J. Mt. Sci. (2019) 16(10): 2215-2231 e-mail: jms@imde.ac.cn http://jms.imde.ac.cn
https://doi.org/10.1007/s11629-019-5480-1

Assessment of causes and future deforestation in the mountainous tropical forest of Timor Island, Indonesia

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Citation: Pujiono E, Sadono R, Hartono, et al. (2019) Assessment of causes and future deforestation in the mountainous tropical forest of Timor Island, Indonesia. Journal of Mountain Science 16(10). https://doi.org /10.1007/s11629-019-5480-1

Abstract: The Mutis–Timau Forest Complex, one of the remaining mountainous tropical forest areas in Timor Island, eastern Indonesia that covers an area of 31,984 ha, tends to decrease gradually. Efforts to secure mountain forest functions and counteract the negative impact of declining forest areas are often constrained by data uncertainty on factors contributing to deforestation. For this reason, this study attempts to develop models of deforestation and predict future deforestation in the Mutis–Timau Forest Complex. We constructed models of deforestation that describe the relationship between deforestation and factors contributing to deforestation using spatial statistical models. In this model, we used the deforestation data for the 1987–2017 period obtained from a previous study as dependent variables and the potential causes of deforestation generated from Geographic Information System spatial analysis as independent variables. Using the probability of deforestation derived from the model, we predicted future deforestation under two different scenarios, namely, business-as-usual (as the reference scenario) and reducing emission from deforestation and forest degradation. Our findings showed that a positive relationship exists between probability of deforestation, distance to the settlement, and population density variables, whereas a negative relationship exists between likelihood of deforestation, elevation, slope, distance to the road, distance to the savanna, and forest management unit variables. During the 2017–2030 period, under the business-as-usual scenario, the Mutis–Timau Forest Complex will lose 1327.65 ha in forest area with an annual deforestation rate of 0.54%. Meanwhile, under the reducing emission from deforestation and forest degradation scenario, the overall forest loss was estimated to be 1237.11 ha with an annual deforestation rate of 0.50%. The predicted area of avoided deforestation in 2017–2030 under the reducing emission from deforestation and forest degradation scenario was 90.54 ha. Such data and information are important for the Mutis–Timau Forest Complex authority in prioritizing actions for combating deforestation and designing appropriate forest-related policies and supporting data for reducing emission from deforestation and forest degradation programme or other incentive schemes in reducing deforestation.

Received: 24-Mar-2019
Revised: 26-May-2019
Accepted: 21-Jul-2019

Keywords: Mountainous tropical forest; Deforestation; Spatial statistical model; Geographic information system; Reducing emission from deforestation and forest degradation

Introduction

The Mutis–Timau Forest Complex (MTFC) is one of the remaining mountainous tropical forest areas in Timor Island, eastern Indonesia that has been exposed to deforestation and degradation. The MTFC is often reffered to as the "heart of Timor Island" because of its important functions, i.e., maintaining the hydrologic cycle processes, playing a critical role as water catchment area, serving as a home for various endemic plants and native Timorese animals, providing various resources for local people (e.g., cattle feeding, building materials, and fuelwood), and shielding the atmosphere from CO_2 emissions (Lentz et al. 1998; Farida et al. 2004; Price et al. 2011). However, these functions are threatened by the fact that the MTFC area tends to decrease gradually, as reported in a previous remote-sensing-based study that stated that the extent of deforestation during the 1987–2017 period was 2231.55 ha with an annual deforestation rate of 0.36% (Pujiono et al. 2019).

The declining mountainous tropical forest areas have fragile ecosystems because of their steep slopes, which can lead to serious environmental problems, e.g., soil erosion, sediment accumulation, landslides, floods, the drying of springs, habitat destruction, the loss of biodiversity, and can have a severe impact on livelihood (Briassoulis 2000; Chakravarty et al. 2011; Price et al. 2011; Haliuc et al. 2018; Kanade and John 2018). Efforts to secure mountain forest functions and develop appropriate actions and policies to counteract the negative impact of deforestation are often constrained by data uncertainty on underlying factors and drivers of deforestation (Turner et al. 1995). In the case of the MTFC, although several previous descriptive studies have proposed the causes of deforestation, i.e., wood collection, boundary and land disputes, livestock grazing, and agricultural expansion (Lentz et al. 1998; Fisher et al. 2003; Kurniadi et al. 2017), only a few studies can spatially and statistically explain the factors contributing to deforestation.

To analyze the factors involved in deforestation, models of deforestation need to be constructed. Kaimovitz and Angelsen (1998) reviewed hundreds of deforestation models and stated that the statistical-based deforestation model is the most widely applied model because of the simplicity of model development (Koomen and Stillwell 2007; NRC-National Research Council 2013). Given certain location issues, the statistical-based deforestation model has evolved into a spatial statistical model that combines remote sensing, Geographic Information Systems (GIS), and multivariate statistical analysis (Serneels and Lambin 2001). Numerous spatial statistical models of deforestation have been established in several tropical countries experiencing large-scale deforestation, such as, Philippines, Cameroon, Bolivia and others countries in Africa, Asia and Latin America (Apan and Peterson 1998; Mertens and Lambin 2000; Geist and Lambin 2001; Mertens et al. 2004). In the case of Indonesia, deforestation modelling studies primarily focused on large islands with large forest areas which are generally dominated by lowland forest types, e.g., Sumatra, Kalimantan and Sulawesi (Gaveau et al. 2009; Linkie et al. 2010; Elz et al. 2015; Purwanto et al. 2015; Wijaya et al. 2015; Ahmad et al. 2016). Meanwhile, a limited number of studies focused on deforestation modelling in relatively small islands with limited forest areas and upland/ mountain forest types, e.g., Lombok (Wulandari 2011). Deforestation in relatively small islands is predicted to have a severe impact because of limited natural resources, fragile ecological systems, high level of forest-dependent people, and vulnerability to extinction of forest-dependent species (Tole 2002). Thus, analyzing the factors contributing to deforestation, particularly in relatively small islands, is necessary.

Regarding the factors involved in the spatial statistical model of deforestation, most of the previous studies considered the direct causes of deforestation, e.g., infrastructure development—spatially represented by distance to the road or distance to the settlement, agricultural extension—spatially represented by distance to existing agriculture, and forest resource extraction—spatially represented by slope (Geist and Lambin 2001; Linkie et al. 2010; Wulandari 2011; Elz et al.

2015; Wijaya et al. 2015; Ahmad et al. 2016). More recently, Hoyos et al. (2018) used spatial representation of climatic data and those aforementioned spatial variables to analyze forest conversion in South America. Meanwhile, deforestation model studies involved the spatial representation of complex factors, e.g., cultural or institutional factors, that were rarely investigated (Swart 2016). In the MTFC area, which is managed by three different forest management units (FMUs) - an operational unit of area dominated by forest cover that has clear boundaries and has socio-economic and ecological goals that are often closely related to the main forest functions, e.g., production forest, protected forest, or conserved forest (FORCLIME 2015) and in which the cultural values of indigenous people are characterized by the existence of forbidden forest (Sumanto and Pujiono 2009) and wild grazing activities (Kurniadi et al. 2017), we predicted that deforestation is not only affected by the factors commonly used in previous deforestation models, e.g., infrastructure expansion, agricultural expansion, and wood extraction, but also influenced by other factors, e.g., institutional and cultural factors (Geist and Lambin 2002). Therefore, the involvement of the previously mentioned factors that characterize the study area conditions in model construction needs to be considered, so that the deforestation model can represent and explain the deforestation processes.

