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Spatial Model Approach on Deforestation of Java Island, Indonesia

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Abstract

Java is the most populated island in the world. In 2000, forest area in Java covered about 2.0 million hectares but in 2005 it decreased to 1.2 million ha. Regardless of the debate on the different methodology of forest inventory applied in 2005 that resulted in under estimation figure, the decrease of forest cover in Java is obvious and needs immediate response. Spatial modeling of the deforestation will assist the policy makers to understand the process and to take it into consideration when decisions are made. Moreover, the result can be used as data input to solve environmental problem resulted from deforestation. We modeled the deforestation in Java by using logistic regression. Percentage of deforested area was considered as the response variable, whilst biophysical and socioeconomic factors that explain the current spatial pattern in deforestation were assigned as explanatory variables. Furthermore, we predicted future deforestation process, and then it was validated with actual deforestation derived from MODIS satellite imagery between 2000-2008.

1. Introduction

Since 2000, population of Java has been growing by 2.08% per year compared to 1.31% in the 1980's. Java accounts for 70% of total population of Indonesia. The population concentrates in only 7 % of land area of Indonesia or 1,026 inhabitants per km^2 (BPS-Statistics Indonesia, 2008). If the rate is assumed to be steady, the population will reach about 212.8 million or 2,070 inhabitants per km^2 in 2050. There are many publications pointed out that population increase will affect land use changes (Ramankutty et al., 2002). In the process of land use changes, there are also activities such as forest clearing for agriculture, wood extraction, settlement and infrastructure expansion that are attributed to deforestation. Angelsen and Kaimowitz (1999) argued that increased population growth leads to increase of demand for forest land and resources, and furthermore, the high rates of deforestation will drive to poverty. Driving of the population growth to the rate of deforestation is also pointed out by Zhang et al. (2000). He stated that population growth in China is the main factor contributed to the loss of natural forest. Studies from Brazil (Andersen, 1996), Mexico (Barbier and Burgess, 1996), and Thailand (Cropper et al., 1997) also gave similar result. However, Sunderlin and Resosudarmo, 1996 pointed out that the impact of population on the deforestation in Indonesia is site-specific.

So far, analyses of deforestation were based on numerical statistical data and less consideration on spatial context, whilst, in fact, it is very important to assist policy makers to understand the process and take it into consideration when decisions are made. Important data on the rate and spatial distribution of deforestation have been provided by the analysis of remote sensing images (DeFries et al., 2000). Furthermore, Lambin (2001) and Angelsen and Kaimowitz (1999) summarized that other researchers had studied deforestation at detailed scales by identifying the causes and underlying driving factors of the processes leading to deforestation. These models make an important contribution to the integrated analysis of the different deforestation trajectories in their environmental and socio-economic context.

Land-use and land cover changes analysis in Java has been investigated by Verburg, Veldkamp, and Bouma (1999). They have predicted that land use change will especially occur in the lowland areas, either directly through construction or indirectly through the demand for higher value crops. The upland areas will stay primarily rural. The models were developed based on rough grid spatial data equals to 40 km x 40 km (1,600 km^2) derived from agricultural surveys of the Central Bureau of Statistics and coupled with provincial forest cover.

The objective of this study is to illustrate possible application of spatial modeling for deforestation by using available forest cover data derived from remote sensing data and social economical data derived from village survey which were mapped on 10 km x 10 km grid spatial data.

2. Methodology

2. 1. An approach for analyzing deforestation

Angelsen and Kaimowitz (1999) explained that there were two types of variables causing the deforestation; first, the immediate causes, which causing the farmers and loggers decided to clear more forests; and second, the underlying causes. Agricultural prices, technological progress in agriculture, accessibility and roads, and timber prices are the immediate causes. Although it is difficult to establish a clear link between deforestation and its underlying causes, namely population growth, land use, forest policy, and cultural factors (Yengoh, 2008), the deforestation rates may increase since the population is growing, and it needs more land for food, fuel wood, timber or other forest products.

Many studies have attributed road infrastructure to one main cause of deforestation. Geist and Lambin (2001) and Krutilla, et al. (1996) argued that the construction of roads requires clearing of vegetation that leads to deforestation. Greater access to forests and markets will accelerate the deforestation. Forest fragments are more accessible than large compact forest, and forests in coastal countries and islands are more accessible than those in continental countries.

