

Article

Flood Risk Assessment Focusing on Exposed Social Characteristics in Central Java, Indonesia

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Abstract: This study analyzes Indonesia, a country marked by significant socioeconomic diversity, to inform the development of holistic flood risk management strategies. We examine the relationship between flood-exposed populations and socioeconomic factors at the regency level, particularly in Central Java, using open data encompassing flood-prone areas, topography, population distribution, and socioeconomic indicators. Key findings include population exposure to flooding varies significantly across the 33 regencies and 7 cities, ranging from 1% to 61% in exposure rate. A notable 5.8-fold difference in average income exists among regencies, with income strongly correlating with higher education rates. Similarly, poverty rates correlate with low educational attainment; there was a very large range in the balance between the size of the exposed economy and the number of exposed poor population in each administrative division. Consequently, we propose a classification system that considers social vulnerability due to poverty, low-education, and economic impacts. The map reflecting these classifications is a risk map that facilitates the understanding of the risk characteristics and the relative risk magnitude of each administrative district. Our analysis underscores the importance of adapting flood risk management strategies to local socioeconomic characteristics and suggests the importance of the use of local wisdom.

Keywords: flood; risk assessment; open data; exposure; socioeconomic status; GIS; Indonesia



Citation: Sigit, A.; Koyama, M.; Harada, M. Flood Risk Assessment Focusing on Exposed Social Characteristics in Central Java, Indonesia. *Sustainability* **2023**, *15*, 16856. <https://doi.org/10.3390/su152416856>

Academic Editor: Andrzej Walega

Received: 13 October 2023

Revised: 7 December 2023

Accepted: 8 December 2023

Published: 14 December 2023



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1. Introduction

Climate change-induced flood disasters are an escalating global concern, poised to increase in intensity in the coming years. Studies have demonstrated the adverse impact of these risks on national economic growth [1]. The dynamics of flood risk, encompassing hazard, exposure, and vulnerability, lead to regional disparities and global trends [2]. Floods represent one of the most frequent natural disasters, resulting in substantial economic losses and fatalities worldwide, surpassing \$40 billion in losses on an annual basis and affecting approximately 250 million people around the world each year, making it the most destructive disaster affecting communities worldwide [3]. For instance, projections indicate that certain regions in Japan will experience between 1.2 and 1.3 times more rainfall by 2050, leading to a significant increase in potential economic losses related to flooding due to climate change [4]. Similarly, in Indonesia, especially Java Island, climate change and urban expansion are anticipated to heighten the risk of riverbank flooding by 76% by 2030, necessitating the urgent implementation of adaptation measures [5]. The mounting threat of flooding in various regions worldwide highlights the need for effective mitigation measures to safeguard vulnerable communities.

However, there exist critical gaps in disaster management systems in each country, particularly in developing nations like Indonesia, where the adoption of infrastructure from developed countries encounters challenges, such as capacity gaps at lower institutional levels, low compliance with laws and regulations, disconnected policies, problems in

communication and coordination, and inadequate resources [6]. Indonesia faces research challenges due to the lack of hydrological data for flood hazard analysis in many regions, potentially leading to high disaster assessment costs. Furthermore, Indonesian society is characterized by a diversity of socioeconomic conditions that significantly influence regional policies, particularly in disaster management. The application of disaster management infrastructure to exposure and vulnerable land-use sites may not be effective, given limited resources in certain areas directly related to their socioeconomic conditions [7]. Consequently, there is a pressing need to develop tailored disaster management strategies, especially for flood-prone areas. Overcoming the lack of detailed hydrological data for flood analysis and the complexities arising from the diverse society is vital to facilitate more economical disaster assessment.

The effectiveness of measures adopted in technologically and economically developed countries may not necessarily translate to developing countries [8]. Flood risk management holds paramount importance in developing nations due to multiple social and natural factors that pose risks to communities. Consequently, the extent of areas facing inundation risk is frequently higher in developing nations than in developed countries. Moreover, vulnerabilities in economic, organizational, and institutional domains may hinder resilience and recovery from major crises in developing countries, leading to significantly higher global vulnerability compared to other nations facing similar risks. The poor, often residing in high-risk regions, are disproportionately vulnerable to flooding in developing nations.

To contribute to effective adaptation strategies, flood risk assessments must focus on the interplay between hazard assumptions and the societal context to which it is exposed. However, many hazard maps in various countries and regions merely depict hazard assumptions. Particularly in regions like Indonesia, characterized by its diverse societal characteristics, analyzing not only the hazard but also the social condition of exposure is imperative. This requires an analysis that not only considers the hazard but also the state of society exposed to it. To develop adaptation strategies at a national level, it is necessary to analyze the relationship between hazards and exposures not only for individual river basins but also for a broad range of analyses, identifying local characteristics and devising tailored measures for each.

This study presents an analysis of Indonesia, a country with highly diverse socioeconomic conditions, as a basis for developing future flood risk management strategies that take a holistic view of the country as a whole. Flood hazard can be assessed either by using process-based models such as inundation simulation or by extracting potentially hazardous areas by focusing on topography. The former approach is expensive and has problems in setting external forces. In this study, the latter approach is adopted to extract potential flood hazard areas using open data. We present the results of an analysis of the topographical characteristics of the population distribution in each regency and the characteristics of the potentially flood-exposed population in Central Java, Indonesia, and discuss how adaptation strategies should be implemented.

2. Materials and Methods

2.1. Method Framework and Materials

The outline of this study is shown in Figure 1. Using four major groups of open data, the relationship between flood hazards and the socioeconomic environment to which they are exposed is analyzed and some considerations for flood risk management are presented. The four groups are hazardous area data, topographic data, population data, and socioeconomic data. Except for socioeconomic data, the other data are open data distributed as raster data that can be analyzed in GIS. In this study, the horizontal resolution of all raster data is unified at approximately 100 m (3-arc second).

