Floresta e Ambiente 2022; 29(4): e20220016
https://doi.org/10.1590/2179-8087-FLORAM-2022-0016
ISSN 2179-8087 (online)

ORIGINAL ARTICLE – Conservation of Nature

# Ten Years Assessment of Shifting Cultivation on Land Cover and Carbon Storage in Timor Island, Indonesia

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## Abstract

The practice of shifting cultivation has led to forest degradation and deforestation in the Sisimeni Sanam Forest Area, with Special Purpose (SSFAwSP). Therefore, this study aims to assess land cover and carbon storage changes of the practiced shifting cultivation in SSFAwSP over the last ten years using 2013, 2016, and 2021 Landsat imagery. A hybrid classification approach that combines the forest canopy density model and supervised classification of maximum likelihood was used to create land cover maps to detect changes in forest land cover and carbon storage. The results showed that for ten years, the extent and annual rates of deforestation, forest degradation, forest regrowth, and changes in carbon storage were 662.62 ha (4%), 319.18 ha (3%), 163.8 ha (1%), and -54.51 kilo Ton C (3%), respectively. This finding indicated that shifting cultivation contributed only 10% and 1% of total deforestation and forest degradation, respectively.

**Keywords:** Forest canopy density, Deforestation, Forest degradation, Forest regrowth, Semi-arid ecosystem.

## 1. INTRODUCTION AND OBJECTIVES

Land use and land cover change (LULCC) have become the major causes of deforestation, habitat degradation, and climate change worldwide (Eddy & Gergel, 2015; Van Vliet et al., 2012). One of the causes of LULCC is shifting cultivation, related to large-scale deforestation and forest degradation at the tropical forest-agriculture border (Mukul & Herbohn, 2016). In India and Sri Lanka, shifting cultivation has been practiced since prehistoric times (Kingwell-Banham & Fuller, 2012) and has played an important role in shaping long-term ecological, political, and social history. It has also affected Bhutanese forests but has been recovered due to the combination of agricultural intensification and imports (Bruggeman et al., 2016). Therefore, tropical forests need to be prioritized as the most important sector for climate change mitigation efforts to prevent expansion and short-term shifting cultivation (Villa et al., 2021).

In 2012, shifting cultivation is expected to increase by approximately 28% in Southeast Asia (Van Vliet et al., 2012). Meanwhile, Laos's real-world example demonstrates a shift in land cover from rubber and sugar cane to cash crops despite the state policy (Vongvisouk et al., 2014). The increase in global demand for certain agricultural products, such as coffee and other seasonal crops, also caused deforestation in Vietnam, expanding the products to new shifting cultivation locations (Meyfroidt et al., 2013). In Indonesia, the dynamics of forest conversion to agriculture are also driven by shifting cultivation that largely uses fire (Nguyen et al., 2022). Therefore, shifting cultivation remains a major source of deforestation and forest degradation in this region.

Indonesia is one of the Southeast Asian countries with a long history of shifting cultivation, which has also been practiced in Borneo for over 200 years (Lawrence & Schlesinger, 2001). Similarly, shifting cultivation has been investigated in Sumatra, such as in Kerinci Seblat National Park (Hariyadi & Ticktin, 2012) and Lampung (Syam et al., 1997), but different in Borneo. Therefore, most of the studies of shifting cultivation are concentrated in Kalimantan and Sumatra, with a focus on land use change (Nugroho et al., 2018), socio cultural (Nugroho et al., 2020), policy and governance (Thaler & Anandi, 2017), as well as biodiversity (Takeuchi et al., 2019).

Shifting cultivation is still practiced by traditional forest users in Indonesia's semi-arid areas, including East Nusa Tenggara Province, where Kapa et al. (2017) investigated the system based on local wisdom in West Timor. Dako et al. (2019 reported that shifting cultivation and fires are the two causes of damage to the Mutis Timau Protected Forest area. Bustan et al. (2020) discovered that the slash-and-burn practice had become a family tradition across different generations in Manggarai Regency, Flores Island. Sudiyono (2015) carried out a similar study on Alor Island; however, several reports on shifting cultivation in East Nusa Tenggara Province's semi-arid areas have primarily focused on cultural themes. Therefore, this study aims to assess the practice of shifting cultivation on land cover and carbon storage changes in the Sisimeni Sanam Forest Area with Special Purpose (SSFAwSP) on Timor Island.

## 2. MATERIALS AND METHODS

### 2.1. Study area

SSFAwSP is geographically located between 09°56'54" - 10°02'22" S and 123°58'20" - 124°01'10" E (Figure 1). The area is 2,973.2 ha, including five rural areas: Ekateta, Camplong II, Sillu, Benu, and Takari Village. The elevation varies from 225 to 525 m above sea level, with mostly 0 - 25% slope levels. In this area, the climatic conditions belong to category E according to Schmidt and Fergusson, with rainfall ranging from 0 - 535 mm/year. The temperature ranges between 24° and 34°C, with a relative humidity of around 75-76%. Meanwhile, the soil types are dominated by Kambisol (39%), followed by Rendzina (35%), and Latosol (26%). Most of the land cover consists of shrubs, dryland forests, and savanna, approximately 51, 29, and 15%, respectively (EFETI Kupang, 2020). Shifting cultivation is practiced in SSFAwSP and is distinguished by the presence of wooden fences on each farm to prevent livestock from entering and eating agricultural crops in the fields.

