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MODELING OF CLIMATE CHANGE VULNERABILITY LEVELS IN INDONESIA: SMOOTHING SPLINES QUANTILE REGRESSION

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Abstract: Indonesia's forest area decreases every year and be the top four countries with the largest primary forest loss in the world. There is 99 percent of Indonesia's territory that is quite vulnerable to being very vulnerable to climate change. Considering the urgency of the climate change issue and the SDGs targets for handling impacts of climate change, this research will focus on the effect of deforestation on the climate change vulnerability levels in Indonesia. The smoothing spline quantile regression modeling was carried out because of the nonlinear relationship between deforestation and climate change vulnerability levels and data contains outlier. The result, deforestation has a significant positive effect on the distribution of villages based on vulnerability to climate change. The higher deforestation rate will increase climate change vulnerability levels. There are four provinces (Bangka Belitung, Riau Islands, South Kalimantan, and East Kalimantan) have a small number of villages with a very vulnerable level of climate change, and five provinces (Banten, East Nusa Tenggara, West Papua, Papua, and North Sumatera) have a large number of villages with a very vulnerable level of climate change. Forest protection strategies and avoiding permanent land conversion are management innovations that need to be implemented.

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1. INTRODUCTION

Forests are complex ecosystems that have a role in almost every species on earth [1]. Forests also play a role in supporting life and controlling environmental systems. Indonesia is one of the countries with the largest forest area globally and automatically acts as one of the largest natural oxygen providers. However, Indonesia's forest area decreases every year and be the top four countries with the largest primary forest loss in the world [2]. As seen from the increasing number of illegal natural forest conversions, the high rate of deforestation has caused Indonesia's nickname as the lungs of the world to begin to fade [3].

Deforestation will cause carbon dioxide and greenhouse gases to be higher and uncontrollable [4]. Currently, greenhouse gas emissions are already 50 percent higher than in 1990 [5]. The emission of greenhouse gases will cause long-term effects in the form of global warming, which will become a problem for the entire world community [6]. Continuous global warming will result in prolonged changes in the climate system and harm the environmental sustainability index [7]. Climate change has an impact on various sectors of people's lives. One of the extreme impacts of climate change is a shift in seasons [8]. Climate change has an impact on the national economy indirectly [9]. As the largest archipelagic country, Indonesia is one of the countries most vulnerable to the negative effects of climate change. There is 99 percent of Indonesia's territory that is quite vulnerable to being very vulnerable to climate change [3]. Information on climate change vulnerability is very important as a supporter of adaptation planning policies and risk reduction in all sectors of the national economy.

The issue of climate change has become a sensitive world issue. The Sustainable Development Goals (SDGs) have carried the theme of climate change as one of the global goals of the 2030 sustainable development agenda. Goal 13 of the SDGs outlines targets and immediate actions to deal with climate change, including a) integrating anticipatory actions on climate change into national policies, strategies, and planning, b) improving education, raising awareness, as well as human and institutional capacities related to mitigation, adaptation, impact reduction and early warning of climate change [5]. The Indonesian government has an important role in climate change issues. In December 2015, Indonesia affirmed its commitment to participate in climate change issues as stated through the Paris Agreement [10]. This commitment synergized with sustainable development efforts as outlined in national policies.

Considering the urgency of the climate change issue and the SDGs targets for handling impacts of climate change, studying the behaviour and distribution of areas at risk of being highly vulnerable to climate change is necessary. This research will focus on the effect of deforestation on the climate change vulnerability levels in Indonesia. The nonparametrics smoothing splines regression modeling was carried out because of the nonlinear relationship between deforestation and the number of villages based on the climate change vulnerability levels in category 5 (very vulnerable). The condition of data containing outliers requires a more robust method, so smoothing splines quantile regression is propose to obtain the most effective analysis in this study. It is hoped that this method will describe the distribution of areas based on vulnerability to climate change in Indonesia more accurately and efficiently.

2. MATERIAL AND METHOD

2.1 Data source. This study uses cross-sectional data sourced from the Statistics Indonesia and the Indonesian Ministry of Environment and Forestry in 2019. The variable are the independent (X) deforestation in Ha units while the dependent variable (Y) is the number of villages based on the climate change vulnerability levels in category 5 (very vulnerable). This research covers 34 provinces in Indonesia. The data was processed using the R Quantreg Software package by Koenker.

The nonlinear relationship between two variables requires a nonparametric method in its analysis such as smoothing splines regression. When the condition of the data containing outliers requires a more robust approach, so smoothing splines quantile regression is used to obtain the most effective analysis.

