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Spatial-Temporal Analysis of Deforestation in Sumatera Island 2011-2019

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Abstract. The existence of forests is threatened with deforestation, which can affect climate disturbances and environmental decay. This study aims to analyze determinants of deforestation in Sumatera Island from 2011-2019. The dependent variable is deforestation, and the independent variables are population density, land fires, road length, GDP of agricultural, fisheries, and forestry, and GDP of mining and excavation. The results show that there is spatial-temporal heterogeneity in deforestation in Sumatera Island from 2011-2019. Furthermore, because of the normality violation, the Robust Geographically and Temporally Weighted Regression (RGTWR) method is used. Analysis shows variables affecting deforestation in Sumatera Island vary in each province and change annually. Land fires were always significant in every province and every year from 2011-2019. To overcome deforestation, the governments need to consider the varying causes of deforestation, more firmly to forestry regulation and establish cooperation with local communities in managing forest.

1. Introduction

Indonesia has the third-largest tropical forest globally after Brazil and The Democratic Republic of Congo [1]. Most of the forest is dispersed in Kalimantan, Sumatera, Papua, and Sulawesi. The existence of forests plays an important role in balancing the environment and brings benefits to humanity. Directly, forests are a source of a variety of industrial goods and materials. For the communities around the forest, forests are a source of food and drink, medicine, equipment, shelter, etc. [1]. Furthermore, forests have another essential benefit of storing biodiversity, climate regulators, CO^2 absorption and oxygenator, waterproofing, etc.

On the other hand, the existence of forests is threatened by the occurrence of deforestation. Based on the press release of Forest Watch Indonesia in 2020, it was mentioned that since 2000-2017 Indonesia had lost more than 23 million hectares of natural forest. Kalimantan, Sumatera, and Sulawesi are three islands in Indonesia with the highest deforestation. Based on the Ministry of Environment and Forestry, deforestation in the three islands is denominated each year. In 2011-2019, the average annual deforestation in Kalimantan and Sumatera respectively reached 278 thousand hectares and 268 thousand hectares. In 2019, deforestation in Kalimantan and Sulawesi declined, but Sumatera has shown a marked increase in deforestation. Those increases can pose a long-term threat to environmental balance. Therefore, the study of deforestation in Sumatera is important to be generated. It is because Sumatera is also one of the islands with considerable forest coverage and plays an important role in the balance of the environment in Indonesia, also in the world.

Deforestation can disturb forest's function as a water absorber, then causing floods and droughts in surrounding areas. Also, deforestation causes the function of forests as climate regulators to be threatened. The result of the Global Canopy Programme says that deforestation and the use of tropical forests are major causes of global greenhouse emissions. It can be lead to an enhanced frequency of extreme incidents, such as drought and other disasters that also affect energy, food, and health resilience [2]. Based on data from National Disaster Management Agency, Sumatera flooded hundreds of times each year, and it has tended to span the last decade. Furthermore, dozens of landslides occur on the island each year. Such conditions would be costly, especially to the people that live in and around the areas.

A previous study indicated a spatial pattern of deforestation in Kalimantan began at points around the coast and spread into the surrounding region [3]. Margono et al. [4] found deforestation in Sumatera 1990 began in three neighboring provinces of Southern Sumatera, Jambi, and Riau. In the following years, deforestation spread around the region and several other points in Sumatera. It indicates a similar spatial pattern of deforestation in Sumatera and Kalimantan.

But, much of the spatial research on deforestation focuses solely on remote sensing analysis [5,6]. Remote sensing has a weakness that indicates only the location and vast deforestation, but it cannot explain the conditions that affect deforestation. In contrast, the socioeconomic and demographic conditions of a region can also influence deforestation. Economic gritty (mainly forestry sector) and population density significantly affect the extent of deforestation in the islands [7]. Population growth would increase the need for such commodities as food production, wood, paper, and so forth. So to meet these needs requires the addition of land to farms and agriculture [2]. But other factors can also make it possible to cause deforestation, such as infrastructure building and natural elements as forest fires. In other literature show that land fires are among the factors behind deforestation [8,9].

Additionally, observation units of the region made it possible to have different characteristics based on spatial heterogeneity [10]. They are not ruling out the possibility that the causes of deforestation vary in a region. Besides spatial factors, the time component is also an important dimension of environmental dynamics [11]. For example, such as Adiningrum et al. [12] shows that not only a diversity effect of independent variables between location on deforestation in Indonesia from 2013-2016 but also between time. Margono et al. [4] also explain a shift in the causes of deforestation in Sumatera from 1950 to the late 1990s.

Based on that background, the goal of this study is to map the widespread of deforestation and recognize the characteristics of suspected variables affected deforestation in the island of Sumatera from 2011 to 2019, identifying the existence of spatial-temporal effect on the widespread deforestation of the province in Sumatera from 2011-2019 and analyzing the determinants of deforestation in Sumatera 2011-2019.

2. Materials and Methods

2.1 Theory

According to the Ministry of Environment and Forestry Rule 2017, deforestation permanently changes forest areas to non-forest areas. While according to the Food and Agriculture Organization (FAO), deforestation is the conversion of forest areas into non-forested areas (such as land for agriculture, urbanization, and others). FAO also mentions that the direct cause of deforestation is logging, conversion of land to agriculture and cattle, urbanization, mining and oil exploitation, acid rain, and forest fires [13].

2.1.1 Robust Regression.

Robust regression is a method that can be used when the error distribution is not normal, or there is an outlier in the regression model [14–16]. One method of robust regression estimate is the MM estimation. This estimation combines high breakdown value estimation and M estimation, so it has a high breakdown point of 50% and an efficiency of up to 95% [14,17,18]. That would be an advantage for the MM estimation over any other estimation method. The formula from robust regression is similar to common OLS regression. But to estimates parameter requires a process of iterations and weight function.

2.1.2 Geographically and Temporally Weighted Regression (GTWR).

Geographically and Temporally Weighted Regression (GTWR) is an extension of the Geographically Weighted Regression (GWR) that not only considers spatial heterogeneity but also accounts for temporal heterogeneity [11]. The common form of the GTWR model is as follows [20]:

$$Y_i = \beta_0(u_i, v_i, t_i) + \sum_k \beta_k(u_i, v_i, t_i) X_{ik} + \varepsilon_i \tag{1}$$

Description:

Y_i	: dependent variable observation *i*
$\beta_0(u_i, v_i, t_i)$	: intercept observation *i*
$\beta_k(u_i, v_i, t_i)$	: local regression coefficient observation *i*, variable *k*
X_{ik}	: independent variable *k* observation *i*
ε_i	: error term
k	: total independent variable
u_i, v_i, t_i	: coordinate and time stamp for observation *i*

Regression coefficients of GTWR are estimated with Weighted Least Square. One of the key components of this estimation is the spatial-temporal weight matrix. GTWR parameter estimation in matrix notation may be written as follows:

$$\widehat{\boldsymbol{\beta}}(u_i, v_i, t_i) = (\boldsymbol{X}^T \boldsymbol{W}_{(i)} \boldsymbol{X})^{-1} \boldsymbol{X}^T \boldsymbol{W}_{(i)} \boldsymbol{y} \tag{2}$$

$\widehat{\boldsymbol{\beta}}(u_i, v_i, t_i)$	: k+1 vector of local regression coefficient observation *i*
$\boldsymbol{X}$	: nT x (k+1) independent variable matrix, with the first column is intercept.
$\boldsymbol{y}$	: column vectors containing dependent variable
$\boldsymbol{W}_{(i)}$	: diagonal matrix containing spatial-temporal weight each observation for observation *i*

2.1.3 Bandwidth.

Bandwidth shows a radius that still affects a particular surveillance location. One method of determining the optimum bandwidth value is Cross-Validation (CV). Optimum bandwidth value will be obtained at the minimum CV value produced [21]. Here are modified CV functions to be used in obtaining spatial-temporal optimum bandwidth [11].

$$CV(b_s, b_t) = \sqrt{\sum_{i=1}^{n} (y_i - \hat{y}_{-i}(b_s, b_t))^2 / n} \tag{3}$$

Description:

$\hat{y}_{-i}(b_s, b_t)$): estimation value, where observation *i* are not included in the estimate parameters process.

