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Modeling and Mapping the Risk of Loss Macro Economics for Natural Disasters

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ABSTRACT— ***This study aims to determine the magnitude of the economic impact caused by natural disasters as well as to map the magnitude of macro- economic risk of loss from each region will be used as a study with Java as the target of studies. The data used in this study is a secondary data in 2011 from the National Disaster Management Agency and Central Bureau of Statistics in Indonesia, while the data analysis methods used are Regression of Dummy Variables and Regression Analysis of Spatial. Outcomes resulting from this study are thematic map that displays economic risk factors and the model estimates the economic losses in the event of a disasters. The results of this study showed a negative relationship between GDP at current prices by the number of occurrences spatially disaster in East Java and Yogyakarta Province and district data for modeling using Spatial Autoregressive Model showed a significant relationship between the value of GDP, population and number of disaster events. Morans'I's values was negatives , meaning that 1 unit increase in the number of disasters and the number of people at risk will decrease the value of GDP (macro-economic) of 0.54531 billion Indonesian rupiah or U.S.$46,076.***

Keywords-- Disaster Losses Macroeconomics, Spatial Autoregressive, Regression Dummy

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1. INTRODUCTION

Based on the Report of the Asia Pacific Disaster Report 2010 prepared by the United Nations Economic and Social Commission for Asia and the Pacific (UN-ESCAP) and the UN-ISDR states that the Asia-Pacific region, including Indonesia, produces a quarter of Gross Domestic Product (GDP) world. However, in the last 30 years 85 percent of deaths and 38 per cent of global economic losses caused by natural disasters also occur in this region.In the Introduction section, present clearly and briefly the problem investigated, with relevant references. The main results should be enunciated.

For Indonesia, it is felt from the impact of disasters. The magnitude of the damage and losses caused by the disaster is huge. For example, the tsunami in Aceh (2004) cause damage and loss of Rp 39 trillion. Successive earthquake in Yogyakarta and Central Java in 2006 (Rp 27 trillion), Jakarta floods of 2007 (Rp 4, 8 trillion), at 2009 Sumatra earthquake (Rp 21.6 trillion), and the eruption of Merapi's mountain in 2010 outside of the impact cold lava of Rp 3.56 trillion. That was A very large number (BNPB, 2012).

The purpose of this research is to create a mapping based on the macro-economic modeling of the cost of damages caused by natural disasters that occurred in Java. The results of this study may provide a benefit in the development of science and technology in the field of risk management as a result of natural disaster losses, and the results of this study have significance in disaster management, particularly for the government to provide disaster relief reserve fund is adequate based on relevant data when events The really happen that the recovery process can be done more quickly, but it can be made the basis for developing a model insurance losses from natural disasters.

2. LITERATURE REVIEW

2.1 Disaster Influence In Economics

Disasters affect the economic system in a variety of ways , and defines the "cost" of a disaster is something that complicated. Pelling et al. (2002), Lindell and Prater (2003), Cochrane (2004), Rose (2004) , in Hallegatte and Ghill

(2008), among others, discuss the typology of the impact of disasters. This typology usually distinguish between direct and indirect losses. Direct losses are a direct consequence of physical disaster phenomena: the consequence of strong winds, stagnant water, or soil movement. Direct losses are often classified direct and non- direct market lost market loss (also sometimes referred to as intangible losses, even though the non-direct market loss is not always tangible). Market loss is a loss for the goods and services traded in the markets, and for that price can easily be observed. Although droughts or heat waves directly affect economic output (especially in agriculture), direct market loss of most disasters (earthquakes, floods, etc.) is the loss of assets, namely damage to the built environment and the goods produced .

Direct non-market loss includes all the damage cannot be repaired or replaced through purchases in the market. For them, no price is easily observable and can be used to estimate losses. This happens, among other things, to the impact of health, loss of life, damage to natural assets and ecosystem loss, and damage to historical and cultural assets. Sometimes, prices for non-market loss can be developed using the indirect method, but these estimates are rarely appropriate (for example, the value of statistical life expectancy).

Indirect losses (also labeled " high-level losses " in Rose, 2004) covers all the losses provoked by the disaster itself, but by its consequences . Each type of disaster has a different approach in defining indirect costs (e.g., Meyer and Messner (2005) and FLOOD Site (2009) for flooding ; Wilhite (2000) and Wilhite et al.

