Modeling the Percentage of NEET in Indonesia with Spatial Cauchy Regression through the Bayesian Analysis Approach

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Abstract— **Indonesia has entered a period of demographic bonus. Human resources must be optimized. The number of children who do not in employment, education or training (NEET) in each province needs attention. Several factors that could contribute to the decline in the NEET percentage are literacy rates and the number of adolescents with computer skills. Increasing these two factors is believed to be able to reduce the percentage of NEET in every province in Indonesia. To find out the relationship between these two factors and how much influence they have on the percentage of NEET, this research is modeled by Cauchy regression and includes spatial effects. The results of the analysis show that the best model is when the spatial effect is modeled by Fernandez Steel Skew Normal conditionally autoregressive (FSSN CAR). This result is seen from the smallest value of the Watanabe Akaike Information Criterion (WAIC) in this model, which is 190.5. The parameter estimated shows that the higher the literacy rate and the number of adolescents with computer skills, the lower the percentage of NEET in each province in Indonesia. The results of this research can be useful for the Indonesian government to increase the number of educational facilities related to these two factors.**

Index Terms—**NEET, Education, Cauchy, CAR, Bayesian**

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I. Introduction

ECONOMY development is very dependent on the quality of human resources [1]. Moreover, from 2020 to 2045 Indonesia will have a demographic bonus. A demographic bonus is a condition where the number of people entering the productive age group is greater than that of the non-productive age group. In the 2020-2045 range, around 70% of Indonesia's population is dominated by people of productive age, namely 15-64 years. This is a big advantage for Indonesia when compared to Japan, where in the future the population will be older. So, Indonesia has a level of productivity that should be better than Japan. However, if this demographic bonus is not accompanied by superior quality human resources and adequate facilities, then the demographic bonus can ~~actually~~ lead to a high number of unemployed and a high number of children who are not in employment, education, or training (NEET). The high number of NEETs can hurt society in the form of criminal acts because Indonesians still have to meet their daily needs.

Many studies have discussed NEET. Research conducted by Schoon and Lyons-Amos examines the role of structural resources and agents in shaping transitional people. In this study, it was concluded that apart from highlighting structural constraints, it is important to conceptualize the role of agents in understanding youth transitions [2]. Research conducted by Lee et al stated that NEET is a measure of mental illness in an individual [3]. The research conducted by Rodwell et al stated that a young person who belongs to NEET is at risk of long-term economic, backwardness, and social exclusion [4] to [8]. Other studies state that the existence of educational facilities, employment opportunities, and training are the main factors that form the basis of the number of NEETs in a government [5] to [8].

Of the several studies mentioned about NEET, no one has considered location. This is important because there is still a possibility that the progress of one city will affect the progress of other cities. With considered location, the distribution of NEET can be seen through mapping. Thus, visually the government can pay attention to the locations of concern. Similarly, research conducted by Chernoyarov et al has used spatial effects to measure the range and the velocity of spacecraft [9]. The spatial effect in their research is important because it will determine the coordinate system for obtaining the emission signal.

This research aims to make a policy for Indonesia to provide recommendations to the provincial government regarding what facilities must be improved to meet good quality standards of human resources. Factors that can be used as variables determining the level of NEET include literacy rates and adolescents with computer skills [10]. To accommodate the percentage of NEET data we used the Cauchy distribution because the Cauchy distribution can be flexible left skewed, right skewed, or symmetrical [11]. In Cauchy regression, we include the spatial effects that are modeled ~~modeled~~ by conditionally autoregressive (CAR) [12] to [14]. We compared the spatial effects through the Normal CAR, Double Exponential (DE) CAR, and Fernandez Steel Skew Normal (FSSN) CAR [15]. We estimated the model using Bayesian analysis. We used the Hamiltonian Monte Carlo (HMC) method [16]. In this research, we use the Stan programming language, this programming language is similar to C++. For C++ performance, it can be seen in the research conducted by Arboleda et al [17]. Estimation by Bayesian analysis has also previously been carried out by Mahmudah et al [18]. In their study, the Bayesian approach was used to estimate the Dagum distribution parameter in cases of dengue fever. Estimation using the classical and the Bayesian approach has also been carried out by Jia et al to estimate the parameters of the Lindley distribution in the case of progressive hybrid censoring schemes [19]. Research that combines generator design, loss function, Bayesian optimization, and self-attention mechanism for small samples has been carried out by Dongping et al [20].

