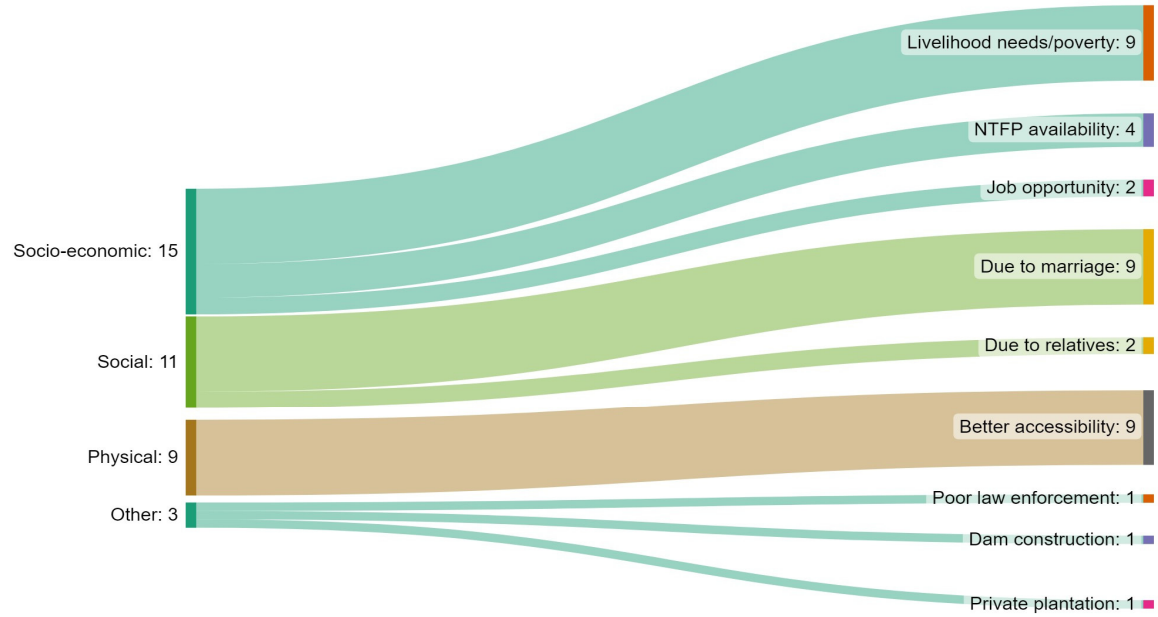


Figure 7. Reasons for increasing numbers of encroaching settlers in the surrounding area during the period of 2010–2020 in relation to frequencies mentioned by the respondents (n = 36) (NTFP = non-timber forest products).

On the question of which other factors might have led to a decrease in encroachment and settlers, 82% (n = 236) of farmers replied that they were not aware of any, whereas 18% (n = 53) named other reasons besides the policy intervention. These included the establishment of commercial forest plantations by private, governmental or unspecified actors. They explained that the establishment of these plantations often led to a situation where farmers had fewer opportunities to encroach on surrounding areas or even became landless. This practice of land grabbing led to farmers' out migration or changes in livelihoods (Figure 8).

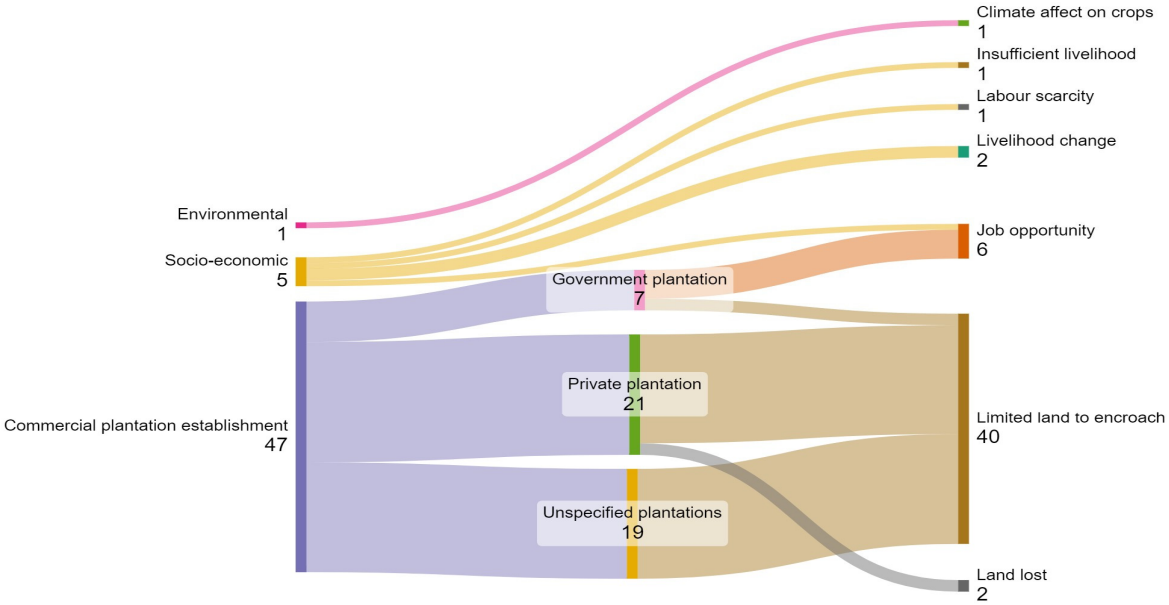


Figure 8. Reasons for decreasing numbers of encroaching settlers in the surrounding area during the period of 2010–2020 in relation to the frequencies mentioned by the respondents (n = 53).

3.3.5. Forest Department's Monitoring and Law Enforcement of Agricultural Encroachment

We also found that the majority of farmers were not aware of any Forest Department law enforcement related to agricultural encroachment. The majority (around 90%) of interviewees responded that the Forest Department did not monitor their agricultural encroachment status after conducting the encroachment survey according to the policy intervention. Only 10% (n = 30) mentioned that the Forest Department followed up with them after recording their encroachment status and warned them not to increase the farmland area by encroaching into the forested land. However, even if they did, none of them experienced any legal action taken by the Forest Department.

