Social vulnerability to earthquake hazard at Pringsewu District, Lampung Province

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Abstract. Earthquakes are still a major issue in Indonesia, one of the earthquake-prone areas is Lampung Province. There are many sources of earthquakes in Lampung, due to the influenced by the Indo Australian Plate against the Eurasian Plate, Semangko Fault, and Tarahan Fault. Tarahan Fault that passes through Pringsewu district and Bandar Lampung City is an active fault where the west side of the fault force moves to the northeast. Judging from the occurrence of the earthquake so far, it should be taken into account the possibility that there is a large buildup of energy in the Lampung area, one of them in Pringsewu. One of the efforts in earthquake disaster mitigation is to know the level of vulnerability, in this study based on its social aspects. This social vulnerability can be known through social vulnerability analysis or Social Vulnerability Index (SOVI). This analysis uses a comparative matrix that gives a broad picture of social vulnerability relative to earthquake hazards. The results showed that the regions with very high social vulnerability were in Gading Rejo Subdistrict while the low social vulnerability was in Ambarawa, Banyumas and Adiluwih Subdistricts.

1. Introduction

Indonesia, based on its geographical location is a country which prone to natural disasters. One of the natural disasters that often occurs is earthquake [1]. According to previous research, the Tanggamus region is an area prone to earthquake disasters [2]. According to Meteorological, Climatological, and Geophysical Agency (BMKG) in 2014, an earthquake is an event that shakes the earth due to the release of energy in the earth that is suddenly marked by a broken layer of rock in the earth's crust. The energy that causes earthquakes is generated by the movement of tectonic plates. The energy produced is emitted in all directions in the form of an earthquake wave so that the effect can be transmitted to the surface of the earth.

Indonesia is geographically located between three main plates, the Indo-Australian Plate, the Eurasian Plate and the Pacific Plate. Sumatra is an area that often experiences the earth easily due to the meeting of the Indo-Australian Plate and the Eurasian Plate [1]. Lampung Province is one of the areas that have become earthquake prone areas in Indonesia. Many earthquake sources in Lampung Province, including the subduction of the Indo Australia plate against the Eurasian Plate, Sesar Semangko, and Sesar Tarahan. Lampung is plugged in from two directions, from the south and from the west. Different from other regions. On Java, subduction from the south while subduction occurs in Sumatra from the west. Tarahan fault that passes through Pringsewu district and Bandar Lampung City is an active fault where the west side of the fault force moves to the northeast.

According to the occurrence of the earthquake so far, it should be taken into account the possibility that there is a large buildup of energy in the Lampung area, one of them in Pringsewu. Coupled with the regional transformation that resulted in Pringsewu District developing rapidly in terms of its social
aspects [3]. The earthquake is still the focus of attention for the public and the government until now. Various efforts were made to reduce the impact that occurred in the event of an earthquake. At present there is not much literature that describes the earthquake in Pringsewu District, especially in its social aspects. This social vulnerability can be known through social vulnerability analysis or Social Vulnerability Index (SOVI).

The limited information and the many factors that can influence the community due to the disaster that have not been analyzed further become a special reason for conducting research on social vulnerability to the earthquake disaster in Pringsewu District. Based on this, a study is needed that can assess how much the level of social vulnerability is taking into account the social aspects that exist in Pringsewu District.

2. Methods
2.1 Data and variables
Data of earthquakes was obtained from Statistics Indonesia (BPS) shows that Indonesia is one of the countries that has a high seismic rate in the world, more than ten times the rate of seismicity in the United States. Tarahan fault that passes through Pringsewu district and Bandar Lampung City is an active fault where the west side of the fault force moves to the northeast. Judging from the occurrence of the earthquake so far, it should be taken into account the possibility that there is a large buildup of energy in the Lampung area, one of them in Pringsewu.

Social impacts can be known through social vulnerability analysis. Social vulnerability is a limitation of society to the impact of natural disasters that affect their ability or resilience in an effort to recover from these impacts [4-6]. Social vulnerability refers to the resilience of communities when confronted by external stresses on human health, stresses such as natural or human caused disasters, or disease outbreaks [7].

