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Research paper

Construction of social vulnerability index in Indonesia using partial least squares structural equation modeling

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Abstract

Social Vulnerability Index (SoVI) is a valuable tool for comparing differences across communities in their overall capacity to prepare for, respond to and recover from natural hazards. Due to its benefits for policymakers and practitioners, SoVI has been widely applied in many countries. Many researchers utilized Exploratory Factor Analysis (EFA) method in SoVI construction. However, the theory says that data from items for EFA have to be normally distributed. In the heart of statistics, not all data follows the Normal distribution. As normality assumption is not a requirement for using Partial Least Squares Structural Equation Modeling (PLS-SEM) method, therefore, this study tries to show the use of PLS-SEM method for SoVI construction. In this study, we utilized reflective formative second order hierarchy model and revealed that many regencies/municipalities with high levels of social vulnerability which located in the Eastern region of Indonesia. These findings highlight the crucial need for strengthening development in the Eastern region of Indonesia.

Keywords: *Social Vulnerability; Natural Hazards; PLS-SEM; Indonesia.*

1. Introduction

Geographically, Indonesia located in the region of the Pacific Ring of Fire, an area that is prone to earthquakes and volcanic eruptions because 90 percent of the earthquakes occur in this region. The Pacific Ring of Fire is along 40,000 km in circular Pacific Ocean basins. Based on the seismic data from 1900 - 2010, it was stated that out of 20 significant earthquakes in the world, 4 of them occurred in Indonesia. This is in line with the data released by National Agency for Disaster Management that shows the earthquakes occur 4000 times per year on average in Indonesia and large earthquakes that damage buildings on average occur 1 to 2 times per year. The earthquakes that often happen in Indonesia often cause colossal loss. For instance, the big earthquake that hit Lombok and Palu in 2018.

There are various concepts and definitions of vulnerability depending on the field of application. The term of vulnerability generally shows the condition of vulnerability to a disaster. Initially, the description of a vulnerability refers to the potential loss when natural disasters occur [1]. This definition then develops towards the human approach [2] where vulnerability is defined as the characteristics of a person or group regarding their capacity to anticipate, cope, combat and recover from the effects of natural disasters [3]. Thus, the capacity of these vulnerable groups is a combination of factors that determine the extent to which a person's or group's life and livelihood [4] are threatened by events that are discrete and identifiable or in society [5]. Regarding the cause of vulnerability, human intervention in the climate [6], and socio-ecological system (for example, land use, dams, deforestation) often triggers extreme natural events [7] at an early stage or makes the damage worse. The impact of these extreme events did not spread evenly within the community.

The Government of Indonesia through BNPB has developed a strategy to reduce the level of vulnerability to disasters and to reduce the risk of many casualties due to natural disasters. One of its strategic plans is to encourage and develop a disaster-aware culture and increase public knowledge about the disaster. However, the level of vulnerability is an essential tool in determining capacity and identifying which groups which are vulnerable, and also in deciding priorities for disaster mitigation programs [8]. When the level of vulnerability in a region has been defined, then it will be more effective and efficient in carrying out disaster mitigation.

The vulnerability can be identified based on various aspects, such as economic, social and infrastructure aspects. Flanagan et. al [9] explained that social vulnerability refers to socioeconomic and demographic factors that will affect community resilience. Their study has shown that in the event of a disaster, socially vulnerable groups tend to be more affected by the disaster and it is difficult to recover from the impact. In other words, the study on social vulnerability can effectively reduce the risks and losses due to the effects of disasters on groups or regions that identified as having the high social vulnerability. Although research on social vulnerability has been shown can help in reducing the risk of disaster impacts, in reality, a study on a social vulnerability in Indonesia is few only and limited to local areas. For example, Utami [10] examined the social vulnerability around Mount Merapi, and Hizbaron et al [11] examined social vulnerability in vulnerable areas in Yogyakarta province.