II. Data Description and Algorithm Introduction

A. Data Description

The dataset in this research is the percentage of NEET in each province in Indonesia as a respon variable Y, and literacy rates X_1 and adolescents with computer skills X_2 as predictor variables. This dataset was retrieved in 2021.

B. Spatial Regression Algorithm

Following are the steps taken to model the percentage of NEET data by regression with spatial effects:

Step 1: Display descriptive statistics so that we can see an overview of the dataset. Here we can see the mean and median values so that it will determine whether the data is skewed to the right or left. This will determine the candidate distribution to be used for analysis.

Step 2: Conduct data mapping on the percentage of NEET in each province. Visually, this map can be seen the close relationship between adjacent provinces. To display visualization with maps, geographic information systems are used as has been done by Sari et al [21].

Step 3: Examine the spatial correlation between the percentage of NEET data in each province in Indonesia. In this research, Moran's I test was used [22]. This test supports the visualization results in the previous step. After knowing that there is a spatial correlation, then the model can be given a spatial effect that is modeled by conditionally autoregressive (CAR) [12], [13].

Step 4: If it is proven that there is a spatial correlation, then each neighborhood of each province can be arranged using queen contiguity [23].

Step 5: Based on the descriptive statistics in Step 1, a distribution is determined that is by the NEET percentage data. In this research used the Cauchy distribution. To test whether the Cauchy distribution fits the data or not, the Kolmogorov-Smirnov hypothesis test is used [24] to [26].

Algorithm 1 HMC Bayesian with Stan Language

Input: N, Y, X_1, X_2, NK, N_edge,node1,node2,Prov

Output: $\beta_0, \beta_0, \beta_0, \sigma$, WAIC

Functions Block
```
functions {
…
}
```
Data Block
```
data {
N : number of observations;
Y : percentage of NEET data;
X1 : literacy rate data;
X2 : adolescents with computer skills data;
NK : number of provinces;
N_edge : number of edges after spatial data
   transform to node;
node1 : node 1 data;
node2 : node 2 data;
Prov : province data using numbering, 1 for the first
   province, 2 for the second province, to 34 for the
   last province;
}
```
Parameters Block
```
parameters {
β0 ;
β1 ;
β2 ;
σ ;
ϕ ;
};
```
Model Block
```
model {
β0 ~ N(0,1) ;
β1 ~ N(0,1) ;
β2 ~ N(0,1) ;
σ ~ Gamma(1,1) ;
ϕ ~ CAR ;
      for (i in 1:N){
            Yi ~ Cauchy(β0 + β1x1i + β2x2i + ϕi, σ) ;
            }
}
```
Generated Quantities Block
```
generated quantities {
      for (I in 1:N){
            log_lik[i]=
            Cauchy_lpdf( Yi | β0 + β1x1i + β2x2i + ϕi, σ );
            }
}
```

Step 6: Running model with several model choices. Models without spatial effects and models with spatial effects. Models with spatial effects are distinguished again based on the modeling of the spatial effects included. Spatial effects are modeled by Normal CAR, Double Exponential CAR,