Thus, in this study, we have assumptions that farmers, landholders or other factors are most likely to convert forest to agricultural use where good access to markets and favourable conditions for farming makes agriculture more profitable. In addition, the spatial model incorporated population/agricultural census and spatial data into geographic information system framework, which allows modelers to take into account many additional variables.

One of the main components required to estimate deforestation in Java is an understanding of the correlation between forests cover change and other georeferenced variables, such as population density, road density and so on. Here, we focused on the conversion of forest cover to non-forest cover from 2000 to 2005 and predict the forest conversion in the future. Map of deforestation shows the historic cumulative change of areas where deforestation occurred from 2000 to 2005 (Fig. 1).

Generating a model of deforestation was based on forest presence-absence of deforestation data from both datasets, and considered the physical environment and socioeconomic data as explanatory variables. The model then can be used to obtain and identify the areas vulnerable to future forest changes.

2. 2. Datasets, data preparation and statistical analysis

2. 2. 1. Datasets and data preparation

In order to analyze spatial patterns of deforestation and make the prediction on deforested areas with a probability of conversion in the future, several datasets were used in the analysis (Table 1).

The information of forest cover in Java was obtained from datasets of land use map of Department of Forestry in 2000, and a land use map of Ministry

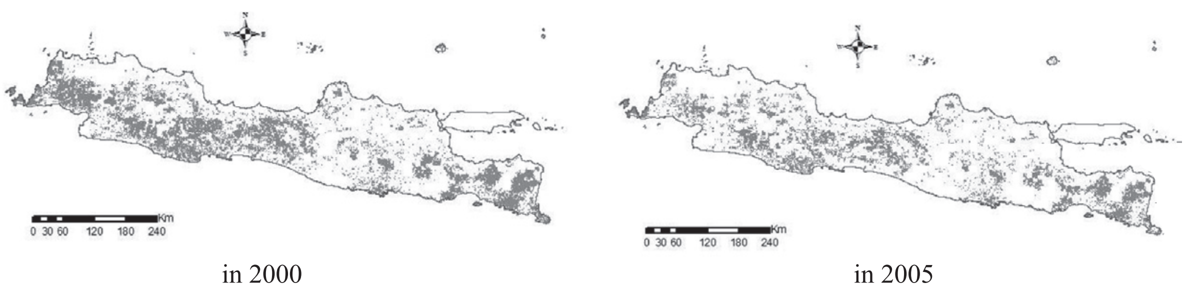

Fig. 1. Forest condition of Java Island in 2000 and 2005

of the Environment in 2005. First we synchronized the datasets with the same definition of forest cover, and then forested areas were separated from non-forested area. The pattern of forest cover represented in the deforested map was the result of the history of deforestation events from 2000 to 2005. Based on the deforestation map we developed binary grid map of deforestation, whereas value 1 represented deforested area and 0 represented non-deforested area. In similar way we developed grid binary maps for population density, percentage of population having agricultural sectors source of income, percentage of population having non-agricultural sectors source of income, road density, elevation and slope. Detailed criteria for defining value of grid whether 1 or 0 are presented in Table 1.

Each data parameter was re-sampled in 10 km grid as unit analysis in the model. Vector grid data of 10 km were made by creating fishnet command in ArcGIS, and further it was attributed by using input parameters such as forest area, road density, slope, elevation, population density, population having agricultural and non-agricultural sector source of income. Grid attributing process for vector data was conducted by Hawth Tools, free add-on extension in ArcGIS version 9.2 (http://www.spatialecology.com/htools) and raster data by ERDAS Imagine 9.1

As explained above the population growth is expected to be potentially the major driver of deforestation. A map of population density from 2000 to 2005 was generated at the village-level using national census data (PODES, *potensi desa*) (Table 1). The population growth is continuously changing in time and space; therefore, simulations were made in this