4. Discussion

4.1. Land Cover Dynamics between Forests and Agricultural Land before and after the Policy

According to the remote sensing results, the majority of land cover changes from forest to agriculture were mainly a result of the expansion of small-scale agriculture by local farmers along an encroachment frontier. In addition to the widespread clearance of small patches for agriculture by local farmers, we also observed deforestation due to land clearance for commercial forest plantations through Taung-ya agroforestry systems [44]. This system, which is commonly practiced in Myanmar, includes slash-and-burn practice [45] and the simultaneous growing of crops and trees at an early stage when the trees are still young. This practice has been criticized for its negative impacts on biodiversity conservation and ecological perspectives [46]. For verification of our findings, we triangulated the results from the remote sensing analysis with the secondary data from the Forest Department and results from the social data analysis resulting from the survey. The remote sensing results aligned with the information sourced from the Forest Department regarding the establishment of monocultural or economically driven tree plantations, characterized by limited species diversity [21]. The results are also reinforced by insights gathered from the survey data collected from local communities. In addition to state forest plantations, the establishment of commercial, private tree plantations has been promoted in degraded forests in the study area since 2006 [47].

Furthermore, the analysis detected that some areas of small-sized agricultural land were reforested during both study periods before and after the policy. The farmers' explanation revealed during the survey was that parts of their agricultural land were taken over by private companies to establish tree plantations. From a reforestation perspective, this could be considered a positive land cover change from agriculture to forest plantations. However, farmers' perceptions indicated substantial conflicts between private companies and local farmers, with overall negative impacts in terms of sustainability outcomes [48]. This can create spillover effects, causing deforestation in additional encroached areas.

4.2. Land Cover Dynamics between Agriculture and other Wooded Lands before and after the Policy

The change detection analysis indicated that agricultural areas were mainly cleared from other wooded lands, especially during the second period. Additionally, some areas initially classified as agricultural areas shifted back to other wooded lands. According to the interviews, part of these land cover changes was due to the practice of leaving fallows in agricultural systems and shifting cultivation. Although farmers who practiced conventional shifting cultivation were rarely encountered during the survey, the remote sensing results pointed to the possibility of a higher relevance of shifting cultivation in more remote areas of the study area. This dynamic was also pointed out in another study conducted by Chan et al. (2022), who mapped the shifting cultivation agriculture area throughout Myanmar [49]. Results of our survey also indicated that most farmers are smallholder farmers practicing farming on small land sizes, with an average of 4.5 ha. Generally, for smallholder farmers, other wooded lands are easier to change to agriculture areas than forests because of their lower tree density, demanding less labor and investment by farmers compared to clearing very dense forests. The land cover analysis also showed that other wooded lands were often located in buffer areas between forests and agriculture areas.

Therefore, protecting those buffer areas with strict monitoring by the Forest Department could be an option to stop further encroachment. Bhusal et al. (2018) showed successful cases of encroaching farmers protecting degraded forests around their farms in Nepal [50]. The responsibility to protect the buffer area should be legally bound to individual farming rights, with clear rules and regulations for better accountability.

4.3. Land Cover Dynamics between Forest and Other Wooded Lands before and after the Policy

Land cover changes from forests to other wooded lands increased more during the second period of the study than the first period. As most agricultural areas were transformed from other wooded lands, effective forest conservation requires a deacceleration of forest degradation to other wooded lands. Official selective logging by the state was practiced until 2015 in the study, after which point it was stopped with a plan of a 10-year logging ban in the Bago mountain range for forest rehabilitation purposes [51]. Previous studies found that illegal logging activities in the study area frequently followed and used extraction roads developed for legal timber extraction [52,53]. The targeted illegally logged species included tree species not only for timber but also charcoal production [52]. Although logging was banned in the study area from 1 May 2016 onwards [14], illegal logging continued [14,54]. Therefore, the protection of the forests from illegal cutting is also an urgent need to stop forest degradation and, consequently, agricultural expansion.

4.4. Effect of the Policy Intervention on Farmers' Agricultural Encroachment

The remote sensing analysis revealed that the rate of forest loss was higher after the policy intervention than before. The main forest loss during the second period was due to the degradation of forest into other wooded lands, followed by agricultural expansion. Before the policy intervention, the main agricultural expansion was found in forested areas; however, it continued its expansion more into other wooded lands than forests after the policy intervention. Remote sensing analysis results showed that the agricultural expansion in the state forests did not significantly reduce after the policy intervention. This was validated by the survey results, indicating that the agricultural encroachment behavior of most interviewed farmers did not change due to the policy intervention. On the contrary, a few farmers (n = 26) mentioned that providing secure land use rights to their encroached areas through the establishment of agroforestry community forests through the policy intervention created incentives for them to encroach more areas or demarcate the encroached areas as their property. In the same study area, Soe & Yeo-Chang (2019) found that providing land use incentives could promote the participation of local people in forest conservation [55]. However, precautionary measures, such as setting clear boundaries between forests to be protected and allowing agriculture followed by strict monitoring, would have to be established to avoid a situation where land use rights for reforestation become an incentive to encroach more areas in forests, as indicated by our results.

Our results also indicated that other socioeconomic and physical factors may attract more settlers, increasing forest encroachment in the study area, including road construction, providing better accessibility and livelihood opportunities. Many studies have already pointed out the negative consequences of roads, including deforestation worldwide [5,24,56,57]. Therefore, we argue that strict monitoring and law enforcement are crucial after new road construction to protect forests from encroachments, and reducing the construction of roads in ecologically sensitive areas is recommended. Furthermore, the establishment of forest plantations was identified as a factor limiting the availability of encroachment areas.

4.5. Weak Monitoring and Law Enforcement

The crucial importance of law enforcement in the context of deforestation associated with agricultural expansion has been pointed out by other studies, including Nasciemento et al. (2020) [58].

Although agricultural encroachment and related encroacher land use rights were discussed and a policy intervention to solve the issue was implemented by governmental

institutions in 2013 at the national level, the analysis reveals that encroachment problems remain. One of the major reasons based on the social survey results was the weakly implemented monitoring and law enforcement activities related to agricultural encroachment, as the majority (90%) reported that Forest Department did not continuously monitor their encroachment status. The insufficient number and limited capacity of field-level staff have been pointed out as major constraints in forest management in Myanmar [59,60]. In this study, we have demonstrated the effectiveness of remote sensing analysis in detecting agricultural encroachment in forests, providing a potential solution for these constraints. Applying remote sensing techniques can increase time, as well as human and financial, resource efficiency. Therefore, providing capacity building on remote sensing and GIS techniques to responsible staff and applying techniques to monitor the development of agricultural expansion can be an effective way to monitor agricultural encroachment in forests. Nowadays, remote sensing satellite images and analysis software can be freely and easily downloaded from open sources. Lechner et al. (2020) also highlighted that applying remote sensing techniques for forest management is cheaper and easier than in the past due to the availability of open sources, which provide preprocessed images [61].