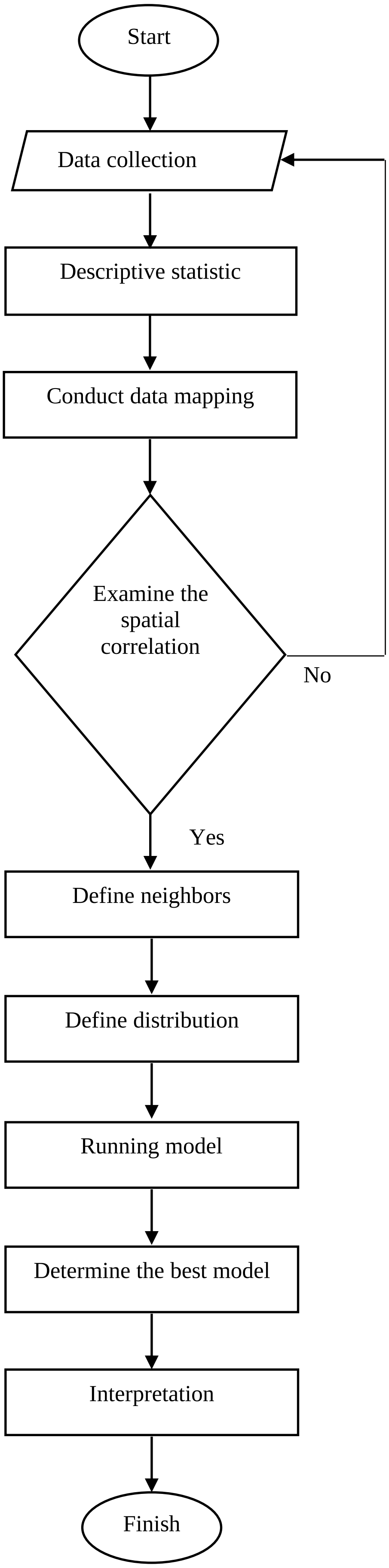

Fig 1. Spatial Regression Flow

and FSSN CAR [15], [27], [28]. To determine the best model, the Watanabe Akaike Information Criterion (WAIC) value is used. The model with the smallest WAIC value is the best [29].

Step 7: Based on the previous step, the results of parameter estimation for the best model are given and interpretation is carried out. Estimation is done using Bayesian HMC through Stan language with the algorithm given in Algorithm 1. The Function Block can be filled with functions for Normal CAR, DE CAR, or FSSN CAR [14], [15], [27], [28], [30]. The detailed flow can be seen in Fig 1.

III. Results and Analysis

A. *Descriptive Statistics*

To find out the characteristics of a dataset, we perform descriptive statistics for our data in TABLE 1.

TABLE 1
DESCRIPTIVE STATISTICS OF NEET DATASET

Variable	Mean	StDev	Min.	Q1	Q2	Q3	Max.
Y	21.9800	3.9410	9.8900	20.1850	21.8650	24.4700	29.4300
X_1	99.5900	1.5070	91.1300	99.8500	99.9000	99.9420	99.9900
X_2	88.4800	11.7200	34.9500	86.4300	91.3600	94.5200	99.0700

where Y is the percentage of NEET, X_1 is the literacy rate, and X_2 is the number of adolescents with computer skills. From TABLE 1, it can be seen that the lowest percentage of NEET is 9.8900 and the highest percentage of NEET is 29.4300. With such a large difference, it is necessary to address provinces with a high percentage of NEET.

Scatter plots describing the relationship between literacy rate and the percentage of NEET and also the number of adolescents with computer skills and the percentage of NEET can be seen in Fig 2 and Fig 3. These two figures show that the relationship between X_1 against Y and X_2 against Y is not linear. Therefore, we cannot use the Normal distribution on Y. And we have to find a suitable distribution for Y.

B. *Conduct Mapping for Dissemination of NEET Percentage Data*

The first step to predicting the existence of spatial correlations between provinces in Indonesia, we present a map of the distribution of NEET percentage data for each province in Indonesia. The mapping results can be seen in Fig 4. The polygons on the map show the provinces in Indonesia. The number of provinces in Indonesia is 34. The colors on the map show the percentage of NEET in each province. If the color of the polygon is close to red then the province has a high percentage of NEET. If the color of the polygon is close to green then the province has a low percentage of NEET. Visually, it can be seen that adjacent provinces have almost the same polygon color. This is an initial indication that there is a spatial correlation between provinces in Indonesia. If the color is redder, the bigger the NEET percentage and conversely, the greener it is, the smaller the NEET percentage.