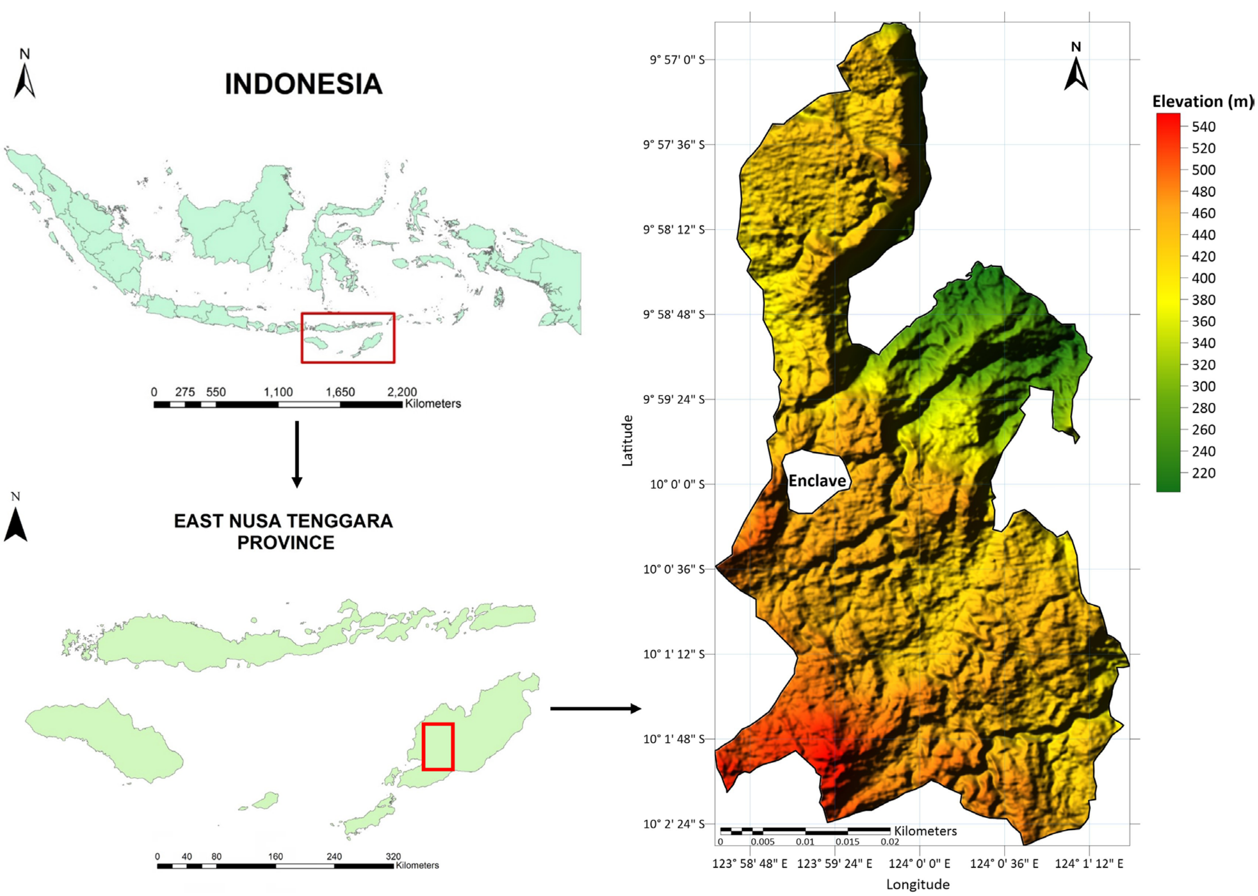


**Figure 1.** The Sisimeni Sanam Forest Area with Special Purpose is situated in the heart of Timor Island and depicted on a digital elevation model.

## 2.2. Procedures

### 2.2.1. Data collections and image pre-processing

This study used multi-temporal Landsat 8 (OLI) satellite imageries for 2021, 2016, and 2013, downloaded from the United States Geological Survey (USGS). Each image is selected considering the base overcast cover, high deceivability of the scene, highest satellite picture quality, and accessibility (Emran et al., 2016). Other data used were vector boundary of SSFAwSP, socio-economic survey data for 2013, 2015, and 2019, boundary survey data for 2018, 2020, and 2021, as well as ground truth data in the form of GPS, geotagged photos for 2013, 2015, 2018, 2019, 2020, and 2021 together with Google Earth images for 2021 (Table 1).

All satellite images are the L1T processed by the USGS, which are referred to and geometric-corrected to the World Geodetic System (WGS84) datum automatically (Storey, 2014). The images are projected using the Universal Transverse Mercator framework (zone UTM 51 South) in GeoTiff format. Subsequently, the geometric and radiometric corrections are made using open-source software Quantum GIS (QGIS) to reduce atmospheric effects that interfere with data processing (Young et al., 2017). The coverage of the six group's satellite imagery was limited according to the vector boundaries of SSFAwSP.

**Table 1.** Sources and acquisition date of each data used.

| Data | Acquisition Date | Source |
|---|---|---|
| Landsat 8, Path/Row 111/67, spatial resolution 30 m | 2021/04/28 | USGS[1] |
| Landsat 8, Path/Row 111/67, spatial resolution 30 m | 2016/08/20 | USGS[1] |
| Landsat 8, Path/Row 111/67, spatial resolution 30 m | 2013/08/28 | USGS[1] |
| Google Earth Image | 2021 | Google Earth |
| Socio-Economic Survey Data | 2013;2015;2019 | EFETI Kupang[2] |
| Boundary Survey Data | 2018;2020;2021 | EFETI Kupang[2] |
| Geotag Photo | 2013;2015;2018;2019;2020;2021 | EFETI Kupang[2] |
| Vector Boundary of the Sisimeni Sanam Forest Area with Special Purpose | 2021 | EFETI Kupang[2] |

[1]USGS= United State Geological Survey, [2]EFETI Kupang= Environmental and Forestry Education and Training Institute of Kupang

### 2.2.2. Land cover classification

Land cover classification was defined by combining the Standard Nasional Indonesia No. 7645-2010; Agriculture, Forestry and Other Land Use of 2006 of Intergovernmental Panel on Climate Change (IPCC); Agus et al. (2014); and Pujiono et al. (2019). The semi-arid land cover class was divided into five classes: highly dense forest, moderately dense forest, shrubs, savanna, and barren land (Table 2). Three land use change types were considered: deforestation, degradation, and the spread of shifting cultivation. Meanwhile, deforestation is the change in land cover from forest to non-forest, while degradation is assumed to be a change in land cover from highly to moderately dense forest, and shifting cultivation development is carried out to improve the location across five land cover classes.

**Table 2.** Description of semi-arid land cover classification class.

| Land Cover Class | Description | Carbon storage a ton of Carbon ha$^{-1}$ (Tosiani, 2015) |
|---|---|---|
| **Forest Area** | | |
| Highly Dense Forest | Natural forest with mineral soil that has been logged, either selective cutting or clear-cutting, marked with logging path (Secondary Forest) | 98.84 |
| Moderately Dense Forest | Also known as industrial plantation forest, namely land planted with industrial forest plants such as Acacia, Eucalyptus, etc. | 98.38 |
| **Non-Forest Area** | | |
| Shrubs | Degraded log over areas on non-wet habitat that are an ongoing process of succession but not yet reach stable forest ecosystem, having natural scattered trees or shrubs. Land overgrown with high shrubs canopies up to 5 m. | 30.00 |
| Savanna/Grass Land | Areas with grasses and scattered natural trees, reeds, and spikes. | 4.00 |
| Barren Land | Bare grounds and areas with no vegetation cover yet, including open exposure areas, craters, sandbanks, sediments, and areas post-fire that has not yet exhibited regrowth. | 2.50 |

Source: modified from land classification system developed by the National Standardization Agency; Intergovermental Panel on Climate Change, Guidelines for National Greenhouse Gas Inventories for Agriculture, Forestry and Other Land Use; Agus et al. (2014); Pujiono et al. (2019).

A forest canopy density (FCD) method was used to analyze tree canopy density in forested land to simplify the land cover classification process (Rikimaru et al., 2002). Free GIS software (QGIS) was used to compute four indices: advanced vegetation, bare soil, shadow, and thermal Index (Table 3). The FCD method that communicated in rate for every pixel was determined and created the FCD map in 2013, 2016, and 2021. All lists and FCD were determined under FCD Mapper Ver.2 programming guidelines.