In addition to monitoring forest cover using remote sensing, community-based monitoring and reporting systems for encroachment and agricultural expansion in forests, as suggested by Fry (2011), have been proven successful in Vietnam [62,63]. As community monitoring and reporting systems (CMRS) have been successfully implemented in Myanmar to control illegal logging and timber extraction activities [64], incorporating the monitoring of agricultural encroachment into the established system would be an efficient strategy for implementation. However, careful and participatory planning before implementation is necessary to avoid potential conflicts and corruption [63].

4.6. Benefits of the Integrated Approach

Throughout this study, we observed the benefits of combining remote sensing techniques and social data analysis.

The study highlighted the advantage of the remote sensing analysis covering a large extent of the area at the landscape scale and provided an overview of the agricultural encroachment dynamics and forest cover change over time. On the other hand, the social analysis explained the social and environmental contexts that cannot be covered by the remote sensing analysis. This was also pointed out as a limitation of studies that rely exclusively on remote sensing [17]. Based on our mixed-method approach, we were able to include detailed information about small-scale farm households and their perception of the policy effects. In addition, we discovered weak monitoring of encroachment behavior, factors affecting settler dynamics and the effect of the policy on their agricultural encroachment behavior through social data analysis.

Therefore, through the combination of remote sensing and social analysis, we were able to gain insights into the dynamics of forest cover and agricultural encroachment before and after the policy intervention. Similar to previous studies that applied an integrated approach to different research topics [19,20,65], we found it to be a useful tool for forestry research, especially within complex and challenging social contexts.

4.7. Limitations and Challenges

As sample households were selected for this study based on data collected by the Forest Department in 2013, the study results do not represent perceptions of unregistered households who settled in these areas after 2013 or in inaccessible areas, even if they were subsequently responsible for forest encroachment. Hence, we recommend a systematic and thorough survey and registration of encroaching farmers, including inaccessible and isolated farmers, to improve data availability and the monitoring process in the future. During ground truth data collection for the remote sensing analysis, we could not access all parts of the study area due to political instability, difficult terrain, weather conditions and COVID restrictions. As a substitute, we derived this information from inaccessible areas

via high-resolution Google Earth and sentinel images. Furthermore, since February 2021, the political situation in Myanmar has worsened due to the military coup, preventing us from carrying out another field survey to gather updated information after 2020.

The policy intervention (2013) facilitated the acquisition of land titles by some farmers for their irrigated paddy fields situated within state forest areas administered by the Agriculture Department. Consequently, these are no longer considered encroachments but are recognized as permanent agricultural areas. However, since the updated map showing the areas that were transferred to the authority of the Agriculture Department was not available, in this study, we defined all agricultural activities inside the borders of the state forest as encroachments, despite the possibility that some fields have been legally recognized as agricultural land. This lack of coordination regarding land titles, conflicting agendas and competing targets among ministries have been general obstacles contributing to deforestation in Myanmar [51,66]. In addition to developing a map with clearly demarcated agricultural and conservation zones, the strict implementation and enforcement of these zones is urgently needed for better forest management. To this end, coordination between responsible departments, mainly the Forest Department and the Agriculture Department, needs to be strengthened [67].

Finally, the lack of a usable district land use map from the Forest Department that delineates the location and boundaries of state and private forest plantations, and agroforestry community forest establishments in the study area (see in [21]) has made it challenging to correlate forest gains with agroforestry community reforestations or larger private and state plantations. The development of a clear map showing different forest management areas is recommended for better management in the future. To compensate for this information gap, we used social survey data.

5. Conclusions

In this study, we demonstrated the benefits of integrating remote sensing techniques and questionnaire surveys in monitoring agricultural encroachment in forests and assessing the outcome of the applied policy. Based on the remote sensing analysis, we were able to reveal the dynamics of land cover and land use change, especially in the context of agricultural encroachment. Using the interview results, we were able to explain the driving factors behind these dynamics and the outcomes of the policy intervention. We showed that using remote sensing data to monitor the status of agricultural expansion in forests is an effective strategy for Myanmar and other countries with limited human and financial resources, while a social survey provides policy makers with information crucial for policy modification. Furthermore, we provided an overview of the outcomes of the forest policy intervention covering a large area of forest landscape. We concluded that the policy intervention (2013), established and designed by the Forest Department to reduce agricultural encroachment, did not lead to a decrease in deforestation nor a decrease in encroachment. In order to decelerate smallholder agricultural encroachments in forests in Myanmar and other countries with similar issues, we suggest prioritizing the protection of degraded forests in the buffer areas between agriculture areas and forests to stop agricultural expansion. Farming rights should be strictly linked with the responsibility to protect nearby forests to prevent further encroachment. During the social survey, we observed forest plantation establishment as a factor limiting available encroachment areas in the study area. However, it should be noted that this also is likely to lead to land use conflicts with local communities or cause the migration of farmers into other areas, which might also be forests with an even higher ecological value. An explicit land use map that distinguishes between areas managed by the Forest Department and other governing bodies is highly advised. The implementation of a combination of remote sensing and community-based monitoring, coupled with meticulous participatory planning, could be a promising system to surmount the resource constraints in monitoring agricultural expansion within forested regions.

