



RISK IDENTIFICATION AND DISASTER MANAGEMENT AT THE VILLAGE LEVEL: PRINCIPAL COMPONENT ANALYSIS APPROACH

Muhammad Fazri^{1,*}, A. Risdawati AP¹, Dian Karinawati Imron², Marthella Rivera Roidatua³, Adelia Oktarina¹, Febrina Elia Nababan¹, Cita Pertiwi¹

¹ Directorate of Economy, Employment, and Regional Development Policy, National Research and Innovation Agency, Indonesia

² Research Center for Social Welfare, Village and Connectivity, National Research and Innovation Agency, Indonesia

³ Directorate of Human Development, Demography, and Culture Policy, National Research and Innovation Agency, Indonesia

*Corresponding author. Email: muhammad.fazri@brin.go.id

ABSTRACT

Indonesia is one of the countries with a fairly high level of disaster proneness. Based on the results of the 2020 Indonesia Disaster Risk Index (IRBI) published by BNPB, out of the number of 514 districts, there are 237 districts with high risk, while 277 districts with moderate risk. The high number of Indonesian disasters can also be seen from the number of disaster events. So far, disaster identification is limited to the district. The disaster risk index also has an area only up to the district. Whereas each village has different location characteristics so that disaster management cannot be equated. Therefore, this study tried to look at the risk of disaster-prone at the village level. The data used is the 2020 Village Potential data by looking at the number of disaster events and also the number of fatalities in each village from 2019 to March 2020. The method used an analysis description approach through data exploration. In addition, using quantitative methods principal analysis components to create an Index that will classify a village whether prone to disaster or not. The results of identification are still many villages that are prone to disaster. From these results, it is mapped that there are 1,158 villages that have high risk, 27,061 medium risk and 46,446 villages are in low risk. This means that about 38 thousand still have a risk of being prone to disasters.

Keywords: Village, Natural Disaster, Principal Component Analysis

1. INTRODUCTION

Disaster insecurity is an issue that cannot be separated from Indonesia's development. The high level of disaster insecurity in Indonesia demands attention in mainstreaming disaster policies in development [1,2]. Through Law Number 24 of 2007 concerning Disaster Management, Indonesia is a country with geographical, geological, hydrological, and demographic conditions that allow disasters to occur so that they can have an impact on national development. Catastrophic events have an impact on the social life and economic conditions of the community. A number of studies have shown that disaster events can give rise to social conflicts, put people in conditions of poverty risk, hamper the education process and cause people to lose their livelihoods [3,4,5]. Disaster events also present challenges in natural resource management for the community. Disaster events close community access to manage land, water sources and other natural resources.

BNPB compiles the Indonesia Disaster Risk Index as a reference in assessing the level of disaster risk. IRBI provides an overview of the assessment of potential loss or loss as a form of disaster risk. The results of the 2020 Indonesia Disaster Risk Index (IRBI) show that out of 514 districts, there are 237 districts with high risk, while 277 districts with moderate risk [6]. Districts with high and moderate levels of disaster risk need integrated disaster mitigation strategies. Disaster mitigation is the initial stage in disaster prevention efforts [7,8]. Important aspects in disaster mitigation include regulation, disaster management, infrastructure provision, improvement of disaster emergency services, collaboration and coordination of parties [9]. Information disclosure and strengthening community capacity in facing disasters also cannot be separated as a form of strengthening the role of disaster response communities.

Disaster mitigation efforts need to be carried out in an integrated manner by involving various stakeholders. Integrated disaster mitigation leads to an understanding and mitigation strategy from the local government level to the government and local communities, namely villages. However, disaster identification including IRBI so far is still limited at the regional level and has not yet reached the Village level. Research on the impact of disasters on rural areas, especially villages, is still limited. Villages have diverse regional characteristics as disaster-prone locations. Research shows that disaster impacts can best be mediated at the local level and are effective risk reduction measures [10]. The implementation and development of disaster mitigation policies at the local level is one of the effective action options that can be carried out [11].

A number of literatures mentions differences between urban and rural areas in responding to disasters. The ability to deal with disasters in the two regions is different in the context of risk and recovery [10]. Rural areas are seen as having minimal access to resources, challenges in the fulfillment of basic services, weaknesses in handling and impacts on declining local economic conditions. Furthermore, challenges to broadband access and the ability to handle hazard mitigation are still low in rural areas.