This study uses the Social Vulnerability Index (SOVI) method to measure social vulnerability to earthquake disasters in Pringsewu District. Social vulnerability is the limitations of the community against the impact of natural disasters that affect their ability or resilience in an effort to recover from the effects. In table 1 showed the variables in this study, socio-economic factors were chosen as independent variables because they can influence the amount of social vulnerability in the research area. The independent variables in this study are based on a summary of the literature on social vulnerability assessment [8-15]. There are 8 initial variables selected in this study, including:

| Indicator | Variable | (Percentage) | Data Source |
|-----------|----------|--------------|-------------|
| Population | X1 | Total of woman population | BPS Pringsewu in 2015 |
|           | X2 | Total of vulnerable population | BPS Pringsewu in 2015 |
|           | X3 | Population density | BPS Pringsewu in 2015 |
| Education | X4 | Total of high school / equivalent students | BPS Pringsewu in 2015 |
| Poverty   | X5 | Total of poor families | BPS Pringsewu in 2015 |
|           | X6 | Total of doctors | BPS Pringsewu in 2015 |
| Facilities and Infrastructure | X7 | Total of nurses / paramedics | BPS Pringsewu in 2015 |
|           | X8 | Total of non-permanent houses | BPS and BPBD Pringsewu in 2015 |

Population indicator, first is the number of women, related to the fact that women are more difficult to recover from disaster compared to men. The greater the number of women, the higher the vulnerability [12,13]. Second, the vulnerable population, there are the number of children under the age of five years and the number of residents above the age group (above 55 years). Age that is too young and too old will increase social vulnerability to earthquakes. Third, population density is related to the density of...
The built-up area in each region. The higher the population density in an area, the more exposed it will be. This happens because in general an area with high population density is the center of the facilities and infrastructure of an area. Educational indicator, there is the number of high school students / equivalent [14]. People with higher levels of education are generally faster and more appropriate to face disasters. The more the number of high school student/equivalent, the lower vulnerability is. The number of poor families was used in poverty indicator. Poverty involves the situation that only people or households that have enough money or high-value assets are more likely to absorb and recover from losses more quickly, that cannot be done by poor families. The more poverty level, the higher the vulnerability.

There are three variable facilities and infrastructure indicator, which are number of doctors, the number of nurses/paramedics, and the number of non-permanent houses. The number of doctors and nurses/nurses is an important source of post-event (earthquake disaster) [16]. Medical personnel are needed to help victims. The lack of proximate medical services will extend the long-term recovery from disasters. Then the number of non-permanent houses is related to the quality of the building. Research and Development Center of the Ministry of Public Work, explains temporary (non-permanent) buildings, namely buildings that have local foundations, do not have sloof, column poles and beams from concrete, even if they are made of wood but with minimal connections. So that influential when a disaster occurs, the family will lose the right to live, the more non-permanent houses the higher the vulnerability.

2.2 Data Analysis

This study uses the Social Vulnerability Index (SOVI) method to measure social vulnerability to earthquake disasters in Pringsewu District. This analysis uses a comparative matrix that provides a broad picture of relative social vulnerability for various hazards. This index is formed by the synthesis of socio-economic variables through a process called the main analysis component. Variables are used to create selected indexes based on broad disasters and social sciences. This approach will show spatially the level of social vulnerability in each district and city [8-14].

1. Collect SOVI input variables especially from population census bodies or population statistics bodies and some other data.
2. Normalize all variables in the form of percentages and per capita values.
3. Verify the accuracy of the dataset using descriptive statistics (i.e. using min, max, mean and standard deviation).
4. Standardize input variables using z-score standartization.
5. Perform Principal Component Analysis (PCA) using varimax rotation and Kaiser criteria for component selection and data reduction. This approach shows the factors that influence social vulnerability in the study area.
6. Detect extreme multicollinearity (confounding) between variables. In the application of factor analysis methods, variables have become intercorrelated.
7. Perform factor analysis methods on the selected variables. factor analysis aims to reduce data and identify the smallest number of general or latent factors for a set of variables.
8. Identify the factors produced, namely the correlation matrix, Kaiser-Meyer-Olkin (KMO) measure of adequacy of sampling and Bartlett statistical tests.
9. Interpretation of general factors and determining the direction of each factor resulted from social vulnerability and calculating the SOVI score produced.