Social Vulnerability Index (from now on will be abbreviated as SoVI) is one of the well-known tools in assessing social vulnerability. The SoVI was first introduced by Cutter [12] to measure and compare the level of social vulnerability among provinces in the United States. However, the theory says that data from items for EFA have to be normally distributed. Not all data follows the Normal distribution.

Other studies on social vulnerability assessments such as Sagala [13] use the Structural Equation Modelling (SEM) model to measure the social resilience of society. Rizal, et al [14]used SEM in their study of coastal community perceptions related to the tsunami disaster for the people of Bengkulu City. SEM method has higher flexibility to connect the existing theory and data. This is the main benefits of SEM compared to PCA, Factor Analysis, discriminant analysis, and multiple regression analysis methods. SEM method can be differentiated into two types, covariance-based SEM (CBSEM) and variance-based SEM or called Partial Least Square (SEM-PLS). However, building an index based on formative indicators is difficult, but it can be solved by examining the distributed literature on developmental signs which show that four major issues for the construction of the index are content specifications, indicator specifications, collinearity indicators, and external validity [15]. Moreover, the tools to measure vulnerability could be involved as a social vulnerability is a multidimensional concept that requires a lot of formation of SoVI from some of its constituent variables [16]. In using SEM-PLS method, it does not require the normal distribution assumption. Therefore this study aims to show the use of SEM-PLS method in construct-ing SoVI and then to map the SoVI index using Quantum GIS software.

2. The concept of social vulnerability

The social vulnerability has many concepts and definitions. For example, Adger [17] views social vulnerability as exposure of individual or group to a sudden and unexpected change and difficulty with their livelihood. While et Cutter al [12] regard social vulnerability as a product of social and regional inequality. Moreover, social vulnerability is a weakness of a social group to the impact of disasters including the tenacity and ability of the group to recover from the impact of the disaster. In identifying and measuring social vulnerability, the critical key is the determination of indicators and criteria for measurement [18]. Some researchers have found that the typical characteristics of individuals affecting social vulnerability [19] [20] are age, race, gender, income, ethnicity, housing status, job title and occupation, disability and educational level [21]. The social vulnerability was influenced by the distribution of income, accessibility, and diversity of economic assets and informal social safety nets [17]. At the same time, factors of socioeconomic status and infrastructure, gender, age, and population growth and the family size affected the level of social vulnerability.

3. Method

3.1. Structural equation model (SEM)

SEM one of a multivariate analysis method that can be used to describe the relationship between linear relationships between observed variables indicator and latent variable simultaneously. Latent variables are unobserved or cannot be measured directly, but they must be measured using some proxy indicators. There are two types of latent variables in SEM which are endogenous latent variable and an exogenous latent variable. An endogenous variable is one that is explained by a model. An exogenous variable is a variable that influences endogenous variables in the model and not affected by other variables.

3.2. Structural equation model partial least square (SEM PLS)

Partial Least Squares (PLS) is a powerful method of analysis, that means the method does not base on any assumptions. The assumption of a multivariate normal distribution is not required on the data, ordinal, intervals and ratios data scales can be used in the model, and the method does not require large samples. In SEM, there are two types of models indicator related to latent variables, i.e.: reflective and formative indicators. Latent variables are measurement variables of a construct in SEM, which cannot be measured directly but can be represented or measured by one or more manifest variables (indicators). Selection of constructs type (reflective or formative model, based on a type of its indicators) depends on what is the priority of the causality relationship between indicators and latent variables [22] . The reflective model assumes that latent variables have an influence on the indicators, or the direction of the causality relationship is from latent variables to the indicators. While the formative model assumes that the indicators influence the latent variables or direction of the causality relationship is from indicators to the latent variable.

Hierarchical latent variable models [23] [24], hierarchical component models, or high-order constructs, are explicit representations of multidimensional constructions which exist at higher levels of abstraction and related to other constructs at the same level of abstraction that fully mediate the significant influence of dimensions. To establish a higher component model, which is usually referred to in the PLS-SEM context, most often involves a test of other second-order constructs which containing two layers of construction. The constructs can be formed as reflective-reflective, reflective-formative, formative-reflective, and formative-formative.