In supporting the development of disaster management policies at the village level, comprehensive data support is needed. Supporting data that can be identified includes disaster risk data, spatial maps of disaster risk, one of which can use ArcGIS, data on community disaster resilient activities, information centers and data visualization as well as the availability of facilities or infrastructure [12,13]. Big Data is also one of the offers in comprehensive disaster management both including numerical and spatial data [14]. The data identified is an important asset for generating solutions in disaster management.

There are various challenges from the village level where villages have different characteristics of disaster risk locations. With the condition of the village which is considered to have limited capabilities, an approach to developing basic disaster data at the village level is needed. Therefore, this study tries to analyze disaster risk at the village level. The data used is village potential data in 2020 by looking at the number of disaster events and the number of deaths in each village from 2020 to May 2021. This study aims to identify village-level disaster risks and find out the extent of disaster mitigation levels in villages. The research was conducted with a quantitative approach through Principal Component Analysis (PCA) and then qualitative and quantitative analysis (Cross Tabulation) was carried out.

2. LITERATURE REVIEW

2.1. Disaster Risk

Disaster Risk Assessment in Indonesia is combined in an Indonesian Disaster Risk Index (IRBI). IRBI is a calculation by including the components of hazard, risk, and capacity in provinces and districts / cities. Hazard components are also used, namely natural events that can cause disasters such as earthquakes, volcanic eruptions, tsunamis, floods, and others. Furthermore, there is a risk component consisting of aspects of (1) physical conditions, (2) socio-cultural, (3) economic, and (4) environmental aspects that are vulnerable to disaster exposure. Then, the capacity component consists of policy and institutional aspects; education and training; mitigation, preparedness and emergency response capacity; and recovery capacity [6].

2.2. Disaster Mitigation

Article 1 paragraph 6 of Government Regulation Number 21 of 2008 concerning the Implementation of Disaster Management, mitigation is defined as a series of efforts made to reduce disaster risk, either through physical development or awareness and increasing the ability to face disaster threats.

Mitigation is defined as any ongoing action taken to reduce or eliminate long-term risks to human property and life. So that mitigation can be said to be a mechanism so that the community can avoid the impact of a potential disaster. His actions can focus on disaster avoidance, in particular avoiding the placement of people and property in dangerous areas. This includes efforts to control hazards through the construction of various special facilities and the application of certain technologies [15].

3. METHOD

The data used in the study is secondary data. Secondary data were obtained through literature studies and supporting data were collected from relevant agencies such as the Central Statistics Agency (BPS). The locations used as the basis for making a Disaster Risk Index at the Village level are 72,665 Villages, as for the data used in Disaster Risk Identification at the Village level, namely the Number of Disaster Events, the Number of Casualties Due to Disasters, Disaster Mitigation in villages obtained from updating the Potential of Villages in 2020 (Central Statistics Agency).

The disasters in question are devoted to this study that occurred in 2019 to March 2020, namely:

1. Landslide
2. Flood
3. Flash floods
4. Earthquake
5. Tsunami
6. Sea tides
7. Whirlwinds/tornadoes/typhoons
8. Erupting mountains
9. Forest and land fires
10. Drought (land)

The method used uses a Quantitative approach with qualitative reinforcement. For Village-Level Disaster Risk Identification using Principal Component Analysis while Knowing the Extent of Disaster Mitigation Levels in villages using cross-tabulation analysis descriptions.

3.1. Principal Component Analysis (PCA)

PCA is used to explain the structure of the variance-covariance matrix of a set of variables through a linear combination of those variables. In general, the main components can be useful for the reduction and interpretation of variables.

There is a variable fruit consisting of n objects. Suppose also that from p the fruit of the variable is made as much k the fruit of the main component (with $k \leq p$) which is a linear combination of the p fruit of the variable. k such main components can replace the p of the variables that make up them without losing much information regarding the whole variable. Generally, PCA is an *intermediate* analysis which means that the results of the main components can be used for subsequent analysis.

In mathematical form, let's just say that Y is a linear combination of variables X_1, X_2, \dots, X_p that can be expressed as

$$Y = W_1X_1 + W_2X_2 + \dots + W_pX_p \quad (1)$$

With:

- W_i is the weight or coefficient for the i -th variable
- X_i is the i -th variable
- Y is a linear combination of the variable X

In the PCA obtained the following measures:

1. The total value of the variance is the information of all the variables of origin that can be explained by their main components.
2. The proportion of the variance of the main component to k to the total variance indicates the magnitude of the percentage of information of the variables of origin contained in the k -th main component.
3. The value of the correlation coefficient between the main components and their variables.

