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A Three Decades Assessment of Forest Cover Changes in The Mountainous Tropical Forest of Timor Island, Indonesia

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Abstract

The Mutis Timau Forest Complex (MTFC), a remained mountainous tropical forest area in Timor Island, located in Indonesia and Timor-Leste border region, tends to decrease gradually. Unfortunately, declined forest area and their rates are not explained by reliable spatial and quantitative information. This study attempts to assess the extent and rate of forest cover changes in the MTFC during the last 30 years. We used Landsat images on three different dates: 1987, 1999, and 2017. Then, we applied a hybrid classification approach that combines the application of Forest Canopy Density model-obtained from four biophysical indices and supervised classification-maximum likelihood classification to generate land cover maps. Finally, we detected forest cover change by comparing land cover map in different years. Results illustrated that the extent and annual rate of deforestation, forest degradation, forest regrowth, and afforestation during 1987–2017 were 2,232 ha (0.36%), 4,820 ha (1.10%), 1,475 ha (0.69%), and 1,252 ha (0.40%), respectively. Such results are important for the MTFC authority to establish appropriate plan and strategies in forest management activities and can be used to support some policies/programs for combating deforestation and forest degradation.

Keywords: forest cover changes, hybrid classification approach, Forest Canopy Density model, mountainous tropical forest

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Introduction

The Mutis Timau Forest Complex (MTFC), one of the remaining forest areas in Timor Island, east of Indonesia, is categorized as a tropical mountain forest with an average elevation of 1,300 meters and 40% of slope average. As the part of mountain forest worldwide, the MTFC plays an important role on providing goods and environmental services essential for the livelihood of both upland and lowland communities (Price et al., 2011). This forest has a function in maintaining hydrological cycle processes and play a critical role as water catchment areas (Lentz et al., 1998). As a hotspot of biodiversity, this mountain forest is a home of various endemic plants and native timorese animals (Farida et al., 2004). This forest provides various resources for local people including cattle feeding building materials, and fuelwood (Lentz et al., 1998). Globally, the mountain forest worldwide also occupies a crucial position in terms of climate change because of their contribution to shielding the atmosphere from CO_2 emissions (Price et al., 2011). Because of those important functions, the MTFC is often referred as the heart of the Timor Island.

Nevertheless, the profitable and benefits of the MTFC are threatened by the facts that this mountain forest area tends to decrease gradually because of the wood collection, boundary and land disputes, livestock grazing, and agriculture expansion (Lentz et al., 1998). Considering the fragile ecosystem of the mountain forest areas due to their steep slopes and often-extreme climates and weather events, the declined and degraded mountain forest area can lead to serious environmental problems, e.g., soil erosion, landslides, increased water runoff or reduced water storage, the drying of springs, the loss of biodiversity, and it can have severe impacts on livelihoods (Price et al., 2011). Efforts for taking appropriate actions and policies to counteract the negative impact of deforestation and to secure mountain forest functions are commonly constrained by three areas of data uncertainty that need better analysis, i.e., (1) the extent and distribution of existing land cover, (2) the rate and distribution of land-cover changes, and (3) underlying factors and drivers of land cover changes (Turner et al., 1995). Forest monitoring through remote sensing based approach, is therefore needed to address those two first areas of data uncertainty (Turner et al., 1995).

Numerous remote sensing-based forest monitoring studies have been conducted in Indonesia. Based on study area, forest monitoring studies have primarily focused on forest monitoring in big islands with large forest area, i.e., Sumatera (Gaveau et al., 2009; Linkie et al., 2010; Broich et al., 2011; Margono et al., 2012; Wijaya et al., 2011; Elz et al., 2015), Kalimantan (Fuller et al., 2010; Broich et al., 2011; Purwanto et al., 2015; Suwarno et al., 2015), Papua (Margono et al., 2014), and Sulawesi (MacDonald et al., 2011; Ahmad et al., 2016). By contrast, only limited researches were focussing on relatively small islands with small forest cover area, e.g., Lombok (Kim, 2016). Forest monitoring in small island is important because forest cover changes on small islands with less forest cover area will be expected in more significant impact for some reasons: the limitation of existing nature resources, high dependence on forest resource, the fragility of ecological systems, and the vulnerability to extinction of forest-dependent species (Tole, 2002).

Based on methods, most of remote sensing based-forest monitoring studies in Indonesia used Landsat imageries and pixel based-supervised classification method as main data and classification approach, respectively (Gaveau et al., 2009; Margono et al., 2012). Despite commonly used for forest monitoring studies in Indonesia, the supervised classification approach was criticized due to the time and cost required for training area establishment, extreme forest complexity, narrow cover type spectral separability, and limited potential for automated processing (Bauer et al., 1994). The use hybrid classification approach that combines the training from unsupervised/other technique with supervised technique is suggested to deal with the limitation (Bauer et al., 1994). Forest Canopy Density (FCD) model that consists of bio-physical phenomenon for assessing the current status of forest based on canopy cover (Rikimaru et al., 2002; Abdollahnejad et al., 2017) is one of unsupervised technique that is highly automated in processing. In addition, the application of FCD model is able to detect forest degradation (Muhammad et al., 2014)-a type of forest cover changes that become main target of tropical forest monitoring over the past decades (Herold et al., 2011; Miettinen et al., 2014; Mitchell et al, 2017). Using multi-temporal Landsat and a hybrid FCD/supervised classification approach, this study aims to investigate land cover changes in MTFC for 30 years (1987–2017).

Methods

Study area The MTFC is located at Timor Island, East Nusa Tenggara Province, which is the eastern part of Indonesia. The northern part of this area is located in the Indonesia-Timor Leste border (Figure 1). Administratively, the MTFC is located in two different districts, called South Central Timor (*Timor Tengah Selatan*, TTS) and North Central Timor (*Timor Tengah Utara*, TTU). The MTFC with the size of 31,984 ha is divided into three forest management units (FMU), i.e., TTU FMU (*Kesatuan Pengelolaan Hutan,* KPH TTU), TTS FMU (KPH TTS), and the Gunung Mutis Nature Reserve (*Cagar Alam Gunung Mutis,* CAGM) that cover an area of 21%, 40%, and 39% of total the MTFC, respectively (Figure 1). Both of the KPH TTU and the KPH TTS have functioned as forest protection, whereas the CAGM has a function as a conservation forest. The overall topography in the MTFC is hilly as a large part of its territory has an average slope of 40% or above and consist of unique mountain forests dominated by homogenous stands of timor mountain gum (*Eucalyptus urophylla*), shrubs, savannas, and several seasonal rivers draining in all directions (Pujiono et al., 2011).

Data We used multi-temporal Landsat satellite imageries and additional spatial data as listed in the Table 1.