The analytical method in this study is quantitative descriptive analysis which is an analysis using data obtained from a sample of the research population analyzed according to the statistical method used. These data are then interpreted into map form. After obtaining the SOVI Score, then classification into five social vulnerability groups used a classification scheme based on the standard deviation of the average to identify various vulnerabilities in sub-districts in Pringsewu District, as following.

- Very high social vulnerability (St.Dev> 1.5) - Low social vulnerability (-1.5 - -0.5 St.Dev)
- High social vulnerability (0.5 - 1.5 St.Dev) - Very low social vulnerability (<- 1.5 St.Dev)
- Medium social vulnerability (-0.5 - 0.5 St.Dev)
A score greater than 1.5 St.Dev shows high social vulnerability, and a score of less than -1.5 St.Dev shows low social vulnerability. Thematic maps based on the classification of the SOVI scores were made using mapping software to display variations in social vulnerability in Pringsewu District.

2.3 The Condition of the Earthquake Disaster in Pringsewu District

Recently, one of the earthquakes that occurred in Pringsewu District, Lampung Province occurred at around 06.46 WIB on October 18, 2014. The magnitude 4.6 earthquake, centered 35 Km Southwest Pringsewu, lasted around 47 seconds at 5,630 LS dan 104,850 BT center in Southwest Pringsewu with a depth of 10 km. This earthquake was a local and not all residents of Lampung felt it. Areas that feel this earthquake include the Kota Agung and Tanggamus while like Kotabumi and Central Lampung do not feel the earthquake centered in Pringsewu. This small earthquake does not have the potential for a tsunami and results from the movement of a fault plate in Sumatra. Kota Agung is a district that is also the center of government (capital) of Tanggamus Regency, Lampung, Indonesia. Kota Agung lies beneath the foot of Mount Tanggamus and on the beach side of Semangko Bay. The Board of Regional Disaster Management (BPBD) of Kota Agung has provided a report due to the earthquake. There were no casualties or damage due to the tremor.

Although there were not many earthquakes centered in Pringsewu District, Pringsewu often felt the tremors from other regions, especially from western Lampung. One of the closest areas of Pringsewu district that often experiences earthquakes is Tanggamus Regency. Based on data from the Central Meteorology and Geophysics Agency (BMKG) in Kotabumi, there was an earthquake on Friday, precisely at 09:04 WIB. May 6, 2016 an earthquake occurred in Tanggamus Regency. The strength of the earthquake was at 5.3 SR. BMKG said that the cause of the earthquake was plate subduction, and was not destructive. The earthquake is located at coordinates 6,460 LS dan 104,270 BT. Located at a distance of 122 kilometers south of Kota Agung, Tanggamus Regency with a depth of 43 km. This earthquake, if viewed from the depth of the hypocenter, is a shallow earthquake due to the subduction activity of the Indo-Australian Plate under the Eurasian Plate. Based on this, many earthquake sources in Lampung, including the subduction of the Indo Australia plate against the Eurasian Plate, Semangko Fault, and Tarahan Fault. Lampung is plugged in from two directions, from the south and from the west. Different from other regions. On Java, subduction from the south while subduction occurs in Sumatra from the west.

3. Result and Discussion

3.1 Disaster conditions in Pringsewu District

To find out the social vulnerability factors that were affected in Pringsewu District, in this study using eight social variables available in 2015. Before getting the value of SOVI. A variable reduction phase is needed that uses Principal Component Analysis (PCA). then from that stage a component or factor will be produced which will be used to measure social vulnerability in each sub-district in Pringsewu District.

| KMO and Bartlett's Test | Kaiser-Meyer-Olkin Measure of Sampling Adequacy | .800 |
| --- | --- | --- |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 76,471 |
|   | df | 28 |
|   | Sig. | .000 |