Author Contributions: S.M.S.: conceptualization, methodology, data collection and analysis, interpretation of results, writing—original draft preparation, reviewing and editing; N.K.: reviewing and

editing, validation and approval; L.B.-F.: reviewing and editing, validation and approval; C.B.S.: support in conceptualization, support interpretation, supervision, reviewing and editing, validation and approval. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement: The authors declare that they obtained the approval of the ZEF Research Ethics Committee of the Center of Development Research, University of Bonn, to conduct the present study based on interviews/surveys. We do not have the specific project identification code from the ethical committee for this paper. According to the regulations from Center of Development Research (ZEF), University of Bonn, authors needed to apply for an ethical clearance from the ethical committee (of ZEF) before conducting the field data collection. We confirmed that the chair of the ethical committee signed and approved the ethical clearance application before the field research.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

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Abbreviations

FD	Forest Department
UNFCCC	United Nations Framework Convention on Climate Change
MoALI	Ministry of Agriculture, Livestock and Irrigation
MoNREC	Ministry of Natural Resources and Environmental Conservation
ROI	Region of interest

Appendix A

Table A1. Satellite images used for the study and their information.

No.	Name of the Satellite Image	Type	Orbit	Captured Date	Resolution
1	LE07_L1TP_132047_20101221_20161211_01_T1	Landsat7	132, 047	21.12.2010	30 m × 30 m
2	LE07_L1TP_133047_20101126_20161211_01_T1	Landsat7	133, 047	26.11.2010	30 m × 30 m
3	LC08_L2SP_132047_20151211_20200908_02_T1	Landsat8	132, 047	11.12.2015	30 m × 30 m
4	LC08_L2SP_133047_20151218_20200908_02_T1	Landsat8	133, 047	18.12.2015	30 m × 30 m
5	LC08_L2SP_132047_20201224_20210310_02_T1	Landsat8	132, 047	24.12.2020	30 m × 30 m
6	LC08_L2SP_133047_20201215_20210314_02_T1	Landsat8	133, 047	15.12.2020	30 m × 30 m

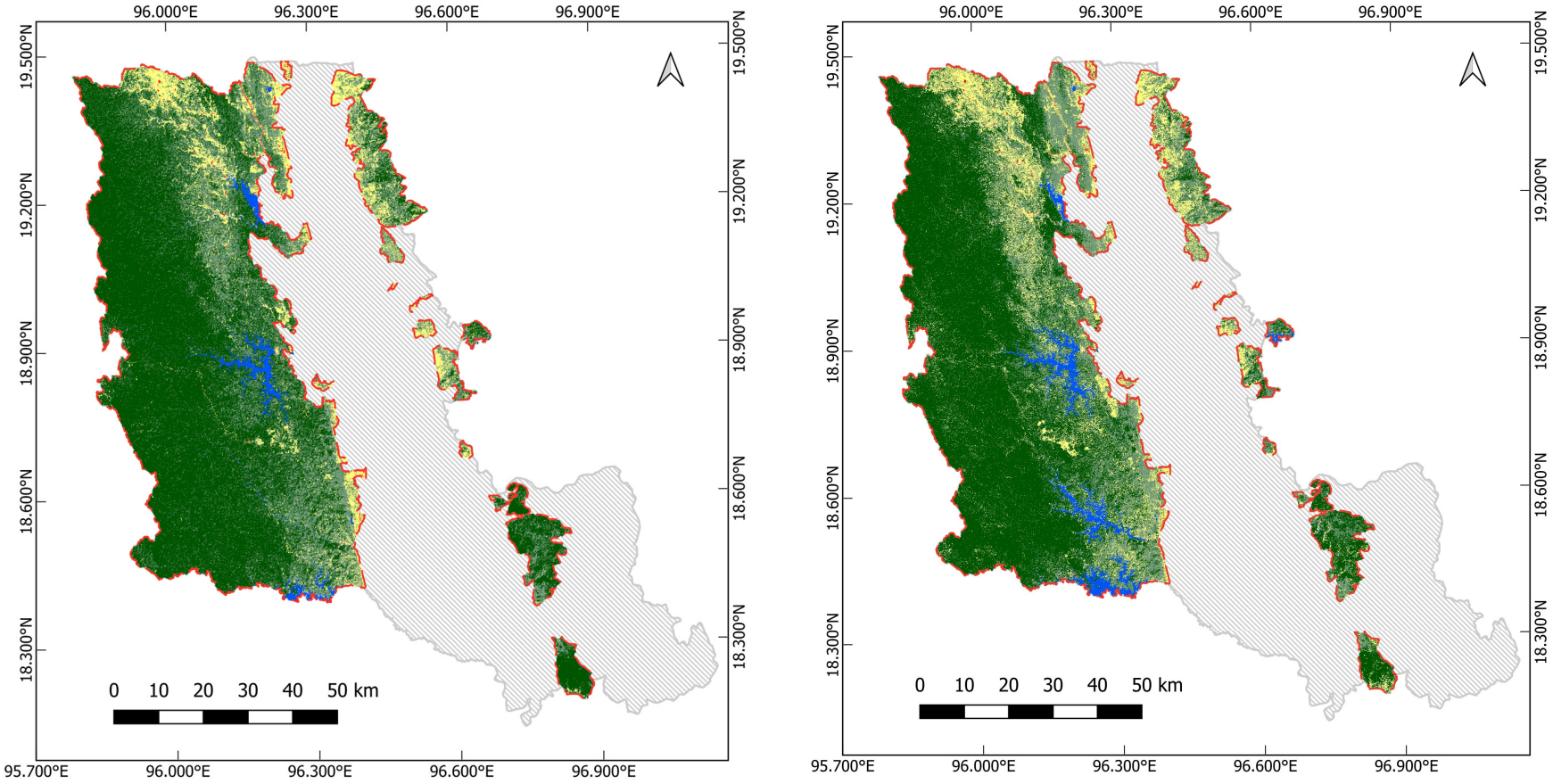
Table A2. Land cover dynamics among different land cover classes between 2010 and 2015 (before the policy intervention).

Area (km^2)		Land Cover in 2015					
		Forest	**Other Wooded Lands**	**Agriculture**	**Water**	**Other**	**Total**
Land cover in 2010	Forest	2739	467	234	63	3	3508
	Other wooded lands	449	659	278	39	2	1430
	Agriculture	53	175	278	12	9	528
	Water	7	2	10	86	1	107
	Other	1	2	7	1	4	15
	Total	3250	1304	808	201	19	5588

Table A3. Land cover dynamics among different land cover classes between 2015 and 2020 (after the policy intervention).