Image pre-processing We applied geometric, atmospheric, and topographic corrections to Landsat imageries as suggested by Young et al. (2017). For the images data set, we geometrically corrected to World Geodetic System (WGS) 1984 datum and Universal Transverse Mercator (UTM) coordinate system Zone 51S using Ground Control Points (GCPs) derived from Indonesian based map. Then, we registered the 1987 and 2017 images for 1999 image using the same reference of GCPs. For registered Landsat images, we performed atmospheric corrections with ATCOR-3, a tool developed by ERDAS Imagine Software that able to correct both atmospheric condition and topographical distortion in rugged terrain (Young et al., 2017). Since we used multi-temporal images (1987, 1999, and 2017) that produced by different sensor under vary of atmospheric conditions, radiometric or images normalization is needed to make the images comparable (Hajj et al., 2008). For image normalization, we used linear regression method with "band-by-band approach" to compare pseudo-invariant features (PIFs), the areas or landscape element that have a nearly constant reflectance value over time (Junior et al., 2013). We used rocky mountain, barren land (bright objects), and water bodies (dark objects), which represent a sufficient range of brightness for the regression equations to be reliable (Themistocleus et al., 2012). Considering it had the lowest cloud cover compared to the other two images, we used the 1999 image as a reference to normalize 1987 and 2017 images. Finally, we determined the study area on the corrected images by performing a subset operation with a guide of the MTFC vector boundary.

Image classification Regarding land cover classification system, we used a modification of a land cover classification system developed by the National Standardization Agency (*Badan Sandardisasi Nasional*, BSN): SNI-*Standard Nasional Indonesia* No. 7645-2010. We modified the forest class into three classes, namely dense forest, moderately dense forest, and open forest, with the reason that this modification was able to analyze forest degradation which requires forest canopy density information. Based on this modification, our classification scheme comprised nine land cover types representing the dominant land cover types in the study area (Table 2).

For estimating crown cover of land cover classes corresponded to forests (i.e., dense-, moderately-, and open forest), we adopted the Forest Canopy Density (FCD) approach. The FCD model comprises bio-physical phenomenon modeling and analysis utilizing data derived from four indices: Vegetation Index, Bare Soil Index, Shadow Index, and Thermal Index (Rikimaru et al., 2002). We calculated FCD that expressed in percentage for each

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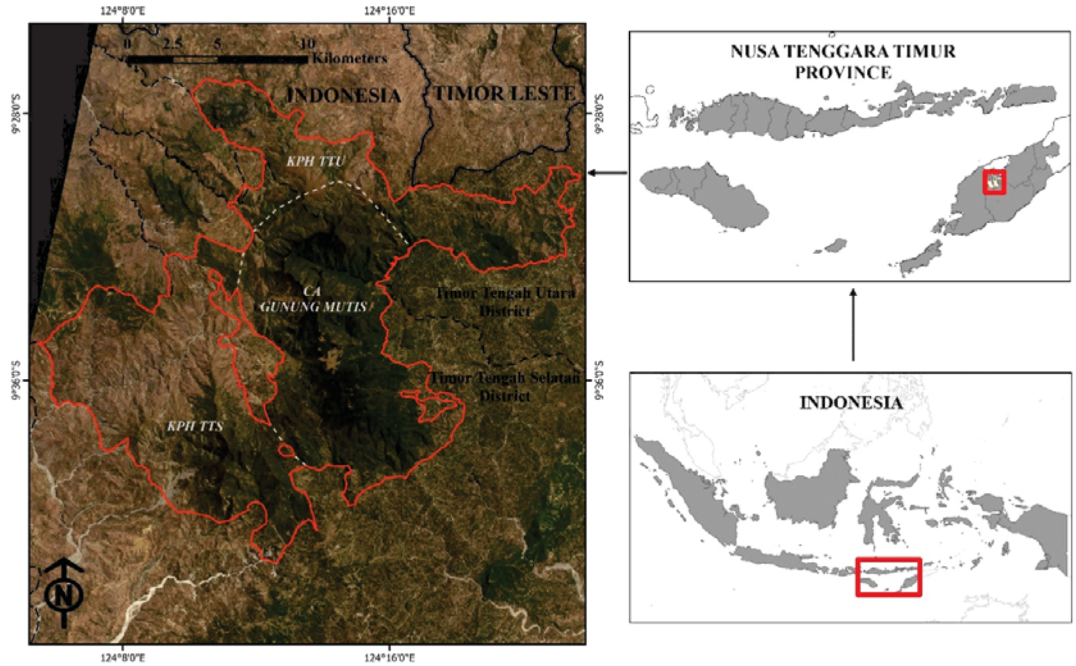

Country Border ( ); District Border ( ); the MTFC Boundary ( ); Forest Management Unit Border ( ).

Figure 1 Location of study area, the MTFC, presented on Landsat 8 imagery (natural color composite-Bands RGB 432).

Table 1 Sources and acquisition date of each data used

Data	Acquisition date	Source
Landsat TM, Path/Row 110/67, spatial resolution 30m	1987/09/20	USGS[1]
Landsat ETM, Path/Row 110/67, spatial resolution 30m	1999/09/08	USGS[1]
Landsat 8, Path/Row 110/67, spatial resolution 30m	2017/10/13	USGS[1]
SPOT 5 (Nusa Tenggara region), spatial resolution 10m	2015	MoEF[2]
Indonesia Base Map, scale: 1:25,000 (*Peta RBI*)	1999; 2013	BIG[3]
SRTM DEM (Digital Elevation Model), 30m x 30m	2015	USGS[1]
Google Earth Image	2004	Google Earth
The MTFC Vector Boundary	2017	MoEF[2]

[1]USGS = United State Geological Survey; [2]MoEF= Ministry of Environment and Forestry, Indonesia; [3]BIG = *Badan Informasi Geospasial* (Geospatial Information Agency), Indonesia

Table 2 Description of Land cover classification class

Land Cover Class	Description
Forest Area	
Dense forest	areas with mature trees; areas with estimated >70% of the existing crown covered by trees
Moderately dense forest	areas with trees; areas with estimated 40−70% of the existing crown covered by trees
Open Forest	areas with scattered trees; areas with estimated 10−40% of the existing crown covered by trees
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
Agricultural land	All land covers associated with agriculture activities on dry/wetland, such as *sawah* (paddy field), mixed garden and *ladang* (agriculture fields)
Savanna	Areas with grasses and scattered natural trees and shrubs.
Settlement	Settlement areas including rural, urban, industrial and other settlements with typical appearance
Waterbody	Sighting of open water including ocean, rivers, lakes, and ponds
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 exhibit regrowth

Sources: Modified from land classification system developed by the National Standardization Agency (*BSN,* 2010) pixel and produced FCD map in 1987, 1999, and 2017. The relevant formulas and algorithms used by the FCD model for the indices are shown in Table 3. We calculated all indices and FCD under guided of FCD Mapper Ver.2 software.