2.2 Smoothing Splines Regression. Regression smoothing splines are matching curve processes with smoothing for a set of observations using the splines function. Estimating $f(x_i)$ with OLS will produce a rough function. The $f(x_i)$ in nonparametric model equation is an unknown function. The smoother function use to minimize the sum of the squares. One way to get a fairly smooth function is to provide a smoothing (penalty). The estimation of the splines function $f(x_i)$ is to minimize [11]:

$$\sum_{i=1}^{n}\left(y_i - f(x_i)\right)^2 + \lambda \int_0^1 [f''(x)]^2 dx \qquad (1)$$

where $\Sigma\left(y_i - f(x_i)\right)^2$ is the sum of the squares of residuals, smoothness size roughness pinalty is $\lambda \int_0^1 [f''(x)]^2 dx$, and λ is smoothness parameters. The role of smoothing parameter (λ) is very important to control the accuracy of the model and smoothness of the curve. The value λ is 0 to ∞. If $\lambda \to 0$ then the accuracy of the model will be high but the curve is less smooth. The curve will tend to follow the pattern of the data, making it look rougher. The distance between the data and the estimate is very close, so (1) will be equal to the sum of the squares of the residuals. Conversely, if $\to \infty$ then the accuracy of the model will be low but the curve is very smooth. The curvature of the curve is very small, even approaching a linear function, so (1) will be equal to the roughness penalty. The curve will tend to move away from the data pattern so that the distance between the data and the prediction is very far. Smoothing parameter (λ) is selected with the criteria of Cross Validation (CV)[12]:

$$CV(\lambda) = \frac{1}{n}\sum_{i=1}^{n}\frac{y_i - f(x_i)}{1 - h_{ii}} \qquad (2)$$

2.3 Smoothing Splines Quantile Regression. Quantile regression is a technique that explains the relationship between the response variable and the predictor variable on the measure of concentration (conditional median) of the response variable and various quantiles. Quantile regression is very well used in data distribution that is asymmetrically distributed, dense at the end of the data distribution, or there are outliers because the resulting estimator will be more efficient [13]. Smoothing splines quantile regression method is a regression modeling that estimates quantile regression use smoothing splines method. The quantile regression solution for smoothing splines is obtained by minimizing [14]:

$$\sum_{i=1}^{n} \rho_\tau\big(y_i - f(x_i)\big) + \lambda \int_0^1 |f''(x)|dx\,;\ 0 = x_0 < x_1 < \cdots\ x_n < x_{n+1} = 1 \qquad (3)$$

The objective function of the smoothing splines quantile regression ($L1$) is not differentiable at the zero point, so no explicit solution is obtained. Therefore, the quantile solution can be obtained by converting function ($L1$) into the form of a system of linear equations that can be solved by LP-problem.

In the final stage of the research, there is a comparison of the Smoothing Splines Regression (the mean approach) to Smoothing Splines Quantile Regression (the median approach) using the Root Mean Square Error (RMSE) value.

2.4 Research Hypothesis. Thomson's theory in [4] stated that forests could reduce carbon dioxide emissions and mitigate climate change. Furthermore, forest management contributing to climate change is strongly influenced by efforts to avoid permanent land conversion (deforestation)[15]. Referring to the theory and previous research, the research hypothesis is deforestation can affect the distribution of climate change vulnerability levels in Indonesia.

3. Main Results

3.1 Climate Change Vulnerability Levels. The number of villages in Indonesia reached 83.931 villages [16]. The Ministry of Environment and Forestry classify these villages based on their level of vulnerability to climate change. There are five levels of classification: level 1 for the non-vulnerable, level 2 for the moderately vulnerable, level 3 for the quietly vulnerable, level 4 for the vulnerable, and level 5 for highly vulnerable villages to climate change [3]. Figure 1 shows the percentage of villages based on the level of vulnerability to climate change in category 5 (very vulnerable). Papua is the region that has the most significant percentage, the second-largest percentage is Sumatera, and the smallest percentage is Maluku Island.