The second order model starts from the first order, which measures lower order constructs, then the lower order constructs used to measure the second stage, i.e. the higher order constructs. However the most popular hierarchical model is the reflective-formative second order hierarchy where the model was used in MIS Quarterly research [25]. Our study will use a model of reflective-formative second order hierarchy to build the SoVI index as shown in Figure 1.

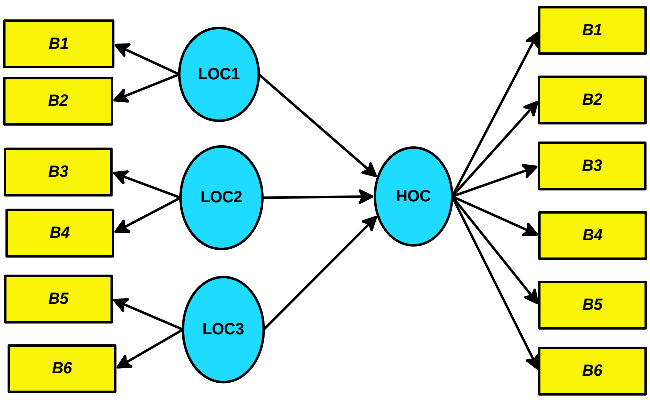

Fig. 1: Reflective-Formative Second Order Hierarchy [25].

3.3. Model evaluation structural equation model partial least square (SEM PLS)

PLS-SEM does not assume any particular distribution for parameter estimation, so parametric techniques to test the significance of parameters are no longer needed [26]. The measurement model for the reflective indicator is evaluated by the convergent and discriminant validity of the indicator and composite reliability of the indicator block. Moreover, formative indicators are evaluated by the substance of the content, i.e., by comparing the relative weights and check the significance of the weights. Convergent validity with reflective model indicators could be assessed based on the correlation between score items/component score and constructs scores-which calculated using PLS. The reflective measure is categorized to be high if the correlation is higher than 0.7, meanwhile preliminary study which has the goal to explore the development of scale measurement of loading values, the correlation lies in the range of 0.5 to 0.6 is considered sufficient.

Discriminant validity reflective model of the indicator is measured from cross-loading value compared to loading value of its construct. Another way to measure discriminant validity is to compare the root of the average variance extracted (AVE) value of each construct to the correlation between the construct and the other constructs in the model, and its value should be higher than 0.5 [27]. Hence AVE formulas:

$$\mathrm{AVE} = \frac{\sum \lambda_i^2}{\sum \lambda_i^2 + \sum_i \mathrm{var}(\varepsilon_i)}$$

Whereλ_i is component loading of indicators and$\varepsilon_i = 1 - \lambda_i^2$. If all indicators are standardized then this measurement equalto average communalities in blocks. Werts et al [28] developed composite reliability to measure a construct, in order to it can be evaluated using two measures, i.e. internal consistency, and Cronbach's alpha. The formula for composite reliability is given as follows:

$$\rho_c = \frac{(\sum \lambda_i)^2}{(\sum \lambda_i)^2 + \sum_i \mathrm{var}(\varepsilon_i)}$$

4. Data analysis

This study uses the 2014 National Socioeconomic Survey (SUSENAS) data set. This study focus to construct a SoVI index by Regency/city for all over regions of Indonesia, which consist of 497 regencies/cities. Variables used in this study refers to the study of Siagian et al [29] where the details of the variables used can be seen in Table 1 below.