Indirect losses can be market or non-market loss. Sometimes, non-monetary consequences of the disaster are not directly included as well, such as the impact on poverty or inequality, reduction of taxes collected, or an increase in the national debt. These issues, among others, (i) the question of appropriate scale between the scale of the event and the scale of measurement of GDP, (ii) the capacity of the GDP be a good proxy for welfare.

2.2 Dummy Variable Regression

Dummy variable is a variable that is used to categorize qualitative data (qualitative data does not have a unit of measurement), the qualitative data that can be used in the regression analysis; it must first be transformed into a quantitative form. Dummy variable is a categorical variable that is suspected to have an influence on the variables that are continuous. Dummy variable is often called a dummy variable, binary, categorical or dichotomous. Dummy variable has only two (2) value is 1 and the value 0, and given the symbol D. Dummy has a value of 1 (D = 1) for one of the categories and zero (D = 0) for the other categories. A value of 0 usually indicates a group that did not receive treatment and 1 indicates the group receiving treatment. Dummy variable has only two (2) value is 1 and the value 0, and given the symbol D.

2.3 Spatial Autoregressive Models

Spatial Autoregressive Models are also called Spatial Lag Model and Mixed Regressive Model. SAR model equations are as follows (Anselin, 1999)

$$\boldsymbol{y} = \rho\boldsymbol{W}\boldsymbol{y} + \boldsymbol{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}. \qquad (1)$$

If the reduced form models such as the matrix then equation (2.4)

$$\boldsymbol{y} = (\boldsymbol{I} - \rho\boldsymbol{W})^{-1}\boldsymbol{X}\boldsymbol{\beta} + (I - \rho\boldsymbol{W})^{-1}\boldsymbol{\varepsilon} \qquad (2)$$

SAR models are one approach to spatial models to account for the influence area of spatial lag in the dependent variable alone. SAR is also called Mixed Model Regression-Autoregressive as combining ordinary regression model with spatial lag regression on the dependent variable (Anselin, 1988). Equation (2) describes the variation in y as a linear combination of adjacent units without the independent variable.

Specification tests most widely performed for autocorrelation spatial statistics derived from development by Moran (Anselin, 1999). Moran's I test is used to determine the spatial dependencies in the regression model (Lesage, 1998). Moran's I coefficient is the development of univariate Pearson correlation in the data (Paradis, 2013). Pearson correlation (ρ) between the variables x and y with a lot of data n is as follows.

$$\rho = \frac{\sum_{i=1}^{n}(x_i-\bar{x})(y_i-\bar{y})}{\left(\sum_{i=1}^{n}(x_i-\bar{x})^2\sum_{i=1}^{n}(y_i-\bar{y})^2\right)^{1/2}} \qquad (3)$$

with x and y is the sample average of the variables x and y. The formula ρ is used to measure whether the variables x and y are correlated. Moran's I was used to measure the correlation between the variables in the data x n. Formula of Moran's I is as follows (Paradis, 2013).

$$I_{Ms} = \frac{n}{S_0}\frac{\sum_{i=1}^{n}\sum_{j=1}^{n}W_{ij}(x_i-\bar{x})(x_j-\bar{x})}{\sum_{i=1}^{n}(x_i-\bar{x})^2} \qquad (4)$$

Moran's I coefficient is used to test spatial independence or autocorrelation between observations or location. The hypothesis is as follows

H_0 :I = 0 (no autocorrelation between locations)

H_1 :I ≠ 0 (there are autocorrelation between locations)

Statistical test used is.

$$Z = \frac{I_{Ms} - E(I_{Ms})}{\sqrt{var\,(I_{Ms})}} \quad (5)$$

where

x_i : *i-th* observation data ($i = 1,2, \ldots n$)

x_j : *j-th* observation data ($j = 1,2, \ldots n$)

$\bar{x}$: mean of observation data

$var\,(I)$: Moran's I variance

$E\,(I)$: *Expected value* Moran's I

Decision making is reject Ho if | Z |> Z_ ((α/2)) at the significant level α. I index value is between -1 and 1. If I> I0 autocorrelation means the data is positive, if I <I0 means negative autocorrelation. Pattern grouping of data between locations and deployment can be seen in the Moran's scatter plot. Moran's scatter plot showing the relationship between the value of observations at a site with an average standardized observations at locations as opposed to the location of the observed (Lee & Wong, 2000).