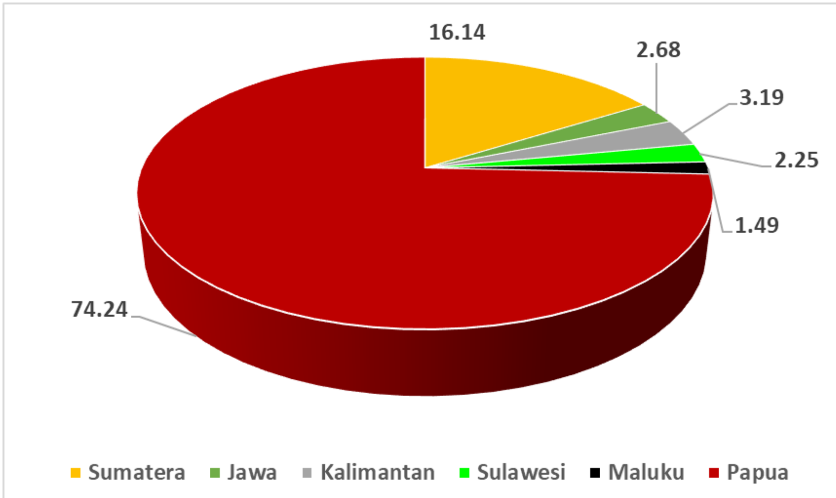

Figure 1. Distribution of villages in the category of very vulnerable to climate change by island

3.2 Deforestation Rate. Indonesia has reduced the gross deforestation rate to a significant negative trend (Figure 2). However, the rate of reforestation rate still fluctuates every year. Compared to the previous year, Indonesia reduced deforestation by 75.03% in 2019 to 119.1 Ha gross deforestation and 3.6 Ha reforestation rate. So accumulatively, the net deforestation in 2019 was 115.46 Ha. The government's various efforts have recently shown significant results. These efforts include the implementation of the Presidential Instruction on Stopping the Granting of New Permits and Improving the Governance of Primary Natural Forests and Peatlands, Controlling Forest and Land Fires, Controlling Peat Damage, Controlling Climate Change, Limiting changes in forest area allocation for the non-forestry sector (HPK), Settlement of Land Tenure. in Forest Areas (PPTKH/TORA), sustainable forest management and forest and land rehabilitation [17].

Figure 2 Indonesia's deforestation and reforestation, 2017-2019

3.3 Smoothing Splines Regression. Data transformation uses a natural logarithm transformation in the initial data preparation to obtain data with a not too large variance.

The plot data distribution pattern can determine the relationship between deforestation and the level of village vulnerability. A nonparametric approach can be used if the slope function and intercept cannot determine the data distribution pattern [18]. The data distribution pattern of the two variables can be seen with the scatter plot in Figure 3.

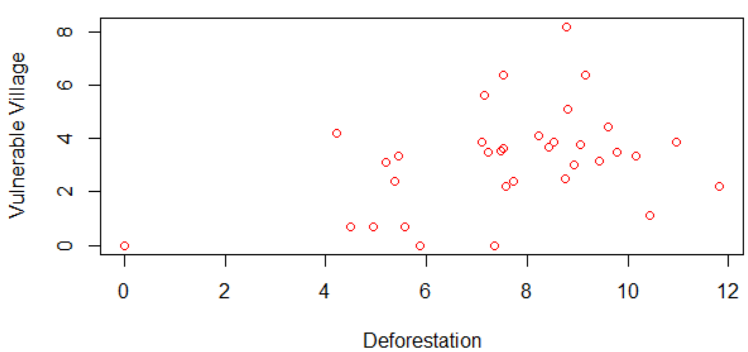

Figure 3. The data distribution of deforestation and climate change vulnerability levels

The data distribution tends to be irregular, so a nonparametric approach is recommended. Smoothing Splines regression modeling perform using the smooth spline function with Cross-Validation (CV) criteria. From the modeling, the following parameters are obtained in Table 1.

Table 1. Smoothing Splines Regression Parameters

Parameters	Value
Spar	1.0340
Lambda	0.0051
Degrees of Freedom	3.9687

The optimum parameters are used to determine the estimator. The Smoothing Splines regression model is obtained, as shown Figure 4.

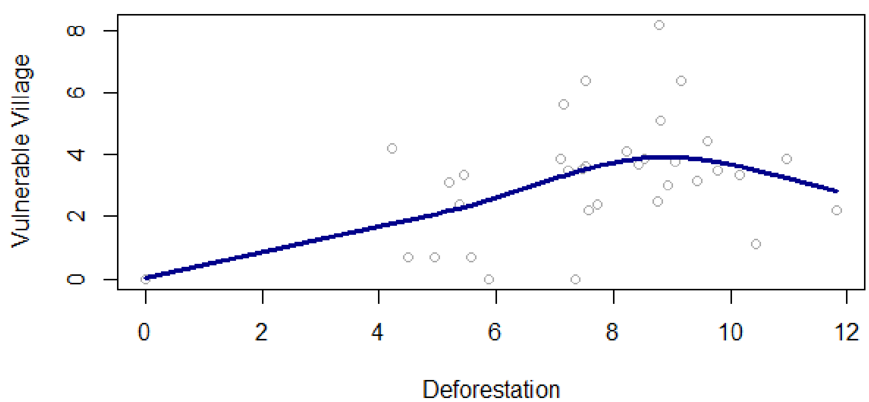

Figure 4 Curve of Smoothing Splines Regression (Mean)