We, therefore, used FCD maps to create training data of land cover classes corresponded to the forest area, whereas training data of land cover classes corresponded to the non-forest area were obtained from a combination of ground survey and high-resolution imageries. Using the training data set, we performed a separability analysis to identify the combination of bands that show the highest distinction between the land cover classes. Redy and Blah (2009) stated that the separability is a statistical measurement based on spectral distances computed for a combination of bands. One of the statistical separability that widely used is divergence which is calculated using the mean and covariance matrix of the class statistic collected in the training phase (Jensen, 2005). As suggested by Jensen (2005), we used transformed divergence (TD) that have a range of values between 0 and 2000, in which, a TD value of 2000 indicated excellent class separation, > 1900 was good separation, while < 1700 was poor separation. By applying selected bands from separability analysis and training data set, we performed a supervised classification-maximum likelihood classification (MLC) algorithm to produce a classified image for 1987, 1999, and 2017. To reduce the salt and pepper effect due to spectral variability, we applied post-classification smoothing using 3 × 3-pixel majority filter to produce a final land cover map for 1987, 1999, and 2017.

Accuracy assessment We assessed the accuracy of land cover maps by comparing classified images with reference data derived from ground truth data or high-resolution imageries. We adopted the equation from multinomial distribution Equation *[1]* to calculate sample size (n) for reference data as suggested by Congalton and Green (1999):

$$n = B\Pi_i(1-\Pi_i)/b_{i^2} \qquad [1]$$

note: n = sample size, B = the upper $(\propto/k) \times 100^{th}$ percentile of the expected percent accuracy with one degree of freedom Π = the proportion of the population in the *i*-th category, b = absolute precision of the sample, = degree of freedom, k = number of land cover classes. ∝

We assessed the accuracy of non-forest classes in 2017-classified images using field data from (1) GPS geotag photos in 2017, (2) Indonesia based map in 2013, and (3) SPOT 5 image in 2015, while the accuracy of classes corresponded to forest area with their canopy density were evaluated based on the Canopy Cover Index Value estimated from hemispherical photographs (using GLAMA-Gap Light Analysis Mobile App (Tichý, 2016). For 1987 and 1999-classified images, we assessed their accuracies using reference data from the Indonesian based map in 1999 and Google Earth imageries in 2004. We took ground referenced data purposively representing all classes of land cover types and considering accessibility. By comparing classified images and reference data, we arranged the cross-tabulated matrixes or error matrix. Finally, from the error matrix, we calculated four indicators of accuracy, namely: producers' accuracy, users' accuracy, overall accuracy, and kappa value (Congalton & Green, 1999).

Change detection analysis We used post-classification change detection analysis that provides quantitative "from–to" information to assess the extent and rate of land cover changes. We calculated the extent of land cover (E) by comparing the area of same land cover types in a different year and estimated their rates (R) by applying a formula suggested by FAO (Puyravaud, 2003), as is described in Equation *[2]*.

$$E = A_2 - A_1 \qquad [2]$$

$$R = \left(\frac{A_2}{A_1}\right)^{1/(t_2-t_1)} \qquad [3]$$

note: t_1 and t_2 = time 1 and time 2, A_1 and A_2 = area of land cover class at time t_1 and t_2

In this study, we focused on four types of land cover changes, i.e., deforestation (from forest to non-forest), forest degradation (reduction of canopy cover within a forest-from higher density forest to lower density forest), forest regrowth (an increase of canopy cover within a forest-from lower density forest to higher density forest), and afforestation (from non-forest to forest). We analyzed forest cover changes for a three-time interval, i.e., 1987–1999,

Table 3 Formula and algorithms used to calculate indices in Forest Canopy Density model

Index		Formula or algorithm
VI		
-	NDVI	= (NIR – Red/NIR + Red)
-	AVI	= [NIR × (256-Red) × (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)] × 100 + 100
SI		= [(256 – Blue) × (256 – Green) × (256 – Red)]$^{1/3}$
TI		= This index is calibrated from the thermal data band
VD		= This index is calculated from the first principal component of VI and BI
SSI		= This index is calibrated for the forested land
FCD		= (VD × SSI + 1)$^{1/2}$ – 1

Note: Landsat bands: Visible bands = Blue, Green, Red; NIR = Near Infrared; SWIR = Swing 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
Sources: Rikimaru *et al*., 2002; Mon *et al*., 2012

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1999–2017, and 1987–2017.

A flowchart summarizing the steps involved in the assessment of forest cover changes are described in Figure 2.

Results and Discussion

Accuracy assessments Overall accuracy and overall kappa values for 1987, 1999, and 2017-classified images were 70.94% (0.64), 75% (0.69), and 75% (0.69), respectively (Table 4). Based on the agreement stated by Congalton (1996), these kappas represent a moderate agreement. Previous studies with similar method-FCD approach (Candrashekhar et al., 2005; Mon et al., 2012; Deka et al., 2013) reported that the overall accuracy was approximately in the range of 60–70%. Overall accuracy in this study was slightly higher than those in the previous study. This difference might be caused by the application of the detailed process in image pre-processing through an ATCOR-3 tool that able to perform atmospheric correction and topographic correction together that provide more corrected images, whereas the previous study only performed atmospheric correction without any topographical correction.

The accuracy assessment of individual categories was also represented with producers' and users' accuracy. For example, for error matrix in 2017 (Table 4c), the producers' and users' accuracy of dense forest were 72.22% and 65%, respectively. It means that even though 72.22% of the reference dense forest class have been correctly identified as dense forest, only 65% of the areas identified as dense forest in the classification were an actually dense forest. In three classified image, the accuracy of moderately dense forest (approximately 60% of producers' accuracy) was relatively lower than the accuracy of other classes. The moderately dense forest was most often confused with dense forest (27% commission error, Table 4a; 22% commission error, Table 4b) and open forest (22% commission error, Table 4c).

In non-forest categories, shrubs were identified as a class that has the lowest accuracy value. They were most often confused with open forest (19% commission error, Table 4a), agriculture (1% commission error, Table 4c), and savanna (1% commission error, Table 4b and Table 4c). In dense shrub areas, it was difficult to distinguish shrub and open forest (19% commission error, Table 4a). In 1999 and 2017, when agricultural land classes increased (Figure 3 and Figure 4), shrub was most often confused with agricultural land (1% commission error, Table 4b and Table 4c). In some areas, it was also difficult to distinguish very sparse shrubs with savanna areas (1% commission error, Table 4c). Therefore, it was reasonable if shrubs would be identified as savanna or agricultural land. This result is in line with the previous study that also found some difficulties for classifying shrubs in particular (Pujiono et al., 2011).