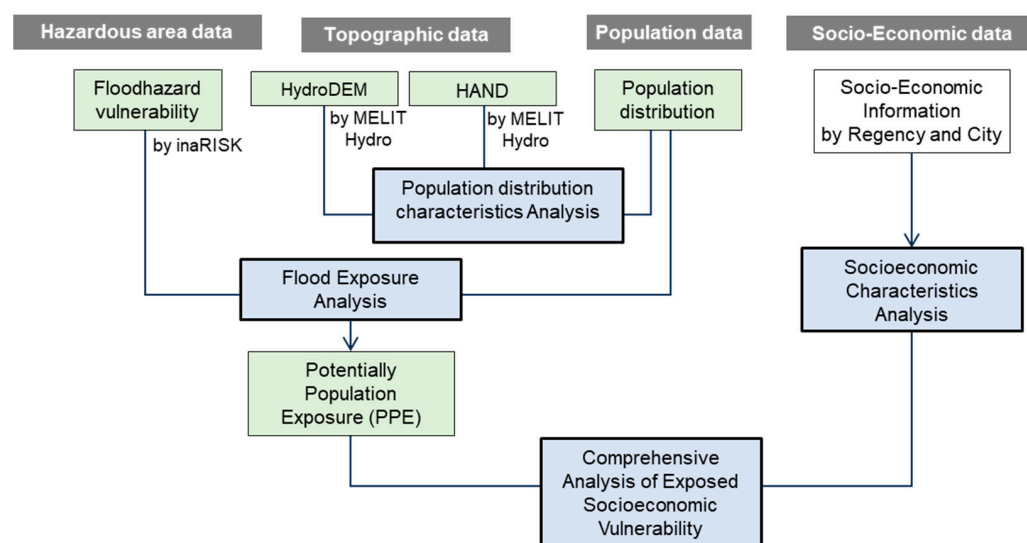


Figure 1. Method framework. All data sets used in the analysis are open data; the green boxes are raster data. The four blue boxes indicate the contents of the data analysis.

The population data and socioeconomic data used in this study are statistical data published on the internet by national organizations, which are re-compiled for each regency and city. Because population and socioeconomic conditions change from year to year, the analysis in this study focused on data for the year 2020.

Table 1 lists the data used in this study. All these data are open data sets and are maintained globally for most types of data. Information on socioeconomic status is likely to vary by country regime but is common at least in the Republic of Indonesia. In some countries, more indicators may be available for socioeconomic conditions.

Table 1. Data groups, data name and sources.

Group	Name	Data Type	Source
Hazardous area data	inaRISK floodhazard vulnerability (layer_bahaya_banjir_bandang) ¹	Raster data set resolution: 3 arc-second	[9]
Topographic data	HydroDEM ²	Raster data set resolution: 3 arc-second	[10]
	HAND (Height Above Nearest Drainage) ²	Raster data set resolution: 3 arc-second	[10]
Population data	Indonesia 100m Population ³	Raster data set resolution: 3 arc-second	[11]
Socioeconomic data	Number of people per age group	Table on website	[12]
	Number of people per educational rank ⁴	PDFs	[12]
	Number of poor people ⁵	Table on website	[12]
	Average income	PDFs	[12]

¹ Data for some of the layers viewable in the inaRISK's web GIS is available for download. ² MERIT Hydro is a global hydrography dataset, developed based on the MERIT DEM and multiple inland water maps. It contains flow direction, flow accumulation, hydrologically adjusted elevations, and river channel width. ³ 2020 estimates of numbers of people per pixel (ppp) with national totals adjusted to match UN population division estimates. ⁴ The educational background of the residents is tabulated in seven ranks. 1–2: no education and finish elementary school, 3–5: finish junior to senior high school, 6–7: diploma to up. ⁵ The "poor" are those who have an average monthly per capita expenditure below the poverty line. To measure poverty, the Indonesian Central Bureau of Statistics uses the concept of the ability to meet basic needs (basic needs method). With this approach, poverty is seen as an economic inability to fulfill basic food and non-food needs measured in terms of expenditure.

The InaRISK was launched in 2016 with support from the United Nations Development Programme (UNDP). It is a portal utilizing ArcGIS for disaster risk assessment. It offers data on disaster-prone areas, affected populations, potential losses (financial and environmental), and integrates with disaster management plans, facilitating risk reduction. The background layer utilized in this model is sourced from the General Guidelines for Disaster Risk Assessment from the Head of Disaster Management Agency Regulation number 02 of 2012 [13], ensuring transparency and traceability in the risk assessment process. The vulnerability rating value in InaRISK is determined by a comprehensive evaluation of the results of the analysis of the following four vulnerability factors: potentially exposed population, potential losses (physical and economic), potential environmental damage, and vulnerability class. Despite the inherent procedural nuances within the regulation, the guideline stands as the official source guiding disaster risk assessment methodologies. The InaRISK serves as a foundation for development planning, spatial data sharing, specific applications (e.g., multi-hazards early warning systems), policy development, and progress monitoring of disaster risk reduction programs [13,14]. In this study, the results of the assessment of flood disaster vulnerability among various types of disasters are used as spatial information to indicate flood hazardous areas.

HydroDEM is a digital elevation model (DEM) data for hydrological analysis that is a modification of the regular digital terrain model (DTM). HAND (height above nearest drainage) is raster data generated from HydroDEM, showing the specific height from the nearest drainage channel from each grid [15]. HAND is considered to be an indicator closely related to land inundation risk and is used for comparison with flood records [16]. Hydro DEM and HAND data maintained for the entire world are distributed through the MERIT Hydro website [10,17]. These data are used to examine the characteristics of the population distribution in relation to the elevation and HAND values.

Population data derived from 2020 estimates of the number of people per pixel (ppp) with national totals adjusted, to match UN population division estimates [18]. Estimated persons per grid square are shown for each mesh with a horizontal resolution of approximately 100 meters. Since the population distribution data are estimates for the year 2020, the following socioeconomic data are also collected for the year 2020.

Socioeconomic data were provided by the local government. Some of the data shown in Table 1 were picked up from tables displayed on the website. Some data were entered into the database by extracting numbers from PDF files of annual reports [12]. Data on socioeconomic conditions were collected in the central part of Java, namely the provinces of Central Java and Yogyakarta. These two provinces were ranked 12th and 13th in terms of the highest percentage of poor people in Indonesia from 2009 to 2017 [19], which were chosen as the study areas in this study. However, information on the education level of the population in the Yogyakarta Province is difficult to collect. The provincial government has indicated that the Yogyakarta Province has many residents moving in and out of the country, making it difficult to compile such information. Despite the absence of accurate education data, the Yogyakarta Province was included in the study due to its significance in the broader socioeconomic context and to capture a representative sample of central Java regions. For this reason, a total of 29 regencies and 6 cities belonging to the Central Java Province are included in the analysis of education levels, reflecting the practical considerations and data availability challenges typical in developing countries.

Using these data, we perform the four analyses indicated by the blue boxes in Figure 1. Population distribution characteristics analysis analyzes the characteristics of the relationship between population distribution and topography in the target area. Flood exposure analysis analyzes the distribution of the population living in areas at risk of potential flood inundation, where flood vulnerability is obtained from the risk mapping analysis by InaRISK. The socioeconomic characteristics analysis focuses on the average income, the poor population, and the level of education as indicators of the socioeconomic status of each regency. Finally, a combined analysis is conducted focusing on both the poor people and economy exposed to flood disasters.

QGIS version 3.14.16-Pi, an open-source desktop geographic information system was used for the GIS-based analysis. Statistical analysis was performed using the general-purpose statistical computing software, R x64 4.1.0 and Microsoft Excel version 2302.