3.2. Research Model

By using the Principal Component Analysis model, it will be formed as a model for calculating the value / score of the Disaster Risk Index with the model:

$$F = \alpha_1 X_1 + \alpha_2 X_2 + \alpha_3 X_3 \quad (2)$$

X_1 : Number of Disaster Events*

X_2 : Number of Casualties Due to Disasters*

X_3 : Disaster Mitigation (1= No disaster mitigation; 0 = No disaster mitigation)

3.3. Village Level Disaster Vulnerability Index Analysis

Based on the results of determining the weight of the PCA, the risk index score of each company observed can be determined. Furthermore, to find out the level of risk of each company, then each such company will be classified according to the following restrictions: high, medium, and low risk. The limit is measured based on the score value with the following approach:

High risk: $< \text{score (average score - 1 standard deviation score)}$

Moderate risk: $(\text{average score} - 1 \text{ standard deviation score}) \leq \text{score} \leq (\text{average score} + 1 \text{ standard deviation score})$

Low risk: $\text{score} = 0$

4. RESULT

Natural disasters at the village level, are still dominated by Natural Disasters Floods, Earthquakes, Landslides, Droughts, and Landslides. More than 5000 Villages experienced the natural disaster. Flood natural disasters occurred in 10321 villages where the was more than 10% of the total villages. Flood disasters not only have a large number of disaster events, but also casualties. In 2019 alone the number of flood events reached 16563 times in 10321 villages, with casualties reaching 2387 in 2019. In early 2020, until March, the number of Flood Disaster Events was already quite high, reaching 10730 Events with Koban Jiwa reaching 2174.

The next biggest disaster event is earthquakes, droughts (land) and landslides, this figure becomes very high where the number of villages that experienced disasters during 2019 to March 2020 reached more than 5000 villages. However, the difference is that in land droughts, the number of casualties reached 1495 people while landslides (215 people) and earthquakes (126). This is very concerning

considering that Indonesia is a country that experiences 6 months of rainy season in most of its regions.

Table 1. Number of Villages, Incidents and Victims of Natural Disasters in Indonesia (2019-March 2020)

| Num | Types of Disasters | Number of Villages Experiencing Disasters | 2019 | | 2020 (Jan-March) | |
|-----|-------------------------------|---|-----------------------|------------|-----------------------|------------|
| | | | Number of Occurrences | Casualties | Number of Occurrences | Casualties |
| a. | Landslide | 5307 | 7696 | 215 | 4496 | 152 |
| b. | Flood | 10321 | 16563 | 2387 | 10730 | 2174 |
| c. | Flash floods | 873 | 970 | 65 | 625 | 36 |
| d. | Earthquake | 5694 | 13392 | 126 | 8484 | 70 |
| e. | Tsunami | 10 | 17 | 0 | 6 | 0 |
| f. | Sea tides | 1092 | 1805 | 93 | 1122 | 78 |
| g. | Whirlwinds/tornadoes/typhoons | 3301 | 3188 | 244 | 1554 | 143 |
| h. | Erupting mountains | 66 | 83 | 0 | 57 | 3 |
| i. | Forest and land fires | 2940 | 4267 | 51 | 563 | 10 |
| j. | Drought (land) | 5547 | 5732 | 1495 | 1402 | 1160 |

Source: Village Potential Data (2020)

4.1. Establishment of Village-Level Disaster Risk Index

As explained in the previous section, the PCA method can be used to reduce the p of a variable to r a new variable called the Main Component ($r < p$) while maintaining the magnitude of the diversity of the original variable. PCA requires that the analyzed variables correlate with each other. The closer the correlation (both positive and negative) between variables, the better the results obtained from PCA. In other words, in PCA a variable will group into a factor consisting of other variables if the variable is correlated with a number of other variables that fall into a certain group of factors.

The data structure used in measuring the weight of each variable for the formation of risk index is Village Potential Data data from 74565 Villages in 2020. The stages of formation of the corporate risk index by the PCA method of the eight indicators above, are presented as follows:

- 1. Data Due Diligence.** The first step in PCA is to calculate the correlation matrix to find out the conditions for the adequacy of the data. One of the methods that can be used is the Kaiser Meyer Olkin (KMO) and the Bartlett Test of Sphericity.

Table 2. KMO and Bartlett's Test

| | | |
|--|--------------------|---------|
| Kaiser-Meyer-Olkin Measure of Sampling Adequacy. | | .500 |
| Bartlett's Test of Sphericity | Approx. Chi-Square | 132.183 |
| | df | 3 |

| | |
|------|------|
| Sig. | .000 |
|------|------|

Bartlett's Test of Sphericity results with Chi-Square 132.183 (df 28) resulted in a significance value of $0.00 < 0.05$. These results suggest that the correlation matrix is not an identity matrix so PCA can be applied to the above eight risk indicators.