In addition to describing the causes of deforestation, models can be used to assess future deforestation under different scenarios (Verburg et al. 2004). We can provide a picture of future alternatives for environmental problems, such as deforestation based on the presence or absence of environmental policies (Alcamo 2008). The recent environmental policy related to deforestation is reducing emission from deforestation and forest degradation (REDD). REDD is a global initiative to provide a financial reward for developing countries that are able to reduce emissions resulting from deforestation and forest degradation (United Nation-REDD PROGRAMME 2010). The MTFC area is one of several locations in Indonesia that was selected as a site for REDD implementation (Mardiastuti 2012). Only a few studies focused on projecting future deforestation under the REDD intervention (Gaveau et al. 2009; Linkie et al. 2010).

The objectives of this study are to develop a spatial statistical model of deforestation using the spatial representation of factors contributing to deforestation and predict future deforestation in the MTFC area under two different scenarios, namely, business-as-usual (BAU) and REDD implementation.

1 Material and Methods

1.1 Study area

The MTFC is located in Timor Island, one of the relatively small islands in eastern Indonesia, and extends within coordinates 124°5'25" to 124°21'44" E and 9°26'57" to 9°41'28" S. The northern part of the MTFC area is located in the Indonesia–Timor Leste border (Figure 1a). Administratively, the MTFC is located in Nusa Tenggara Timur (NTT) Province and distributed in two different districts, i.e., Timor Tengah Selatan (TTS) and Timor Tengah Utara (TTU) Districts. The climate of the MTFC area is tropical with two major seasons, i.e., the dry season (April to October) and the rainy season (November to March). The average temperature is 27°C and there is a variation since in lower elevation (lowland and coastal region) temperature get as 32°C while in the high mountains it may relatively cool, about 23°C. The average annual precipitation is approximately 1600 millimeters which occurs between November to March, with little to no precipitation during the remaining months (BMKG 2019). The MTFC covers an area of approximately 31,984 ha and consists of forests dominated by homogenous natural stands of Timor mountain gum (*Eucalyptus urophylla*), shrubs, savannas, and several seasonal rivers draining in all directions (Figure 1b) (Pujiono et al. 2011). Forests in the MTFC can be categorized as mountain forests because they have an average altitude of approximately 1,300 m above the mean sea level with an average slope of 40% or greater (Pujiono et al. 2019). Furthermore, within the MTFC area, the peak of Mount Mutis with an altitude of 2,427 m is identified as the highest place in Timor Island (Pujiono et al. 2011). The MTFC is divided into three FMUs, i.e., Timor Tengah Utara FMU (KPH TTU), Timor Tengah Selatan FMU (KPH TTS), and

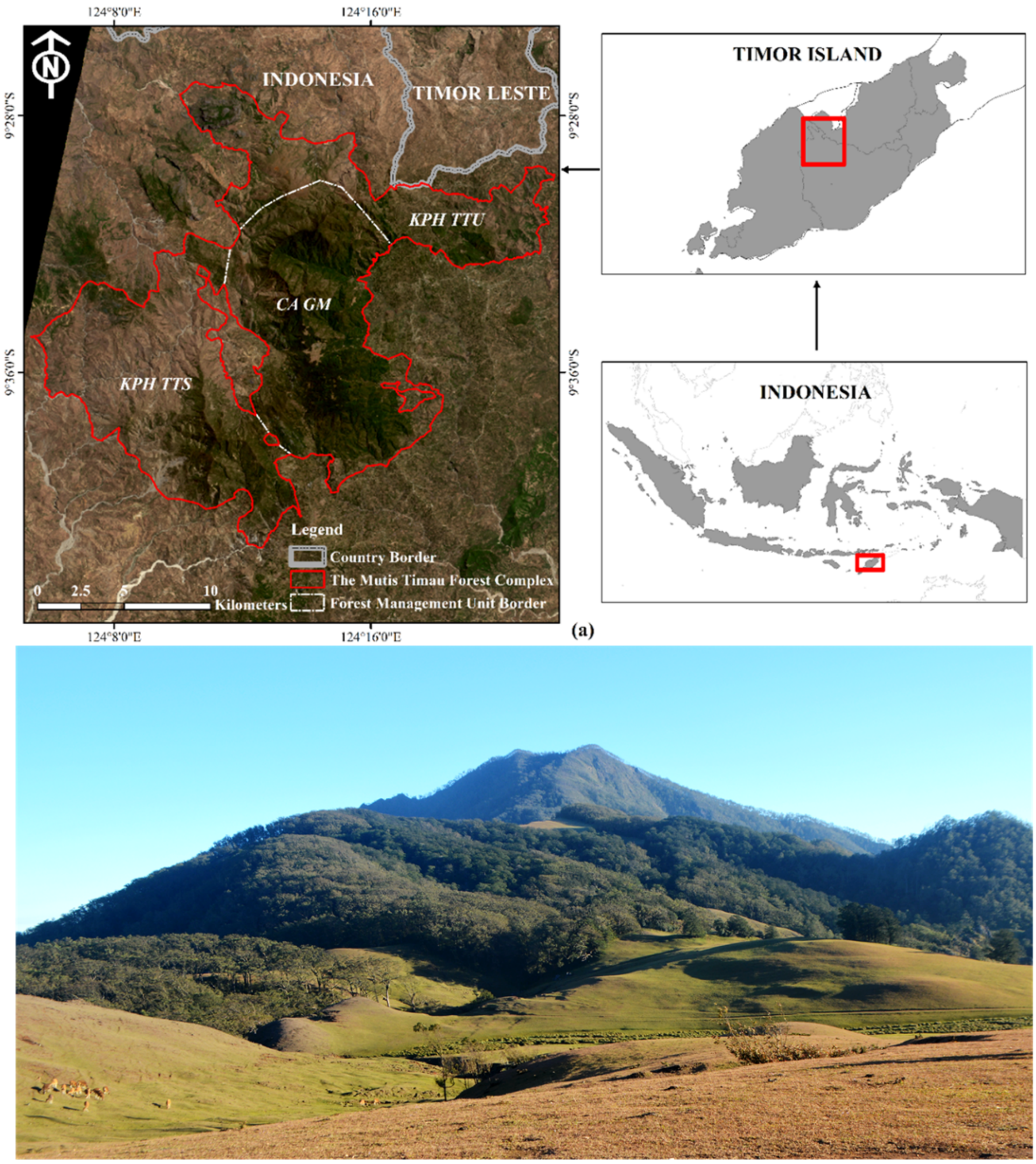

Figure 1 Location of the study area. (a) The Mutis-Timau Forest Complex, presented as Landsat 8 imagery (natural color composite—RGB Band 432); (b) Mountain forest vegetation and their surrounding savanna.

the Gunung Mutis Nature Reserve (CAGM), that cover 21%, 40%, and 39% of the total area of the MTFC, respectively (Figure 1a). Both the KPH TTU and KPH TTS function as protected forests, whereas the CAGM functions as conserved forest.

1.2 Data

We used spatial data, as listed in Table 1.