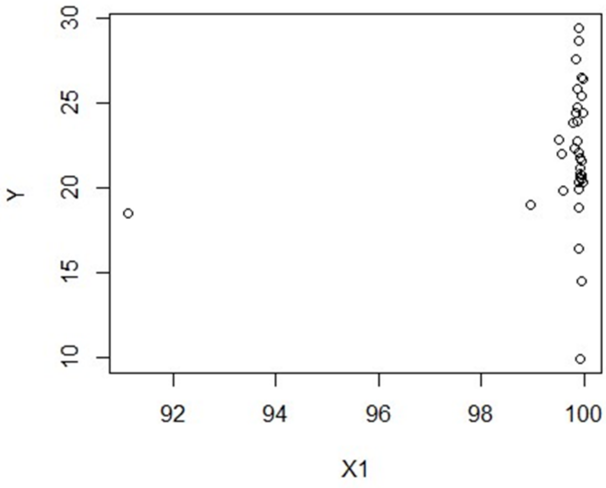

Fig 2. Scatter plot of X_1 against Y

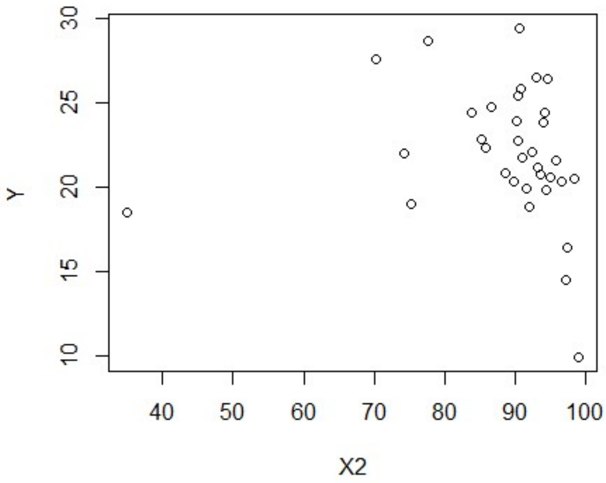

Fig 3. Scatter plot of X_2 against Y

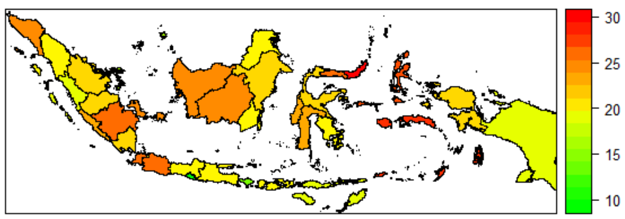

Fig 4. Mapping of the percentage NEET in Indonesia

C. *Hypothesis Test for Spatial Dependencies*

Apart from visual analysis, we also provide a hypothesis test to test the existence of spatial correlations between provinces in Indonesia using Moran's I test. The hypothesis test used is

H_0: There is a spatial correlation

H_1: There is no spatial correlation

Moran's I test statistic has been obtained for 0.1812 and p-value 0.2239. By using an α of 5%, it can be concluded that the data on the percentage of NEET between provinces in Indonesia has a spatial correlation. This result supports the initial assumption with the map shown in Fig 4. Because it has been statistically proven that there is a spatial correlation, it is necessary to show the provinces that are adjacent to each other. To determine neighbors between provinces, Queen Contiguity is used. So, the neighbors for each province are given in TABLE 2.

TABLE 2
NEIGHBORING PROVINCES IN INDONESIA USE QUEEN CONTIGUITY

Province	Poly ID	Number of adjacent provinces	Adjacent provinces
Aceh	1	1	34
Bali	2	0	
Banten	3	2	9,6
Bengkulu	4	4	33,32,19,8
DI Yogyakarta	5	1	10
DKI Jakarta	6	2	9,3
Gorontalo	7	2	29,31
Jambi	8	5	33,32,26,18
Jawa Barat	9	3	3,6,10
Jawa Tengah	10	3	11,5,9
Jawa Timur	11	1	10
Kalimantan Barat	12	2	14,15
Kalimantan Selatan	13	2	14,15
Kalimantan Tengah	14	3	13,15,12
Kalimantan Timur	15	4	16,14,13,12
Kalimantan Utara	16	1	15
Kep. Bangka Belitung	17	0	
Kep. Riau	18	1	8
Lampung	19	2	33,4
Maluku	20	0	
Maluku Utara	21	0	
Nusa Tenggara Barat	22	0	
Nusa Tenggara Timur	23	0	
Papua	24	1	25
Papua Barat	25	1	24
Riau	26	3	34,32,8
Sulawesi Barat	27	2	29,28
Sulawesi Selatan	28	3	30,29,27
Sulawesi Tengah	29	4	30,27,28,7
Sulawesi Tenggara	30	2	28,29
Sulawesi Utara	31	1	7
Sumatera Barat	32	4	34,4,8,26
Sumatera Selatan	33	3	19,4,8
Sumatera Utara	34	3	26,32,1

Ploy ID column is the identity of the province given in the form of a polygon on the map. Number of adjacent provinces column is the number of provinces that adjacent with the province being observed. Adjacent provinces column is a list of provinces that are adjacent with the province being observed. For example, Banten province has 2 neighbors, namely provinces 9 and 6. Where province 9 is Jawa Barat and province 6 is DKI Jakarta.