Closeness of the relationship between the location of the autoregressive models expressed in the weighting matrix spatial. Matrix Spatial weighting (**W**) is known by the distance or intersection (contiguity) between one region to another region (Lesage and Pace, 2009). There are several types of contact (contiguity) is as follows: Contiguity linear (Intersection Edges), Rook Contiguity (Intersection Side), Bhisop Contiguity (Intersection Angle), Double linear Contiguity (Intersection Two Edges), Double Rook Contiguity (Intersection Two Sides), Queen Contiguity (Intersection Side-Angle), Customized Contiguity. In this paper we use Queen Contiguity (Intersection Side-Angle).

3. RESEARCH METHODS

This study will use secondary data from the National Disaster Management Agency to obtain catastrophic events as well as the damage caused by the disaster in 2011**.** In addition, the data needed to get the data from BPS GDP**,** and demography in each study area in 2011**.** Primary data collection was also carried out to clarify the secondary data if necessary.

Spatial Econometrics models used in this study are as follows

$$y = \rho W y + X\beta + \varepsilon \quad (6)$$

where :

y = Macroeconomic risk value based on the GDP loss
ρ = scalar parameters
β = Vector of regression coefficients
W= Spatial weights matrix
ε = Error multivariate normal distribution with a mean of μ and variance $\sigma^2 l_n$.

While the variables are as follows X_{ik}.

X1 = Number of resident population per city/county

X2 = Number of disasters (includes all floods, landslides, volcanic eruptions, etc.)

X3 = Number of fatalities (includes deaths, injuries, loss, suffering, and displacement)

X4 = Total damage to homes (includes submerged homes, severely damaged, moderately damaged, and light damage)

X5 = Total damage to public facilities (includes educational facilities, health care, places of worship, offices, factories, and stores)

X6 = Number of poor peoples

The data analysis methods used in this study are:

1. To achieve the first objective is to determine the characteristics of the natural disasters that have occurred in Java as well as damages resulting there from descriptive analysis by line diagrams and histograms for the variables *X*.

2. To achieve the second objective, namely macro-economic modeling of the cost of damages caused by natural disasters performed on aggregate data is data to detailed data for the province and district level data each with the following stages
   a. Determine the weighting between the locations of the weighting matrix. After the matrix **W** is formed by the elements (*Wij*) is 1 and 0, is done coding to get the weighting matrix **W**.
   b. Regression modeling using the Ordinary Least Square (OLS), which includes estimates of parameters, the model estimates of significance, test the assumption of residual IIDN (identical, independent, and normally distributed)
   c. Perform testing dependency and spatial heterogeneity or correlation
   d. Identifying the presence of spatial effects by using the LM test. Testing the LM test is performed to find the appropriate model
   e. Estimate the parameters, parameter significance testing, and regression testing of residuals assumption of spatial econometric models are formed.
   f. Interpret a model which has been obtained.

4. RESULT

4.1 Characteristics of the disaster and its consequences

Characteristics disaster here only use the data in 2011 as the last year to facilitate the discussion which is based on Figure 1, catastrophic events are more common in Central Java in the amount of 946 disaster events within one year, followed by East Java (578 events) and West Java (378 events). However if in the view based on the type of disasters that occur most often as many as 620 flood events, where the province's most frequent floods are the Central Java as many as 276 events.

So based on the above data the province's most vulnerable in the face of disasters during 2011 is primarily the province of Central Java Landslide and flood disaster. Natural disasters always result in many human casualties or damage, homes, infrastructure, and land.