2.2. Study Area

The study area is set in the Central Java Province and Yogyakarta Province, Java Island, Indonesia, presented in Figure 2. These two provinces include 33 regencies and 7 cities with a total population of about 40 million. Regency (kabupaten in Indonesian) and city (kota in Indonesian) belong to the same level in Indonesia's administrative divisions, and city is often a developed town. The topography of the study area covers from mountainous areas to the lowlands of the coastal alluvial plain, and the socioeconomic status is highly diverse. This area is also prone to various climatic hazards, including floods, landslides, and droughts, while non-climatic hazards encompass earthquakes and volcanic activity due to its tectonic location [20]

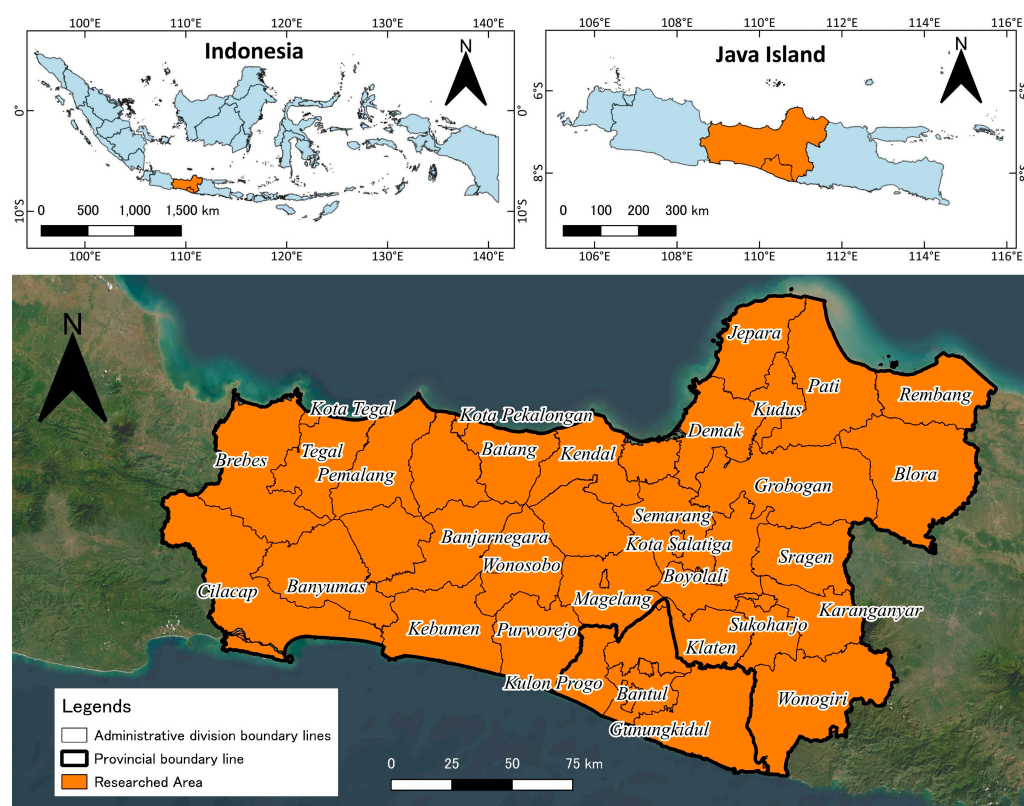


Figure 2. Study area. The Republic of Indonesia is the largest island nation in the world. It consists of more than 17,000 islands spread between Southeast Asia and Australia. The land area is about 2 million square kilometers. The main islands are Java, Bali, Sumatra, Kalimantan, Sulawesi, and Papua.

2.3. Analysis

2.3.1. Population Distribution Characteristics

The relationship between estimates of numbers of people per pixel (ppp), elevation, and HAND values are analyzed. Elevation is an indicator of where the population is distributed in the range from the coastal alluvial plain to the mountains. The HAND value indicates the specific height from the nearest drainage channel [15], and a low HAND value indicates ease of water use, but may also indicate a high risk of water-related disasters. The GIS-based analysis conducted in this study often involves analyzing the relationship between the ppp raster, which shows the estimated distribution of the population, and other raster layers. Therefore, the ppp raster was converted into point data with values

at the center point of each pixel using the `r.to.vect` command of GRASS, and the values of other raster data, HydroDEM and HAND were extracted and added to the point data. The relationship between the `ppp`, elevation, and HAND values given to each point is examined. In the following analysis using `ppp` rasters, the analysis is performed by giving other raster values to the point data, which is converted from the `ppp` raster into point data. When aggregation is performed for a certain range, a polygon indicating the aggregation range is used to aggregate the values of the point clouds contained in the polygon.

2.3.2. Flood Exposure Analysis

The maps of flood disaster vulnerability assessment results from the `inaRISK` geospatial database [13,14], which is the disaster risk information published by the Indonesian government, are used as information on potential flood hazardous areas. The results of the vulnerability assessment to flooding are expressed as a 0–1 value for each grid in the raster data, with higher numbers indicating greater vulnerability.

We defined the potentially exposed population (`pep`) by multiplying the vulnerability assessment values (ranging from 0 to 1) for each pixel with the estimated population per pixel (`ppp`), aggregating them by administrative divisions. Figure 3a illustrates the distribution of `ppp` in the study area, while Figure 3b displays the flood vulnerability assessment results generated by `inaRISK`.