Land cover map Quantitative assessment on the land cover

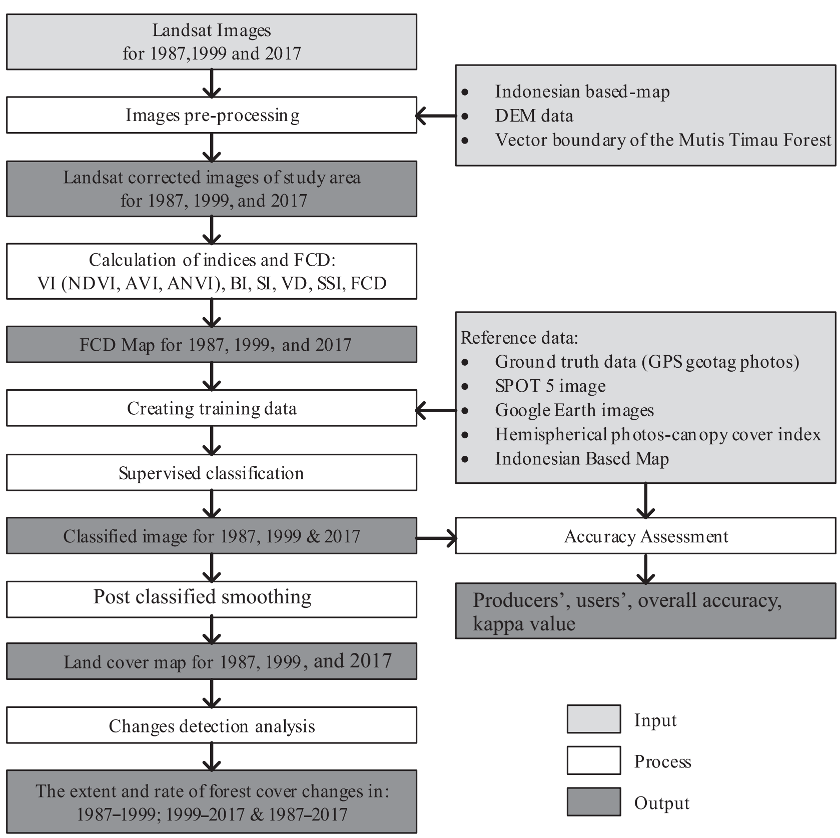

Figure 2 Flowchart of the steps involved in the assessment of the extent and rate of forest cover changes.

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Table 4 Accuracy assessment for three classified images: (a) 1987; (b)1999, and (c) 2017

(a) 1987

1987- Classified data	Reference data									Row total	Users' acc.(%)	Kappa
	Df	Mdf	Of	Shr	Agr	Svn	Set	Wb	Bl			
Df	16	7	3	2						28	57.14	0.45
Mdf	9	17	2	1						29	58.62	0.47
Of		2	21	5						28	75.00	0.68
Shr	1			16						17	94.12	0.92
Agr					5					5	100.00	1.00
Svn				1		2				3	66.67	0.66
Set							1			1	100.00	1.00
Wb								1		1	100.00	1.00
Bl				1					3	4	75.00	0.74
Column total	26	26	26	26	5	2	1	1	3	116		
Prod.'s acc. (%)	61.54	65.38	80.77	61.54	100	100	100	100	100			
Total correct	82											
Overall acc. (%)	70.94											
Overall kappa	0.64											

(b) 1999

1999- Classified data	Reference data									Row total	Users' acc.(%)	Kappa
	Df	Mdf	Of	Shr	Agr	Svn	Set	Wb	Bl			
Df	20	6	3	1						30	66.67	0.58
Mdf	4	18	7	1						30	60.00	0.50
Of	2	3	17	1						23	73.91	0.67
Shr				28						28	100.00	1.00
Agr				1	6					7	85.71	0.85
Svn				2		2				4	50.00	0.49
Set							1			1	100.00	1.00
Wb								1		1	100.00	1.00
Bl				2					5	7	71.43	0.70
Column total	26	27	27	36	6	2	1	1	5	131		
Prod.'s acc. (%)	76.92	66.67	62.96	77.78	100	100	100	100	100			
Total correct	98											
Overall acc. (%)	75											
Overall kappa	0.69											

(c) 2017

2017- Classified data	Reference data									Row total	Users' acc.(%)	Kappa
	Df	Mdf	Of	Shr	Agr	Svn	Set	Wb	Bl			
Df	13	2	5							20	65.00	0.59
Mdf	5	17	6							28	60.71	0.51
Of		7	21	1						28	72.41	0.63
Shr				26						26	100.00	1.00
Agr				3	9					12	75.00	0.73
Svn				3		2				5	40.00	0.39
Set							1			1	100.00	1.00
Wb								2		2	100.00	1.00
Bl									4	4	100.00	1.00
Column total	18	26	32	33	9	2	1	2	4	126		
Prod.'s acc. (%)	72.22	65.38	65.63	78.79	100	100	100	100	100			
Total correct	95											
Overall acc. (%)	75.00											
Overall kappa	0.69											

Df = dense forest; Mdf = moderately dense forest; Of = open forest; Shr = shrubs; Agr = agricultural land; Svn = savanna; Set = settlement; Wb = water body; Bl = barren land

map in three different years shows that forests were the dominant land cover type and cover approximately 60% of the MTFC, while settlements were identified as smallest land cover types with cover the area less than one percent of the MTFC (Figure 3). Within the MTFC, the area of dense forests, moderately forests, and open forests had almost the same proportions in 1987 and 1999, with the proportion of 23% and 20% of total the MTFC area, respectively. Whereas, in 2017 the area of open forests was greater than moderate forests and dense forests (Figure 3). The proportion of forest area to total area of forest management unit for KPH TTS, the KPH TTU, and CAGM was approximately 40%, 50%, and 80%, respectively (Figure 3).

Spatial distribution of land cover classes shows that forest classes were commonly found in the middle, while, non-forest classes, e.g., agricultural land and settlements, were found along the MTFC boundary (Figure 4). Based on the forest management unit, forest classes were evenly distributed throughout the CAGM (Figure 4). In the KPH TTS area, forest classes were distributed in the southern and northern parts, while the middle part was dominated by shrubs class. Forest was also found in the northwestern and the southeastern part of the KPH TTU area (Figure 4). There was an increase in agriculture in the central part of KPH TTU in the 1999 (Figure 4b) land cover map, and it has been continued at the same location with additional locations in the southeastern part of CAGM in the 2017 land cover map (Figure 4c).

Land cover changes The change in each land cover classes during three-time intervals of change detection analysis (1987–1999, 1999–2017, and 1987–2017) illustrates that dense forest tends to decrease gradually. Meanwhile, agriculture and settlement tend to increase (Figure 5) slightly. The changes in the remaining classes were dynamic in which there is an increase in the period and a decrease in

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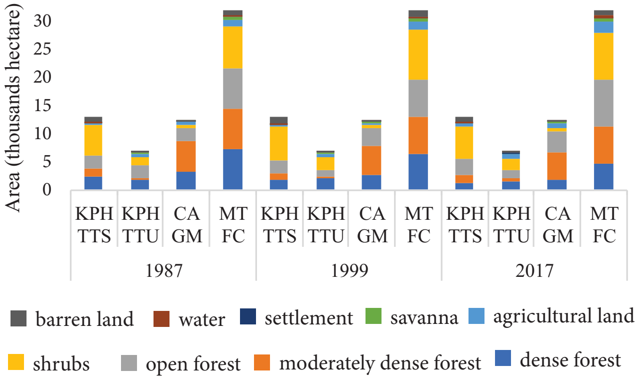
another period (Figure 5).