Table 1: Social Vulnerability Indicators

Indicators	Descriptions
No Elec	Percentage of households without electrical lighting
LowEdu	Percentage of population aged 15 and above with low education attainment
Poor	Percentage of poor households
Illiteracy	Percentage of illiterate people
FHH	Percentage of female-headed household
Female	Percentage of female
Elder	Percentage of elderly people
PGR	Population growth rate
toddler	Percentage of toddlers (less than 5 years old)
Avg	Average of family size

1) Social Vulnerability Construct

a) Gender, Age, and Population Growth (GAP) Latent Variable GAP Latent Variable is a subtracting variable of the index, differ from two other latent variables. GAP latent variable has four indicators: Female-headed household (FHH), Female, population growth (PopGrowth) and Elder. Female-headed household (FHH), Female and elderly (Elder) Indicators have positive influence positively to GAP, whereas PopGrowth indicator to be a subtractor GAP. Lowe et al [30] states that women, the elderly and children have a profound effect on health psychology and physically during the floods in America. Furthermore, the elderly with age 65 years and above more experienced physical health disruption, while women have more risk to psychological disorders. Siagian et al [29]states that the percentage of female variables, percentage of female heads of households, and the percentage of children positively affect one of the factors that build SoVI. Cutter and Finch [20] suggest that population change and population density have a significant impact on the tendency of social vulnerability temporally. Also, families with the female-headed household are particularly vulnerable when facing disasters. The increased social vulnerability occurs due to extreme contraction or population growth.

b) Social, Economic, and Infrastructure (SEI) Latent Variable SEI latent variable in this study has four indicators, i.eIlliteracy, Poor, Non-Electrical, and LowEdu. The four indicators have a positive influence on SEI latent variables score. Also, the socio-economic factor is one of the most prominent characteristics in the study of social vulnerability. In general, socio-economic includes matters relating to household income, poverty, unemployment, education status, welfare level, and housing. Siagian et al [29] also mention that poverty makes someone unable to access higher education and electricity. This has an impact on the lack of ability to provide first aid equipment to deal with disasters. As a result, recovery in the face of disaster will take a very long time. In this study, the education factor is approached by two indicators, which are the percentage of illiterate population and percentage of the population with low education.

c) Family Structure (FS) latent variable. In this study, the FS latent variable is formed by two indicators: toddler and average of household size (Avg). Chen et al [19]state that family size is an important element and has an influence on the vulnerability of disaster in China. This study also mentions that the value of the factor of the family size shows a high value. Siagian et al [29] also mention that the household size and the number of children aged under five years old causing recovery from the impact of disasters will be tight, especially for developing countries such as Indonesia.

4.1. SoVI Construction using PLS-SEM

The first order latent variables used in this study refers to the factors formed by Siagian et al [29], those are Socioeconomic and Infrastructure Status (SEI); Gender, Age and Population Growth (GAP); and Family Structure (FS). The Socioeconomic and Infrastructure Status (SEI) factor has four indicators: NoElec, LowEdu, Poor, and Illiteracy. The Gender, Age, and Population Growth (GAP) factor have four indicators, which are FHH, Female, Elder, and PGR. Meanwhile, the Family Structure (FS) factor has two indicators, which are toddler and Avg. Then the reflective-formative second-order hierarchical conceptual model used in our study can be seen in Figure 2.

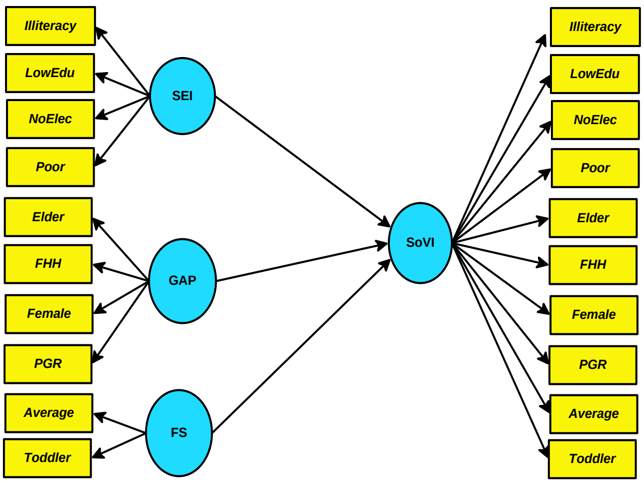

Fig. 2: A Conceptual Model of SoVI.