Table 1. Data used, assumption and criteria in the deforestation model

Data	Source	Assumption	Criteria
Deforestation	Analysis from Land use map by Department of Forestry (Land cover in 2000) and Ministry of Environment (Land cover in 2005)	Analyzed from forest cover change from 2000 to 2005, and the ideal threshold was a half of grid size (100km^2). But, since that threshold was not significant, 20 km^2 was used as a threshold for deforestation	Deforestation > 20 km^2= 1 Deforestation < 20 km^2 = 0
Slope	Generated from SRTM DEM USGS (2004), Shuttle Radar Topography Mission 90 x 90m, Global Land Cover Facility, University of Maryland, College Park, Maryland, February 2000.	Mean of slope threshold was 15%, with assumption: slope 15% above is unsuitable for agriculture and settlement	Slope > 15% = 0 Slope < 15% = 1
Elevation	Generated from SRTM DEM USGS (2004), Shuttle Radar Topography Mission 90 x 90m, Global Land Cover Facility, University of Maryland, College Park, Maryland, February 2000.	Mean of elevation threshold was 200 m.asl, with assumption that areas with elevation below 200 m.asl is very vulnerable	Elevation < 200 m = 1 Elevation > 200 m = 0
Population density	Analyzed from BPS-Statistics Indonesia, data PODES 2000 and 2005	Threshold was the mean of population, with assumption that since population density is increasing, deforestation rate also will be increasing	Population density > mean = 1 Population density < mean = 0
Road density	Extracted from Base and Topographic map Scale 1:25.000 by National Coordinating Agency for Surveys and Mapping, Indonesia (1999)	Threshold was the mean of road density, with assumption that the higher road density, the pressure to forest also is increasing	Road density > mean = 1 Road density < mean = 0
Population having agricultural sector source income	Analyzed from BPS-Statistics Indonesia, data PODES 2000 and 2005	Threshold was the mean of percentage of population having income from agricultural	Population having agricultural sector source income > mean = 1 Population having agricultural sector source income < mean = 0
Population having non-agricultural sector source income	Analyzed from BPS-Statistics Indonesia, data PODES 2000 and 2005	Threshold was a mean of percentage of population having income from non- agricultural sector	Population having non-agricultural sector source income < mean = 1 Population having non-agricultural sector source income > mean = 0

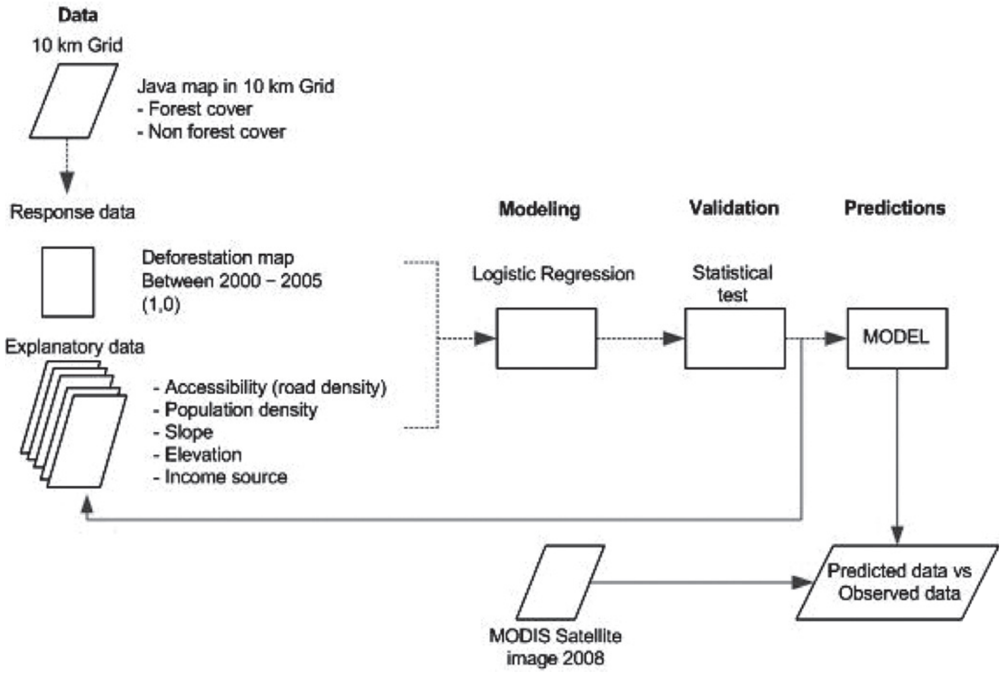

Fig. 2. Flowchart of the methodology in this study

study. Two scenarios were used, namely an increase of those independent variables as high as 2% for normal/moderate scenario and an increase of 6% of those variables for extreme scenario (Fig. 2).