D. Determining the Appropriate Distribution of Percentage of NEET

Before modeling, we have determined the distribution that is supposedly appropriate for the percentage of NEET data
H_0: The data follows the Cauchy distribution
H_1: The data does not follow the Cauchy distribution
By using the Kolmogorov-Smirnov test, a p-value of 0.8602 was obtained. With α of 5% it can be concluded that the percentage of NEET data follows the Cauchy distribution with the with parameter $\mu = 21.7520$ and $\sigma = 2.0218$. This result supports the initial assumption that the relationship between X_1 against Y and X_2 against Y is not linear, so it cannot be analyzed using the Normal distribution.
In Fig 5, the histogram for the percentage of NEET data against the probability density function of the Cauchy distribution is given. The result is quite appropriate because Y has a left skew. If the analysis is carried out with the Normal distribution, it is not appropriate because the Normal distribution is symmetrical.

E. Modeling with Spatial Effects

At this stage, a model without spatial effects is compared, with the spatial effects of Normal CAR, Double Exponential CAR, and FSSN CAR. Model 1 is the Cauchy regression without spatial effect, Model 2 is the Cauchy regression with the Normal CAR, Model 3 is the Cauchy regression with the Double Exponential CAR, and Model 4 is the Cauchy regression with the FSSN CAR CAR.
Model 1:

$$y_i \sim \text{Cauchy}\left(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i}, \sigma\right)$$

Model 2

$$y_i \sim \text{Cauchy}\left(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \phi_i, \sigma\right)$$

$$\phi_i \sim N_n\left(n,\ \text{node 1, node 2}\right)$$

Model 3

$$y_i \sim \text{Cauchy}\left(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \phi_i, \sigma\right)$$

$$\phi_i \sim DE_n\left(n,\ \text{node 1, node 2}\right)$$

Model 4

$$y_i \sim \text{Cauchy}\left(\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \phi_i, \sigma\right)$$

$$\phi_i \sim FSSN_n\left(n,\ \text{node 1, node 2}\right)$$

For the four models that have been written, it is necessary to estimate parameters. The estimation used is using Bayesian analysis. Bayesian analysis requires information from previous events or what is called a prior in the form of a distribution. Prior distribution is needed for each parameter. Priors for each parameter for Model 1 until Model 4 are given in
TABLE *3*.
To compare the four models, Watanabe Akaike Information Criterion (WAIC) is used. WAIC for the four models is given in TABLE 4. Based on TABLE 4, the smallest WAIC is for Model 4. It can be concluded that the best model is Model 4 or a model with the FSSN CAR. The parameter estimation results for Model 4 are given in TABLE 5.
Based on TABLE 5, the parameter estimation results are given in the Mean column. Standard errors for parameter estimates are given in the SE of Mean column. Then a 95% credible interval is given. If the 95% interval contains the number 0 then the parameter is not significant. Then, n eff column is the number of HMC samples used in the iteration. R hat is an indication of the convergence of the estimators. If the value is close to 1 then it is close to convergent. From TABLE 5, it can be seen that the parameters for X_1 and X_2 are significant and are in a convergent state.
From the parameter estimation results for each model, a thematic map for each model can be displayed. The results of the thematic map regarding the percentage of NEET with the predictor variables the literacy rate and number of adolescents with computer skills for the four models can be seen in Fig 6 until Fig 9.