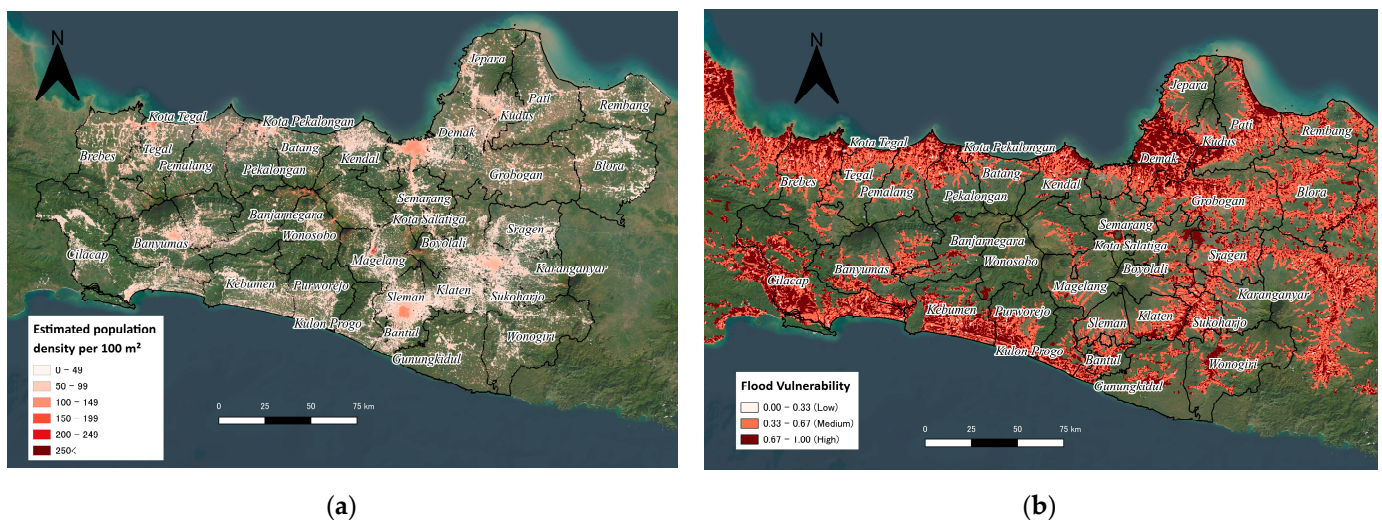


Figure 3. (a) 2020 estimated population per pixel (`ppp`) in study area. Population density increases from white to red; (b) flood hazard vulnerability by `inaRISK`. Flood vulnerability ratings are expressed as a value ranging from 0 to 1, increasing from white to red.

The potential exposed population P_{ep} can be expressed by the following equation (Equation (1)) assuming that the estimated population per pixel as P_{pp} and the vulnerability assessment values for floods as V_f , where the subscript i denotes each pixel and A denotes the classification of the aggregation area. In this study, P_{ep} is aggregated using polygons that indicate the boundaries of the regency and city.

$$P_{ep} A = \sum_{i \in A} P_{pp} i \cdot V_f i \quad (1)$$

Furthermore, the exposure rate R_{exp} is defined as shown in Equation (2). When the exposure rate for each administrative division is defined as R_{exp} , R_{exp} is simply defined as P_{ep} divided by the total population, denoted as P_{all} . The exposure rates R_{exp} for each administrative division calculated here will be used in the comprehensive analysis.

$$R_{exp} A = P_{ep} A / P_{all} A \quad (2)$$

2.3.3. Socioeconomic Characteristics

A correlation analysis was performed on the relationships among the socioeconomic indicators collected. The purpose of this analysis is to understand the diversity of socioeconomic conditions in the study area and to identify dominant socioeconomic indicators. Before conducting the correlation analysis, the items were aggregated due to the large number of items included in the socioeconomic database. Variables related to socioeconomic condition for each regency and city are listed in Table 2.

Table 2. Variables related to socioeconomic condition for each regency and city.

Data Source	Variable (Abbreviation)	Definition
Number of people per age group	Total population (Pop.All)	-
	Working age population (Pop.Work)	Aged 15–64 years
	Old age population (Pop.Old)	Aged 65 years and older
	Children population (Pop.Child)	Aged under 14 years
	Working age population ratio (Work.Ratio)	Pop.Work/Pop.All
	Old age population ratio (Old.Ratio)	Pop.Old/Pop.All
Number of people per educational rank	Children population ratio (Child.Ratio)	Pop.Child/Pop.All
	Low educated population (Pop.LowEdu)	No education or finish elementary school (rank 1–2 in original database)
	Middle educated population (Pop.MidEdu)	Finish junior to senior high school (rank 3–5 in original database)
	High educated population (Pop.HighEdu)	Diploma to up (rank 6–7 in original database)
	Low educated population ratio (LowEdu.Ratio)	Pop.LowEdu/(Pop.Work + Pop.Old)
	Middle educated population ratio (MidEdu.Ratio)	Pop.MidEdu/(Pop.Work + Pop.Old)
Number of poor people	High educated population ratio (HighEdu.Ratio)	Pop.HighEdu/(Pop.Work + Pop.Old)
	Poor population (Pop.PoorPeople)	-
Average income	Poor population ratio (PoorRatio)	Pop.PoorPeople/Pop.All
	Average Income	-

2.3.4. Comprehensive Analysis of Exposed Socioeconomic Vulnerability

By combining the exposure rates of the population obtained from the flood exposure analysis and the indicators obtained from the socioeconomic characteristics analysis, the characteristics of flood disaster risk for each administrative division are analyzed. The results of this analysis are then used for mapping to contribute to the formulation of countermeasures.

3. Results

3.1. Relationship between Topography and Population Distribution

The relationship between the population distribution in the study area and the respective elevation and HAND values is shown in Figure 4. As shown in Figure 4a, the highest elevation in the study area is over 3000 m, but most of the population is distributed in the lowlands. In total, 17% of the population is distributed on lands below 10 m elevation alone, and 81% on lands below 300 m elevation. Figure 4b shows the relationship between population distribution and HAND values: the percentage of the population living on land with a HAND value of 10 m or less amounts to 68%. From the relationship between Figure 4a,b, it can be understood that land with a small HAND value, i.e., land close to rivers and drainage channels, is used as a residential area, even if the land is at a high elevation. Low HAND values are directly related to the risk of flood inundation, and a significant proportion of the population living in the study area has the potential to be exposed to flooding.

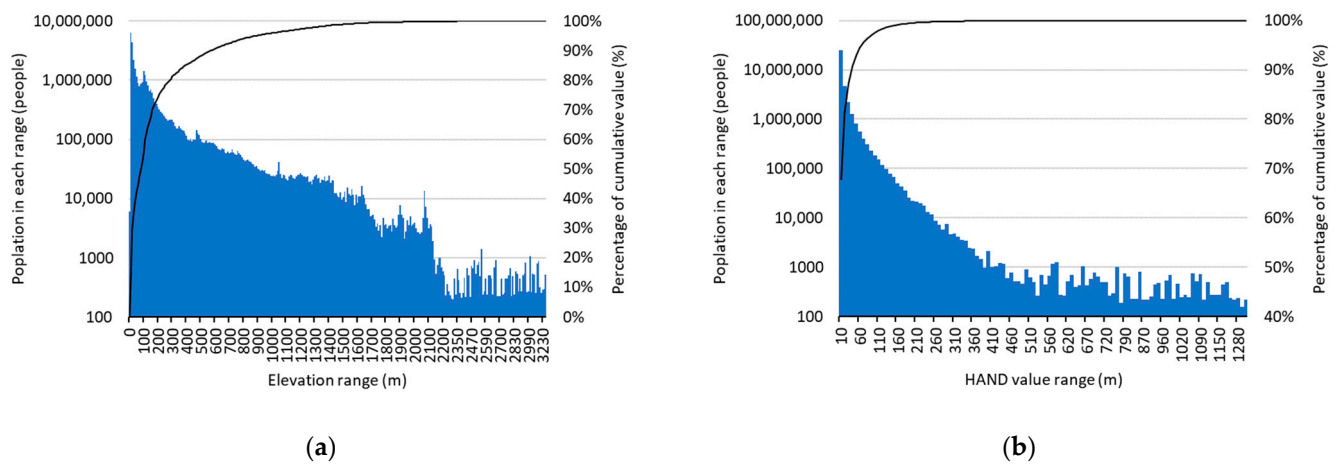


Figure 4. (a) Relationship between elevation and population distribution in study area; (b) Relationship between HAND value and population distribution in study area. Each population count is a summary of the population per pixel (ppp) value for every 10 m of elevation and HAND value. The percentage of cumulative values is indicated by the black line.