Figure 1. Test of analysis of Kaiser-Meyer-Olkin (KMO) and Barlett’s test

Factor analysis can be done by a number of statistical packages. The author uses SPSS to carry out factor analysis methods for eight variables to determine the significant factors that affect certain people and places more vulnerable than others. The KMO statistical test at the sample size is 0.800, indicating that the data is suitable for factor analysis. Sharma (1996) notes that KMO sizes greater than 0.70 are appropriate. In addition, in the table there is also a Bartlett test to find out the relationship between variables in multivariate cases. Multivariate data is said to have a relationship between variables if the Bartlett test value is less than alpha (0.05). In table 1, the Bartlett test value is 0.000 so it is concluded that the data used correlates between variables.
After conducting a statistical test which shows that the multivariate analysis is feasible to use, especially the main component analysis method and factor analysis. Then in the research to analyze factors using Principal Component Analysis (PCA). Eigenvalue greater than one can be used to determine the number of factors that adequately explain the correlation between variables (Sharma, 1996). In table 2, exactly in the Initial Eigenvalues column, there are two factors that have more than one eigenvalue with 94.208 percent representing the variables of the data reduction process.

| Component | Initial Eigenvalues | Extraction Sum of Squared Loadings | Relation Sum of Squared Loadings |
|-----------|---------------------|------------------------------------|----------------------------------|
|           | Total               | % of Variance | Cumulative %   | Total | % of Variance | Cumulative %   | Total | % of Variance | Cumulative %   |
| 1         | 6.516               | 81.455      | 81.455        | 6.516 | 81.455      | 81.455        | 3.031 | 47.885        | 47.885        |
| 2         | 1.020               | 12.753      | 94.209        | 1.020 | 12.753      | 94.209        | 3.706 | 46.023        | 94.209        |
| 3         | .164                | 2.053       | 96.013        | .164  | 2.053       | 96.013        | .2706 | 46.295        | 94.209        |
| 4         | .050                | .624        | 99.637        | .050  | .624        | 99.637        | .087  | 46.382        | 94.209        |
| 5         | .030                | .377        | 99.957        | .030  | .377        | 99.957        | .087  | 46.382        | 94.209        |
| 6         | .019                | .246        | 99.955        | .019  | .246        | 99.955        | .087  | 46.382        | 94.209        |
| 7         | .007                | .085        | 100.000       | .007  | .085        | 100.000       | .087  | 46.382        | 94.209        |

Figure 2. Variables of factor analysis

The first factor representing 81.455 percent of the overall variable was the number of female population, population density, number of high school students / equivalent and number of nurses. Whereas the second factor which represented 12.753 percent of the overall variables included the number of vulnerable age population, the number of doctors, the number of non-permanent homes and the number of poor (pre-prosperous) families. The SOVI score was constructed by weighting each factor score with the percentage variance explained divided by the total variance explained by the general extracted factors.

In this way, factors with a higher variant contribute more to the value of SOVI. Before getting the SOVI score, we need to know the weight of each by dividing the percent variance of each factor with the percent cumulative variant so that it is obtained for the first factor weighing 0.8646 and the second factor weighing 0.1353 SOVI scores for each sub-district in Pringsewu district can be calculated as follows:

\[
\text{SOVI} = (0.8646 \times \text{factor 1}) + (0.1353 \times \text{factor 2})
\]

Table 2. SOVI score in each sub-district

| Sub-district | SOVI   |
|--------------|--------|
| Pardasuka    | 0.1936 |
| Ambarawa     | -1.0126|
| Pagelaran    | -0.5841|
| Pringsewu    | 0.7976 |
| Gading Rejo  | 1.8523 |
| Sukoharjo    | -0.0743|
| Banyumas     | -0.6055|
| Adiluwih     | -0.5306|

The more positive the SOVI score, the higher social vulnerability, the more negative it becomes, the lower social vulnerability. The results of the analysis show that the Sovi score ranges from 1.8523 (highest social vulnerability) to -1.0126 (lowest social vulnerability). The highest social vulnerability is found in Gading Rejo sub-district and the lowest social vulnerability is in Ambarawa sub-district.