So, for kernel gaussian function, spatial-temporal weight function would be [11]:

$$w_{ijS,T}^t = exp\left(-\frac{d_{Sij}^2}{b_{St}^2}\right) * exp\left(-\frac{d_{Tij}^2}{b_T^2}\right) \tag{4}$$

2.1.4 *Robust Geographically and Temporally Weighted Regression (RGTWR).*

Robust Geographically and Temporally Weighted Regression (RGTWR) extends GTWR's method because of outlier and normality violations [14,22]. Parameter estimation of RGTWR is similar to the robust method, but the weight function used is a combination of robust regression and spatial-temporal weight [23]. Here is the phase of the RGTWR with MM estimation method for estimated parameters [19,23]:

1. Calculating robust regression coefficient with S estimation as follows:
   a. Calculating regression coefficients by using Ordinary Least Square (OLS).
   b. Calculating error of the OLS.
   c. Calculating the scale of S estimation ($\hat{\sigma}_s$):

$$\hat{\sigma}_s = \begin{cases} \frac{median|e_i - median(e_i)|}{0,6745}, & iteration = 1 \\ \sqrt{\frac{1}{nK}\sum_{i=1}^{n} w_i\, e_i^2}\,, & iteration > 1 \end{cases} \tag{5}$$

e_i is an error in every iteration. In the first iteration, e_i is error from the OLS model.
K = constant = 0,199

d. Calculating $u_i = \frac{e_i}{\hat{\sigma}_i}$

e. Calculating weight w_i :

$$w_i = \begin{cases} \begin{cases} \left[1 - \left(\frac{u_i}{c}\right)^2\right]^2 & if\ |u_i| \le c \\ 0 & if\ |u_i| > c \end{cases} & for\ iteration = 1 \\ \frac{\rho(u_i)}{(u_i)^2} & for\ iteration > 1 \end{cases} \tag{6}$$

$$\rho(u_i) = \begin{cases} \frac{c^2}{6}\left[1 - \langle 1 - \left(\frac{u_i}{c}\right)^2 \rangle^3\right] & if\ |u_i| \le c \\ \frac{c^2}{6} & if\ |u_i| > c \end{cases} \tag{7}$$

c = Tukey constant= 1,547
$\boldsymbol{\omega}_m = diag(w_1, w_2, \ldots, w_n)$

f. Calculating $\widehat{\boldsymbol{\beta}}_S$ with *Weighted Least Square* and the error component.

$$\hat{\beta}_S = (X^T W \omega_m X)^{-1} X^T W \omega_m Y \tag{8}$$

$\boldsymbol{W}$: diagonal matrix containing spatial-temporal weight

g. Repeat c through f to acquire convergent $\widehat{\boldsymbol{\beta}}_S$ value with *Iteratively Reweighted Least Square* (IRLS) procedure. At that iteration, $\boldsymbol{\omega}_m$ value would change in every iteration.

Where convergent $\widehat{\boldsymbol{\beta}}_S$ is estimator acquired from RGTWR with S estimation.

2. Calculating error from S estimation model that has been formed before on step 1g.

3. Calculating the scale of robust estimation ($\hat{\boldsymbol{\sigma}}_i$) value:

$$\hat{\sigma}_i = \begin{cases} \frac{median|e_i - median(e_i)|}{0,6745}, & iteration = 1 \\ \sqrt{\frac{1}{nK}\sum_{i=1}^{n} w_i e_i^2}\,, & iteration > 1 \end{cases} \tag{9}$$

K = constant = 0,199
w_i is a weight function
e_i is an error in every iteration. In the first iteration, e_i is error from S estimation.

4. Calculating $u_i = \frac{e_i}{\hat{\sigma}_i}$

5. Calculating w_i :

$$w_i = \begin{cases} \left[1 - \left(\frac{u_i}{4,685}\right)^2\right]^2, & |u_i| \le 4,685 \\ 0, & |u_i| > 4,685 \end{cases} \tag{10}$$

$\omega_m = diag(w_1, w_2, \ldots, w_n)$

6. Calculating $\hat{\boldsymbol{\beta}}_M M$ with *Weighted Least Square* and the error component.

$$\hat{\beta}_M M = \left(X^T W \omega_m X\right)^{-1} X^T W \omega_m Y \qquad (11)$$

7. Repeat step 3 through step 6 to acquire convergent $\hat{\boldsymbol{\beta}}_M M$.
   Where convergent $\hat{\boldsymbol{\beta}}_M M$ is estimator acquired from RGTWR with MM estimation

2.2 Scope

This study includes ten provinces located in Sumatera. The period used is 2011-2019. The dependent variable (Y) of this study is deforestation, with data used is the netto vast (in thousands of hectares). The independent variables used are population density in people/kilometers^2 (X1), land fires in thousand hectares (X2), road length in kilometers (X3), GDP of agricultural, fisheries, and forestry in billion IDR (X4), and GDP of mining and excavation in billion IDR (X5). Those variables are chosen based on previous research and the FAO framework [13]. Moreover, a high population will pressure the environment, especially to meet human needs. Therefore, it is not uncommon for the region to tackle the demand [2]. Some previous research also claimed that significant population densities affect the genesis of deforestation [5,7,23–28]. Land fires are also one of the factors that can cause deforestation [8,9]. Infrastructure development can also increase deforestation. The variable that can use to determine the condition is the road length. Previous studies also suggest that the forest distance factors to the road significantly impact the chances of deforestation or the replacement of forest land [5,6,23,24,26,27,29–32]. In addition, increased food demand will increase agricultural production needs. Increasing demand is also closely associated with the need for land [28,31,33]. The mining sector is also one of the economic pillars of several regions in Indonesia. It is also linked to an increase in the chances of deforestation becoming a mining region [3,34]. According to the Kuznets theory, environmental exploitation is inevitable when a country's economic development is still low. When economic growth is high, exploitation of the environment will decrease [35]. The land is a key component in the economic development of a region. So economic development will impact land-use dynamics. Deforestation is the end result of competition for land use in order to increase people's welfare [36]. At the regional level, PDRB is one of the indicators that could describe the magnitude of economic development.

All the data used is collected from Statistics Indonesia (BPS), the Ministry of Environment and Forestry, and the Highways Office. The detailed data sources are:

1. Vast deforestation based on annual publication from Ministry of Environment and Forestry (*Deforestasi Indonesia)*.
2. Population density is from the website of BPS.
3. Land fire is collected from the publication of BPS (*Publikasi Statistik Lingkungan Hidup*) and the Directorate of Forest and Land Fire Control, Ministry of Environment and Forestry.
4. Total length of road based on annual publication from BPS (*Statistik Indonesia*) and publication from the Highways Office (*Publikasi Kondisi Jalan*).
5. GDP of agricultural, fisheries, and forestry based on the website of BPS in each province in Sumatera.
6. GDP of mining and excavation based on the website of BPS in each province in Sumatera.

2.3 Analysis Method

The methods of analysis are descriptive and inferential analysis. Descriptive analysis with a thematic map illustrates the change and frequency of research variables in the provinces of Sumatera Island from 2011-2019. The inferential analysis used in this research is Robust Geographically and Temporally Weighted Regression (RGWTR). RGTWR methods can show the impact of the independent variable on the dependent variable by considering the existence of spatial and temporal heterogeneity on data that contains either an outlier or a normality violation [14,22]. Alfa (α) used in each test is 10%. Based on [11,24–31], the inferential analysis steps are as follows:

1. Forming a global regression model with Ordinary Least Square (OLS).
2. Detecting multicollinearity with Variance Inflation Factor (VIF) value [32].

3. Testing error normality.
4. Testing spatial heterogeneity with the Breusch-Pagan test [33] and identifying temporal heterogeneity with a boxplot.
5. Choosing optimal spatial-temporal bandwidth [11] with fixed kernel Gaussian function.
6. Because of a normality violation, spatial and temporal heterogeneity on the data, modeling can be applied by the RGTWR method [19,22,23].
7. In the robust stages, the MM estimator is used for having a high breakdown point and high efficiency than other robust estimation methods [14,17,18].
8. Generating partial test for RGTWR parameters [34].
9. Making an independent variable signification map based on time and location.
10. Analyzing the result of modeling with RGTWR.

The analysis flowchart can be seen in Figure 1.

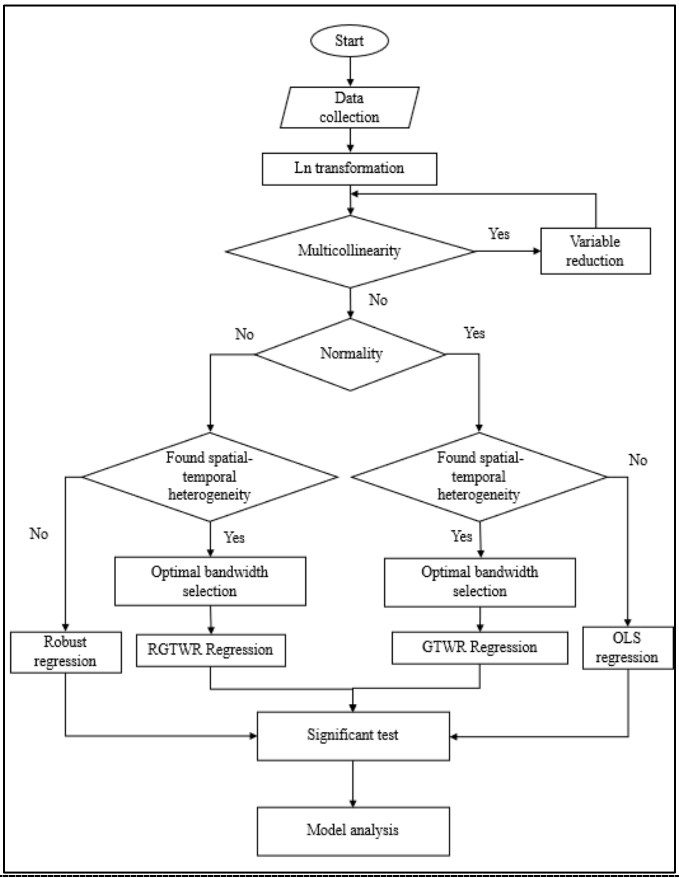

Figure 1. Analysis flowchart

3. Results and Discussion

3.1 Descriptive Analysis

3.1.1 Description of Sumatera Island Deforestation in 2011 to 2019.

According to data on the Ministry of Environment and Forestry annual publication, from 2011 to 2019, the island of Sumatera has always lost extensive forests at high levels. Each year the island records an average of deforestation of over 250 thousand hectares. The total of deforestation varies in magnitude from 2011 to 2019. In 2015, Sumatera suffered the highest deforestation, which was recorded at 519,044 hectares. The provinces of South Sumatera and Riau are provinces that contribute higher to deforestation than other provinces, with several 290,777 and 135,30,70 hectares, respectively (see Figure 2). Figure 2 also shows that the extent of deforestation in Sumatera tends to show a downward trend. According to Margono et al. [4], the widespread decline of deforestation is not only a result of system reforms that have occurred but also because of the increasing thinning of forest reserves.