In the non-forest areas, we used a combination of socio-economic survey data, Google earth images, geotagged photos, and boundary survey data to determine the distribution of shifting cultivation accurately. A combination of several Landsat 8 bands was also used to detect non-forest land classification forms accurately, including a combination of bands 7 (SWIR-2), 6 (SWIR-1), and 4 (Red) to detect settlements; band combination 6 (SWIR-1), 5 (NIR), and 2 (Blue) to detect agricultural land; and a combination of bands 5 (NIR), 6 (SWIR-1), and 4 (Red) to distinguish between soil and water bodies (Acharya & Yang, 2015).

The training data from the previous land cover classification analysis were compiled using the FCD method and available data from the field. A supervised maximum likelihood classification (MLC) algorithm was carried out to classify images for 2021, 2016, and 2013. Furthermore, post-classification smoothing using a 3 x 3 m – pixel majority filter reduces the salt and pepper effect due to spectral effects variability. The image classification was converted to vector format to easily measure the area and carbon stock of each type of land cover classification.

**Table 3.** Formulae and algorithms used to calculate indices in Forest Canopy Density mapper.

| Index | | Formula or Algorithm for Landsat 8 (OLI) |
|---|---|---|
| VI | | |
| | NDVI | = (NIR – Red)/(NIR + Red) |
| | AVI | = $[NIR \times (65536\text{-}Red) \times (NIR - Red) + 1]^{1/3}$ , (NIR – Red)>0 |
| | ANVI | = This index is derived from NDVI and AVI by PCA |
| BI | | = [(SWIR1 + Red) – (Blue + NIR) / (SWIR1 + Red) + (Blue + NIR)] × 25600 + 25600 |
| SI | | = $[(65536 - Blue) \times (65536 - Green) \times (65536 - Red)]^{1/3}$ |
| TI | | = This index is calibrated from the thermal data band or atmospheric correction |
| FD | | = This index is calculated from the first principal component of VI and BI |
| SSI | | = This index is calculated from the first principal component of SI and TI |
| FCD | | = $(VD \times SSI + 1)^{1/2} - 1$ |

Note: Landsat bands: Visible bands= Blue, Green, Red; NI= Near Infrared; SWIR= Shortwave Infrared Indices; VI= Vegetation Index; NDVI= Normalize Difference Vegetation Index; AVI= Advance Vegetation Index; ANVI= Advanced Normalize Vegetation Index; BI= Bare Soil Index; TI= Thermal Index; VD= Vegetation Density; SSI= Scaled Shadow Index; FCD= Forest Canopy Density

Maximum raster value of Landsat 8 (OLI) is 65536.

Sources: Modified from Rikimaru et al. (2002); Mon et al. (2012); Pujiono et al. (2019).

### *2.2.3. Accuracy assessment*

The accuracy assessment was carried out by comparing each land cover classification result from QGIS classification with Google satellite imagery, previous geotagged data, socio-economic, and boundary surveys. When the reference data was inaccurate, the assessment results showed that many errors occurred during the land cover classification process (Negasa et al., 2020). For this purpose, we randomly selected five samples from each land cover class.

Producer's accuracy is map's accuracy according to the perspective of the mapmaker (the producer), as explained in equation [1]. This accuracy showed that natural elements on the ground are frequently displayed on the arranged guide accurately or the likelihood that a specific land front of space is named. It is also the number of reference locales arranged precisely isolated by the complete number of reference destinations for that class.

User accuracy is the precision according to a user's perspective, as described in the equation [2]. It shows the class frequency on the map available on the ground. User accuracy supplements the commission error, which indicates that user accuracy= 100% commission error. It is computed by taking the all-out number of correct classifications for a specific class and separating it by the row total.

The overall accuracy equation [3] was used to compute precision for the entire image across all classes in the characterized image. The aggregate accuracy of the map for all the classes can be depicted using overall accuracy, which ascertains the extent of pixels accurately ordered.

$$Accuracy_{producer} = \frac{\text{Total numer of pixels in a classification}}{\text{Total number of pixels of that classification got from the reference data (i.e., row total)}} \ldots[1]$$

$$Accuracy_{user} = \frac{\text{Total number of pixels in a classification}}{\text{Total number of pixels of that classification got from the reference data (i.e., colum total)}} \ldots[2]$$

$$Overall\ Accuracy = \frac{\text{Sum of the diagonal elements}}{\text{Total number of accuracy sites pixels colum total}} \ldots[3]$$

The Kappa statistics value is a proportion of the arrangement between classification and reference data (Wang et al., 2012; Mishra et al., 2020). Cohen (1968) classified the Kappa values into six groups, namely (1) < 0 addressed poor opportunity of accuracy, (2) from 0.10 to 0.20 addressed slight opportunity of accuracy, (3) from 0.21 to 0.40 addressed fair (4) from 0.41 to 0.60 addressed moderate (5) from 0.61 to 0.80 addressed substantive, and (6) from 0.81 to 0.99 addressed almost perfect opportunity of accuracy. A Kappa accuracy value of 50% - 90% is adequate (RSPO, 2017); however, Kappa coefficients above 0.6 are used as a threshold for acceptable accuracy values. In the field of remote sensing, a Kappa coefficient greater than 0.6 shows that the translation result is adequately accurate; therefore, no reevaluation is required.

### *2.2.4. Changes detection and carbon storage analysis*

The method of Garai & Narayana (2018) was used to calculate the percentage of LULCC (equation 4) with the formula below:

$$Change\ Percentage = \frac{(LULC\ Area_{present} - LULC\ Area_{previous})}{LULC_{previous}} \ x\ 100\% \ldots[4]$$

In addition to evaluating carbon stocks changes in various land cover classifications, the calculation method developed by the IPCC was used by combining country/site-specific emission factors and IPCC default emission factors. The equation [5] for calculating changes in carbon stock in all land use categories is as follows:

$$\Delta C_{AFOLU} = \Delta C_{FL} + \Delta C_{CL} + \Delta C_{GL} + \Delta C_{WL} + \Delta C_{SL} + \Delta C_{OL} \ldots[5]$$

Note: ΔC= Carbon stock change; AFOLU= Agriculture, Forestry and Other Land Use; FL= Forest Land; CL= Crop Land; GL= Grass Land; WL= Wet Land; SL= Settlements; OL= Other Land.

## 3. RESULTS

### *3.1. Accuracy and land cover map*

The overall accuracy and Kappa coefficient were 80% and (0.75), 80% and (0.75), and 75% and (0.65) for images classified in 2013, 2016, and 2021, respectively (Table 4). Furthermore, producer and user accuracy are used to assess the accuracy of each forest type category, including the accuracy matrix of highly dense forest in 2013 (Table 4), which was 83.33% and 100%, representing the accuracy of producers and users, respectively. Although the reference highly dense forest class was accurately identified in 100% of the cases, only 83.33% had a true value. Moderately dense forests are also frequently confused with shrubs, leading to a producer accuracy of only 50% in 2021.

The map's spatial distribution of land cover showed that forest areas are located at the map's north end, north center, and east edge, while savanna, shrubs, and bare land are at the south center and top west (Figure 2). The forest is in this section because most of the area has steep topography, river flow paths, and springs protected by the local community. In contrast to the type of land cover, namely savanna, shrubs, and barren land, the locations are typically close to residential areas/enclaves.