3.2. Flood Exposure Rate and Potentially Exposed Population

The potentially exposed populations P_{ep} and the exposure rates R_{exp} are shown in Figure 5. Figure 5a shows the results of aggregating the P_{ep} defined by Equation (1) for each administrative division. We obtained a distribution of potentially exposed population between 2004 and 910,768 people spread across each administrative division.

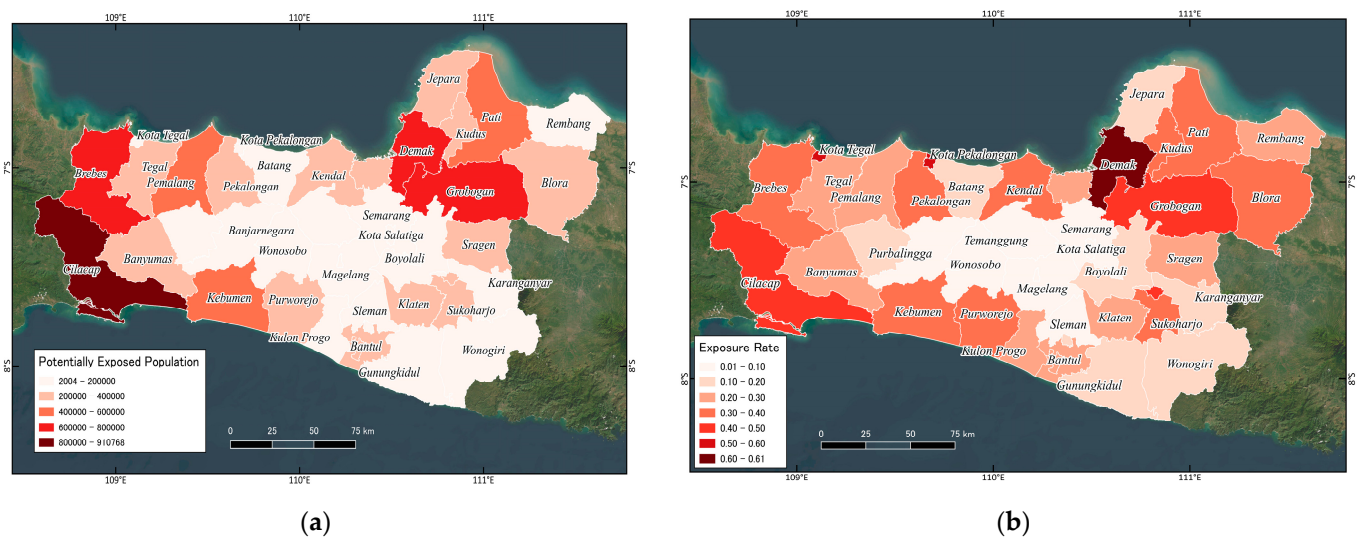


Figure 5. (a) Potentially exposed population P_{ep} in each administrative division. The number of populations potentially exposed to flooding is expressed as increasing from white to red; (b) Estimation of exposure rate R_{exp} in the study area. The exposure rate increases from white to red.

Figure 5b shows the exposure rate R_{exp} defined by dividing the potential population exposed P_{ep} by the total population P_{all} as shown in Equation (2). The R_{exp} ranged from 1 to 61%, highlighting significant disparities among administrative divisions. The most noteworthy instance is the Demak Regency, where the R_{exp} reaches 61%. The administrative division with the largest disaster-exposed population P_{ep} is the Cilacap Regency. Although it has a 47% exposure rate, the high number of people living in the Cilacap Regency has resulted in the highest number of people potentially exposed compared to other regions, 910,768.

3.3. Results of Analysis of Socioeconomic Indicators

Table 3 lists the aggregate values of the socioeconomic indicator variables included in the tabulation. The total population indicates the size of the administrative division, with a 16.3-fold difference between the smallest and the largest. The population structure in terms of age groups (working age, old people, and children) does not show much difference, but the proportion of old people and the proportion of children in each administrative division differs more than that of the working age group.

Table 3. Aggregate values of the socioeconomic indicator variables.

Variable	Average	Max	Min	Standard Deviation	Range (Max/Min)
Total population (Pop.All)	1,004,619	1,978,759	121,526	444,769	16.3
Working age population (Pop.Work)	697,902	1,395,454	86,145	311,493	16.2
Old age population (Pop.Old)	80,568	153,672	11,008	35,248	14.0
Children population (Pop.Child)	226,150	449,726	24,373	104,478	18.5
Working age population ratio (Work.Ratio)	0.70	0.71	0.61	0.02	1.2
Old age population ratio (Old.Ratio)	0.08	0.15	0.05	0.02	2.7
Children population ratio (Child.Ratio)	0.22	0.28	0.19	0.02	1.5
Low educated population (Pop.LowEdu)	373,014	905,799	20,636	195,665	43.9
Middle educated population (Pop.MidEdu)	377,045	755,050	61,965	158,207	12.2
High educated population (Pop.HighEdu)	56,193	240,963	14,554	39,573	16.6
Low educated population ratio (LowEdu.Ratio)	0.44	0.63	0.21	0.11	2.9
Middle educated population ratio (MidEdu.Ratio)	0.48	0.64	0.34	0.07	1.9
High educated population ratio (HighEdu.Ratio)	0.08	0.19	0.03	0.04	5.7
Poor population (Pop.PoorPeople)	111,416	308,780	9270	61,604	33.3
Poor population ratio (PoorRatio)	0.11	0.18	0.05	0.03	3.7
Average Income	2707	7258	1244	1473	5.8

The differences in population composition by administrative division are larger than those by age group in terms of population composition by education level. The range of percentages for the lower education (no education or finish elementary school) group is 2.9, and the range of percentages for the high education (diploma to up) group is as large as 5.7.

The minimum and maximum poverty rates are 0.05 and 0.18, respectively, with a range of 3.7. The 33.3-fold difference in the number of poor people suggests that the poverty rate may be higher in the boroughs with larger populations. The range of average annual income (in Indonesian Rupiah) is 5.8, indicating that the economic disparity by administrative division is very large. As shown above, the disparities in educational levels and economic status in the study area are very large, indicating the diversity of the social environment.