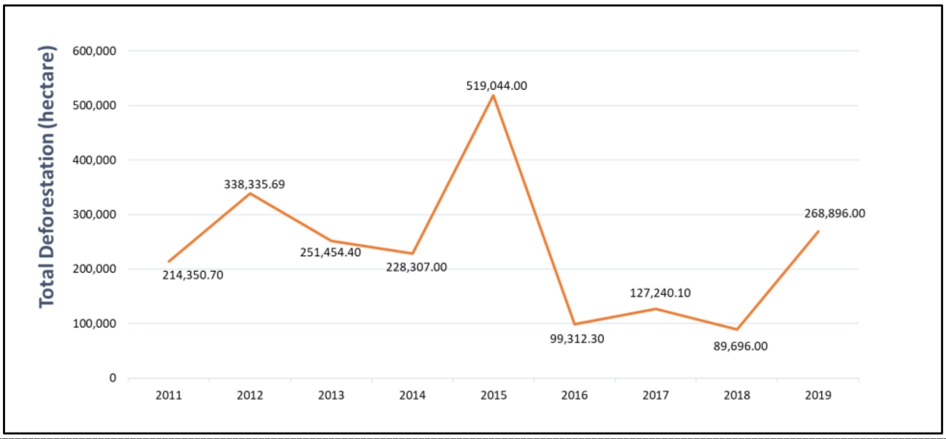

Figure 2. Total deforestation (hectares) in Sumatera 2011-2019.

When viewed by the province, there are several conditions where the deforestation rate has a negative sign. For example, in 2014 in Jambi Province, the area of deforestation was recorded at -9,941.4 hectares. This means that the area of reforestation that occurs exceeds the area of deforestation that occurs in the province. Similar cases also occurred in Lampung Province in 2016, Bangka Belitung Islands in 2013, and Riau Islands in 2018. Figure 3 shows that there are only a few provinces from the entire study period that experienced deforestation in the smallest group.

In general, the three most dominant provinces contributed to deforestation, namely Southern Sumatera, Riau, and Jambi. In the province of Riau, from 2011 to 2019, deforestation has always been at a rate of more than 22 thousand hectares, except in 2017 for just 8,679 hectares. Meanwhile, in South Sumatera Province, the total deforestation since 2011 is more than 430 thousand hectares, and in Jambi Province, it is more than 280 hectares. If combined with all of Sumatera, total deforestation from 2011-2019 is over 2 million hectares.

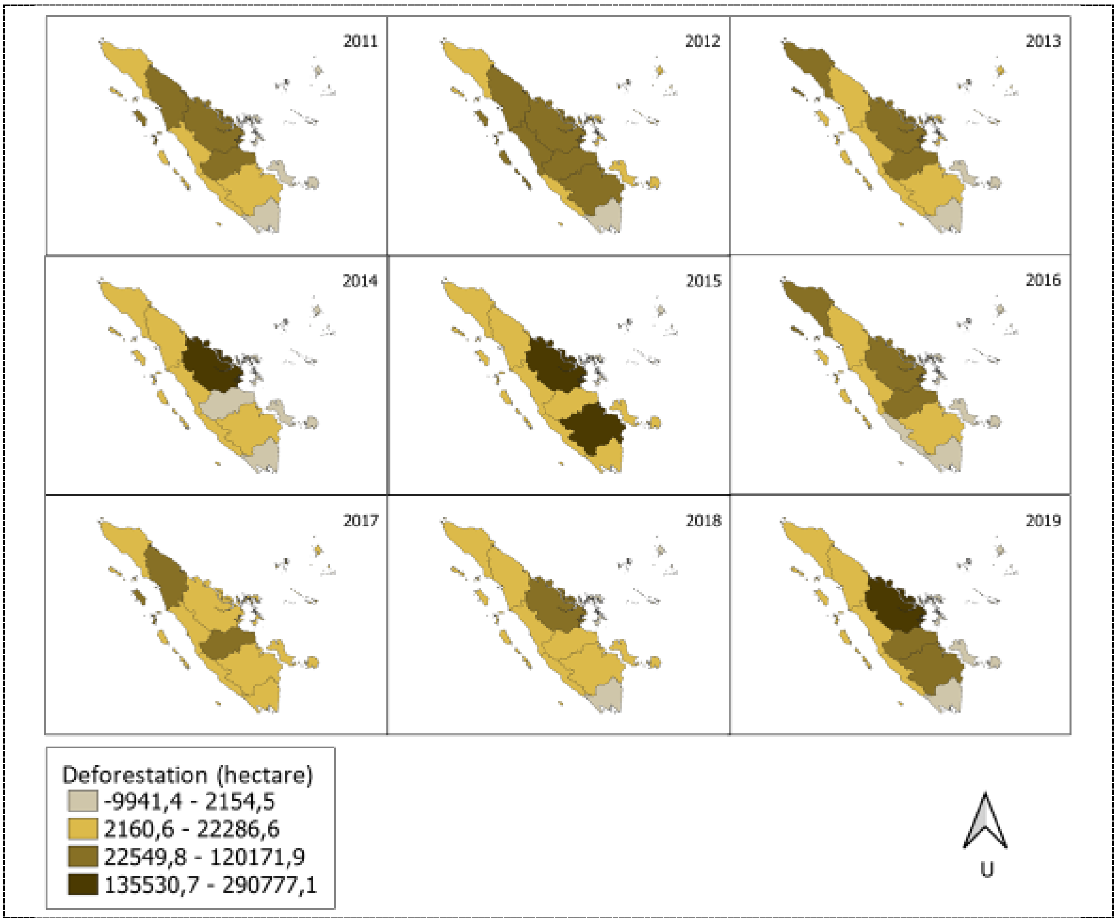

Figure 3. Deforestation (hectares) by the province in Sumatera 2011-2019.

3.1.2 Description of Sumatera Island Population Density 2011 to 2019.

The population is one of the fundamental causes of deforestation. Where the higher the population also means an increase in the need for land for housing, consumption commodities, and so on. So, to meet these needs, additional land is needed for plantations and agriculture [2]. Based on data from BPS, population density in each province on the island of Sumatera always increases every year. Riau Islands is a province with the highest trend of increasing population density than other provinces. The provinces of Lampung, Riau Islands, and North Sumatera are provinces with the highest population density than other provinces. Based on Figure 4, from 2011 to 2019, the population density in Jambi and Riau Provinces was only in the class of 63.14 to 90.65 people/km.

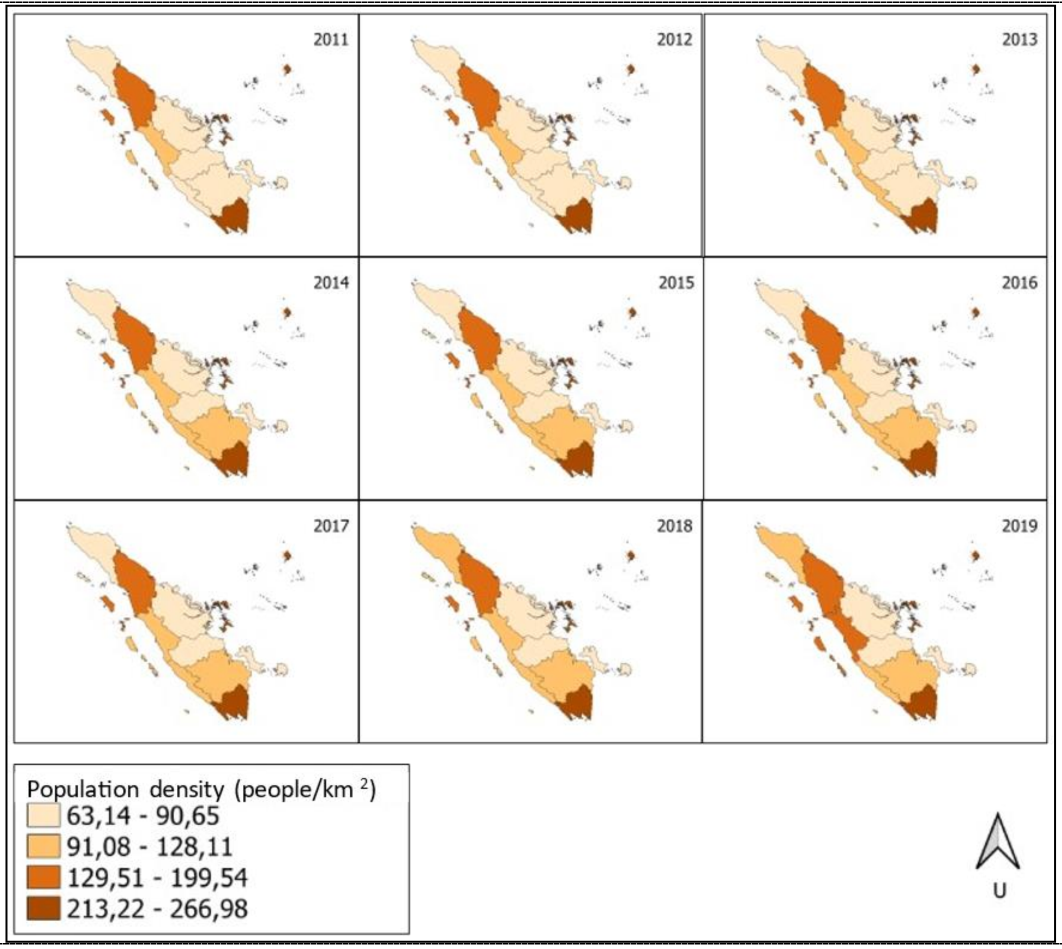

Figure 4. Population density by the province in Sumatera 2011-2019.