3.4 Smoothing Splines Quantile Regression. The mean regression approach is not suitable if the data distribution contains outliers. Quantile regression can be a solution efficiently because it can accommodate outliers and capture information on the distribution of data through various quantile lines. Outliers identification uses a boxplot of smoothing splines regression's residuals, as shown below. Figure 5 shows that the relationship between the two variables indicates the presence of outliers.

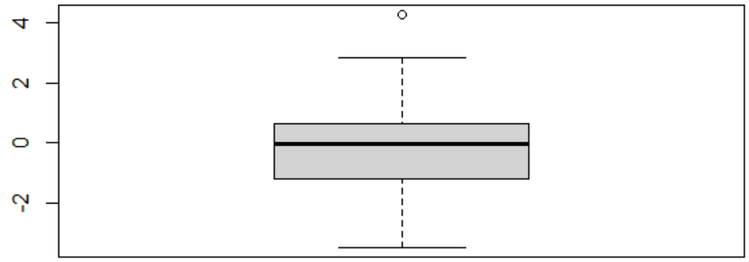

Figure 5. Residual boxplot of smoothing splines regression

Based on eq 3, the Smoothing Splines Quantile Regression Model (Median, τ=0.5) is obtained in Figure 6.

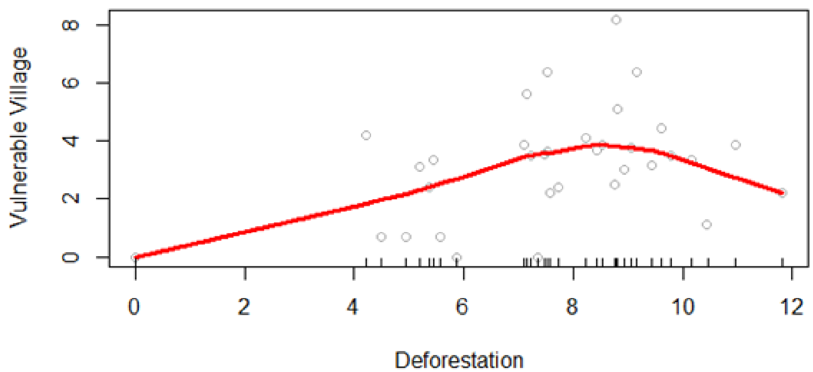

Figure 6. Residual boxplot of smoothing splines regression

Quantile regression can also obtain various quantile values so that there are as many regression lines as the desired quantile [14]. Models will make five parts, modeling of deforestation and the climate change vulnerability levels uses quantile values of 0.2, 0.4, 0.6, and 0.8. The resulting smoothing spline quantile regression model is as follows:

$$\hat{y}_{0.2} = -4.83x10^{-9} + 0.59(x - x_1) + \cdots + 2.19(x - x_{34}) \quad (4)$$

$$\hat{y}_{0.4} = -3.58x10^{-9} + 0.65(x - x_1) + \cdots + 2.19(x - x_{34}) \quad (5)$$

$$\hat{y}_{0.6} = 2.39x10^{-10} + 2.09(x - x_1) + \cdots + 2.56(x - x_{34}) \quad (6)$$

$$\hat{y}_{0.8} = 4.52x10^{-9} + 2.74(x - x_1) + \cdots + 2.38(x - x_{34}) \quad (7)$$

This modeling uses a unique predictor value (knots). Due to the unique value of 34 data, the number of knots formed is 34.

Deforestation has a significant positive effect on the number of villages based on vulnerability to climate change. The higher deforestation rate will increase the level of vulnerability to climate change. One of the impacts of deforestation is a decrease in the quality of the atmosphere that occurs in climate change [19]. Deforestation has a severe impact on global warming, which results in disasters, food threats, and climate change [6]. The innovation in forestry management is needed to solve climate change in Indonesia [15]. One of the management innovations is a forest protection strategy, avoiding permanent land conversion.