"From–to" detection analysis shows that in the two-time interval (1987–1999 and 1999–2017), 65% of the MTFC area was unchanged and the remaining 35% of the area was changed (Table 5). The dominant land cover changes in three time period were "dense forest to open forest," "moderate dense forest to open forest," "open forest to shrubs," "open forest to agriculture", and "shrubs to agriculture" (Table 5).

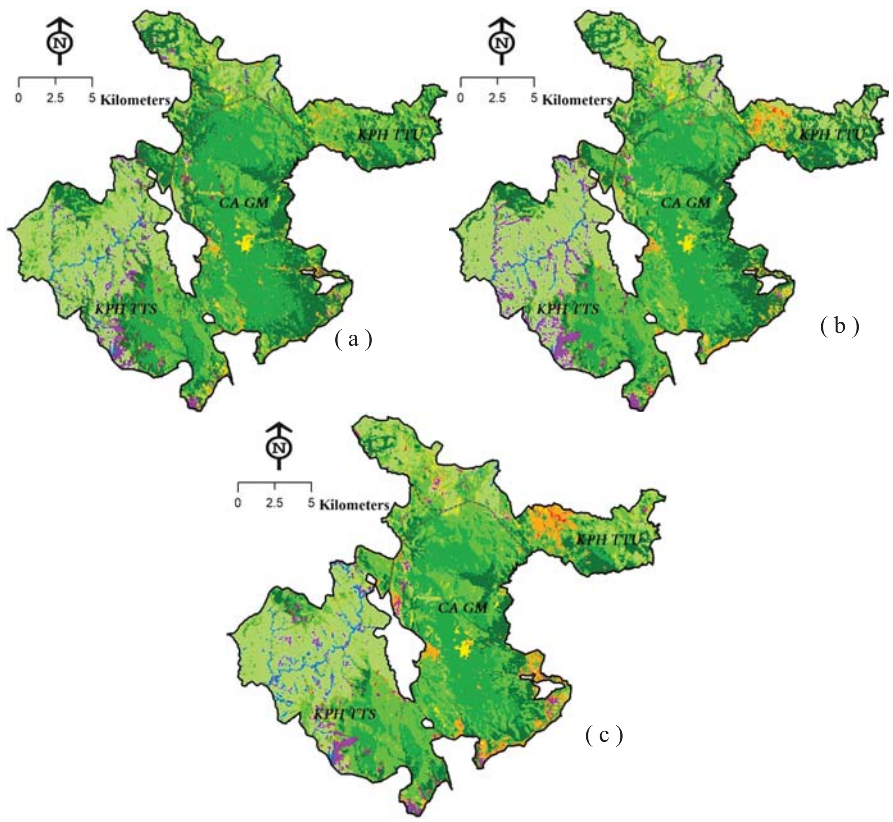


KPH TTS = *Kesatuan Pengelolaan Hutan Kabupaten* Timor Tengah Selatan; KPH TTU = *Kesatuan Pengelolaan Hutan Kabupaten* Timor Tengah Utara; CA GM = *Cagar Alam* Gunung Mutis.

Figure 3 Stacked histogram describing the extent of land cover classes in three forest management unit within the MTFC in 1987, 1999, and 2017.

Figure 6a represents the extent, and rate of four types of forest cover changes in the MTFC calculated from 'from–to' detection analysis. The extent and rate of deforestation during 1987–1999 was higher than those in the period 1999–2017 (Figure 6a). Forest degradation was identified as a type of forest cover change that have the highest extent and rate of change both in all three periods (Figure 6a). The annual extent and annual rate of deforestation, forest degradation, forest regrowth, and afforestation during 1987–2017 in the MTFC were 74.38 ha (0.36%), 160.67 ha (1.10%), 49.17 ha (0.69%), and 41.74 ha (0.40%), respectively (Figure 6a). In each forest management unit, the annual extent and annual rate of deforestation in KPH TTU, KPH TTS, and CAGM during 1987–2017 were 32.55 ha (0.82%), 25.51 ha (0.44%), and 16.31 ha (0.15%), respectively (Figure 6b).

Spatial distribution of forest cover changes in three forest management units within the MTFC describes that the middle part of the KPH TTU was identified as the region with the most deforestation sites in the period of 1987–1999 (Figure 7a). From 1999 through 2017, deforestation mostly occurred in the southeastern part of the CAGM (Figure 7b). During 1987–2017, deforestation mainly was happened in the MTFC boundary (Figure 7c).



Dense forest (); moderate dense forest (); open forest (); shrubs (); agricultural land (); savanna (); settlements (); water bodies ( ); barren land ().

Figure 4 Spatial distributions of land cover classes of three forest management unit within the MTFC in three different years: (a) 1987, (b) 1999, and (c) 2017.

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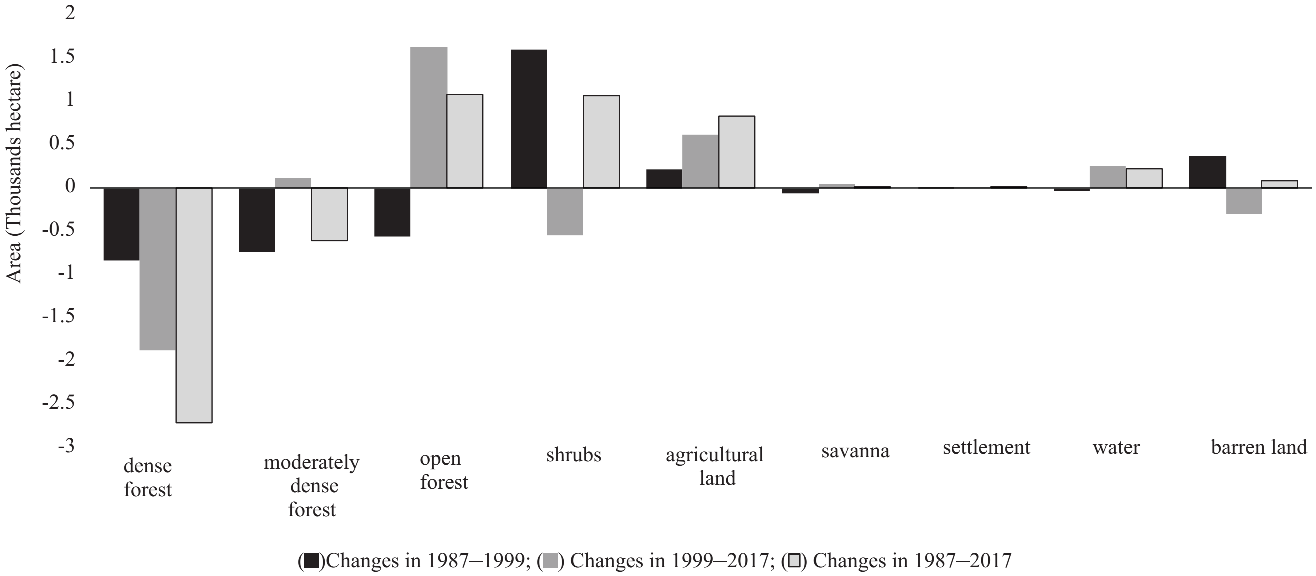

Figure 5 The change in land cover classes obtained from change detection analysis for three time intervals.