Table 4 shows the results of a cross-correlation analysis to analyze the interrelationships among these socioeconomic indicator variables. The significance of the correlation coefficient was confirmed by the *p*-value of Holm's method. Correlation coefficients with *p*-values less than 0.05 were considered statistically significant; correlation coefficients with *p*-values greater than 0.05 are not listed in the table. Table 4 does not show the indicators for age groups for each administrative division. This is because these indicators showed high correlations with the total population, but no significant correlations with the other indicators. In other words, the age structure does not seem to affect the poverty rate or the average income. Typical trends that can be read from Table 4 are as follows:

- The larger the population, the higher the number of residents with lower education level (Pop.LowEdu vs Pop.All);
- The high educated population ratio is strongly positively correlated with the ratio of the middle-educated population and strongly negative correlated with the ratio of the low educated population (HighEdu.Ratio vs MidEdu.Ratio and LowEdu.Ratio);
- The number of poor people is strongly correlated with the low-educated population and with the total population (Pop.PoorPeople vs Pop.LowEdu and Pop.All);
- It is not surprising that the poverty rate is highly correlated with the number of poor people, but a high positive correlation is observed for the population with

- low levels of education and for the percentage of the population with low levels of education (Poor.Ratio);
- The percentage of the population with a high level of education has the highest positive correlation with average income, and the percentage of the population with a medium level of education also shows a positive correlation (Average Income).

Table 4. Cross-correlation matrix for socioeconomic indicator variables. The significance of the correlation coefficient was confirmed by the p -value of Holm's method. Correlation coefficients with p -values less than 0.05 were considered statistically significant; correlation coefficients with p -values greater than 0.05 are not listed in the table. The red color indicates the high direct linear relationship, and the blue color indicates the high inverse linear relationship. N.S. means "not significant".

	Pop. All	Pop. LowEdu	Pop. MidEdu	Pop. HighEdu	LowEdu. Ratio	MidEdu. Ratio	HighEdu. Ratio	Pop.Poor People	Poor. Ratio	Average Income
Pop.All										
Pop.LowEdu	0.91									
Pop.MidEdu	0.94	0.72								
Pop.HighEdu	N.S.	N.S.	0.70							
LowEdu.Ratio	N.S.	0.74	N.S.	N.S.						
MidEdu.Ratio	N.S.	−0.74	N.S.	N.S.	−0.97					
HighEdu.Ratio	N.S.	−0.64	N.S.	N.S.	−0.91	0.80				
Pop.PoorPeople	0.85	0.93	0.68	N.S.	0.64	−0.64	N.S.			
Poor.Ratio	N.S.	0.61	N.S.	N.S.	0.66	−0.65	−0.60	0.80		
Average Income	N.S.	N.S.	N.S.	N.S.	−0.77	0.68	0.83	N.S.	N.S.	

The above results show that there is a large disparity between the level of education and the economic situation in the study area. A clear positive correlation was observed between educational level and economic affluence, confirming that it is not the age structure but the difference in educational level that causes the economic disparity.

3.4. Comprehensive Analysis of Exposed Socioeconomic Vulnerability

The results of the analysis so far indicate a wide range of flood exposure rates and socioeconomic status for each administrative division. The comprehensive analysis presents the characteristics of each administrative division within the study area, focusing on the two axes of the socioeconomic situation: the number of poor people exposed to disasters and the economy exposed to disasters.

The reasons for focusing on the number of poor people are: (1) there is a strong relationship between the number of poor people and a low level of education [21]; (2) both poverty and a low level of education are thought to reduce disaster preparedness and make access to mitigation measures more difficult [22]; (3) the number of poor people is directly related to vulnerability in disaster preparedness in each administrative division. Thus, the number of poor people exposed to disasters can be an important indicator of social vulnerability due to poverty and low education. The number of poor exposed to a disaster, P_{exp} is calculated by multiplying the population of poor (Pop.PoorPeople) in each borough by the exposure rate, R_{exp} .

The economy that may be exposed to a disaster, E_{exp} is calculated by multiplying the total income of the inhabitants of the administrative division, obtained by multiplying the total population by the average income, by the exposure rate R_{exp} . Although it is known that there are various methods for estimating the economic damage caused by floods [23–25], this study will use a very simple indicator as a measure of the size of the economy that may be affected by floods in each administrative division.

The number of potentially exposed poor people P_{exp} for each administrative division ranges from 101 to 102,150 people, and the amount of economic potential exposed for each administrative division ranges from IDR 8 million to IDR 3.02 billion. The distribution of P_{exp} and E_{exp} are shown in Figure 6. In the figure, the population of potentially exposed

poor people illustrates the amount of exposure in the administrative divisions in Central Java to flood risk, while the rate of potentially exposed economies indicates the magnitude of losses that may occur due to being affected by flooding.

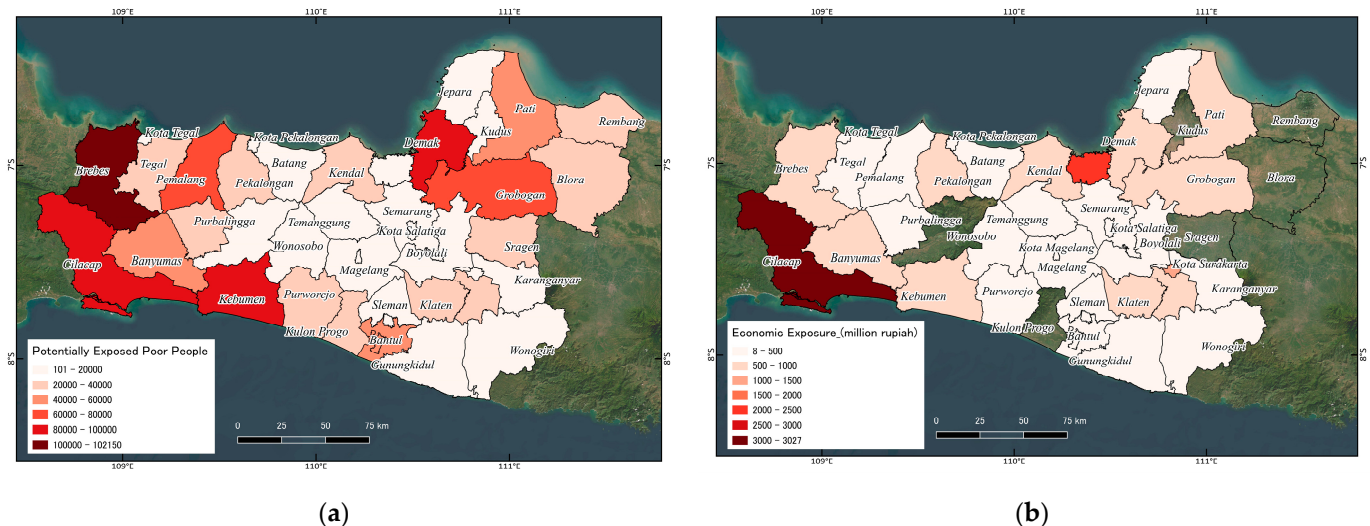


Figure 6. (a) Potentially exposed poor population P_{exp} in the study area. The number of poor people exposure increases from white to red; (b) Exposed economy E_{exp} in each administrative division. The rate of potentially exposed economy to flooding E_{exp} is expressed as increasing from white to red. Economic data were not available for Banjarnegara, Blora, Kudus, Kulonprogo, Rembang and Sragen.