Furthermore, the estimated value of climate change vulnerability based on deforestation is shown in Figure 7. Using a nonparametric approach will limit the estimation to only internally driven data. Figure 7. shows that four provinces are below the 0.2 quantile, which means that these provinces have a small number of villages with a very vulnerable level of climate change. These provinces are Bangka Belitung, Riau Islands, South Kalimantan, and East Kalimantan. There are five provinces with a value above the quantile 0.8 which means that these provinces have a large number of villages with a very vulnerable level of climate change. These provinces are Banten, East Nusa Tenggara, West Papua, Papua, and North Sumatera.

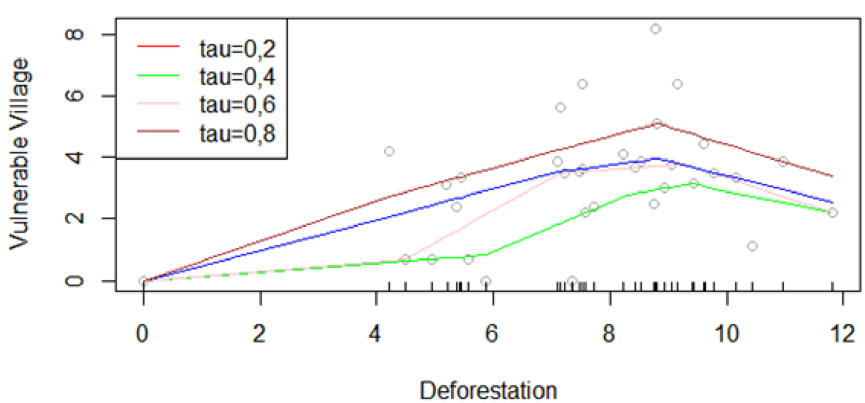

Figure 7. Curve of smoothing splines quantile regression

3.5 Best Model Selection. The quantile approach is more efficient than the mean approach for asymmetric data distribution and the presence of outliers. The smoothing splines quantile regression model (median, τ=0.5) will be compared with the smoothing splines (mean) regression to find out the best model. The comparison of the two models can be seen in Figure 8.

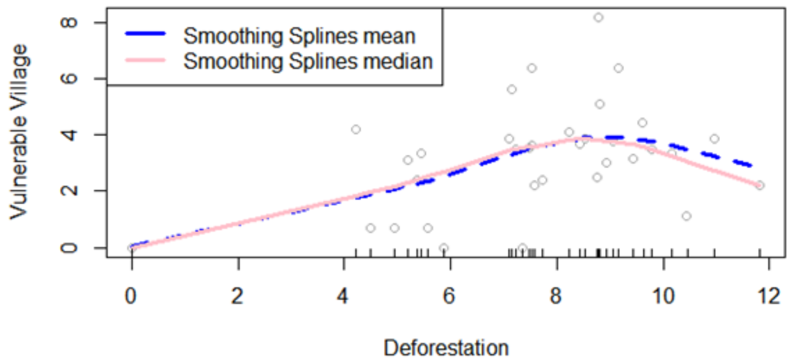

Figure 8. The comparison of smoothing splines mean and median

The performance test of the models uses the Root Mean Square Error (RMSE) in Table 2.

Table 2 Smoothing Splines Regression Parameters

Regressions	RMSE
Smoothing Splines Regression (Mean)	1.5854
Smoothing Splines Quantile Regression (Median)	1.1469

The RMSE of Smoothing Splines Regression (Mean) has a higher value. The use of OLS is susceptible to produce an enormous residual value. Therefore, smoothing splines quantile regression is the best model of climate change vulnerability levels in Indonesia.

4. CONCLUSION

The climate change issue has the attention of many countries in the world, including Indonesia. Based on the results, the following conclusions: smoothing splines quantile regression is the best model for climate change vulnerability levels in Indonesia. Deforestation has a significant positive effect on the distribution of villages based on vulnerability to climate change. The higher deforestation rate will increase the level of vulnerability to climate change. There are four provinces (Bangka Belitung, Riau Islands, South Kalimantan, and East Kalimantan) have a small number of villages with a very vulnerable level of climate change, and five provinces (Banten, East Nusa Tenggara, West Papua, Papua, and North Sumatera) have a large number of villages with a very vulnerable level of climate change. Deforestation has a severe impact on global warming, which results in disasters, food threats, and climate change and the innovation in forestry management is needed to solve climate change in Indonesia. Forest protection strategies and avoiding permanent land conversion are management innovations that need to be implemented. In this research, the smoothing splines quantile regression model is limited to one predictor. It is necessary to develop additional variables to provide more information in modeling climate change vulnerability levels in Indonesia.

CONFLICT OF INTERESTS

The authors declare that there is no conflict of interests.

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