1.3 Measurement of the dependent and independent variables

We used deforestation data for the 1987–1999 and 1999–2017 periods derived from a previous study that produced land cover maps obtained from interpretation of multi-temporal and multi-sensor Landsat images, i.e., Landsat-5 Thematic Mapper (TM) on 20 September 1987, Landsat-7 Enhanced Thematic Mapper plus (ETM+) on 08

Table 1 A summary of the spatial data used to generate variables for the logistic regression models of the factors contributing to deforestation in the Mutis-Timau Forest Complex

Data	Sources	Unit	Notes
Dependent variables			
Deforestation	Deforestation map 1987–1999 Deforestation map 1999–2017 (Pujiono et al. 2019)	Categorical	Deforested = 1; Non-deforested = 0
Independent variables			
Distance to the settlement	Settlement map—extracted from the Indonesia Base Map scale 1:25,000 (BIG 2013)	Meter	Reclassified into 500 m intervals
Distance to the road	Road map—extracted from the Indonesia Base Map scale 1:25,000 (BIG 2013)	Meter	Reclassified into 500 m intervals
Distance to existing agriculture	Agricultural map—extracted from the Indonesia Base Map scale 1:25,000 (BIG 2013)	Meter	Reclassified into 500 m intervals
Distance to the river	River map—extracted from the Indonesia Base Map scale 1:25,000 (BIG 2013)	Meter	Reclassified into 500 m intervals
Distance to the savanna	Savanna map—extracted from the Indonesia Base Map scale 1:25,000 (BIG 2013)	Meter	Reclassified into 500 m intervals
Distance to the forest edge	The Mutis–Timau Forest Boundary (MoEF 2017)	Meter	Reclassified into 500 m intervals
Slope	SRTM DEM, 30 m resolution (USGS 2015)	Meter	Reclassified into 5 classes
Elevation	SRTM DEM, 30 m resolution (USGS 2015)	Meter	Reclassified into 100 m intervals
Population density	Population density data in 1987, 2007, and 2017 (BPS, 2007, 2017)	Person/km²	Population density by villages
Management	The Mutis–Timau Forest Boundary (MoEF 2017)	Forest management unit	Population density by villages

Notes: BIG = Badan Informasi Geospasial (Geospatial Information Agency), Indonesia; MoEF = Ministry of Environment and Forestry, Indonesia; USGS = United States Geological Survey, USA; BPS = Badan Pusat Statistik (Central Bureau Statistic), Indonesia

September 2009 and Landsat-8 Operational Land Imager (OLI) on13 October 2017 (Pujiono et al. 2019) as the dependent variable in model construction. We classified deforestation data into binary or dichotomous variable (in which there are only two possible outcomes) coded as “1” (presence of deforestation) or “0” (absence of deforestation). We considered the factors contributing to deforestation, namely, infrastructure expansion, agricultural expansion, forest extraction, demographic, cultural, and institutional, as the independent variables (Geist and Lambin 2001; Kissinger et al. 2012). Infrastructure expansion was spatially represented by distance to the settlement and distance to the road; agricultural expansion was spatially represented by distance to existing agriculture, distance to the forest edge, and distance to the river; and forest extraction was spatially represented by slope (Geist and Lambin 2001). Regarding the cultural factors, we used distance to the savanna and elevation to represent wild grazing activity and location of customary/ forbiden forest, respectively (Sumanto and Pujiono 2009; Kurniadi et al. 2017). By contrast, we used population density and FMUs to represent the demographic and institutional factors, respectively. We conducted GIS spatial analysis (Euclidean distance) of the Indonesia Base Map (*Peta RBI*) data to generate independent variables of distance to the road, distance to the settlement, distance to existing agriculture, distance to the savanna, and distance to the river. We also used the Euclidean distance tool to analyze the MTFC vector boundary to produce the distance to the forest edge variable. Using time series population data obtained from the Statistical Bureau and the map of designated forest area, we generated the maps of population density and FMU variables, respectively. We extracted digital elevation model data to generate the slope and elevation variables. We integrated all of these variables in a GIS and co-registered it geometrically with the deforestation maps. We prepared all spatial-based variables under the guidance of the software tools of ArcGIS 10.4.1. (ESRI - Environmental Systems Research Institute 2016).

1.4 Sampling procedures

The unit of analysis was a pixel with the dimensions of 30 m × 30 m (Landsat imagery pixel size). We calibrated the spatial statistical model of deforestation in the MTFC for two time periods (i.e., 1987–1999 and 1999–2017). From a total of 358,380 pixels that covered the entire MTFC area, we only evaluated the forest areas. Consequently, the pixel numbers in the 1987–1999 data were 240,487 pixels (67% of the total pixels), which consisted of 205,086 pixels (unchanged forest) and 35,401 pixels (deforested area). In the 1999–2017 period, the pixel numbers were 216,994 pixels (60% of the total pixels), which consisted of 197,323 pixels (unchanged forest) and 19,671 pixels (deforested area). Given the effect of spatial autocorrelation, previous studies proposed that the distance between samples (pixel) should be at least 1 km (Merten and Lambin 2000; Linkie et al. 2004; Bavaghar 2015). In the case of the MTFC area, a minimum distance of 500 m between pixels was used instead because of the relatively limited areal extent (Bavaghar 2015). Using Hawth's analysis tools for ArcGIS 10.4.1, we randomly selected 748 pixels (0.31% of the total 1987 forest pixels) and 752 pixels (0.35% of the total 1999 forest pixels) as the final sample within the 1987–1999 and 1999–2017 periods, respectively. For every sample observation (pixel-based data), we recorded the values of the dependent and independent variables for statistical analysis.

1.5 Pre-diagnostic tests for logistic regression: spatial autocorrelation and multicollinearity analyses

In the spatial statistical model, the statistical problems that are commonly detected are the presence of spatial autocorrelation between dependent variables and collinearity between independent variables (Merten and Lambin 2000; Linkie et al. 2004). Therefore, we investigated the presence of spatial autocorrelation on sample observations of deforestation using Moran's *I* index obtained from the spatial autocorrelation tools of ArcGIS 10.4.1. Moran's *I* index commonly ranges from a negative value (−1) to a positive value (1), with Moran's *I* index having positive values when similar sample observations (e.g., presence of deforestation) cluster together and negative values when different sample observations (e.g., both presence and absence of deforestation) cluster together (Htun 2013). For further statistical analysis, the expected Moran's *I* index is approximately 0, which indicates that sample observation is independent of other observations. The second statistical problem, i.e., multicollinearity, will occur when an independent variable has a robust relationship with the other independent variables in the multiple regression analysis (Shu 2003). Therefore, we tested the collinearity between independent variables with two indicators, i.e., correlation coefficient and variance inflation factor (VIF) using the Statistical Package for the Social Sciences (SPSS 23) tools. Multicollinearity between independent variables becomes a problem in a regression analysis when the correlation coefficient is equal to or greater than 0.80 and the VIF value is equal to or greater than 10 (Shu 2003; Swart 2016). Therefore, independent variables that exhibited correlation coefficients greater than 0.8 and VIF values greater than 10 were excluded from the models.