3.2 Social Vulnerability Classification

To be able to describe the regional level based on social vulnerability in each sub-district in Pringsewu District, the social vulnerability index value needs to be span and classified into five levels based on standard deviations ranging from <-1.5 from standard deviations which indicate low social vulnerability to value> 1.5 standard deviation which indicates high social vulnerability. Based on the data processed,
the standard deviation of the SOVI score is 0.87512 so that the upper and lower limits of each class can be seen as shown in table 3 below:

| Class         | Range score SOVI       | Sub-district                  |
|---------------|------------------------|--------------------------------|
| > 1.5 St. Dev | 1.31268 – infinity     | Gading Rejo                   |
| 0.5 – 1.5 St.Dev | 0.43756 – 1.31268    | Pagelaran, Pringsewu          |
| -0.5 – -0.5 St.Dev | -0.43756 – 0.43756 | Sukoharjo, Pardasuka          |
| -1.5 – (-0.5) St.Dev | -1.31268 – 0.43756 | Ambarawa, Banyumas, Adiluwih  |
| < 1.5 St.Dev | -infinity – (-1,31268) | -                              |

In able.3, it can be seen that in the first class (> 1.5 St.Dev) with the highest social vulnerability was found in Gading Rejo Subdistrict. In the second class (0.5 - 1.5 St.Dev) found in Pagelaran Subdistrict and Pringsewu Subdistrict. In the third class (-0.5 - 0.5 St.Dev) it was found in Pardasuka Subdistrict and Sukoharjo Subdistrict. In the fourth class (-1.5 - -0.5 St.Dev) found in Ambarawa Subdistrict, Banyumas Subdistrict and Adiluwih Subdistrict. Whereas for the fifth class (< -1.5 St.Dev) there is no sub-district in Pringsewu district included in this class based on the calculation of the SOVI score that has been obtained.

The first factor representing 81.455 percent of the overall variable was the number of female population, population density, number of high school students / equivalent and number of nurses. Whereas the second factor which represented 12.753 percent of the overall variables included the number of vulnerable age population, the number of doctors, the number of non-permanent homes and the number of poor (pre-prosperous) families. The SOVI score was constructed by weighting each factor score with the percentage variance explained divided by the total variance explained by the general extracted factors. In this way, factors with a higher variant contribute more to the value of SOVI. Before getting the SOVI score, we need to know the weight of each by dividing the percent variance of each factor with the percent cumulative variant so that it is obtained for the first factor weighing 0.8646 and the second factor weighing 0.1353 SOVI scores for each sub-district in Pringsewu district can be calculated as Figure 3.

Figure 3 shows that the area with the highest social vulnerability (> 1.5 St. Dev) is in the west of Pringsewu District, Gading Rejo subdistrict. Gading Rejo Subdistrict is the most poor sub-district with 6289 people out of 30,501 families in Pringsewu district or as much as 20% of the poor families in Pringsewu district. With the number of poor people in this area, it can be said that adaptive capacity in the poverty variable, Gading Rejo Subdistrict is the lowest in Pringsewu District. This high number of poverty allows the community to absorb and recover from losses that are more difficult than those that are not poor (have enough money or high value assets). Then for the population density in Gading Rejo Subdistrict, this sub-district is one of the regions with a low population density of only 843 people / km² out of an area of 88.71 km².
Although in terms of exposure, the population density is small, for the population of vulnerable age and female population in this sub-district is high after Pringsewu Sub-district, with a population of vulnerable age of 16,266 people from 86,978 people or around 18% of the total vulnerable population in Pringsewu District and the total population of women was 35,108 people from 186,693 inhabitants, the total female population or 18% of the total female population in Pringsewu district. The amount of poverty in Gading Rejo Subdistrict is also directly proportional to the number of non-permanent houses due to economic incapacity. The number of non-permanent houses in Gading Rejo Subdistrict is 6266 houses or around 24% of the number of non-permanent houses in Pringsewu district, which is 25,467 houses. So, in terms of sensitivity, namely the large number of vulnerable age populations, the number of female residents and non-permanent homes, Gading Rejo Subdistrict becomes a sensitive area in the event of an earthquake.