As indicates in the results, the existence of settlements and agriculture within the MTFC were shown by land cover maps in 1987, 1989, and 2017. These settlements are parts of 27 villages located around the MTFC area, and some of those are located inside the MTFC area. In a broader scope, these villages are parts of 25,800 villages (34% of total villages in Indonesia) that identified as forest fringe villages (MoEF, 2018). Indonesian Statistical Bureau found that most people in the village around the MTFC have a livelihood as dryland farmers. Population growth with their needs, force people to convert and modify forest area in various ways, some of them are agriculture expansion and the development of the new settlement area. Thus, it is reasonable if the increase of agricultural land and settlements area is directly proportional to declined forest cover area, as highlighted by the previous study which found that people activities, e.g., agriculture expansion, infrastructure, or settlement expansion, are the main drivers of deforestation in the tropical region (Geist & Lambin, 2002; Hosonuma et al., 2012).

The results indicated that the annual extent (6 ha) and annual rate of deforestation (0.03%) in the MTFC during 1999–2017 is nearly similar than those in past study on mountain forest monitoring in Indonesia during 2000–2012 which found that the annual extent and rate of forest loss were 5 ha and 0.04%, respectively (Margono, 2014). The annual extent and annual rate of deforestation in mountain forest type are a lower than those in other forest types, i.e., lowland forest that have deforestation extent of 254 ha year^{-1} and deforestation rate of 0.60% year^{-1} (Margono, 2014). Giving the fact that most people live in a lowland area, lowland forests were identified as the first forests affected by anthropogenic disturbances. At the national level, during 2000–2012, more than half deforestation occurred within accessible lowland forests, while mountain forests are more preserved by topographical features and less forest conversion (Margono, 2014). Therefore, it is reasonable if deforestation extent and rate in lowland forest is higher than those in the mountain forest.

The results also indicated that there is a difference in the deforestation extent and rate under different time periods of analysis. Under different time period of analysis, the differences in deforestation extent and rate might be caused by the difference of political condition at those period times. Related to the political condition, at least two key events have been occurred in the study area, namely the fall of Suhartos' regime in May 1998 and East Timorese referendum in August 1999, that following by political crisis. Previous studies have highlighted the explosion of illegal logging caused by political instability in Indonesia during the late of the 1900s (Burgess et al., 2010). Based on this fact, it is reasonable that the deforestation rates within the MTFC in 1987–1999 was higher than those in 1999–2017. This statement is in line with the latest forest assessment, the State of Indonesia Forest 2018 published by Indonesia Ministry of Environment and Forestry that reported the annual rate of deforestation within forest areas in Indonesia (120.60 million ha) was approximately 1.77% during 1990–1999, and in the period of 2000–2017, its rate has declined to be 0.44%.

The result revealed that there is a difference in the extent and rate of deforestation under differences in forest management units. This might be caused by the difference in the quality of forest governance in each forest management unit. An assessment on some forest governance indicators, i.e. the independence of forest agency from political interference, capacity of forest agency staff, law enforcement, and coordination/stakeholder involvement in land management policies (Mulyani & Jepson, 2013; Suwarno et al., 2015), showed that forest governance in both

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Table 5 'From-to' change detection analysis for three time intervals: (a) 1987–1999; (b) 1999–2017 and (c) 1999–2017 in the MTFC

(a) 1987−1999

1987− Land cover classes	1999−land cover classes (ha)									Total 1987
	Df	Mdf	Of	Shr	Agr	Svn	Set	Wb	Bl	
Df	4,410	816	1,157	439	177	9	1	1	236	7,246
Mdf	698	5,324	1,106	76	67	5			36	7,312
Of	1,043	323	3,598	1,389	543	66	7	13	126	7,108
Shr	126	38	175	6,287	189	75	9	52	331	7,281
Agr	97	53	387	213	421	46	15	12	84	1,328
Svn	6	2	93	70	72	183	3		13	442
Set	1	0	7	16	15	0	2	0	1	42
Wb	1	3	1	47	7		1	130	97	285
Bl	32	22	31	355	56	5	6	41	392	939
Total 1999	6,413	6,581	6,556	8,892	1,546	388	43	249	1,317	31,984

(b) 1999−2017

1999 – Land cover classes	2017− land cover classes (ha)									Total 1999
	Df	Mdf	Of	Shr	Agr	Svn	Set	Wb	Bl	
Df	3,266	1,022	1,526	217	298	9	1	5	69	6,413
Mdf	456	4,822	1,105	102	57	3		5	31	6,581
Of	534	551	4,495	395	420	69	1	0	90	6,556
Shr	124	127	586	6,905	520	120	15	159	335	8,892
Agr	106	125	281	167	692	59	13	8	95	1,546
Svn	7	5	49	90	53	169	0	0	15	388
Set	3	1	1	3	18	2	9	0	4	43
Wb	0	2	3	60	3	0	1	162	18	249
Bl	47	46	145	406	105	14	9	176	368	1317
Total 2017	4,542	6,701	8,191	8,345	2,168	444	50	516	1,025	31,984

(c) 1987−2017

1987 – Land cover classes	2017−land cover classes (ha)									Total 1987
	Df	Mdf	Of	Shr	Agr	Svn	Set	Wb	Bl	
Df	3,290	1,117	1,911	404	327	15	2	14	166	7,246
Mdf	453	4,898	1,792	92	46	4	0		26	7,312
Of	569	453	3,717	1,251	846	74	6	51	142	7,108
Shr	50	57	329	5,950	343	104	13	155	280	7,281
Agr	113	106	282	181	431	78	15	27	95	1,328
Svn	28	14	71	90	66	162	0		11	442
Set	1	3	4	10	19	1	2		3	42
Wb	1	4	5	64	5	0	1	172	33	285
Bl	38	50	80	304	86	6	11	96	269	939
Total 2017	4,542	6,701	8,191	8,345	2,168	444	50	516	1,025	31,984

Df = dense forest; Mdf = moderately dense forest; Of = open forest; Shr = shrubs; Agr = agricultural land; Svn = savanna; Set = settlement; Wb = water body; Bl = barren land

KPH TTU and KPH TTS is considered weaker than those in CAGM. Based on this condition, it is reasonable if the deforestation rate in KPH TTU and KPH TTS is higher than those in the CAGM.