1.6 Statistical analysis: logistic regression

On the basis of the pixel-based sample that consisted of recorded deforestation data for the 1987–1999 and 1999–2017 periods as dependent and independent variables (absence of multicollinearity), respectively, we established a logistic regression model—a regression type that is applied when the dependent variable is a dichotomy (binary type) and the independent variables are of any type (Hosmer and Lemeshow 2000). Using the 95% confidence level, we examined which independent variable is significantly correlated with the probability (the likelihood) of a pixel being deforested. We also determined the Wald chi-square value to describe the relative importance of the contributions of the independent variables (Mon et al. 2012). To facilitate model interpretation, we used the odds ratio value—an odds ratio value greater than 1 indicates that an increase of one unit of the independent variable will increase the likelihood of the forest area being deforested, whereas an odds ratio value less than 1 indicates that an increase of one unit of the independent variable will decrease the probability of deforestation occurrence (Mon et al. 2012). We conducted all statistical analyses under the guidance of the logistic regression tools in the SPSS 23 software package (IBM Corp. 2015).

1.7 Post-diagnostic tests for logistic regression: model evaluation

We evaluated the performance of the model using R^2. As proposed by Swart (2016), the R^2 value of logistic regression is lower than the R^2 value of regular regression because of the binary response variable (Swart 2016). The R^2 value of 0.2–0.4 indicates the good fit of the logistic regression model (Bavaghar 2015). We also conducted a statistical test of the Hosmer and Lemeshow goodness-of-fit to evaluate the overall goodness-of-fit of the logistic regression models—if the goodness-of-fit is greater than 0.05, then no difference exists between the observed deforestation occurrences and the predicted deforestation occurrences, indicating that models can predict appropriate data to an acceptable level (Mon et al. 2012). We validated the degree performance of the model using the receiver operating curve (ROC) calculated by comparing the probability of deforestation (using 0.5 as the default value, where <0.5 = unchanged forest, ≥0.5 = deforested area) with the actual deforestation (Bavaghar 2015; Swart 2016). Specifically, we used the area under the curve (AUC) to validate the logistic regression model—an AUC value of 0.5 indicates that the accuracy of the model is equal to a random model, whereas AUC values of 0.6, 0.7, 0.8, 0.9, and 1 indicate that model accuracies are sufficient, good, very good, excellent, and perfect (without error), respectively (Bavaghar 2015; Swart 2016). We calculated the ROC and AUC values under the guidance of the ROC tools in SPSS 23. From two logistic regression equations obtained from two assessment periods (i.e., 1987–1999 and 1999–2017), we only selected one of the best logistic regression models on the basis of its R^2 and AUC values to predict the probability of future deforestation in 2017–2030.

1.8 Mapping deforestation probability and predicting future deforestation in 2017–2030 under different scenarios

We predicted future deforestation in 2017–2030 under two possible scenarios: (a) the baseline or BAU and (b) REDD implementation. The BAU scenario assumed that no significant action was taken to combat deforestation, whereas the REDD scenario assumed that REDD was implemented in the MTFC area. Under the BAU scenario, we assumed that the rate of deforestation will follow the trend of deforestation or decreasing forest cover. Under the BAU scenario, we predicted forest cover in 2030 using previous forest cover data (i.e., 1987, 1999, and 2017) and the historical extrapolation method (Huettner et al. 2009). Therefore, we determined the extent and rate of future deforestation (2017–2030) based on the observed forest cover in 2017 and the predicted forest cover in 2030. The REDD scenario assumed that the rate of deforestation in 2017–2030 will be 0.5% lower than the rate of deforestation under the BAU scenario. This assumption is based on the recent Indonesian Government Policy—post-Paris Agreement which signed on 22 April 2016, Indonesia has strengthened its commitment through the first Nationally Determined Contributions submitted to the United Nations Framework Convention on Climate Change (UNFCCC) in November 2016 with the unconditional target of 29% and the conditional target of up to 41% under the BAU scenario by 2030 (KLHK 2018).

After calculating the extent of future deforestation in the 2017–2030 period under both BAU and REDD scenarios, we mapped the spatial distribution of future deforestation using the probability values derived from the logistic regression model. We assumed that the forest with a high probability value will be deforested first, followed by the forest with a low probability value. In this study, we accumulated pixels with the highest probability values until the aggregate sum of the pixel's area is equal to the areal extent of future deforestation. When the total area of pixel accumulation with the highest probability is equal to the total area of future deforestation, a probability threshold value would be obtained. Forest areas that have a probability value less than the probability threshold were identified as remaining forests, whereas forest areas with a probability value greater than the probability threshold were identified as future deforestation areas.

2 Results and Discussion

2.1 Spatial autocorrelation and collinearity

The spatial autocorrelation test indicated that Moran's I coefficients range from 0.24 (using the 1987-1999 data) and 0.39 (using the 1999–2017 data), indicating a weak spatial autocorrelation between sample observations of deforestation (dependent variable). The collinearity analysis showed that Spearman's correlation coefficient ranges between 0.01 and 0.74 (lower than the threshold value of the collinearity coefficient, i.e., 0.8). Another indicator, i.e., VIF, ranges from 1.21 to 3.82 (lower than the threshold value of VIF, i.e., 10). Both Spearman's correlation coefficient and VIF showed that collinearity was not observed in 10 of the spatial-based independent variables in the two deforestation periods (i.e., 1987–1999 and 1999–2017). Hence, all 10 independent variables, i.e., distance to the settlement, distance to the road, distance to existing agriculture, distance to the forest edge, distance to the savanna, distance to the river, elevation, slope, population density, and FMU, could be involved in the logistic regression analysis.

2.2 Logistic regression model of deforestation

The logistic regression model indicated that the likelihood of deforestation during the 1987–1999 period was significantly correlated with the distance to the settlement, distance to the savanna, elevation, population density, and FMU variables (Table 2). As indicated by the odds ratio values shown in Table 2, the model indicated that, during the 1987–1999 period (Table 2), increasing distance to the settlement and population density increase the likelihood of deforestation by 11% (1.110–1) and 2.9% (1.029–1) for every 500 m away from the settlement and for every increase in population density by 1 person/km², respectively. By contrast, the likelihood of a pixel being deforested decreased by 7.3% (0.917-1), 34.1% (0.659-1), and 59.4% (0.406-1) for every 500 m away from the savanna, every increase in elevation by 100 m, and every increase in the number of FMUs by one unit, respectively (Table 2).

The results of the logistic regression model indicated that the probability of deforestation in the 1999–2017 period was significantly correlated with the distance to the road, distance to the savanna, slope, elevation, and population density variables (Table 2). Table 3 shows that the probability of deforestation increased by 1.8% for every increase in population density by 1 person/km². By contrast, the likelihood of the forest area being converted to non-forest area decreased by 33%, 15.1%, 26.8%, and 24.1% for every 500 m away from the road, every 500 away from the savanna, every increase in the steepness of the slope, and every increase in elevation by 100 m, respectively.