In order to quantitatively validate our predictions of deforestation, we used MODIS satellite images in 250 m resolution with 16-day composite which were acquired in February 2000, February 2008, August 2000 and August 2008. The image MODIS was obtained from Land Processes Distributed Active Archive Center, U.S. Geological Survey, http://lpdaac.usgs.gov/datapool /datapool.asp.

Pixels forest value of MODIS was identified and classified from MODIS datasets in different season data in order to get annual forest and non-forest coverage. Then, a forest-non forest maps were resampled to 10 km grid size.

2. 2. 2. Statistical modeling

As explained in Table 1, the six independent variables were used as predictors in the analysis. Logistic regression as statistical modeling was employed for estimating event probabilities of the occurrence of the deforestation as a dichotomous dependent variable. The regression coefficients obtained were used for integrating the spatial layers and the result was aggregated using a logit transformation [$P = \{exp(a+BX..)/1+(exp(a+BX..)\}$] to obtain the probabilistic map of deforestation.

The initial specification of the model, based on theoretical considerations and data availability, was:

$$P=\left\{\frac{\exp(a+\beta_1 c\_pop++\beta_1 c\_elev+\beta_1 c\_road+\beta_1 c\_ptdens+\beta_1 c\_nptdens)}{1+\exp(a+\beta_1 c\_pop++\beta_1 c\_elev+\beta_1 c\_road+\beta_1 c\_ptdens+\beta_1 c\_nptdens)}\right\}$$

Where:
P: probability of the occurrence of deforestation; a: intercept; c_popdens: population density; c_elev: elevation; c_road: road density; c_ptdens: percentage of population having agricultural sectors source of income; c_nptdens: percentage of population having non-agricultural sectors source of income

Spatial modeling was done using logistic regression to predict the future spatial location of forest conversion, whereby the predictions using two kinds of population growth rate were 2% (normal/moderate) and 6% (extreme).

Results of logistic regression models are often judged as successful if predicted probabilities, i.e. $P > 0.5$ correspond with the observed occurrence and value $P < 0.5$ with the absence of occurrence. Finally, we validated the deforestation map predicted in 2008 as a result of deforestation modeling with observed data of cleared forest/non-forest areas, which was interpreted from MODIS satellite imagery. Our aim was to validate only the approximate location of predicted forest conversion, and not to quantify the change. Then, the model was used to predict the occurrence of deforestation in 2020.

3. Results and Discussion

3. 1. Forest change detection

Most of the remaining forest areas in 2005 was situated in high elevation and steep slopes as stated by Verburg, Veldkamp, and Bouma (1999), since lowland forest in Java had been converted to other land cover type, such as agriculture, shrimp pond and plantation in 1990's (FWI/GFW, 2002). From 2000 to 2005, the deforested areas located in the quietly steep slope and steep volcanic slope were 31.5 % and 40.1%, respectively. Most of the forest conversion was due to agricultural expansion such as for paddy field, upland agriculture, cash crops plantation, and small area for settlement development (Fig. 3). With regard to the provincial distribution, the highest deforestation occurred in East Java, followed by West Java and Banten, Central Java and Jogyakarta.