Area (km^2)		Land Cover in 2020					
		Forest	**Other Wooded Lands**	**Agriculture**	**Water**	**Other**	**Total**
Land cover in 2015	Forest	2460	564	193	33	2	3252
	Other wooded lands	282	635	380	7	2	1306
	Agriculture	143	201	432	22	11	809
	Water	14	5	20	161	1	201
	Other	1	1	10	1	7	20
	Total	2900	1406	1035	224	23	5588

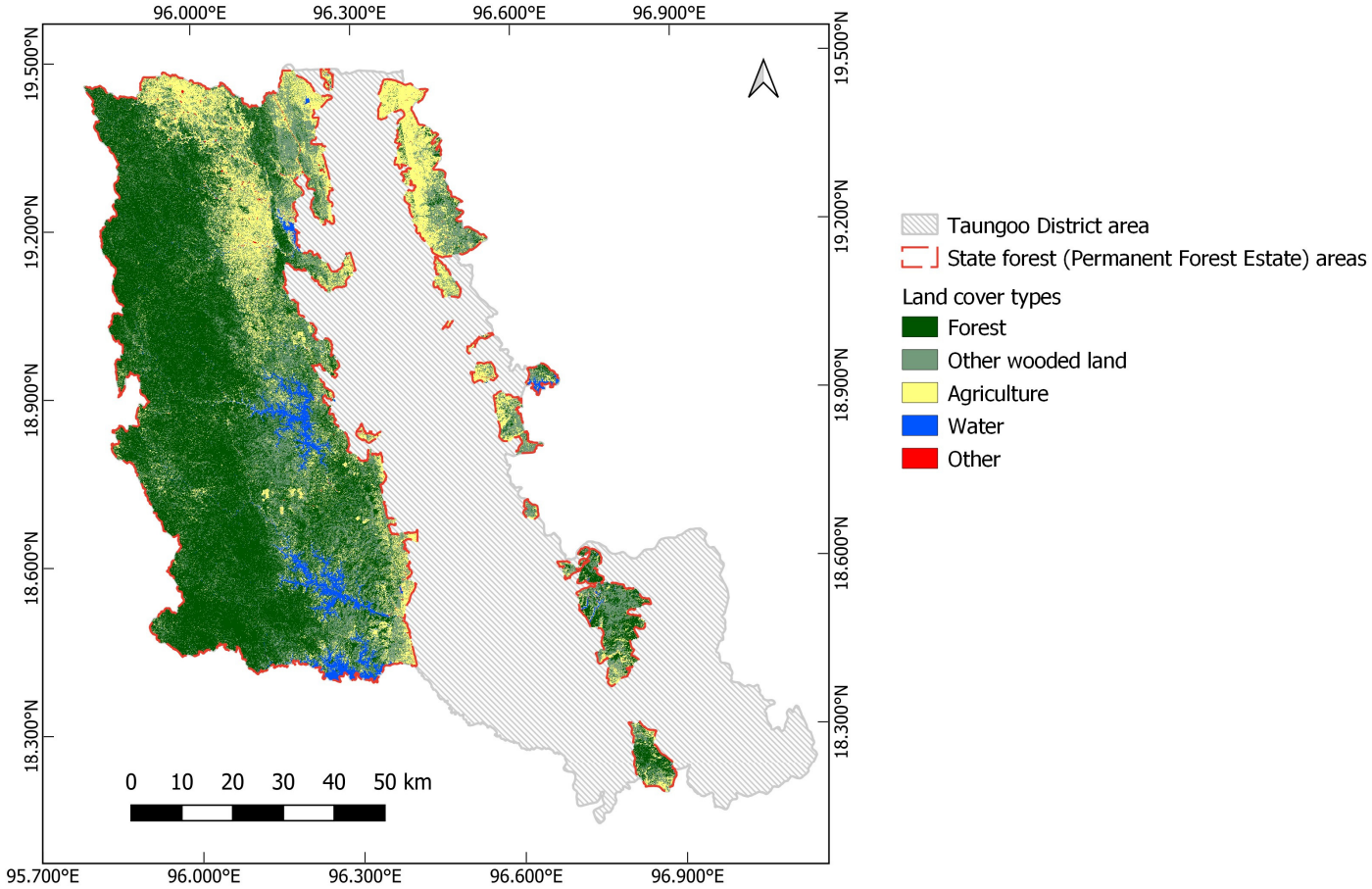
Appendix B



(**a**)

(**b**)

Figure A1. *Cont.*



(**c**)

Figure A1. Land cover classification map of the state forest areas in Taungoo District in different study years: (**a**) 2010, (**b**) 2015 and (**c**) 2020.

Appendix C. Questionnaires Used in the Survey

Do you agree to provide your consent for your participation in the survey and publication of the results?

Household characteristics

1. Interviewee' name. . .. ., Date.....
2. Village. . .. . .community forest group name. . .. .
3. Household size/how many persons live in this household?

No.	Farmers	Non-Farmers		Gender	Age	Nationality	Education
		Jobs	Income				
1							
2							
3							

4. Current land holdings

	Type of Land Use	Size	Estimated Annual Income from Land
1	Community Forests		
2	Ya (dry farms)		
3	Lae (paddy fields)		
4	. . ..		

5. Which year did you start settling here?
6. What previous job/ livelihood did you do before?
7. How did you get the current farming land?
   a. Self-clearance b. as heritage c. bought it
8. Do you practice shifting cultivation now?
9. If not in question 8, did you practice shifting cultivation before? If yes, why did you change the practice?
10. Farm size dynamics history

Settlement Year	2005	2010	2015	2020
Farm size				
Household population				
Reason of change				

11. Did the policy intervention affect your encroachment behaviour? Please choose or answer how did it affect your behaviour.
    a. I expanded more farms due to the policy intervention.
    b. I reduced my farm size due to the policy intervention.
    c. I moved out or stopped farming due to the policy intervention.
    d. I started encroaching on farms due to the policy intervention.
    e. I started demarcating land as my farms due to the policy intervention.
    f. Other
12. Do you think encroaching farmers increased in this area due to the policy intervention?
13. Are there any other reasons that cause more settlers/farmers to move to this area apart from the policy? What are those?
14. Do you think encroaching settlers/farmers decreased in this area due to the policy intervention?
15. Are there any other reasons that caused more settlers/farmers to move out from this area apart from the policy? What are those?
16. After recording/ surveying the encroachment status in 2013, did the Forest Department control/ monitor the development or status of the encroachment in the follow-up years? If yes, when and how often?