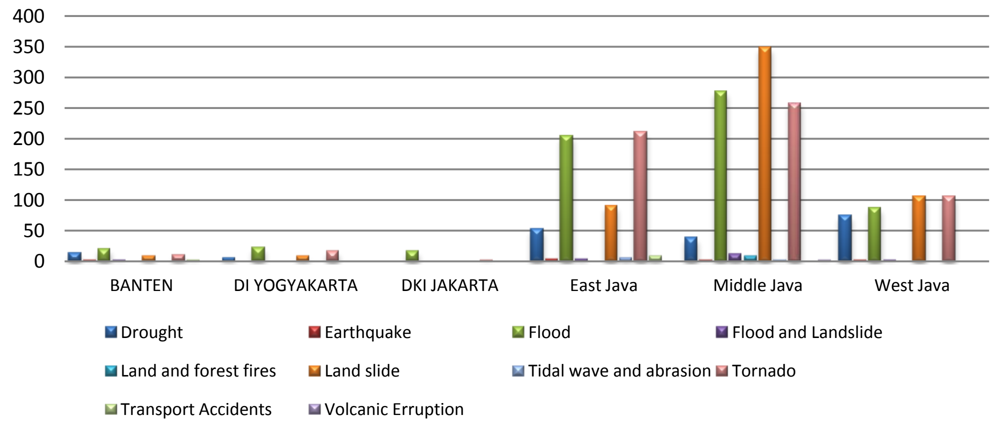

Figure 1: The Number of Disasters in 2011 in Each Province on The Island of Java

Based on the results of data processing turned out for the best variable Y is modeled variable GDP at current prices, whereas a significant variables X is a variable number of disasters and a dummy variable regions with the results as shown in Table 1 and Equation 7.

$$\text{GDP at current prices} = 3.26 - 0.000324 \text{ Number of disasters} + 12.9\, D1 + 11.5\, D2 + 5.40\, D3 - 2.37\, D4 + 11.5\, D5 \quad (7)$$

where the value of 1 for the dummy variables D1 to Jakarta to West Java D2, D3 for Central Java, D4 to D5 Yogyakarta and East Java and Banten value to zero, the analysis of the modeling results indicate that the number of disasters significantly reduce GDP at current prices the value of 0.0000324 for each increase in the number of events or the more catastrophic disasters in the region will reduce the value of GDP of the region, if the amount of data directly from a catastrophic loss is known to be much better at detecting what percentage of contribution in reducing the value of GDP of a region.

Further modeling is done by adding a spatial weights in the model to solve the case heteroscesdasticity and Local Indicator using Spatial Association (LISA) popularized by Anselin (1995), the obtained value of Moran's I is -0.2627 which means suggests that there is a negative relationship on spatial autocorrelation, or relationships Low High Low High or between GDP and GDP weights in the model. So the value of GDP of a region will tend to fall if there are catastrophic events in other regions. This is consistent with the initial allegation of research that there is a spatial effect of catastrophic events with a reduction in macroeconomic conditions represented by the value of GDP at current prices.

Based on Figure 2 areas of East Java and Yogyakarta significant at α = 0.01 with Low-High relations in the region, which means a low number of catastrophic events has spatial autocorrelation relationship with the value of GDP at current prices, or an increase in disaster events in a spatial region of influence decrease value of GDP at current prices in surrounding areas, while other areas of the province in addition to the above does not have a significant influence.

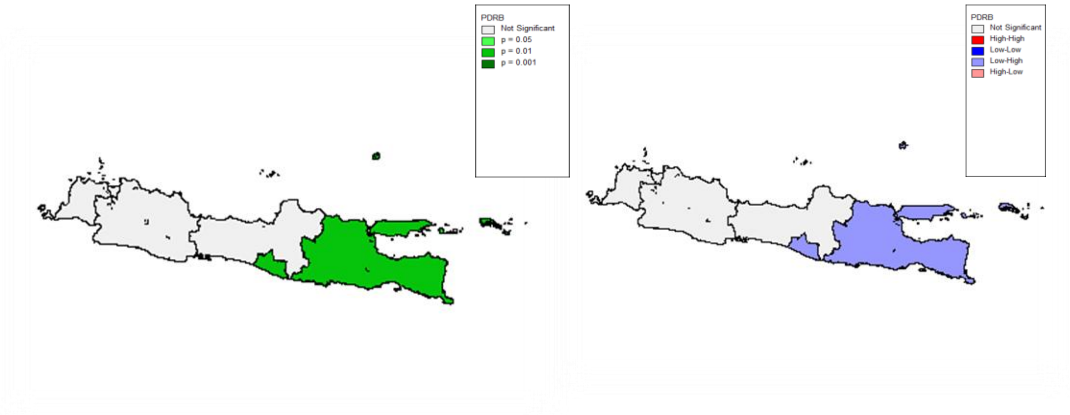

Figure 2: LISA maps for GDP relationship with Disasters

Before doing modeling Spatial Autoregressive Model (SAR) election prior spatial model with the Lagrange Multiplier (LM) test. Lagrange multiplier is used to detect the specific spatial dependencies are dependencies in lag, error, or both (lag and error).