**Table 4.** Accuracy Assessment for three Classified Image in 2013, 2016, and 2021.

| Land Cover Class | 2013 | | | | | 2016 | | | | | 2021 | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | TPC | TPP | TPU | PA (%) | UA (%) | TPC | TPP | TPU | PA (%) | UA (%) | TPC | TPP | TPU | PA (%) | UA (%) |
| **Bl** | 5 | 6 | 5 | 83.33 | 100.00 | 4 | 5 | 5 | 80.00 | 80.00 | 4 | 4 | 5 | 100.00 | 80.00 |
| **Sav** | 3 | 5 | 5 | 60.00 | 60.00 | 4 | 7 | 5 | 57.14 | 80.00 | 4 | 5 | 5 | 80.00 | 80.00 |
| **Shr** | 3 | 3 | 5 | 100.00 | 60.00 | 3 | 4 | 5 | 75.00 | 60.00 | 3 | 6 | 5 | 50.00 | 60.00 |
| **MDF** | 4 | 5 | 5 | 80.00 | 80.00 | 4 | 4 | 5 | 100.00 | 80.00 | 3 | 6 | 5 | 50.00 | 60.00 |
| **HDF** | 5 | 6 | 5 | 83.33 | 100.00 | 5 | 5 | 5 | 100.00 | 100.00 | 4 | 4 | 5 | 100.00 | 80.00 |
| **OA** | | | | 80.00 | | | | | 80.00 | | | | | 75.00 | |
| **OKS** | | | | 0.75 | | | | | 0.75 | | | | | 0.65 | |

Note: Bl= Barren Land; Hdf= Highly Dense Forest; Mdf= Moderately Dense Forest; Sav= Savanna; Shr= Shrub; TPC= Total pixels in a class; TPP= Total pixels for Producers Accuracy; TPU= Total pixel for User Accuracy; PA= Producers Accuracy; UA=User Accuracy; OA= Overall Accuracy; OKS= Overall Kappa Statistics.

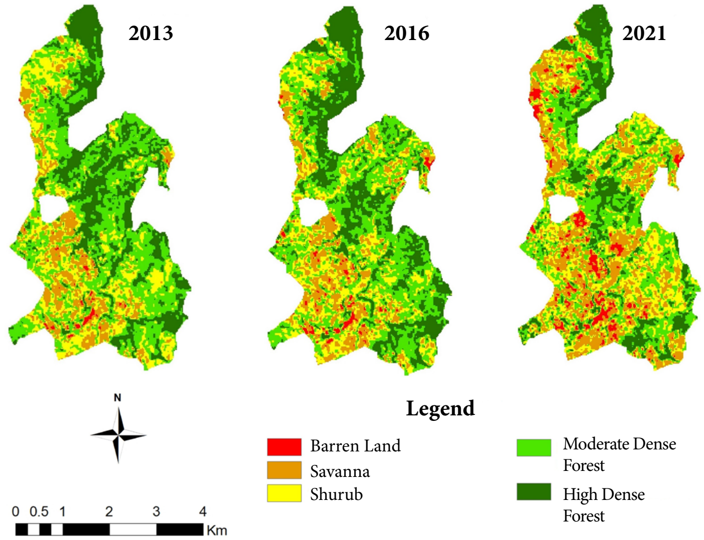


**Figure 2.** Land use and land cover map of 2013, 2016, 2021 in the Sisimeni Sanam Forest Area with Special Purpose.

## *3.2. Land cover and carbon storage changes*

Most land cover types did not change from 2013 to 2016, despite appearing denser. In 2016, the land cover appeared denser due to a change of approximately 18% from moderately dense forest to the highly dense forest, including a 13% increase from savanna to shrub and 25% from shrub to moderately dense forest. However, there was a 24% change from highly dense forest to moderately dense forest and a 16% from shrub to savanna (Table 5a).

Several changes occurred between 2016 to 2021 from dense to less dense, with a minimum of two types of land cover change, including the moderately dense forest, which lost approximately 53% of its territory to shrubs and 35% to savanna, while only 8% changed to highly dense forest. Similarly, shrub also lost approximately 67%, dominated by savanna (53%) and moderately dense forest (9%). Other factors contributing to the decrease in land cover density included a transition from highly dense forest to the moderately dense forest of approximately 42% and savanna to the barren land with 20%, where 9% became shrub. Furthermore, only 13% of the barren land is overgrown with savanna and shrubs (Table 5b). As a result of this condition, the barren land and savanna area has increased sixfold and twofold, respectively, by 2021 (Table 5c).

**Table 5.** 'From to' detection change analysis for three times intervals: (a) 2013 – 2016; (b) 2016 – 2021; and (c) 2013 – 2021 in the Sisimeni Sanam Forest Area with Special Purpose.

**a) 2013 – 2016**

| 2013 Land Cover Classes | 2016 – Land Cover Classes (ha) | | | | | Total 2013 |
|---|---|---|---|---|---|---|
| | Bl | Hdf | Mdf | Sav | Shr | |
| **Bl** | 16.93 | 0 | 0 | 2.05 | 0.02 | 19.01 |
| **Hdf** | 0 | 591.47 | 186.65 | 1.55 | 13.40 | 793.06 |
| **Mdf** | 0.25 | 229.82 | 829.59 | 47.22 | 182.05 | 1,288.94 |
| **Sav** | 23.44 | 0.14 | 6.08 | 316.90 | 51.76 | 398.32 |
| **Shr** | 0.58 | 2.01 | 164.16 | 101.55 | 382.36 | 650.66 |
| **Total 2016** | 41.20 | 823.45 | 1,186.47 | 469.27 | 629.59 | 3,149.98 |

**b) 2016 – 2021**

| 2016 Land Cover Classes | 2021 – Land Cover Classes (ha) | | | | | Total 2016 |
|---|---|---|---|---|---|---|
| | Bl | Hdf | Mdf | Sav | Shr | |
| **Bl** | 35.90 | 0 | 0 | 5.00 | 0.32 | 41.21 |
| **Hdf** | 0 | 430.52 | 341.58 | 4.52 | 46.09 | 822.72 |
| **Mdf** | 1.69 | 91.05 | 558.03 | 122.90 | 412.75 | 1,186.42 |
| **Sav** | 92.88 | 0.38 | 5.13 | 328.18 | 42.66 | 469.23 |
| **Shr** | 7.34 | 4.01 | 55.31 | 331.05 | 231.75 | 629.45 |
| **Total 2021** | 137.81 | 525.95 | 960.06 | 791.64 | 733.56 | 3,149.03 |