In terms of exposure, adaptive capacity and sensitivity, Gading Rejo Subdistrict is indeed the most vulnerable area, so special attention is needed from the pre-disaster aspect to prevent fatalities or damage and post-disaster for disaster recovery. In low social vulnerability there are three sub-districts with low Social Vulnerability (-1.5 - (-0.5)) St.Dev, namely Ambarawa, Banyumas and Adiluwih Subdistricts (Peta.1). Ambarawa Subdistrict which in terms of exposure is the smallest population density of only 108 people / km², then Banyumas Subdistrict 504 people / km² with an area of 39.85 km², and Adiluwih Subdistrict from the total area of Pringsewu district which is 30.99 km² so in terms of the exposure of these three sub-districts is low.

Then in terms of sensitivity there is a population of vulnerable age, female population and number of non-permanent houses. The number of vulnerable age population in Amabarawa Subdistrict is 7,247 people or around 8%, Banyumas Sub-district is 6,511 people or around 6%, and Adiluwih Subdistrict is 6,543 people or around 7% of the total vulnerable age population which amounts to 86,987 inhabitants. This amount is quite low so that the sensitivity of the three sub-districts is also low. The population of women in Amabarawa Subdistrict is 16,519 people, or about 8%. Banyumas Subdistrict as many as 9,689 people or 5% and Adiluwih Subdistrict as many as 16,766 people or 8% of the total female population in Pringsewu district. Then the number of non-permanent houses in Amabarawa Subdistrict is 560 houses or around 2%, Banyumas Sub-district 2,304 houses or 9% of Adiluwih Subdistricts as many as 1,461
houses or 5% of the total non-permanent houses totaling 25,467 houses. With a population of vulnerable age, a low population of women and a low number of non-permanent houses, the sensitivity of this area is also low so that the area is strong enough to deal with earthquake disasters.

In terms of adaptive capacity, the number of poor families, the number of high school / equivalent students, the number of doctors and the number of nurses or paramedics. The number of poor families in Ambarawa Subdistrict is 2,388 families or 7%, Banyumas Subdistrict as many as 1,598 families or 5% and Adiluwih Subdistrict including low as many as 2,731 families or 8% of the total poor families of 30,501 families. Then the number of high school / equivalent students in Ambarawa sub-district is 2,451 people or around 13%, Banyumas sub-district as many as 670 people or around 3% and Adiluwih sub-district 885 people or around 5% of the total number of high school / equivalent students which is 17,688 inhabitants. Communities with a high level of education such as high school / equivalent are usually more open and also more resistant to a shock so that the three sub-district communities are considered to be quite resilient in the face of disasters.

Then for the number of doctors in Ambarawa Subdistrict only 2 doctors and 13 nurses / mantri, Banyumas Subdistrict only only 1 doctor and 15 nurses / paramedics, and Adiluwih Subdistrict only only 1 doctor and 20 nurses / paramedics. Although the adaptive capacity is lacking, the low poverty variable, the number of low-age population, low female population and the number of non-permanent houses makes this sub-district exposure and sensitivity low and there are a number of adaptive capacity components such as the number of poor families who tend to make low this area has a low social vulnerability compared to the whole region in Pringsewu District.

4. Conclusion
The approach to the Social Vulnerability Index (SOVI) method is a method that has the potential as a tool to identify or monitor the social vulnerability of a region spatially and temporarily. This research is considered as an initial effort to support prevention, mitigation, preparedness and reduction of vulnerability in Pringsewu District. The SOVI approach was used to measure the social vulnerability of sub-districts in Pringsewu District to natural hazards in this case of earthquake and to determine the driving factors. The results showed in this study that 2 factors or components produced 94.208% of variables affecting social vulnerability. Based on the results of the SOVI analysis, it was found that in 2015, there were areas with very high levels of vulnerability (> 1.5 St. Dev) consisting of only one sub-district, namely Gading Rejo District. Areas that have high social vulnerability (0.5 - 1.5 St.Dev) are found in Pagelaran and Pringsewu Districts. Regions that have moderate class social vulnerability (-0.5- 0.5 St.Dev) are found in Sukoharjo and Padasuka Subdistricts. Finally there are three sub-districts with low Social Vulnerability (-1.5 - (-0.5)) St.Dev, such as Ambarawa, Banyumas and Adiluwih subdistricts. The very high vulnerability occurs in regions with high population density characteristics, high number of vulnerable ages, high female population, high number of poor people and many non-permanent homes. So that special attention is needed to areas that have a high pre-disaster vulnerability for the prevention of many opportunities for casualties or damage and post-disaster for recovery from disasters after an earthquake has occurred.