Based on the test P - Value of Moran 's I is 0.001343 (reject Ho) means no spatial dependencies in the regression error . Test Lagrange Multiplier (lag) aims to identify an association between Districts / Municipality where the P - value of 0.000540 Value LM lag (less than α = 0.10), the conclusion is that there is a lag of spatial dependencies, so it can continue to manufacture Spatial Autoregressive Model.

Test Lagrange Multiplier (error) aims to identify an association between Districts/Municipality. Lagrange Multiplier Test SARMA aims to identify the phenomenon of identifying the presence of a combination of lag dependencies and dependencies among errors Districts /Municipality. Based on the calculations can be seen that the P - value of 0.000856 Value LM SARMA (less than α = 0.05) , the conclusion is reject H0 , which means there are dependencies spatial lag and error , so it can continue to mix modeling .

Based on Lagrange Multiplier testing that has been done, then the next is to do modeling spatial autoregressive (SAR) . Here is an acquired SAR modeling.

Based on Table 1 it can be seen that the value Rsq = 61.49% means that the model is able to explain the variation of GDP by 61.49% and the remaining 38.51% is explained by other variables outside the model. P-Value is significant at α = 10% is a variable X1 (Population) and X2 (Total Disaster). Here is the resulting SAR modeling.

Table 1: Estimation Parameter SAR

Variable	Coefficient	Z	P-Value
ρ	0.22981	4.23890	0.0000225
Intercept	5.78214	12.38779	0.0000000
X_1	8.346509e-007	9.81767	0.0000000
X_2	-0.01490	-1.87569	0.0606979
X_3	-0.00035	-1.61279	0.1067911
X_4	0.00017	1.52532	0.1271790
X_5	0.00168	0.94008	0.3471788
Rsq = 61,49% α = 10%			

$$y_1 = 0{,}2298 \sum_{j=1, i \neq j}^{n} w_{ij} y_j - 0{,}0000008346 X_{1i} - 0{,}0149 X_{2i} + \varepsilon_i \qquad (11)$$

where :

Yi = GDP in constant Districts / Municipality to-i (in value of GDP)
X1i = Human population Districts / Municipality to-i
X2i = Number of disasters in Districts / Municipality to-i
Wij = Spatial weighting matrix
ε_i = Residual of Districts / Municipality to i

SAR models can be interpreted that if other factors held constant, if the population in the Districts / Municipality increased by 1 unit then can add to GDP constant at 0.0000008346 and the number of disaster events decreased by 1 unit, it will increase the value of GDP constant at 0.0149 unit.

4.2 LISA Map Analysis

We can see on Figure 4. Note that the Districts / Municipality are included in the Low- High, it means that if the number of disaster events in a Districts/ Municipality rises, the value of GDP will go down. While the High-Low can be interpreted as the number of disasters in a Districts/ Municipality down, then the value of GDP will rise. Below is a table listing classification Districts /Municipality based on the LISA Cluster Map.

We can see on Figure 5. note that the significance value Districts/Municipality that goes in the category of Low-High (if the number of disaster events in a Districts Municipality rises, the value of GDP will go down) and High-Low (if the number of disaster events in a Districts/Municipality down, then the value GDP will rise).