A comparison of the spatial distribution trends of P_{exp} and E_{exp} shown in Figure 6a,b, respectively, the two distributions are quite different. For example, P_{exp} is the highest in the Brebes Regency, but the E_{exp} , which indicates the size of the economy exposed to flood disasters in the regency, is not as high. On the other hand, in the Cilacap Regency where E_{exp} is maximum, both P_{exp} and E_{exp} are high. Both P_{exp} and E_{exp} are calculated from the exposure ratio R_{exp} shown in Figure 5b, there are variations in the combination of P_{exp} and E_{exp} , which may represent the socioeconomic characteristics of the area.

Therefore, we examine the relationship between these two indices to determine flood risk classifications focusing on socioeconomic characteristics of exposure to flood disasters. Figure 7 shows the scatterplot graph under analysis visually represents the relationship between two critical variables: the potentially exposed poor population P_{exp} and the exposed economy in administrative divisions. This figure aims to shed light on the vulnerability of different regions in Central Java and Yogyakarta to flooding, considering both the social vulnerability due to poverty and low-education and the economic impact.

The horizontal axis represents the exposed economy E_{exp} . It is also divided into three domains, indicating “Low”, “Medium”, and “High” levels of economic loss risks. The vertical axis represents the potentially exposed poor population, P_{exp} . It is divided into three domains, indicating “Low”, “Medium”, and “High” levels of social vulnerability. The two threshold values for each domain were defined by the average value and average + 1 standard deviation value, respectively. A diagonal line from bottom-left to top-right provides a reference for assessing trends and relationships between the two variables, create a section that focuses more on the human impact and a section that focuses more on the economic impact. The diagonal line was defined to pass through the point where the two variables are both zero and the intersection of the two lines that are thresholds. Classifications based on these lines of demarcation make it possible to discuss the extent to which each administrative division is exposed to flood risk, both in terms of vulnerability due to poverty and low education, and in terms of the size of the exposed economy to flooding.

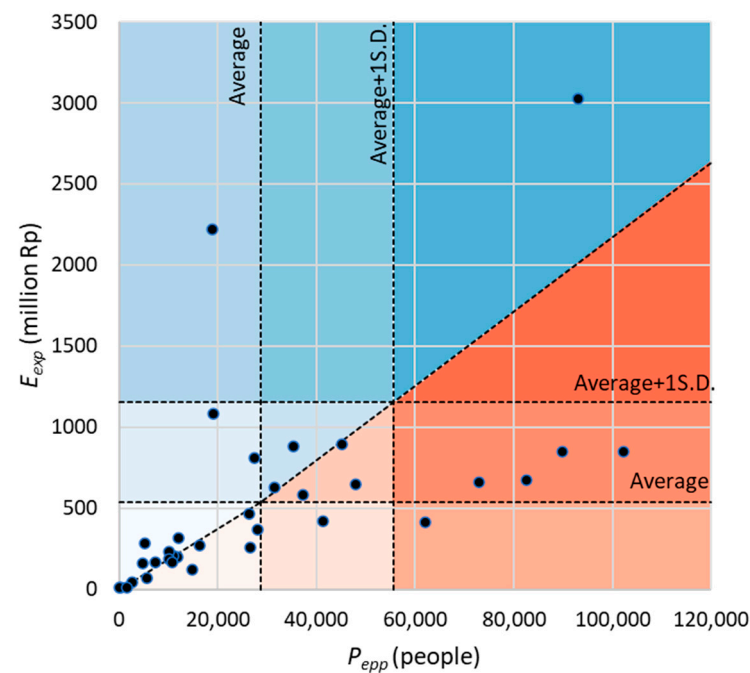


Figure 7. Scatterplot of the relationship between the potentially exposed poor population P_{exp} and exposed economy E_{exp} . The two threshold values for each section were defined by the average and average + 1 standard deviation, respectively. The diagonal line was defined to pass through the point where the two variables are both zero and the intersection of the two lines that are thresholds.

Figure 8 shows a map of risk assessment results focusing on the vulnerability of societies exposed to flooding and the size of their economies in Central Java, Indonesia. For each administrative division, the results of the classification based on domains in Figure 7 are displayed. This figure is the highlight of the study and is a risk map that facilitates the understanding of the risk characteristics and relative risk magnitude of each administrative district for decision makers considering measures to increase mitigation and preparedness for flood risk.

The blue-colored divisions indicate areas where the risk of exposure of the economy to flooding is relatively greater than the vulnerability resulting from the exposure of the poorer, less educated population. Conventional flood mitigation approaches, such as infrastructure development and flood control through land use planning, are effective in areas with significant economic exposure to flooding. The large economies in these regions make the benefits of such investments substantial and proportionate to the cost of disaster prevention. Similarly, measures to increase preparedness, such as forecasting and warning systems and evacuation plans for residents, are also expected to have some effectiveness. This is because residents in areas with higher average incomes generally have higher levels of education and may be more receptive to these measures.

The red-colored divisions indicate areas where many poor and less educated people are exposed to flooding, but where the economic exposure is relatively small. In these areas, the benefits of investing in high-cost infrastructure are small, and public awareness campaigns to increase the preparedness of the residents may be less effective. This is because, in general, poor and low-educated residents in developing countries tend to be less receptive to scientific information and the provision of information by official institutions [26].