3.1.3 Description of Sumatera Island Land Fires in 2011-2019.

One of the factors causing the loss of forest cover is the occurrence of land fires, either intentionally or naturally. Long droughts generally cause land fires that occur naturally as the impact of El-Nino can cause drought, so it will easily trigger fires. While land fires are due to human intervention, one of which occurs due to land clearing for plantations or agriculture carried out by burning land.

According to the Ministry of Environment and Forestry, land fires always occur every year on the island of Sumatera. From 2011 to 2013, the number of land fires on Sumatera Island published by the Ministry of Environment and Forestry still showed a value of fewer than two thousand hectares per year. However, in 2014 it began to show an increase in land fires, where the total fire area reached more than 16 thousand hectares. Meanwhile, 2015 was the worst period for land fires on the island of Sumatera. In that year, the area of land fires that occurred reached 1,048,635.12 hectares. Provinces that contributed the highest area of land fires in that period were South Sumatera (646,298.8 hectares), Riau (183,808.59 hectares), and Jambi (115.634.34 hectares). These three provinces again contributed to the vast number of land fires that occurred in 2019 (see Figure 5).

Besides one of the causes of deforestation, land fires also cause several other negative impacts. Most of these impacts include ecological damage, decreased biodiversity, declining forest economy and soil productivity, climate change, and smoke pollution that disturbs local communities and even neighboring countries, as well as disruption of land, river, lake, sea, and air transportation [48].

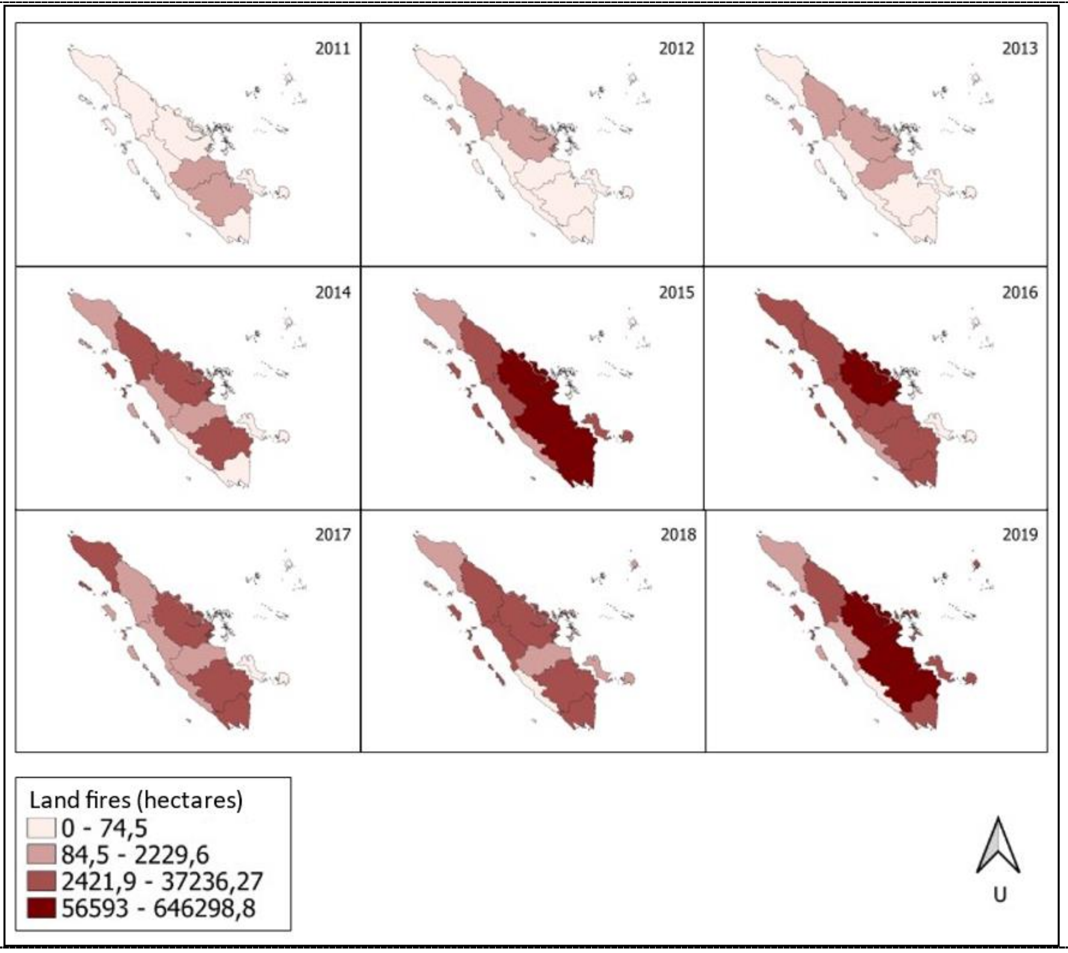

Figure 5. Land fires by the province in Sumatera 2011-2019.

3.1.4 Description of Sumatera Island Road Length in 2011-2019.

In addition to land fires, land clearing for infrastructure development (such as road construction) or economic activity is also one of the causes of forest cover loss. The main function of the existence of the road is as a liaison between regions. In Sumatera itself, according to a report by the Committee for the Acceleration of Priority Infrastructure Provision (KPPIP), in 2015, construction began to construct the Trans Sumatera Toll Road (JTTS). The toll road, which is planned for completion in 2024, will later have a length of up to 304 km and connect the island of Sumatera from Aceh to Bakauheni. The report also stated that in 2017, several toll roads had started operating, such as the Medan-Binjai section in North Sumatera, the Palembang-Indralaya section in South Sumatera, and the Bakauheni-Terbanggi Besar section in Lampung.

Based on data collected from 2011 to 2019, the total length of roads owned by each province on the island of Sumatera does not change much every year. The trend of total road length in each province tends to show an increase every year. However, from 2016 to 2019, the increase in road length in most provinces on the island of Sumatera was not as much as in previous years. Based on Figure 6, North Sumatera is the province with the highest total road length compared to other provinces. While the Riau Islands, Bangka Belitung Islands, and Bengkulu are the three provinces that have the shortest road length. However, this is quite reasonable considering the three provinces also have the lowest area compared to other provinces.