As indicated by the Wald chi-square values (Tables 2 and 3), elevation is the most important independent variable for estimating the probability of deforestation during the two time periods (i.e., 1987–1999 and 1999–2017). By contrast, distance to the savanna and population density are the variables that have the smallest influence on the likelihood of deforestation in the 1987–1999 and

Table 2 Results of the logistic regression analysis of deforestation in the MTFC during the 1987–1999 period

Variables	Parameter estimates	Std. Error	Wald	Significance	Odds ratio
Distance to the settlement*	0.104	0.041	6.353	0.012	1.110
Distance to the road	−0.094	0.088	1.155	0.282	0.910
Distance to existing agriculture	−0.045	0.077	0.340	0.560	0.956
Distance to the forest edge	0.167	0.110	2.316	0.128	1.182
Distance to the savanna*	−0.087	0.039	5.012	0.025	0.917
Distance to the river	0.033	0.053	0.377	0.539	1.033
Slope	−0.169	0.103	2.682	0.101	0.844
Elevation*	−0.417	0.049	72.042	0.000	0.659
Population density 1987*	0.029	0.007	15.585	0.000	1.029
Management unit*	−0.902	0.175	26.649	0.000	0.406
Constant	3.334	0.771	18.699	0.000	28.049

Notes: n = 748; Nagelkerke R^2 = 0.448; overall percentage prediction = 81.80%; Hosmer and Lemeshow test: chi-square = 6.137, df = 8, sig. = 0.632; ROC = 0.862. *Parameter estimates are significant at the 0.05 confidence level.

Table 3 Results of the logistic regression analysis of deforestation in the MTFC during the 1999–2017 period

Variables	Parameter Estimates	Std. Error	Wald	Significance	Odds Ratio
Distance to the settlement	0.067	0.039	2.976	0.085	1.070
Distance to the road*	−0.261	0.091	8.268	0.004	0.770
Distance to existing agriculture	0.043	0.082	0.273	0.601	1.044
Distance to the forest edge	0.168	0.112	2.256	0.133	1.182
Distance to the savanna*	−0.164	0.042	15.183	0.000	0.849
Distance to the river	−0.075	0.052	2.025	0.155	0.928
Slope*	−0.312	0.102	9.388	0.002	0.732
Elevation*	−0.276	0.047	34.912	0.000	0.759
Population density 1987*	0.017	0.006	8.013	0.005	1.018
Management unit	−0.284	0.156	3.319	0.068	0.752
Constant	2.801	0.747	14.047	0.000	16.466

Notes: n = 752; Nagelkerke R^2 = 0.261; overall percentage prediction = 82.70%; Hosmer and Lemeshow test: chi-square = 9.747, df = 8, sig. = 0.283; ROC = 0.791. *Parameter estimates are significant at the 0.05 confidence level.

1999–2017 periods, respectively.

2.3 Model evaluation

As indicated by the coefficient of determination represented by the Nagelkerke R^2 value, the logistic regression models were able to explain approximately 45% and 26% of the variability in the probability of deforestation occurrence for the 1987–1999 and 1999–2017 periods, respectively (Tables 2 and 3). Another indicator, i.e., Hosmer and Lemeshow test, has a significance value of more than 0.05 in the two time periods (Tables 2 and 3), indicating that the models predict the fit of the data to an acceptable level. The ROC of the two time periods showed that the curves tend to become relatively close to the upper left corner and relatively far from the diagonal line, indicating that the models are quite accurate. The AUC values of the two assessment periods were 0.86 (1987–1999) and 0.79 (1999–2017), indicating that the model accuracy is good and able to correctly categorize the forest areas that are really deforested area and unchanged forest. Therefore, on the basis of the coefficient of determination and AUC values, in which the Nagelkerke R^2 and AUC values in the 1987–1999 period are higher than those in the 1999–2017 period, we selected the deforestation model of the 1987–1999 period to map the probability of deforestation.

2.4 Probability of deforestation

Figure 2 depicts the map of deforestation probability (Figure 2a); the map of predicted deforestation in the 1987–1999 period, which is determined by probability values ≥ 0.5 (Figure 2b); and the observed deforestation maps in the 1987–1999 period (Figure 2c). The map of deforestation probability depicts that the northern areas of the MTFC are categorized as the most likely areas to be deforested in the future (Figure 2a). By contrast, the remaining forest areas, particularly in the middle part, were classified as the less susceptible areas to be deforested (Figure 2a).

2.5 Future deforestation under different scenarios

Under the BAU scenario, the forest cover in 2030 was predicted to be 18,107.13 ha using historical extrapolation—a method of trend analysis (Figure 3). From the comparison of this prediction and the forest cover in 2017, deforestation in the MTFC during the 2017–2030 period will be 1327.65 ha with an annual deforestation rate of 0.54%. By examining the deforestation rate and probability value obtained from the model, we obtained a probability threshold of 0.61. The forest areas in 2017 that have a probability value greater than 0.61 were identified as areas that are likely to be deforested in the 2017–2030 period under the BAU scenario (Figure 4a).

The REDD scenario assumed that the rate of deforestation in the 2017–2030 period will be 0.50% lower than the rate of deforestation under the BAU scenario. Under the REDD scenario, the forest cover in 2020 was predicted to be 18,197.67 ha (Figure 3). During the 2017–2030 period, the overall forest loss was estimated to be 1237.11 ha

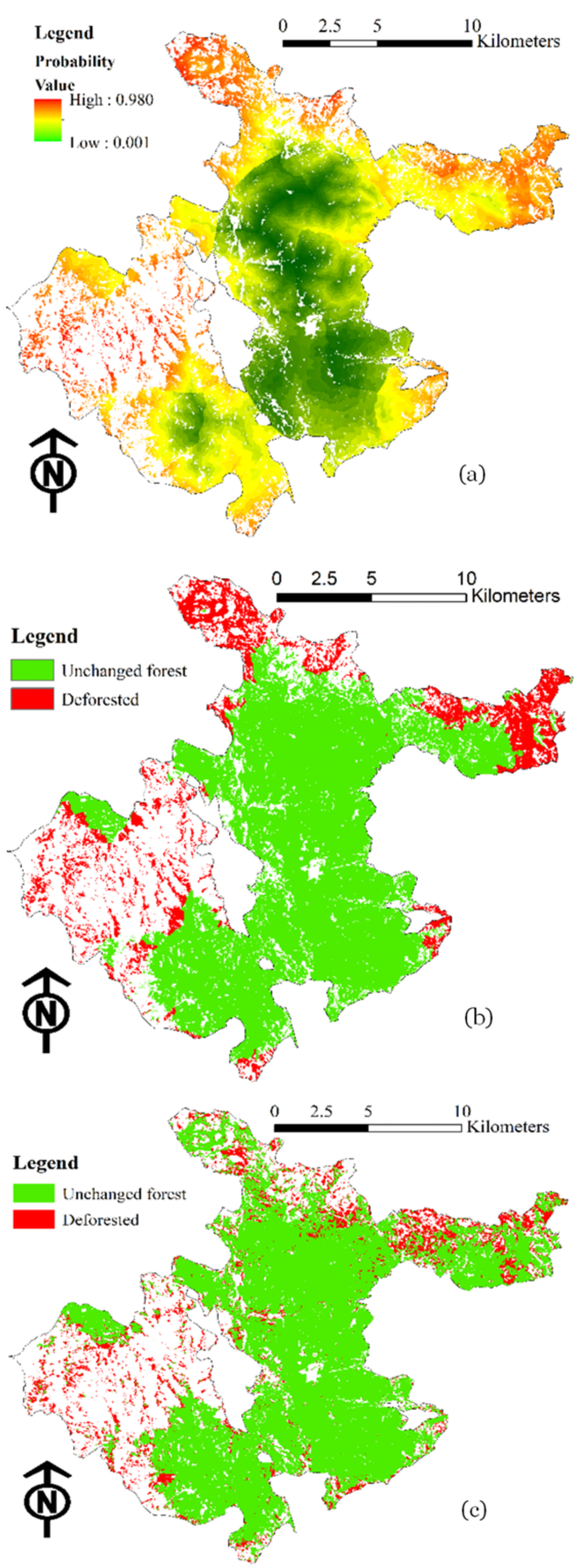

Figure 2 (a) Probability of deforestation map; (b) predicted deforestation map of the 1987–1999 period; and (c) observed deforestation map of the 1987–1999 period.