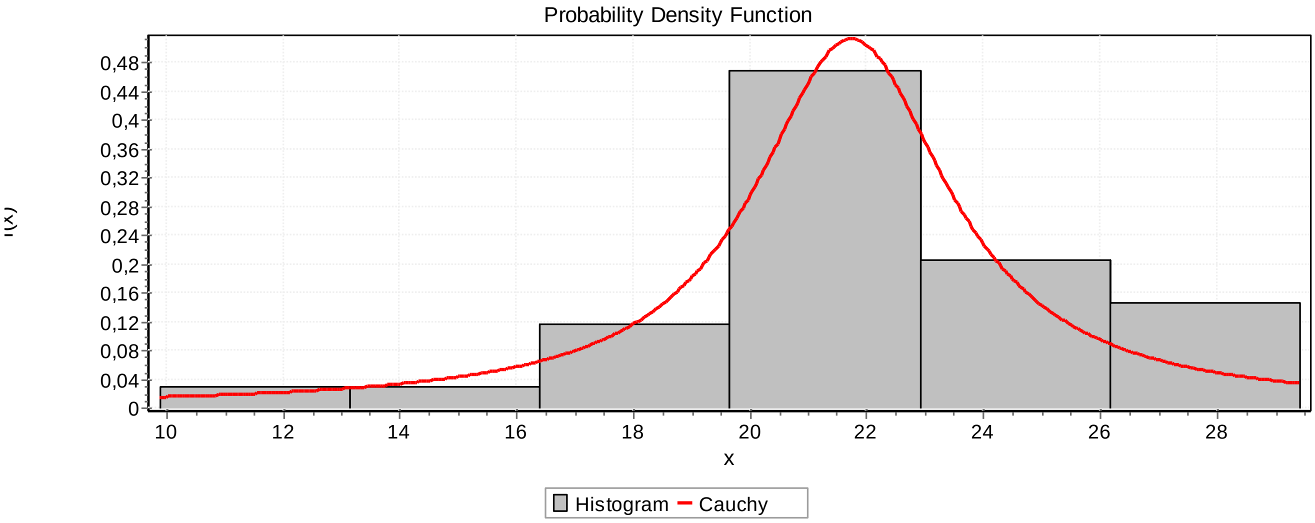

Fig 5. Histogram for the percentage of NEET data

TABLE 3.
PRIOR MODEL 1 UNTIL MODEL 4

Model	Parameter	Prior
Model 1	β_0	Normal (0,1)
	β_1	Normal (0,1)
	β_2	Normal (0,1)
	σ	Gamma (1,1)
Model 2	β_0	Normal (0,1)
	β_1	Normal (0,1)
	β_2	Normal (0,1)
	ϕ	$\phi_i \sim N_n(n,\ \text{node 1, node 2})$
	σ	Gamma (1,1)
Model 3	β_0	Normal (0,1)
	β_1	Normal (0,1)
	β_2	Normal (0,1)
	ϕ	$\phi_i \sim DE_n(n,\ \text{node 1, node 2})$
	σ	Gamma (1,1)
Model 4	β_0	Normal (0,1)
	β_1	Normal (0,1)
	β_2	Normal (0,1)
	ϕ	$\phi_i \sim FSSN_n(n,\ \text{node 1, node 2})$
	σ	Gamma (1,1)

TABLE 4
WAIC FOR MODEL 1-4

Model	WAIC
Model 1	198.6
Model 2	193.6
Model 3	195.7
Model 4	190.5

TABLE 5
ESTIMATION RESULTS FOR MODEL 4

Par.	Mean	SE of Mean	2.5%	97.5%	n eff	R hat
β_0	0.8113	0.0054	0.0851	1.7660	7,730	1
β_1	-0.2013	0.0001	-0.2807	-0.1195	6,131	1
β_2	-0.0140	0.0001	-0.0187	-0.0089	7,276	1
σ	2.8879	0.0025	2.4555	3.3557	8,419	1

The four figures, Model 2 and Model 3 have the same results. Model 1 and Model 4 have different patterns. Model 1 is Cauchy regression without spatial effect and Model 4 is Cauchy regression with FSSN CAR. The darker the green color, the higher the percentage of NEET.

F. *Interpretation of the Best Model*

Based on TABLE 5, the estimated regression parameters β_0, β_1, and β_2 are significant. That is, if the literacy rate and the number of adolescents with computer skills increase, increases by 1 unit, the NEET percentage will decrease by 0.2013. Then, if the number of adolescents with computer skills increases by 1 person, the NEET percentage will decrease by 0.0140. Thus, the literacy rate and the number of adolescents with computer skills in each province need to be increased to reduce the percentage of NEET in that province.

Fig 6. Thematic map for Model 1

Fig 7. Thematic map for Model 2

Fig 8. Thematic map for Model 3

Fig 9. Thematic map for Model 4

IV. Conclusion

Several conclusions can be drawn from this research. The first is, based on Moran's I test show that the percentage of NEET data in each province in Indonesia has a spatial correlation. Thus, modeling the percentage of NEET data will likely be better if it uses spatial effects. Second, based on the Kolmogorov-Smirnov test, the distribution that fits the NEET percentage data is the Cauchy distribution. This is also supported by a histogram against the probability density function of the Cauchy distribution. Third, based on WAIC, the best percentage of NEET data is modeled by Cauchy regression with spatial effects modeled by FSSN CAR. This fact is demonstrated by the WAIC, for Model 4, namely the model that with the CAR FSSN spatial effect, which has the smallest WAIC. Finally, with increasing literacy rates and adolescents with computer skills, the percentage of NEET in every province in Indonesia could decrease. This means that the Indonesian government must improve facilities to increase literacy rates and the number of adolescents with computer skills, especially for provinces with a fairly high percentage of NEET.

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