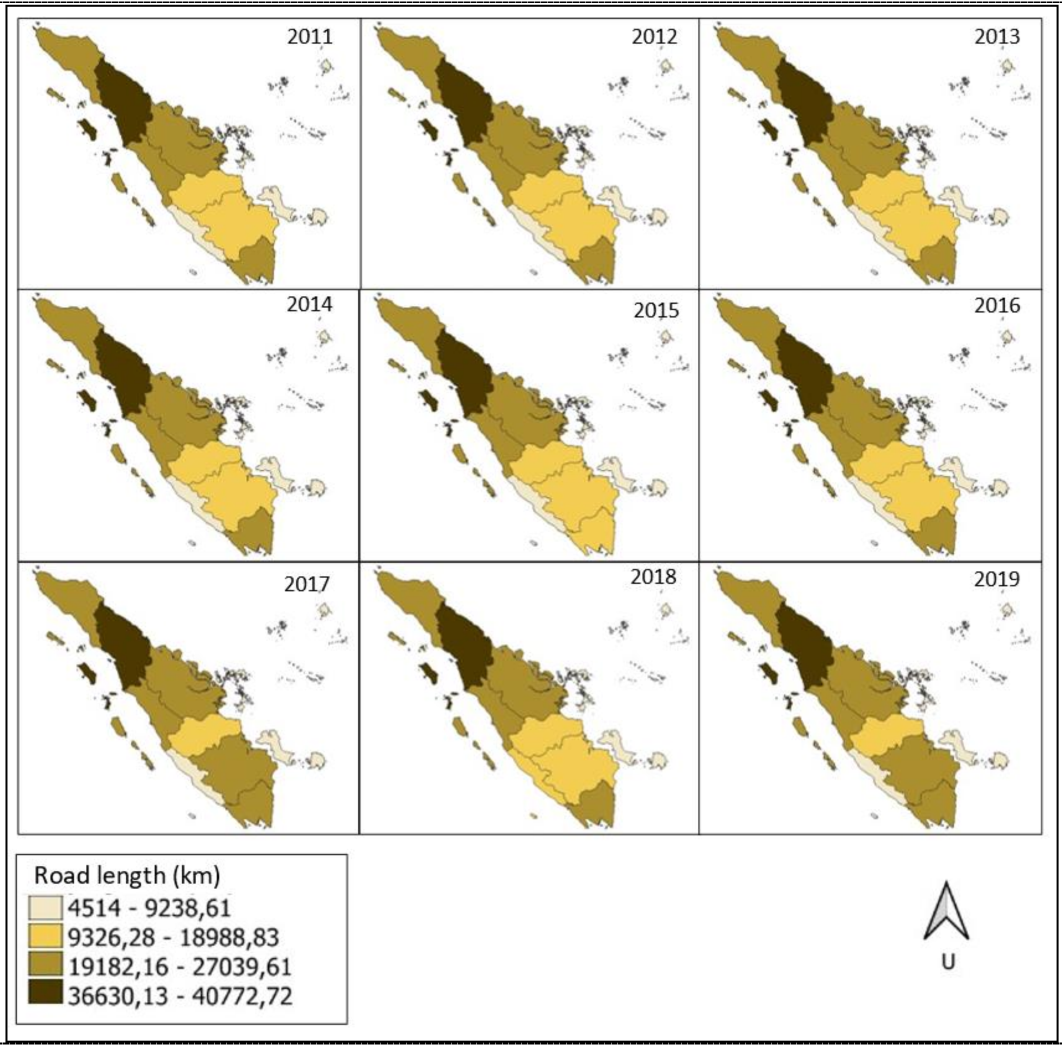

Figure 6. Road length by the province in Sumatera 2011-2019.

3.1.5 Description of Sumatera Island GDP of Agriculture, Fisheries, and Forestry in 2011-2019.
The need for land for economic activities is also one of the causes of deforestation, for example, such as clearing land for plantations, agriculture, or mining. Palm oil is one of the most widely developed commodities. Based on the report on oil palm plantations issued by the Financial Services Authority in 2017, almost 70% of the total oil palm plantations in Indonesia are located on the island of Sumatera. Riau Province in 2014 was the province with the largest oil palm plantation in Indonesia, with an area of 2.3 million hectares. The measure that can be used to see the sector's role in the economy is the Gross Domestic Product (GDP).

Based on data from BPS, sector one GDP consisting of agriculture, fisheries and forestry have increased every year. The provinces of Riau and North Sumatera are provinces that have a total GDP of agriculture, fisheries, and forestry with a value of more than 94 trillion rupiahs each year. Only in 2011 alone, the GDP of agriculture, fisheries, and forestry in North Sumatera Province were worth less than 94 trillion rupiahs (see Figure 7). Then, the provinces of Riau Islands, Bangka Belitung Islands, and Bengkulu have the lowest GDP of agriculture, fisheries, and forestry compared to other provinces.

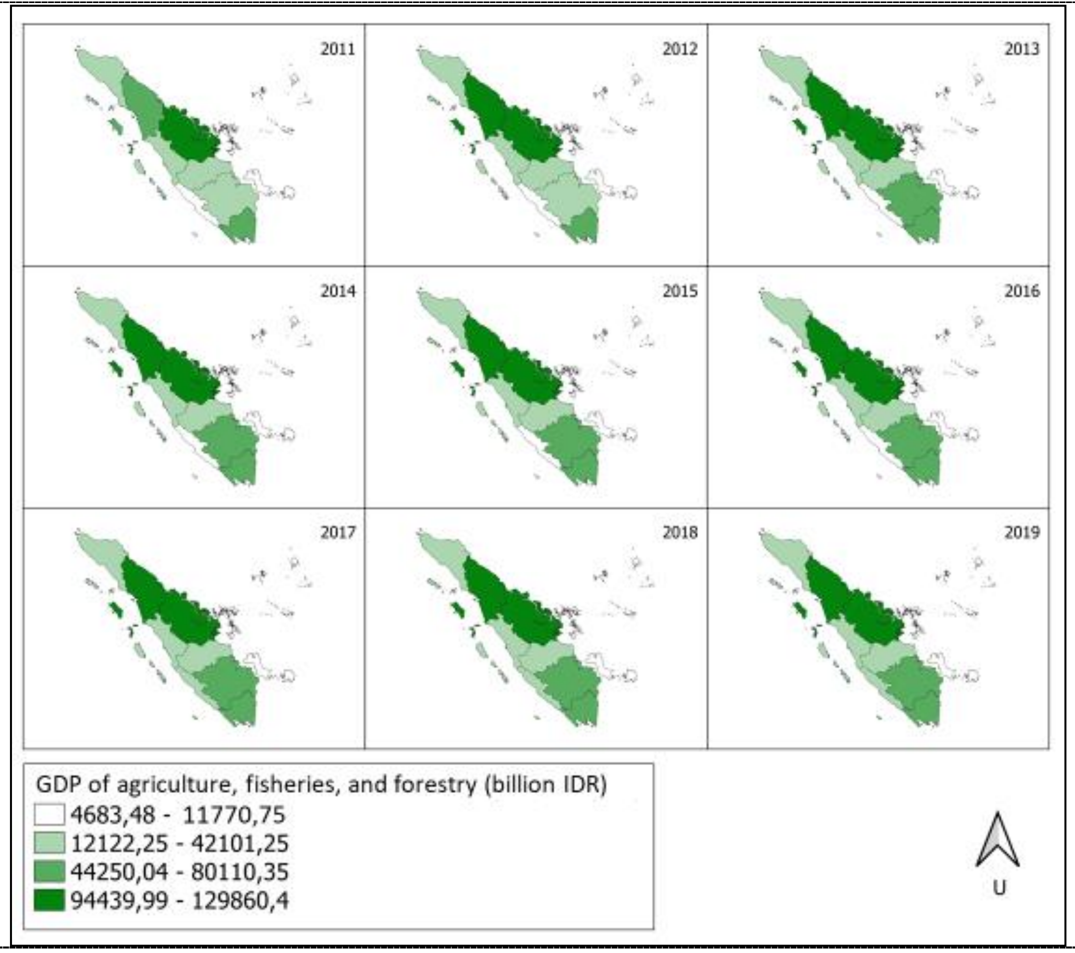

Figure 7. GDP of agriculture, fisheries, and forestry by the province in Sumatera 2011-2019.

3.1.6 Description of Sumatera Island GDP of Mining and Excavation in 2011-2019.

In addition to the plantation and agricultural sectors, the clearing of forest land for the fulfillment of economic activities can also occur because of activities in the mining sector. The magnitude of the role of this sector can be reflected in the GDP of mining and quarrying. Based on data from BPS, the GDP of this sector in Aceh and Riau Provinces tends to show a downward trend every year. However, based on the Riau Provincial Government website, the mining sector is still the leading commodity in the energy and mineral resources sector in the province.

While in other provinces, it has increased every year. If viewed based on the map in Figure 8 below, only West Sumatera Province experienced a shift in classification classes. Where in 2011 and 2012, the province had a mining and quarrying GDP value of class 1.2576 to 5.2823 trillion rupiahs, changing from 2013 to 2019 to class 5.6567 to 25.9954 trillion rupiahs.