To construct SoVI using PLS-SEM, we used SMARTPLS2 software. SMARTPLS is a graphical user interfacesoftware for variance-based structural equation modeling (SEM) using the partial least squares (PLS) path modeling method [31]. The steps to constructs SoVI are as follows: Prepare the data and define variables which will be used, and arrange it according to the format required in SMARTPLS 2. Then,

a) Define a reflective - formative second order hierarchy model.
b) Model evaluation:
- •Construct Reliability and Validity
- •Find the parameter model
- •Compute weights of each latent variable

c) Compute SoVI indexes.

Descriptive statistics show two indicator variables, the percentage of households without electricity are the percentage of population over 15 years of age with low education, have standard deviation higher than 10. It means theirdistribution is wide and in line with the range Meanwhile, other indicators were not to vary.

1) Model Measurement

This study use SMART PLS 2 with PLS Algorithm option anduse Path Weighting Scheme [32]. Path weighting performs weighting from neighboring latent variables in the manner that neighboring latent variables are a consequence of the latent variables we estimate. Evaluation of measurement model on PLS-SEM uses two way of tests that are the test of validity and test of reliability. The validity test can be done by looking at convergent validity and discriminant validity of the indicator. The evaluation of discriminant validity performed by comparing the square root of average variance extracted (SRAVE) value against the cross loading of the indicator. If the square root of average variance extracted (SRAVE) value is larger than the cross loading value then it can be said to it has good discriminant validity [27]. Meanwhile, [33] compare SRAVE against the correlation among latent variables.

Composite reliability for GAP, SEI, and FS latent variables respectively are 0.71, 0.89, and 0.88. The three latent variables have values greater than 0.6, means that the predefined indicator has good capability to measure each latent variable (construct), in other words, they are reliable. The AVE valueof GAP, SEI, and FS latent variables are 0.68, 0.67, and 0.79 respectively, which indicate a good convergent validity (where AVE value higher than 0.5), or the convergent validity criterion has been met.

Table 2: Cross Loading From Indicators to Its Latent Variable

	Gender, Age and Pop Growth	Soc-Eco and Infrastructure	Family Structure
Toddler	-0.229	-0.031	0.884
Avg	-0.147	0.075	0.892
FHH	0.827	-0.315	-0.062
pop growth	-0.756	0.179	0.210
Female	0.893	-0.265	-0.072
Elder	0.817	-0.274	-0.359
Illiteracy	-0.283	0.916	-0.118
Poor	-0.171	0.820	0.139
NonElec	-0.435	0.917	0.133
LowEdu	0.026	0.582	-0.198

A good convergence validity value also indicated by the higher correlation between the indicators that build a constructed variable and its latent variable score. Table 2 clearly shows that the correlation between each latent variable forming indicator and its own latent variable is high and higher than its correlation to other latent variables. For example, the percentage of the population aged less than 5 years and average ART correlates higher to family structure latent variables than correlates to other latent variables, as well as other indicators that correlate higher to its own latent variables than correlates to other latent variables.

2) Model Parameter

Since the purpose of this study is to obtain the weightswhich will be used to build SoVI index, then we need to consider the outer weight of the indicatorswhich can be seen in Table 5.

Table 3: Outer Weight of Each Latent Variable

Latent Variables	Indicator	Outer weight
Family Structure (FS)	Toddler	0.884
	Avg	0.892
Gender, Age and Population (GAP)	FHH	0.827
	pop growth	-0.756
	Female	0.893
	Elder	0.817
Soc-Eco and Infrastructure (SEI)	Illiteracy	0.916
	Poor	0.820
	NonElec	0.917
	LowEdu	0.582