Previous studies on forest degradation have been highlighted that human activities such as livestock grazing, shifting cultivation, and the wood collection could be as drivers of declined forest cover quality (Montgomery, 2015; Kurniadi et al., 2017). It is widely known that East Nusa Tenggara (*Nusa Tenggara Timur*, NTT) Province is the fourth largest livestock producer in Indonesia (BPS, 2016). Livestock in NTT which is dominated by cattle, buffalo, and horses are commonly wildly grazed in the savanna or open forest. Uncontrolled wild grazing activities which have some impacts, e.g., increasing soil compaction, decreasing soil porosity, and reducing soil infiltration become inhibiting factors on natural regeneration process (Kurniadi et al., 2017). In addition to wild grazing activities, most of the upland farmer family in NTT Province had previously practicing “slash–burn” or widely known as shifting cultivation (Montgomery, 2015). Increasing the frequency of shifts also meant increasing annual burning, with the resulting smoke and sometimes also become an initial cause of forest fire (Montgomery, 2015). Another fact states that NTT is the province with the most significant number of firewood user (approximately 80% of the total household in NTT) in Indonesia during the last decades (BPS, 2016). In line with previous studies, such three identified activities, i.e., wild grazing, slash-burn practicing, and firewood extraction, with their supporting facts, can be identified as factors leading to forest degradation in the MTFC area.

In addition to the negative forest cover change types, i.e.,

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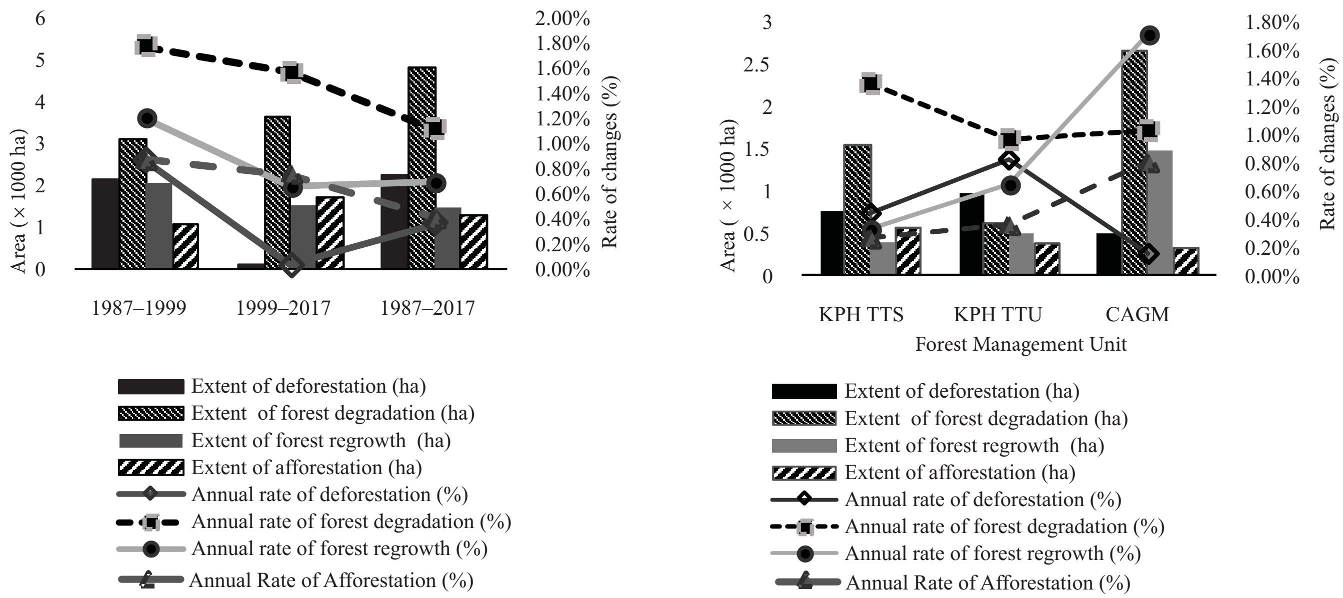
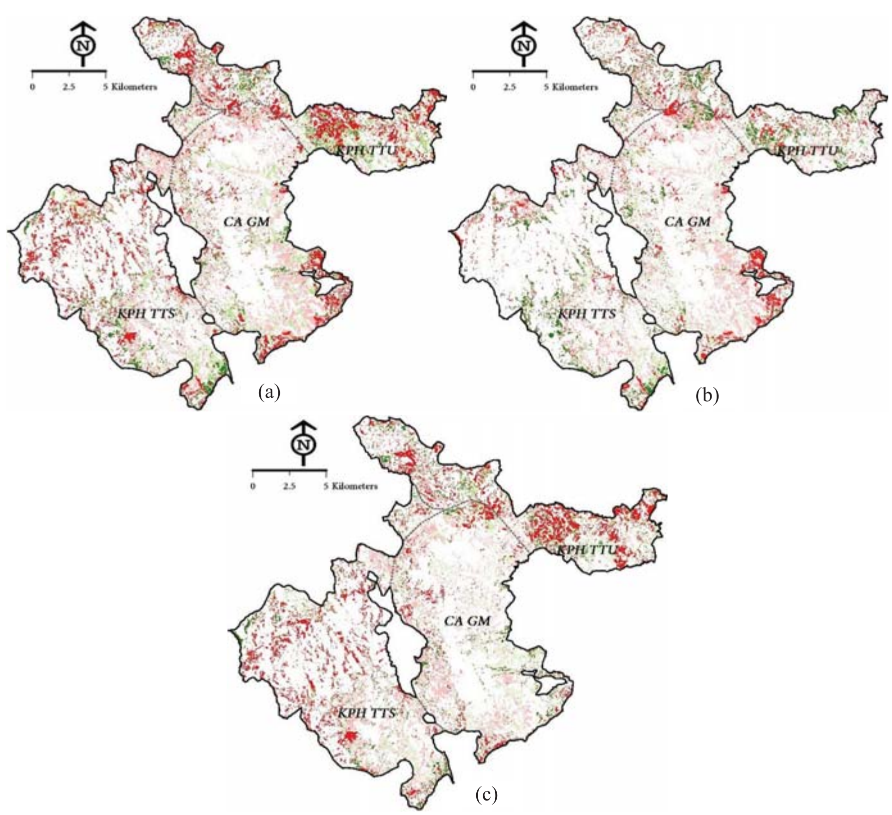


KPH TTS = *Kesatuan Pengelolaan Hutan Kabupaten* Timor Tengah Selatan; KPH TTU = *Kesatuan Pengelolaan Hutan Kabupaten* Timor Tengah Utara; CA GM = *Cagar Alam* Gunung Mutis)

(a) (b)

Figure 6 (a) The extent and annual rate of forest cover changes for three time intervals in the MTFC and (b) the extent and annual rate of forest cover changes in each forest management units in 1987–2017.