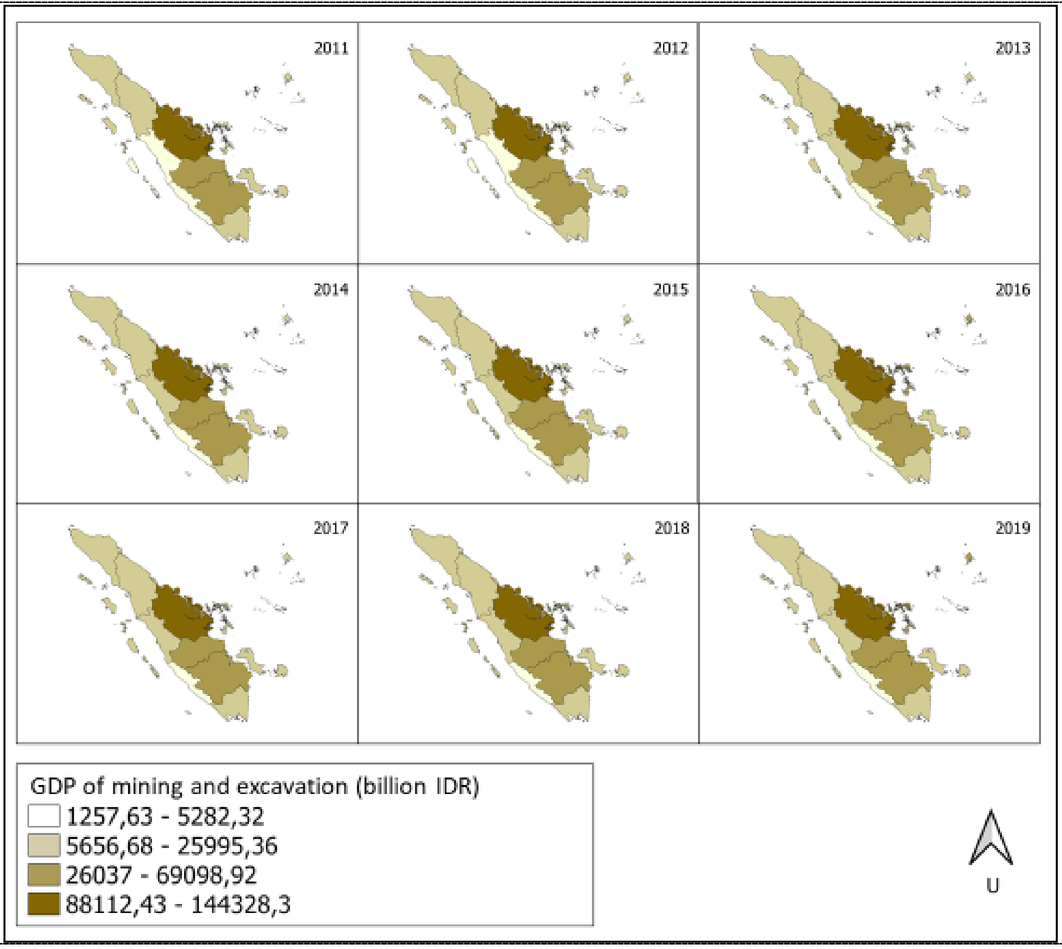

Figure 8. GDP of mining and excavation by the province in Sumatera 2011-2019.

3.2 Deforestation Modelling in Sumatera Island

3.2.1 Global Regression Model of Deforestation in Sumatera with OLS.

The first step in the inferential analysis is to form an OLS regression model. The estimate can be seen in Table 1.

Table 1. Results of modeling use OLS

Variable	Coefficient	*Standard error*	*t-value*	*p-value*
Intercept	-30,8418	71,9463	-0,429	0,6693
ln X1	-21,3201	6,8244	-3,124	0,00245
X2	0,3146	0,0402	7,819	$1,39 \times 10^{-11}$
ln X3	1,2399	14,3234	0,087	0,9312
ln X4	6,2168	10,0277	0,620	0,5370
ln X5	7,6666	3,2128	2,386	0,1927
Adjusted R-squared	0,5764		*R-Squared*	0,6002
F-statistics	25,22		*SSE*	70.651

The model of OLS used is as follows:

$$Y_{it} = \beta_0 + \beta_1 lnX1_{it} + \beta_2 X2_{it} + \beta_3 lnX3_{it} + \beta_4 lnX4_{it} + \beta_5 lnX5_{it} + \varepsilon_{it} \quad (12)$$

Description:
Y_{it} : deforestation location *i*, time *t*
β_0 : intercept
$\beta_{1,2,\dots,5}$: regression coefficient
$X1_{it}$: population density province *i*, time *t*
$X2_{it}$: land fires province *i*, time *t*
$X3_{it}$: road length province *i*, time *t*
$X4_{it}$: GDP of agricultural, fisheries, and forestry province *i*, time *t*
$X5_{it}$: GDP of mining and excavation province *i*, time *t*
ε_{it} : error term

Based on multicollinearity detection using the VIF value, it is found that VIF X4 is more than 10. Therefore, the X4 variable is removed from the model. In the next model, there are only four independent variables used. The estimation after the X4 variable is removed from the model can be seen in Table 2.

Table 2. Results of modeling use OLS without X4

Variable	Coefficient	Standard error	*t-value*	*p-value*
Intercept	-56,2126	58,9593	-0,9534	0,3431
ln X1	-21,5158	6,7923	-3,1667	0,0021
X2	0,3161	0,0400	7,8988	0,0000
ln X3	9,5940	4,8383	1,9829	0,0506
ln X5	8,7158	2,7210	3,2031	0,0019
Adjusted R-squared	0,57949	*R-Squared*	0,59836	
F-statistics	31,6614	*SSE*	70.974	

The model formed are as follows:

$$Y_{it} = \beta_0 + \beta_1 lnX1_{it} + \beta_2 X2_{it} + \beta_3 lnX3_{it} + \beta_5 lnX5_{it} + \varepsilon_{it} \tag{13}$$

Based on the VIF value of the model, there are no variables that have VIF > 10. It can be concluded no multicollinearity between independent variables. The normality test of the error with the Jarque-Bera test shows a p-value of $2{,}2\times10^{-16}$. Therefore, the error is not normal. Because of the violation of normal assumption, it makes modeling with OLS irrelevant.

3.2.2 Spatial and Temporal Heterogeneity.
Spatial heterogeneity with the Breusch-Pagan test shows the test statistics of 18,736 with degrees of freedom=4 and a p-value of 0,0008857. Based on this result, it is inconclusive that there is spatial heterogeneity between observational locations. The temporal heterogeneity detection with the boxplot shows that extensive deforestation data varies enormously annually. It indicates a temporal heterogeneity of deforestation data in Sumatera Island from 2011 to 2019 (see Figure 9).

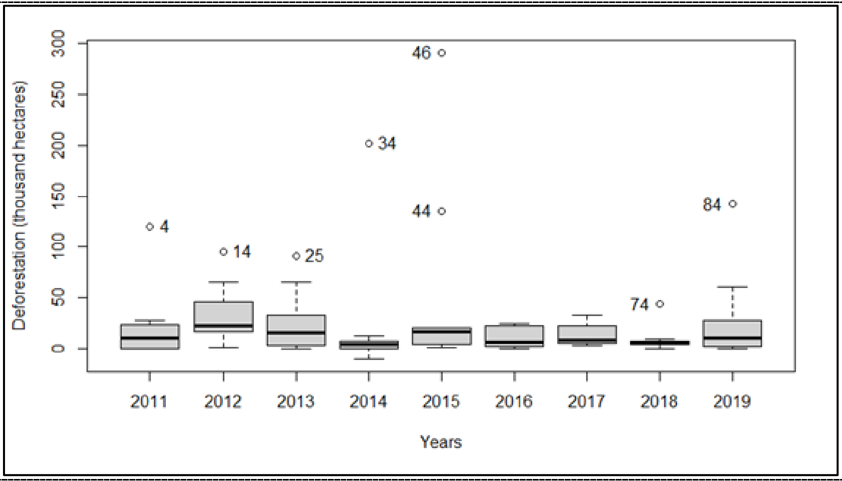

Figure 9. Annual boxplot of deforestation in Sumatera 2011-2019.

3.2.3 RGTWR Model of Deforestation in Sumatera Island.

The regression coefficient and the significance produced by RGTWR methods vary in each province and year. There are 90 model equations established to describe the vast deforestation in each province and Sumatera Island from 2011 to 2019. One example of the model formed is as follows:

$$\hat{Y}_{Riau\ 2011} = -63{,}5368 - 23{,}2352\ \mathit{ln}\ X1^{*} + 0{,}3511\ X2^{*} + 11{,}1523\ \mathit{ln}\ X3^{*} + 9{,}1731\ \mathit{ln}\ X5^{*}$$

*) significant in significant level 0,1

Based on the example of the equation, the coefficient values can be interpreted as follows:

1. The coefficient of X1 means that each increased in population density by 1 percent would decrease deforestation by 0,232 thousand hectares in Riau in 2011, assuming another variable is constant.
2. The coefficient of X2 means that each increased area of land fires amounting to 1.000 ha would increase deforestation area by 351,1 hectares in Riau in 2011, assuming another variable is constant.
3. The coefficient of X3 means each increased 1 percent of the road length would increase deforestation by 0,111 thousand hectares in Riau in 2011, assuming another variable is constant.
4. The coefficient of X5 means that each increased in GDP of mining and excavation by 1 percent would increase deforestation by 0,091731 thousand hectares in Riau in 2011, assuming another variable is constant.

With significance level 0,1 forming four groups according to significant variables affected vast deforestation. The variable significance growths that affected extensive deforestation in Sumatera almost always shift annually (see Figure 10). The global R^2 value acquired from the RGTWR model is 0,6414. Its means that independent variables used in this research were able to explain 64,14% variations of deforestation on the island of Sumatera in 2011-2019.