Based on Table 3, measurement model for each latent variablecan be formed as follows:

$$\text{GAP} = 0.827_{\text{FHH}} - 0.756_{\text{PopGrowth}} + 0.893_{\text{Female}} + 0.817_{\text{Elder}}$$

$$\text{SEI} = 0.916_{\text{Literacy}} + 0.820_{\text{Poor}} + 0.917_{\text{NonElec}} + 0.582_{\text{LowEdu}}$$

$$\text{FS} = 0.884_{\text{Toodler}} + 0.892_{\text{Avg}}$$

Then, using PLS-SEM algorithm we have the structural model as follows:

$$\text{SoVI} = -0.638_{\text{GAP}} + 0.563_{\text{SEI}} + 0.117_{\text{FS}}$$

3) Build SoVI Index

To build SoVi index, the process does not directly use the above structural equation model, but first it need to convert the weights of each indicator and its latent variables. All weightsconvert toa value withrange 0 to 100. Thus, if the maximum value is multiplied by the value of outer weight, then converted to a scale of 1-10 into the structural equation for each latent variable and the results are following:

$$\text{GAP (2)} = \left(0.827_{\text{FHH}} - 0.756_{\text{PopGrowth}} + 0.893_{\text{Female}} + 0.817_{\text{Elder}}\right) * \frac{10}{178.085}$$

$$\text{GAP (2)} = \left(0.827_{\text{FHH}} - 0.756_{\text{PopGrowth}} + 0.893_{\text{Female}} + 0.817_{\text{Elder}}\right)$$

$$\text{SEI (2)} = \left(0.961_{\text{Literacy}} + 0.820_{\text{poor}} + 0.917_{\text{NonElec}} + 0.582_{\text{LowEdu}}\right) * \frac{10}{323.353}$$

$$\text{SEI(2)} = 0.028_{\text{Literacy}} + 0.025_{\text{poor}} + 0.028_{\text{NonElec}} + 0.018_{\text{LowEdu}}$$

$$\text{FS(2)} = \left(0.884_{\text{Toodler}} + 0.829_{\text{Avg}}\right) * \frac{10}{177.541}$$

$$\text{FS(2)} = 0.050_{\text{Toddler}} + 0.050_{\text{Avg}}$$

Then, path coefficient is used to build SoVI, where maximum value of SoVI latent variable is 42,765, therefore the equation to build SoVI is given below:

$$\text{SoVI} = (-0.638_{\text{GAP}} + 0.563_{\text{SEI}} + 0.117_{\text{FS}}) * \frac{10}{42.765}$$

$$\text{SoVI}_2 = 0.050_{\text{Toodler}} + 0.050_{\text{Avg}}$$

4) Interpretation

SoVI index resulted can illustrate the different levels of social vulnerability among regencies/cities in Indonesia. In Table 4, seventeenregencies in Papua, two regencies in West Papua and one regency in East Nusa Tenggara are among the most vulnerable, which has the highest SoVI index. Regencies in Papua and Papua Barat provinces which has SoVI index within first 20 highest commonly locatedin the highland area. Geographical factors are also suspected has a role as a driving factor of social vulnerability of a society becauseit has an impact on the transportation routes that play an important role in the evacuation process when natural disasters occur. BNPB [34] on its official web stated that Papua province, the eastern part of Indonesia with 29 regencies and 3 million populations,have a moderate and high risk of disasters, such as the earthquake, tsunami, extreme weather, flood, landslide, and drought. The result of this study also in line with the results of Siagian, et al [29]where it used the year 2010 data, that was three of the top ten regencies with the highest SoVI are located in Papua.