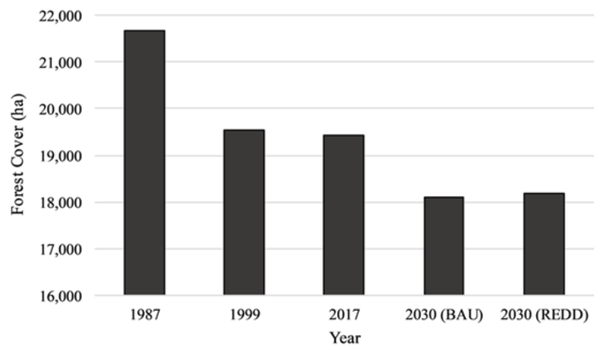

Figure 3 Trend of forest cover and predicted future forest cover in 2030 under the BAU and REDD scenarios.

with an annual deforestation rate of 0.50%. By examining the deforestation rate and probability value from the logistic regression model, we obtained a probability threshold of 0.62. The forest areas in 2009 that have a probability value greater than 0.62 were identified as areas that are likely to be deforested in the 2017–2030 period under the REDD scenario (Figure 4b).

We can determine the areas of avoided deforestation by comparing the forest cover under the BAU and REDD scenarios. The area of avoided deforestation was determined to be 90.54 ha. The distribution of avoided deforestation was located in the range of 0.61–0.62 of the probability value (Figure 4c).

2.6 Discussions

As emphasized in previous studies (Linkie et al. 2010; Htun et al. 2013; Purwanto et al. 2015; Ahmad et al. 2016), this study also determined that deforestation is likely to occur at low elevation in both periods (i.e., 1987–1999 and 1999–2017). This result indicates that altitude or elevation is a natural obstacle for people in forest extraction or logging activities (Geist and Lambin 2001; Geist and Lambin 2002; Htun et al. 2013; Kanade and John 2018). The high probability of deforestation at low elevation forest area could also be associated with agricultural expansion and infrastructure expansion (Htun et al. 2013; Kanade and John 2018). In the case of the MTFC, elevation can also be linked to cultural factors, i.e., the existence of indigenous people with their belief that forests located in the mountain or at high elevation are a place for their ancestors (Sumanto and Pujiono

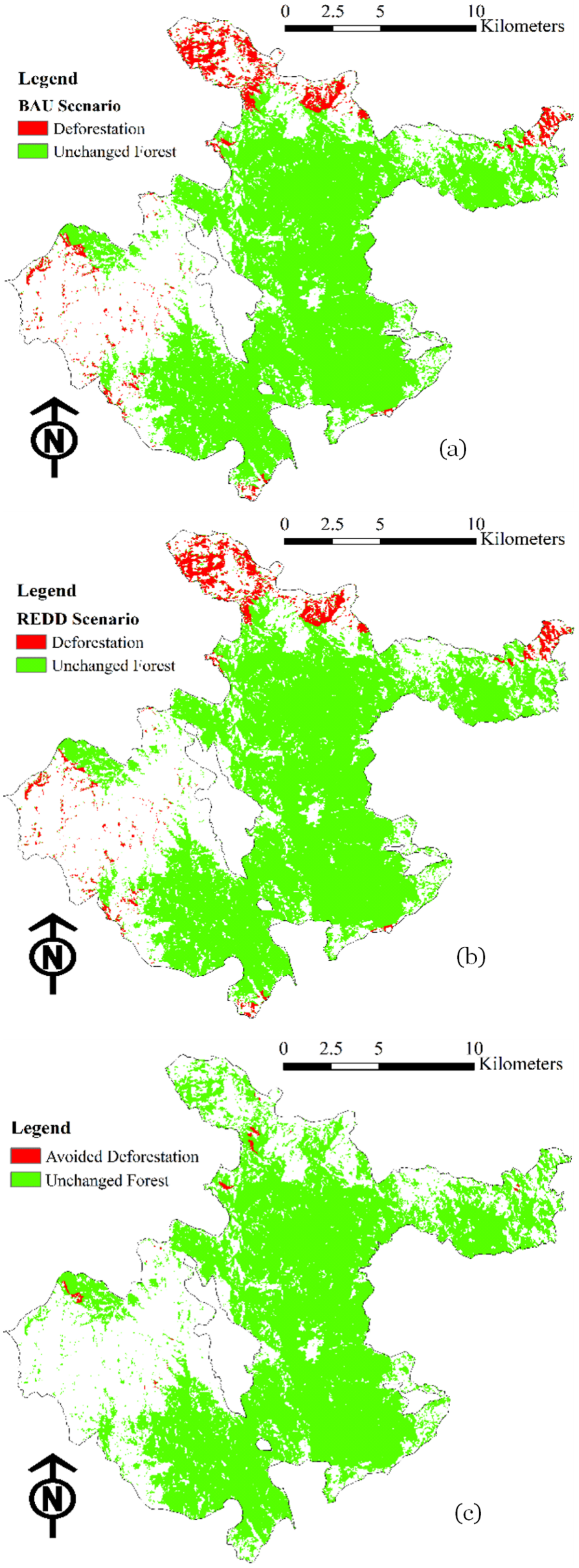

Figure 4 Map of future deforestation in the 2017–2030 period under two scenarios. (a) BAU; (b) REDD; and (c) map of avoided deforestation in the 2017–2030 period.

2009). Personal observations showed that the forest area around the peak of the mountain are commonly considered as forbidden forest or *hutan larangan*, and sanctions will be imposed on anyone who logs or extracts forest resources without permission from the leader of indigenous people (Sumanto and Pujiono 2009). Therefore, the likelihood of deforestation occurrence reasonably decreases with the increase in elevation.

In both time periods (i.e., 1987–1999 and 1999–2017), the population density variable also has a significant correlation with the likelihood of deforestation. This finding is consistent with that of previous studies (Wijaya et al. 2015; Ahmad et al. 2016), in which the increase in the population/ demography aspect will increase the probability of deforestation. The impact of forest extraction and exploitation by local people can lead to forest depletion in areas with high population density (Mon et al. 2012). Population growth, along with their needs, forces people around or in the forest area to convert and modify forest into other types of land use, e.g., agriculture and infrastructure (i.e., roads and settlements) (Geist and Lambin 2002; Hosonuma et al. 2012).

This study also determined that the risk of deforestation will increase in forest located close to the savanna in both study periods. This study used the distance to the savanna to represent wild grazing activity, which has become a culture for local people. As a part of NTT Province, which is known to be the fourth largest livestock producer in Indonesia (BPS 2016), most people in and around the MTFC area have livestock as one form of additional livelihood to support their main livelihood of subsistence farming. As a part of their culture, local people commonly wildly graze their livestock, which is dominated by cattle, buffalo, and horses, in the savanna or open forest. Uncontrolled wild grazing activities have severe impacts, e.g., increasing soil compaction and decreasing soil porosity and soil infiltration, that become inhibiting factors on the natural regeneration process (Kurniadi et al. 2017). Therefore, the likelihood of deforestation occurrence reasonably increases in the forest area close to the savanna.