- 2. Calculating Communality.** Communality shows how much the variance can be explained by the extracted factor or component (the formed factor). Based on Table 2, in general, the initial variable has a fairly large communality value, which is above 0.5. This can be interpreted to mean that the overall variables used have a fairly strong relationship with the factors formed. In other words, the greater the value of the communality, the better the PCA, since the greater the characteristics of the variables of origin that can be represented by the formed factor.

Table 3. Score of Communality

| | Initial | Extraction |
|----|---------|------------|
| X1 | 1.000 | .522 |
| X2 | 1.000 | .956 |
| X3 | 1.000 | .564 |

Extraction Method: Principal Component Analysis.

- 3. Calculating Total Variance Explained.** The next step in PCA is to look for factors or extracting factors. Factor extraction is a method used to reduce data from several indicators to produce fewer factors or components and is able to explain the correlation between the observed indicators. PCA is an analytical technique to transform the original variables that are still correlated with each other into

a new set of variables that are no longer correlated. Those new variables are referred to as the main components.

4. **The determination of the number of components in the PCA** is carried out by looking for variables or components that are not correlated with each other, free from each other, but are less numerous than the initial variable. Although it produces a smaller number of variables, the component absorbs most of the information contained in the initial variables which are more numerous and can contribute to the variance of all variables. In PCA, the determination of such components refers to the *value of the eigenvalue*, which indicates the magnitude of the contribution of the component to the variance or diversity of the entire initial variable. In this case, if the *obtained eigenvalue* value is greater than one, then the formed component can be preserved, on the contrary if the *eigenvalue* value is less than one, then the component cannot be used.

Table 4. Eigenvalue value for Each Component

| Component | Initial Eigenvalues | | |
|-----------|---------------------|---------------|--------------|
| | Total | % of Variance | Cumulative % |
| 1 | 1.042 | 34.732 | 34.732 |
| 2 | 1.000 | 33.340 | 68.072 |
| 3 | .958 | 31.928 | 100.000 |

Table 4 presents the results of *eigenvalue calculations* for the formation of a disaster risk index, the percentage of total diversity (*percent of Variance*) and cumulative total diversity (*Cumulative percent*) capable of being explained by the diversity of the components formed. Based on Table 4, of the 3 components formed, there are 2 components that have an *eigenvalue* greater than one. Component 1 has an *eigenvalue* of 1.042, Component 2 is 1.00, and Component 3 is 0.958,

Meanwhile, in Table 4 there is also a '*percent of Variance*' column that shows the percentage of variance or diversity that can be described by each component and a "*Cumulative percent*" column that describes the cumulative of each component simultaneously. The amount of diversity that Component 1 is able to explain is 34,732 percent. The diversity that Components 1 and 2 are capable of explaining is 68,072 percent. Based on the *eigenvalue* of the four components greater than 1, and the magnitude of the cumulative percentage of the two components of 68.072 percent, it can be concluded that the two components can represent the diversity of the initial variables.

5. **Calculating the Component Matrix.** Table 5 presents a component matrix that shows the magnitude of the correlation of each variable in the formed component, or loading factor. Based on

Table 5, it can be seen that there are three factors or components formed from three indicators of risk.

Table 5 Component Matrix

| VAR | Component | |
|-----|-----------|-------|
| | 1 | 2 |
| X1 | .723 | .007 |
| X2 | .208 | .955 |
| X3 | .690 | -.296 |

Extraction Method: Principal Component Analysis.

1. **Determining the Equation of Factors**
Determining the equation of factors is done by selecting *the loading factor* with the largest absolute value in each component. In this case, *the loading factor* with the largest absolute value will be selected as the weight of each variable that will be used to measure the risk index.

Table 6. Factors Affecting Disaster Risk

| No | Component | Variable | Loading Factor |
|----|-----------|----------|----------------|
| 1 | K1 | X1 | 0.723 |
| 2 | K2 | X2 | 0.955 |
| 3 | K1 | X3 | 0.690 |

From Table 6, it can be seen that the variables derived from the first component (K1) are X₁ and X₃. The variables derived from the second component (K2) are X₂. Furthermore, after obtaining the factor formed through the reduction process, the next stage is to determine its safety. Through this equation, the score of each factor can be calculated from each village. The equation created is similar to multiple linear regression, only in its factor equation there is no constant. Using the results from Table 6, then the equation for the new factor formed is as follows:

$$F = 0.723 X_1 + 0.955 X_2 + 0.690 X_3$$

The factor scores resulting from the above equation can be used to replace the scores on the original free variables. Thus the variables X₁-X₃ reflecting the village-level disaster risk ratio can be used to measure the Disaster Risk Index at the Village Level.