Table 4: Regencies/Cities Which Has the Highest and Lowest SoVI

No	Regency/city	Province	SoVI	Regency/city	Province	SoVI
1	Nduga	Papua	0.61	Yogyakarta	DIYogyakarta	-0.54
2	Lanny Jaya	Papua	0.53	Kota Madiun	Jawa Timur	-0.50
3	Puncak	Papua	0.51	Surakarta	Jawa Tengah	-0.48

4	Mamberamo Tengah	Papua	0.50	Salatiga	Jawa Tengah	-0.48
5	Yahukimo	Papua	0.45	Bukittinggi	Sumatera Barat	-0.47
6	Intan Jaya	Papua	0.45	Malang	Jawa Timur	-0.47
7	Pegunungan Bintang	Papua	0.42	Jakarta Pusat	DKI Jakarta	-0.47
8	Tolikara	Papua	0.40	Magelang	Jawa Tengah	-0.46
9	Puncak Jaya	Papua	0.38	Soppeng	Sulawesi Selatan	-0.46
10	Paniai	Papua	0.28	Pematang Siantar	Sumatera Utara	-0.46
11	Mamberamo Raya	Papua	0.27	Tulungagung	Jawa Timur	-0.46
12	Yalimo	Papua	0.27	Samosir	Sumatera Utara	-0.45
13	Asmat	Papua	0.23	Pariaman	Sumatera Barat	-0.45
14	Jayawijaya	Papua	0.20	Sleman	DIY	-0.45
15	Deiyai	Papua	0.18	Manado	Sulawesi Utara	-0.45
16	Dogiyai	Papua	0.17	Blitar	Jawa Timur	-0.45
17	Mappi	Papua	0.17	Pidie	Aceh	-0.45
18	Tambrauw	Papua Barat	0.11	Medan	Sumatera Utara	-0.44
19	Teluk Wondama	Papua Barat	0.04	Kediri	Jawa Timur	-0.44
20	Sumba Barat Daya	NTT	0.04	Tomohon	Sulawesi Utara	-0.44

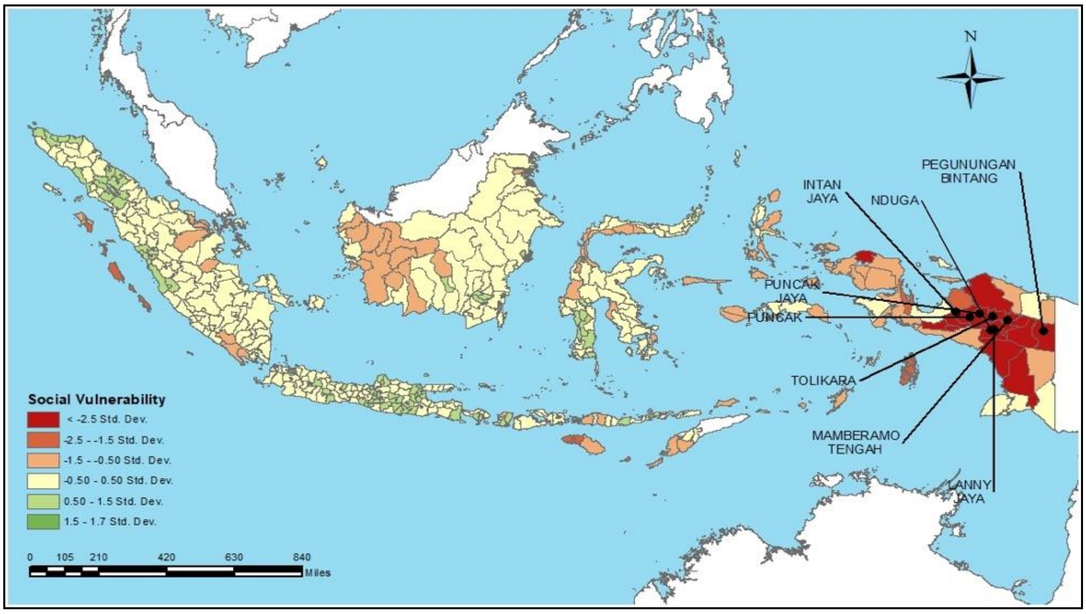

Fig. 3: Variation of Social Vulnerability of Indonesia in 2014.