References

1. Curtis, P.G.; Slay, C.M.; Harris, N.L.; Tyukavina, A.; Hansen, M.C. Classifying drivers of global forest loss. *Science* **2018**, *361*, 1108–1111. [CrossRef]
2. Jayathilake, H.M.; Prescott, G.W.; Carrasco, L.R.; Rao, M.; Symes, W.S. Drivers of deforestation and degradation for 28 tropical conservation landscapes. *Ambio* **2021**, *50*, 215–228. [CrossRef]
3. Kissinger, G.; Herold, M.; De Sy, V. *Drivers of Deforestation and Forest Degradation: A Synthesis Report for REDD+ Policymakers*; Lexeme Consulting: Vancouver, BC, Canada, 2012.
4. Lim, C.L.; Prescott, G.W.; De Alban, J.D.T.; Ziegler, A.D.; Webb, E.L. Untangling the proximate causes and underlying drivers of deforestation and forest degradation in Myanmar: Forest Degradation in Myanmar. *Conserv. Biol.* **2017**, *31*, 1362–1372. [CrossRef] [PubMed]
5. Naing Tun, Z.; Dargusch, P.; McMoran, D.; McAlpine, C.; Hill, G. Patterns and Drivers of Deforestation and Forest Degradation in Myanmar. *Sustainability* **2021**, *13*, 7539. [CrossRef]
6. Oo, T.; Hlaing, E.; Aye, Y.; Chan, N.; Maung, N.; Phyoe, S.; Thu, P.; Pham, T.; Maharani, C.; Moeliono, M. *The Context of REDD+ in Myanmar: Drivers, Agents and Institutions*; Center for International Forestry Research (CIFOR): Bogor, Indonesia, 2020; Volume 202, ISBN 602-387-130-5.
7. MoNREC. The Forest Law, 2018; Naypyidaw, Myanmar. 2018. Available online: https://www.rinya.maff.go.jp/j/riyou/goho/kunibetu/mmr/pdf/document_mmr20.pdf. (accessed on 20 November 2023).
8. Ananda, T. Record of 15th Day Discussion from the Fourth Regular Meeting of the First National Parliment. Available online: https://transcripts.theananda.org (accessed on 10 December 2023).
9. President's Office. Executive Order to Degazette Forests, (Registration number 13 (1/7)), Naypyidaw, Myanmar. 2013. Available online: https://openknowledge.worldbank.org/bitstreams/ca62e50f-0cc3-52e7-b544-5946fd16313c/download (accessed on 20 November 2023).
10. San, S.M.; Kumar, N.; Biber-Freudenberger, L.; Schmitt, C.B. Agroforestry-based community forestry as a large-scale strategy to reforest agricultural encroachment areas in Myanmar: Ambition vs. local reality 2023. *Ann. For. Sci.* **2023**, *80*, 27. [CrossRef]
11. Ghate, R.; Nagendra, H. Role of monitoring in institutional performance: Forest management in Maharashtra, India. *Conserv. Soc.* **2005**, *3*, 509–532.
12. Blackman, A. Evaluating forest conservation policies in developing countries using remote sensing data: An introduction and practical guide. *For. Policy Econ.* **2013**, *34*, 1–16. [CrossRef]
13. Pham, T.T.; Hoang, T.L.; Nguyen, D.T.; Dao, T.L.C.; Ngo, H.C.; Pham, V.H. *The Context of REDD+ in Vietnam: Drivers, Agents and Institutions*, 2nd ed.; Center for International Forestry Research (CIFOR): Bogor, Indonesia, 2019; ISBN 978-602-387-121-6. [CrossRef]
14. Trends, F. *Illegal Logging and Associated Trade in Myanmar: Impacts of Government Measures to Address Illegal Logging*. Forest Trends: 2021. p. 54. Available online: https://www.forest-trends.org/publications/illegal-logging-and-associated-trade-in-myanmar/ (accessed on 10 November 2023).
15. Zeng, Z.; Estes, L.; Ziegler, A.D.; Chen, A.; Searchinger, T.; Hua, F.; Guan, K.; Jintrawet, A.; Wood, E.F. Highland cropland expansion and forest loss in Southeast Asia in the twenty-first century. *Nat. Geosci.* **2018**, *11*, 556–562. [CrossRef]
16. Nandasena, W.D.K.V.; Brabyn, L.; Serrao-Neumann, S. Using Remote Sensing for Sustainable Forest Management in Developing Countries. In *The Palgrave Handbook of Global Sustainability*; Springer International Publishing: Cham, Switzerland, 2022; pp. 1–22. ISBN 978-3-030-38948-2.
17. Walker, P.A.; Peters, P.E. Making Sense in Time: Remote Sensing and the Challenges of Temporal Heterogeneity in Social Analysis of Environmental Change—Cases from Malawi. *Hum. Ecol.* **2007**, *35*, 69–80. [CrossRef]
18. Ishtiaque, A.; Masrur, A.; Rabby, Y.W.; Jerin, T.; Dewan, A. Remote Sensing-Based Research for Monitoring Progress towards SDG 15 in Bangladesh: A Review. *Remote Sens.* **2020**, *12*, 691. [CrossRef]
19. Kimutai, D.; Watanabe, T. Forest-Cover Change and Participatory Forest Management of the Lembus Forest, Kenya. *Environments* **2016**, *3*, 20. [CrossRef]
20. Tripathi, S.; Subedi, R.; Adhikari, H. Forest Cover Change Pattern after the Intervention of Community Forestry Management System in the Mid-Hill of Nepal: A Case Study. *Remote Sens.* **2020**, *12*, 2756. [CrossRef]
21. Forest Department. *District Level Forest Management Plan (2016–2017 to 2025–2026), Taungoo District, Bago Division Part 1*; Forest Department, Ministry of Natural Resources and Enviornmental Conservation: Naypyidaw, Myanmar, 2015.
22. Myo, H.T.; Zin, W.W. *Shwe Kyi Pyar Assessment of Future Climate for Bago Region and Its Impact on Streamflow*; Yangon University: Yangon, Myanmar, 2019.
23. Kant, P.; Oo, T.N.; Hwan-Ok, M. Report on Construction of Forest Reference Emission Level/Forest Reference Level in Taungoo District, Bago Yoma, Myanmar; 2014. Available online: https://www.itto.int/files/itto_project_db_input/2986/Technical/Report%20on%20construction%20of%20FREL_FRL%20in%20Taungoo%20District%20(Dr%20Promote%20Khant)(Eng).pdf?v=1481685009 (accessed on 20 November 2023).
24. Shimizu, K.; Ahmed, O.S.; Ponce-Hernandez, R.; Ota, T.; Win, Z.C.; Mizoue, N.; Yoshida, S. Attribution of Disturbance Agents to Forest Change Using a Landsat Time Series in Tropical Seasonal Forests in the Bago Mountains, Myanmar. *Forests* **2017**, *8*, 218. [CrossRef]