**Table 5.** Continuation

**c) 2013 – 2021**

| 2013 Land Cover Classes | 2021 – Land Cover Classes (ha) | | | | | Total 2013 |
|---|---|---|---|---|---|---|
| | Bl | Hdf | Mdf | Sav | Shr | |
| **Bl** | 17.40 | 0 | 0 | 1.57 | 0.06 | 19.03 |
| **Hdf** | 1.09 | 388.77 | 319.18 | 20.86 | 62.02 | 791.93 |
| **Mdf** | 5.09 | 133.28 | 571.10 | 171.48 | 408.07 | 1,289.01 |
| **Sav** | 104.86 | 0.15 | 4.95 | 255.76 | 32.28 | 398.00 |
| **Shr** | 9.44 | 3.44 | 64.46 | 341.95 | 231.14 | 650.43 |
| **Total 2021** | 137.88 | 525.64 | 959.68 | 791.63 | 733.58 | 3,148.41 |

Note: Bl= Barren Land; Hdf= Highly Dense Forest; Mdf= Moderately Dense Forest; Sav= Savanna; Shr= Shrub

Since the value of carbon stocks is directly affected by changes in land cover, it decreases significantly between 2016 and 2021, with a value of 36% and 19% in highly and moderately dense forests, in 2021, respectively. The barren land has the highest increase in carbon stock percentage in 2021 (234%); however, the increase is insignificant since the value of carbon stock per ha is excessively small (2.5 tons/ha) (Figure 3). When compared to changes in carbon stocks from 2013 to 2016, there were no significant differences in general, although there was an increase in carbon storage in a highly dense forest of around 4% and a decrease in the carbon stock of around 8% and 3% in moderately dense forest and shrub, respectively (Figure 3).

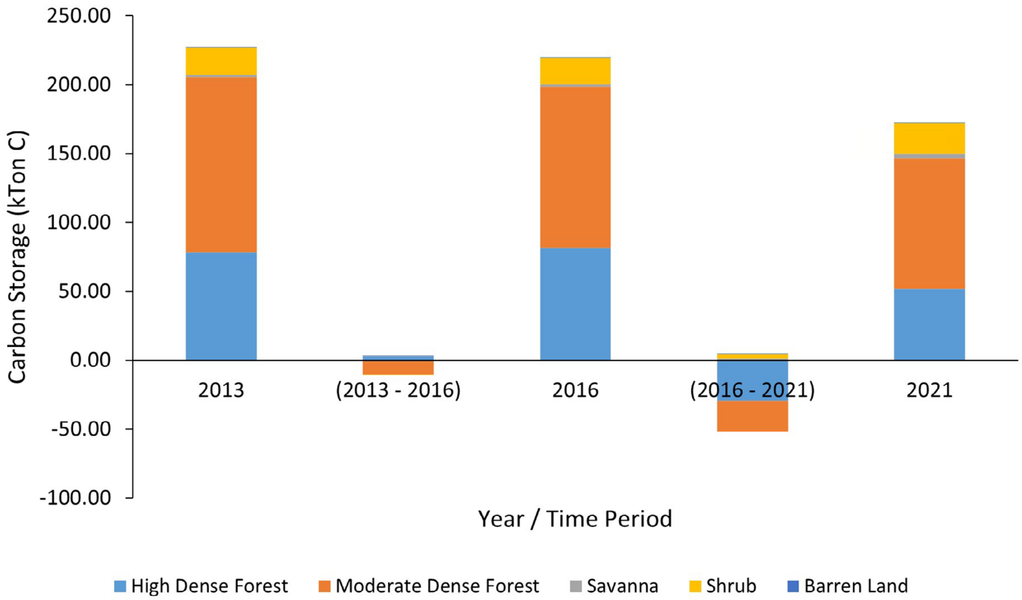


**Figure 3.** Stacked histogram of carbon storages and their changes for 2013 – 2016, 2016 – 2021, 2013 – 2021 in the Sisimeni Sanam Forest Area with Special Purpose.

### *3.3. Linking deforestation and forest degradation to shifting cultivation development*

Deforestation and forest degradation were discovered to be increasing within 2013 - 2021. In SSFAwSP, total deforestation and forest degradations were 12% and 14% of the forest area, respectively, from 2013 to 2016. Shifting cultivation contributed with about 17% to total deforestation and 3% to forest degradation. The incidence of deforestation and forest degradation increased from 2016 to 2021, with the total value increasing to 29%, while shifting cultivation was responsible for only 7% of deforestation and 0.9% of forest degradation (Table 6). When all deforestation and forest degradation incidents from 2013 to 2021 are considered, total deforestation was 32%, and forest degradation was 24% of the total forest area. Shifting cultivation was also responsible for only 10% of deforestation and 1% of forest degradation, showing that shifting cultivation was responsible for not more than 10% of total deforestation and forest degradation in SSFAwSP (Table 6).

**Table 6.** Deforestation and forest degradation due to shifting cultivation by the land cover for three times intervals: (a) 2013 – 2016, (b) 2016 – 2021, and (c) 2013 – 2021 in the Sisimeni Sanam Forest Area with Special Purpose.

**2013 – 2016**

| Shifting Cultivation Location | Forest Degradation Caused by Shifting Cultivation (ha) | Total Forest Degradation 2013 – 2016 (ha) | Deforestation Caused by Shifting Cultivation (ha) | | | Total Deforestation 2013 – 2016 (ha) |
|---|---|---|---|---|---|---|
| | MDF | | BL | Sav | Shr | |
| **HDF** | 6.51 | 186.65 | 0 | 0.55 | 1.34 | 14.94 |
| **MDF** | 0 | 0 | 0.01 | 9.97 | 30.25 | 229.53 |
| **Total** | 6.51 | 186.65 | 0.01 | 10.52 | 31.60 | 244.47 |

**2016 – 2021**

| Shifting Cultivation Location | Forest Degradation Caused by Shifting Cultivation (ha) | Total Forest Degradation 2016 – 2021 (ha) | Deforestation Caused by Shifting Cultivation (ha) | | | Total Deforestation 2016 – 2021 (ha) |
|---|---|---|---|---|---|---|
| | MDF | | BL | Sav | Shr | |
| **HDF** | 2.98 | 341.58 | 0 | 0.06 | 0.49 | 50.61 |
| **MDF** | 0 | 0 | 0.12 | 16.49 | 23.01 | 537.34 |
| **Total** | 2.98 | 341.58 | 0.12 | 16.56 | 23.49 | 587.95 |

**2013 – 2021**

| Shifting Cultivation Location | Forest Degradation Caused by Shifting Cultivation (ha) | Total Forest Degradation 2013 – 2021 (ha) | Deforestation Caused by Shifting Cultivation (ha) | | | Total Deforestation 2013 – 2021 (ha) |
|---|---|---|---|---|---|---|
| | MDF | | BL | Sav | Shr | |
| **HDF** | 4.13 | 319.18 | 0.02 | 2.45 | 3.03 | 83.98 |
| **MDF** | 0 | 0 | 1.63 | 31.91 | 28.50 | 584.64 |
| **Total** | 4.13 | 319.18 | 1.64 | 34.36 | 31.53 | 668.62 |

Nore: Bl= Barren Land; Hdf= Highly Dense Forest; Mdf= Moderately Dense Forest; Sav= Savanna; Shr= Shrub

The deforested and degraded forest areas that have regenerated were assessed by comparing the total value of deforestation and forest degradation in 2013 – 2021 with 2013 – 2016 and 2016 – 2021 (Figure 4). Between 2013 and 2021, the deforested and degraded forest areas returned to the highly dense forest by 9% and 19%, respectively. The forest area that was deforested and degraded due to shifting cultivation grew to the highly dense forest by 14% and 2.9%, respectively. Although these areas can regenerate, deforestation and forest degradation need to be avoided because the regrowth rates of deforested and degraded forest areas are only about 1% and 2.5% per year, respectively. The regrowth of the deforested area in the former shifting cultivation site was much greater than the same activity in the degraded area. This regrowth condition appears to be the result of several factors such as shifting cultivation, which does not open up intensive land and leaves a few trees, farmers planting trees between crops, the selecting of animal feed crops (*Leucaena leucocephala*) as staple crops on their land, and minimizing excessive damage to the forest area around, which can cause forest degradation.