5. References
[1] Salim R dan Santosa B J 2014 Analisa Pola Bidang Sesar pada Zona Subduksi di Wilayah Selatan Pulau Sumatera dari Event Gempa pada Tahun 2011-2014 Jurnal Teknis POMITS 3
[2] Anwar H Z, Ruslan M, Comaluddin, Kumoro Y dan Fuadi M B 2008 Kajian Resiko Bencana Alam Di Tanggamus, Propinsi Lampung Prosiding pemaparan hasil penelitian puslit geoteknologi pp 85-98
[3] Wiratmo H F dan Sagala S A 2015 Analisis Sovi untuk Kerentanan Sosial Akiat Bencana Banjir di Kota Bandar Lampung Jurnal Perencanan Wilayah dan Kota A SAPPK 4 p 253
[4] Apotsos A 2019 Mapping relative social vulnerability in six mostly urban municipalities in South Africa Applied Geography 105 pp 86-101
[5] Cerchiello V, Ceresa P, Monteiro R. and Komendantova N 2018 Assessment of social vulnerability to seismic hazard in Nablus, Palestine *International Journal of Disaster Risk Reduction* **28** pp 491–506

[6] Zhang W, Xu X and Chen X 2017 Social vulnerability assessment of earthquake disaster based on the catastrophe progression method: A Sichuan Province case study *International Journal of Disaster Risk Reduction* **24** pp 361-372

[7] Gu H, Du S, Liao B, Wen J, Wang C, Chen R. and Chen B 2018 A hierarchical pattern of urban social vulnerability in Shanghai, China and its implications for risk management *Sustainable Cities and Society* **41** pp 170-179

[8] Cutter S L and Boruff B J 2003 Social vulnerability to environmental hazards *Soc Sci Q* **84** (2) pp 242–261

[9] Cutter S L and S Derakhshan 2019 Implementing Disaster Policy: Exploring Scale and Measurement Schemes for Disaster Resilience *Journal of Homeland Security and Emergency Management* **16**

[10] Cutter S L, Emrich C T, Webb J J and Morath D 2009 Social Vulnerability to Climate Change Variability Hazards: A Review of the Literature *Final Report to Oxfam America* Available: http://adapt.oxfamamerica.org/resources/ Literature_Review.pdf

[11] Cutter S L, Emrich C T, Gall M and Reeves R 2018 Flash Flood Risk and The Paradox of Urban Development Natural Hazards Review **19**

[12] Cutter S L 2018 *Linkages Between Vulnerability and Resilience, Chapter 12 in Sven Fuchs and Thomas Thaler (eds.) Vulnerability and Resilience to Natural Hazards* (Cambridge University Press) pp 257-270

[13] Castree N, Hulme M and Proctor J D (eds.) 2018 *The Companion to Environmental Studies* (London & New York: Routledge) pp 86-89

[14] Cutter S L 2017 *The Perilous Nature of Food Supplies: Natural Hazards, Social Vulnerability, and Disaster Resilience Environment: Science and Policy for Sustainable Development* **59** (1) pp 4-15

[15] Dintwa K F, Letamo G and Navaneetham K 2019 Quantifying social vulnerability to natural hazards in Botswana: An application of cutter model *International Journal of Disaster Risk Reduction* **37** pp 1-12

[16] Fatemi F, Ardalan A, Mansouri N and Mohammadfam I 2017 Social vulnerability indicators in disasters: Findings from a systematic *International Journal of Disaster Risk Reduction* **22** pp 219-227