Table 4 also shows that Yogyakarta city and Sleman regency in the province of Yogyakarta has the lowest SoVI index. This result was in line with Joakim [35] which choose D.I Yogyakarta province as the locus to measure the resilience level of community in facing disaster after the 2006 earthquake. It was also in line with Kidokoro [36] which describes the characteristics of vulnerability in D.I Yogyakarta and Jawa Tengah, viewed from the physical condition and socio-economic conditions in areas affected by disasters. In addition, it explains how plans for post-disaster rehabilitation and reconstruction.

Bukit tinggi and Pariaman are two regencies in Sumatra Barat province with very high resilience level on facing disaster. This is because the local government has made local regulation (Perda) about disaster management in 2008-2012 [37]. In addition, Sumatera Barat Province is a pilot study area for tsunami early warning system developed by several international organizations. Identification of thelevel of social vulnerability ofregencies/cities from highest to the lowest using the standardization classification. The regencies/cities classify into 5 groups. The first group is regencies/cities with a very low level of social vulnerability, or it can be said that the grouphas very high levels of social resilience. The second group is regencies/cities with low levels of social vulnerability, or the grouphas high levels of social resilience. The third group is regencies/cities with moderate social vulnerability level, or the group has moderate levels of social resilience. The fourth group is regencies/cities with high levels of social vulnerability, or the group has low levels of social resilience. While the fifth group is the regencies/cities with a very high level of social vulnerability, or the group has very low levels of social security. Figure 3 presents a map of the level of social vulnerability ofregencies/cities in Indonesia which compute usingPLS-SEM. Based on this figure, the percentage for regencies/cities with very low levels of social vulnerability (group 1) is around 52.7 percent, while districts with very high social vulnerability level (group 5) are about 1.6 percent. Group 1 is concentrated in the islands of Java and Sumatra. When this is attributed to the frequent occurrence of disasters in the region and the various programs that have been run by the government and the community then this demonstrates the successful participation of governments and communities in disaster preparedness by learning from previous disaster experiences. In Sumatera Barat, Sumatra Utara and Aceh, some regencies already have very low levels of social vulnerability. That is, the regencies/cities in those provinces already have social resilience in facing disaster. For example,in Sumatra Barat, Provincial Agency of Disaster Mitigation (BPBD) already has determined the priority zone of disaster mitigation and mapping of its disaster zone.

Differ from western Indonesia, eastern Indonesia in general still has a high level of social vulnerability, particularly in the provinces of Papua and West Papua. Only a few districts/cities have low levels of social vulnerability. Groups 4 and 5 with high and very high social vulnerability are in Papua Province. This shows the role of government and society is not optimal in reducing disaster risk in this region. Therefore this area became the focus of the master plan of the BNPB strategic plan, the Papua region being a priority area.

5. Conclusion

Based on the above discussion, the SEMPLS method with a reflective - formative second order hierarchy model can be used to

obtain the index of social vulnerability. The GAP, SEI and FS factors, as latent variables in this study, are well established in constructing the SoVI index structurally. The results can be said to be closer to real facts, such as for high SoVI values, seventeen districts among the highest are from Papua Province and most areas with mountain topography. Although some districts have coastal and swamp topography, access to public facilities is very difficult. This is in line with Cutter (2003) which said the location of the vulnerability will have an impact on the disaster mitigation process. Almost all areas in the provinces of Papua and West Papua are remote areas. Based on the map of the distribution of the level of social vulnerability, provinces in eastern Indonesia, especially Papua and Papua Barat, become focus and priority areas in terms of having low levels of social resilience.
Suggestions for further study by incorporating topographic variables as control of the SoVI index formed, so that with the information the government can better prepare to anticipate early in the disaster management process if the area with a high vulnerability index is affected by a natural disaster. Local governments through the Regional Disaster Management Agency (BPBD), particularly in Papua and West Papua, need to conduct a comparative study to the West Sumatra government, which has conducted a pilot study in disaster management. While from the side of the methodology needs to be done improvements by adding variables that can be used as a proxy to measure SoVI directly so that it will increase the value of the AVE and its composite reliability.

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