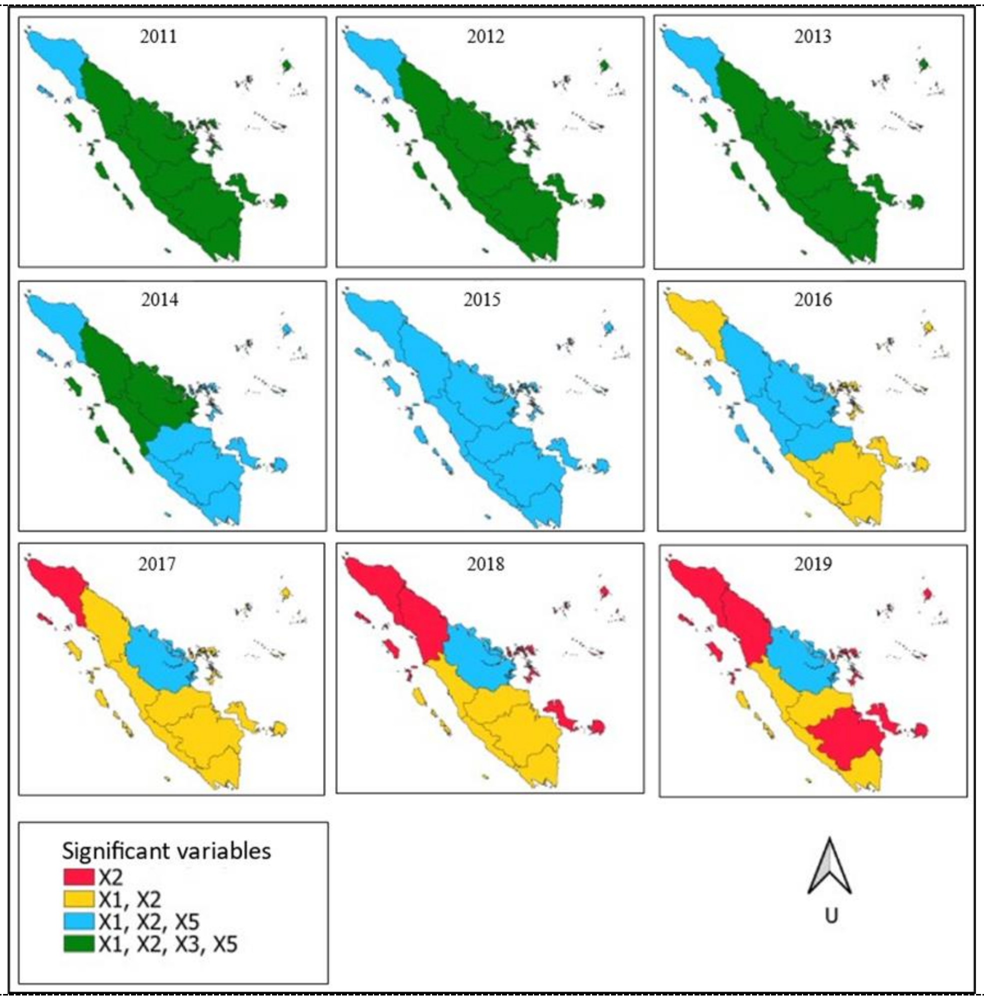

Figure 10. The distribution map of the provincial group book on the island of Sumatera is based on significant variables using the RGTWR method.

In general, from the coefficient estimates, population densities negatively relate to extensive deforestation in all the provinces at all periods. The notion that increased population densities could increase land requirements and thus increase deforestation has been inconsistent with the study results. The trend of increased population density is incompatible with the widespread decline of deforestation in Sumatera Island. It has also been shown that population growth can enhance technological progress and institutional change to reduce pressure on forested areas [7]. An example of the institutional change in the management of forest areas involves people. Some of the forest regions of North Sumatera have also applied this where communities manage forested areas. Examples are the village of Singengu, Mandailing Natal [35], the ecotourism area Tangkahan Mount Leuser National Park [36], and Dairi [37].

The land fires area always has a significant impact on deforestation in each province and each period. The results suggest that the incidence of land fires consistently contributed to deforestation in Sumatera Island. These results are inconsistent with Dimobe et al. [8] and Tuffour-Mills et al. [9], which suggests that land fires are one of the causes of deforestation. Another study also indicated that land fires were one of the greatest threats to destroying natural forests in Indonesia [38].

Variables of road length are always favorably connected to the extensive deforestation in every province of Sumatera Island. From 2011 to 2014, this variable significantly affected deforestation in much of the province of Sumatera Island. But from 2015 to 2019, road length has no longer affected considerably widespread deforestation.

GDP of mining and excavation always has a positive effect on extensive deforestation in the entire province from 2011 to 2019. The results correspond to previous studies that identify mining operations as a direct cause of deforestation [39]. From 2011 to 2015, the GDP of mining and excavation has always significantly affected extensive deforestation in every province in Sumatera Island. But in 2016, this variable began to have no significant impact on several provinces. Then, from 2017 to 2019, the GDP of mining and excavation showed no significant effect on the extensive deforestation in each province, except in Riau. Only in Riau, mining and excavation variables have always significantly affected extensive deforestation from 2011 to 2019. Such conditions coincided with the GDP of mining and excavation of the highest-value province of Riau. The significant change in the GDP of mining and excavation in Sumatera is also supported by the declining number of mineral and coal mining business permits in 2018 and 2019 [40,41].

4. Conclusion

The study results that deforestation on Sumatera Island varies from 2011-2019, with the highest peak in 2015. The largest provinces contributing to the extensive investment growth in Sumatera Island are Riau, Jambi, and South Sumatera. There is a spatial and temporal heterogeneity of deforestation in Sumatera from 2011 to 2019. So, modeling with RGTWR can provide more representative results than with the global regression model. Population densities, road length, GDP of agriculture, fisheries and forestry, and GDP of mining and excavation in each province change little annually. The area of land fires varied widely in every province from 2011 to 2019. Provinces that contribute the highest total area of land fires are Riau, Jambi, and South Sumatera. Using the RGTWR model, forming four significant variable groups affected extensive deforestation in Sumatera Island from 2011 to 2019. The significance of the variable is changing over time each year. Forest fires have always significantly affected extensive deforestation in every province over an entire period of research.

The suggestions that can be made from this research are:

1. The central government would need to coordinate forest management with local governments, considering the differences in the characteristics and diversity behind deforestation in the entire province of Sumatera Island.
2. Local governments also need to increase cooperation with local communities in managing forests, thus reducing the persistent pressure on forest areas.
3. Government should be firmer in enforcing the rules related to land burning and should cooperate with the people and agents involved in forest sustainability to monitor and prevent arson or natural wildfires. Considering bushfires have always had a significant effect on annual deforestation in the provinces of Sumatera Island.
4. While further research could combine with image analysis, and thus provide stronger support information on the causes of deforestation.

References

[1] Sumargo W, Nanggara SG, Nainggolan FA, Isnenti A. Potret Keadaan Hutan Indonesia Periode Tahun 2000-2009. 2011. 54 p.

[2] Rautner M, Leggett M, Davis F. Buku Kecil Pendorong Besar Deforestasi. Oxford: Global Canopy Programme; 2013. 11–225 p.

[3] Maksum FM. Pengaruh Kegiatan Perekonomian terhadap Deforestasi di Kalimantan Tahun 2016 (Penerapan Model Regresi Spasial). Politeknik Statistika STIS; 2019.

[4] Margono BA, Turubanova S, Zhuravleva I, Potapov P, Tyukavina A, Baccini A, et al. Mapping and monitoring deforestation and forest degradation in Sumatera (Indonesia) using Landsat time series data sets from 1990 to 2010. Environ Res Lett. 2012;7(3):034010.

[5] Dariono D, Siregar YI, Nofrizal N. Analisis Spasial Deforestasi dan Degradasi Hutan di Suaka Margasatwa Kerumutan Provinsi Riau. Din Lingkung Indones. 2018;5:27–33.

[6] Febriani I, Prasetyo LB, Dharmawan AH. Deforestation in Tahura Sekitar Tanjung Province Jambi. J Nat Resour Environ Manag. 2017;7(3):195–203.

[7] Isnaini DN, Agustina N. Aplikasi Regresi Data Panel dalam Menentukan Determinan Deforestasi di Kalimantan Periode 2014-2018. Politeknik Statistika STIS; 2019.

[8] Dimobe K, Ouédraogo A, Soma S, Goetze D, Porembski S, Thiombiano A. Identification of Driving Factors of Land Degradation and Deforestation in The Wildlife Reserve of Bontioli