The results indicated that the FMU variable also has a significant correlation with the probability of deforestation during the 1987–1999 period. Forests managed by the local government (KPH) have a greater likelihood of deforestation occurrence than those forests managed by the central government (CAGM). The differences in the probability of deforestation between CAGM and KPH might be caused by the difference in the quality of forest governance in each FMU. Personal observations of several forest governance indicators, i.e., ratio of the number of forest agency staff and the extent of forest area, the political influence from local government leader to forest agency, law enforcement, and stakeholder involvement in land management policies (Suwarno et al. 2015), showed that forest governance in KPH is considered weaker than that in CAGM. This finding is consistent with that from a previous study in which weak forest governance and institutions are identified as critical underlying drivers of deforestation (Kissinger et al. 2011).

Similar to that reported in a previous study (Htun et al. 2013), this study also determined that the risk of deforestation is estimated to increase in forest located far from settlements in the 1987–1999 period. This finding can be interpreted that the forest near the settlement may have been deforested before the 1987–1999 period, so that the probability of deforestation in the remaining forests located far from the settlement during the 1987–1999 period increases. By contrast, this result is different from the findings of most of the previous studies that emphasized that the probability of deforestation occurrence will increase if the forest is located close to the settlement (Linkie et al. 2010; Bavaghar 2015). This difference is probably caused by the differences in the level of analysis and spatiotemporal aspects (Hosonuma et al. 2012).

In the second period (i.e., 1999–2017), the distance to the road variable has a significant correlation with the likelihood of deforestation. As highlighted in previous studies (Htun et al. 2013; Wijaya et al. 2015), this study emphasized that the likelihood of deforestation will increase in forest located close to the road. As a consequence of regions that are located on the country border (Indonesia–Timor Leste), the development of infrastructure, particularly roads, within the MTFC area becomes an unavoidable thing. The existence of the road will facilitate easy access of the people to their socioeconomic interests. However, the existence of the road will negatively affect the accessibility of the forest, e.g., forest adjacent to the road. In the case of the MTFC area, this scenario is likely to be related to illegal logging activities. The decreased frequency of forest patrol due to limited forest agency staff (forest ranger) made the forest area close to road the main target of illegal logging activities.

Slope emerged as a significant variable for the probability of deforestation during the 1999–2017 period. Similar to the findings of other studies (Linkie et al. 2010; Purwanto et al. 2015; Wijaya et al. 2015), this study also determined that the likelihood of deforestation is high in low or gentle slopes. Gently sloping forests are more accessible for the activities of local people, e.g., forest resource extraction and firewood collection. Notably, NTT Province (the study area) has the largest number of firewood users in Indonesia during the past decades (BPS 2016). At least 80% of the total number of households in NTT Province use firewood for their livelihood (BPS 2016). Therefore, forests located in gently sloping areas are likely to be deforested.

Following Geist and Lambin's framework (2002), this study identified that the proximate or direct causes of deforestation in the MTFC are forest resource extraction (spatially represented by elevation and slope), infrastructure expansion (spatially represented by distance to the settlement and distance to the road), whereas the underlying or indirect causes of deforestation are demography (spatially represented by population density map), institutional (spatially represented by FMU), and cultural (spatially represented by distance to the savanna as a representation of wild grazing and elevation as a representation of the location of forbidden forest). Even if the spatial statistical models developed in this study could provide good insights into spatial information, they could not render the human decision-making and social aspects into pixels (Geoghegan 1998; Koomen and Stillwell 2007). Agarwal et al. (2002) stated that human decision-making is an aspect that should be considered in the land use and land cover change (LULCC) model to complete the spatiotemporal aspects. Human decision-making could also be assumed to be the "glue" that combines the biophysical aspect of the environmental system and the socioeconomic aspect of the human system

(Haggit et al. 2003). Further study using agent-based models (ABM), a type of process-based model (NRC 2013), will provide valuable insights into the human decision-making aspect of our findings (Parker et al. 2002).

Another limitation of this study is that some important factors related to deforestation, e.g., climate and fire, have yet to be fully explained. Numerous studies emphasized that there are interrelationship between deforestation and climate of which extreme climate is one of the causes of deforestation, while at the same time deforestation has impacts on some variables of regional climate (Coe et al. 2013; Hoyos et al. 2018; Wang and Myant 2016). Hoyos (2018) stated that the increase in annual precipitation during the period 1930-2000 in northeastern area of Gran Chaco forest area in South America made agricultural business more profitable and triggered conversion of forest to agriculture area. Meanwhile, a phenomenon of rising sea surface temperatures, called El Niño Southern Oscillation (ENSO), lead to a decrease in rainfall so that it is often associated with droughts and fires. In the last two decades, El Niño has had an impact on two dramatic fires in Indonesia, which damaged approximately 4.5 million hectares (in 1997/1998) and 0.7 million hectares (in 2015) of lowland and peatland forests which were mostly located in Sumatra, Kalimantan and Papua Islands (Tacconi 2003; World Bank 2016). Several studies in tropical regions revealed that deforestation has significance impacts on in regional climate, i.e., decreasing evapotranspiration, decreasing precipitation, delaying the onset of the rainy season, increasing temperature due to increased greenhouse gas concentrations (Coe et al. 2013; Wang and Myant 2016). In this study, we could not been able to quantitatively show the interrelationship between climate and deforestation due to the limitations of time series climate data. Neverthless, based on information from the people live in or around the MTFC area, they felt that the air temperature was not as cold as before, the agricultural crop planting schedule was shifted due to delayed rainy season and the frequency of mountain fog appearance was decreased, as results of reduced forest area in last decades. Deforestation modelling by involving climate and fire variables is one of prospective topic for future research.

The MTFC was one of the forest areas in Indonesia that was selected for the REDD implementation project (Mardiastuti 2012). This project was initiated by making a memorandum of understanding that was signed in September 2009. The name of the project was The TEBE Project—“Towards Enabling Mitigation of Climate Change Through Promotion of Community-Based Economic Growth” that aims to appropriately manage forests in the MTFC area. To achieve this goal, the KYEEMA Foundation (the project initiator) and the Australian Government (the funder), in collaboration with several local NGOs, used community engagement as the main strategy. The progress report of The TEBE Project in 2012 showed that the completed activities were consultations with various stakeholders and participatory rural appraisal and community-based assessment trainings for baseline data collection (Mardiastuti 2012). Although the progress of the REDD implementation was considered unsatisfactory, this project is considered a good step in securing the important benefit of mountain forests in the MTFC area. Personal observations of the MTFC area showed that several constraints on REDD implementation are in accordance with the findings of Howell and Bastiansen (2015) who conducted collaborative research with several institutions in Indonesia related to the REDD projects in Indonesia during 2010–2015 on the existence of conflicts of interest between stakeholders, land ownership conflicts (unclear tenure rights), local communities that are usually skeptical and still confused about the REDD concept, the assumption of the local people that REDD will eliminate their customary rights, uncertainty in the method of carbon emission calculation, and how payment will be distributed. As illustrated in this study, successful REDD implementation would reduce the rate of deforestation in the future. The low rate of deforestation could be achieved because REDD would compensate people around or in the forest area for protecting the forest. Figure 5 illustrates the basic concept of REDD linked to the scenario developed in this study (i.e., BAU and REDD implementation scenarios).