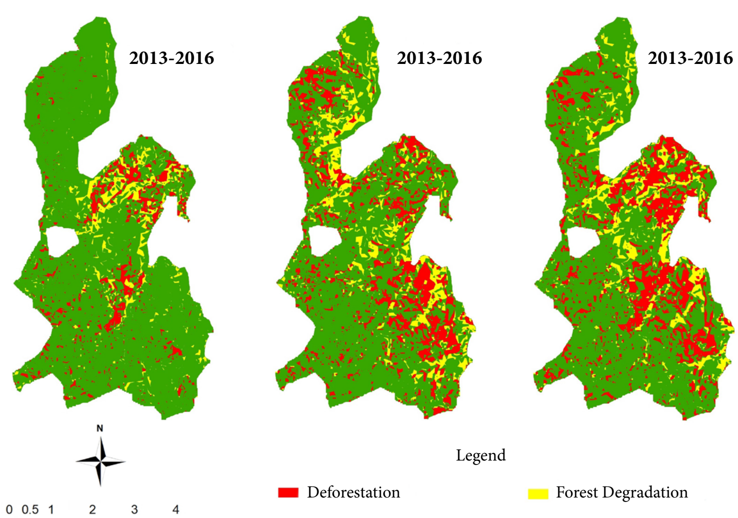


**Figure 4.** Deforestation and forest degradation map of 2013 - 2016, 2016 - 2021, 2013 - 2021 in the Sisimeni Sanam Forest Area with Special Purpose.

## 4. DISCUSSION

### *4.1. Accuracy assessment*

In comparison to other methods, such as MLC and multiple linear regression, FCD Mapper has the highest overall accuracy and Kappa coefficient for monitoring tropical mixed deciduous vegetation in Myanmar (Mon et al., 2012). Using MLC, Meyfroidt et al. (2013) reported relatively low overall accuracy land cover maps in the coffee-growing areas of Dak Lak and Dak Nong provinces, Vietnam, between 2000 and 2010. Therefore, FCD method was used to assess the forest cover changes (Pujiono et al., 2019) and to investigate the land cover changes and carbon storage (Sadono et al., 2022).

Savanna was the class with the lowest accuracy values in the non-forest category, with approximately 60% and 57.14% in 2013 and 2016, respectively. However, a little difficulty was encountered in this study by distinguishing sporadic shrubs and savanna and dense shrubs and moderately dense forest, which occurred due to seasonal conditions in semi-arid ecosystems. The Landsat 8 data were collected during the dry season to show the current state of the semi-arid ecosystem, leading to difficulty of distinguishing between savanna and sporadic shrubs and dense shrubs and moderately dense forests. This result is in line with the previous study by Bruggeman et al. (2016), Gemitzi et al. (2021), Meyfroidt et al. (2013), and Pujiono et al. (2019), which discovered a difficulty in differentiating between very sparse shrubs and savannas. Therefore, shrubs in semi-arid ecosystems are commonly identified as savanna or agricultural land (Pujiono et al., 2019).

### *4.2. Changes of land cover and carbon storage*

The results indicated a trend toward converting heavily forested areas into open spaces between 2013 and 2021. According to the forest transition theory, SSFAwSP is entering a phase of highly deforestation (Mattsson, 2012), where the forest area continues to decline, starting with a reduction in forest area dominance from 65% in 2013 to 46% in 2021. Although reforestation is occurring in several locations, the rate of deforestation is higher, which makes forest gains to be ineffective. This finding is different from previous study by Mishra et al. (2020), which discovered an increase in the forest areas that had entered a low forest cover but is increasing through reforestation phase.

Barren land and savanna experienced significant increases in non-forest areas, with 724% and 198%, respectively, from 2013 to 2021. This phenomenon is in line with a previous study, which discovered a significant increase in barren land (Ogato et al., 2021), agriculture, grassland, and settlements (Negassa et al., 2020), and a continuous decrease in the forest area. Furthermore, an increase in shrubs, which was as significant as in barren land and savanna, of approximately 113% between 2013 and 2021. This vast expanse of barren land is exacerbated further by the use of fire in land clearing (Nguyen et al., 2022). During land clearing, moderately dense forests and shrubs are typically cleared and burned, though some trees are left for shade. On the other hand, the increase in shrubs was also discovered in the study by Nugroho et al. (2018), which stated that the increase in shrubs was one of the forest recovery processes from abandoned agriculture areas. This increase is expected to reduce land vulnerability to soil erosion and flooding (Ogato et al., 2021).

Changes in land cover have an immediate impact on carbon storage. Because the value carbon content of existing forest land per hectare is quite high, accounting for approximately 90% of total carbon, the loss of forest land cover results in a significant decrease in carbon stock. A previous study showed that forests are the main carbon pool (Gemitzi et al., 2021), with approximately 92% of the total area (Avitabile et al., 2016). The massive reduction in carbon stock (-55%) between 2016 and 2021 was due to the conversion of forest areas to shrubs, even when they can still mitigate the effects of environmental disasters (Ogato et al., 2021).

### *4.3. Management implication to shifting cultivation development*

Between 2013 and 2021, total deforestation was 32%, or about 4% per year, nearly four times greater than the FAO's deforestation data for Indonesia (Kuntz & Siegert, 1999). Total deforestation is also partially offset by 1% of annual forest regrowth from 2013 to 2021; therefore, due to the large disparity, forested areas are being converted into open areas for expansion, in contrast to a previous study which discovered that the difference between deforestation and forest regrowth was only 0.12% (Avitabile et al., 2016) and 0.31% (Meyfroidt et al., 2013). According to Meyfroidt et al. (2013), the rate of forest degradation is lower than deforestation, approximately 24% between 2013 and 2021, or 3% per year. The growth of shrubs into the moderately dense forest at about 1.2% per year helps balance total forest degradation because changes in land cover type from shrub to moderate dense forest showed the stages of forest regrowth that originated from farmers abandoning their shifting cultivation areas (Nugroho et al., 2018).