25. San, S.M.; (Center for Development Research (ZEF), University of Bonn, Genscherallee 3, Bonn, Germany); Kumar, N.; (Center for Development Research (ZEF), University of Bonn, Genscherallee 3, Bonn, Germany); Biber-Freudenberger, L.; (Center for Development Research (ZEF), University of Bonn, Genscherallee 3, Bonn, Germany); Schmitt, C.B.; (Center for Development Research (ZEF), University of Bonn, Genscherallee 3, Bonn, Germany). Personal communication, 2020.
26. US, G.S. Landsat Products. Available online: https://earthexplorer.usgs.gov/ (accessed on 10 December 2022).
27. Congedo, L. Semi-Automatic Classification Plugin: A Python tool for the download and processing of remote sensing images in QGIS. *J. Open Source Softw.* **2021**, *6*, 3172. [CrossRef]
28. Tempa, K.; Aryal, K.R. Semi-automatic classification for rapid delineation of the geohazard-prone areas using Sentinel-2 satellite imagery. *SN Appl. Sci.* **2022**, *4*, 141. [CrossRef]
29. *FAO Global Forest Resources Assessment 2015: Country Report, Myanmar*; FAO: Rome, Italy, 2014; pp. 1–86. Available online: https://www.fao.org/3/az283e/az283e.pdf (accessed on 20 November 2023).
30. Wohlfart, C.; Bevandam, M.; Horning, N.; Leutner, B.; Wegmann, M. Field data for remote sensing data analysis. In *Remote sensing and GIS for Ecologists: Using Open Source Software (Data in the Wild)*; Pelagic Publishing: Exeter, UK, 2016; ISBN 978-1-78427-028-5.
31. Tucker, C.J.; Sellers, P.J. Satellite remote sensing of primary production. *Int. J. Remote Sens.* **1986**, *7*, 1395–1416. [CrossRef]
32. Huang, S.; Tang, L.; Hupy, J.P.; Wang, Y.; Shao, G. A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing. *J. For. Res.* **2021**, *32*, 1–6. [CrossRef]
33. Pettorelli, N.; Vik, J.O.; Mysterud, A.; Gaillard, J.-M.; Tucker, C.J.; Stenseth, N.C. Using the satellite-derived NDVI to assess ecological responses to environmental change. *Trends Ecol. Evol.* **2005**, *20*, 503–510. [CrossRef]
34. Kumar, N.; Tischbein, B.; Kusche, J.; Beg, M.K.; Bogardi, J.J. Impact of land-use change on the water resources of the Upper Kharun Catchment, Chhattisgarh, India. *Reg. Environ. Chang.* **2017**, *17*, 2373–2385. [CrossRef]
35. Madhura, M.; Venkatachala, S. Comparison of supervised classification methods on remote sensed satellite data: An application in Chennai, South India. *Int. J. Sci. Res.* **2015**, *4*, 1407–1411.
36. Patil, M.B.; Desai, C.G.; Umrikar, B.N. Image classification tool for land use/land cover analysis: A comparative study of maximum likelihood and minimum distance method. *Int. J. Geol. Earth Environ. Sci.* **2012**, *2*, 189–196.
37. Kamusoko, C. Land Cover Classification Accuracy Assessment. In *Optical and SAR Remote Sensing of Urban Areas*; Springer Geography; Springer: Singapore, 2022; pp. 105–118. ISBN 9789811651489.
38. Olofsson, P.; Foody, G.M.; Herold, M.; Stehman, S.V.; Woodcock, C.E.; Wulder, M.A. Good practices for estimating area and assessing accuracy of land change. *Remote Sens. Environ.* **2014**, *148*, 42–57. [CrossRef]
39. Congalton, R.G. A Comparison of Sampling Schemes Used in Generating Error Matrices for Assessing the Accuracy of Maps Generated from Remotely Sensed Data. *Photogramm. Eng. Remote Sens.* 1988. Available online: https://scholars.unh.edu/faculty_pubs/1249/ (accessed on 10 November 2023).
40. Anderson, J.R. *A Land Use and Land Cover Classification System for Use with Remote Sensor Data*; US Government Printing Office: Washington, DC, USA, 1976; Volume 964, pp. 1–28.
41. Geremew, A.A. Assessing the Impacts of Land Use and Land Cover Change on Hydrology of Watershed: A Case Study on Gigel-Abbay Watershed, Lake Tana Basin, Ethiopia. Master Thesis, Universidade Nova de Lisboa, Lisbon, Portugal, 2013. Available online: http://hdl.handle.net/10362/9208 (accessed on 10 November 2023).
42. Horning, N.; Leutner, B.; Wegmann, M. Land Cover or Image Classification Approaches. In *Remote Sensing and GIS for Ecologists: Using Open Source Software*; Wegmann, B., Leutner, B., Dech, S., Eds.; Pelagic Publishing Ltd.: Exeter, UK, 2016; pp. 166–298. ISBN 9781784270285.
43. Puyravaud, J.-P. Standardizing the calculation of the annual rate of deforestation. *For. Ecol. Manag.* **2003**, *177*, 593–596. [CrossRef]
44. Mon, M.S. Land Use Planning Process in Myanmar; Presented at International LCLUC Regional Science Team Meeting in South and Southeast Asia, Yangon, Myanmar. January 2016. Available online: https://lcluc.umd.edu/documents/land-use-planning-process-myanmar (accessed on 20 November 2023).
45. Forest Department. *Standard Operating Procedure for Artificial Regeneration, Weeding and Fire Protection*; Ministry of Enviornmental Conservation and Natural Resources: Naypyidaw, Myanmar, 2016.
46. Keenan, R.J.; Kimmins, J.P. The ecological effects of clear-cutting. *Environ. Rev.* **1993**, *1*, 121–144. [CrossRef]
47. Chan Ko Ko, A.; Ying, Z.; Theint Htun, T. Study on Socioeconomic Impacts of Private Forest Plantations on Local Livelihood in Pyu Township, Taungoo District, Bago Region, Myanmar. *Int. J. Sci.* **2017**, *3*, 43–54. [CrossRef]
48. Gerber, J.-F. Conflicts over industrial tree plantations in the South: Who, how and why? *Glob. Environ. Chang.* **2011**, *21*, 165–176. [CrossRef]
49. Chan, N.; Swe, K.N.; Kyaw, K.T.W.; Ko Ko, L.M.; Win, K.; Aung, N.N.; Oo, T.; Maung Maung, Z.; Thein, Z.Z.W. Assessing swidden land use in Myanmar by decision tree-based detection method using landsat imagery. *CABI Agric. Biosci.* **2022**, *3*, 67. [CrossRef]
50. Bhusal, P.; Paudel, N.S.; Adhikary, A.; Karki, J.; Bhandari, K. Halting Forest Encroachment in Terai: What Role for Community Forestry? *J. For. Livelihood* **2018**, *20*, 15–34. [CrossRef]
51. World Bank. Myanmar Country Environmental Analysis: Forest Resources Sector Report; 2019. Available online: https://openknowledge.worldbank.org/entities/publication/0e4e46ce-9d76-5211-81a1-306e164a1bbc (accessed on 20 November 2023).
52. Saung, T.; Khai, T.C.; Mizoue, N.; Ota, T.; Kajisa, T. Condition of Illegally Logged Stands Following High Frequency Legal Logging in Bago Yoma, Myanmar. *Forests* **2021**, *12*, 115. [CrossRef]