Similar to REDD, a zero-deforestation agreements of the Colombian Mainstream Sustainable Cattle Ranching project (MSCR) in

Columbia (Pedraza et al. 2018) can be adopted as a payment for the environmental services (PES) scheme at the study area, since there are a similarity on the existence of small holder cattle ranching farmers in both areas. In this project, farmers make a deal through the signing of a contract to a zero-deforestation agreement inside their land farms during the project's periods. They accept materials, technical and financial assistances associated with the development of silvopastoral system - the integration of trees and shrubs in pastures with animals for economic, ecological and social sustainability, for improving ecosystem functions of deforested/ degraded areas (Pedraza et al. 2018). Implementation of a sustainable silvopastoral system based-incentive in the MTFC area is expected to be acceptable by community and successful because the silvopastoral system is in line with the Timorese people concept of the life, called, '*Mansian-Muit-Nasi, na bua'* (in Timorese language) which means that humans, livestock and forests are an inseparable and interdependent each other, where humans get benefits from livestock, livestock search for foods in forests and forests is preserved by humans (Sumanto and Pujiono 2009).

In addition to REDD, which is a global initiative, policies or programs related to deforestation prevention are also implemented by the Indonesian government—some of which are also applied in the MTFC, i.e., revision of designated forest area, community forestry (*Hutan Kemasyarakatan—HKm*), and land as Object of Agrarian Reform (*Tanah Objek Reformasi Agraria—TORA*). The number of settlements inside the MTFC area (under the Ministry of Forestry Decree (*SK-Menhut*) no. 89/1983) began to reduce since the implementation of new designated forest area under *SK-Menhut* nos. 423/1999 and 3911/2014. The reduction in the number of settlements within the MTFC is expected to minimize deforestation. In relation to community forestry, approximately 810 ha of the MTFC area has been defined as community forestry area on the basis of *SK-Menhut* no. 182/2015. The implementation of community forestry (*HKm*) aimed to avoid deforestation and improve the welfare of the people. The TORA is a program intended to resolve land disputes within the MTFC area. The settlement, one of the land cover types in this study, which was established within the MTFC in 1987, could be one of the potential sites to be considered in the TORA (Pujiono et al. 2019). The prohibition of shifting cultivation as outlined in village regulations and applied to majority of villages in and around the MTFC area since 2000 can be considered as one of the initiatives at the local level which has a positive effect on the mountain forest management. Remote sensing-based evidence revealed that the rate of deforestation in the MTFC for the period 2000-2017 is less than those in the period of 1987-1999

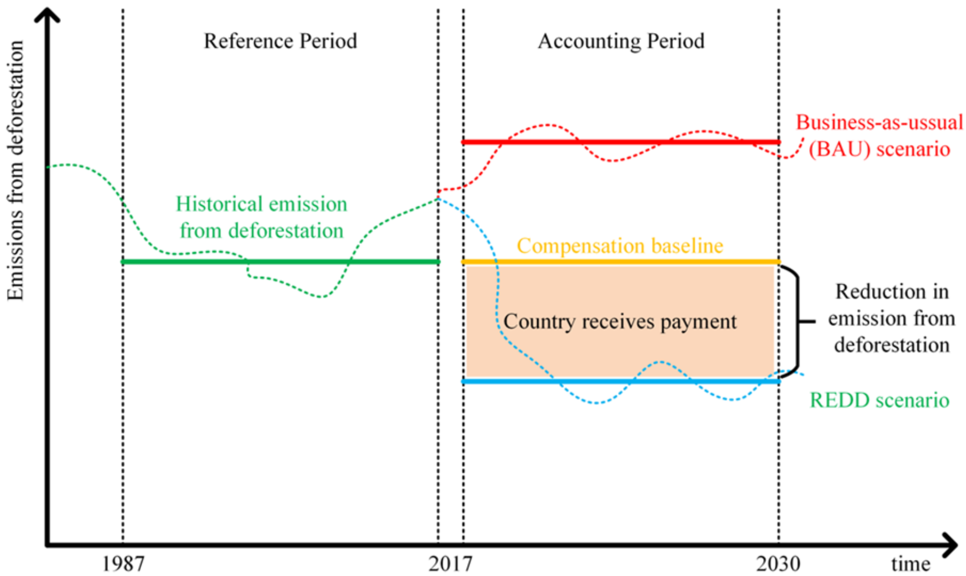

Figure 5 Basic concept of REDD (modified from Bush 2011).

(Pujiono et al. 2019). For further research, the previously mentioned programs can be considered the scenarios in predicting future deforestation or other LULCC.

3 Conclusions

In this study, a spatial statistical model can be used as an alternative method for explaining the causes of past deforestation and predicting future deforestation. This model is relatively easy to construct and provides some statistical and spatial information in describing the potential causes of deforestation. By anticipating the collinearity problem and reducing the effect of spatial autocorrelation in the sampling design step, this model exhibited a satisfactory performance in the validation step. Our findings emphasized that a positive relationship exists between probability of deforestation, distance to the settlement, and population density variables, whereas a negative relationship exists between deforestation probability, elevation, slope, distance to the road, distance to the savanna, and FMU variables. Even if this study could provide good insights into spatial information of past and future deforestation, it could not represent the human decision-making and social aspects. Therefore, developing other types of deforestation models, e.g., ABM, which are able to provide valuable insights into human decision-making in deforestation processes, is important.

In relation to future deforestation, we determined that, during the 2017–2030 period under the BAU scenario, the MTFC will lose 1,327.65 ha in forest area with an annual deforestation rate of 0.54%. Under the REDD scenario, the overall forest loss was estimated to be 1,237.11 ha with an annual deforestation rate of 0.50%. The predicted area of avoided deforestation in the 2017–2030 period under the REDD scenario was 90.54 ha. The location of future deforestation was successfully predicted by combining the threshold of the probability value obtained from the model and the rate of deforestation derived from the trend analysis. For future studies, other forest-related policies, e.g., community forestry and *TORA*, need to be included as scenarios for predicting future deforestation.

Overall, this study demonstrated the benefits of GIS and statistical analysis as exploratory tools in understanding deforestation processes, identifying factors contributing to deforestation, and predicting future deforestation. Such data and information are important for the MTFC authority in prioritizing actions for combating deforestation and designing appropriate forest-related policies and supporting data for REDD or other incentive schemes in reducing deforestation.

Acknowledgements

This study is funded by the Ministry of Environment and Forestry Republic of Indonesia through the research funding assistance program. We express our gratitude to BBKSDA NTT, the local government of TTU - TTS districts and people of the Mutis Timau forest fringe villages for research permit and assistance in data collection. We thank to Muhammad Alif K. Sahide for comments on an earlier version of the manuscript in Scientific Writing Workshop organized by Faculty of Forestry Universitas Gadjah Mada. We are also grateful to Badan Penerbit dan Publikasi Universitas Gadjah Mada and Enago for language editing service.

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