Table 2: Ooutcomes LISA Cluster Map

<table>
<tr><td></td><td>Value</td><td colspan="2">District / municipality</td></tr>
<tr><td>Not Significant</td><td>0</td><td colspan="2">(In addition to the cities mentioned below)</td></tr>
<tr><td>High-High</td><td>1</td><td colspan="2">Distric Cilacap</td></tr>
<tr><td>Low-Low</td><td>0</td><td colspan="2">-</td></tr>
<tr><td>Low-High</td><td>3</td><td>1. Distric Kuningan
2. Municipality Banjar
3. Distric Banyumas
4. Distric Banjarnegara
5. Distric Kebumen
6. Distric Purworejo
7. Distric Boyolali
8. Distric Sukoharjo</td><td>9. Distric Karanganyar
10. Distric Temanggung
11. Distric Tegal
12. Municipality Salatiga
13. Distric Gunung Kidul
14. Distric Pacitan
15. Distric Magetan</td></tr>
<tr><td>High-Low</td><td>4</td><td>1. Municipality South of Jakarta
2. Municipality Central of Jakarta
3. Municipality East of Jakarta
4. Municipality West of Jakarta</td><td>5. Mucipility North of Jakarta
6. Distric Malang
7. Distric Tangerang
8. Municipality Tangerang</td></tr>
<tr><td>Neighborless</td><td>5</td><td colspan="2">Archipelago Seribu</td></tr>
</table>

4.3 Mapping Macro Economic Losses Due to Disasters

Mapping Macro Economic Losses Due to this disaster but displayed in the form of static GIS maps based Spatial Autocorrelation models that have been discussed in the previous, this study also created a GIS application that can be used dynamically based on models that get the data in each variable that can be replaced in accordance with the incident.

This application was created with the aim to facilitate the calculation of the statistical models used to predict the macro-economic losses due to disasters as well as mapping the correlation between GDP and catastrophic events, so as to determine the level of vulnerability of an area in the event of a disaster, whether it will affect GDP significantly.

5. CONCLUSIONS

Based on data Total Disaster in the year 2011 showed that the area of East Java and Central Java has the largest number of events, where the incidence of frequent disasters are floods, landslides and tidal waves, based on the description of the human toll, home and facility areas shows dark areas with the most casualties that need more attention from the local government to prepare.

The use of dummy regression models for provincial aggregate data to see the relationship between the variables of GDP by the number of disaster events show that there is a significant relationship between the number of disaster events with a decrease in the value of GDP (negative correlation) where if there is an increase in the number of disasters in the province will decrease the value of GDP Districts / the Municipality , however, this dummy regression model showed that

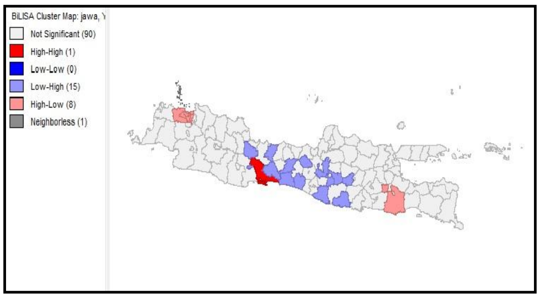

Figure 4: LISA Cluster Map

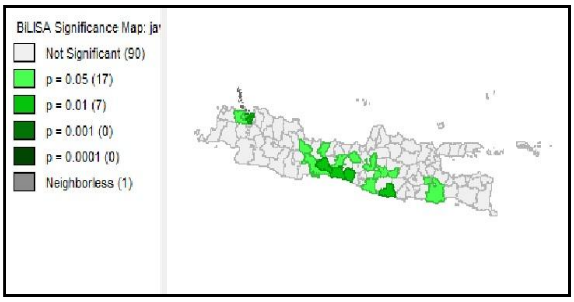

Figure 5: LISA Significance Map

heteroscedasticity case shows that there is a spatial relationship on the model , and by using the LISA method for the detection of spatial relationships in the model showed that there are two provinces that demonstrate the significance of spatial relations , namely East Java and the Province of Yogyakarta , it means disaster events in these two provinces showed the potential risk of impairment GDP (macroeconomic risks have a large enough).

Furthermore, by using a data modeling Districts in get results that are significantly Autoregressive Spatial Model shows the relationship between the value of GDP , total population and the number of disaster events with I'Moran negative correlation , meaning that the increase in the number of disasters and the number of people at risk will decrease the value GDP (macro- economic) of 0.54531 billion or U.S.$46,076, and by using LISA are 34 Districts / Municipality scattered throughout the provinces in Java , so in particular in those areas in need of disaster relief funds more prepared.

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