(Burkina Faso, West Africa). Glob Ecol Conserv [Internet]. 2015;4:559–71. Available from: http://dx.doi.org/10.1016/j.gecco.2015.10.006
[9] Tuffour-Mills D, Antwi-Agyei P, Addo-Fordjour P. Trends and Drivers of Land Cover Changes in a Tropical Urban Forest in Ghana. Trees, For People [Internet]. 2020;2(June). Available from: https://doi.org/10.1016/j.tfp.2020.100040
[10] Bustaman U, Sofa WA, Larasati DN, Sari AK, Yuniarti, S.P ZH, et al. Geographically Weighted Regression (GWR) Untuk Analisis Data Sosial dan Ekonomi. Jakarta: Badan Pusat Statistik; 2013.
[11] Fotheringham AS, Crespo R, Yao J. Geographical and Temporal Weighted Regression (GTWR). Geogr Anal. 2015;47(4):431–52.
[12] Adiningrum TZ, Prahutama A, Santoso R. Pemodelan Deforestasi Hutan Lindung di Indonesia Menggunakan Model Geographically and Temporally Weighted Regression (GTWR). J Gaussian. 2018;7(3):314–25.
[13] Holmgren P, Govil K. Manual on Deforestation, Degradation, and Fragmentation Using Remote Sensing and Gis Prepared. FAO; 2007.
[14] Chen C. Paper 265-27 Robust regression and outlier detection with the ROBUSTREG procedure. Proc Twenty-Seventh Annu SAS Users Gr Int Conf [Internet]. 2002; Available from: http://scholar.google.com/scholar?hl=en&btnG=Search&q=intitle:Robust+Regression+and+Outlier+Detection+with+the+ROBUSTREG+Procedure#0
[15] Hidayatulloh FP, Yuniarti D, Wahyuningsih S. Regresi Robust Dengan Metode Estimasi-S Robust Regression Method To Estimate - S. J Eksponensial. 2015;6(2):163–70.
[16] Rahman MB, Widodo E. Perbandingan Metode Regresi Robust Estimasi Least Trimmed Square , Estimasi Scale , dan Estimasi Method Of Moment. Pros Semin Nas Mat. 2018;1:426–33.
[17] Wilcox RR. Introduction to Robust Estimation and Hypothesis. San Diego: Academic Press; 2005.
[18] Wu B, Li R, Huang B. A Geographically and Temporally Weighted Autoregressive Model with Application to Housing Prices. Int J Geogr Inf Sci. 2014;28(5):1186–204.
[19] Fotheringham AS, Brunsdon C, Charlton ME. Geographically Weighted Regression: A Method for Exploring Spatial Nonstationarity. Geogr Anal. 1996;28(4):281–98.
[20] Erda G, Indahwati, Djuraidah A. Outlier handling of Robust Geographically and Temporally Weighted Regression. J Phys Conf Ser. 2019;1175(1).
[21] Febawanti. Pemodelan Robust Geographically Weighted Regression (RGWR) pada Data yang Mengandung Pencilan. Universitas Brawijaya; 2017.
[22] Maziyah AM. Penggunaan Regresi Robust Dengan Estimasi-S Dan Estimasi-MM Dalam Pengembangan Sistem Pendukung Keputusan Guna Memprediksi Tingkat Produksi Padi. Departemen Matematika FMIPA ITS. ITS; 2017.
[23] Ahmad A, Saleh MB, Rusolono T. Spatial Modeling of Deforestation in Fmu of Poigar, North Sulawesi. J Penelit Kehutan Wallacea. 2016;5(2):159–69.
[24] Bera B, Saha S, Bhattacharjee S. Forest Cover Dynamics (1998 to 2019) and Prediction of Deforestation Probability Using Binary Logistic Regression (BLR) Model of Silabati Watershed, India. Trees, For People. 2020;2.
[25] Chuang YC, Shiu YS. Relationship between landslides and mountain development—Integrating geospatial statistics and a new long-term database. Sci Total Environ [Internet]. 2018;622–623:1265–76. Available from: https://doi.org/10.1016/j.scitotenv.2017.12.039
[26] Nahib I, Turmudi, Suwarno Y. Spatial Modeling on Deforestation in Tasikmalaya Regency, West Java Province. Maj Ilm Globë. 2015;17(2):155–64.
[27] Setiawan H, Jaya INS, Puspaningsih N. Model Spasial Deforestasi di Kabupaten Konawe Utara dan Konawe Provinsi Sulawesi Tenggara. Media Konserv. 2015;20(2):166–76.
[28] Wijaya PA. Model Spasial Deforestasi Di Provinsi Jambi. Institut Pertanian Bogor; 2015.
[29] Bos AB, De Sy V, Duchelle AE, Atmadja S, de Bruin S, Wunder S, et al. Integrated Assessment of Deforestation Drivers and Their Slignment with Subnational Climate Change Mitigation Efforts. Environ Sci Policy [Internet]. 2020;114(September):352–65. Available from: https://doi.org/10.1016/j.envsci.2020.08.002

[30] Corona R, Galicia L, Palacio-Prieto JL, Bürgi M, Hersperger A. Local Deforestation Patterns and Driving Forces in A Tropical Dry Forest in Two Municipalities of Southern Oaxaca, Mexico (1985-2006). Investig Geogr [Internet]. 2016;2016(91):86–104. Available from: http://dx.doi.org/10.14350/rig.50918
[31] Hultera, Prasetyo LB, Setiawan Y. Model Spasial Potensi Deforestasi 2020 & 2024 dan Pendekatan Pencegahannya, Kabupaten Kutai Barat. J Nat Resour Environ Manag. 2020;10(2):294–306.
[32] Rosalia PZ. Analisis Penyebab Alih Fungsi Lahan Pertanian Ke Lahan Non Pertanian Kabupaten/Kota Provinsi Jawa Tengah 2003-2013. Eko Reg. 2015;10(10):17–22.
[33] Juniyanti L, Prasetyo LB, Aprianto DP, Purnomo H, Kartodihardjo H. Land-Use/Land Cover Change and Its Causes in Bengkalis Island, Riau Province (from 1990-2019). J Nat Resour Environ Manag [Internet]. 2020 Oct 1 [cited 2020 Nov 30];10(3):419–34. Available from: http://journal.ipb.ac.id/index.php/jpsl/article/view/31164
[34] Hoffmann C, García Márquez JR, Krueger T. A Local Perspective on Drivers and Measures to Slow Deforestation in the Andean-Amazonian Foothills of Colombia. Land use policy. 2018;77(April):379–91.
[35] Brauch HG, Spring ÚO, Mesjasz C, Grin J, Dunay P, Behera NC, et al. Globalization and Environmental Challenges Reconceptualizing Security in 21st Century. Vol. 3. 2007.
[36] Djaenudin D, Oktaviani R, Hartoyo S, Dwiprabowo H. Pengaruh Faktor Ekonomi Terhadap Dinamika Penggunaan Lahan Di Indonesia. IPB; 2016.
[37] Wei Q, Zhang L, Duan W, Zhen Z. Global and geographically and temporally weighted regression models for modeling PM2.5 in Heilongjiang, China from 2015 to 2018. Int J Environ Res Public Health. 2019;16(24).
[38] Liu Y, Chen ZM, Xiao H, Yang W, Liu D, Chen B. Driving factors of carbon dioxide emissions in China: an empirical study using 2006-2010 provincial data. Front Earth Sci. 2017;11(1):156–61.
[39] Huang B, Wu B, Barry M. Geographically and temporally weighted regression for modeling spatio-temporal variation in house prices. Int J Geogr Inf Sci. 2010;24(3):383–401.
[40] Putra Z, Wijayanto H, Aidi MN. Robust Geographically and Temporally Weighted Regression Using S-estimator in Criminal Case in East Java Province. Int J Sci Basic Appl Res [Internet]. 2019;48(3):24–36. Available from: https://core.ac.uk/download/pdf/249336783.pdf
[41] Chen Y, Li M, Su K, Li X. Spatial-Temporal Characteristics of the Driving Factors of Agricultural Carbon Emissions: Empirical Evidence from Fujian, China. Energies. 2019;12(16).
[42] Erda G, Djuraidah A. A Comparison of GTWR and Robust GTWR Modelling. 2018;4(9):453–7. Available from: http://ijsrset.com/IJSRSET184993
[43] Kartiko SH, Novianti P. Application of Geographically and Temporally Weighted Regression (GTWR) in the Case of DBD in Yogyakarta City and Sleman District. AECON. 2021;76–87.
[44] Sholihin M, Mohamad Soleh A, Djuraidah A. Geographically and Temporally Weighted Regression (GTWR) for Modeling Economic Growth using R. IJCSN -International J Comput Sci Netw. 2017;6(65):800–5.
[45] Kutner MH, Nachtsheim CJ, Neter J, Li W. Applied Linear Statistical Models Fifth Edition. Fifth Edit. Vol. 29, Journal of Quality Technology. New York: McGraw-Hill/Irwin; 2005.
[46] Anselin L. Spatial Econometrics: Methods and Models. Vol. 65, Economic Geography. Santa Barbara: Springer Science & Business Media Dordrecht; 1988.
[47] Leung Y, Mei CL, Zhang WX. Statistical tests for spatial nonstationarity based on the geographically weighted regression model. Environ Plan A. 2000;32(1):9–32.
[48] Rasyid F. Permasalahan dan Dampak Kebakaran Hutan. J Lingk Widyaiswara [Internet]. 2014;1(4):47–59. Available from: http://juliwi.com/published/E0104/Paper0104_47-59.pdf
[49] Nuraini C. Kearifan Lingkungan dalam Pengelolaan Hutan, Tanah dan Sungai di Desa Singengu, Kecamatan Kotanopan Kabupaten Mandailing Natal, Sumatera Utara. J Mns dan Lingkung. 2015;22(1):100–5.
[50] Yusnikusumah TR, Sulistyawati E. Evaluasi Pengelolaan Ekowisata di Kawasan Ekowisata

Tangkahan Taman Nasional Gunung Leuser Sumatera Utara. J Perenc Wil dan Kota. 2016;27(3):173–89.
[51] Silaen PCP. Analisis Spasial Degradasi dan Deforestasi Serta Arahan Rencana Pengembangan Perekonomian Masyarakat di Kabupaten Dairi [Internet]. Universitas Sumatera Utara; 2019. Available from: https://library.usu.ac.id
[52] Jazui A. Kebakaran Hutan dan Lahan Di Riau Menurut Perspektif Hukum Lingkungan. Rechts Vinding. 2019;1–5.
[53] ESDM. Gambaran Pertambangan Mineral dan Batubara Indonesia. Jakarta; 2018.
[54] Minerba D. KEGIATAN PENGELOLAAN PERTAMBANGAN MINERAL & BATUBARA OVERVIEW 2019. Jakarta; 2019.