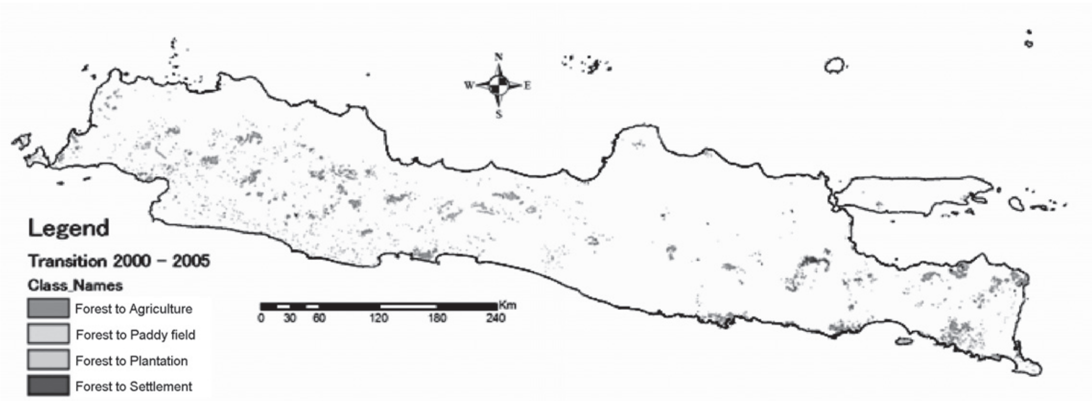

Fig. 3. Transition forest cover in Java from 2000 to 2005.

3. 2. Predictions of deforestation

The result of logistic regression is presented in the equation below and the result of goodness of fit of variables is presented in Table 2.

$$P = \frac{e^{(-18.74 - 16.681\,(c\_pop) + 0.967\,(c\_elev) - 0.683\,(c\_road) - 1.597\,(ptdens) + 15.445\,(c\_nptdens)}}{1 + e^{(-18.74 - 16.681\,(c\_pop) + 0.967\,(c\_elev) - 0.683\,(c\_road) - 1.597\,(ptdens) + 15.445\,(c\_nptdens)}}$$

where:
P: probability of the occurrence of deforestation; a: intercept; c_popdens: population density; c_elev: elevation; c_road: road density; c_ptdens: percentage of population having agricultural sectors source of income; c_nptdens: percentage of population having non-agricultural sectors source of income

Based on goodness fit test (Table 2) population density, road density, and percentage of population having agricultural sectors source of income were significant in predicting deforestation process. The equation above showed that those variables were having negative impact on forest cover areas.

Under the normal/moderate scenario, in 2020 only one district/municipality in Banten would face deforestation problem, meanwhile in West Java, Central Java, Yogyakarta and East Java there would be 7 districts, 22 districts, 4 districts and 6 districts, respectively. Under the extreme scenario, the number

Table 2. Goodness of fit test of variables

Factor	B	S.E.	Wald	df	Sig.	Exp(B)
c_slope	1.163	.319	13.309	1		
c_pop	-16.681	1685.371	.000	1	.992	.000
c_elev	.967	.279	11.982	1	.001	2.629
c_road	-.683	.621	1.211	1	.271	.505
c_ptdens	-1.597	.390	16.784	1	.000	.203
c_nptdens	15.445	1871.765	.000	1	.993	5102496.376

Where :
B: estimated logit coefficient, S.E : Standard Error of the coefficient, Wald = $[B/S.E]^2$, df : degree of freedom, Sig : significance level of the coefficient, Exp(B) : is the odds ratio of the individual coefficient

of deforested districts of Banten, West Java, Central Java, Yogyakarta and East Java would be 2 districts, 11 districts, 18 districts, 5 districts, 26 districts, respectively (Fig. 4). Regarding watershed boundary, in 2020 the number of watersheds that would be expected to face serious deforestation is 47 watersheds under the normal scenario, and almost three times as much (123 watersheds) under the extreme scenario (Fig. 5).

Policy implication of the result model prediction is that the government should take more attention to the population problem and have to create non-agricultural sectors jobs in order to reduce pressure on forest, especially at district which will face serious deforestation. Un-resolved conflict of forest border between community and the government as underlying factor of state forest (government forest area) encroachment (Prasetyo, et al. 2008) should be mediated.

3.3. Model Validation

The logistic regression model was also used to predict the deforestation in 2008, and was validated using observed deforestation data derived from MODIS satellite imagery taken in 2000 and 2008). The validation result showed that the overall accuracy of the model is 88.70%, and the producer accuracy and user accuracy for un-deforested area were 95.76% and 92.44% respectively. Meanwhile, the producer accuracy and user accuracy for deforested area were 2.97% and 13.64%, respectively. Therefore, the model could predict un-deforested area with high confidence, but it was still low and needed to be developed for deforested areas.