Shifting cultivation is a tradition practiced by the people of East Nusa Tenggara Province, particularly in the western part of Timor Island (Dako et al., 2019). Although it only accounts for 10% of total deforestation, farmers continue to extend shifting cultivation to another forested land (Dako et al., 2019) whether HDF or MDF with a tendency to expand the previously abandoned shifting cultivation land. This continue expansion of abandoned land is because there are no intensive and permanent agricultural activities of current cultivation areas, in contrast to the discovery of Bruggeman et al. (2016), which stated that agricultural intensification causes reforestation of degraded forest areas.

The shifting cultivation pattern in SSFAwSP is similar to the pattern in the North Central Timor district (Dako et al., 2019). Farmers typically cultivate the land until the third year, and when production and soil fertility begin to decline, they open land in a new location by performing the same activities as on the previous land. Before relocating to the new land, farmers planted timbers, such as *Acacia mangium*, *Eucalyptus urophylla*, and *Tectona gradis*; multi purpose tree species, such as *Leucaena leucocephala*, *Mangifera indica*, and *Citrus sp*.; and other annual plants. Meanwhile, farmers will return to their first land after 5-8 years of leaving the first field (Dako et al., 2019). According to Meyfroidt et al. (2013), shifting cultivation is the primary cause of deforestation at their study site in Vietnam, in contrast, the traditional shifting cultivation in SSFAwSP has a positive side effect by replanting timber and plantations before moving to another land (Dako et al., 2019). Reduction of opening forested land for shifting cultivation combined with technologies of intensive farming patterns on marginal lands can be used as an abandoned open land rehabilitation strategy. However, this strategy needs to be implemented with caution since there is still a chance that the abandoned open area will fail to regenerate naturally (Fawzi et al., 2019).

## 5. CONCLUSIONS

SSFAwSP's land cover has remained forest-dominated from 2013 to 2021, despite a declining trend in area and carbon storage. To anticipate this declining trend, deforestation and forest degradation must be monitored and controlled, particularly in the occurrence of forest fires and illegal logging, since shifting cultivation is responsible for only 10% of total deforestation. To improve land cover and increase carbon storage, there is a need of an innovative strategy for marginal land rehabilitation that combines reduction of land expansion for shifting cultivation and technology of intensive and permanent agriculture because farmers plant trees when they neglect their abandoned shifting cultivation.

## SUBMISSION STATUS

Received: 16 Feb. 2022
Accepted: 05 Dec. 2022
Associate editor: Fernando Gomes

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## REFERENCES

Acharya TD, Yang IT. Exploring Landsat 8. International Journal of IT, Engineering and Applied Sciences Research 2015; 4(4): 4–10. http://earthobservatory.nasa.gov/IOTD/.

Agus F, Santosa I, Dewi S, Setyanto P, Thamrin Y, Wulan, C et al. Pedoman Teknis Perhitungan Baseline Emisi dan Serapan Gas Rumah Kaca Sektor Berbasis Lahan: Buku I Landasan Ilmiah. Republik Indonesia, 1 – 120. Available from: www.bappenas.go.id; 2014.

Avitabile V, Schultz M, Herold N, de Bruin S, Pratihast AK, Manh, CP et al. Carbon emissions from land cover change in Central Vietnam. Carbon Management 2016; 7(5–6): 333–346. https://doi.org/10.1080/17583004.2016.1254009.

Bruggeman D, Meyfroidt P, Lambin EF. Forest cover changes in Bhutan: Revisiting the forest transition. Applied Geography 2016; 67: 49–66. https://doi.org/10.1016/j.apgeog.2015.11.019.

Bustan F, Mahur A, Nau AST. Karakteristik Dan Dinamika Sistem Pertanian Lahan Kering Dalam Kebudayaan Manggarai. Jurnal Lazuardi 2020; 3(1): 344–367.

Cohen J. Weighted kappa: Nominal scale agreement provision for scaled disagreement or partial credit. Psychological Bulletin 1968; 70(4): 213–220. https://doi.org/10.1037/h0026256.

Dako FX, Purwanto RH, Faida LRW, Sumardi. Identifikasi Kerusakan Antropogenik Kawasan Hutan Lindung Mutis Timau Di Pulau Timor Bagian Barat Dan Upaya Penanggulangannya. Journal of Natural Resources and Environmental Management 2019; 9(2): 437–455. https://doi.org/10.29244/jpsl.9.2.437-455.

Eddy IMS, Gergel SE. Why landscape ecologists should contribute to life cycle sustainability approaches. Landscape Ecology 2015; 30(2): 215–228. https://doi.org/10.1007/s10980-014-0135-7.

EFETI Kupang. Rencana Pengelolaan Jangka Panjang Kawasan Hutan Dengan Tujuan Khusus (KHDTK) Diklat Kehutanan Sisimeni Sanam 2020 – 2039. EFETI Kupang; 2020.

Emran A, Rob MA, Kabir MH, Islam MN. Modeling spatio-temporal shoreline and areal dynamics of coastal island using geospatial technique. Modeling Earth Systems and Environment 2016; 2(1): 1–11. https://doi.org/10.1007/s40808-015-0060-z.

Fawzi NII, Indrayani AM, DeKay K. Forest Change Monitoring and Environmental Impact in Gunung Palung National Park, West Kalimantan, Indonesia. Jurnal Ilmu Lingkungan 2019; 17(2): 197–204. https://doi.org/10.14710/jil.17.2.197-204.

Garai D, Narayana AC. Land use/land cover changes in the mining area of Godavari coal fields of southern India. Egyptian Journal of Remote Sensing and Space Science 2018; 21(3): 375–381. https://doi.org/10.1016/j.ejrs.2018.01.002.

Gemitzi A, Albarakat R, Kratouna F, Lakshmi V. Land cover and vegetation carbon stock changes in Greece: A 29-year assessment based on CORINE and Landsat land cover data. Science of the Total Environment 2021; 786: 147408. https://doi.org/10.1016/j.scitotenv.2021.147408.

Hariyadi B, Ticktin T. From Shifting Cultivation to Cinnamon Agroforestry: Changing Agricultural Practices Among the Serampas in the Kerinci Seblat National Park, Indonesia. Human Ecology 2012; 40(2): 315–325. https://doi.org/10.1007/s10745-012-9481-8.

Kapa MJ, Gunawan T, Hardoyo SR. Sistem Pertanian Perladangan Tebas Bakar Berbasis Kearifan Lokal Pada Wilayah Bercurah Hujan Eratik Di Timor Barat. Jurnal Pendidikan Geografi 2017; 4(2): 10–19.

Kingwell-Banham E, Fuller DQ. Shifting cultivators in South Asia: Expansion, marginalisation and specialisation over the long term. Quaternary International 2012; 249: 84–95. https://doi.org/10.1016/j.quaint.2011.05.025.

Kuntz S, Siegert F. Monitoring of deforestation and land use in Indonesia with multitemporal ERS data. International Journal of Remote Sensing 1999; 20(14): 2835–2853. https://doi.org/10.1080/014311699211822.

Lawrence D, Schlesinger WH. Changes in Soil Phosphorus during 200 Years of Shifting Cultivation in Indonesia. Ecology 2001; 82(10): 2769. https://doi.org/10.2307/2679959.