Based on the results of determining the weight of the PCA, the risk index score of each observed village can be determined. Furthermore, to find out the level of risk of each village, then each such company will be classified. From these results, it is mapped that there are 1158 villages that have high risk, 27061 medium risk and 46446 villages are in low risk. This means that about 38 thousand still have a risk of being prone to disasters.

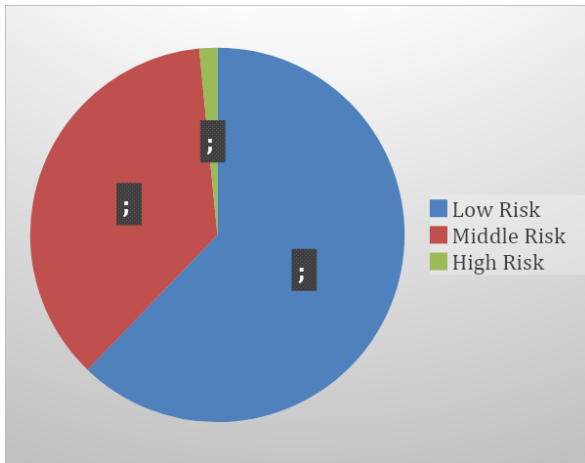


Figure 1. Village Distribution Based on Risk Level

4.2. Village Disaster Mitigation System

It can be seen before that there are still many villages that have experienced disasters and have a risk of disasters, both medium and high. But the extent to which the village has disaster mitigation. Table 7 mentions Villages That Have a natural disaster early warning System 5454 Villages, Villages That Have a tsunami-specific early warning System 516 Villages. Villages That Have Safety Equipment (inflatable boats, tents, masks, etc.) 7553 Villages Have Signs and disaster evacuation routes 4950 Villages. Villages that have the manufacture, maintenance, or normalization: rivers, canals, embankments, ditches, drainage, reservoirs, beaches, etc. 23011 Villages.

Table 7. Village Disaster Mitigation System

| Indicator | Number of villages |
|--|--------------------|
| Villages Have a natural disaster early warning system | 5,454 |
| Villages Have a tsunami-specific early warning system | 516 |
| The Village Has Safety equipment (inflatable boats, tents, masks, etc.) | 7,553 |
| Villages Have Signs and disaster evacuation routes | 4,950 |
| The existence of Creation, maintenance or normalization: rivers, canals, embankments, ditches, drainage, reservoirs, beaches, etc. | 23,011 |

Furthermore, If cross-tabulation is carried out between villages that experience disasters and disaster mitigation systems, it can be seen (Table 8.) that there are still many villages that experience disasters that do not have disaster mitigation (22765 villages) only 2403 villages have disaster mitigation. Likewise, with

villages not experiencing disasters, there are still 46446 villages that do not have disaster mitigation.

Table 8. Cross Tabulation: Disaster Occurrence and Disaster Mitigation

| | Lack of Disaster Mitigation | Have Disaster Mitigation |
|-----------------------|-----------------------------|--------------------------|
| No Disaster | 46446 | 3051 |
| Experiencing Disaster | 22765 | 2403 |

The data result shows that villages is significant element to address range of disaster risk. Local territorial approaches need to be a concern and the development of numerical and spatial databases would encourage comprehensive disaster mitigation process at the local level.

5. CONCLUSIONS AND RECOMMENDATION

At the village level, disasters can still be said to be quite a lot, especially in Floods, Earthquakes, Landslides, and Droughts (Land). In reality the villages that experienced the disaster Most have no disaster mitigation. Based on PCA testing, most of them are still at low risk (62%) but there are still many villages that have moderate risk (36%) and high risk (2%). This should be a concern for the Government.

The Village Fund given annually can actually be used as a solution for villages to reduce the risk of impacts from disasters by holding disaster mitigation programs. Through the Village Fund The village government can make simple mitigations to reduce the risk of impacts from disasters .

AUTHORS' CONTRIBUTIONS

Muhammad Fazri, A. Risdawati AP, Dian Karinawati Imron, Marthella Rivera Roidatua, Adelia Oktarina, Febrina Elia Nababan, Cita Pertiwi are the main author. All author has equal contribution to the research study from formulation of the study framework, process, analysis and to the writing of the manuscript.

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