4. Conclusion

This study showed the utility of a combination of statistical modeling approach and spatial analysis in order to analyze and predict deforestation. Population density, road density and agricultural source of income were found to be the important variables in the model for explaining the pattern of deforestation observed in Java, however, the accuracy of prediction should be increased especially for deforested areas. The involvement of some variables such as land tenure status, forest distance from road, and other socio-economic data (level of income, level of education), which have contributed to deforestation might be incorporated in the model.

Acknowledgement

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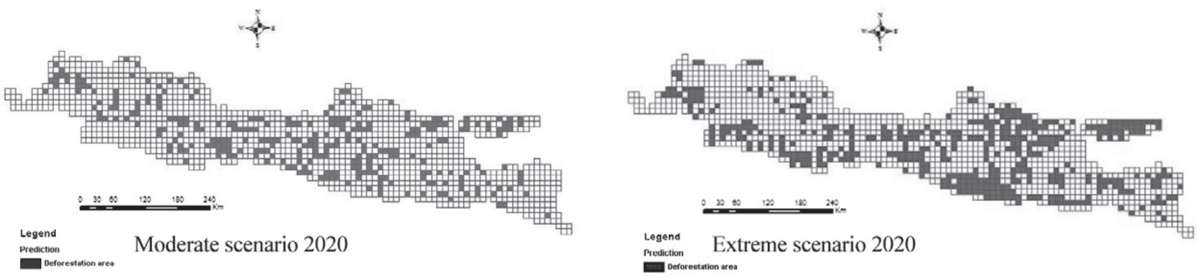

Fig. 4. Deforestation prediction in moderate and extreme scenarios in 2020

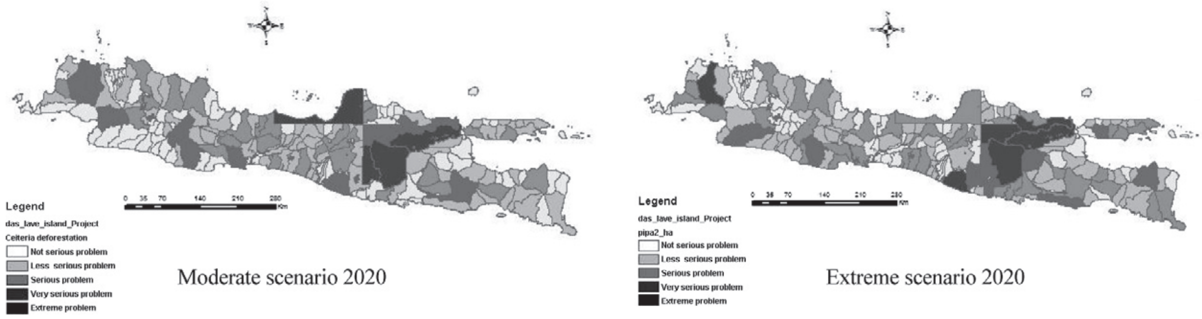

Fig. 5. Deforestation prediction with regard to watershed boundary.

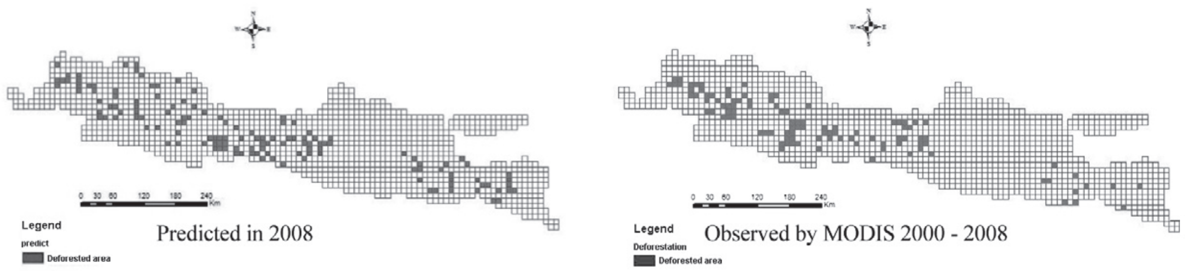

Fig. 6. Comparison of deforested and un-deforested areas predicted in 2008 and bserved deforestation by MODIS 2000-2008

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