Mattsson E. Forest And Land Use Mitigation And Adaptation In Sri Lanka: Aspects In The Light Of International Climate Change Policies [Dissertation]. University of Gothenburg; 2012.

Meyfroidt P, Vu TP, Hoang VA. Trajectories of deforestation, coffee expansion and displacement of shifting cultivation in the Central Highlands of Vietnam. Global Environmental Change 2013; 23(5): 1187–1198. https://doi.org/10.1016/j.gloenvcha.2013.04.005.

Mishra PK, Rai A, Rai SC. Land use and land cover change detection using geospatial techniques in the Sikkim Himalaya, India. Egyptian Journal of Remote Sensing and Space Science 2020; 23(2): 133–143. https://doi.org/10.1016/j.ejrs.2019.02.001.

Mon MS, Mizoue N, Htun NZ, Kajisa T, Yoshida S. Estimating forest canopy density of tropical mixed deciduous vegetation using Landsat data: A comparison of three classification approaches. International Journal of Remote Sensing 2012; 33(4): 1042–1057. https://doi.org/10.1080/01431161.2010.549851.

Mukul SA, Herbohn J. The impacts of shifting cultivation on secondary forests dynamics in tropics: A synthesis of the key findings and spatio temporal distribution of research. Environmental Science and Policy 2016; 55: 167–177. https://doi.org/10.1016/j.envsci.2015.10.005.

Negassa MD, Mallie DT, Gemeda DO. Forest cover change detection using Geographic Information Systems and remote sensing techniques: a spatio-temporal study on Komto Protected forest priority area, East Wollega Zone, Ethiopia. Environmental Systems Research 2020; 9(1): 1–14. https://doi.org/10.1186/s40068-020-0163-z.

Nguyen CH, Setyaningsih CA , Jahnk SL, Saad A, Sabiham S, Behling H. Forest Dynamics and Agroforestry History since AD 200 in the Highland of Sumatra, Indonesia. Forests 2022; 13(1473): 1-22. https://doi.org/10.3390/f13091473

Nugroho HYSH, van der Veen A, Skidmore AK, Hussin YA. Expansion of traditional land-use and deforestation: a case study of an adat forest in the Kandilo Subwatershed, East Kalimantan, Indonesia. Journal of Forestry Research 2018; 29(2): 495–513. https://doi.org/10.1007/s11676-017-0449-9.

Nugroho HYSH, Skidmore A, Hussin YA. Verifying Indigenous based-claims to forest rights using image interpretation and spatial analysis: a case study in Gunung Lumut Protection Forest, East Kalimantan, Indonesia. GeoJournal 2020; 0123456789. https://doi.org/10.1007/s10708-020-10260-x.

Ogato GS, Bantider A, Geneletti D. Dynamics of land use and land cover changes in Huluka watershed of Oromia Regional State, Ethiopia. Environmental Systems Research 2021; 10(1). https://doi.org/10.1186/s40068-021-00218-4.

Pujiono E, Sadono R, Hartono, Imron MA. A three decades assessment of forest cover changes in the mountainous tropical forest of Timor Island, Indonesia. Jurnal Manajemen Hutan Tropika 2019; 25(1): 51–64. https://doi.org/10.7226/jtfm.5.1.51.

Rikimaru A, Roy PS, Miyatake S. Tropical forest cover density mapping. Tropical Ecology 2002; 43(1): 39–47.

RSPO. RSPO Guidance for Land Use Change Analysis. October 2015, 0–16. Available from: https://rspo.org/publications; 2017.

Sadono R, Khan K, Kusuma AF, Siregar DI, Yuwono T, Peday HFZ, Ruhimat IS. Land cover and carbon storage in a certified sustainable community forest in Sumberejo village, Wonogiri, Central Java, using landsat data series 2000, 2015 and 2020. Agriculture and Forestry 2022; 68(3): 183–198. DOI:10.17707/AgricultForest.68.3.15.

Storey J, Choate M, Lee K. Landsat 8 operational land imager on-orbit geometric calibration and performance. Remote Sensing 2014; 6(11): 11127–11152. https://doi.org/10.3390/rs61111127.

Sudiyono. The History And Dynamic Of Customary Land Tenure In The Village Of Probur Utara Habollat, Alor District. Jurnal Masyarakat & Budaya 2015; 17(2): 185–206.

Syam T, Salam AK, Utomo M, Mahi AK, Lumbanraja J, Nugroho, SG et al. Land use and cover changes in a hilly area of south sumatra, indonesia (from 1970 to 1990). Soil Science and Plant Nutrition 1997; 43(3): 587–599. https://doi.org/10.1080/00380768.1997.10414785.

Takeuchi R, Wahyudi I, Aiso H, Ishiguri F, Istikowati WT, Ohkubo, T et al. Anatomical characteristics and wood properties of unutilized

Artocarpus species found in secondary forests regenerated after shifting cultivation in Central Kalimantan, Indonesia. Agroforestry Systems 2019; 93(2): 745–753. https://doi.org/10.1007/s10457-017-0171-9.

Thaler GM, Anandi CAM. Shifting cultivation, contentious land change and forest governance: the politics of swidden in East Kalimantan. Journal of Peasant Studies 2017; 44(5): 1066–1087. https://doi.org/10.1080/03066150.2016.1243531.

Tosiani A. Buku Kegiatan Serapan dan Emisi Karbon. Direktorat Inventarisasi dan Pemantauan Sumber Daya Hutan Direktorat Jendral Planologi Kehutanan dan Tata Lingkungan Kementerian Lingkungan Hidup dan Kehutanan 2015.

Van Vliet N, Mertz O, Heinimann A, Langanke T, Pascual U, Schmook, B et al. Trends, drivers and impacts of changes in swidden cultivation in tropical forest-agriculture frontiers: A global assessment. Global Environmental Change 2012; 22(2): 418–429. https://doi.org/10.1016/j.gloenvcha.2011.10.009.

Villa PM, Rodrigues AC, Martins SV, de Oliveira Neto SN, Laverde AG, Riera-Seijas A. Reducing intensification by shifting cultivation through sustainable climate-smart practices in tropical forests: A review in the context of UN Decade on Ecosystem Restoration. Current Research in Environmental Sustainability 2021; 3: 100058. https://doi.org/10.1016/j.crsust.2021.100058.

Vongvisouk T, Mertz O, Thongmanivong S, Heinimann A, Phanvilay K. Shifting cultivation stability and change: Contrasting pathways of land use and livelihood change in Laos. Applied Geography 2014; 46: 1–10. https://doi.org/10.1016/j.apgeog.2013.10.006.

Wang SQ, Zheng XQ, Zang XB. Accuracy assessments of land use change simulation based on Markov-cellular automata model. Procedia Environmental Sciences 2012; 13: 1238–1245. https://doi.org/10.1016/j.proenv.2012.01.117.

Young NE, Anderson RS, Chignell SM, Vorster AG, Lawrence R, Evangelista PH. A survival guide to Landsat preprocessing. Ecology 2017; 98(4): 920–932. https://doi.org/10.1002/ecy.1730.