53. Win, Z.C.; Mizoue, N.; Ota, T.; Kajisa, T.; Yoshida, S.; Oo, T.N.; Ma, H. Evaluating the condition of selectively logged production forests in Myanmar: An analysis using large-scale forest inventory data for yedashe township. *J. For. Plan.* **2018**, *23*, 1–8. [CrossRef]
54. Forest Department. Data of Illegal Logging. In *List Arrested Illegally Cut Timber Offender Veh.*; 2019. Available online: https://www.forestdepartment.gov.mm/illegal_loging (accessed on 30 April 2020).
55. Soe, K.T.; Yeo-Chang, Y. Perceptions of forest-dependent communities toward participation in forest conservation: A case study in Bago Yoma, South-Central Myanmar. *For. Policy Econ.* **2019**, *100*, 129–141. [CrossRef]
56. Acheampong, E.O.; Sayer, J.; Macgregor, C.J. Road improvement enhances smallholder productivity and reduces forest encroachment in Ghana. *Environ. Sci. Policy* **2018**, *85*, 64–71. [CrossRef]
57. Ibisch, P.L.; Hoffmann, M.T.; Kreft, S.; Pe'er, G.; Kati, V.; Biber-Freudenberger, L.; DellaSala, D.A.; Vale, M.M.; Hobson, P.R.; Selva, N. A global map of roadless areas and their conservation status. *Science* **2016**, *354*, 1423–1427. [CrossRef]
58. Nascimento, N.; West, T.A.P.; Biber-Freudenberger, L.; Sousa-Neto, E.R.D.; Ometto, J.; Börner, J. A Bayesian network approach to modelling land-use decisions under environmental policy incentives in the Brazilian Amazon. *J. Land Use Sci.* **2020**, *15*, 127–141. [CrossRef]
59. Cho, B.B.; Naing, A.K.; Than, M.M.; Gritter, D.; Sapkota, L.M.; Stephan, P.; Lewin, A.; Thaung, T.L. *Stabilizing and Rebuilding Myanmar's Working Forests: Multiple Stakeholders and Multiple Choices*; The Nature Conservancy and RECOFTC-The Center for People and Forests: Bangkok, Thailand, 2017; Available online: https://www.recoftc.org/publications/0000315 (accessed on 15 November 2023).
60. Myint Aung, U. Policy and practice in Myanmar's protected area system. *J. Environ. Manag.* **2007**, *84*, 188–203. [CrossRef]
61. Lechner, A.M.; Foody, G.M.; Boyd, D.S. Applications in Remote Sensing to Forest Ecology and Management. *One Earth* **2020**, *2*, 405–412. [CrossRef]
62. Tien, N.H.; Anh, N.T.; Wataru, Y. *Promoting Village-Based Forest Protection against Encroachment in Thanh Hoi Commune, Tan Lac District, Hoa Binh Province, Vietnam*; Japan International Coperation Agency (JICA) and Sustainable Natural Resource Management Project (SNRM): Ha Noi, Vietnam, 2020; p. 8.
63. Fry, B.P. Community forest monitoring in REDD+: The 'M'in MRV? *Environ. Sci. Policy* **2011**, *14*, 181–187.
64. Forest Department. Community Monitoring and Reporting System. CMRS. Available online: https://www.forestdepartment.gov.mm/node/24072 (accessed on 20 November 2023).
65. Da Ponte, E.; Mack, B.; Wohlfart, C.; Rodas, O.; Fleckenstein, M.; Oppelt, N.; Dech, S.; Kuenzer, C. Assessing Forest Cover Dynamics and Forest Perception in the Atlantic Forest of Paraguay, Combining Remote Sensing and Household Level Data. *Forests* **2017**, *8*, 389. [CrossRef]
66. Prescott, G.W.; Sutherland, W.J.; Aguirre, D.; Baird, M.; Bowman, V.; Brunner, J.; Connette, G.M.; Cosier, M.; Dapice, D.; De Alban, J.D.T.; et al. Political transition and emergent forest conservation issues in Myanmar. *Conserv. Biol.* **2017**, *31*, 1257–1270. [CrossRef]
67. RECOFTC. *Assessing Forest Governance in Myanmar: Identifying Key Challenges and Interventions to Strengthen Governance*; RECOFTC-The Center for People and Forests: Bangkok, Thailand, 2018; Available online: https://www.recoftc.org/publications/0000309 (accessed on 12 November 2023).

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