Forest management unit border ( ); deforestation ( ); forest degradation ( ); forest regrowth ( ); afforestation ( ); unchanged area ( ).

Figure 7 Spatial distributions of forest cover changes within the MTFC within three time periods: (a) 1987 –1999, (b) 1999–2017 and (c) 1987–2017.

deforestation and forest degradation, analysis of land changes in the MTFC also found the positive forest cover changes, namely: forest regrowth and afforestation. Forest regrowth also called forest improvement, or the natural growth of the tree might mainly cause forest regeneration. Trees can survive and grow under unique combinations of environmental factors such as nourishment, moisture, light, and space (Ward et al., 2006). Interaction these environmental factors at the scale of the seedling will determine the ability of seedling to germinate become established, survive, and grow (Ward et al., 2006). In case of afforestation, the National Movement of Forest and Land Rehabilitation (*Gerakan Nasional Rehabilitasi Lahan*) launched in 2003, "One man One Tree Movement" and "One Billion Indonesia Trees" launched in 2009 are some governments programs that programs intended for increasing the areal extent of afforestation and reducing the degraded land.

Considering the negative impact of deforestation and forest degradation, various stakeholder has formulated some policies or programs. We describe the following deforestation related policies:

(1) Revision on forest designated area policy

According to the Ministry of Forestry Decree No. 89/1983 on forest designated area in NTT, there were some settlements within the forest area. With the enclave policy, the number of settlements inside the MTFC area began to reduce since the implementation of newer forest designated area under Ministry of Forestry Decree No. 423/1999 and Ministry of Forestry Decree No. 3911/2014. Reducing a number of settlements within the MTFC was expected to minimize deforestation and forest degradation.

(2) Reducing Emission from Deforestation and Forest Degradation (REDD)

The MTFC area is one of several locations in Indonesia that was selected as the site for REDD implementation. REDD project was initiated by making a memorandum of understanding (MoU) that was signed in September 2009 (Pujiono et al., 2011). The KYEEMA Foundation, with funding support from Australian Government (AusAID), has worked with the local non-government organization, to develop a REDD project that will enable communities to manage the MTFC better and materially benefit from REDD.

(3) Community forestry

Approximately 12% of the KPH TTU area or equal to 810 ha have defined as community forestry areas based on Ministry of Forestry Decree No. 182/2015. This area has been distributed to six forest farmer groups with a total membership of 423 households. Success stories of social forestry program on avoiding deforestation and improving people welfare in Indonesia have been highlighted by previous studies (Santika et al., 2017; MoEF, 2018). Regarding this fact, further research is needed to find out the effectiveness of community forestry implementation within the MTFC in reducing deforestation.

(4) Land Object of Agrarian Reform (*Tanah Objek Reformasi Agraria-TORA*)

Based on the Ministry of Forestry Decree No.180/2017 on Indicative Map of Forest Allocation Area for Land Provision of TORA (*Peta Indikatif Alokasi Kawasan Hutan untuk* TORA), the redistribution of land from forest release is allocated 4.85 million ha. Of these areas, NTT Province has been identified as having a potential area for TORA of 87,700 ha. The settlement, one of the land cover types in this study, which was found within the MTFC from 1987 to present, could be one of the potential sites to be considered in the TORA.

(5) Customary law

The indigenous peoples within the MTFC consider that forests and mountains are a place for their ancestral (Sumanto & Pujiono, 2009). Some forest area is therefore considered as forbidden forests (*hutan larangan*), and there will be sanctions for anyone who logs or extracts other forest resources. The existence of indigenous peoples and their customary laws still exist today, and some of them are more obey their law than formal law established by the government (Sumanto & Pujiono, 2009). Therefore, it is reasonable that in prohibited forest areas, e.g., around the peak of Mount Mutis, there is no significant change in forest cover.

There are some benefits in this study. It was found that the use of hybrid FCD model/ supervised classification approach is a simple method to visualize and quantify the forest cover changes. This study also demonstrated the usefulness of FCD model as exploratory tools in estimating forest changes processes, e.g., deforestation, forest degradation, forest regrowth, and afforestation. Technically, the FCD model that used as an approach for generating forest canopy density map is required very less time as compared to other conventional methods (Candrashekhar et al., 2005). This technique was highly automated in processing, so this method was ideal for large area application (Bauer et al., 1994) as same as Indonesian forest areas. Economically, by using satellite imageries freely with moderate resolution as main data, this approach could be identified cost-effective method. Even it did not provide information in a deep stage, this method could detect forest canopy density class and their changes that could be used as basic information for forest management activities, e.g. planning afforestation, reforestation and rehabilitation activities; planning silvicultural system; planning timber extraction; and wildlife habitat management (Candrashekhar et al., 2005).

However, there are some limitations to this study. Firstly, the main data was Landsat images that only have a medium resolution. Hence, the areas below the pixel size were very difficult to detect and sometime could not be detected. For future study, it is important to use high-resolution satellite data, e.g., synthetic aperture radar (SAR) and/or LiDAR data. Thereby, the small change can be detected (Mitchell et al., 2017). Secondly, FCD model also has some limitations, e.g., (1) sensor specific (use the sensor that only provides thermal band) and (2) only consider on the bio-physical phenomenon in index calculation (Candrashekhar et al., 2005). It is important to use another sensor and develop the model that involve more related factors in further research. Thirdly, this study only illustrated forest cover changes with their predictive driving factors based on previous studies. The establishment of a model of forest cover changes is therefore required to describe actual factors influencing forest changes within the MTFC in future research.

Conclusions

Our study demonstrated that the hybrid classification - combining FCD model and supervised classification, proved to be a technically and economically advantageous approach and allowed us to visualize and to quantify land cover within the MTFC over time with the moderate level of accuracy. In three different years (1987, 1999, and 2017) of land cover maps, the study found that forests are the dominant land cover type which covers about 60% of total the MTFC area. Analysis of forest cover changes in three time periods (1987–1999, 1999–2017, and 1987–2017) described that approximately 35% of the MTFC area was changed. The changes were dominated by deforestation and forest degradation which were indicated by the tendency of a decline in dense forest area and an increase in the field of agriculture and settlement for three periods of analysis. Although found on a small scale, positively forest cover changes (forest regrowth and afforestation) were found. Our study has estimated that during three decades (1987–2017), the annual extent and annual rate of deforestation, forest degradation, forest regrowth, and afforestation were 74.38 ha (0.36%), 160.67 ha (1.10%), 49.17 ha (0.69%), and 41.74 ha (0.40%), respectively. For future research, it is important to develop a model that can be used to explain the factors contributing to forest cover changes in the MTFC area.

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