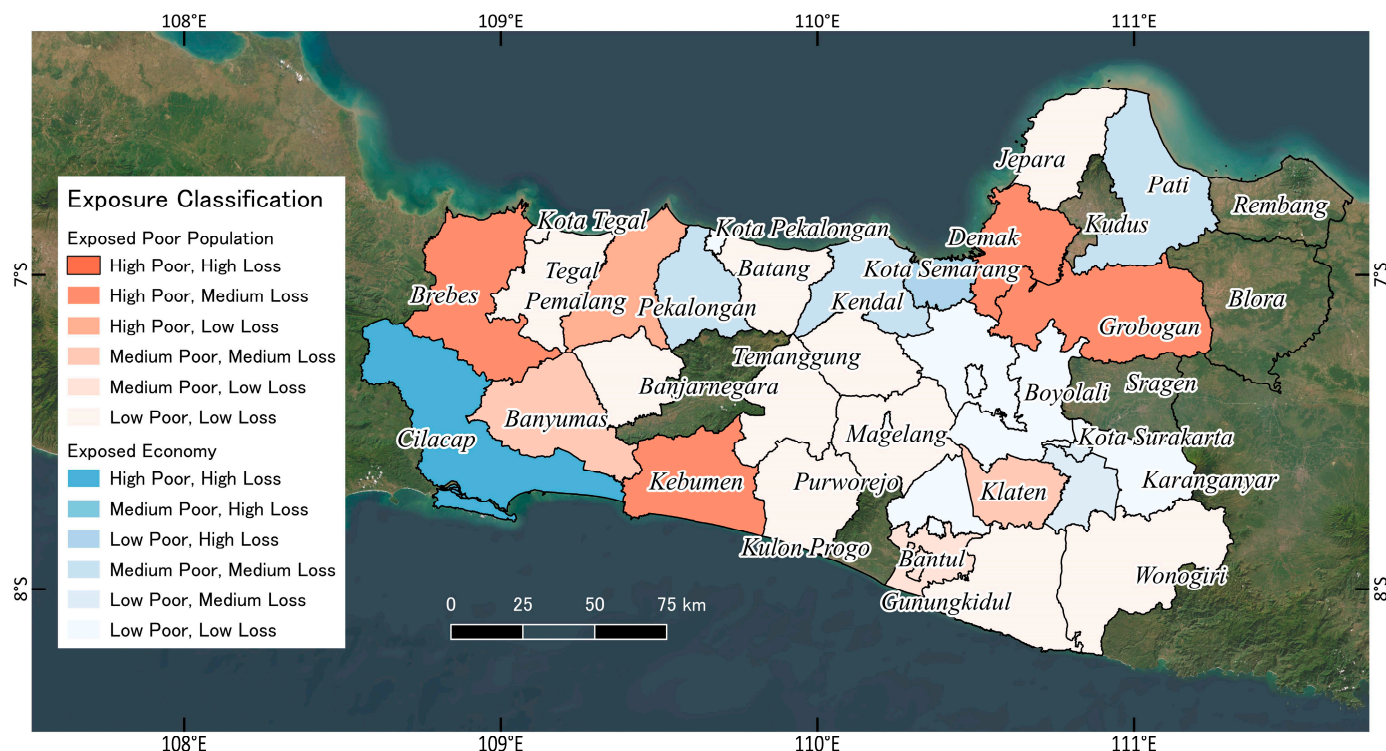


Figure 8. Map of the risk assessment results focusing on the vulnerability of societies exposed to flooding and the size of their economies in Central Java, Indonesia. The Regencies of Banjarnegara, Blora, Kudus, Kulonprogo, Rembang, and Sragen were not included in the analysis due to the lack of economic data.

Traditionally, the people of Java in Indonesia have coped with flood risk through adaptive measures such as elevated housing [27], water management systems, and community-based responses, relying on local knowledge and cooperation [28]. But, an alternative approach utilizing local wisdom is possibly more adequate for areas characterized by low income and education [29,30]. Indonesia has already begun to utilize local wisdom in early warning systems against disasters, and similar approaches are likely to be effective in reducing vulnerability to flood risks. Local wisdom often includes a deep understanding of local environmental conditions, natural resources, and sustainable practices. Furthermore, local wisdom is an ancestral asset for the local community, and is therefore expected to be highly acceptable even at low levels of education. Incorporating it into flood mitigation strategies has the potential to be more effective, efficient and economical in the red-colored divisions.

4. Discussion

In this study, we proposed an analytical method focusing on the characteristics of societies exposed to flooding using open data, and presented the results through a case study in Central Java, Indonesia. This method not only calculates the exposure rate of residents in each administrative district, but also proposes a classification method and an analysis focusing on the characteristics of the exposed residents and the size of the economy. In particular, we focus on the degree of exposure to flood disasters of residents with poverty and low levels of education as factors that contribute to social vulnerability.

The vulnerability of low education and poverty affects the level of risk to flood disasters [31]. Low education levels can lead to limitations in accessing and understanding flood-related information and reduced adoption of preparedness measures [32]. Poverty due to lack of financial resources can lead to limited social networks for effective response [33]. Based on the results of the analysis of socio-economic indicators, there is a large gap between education levels and economic circumstances in the study areas. A clear

positive correlation is seen between education levels and economic prosperity, confirming that differences in education levels cause economic disparities.

The results of the analysis of available data require a strategy tailored to existing conditions through area-specific flood risk management, as well as adaptation to local socio-economic conditions. From the results of the level of exposed population, the number of exposed populations, the number of poor populations exposed, and the economy exposed, we produced exposure areas that focus on poor population exposure and economic exposure, varying in each administrative division. Detailed information on potential exposure depicted on the map provides clear information for interested actors, where policies in disaster management have the potential to be more targeted according to the social and economic conditions of the community.

This study conducted a GIS-based exposure analysis and integration of socio-economic data. The advantage of this method is its effectiveness in providing a comprehensive view of flood risk and the potential for efficient targeting of resources for future policymakers. This can be seen in the availability of potential flood exposure data through InaRISK and population data through the World Pop Hub [11], where information is open-sourced and systematically analyzed through GIS. Data on population characteristics are also available as an open source through Indonesia's Central Bureau of Statistics (BPS) [12], making exposure targets clearer and potential policy treatments more targeted.

Some studies have also emphasized spatial analysis and the integration of social vulnerability and economic factors into flood risk assessment. Examples include studies in the United States [34], China [35], and the Netherlands [36]. There are some differences, research in United States, China, and the Netherlands utilize or propose social vulnerability indices (SoVI), this study introduces a unique classification system considering poverty, low education, and economic impact. The diverse geographical focuses, encompassing China, the United States, the Netherlands, and Indonesia, showcase the global applicability of these approaches. Each study underscores the need for flood risk management strategies tailored to local socio-economic characteristics, which in this study reflects an emphasis on strategies tailored to the significant socio-economic diversity in Indonesia. The differences in variables, methodology, and temporal aspects across the abstracts highlight the versatility of approaches in addressing the complex interplay of social vulnerability and economic factors in diverse contexts.

However, there are limitations found in the research that has been conducted. First, this research tends to be dependent on the accuracy and availability of input data. This can be seen in the most updated population data for the study area in the 2020 data [11]. Second, available hazard data in this study is static. Key data in InaRISK is contributed by the United Nations Development Program (UNDP), and information on whether the hazard is current is limited [13,14]. Third, socio-economic conditions of communities are dynamic, and this study focuses on the static economic condition data recorded by the Central Bureau of Statistics.

One of the problems with this method and a possible improvement of the methodology is that land use is not taken into account in the exposure analysis. In this study, the exposure rate R_{exp} was set based on the exposed population to the total population of the regency and city. However, the economy and the poor affected by exposure are likely to vary depending on land use. A more sophisticated analysis of the vulnerability of exposed societies will be possible by taking into account the land use of the lands exposed to flood disasters. Open data on land use could be used in combination with this methodology to provide a more realistic assessment for disaster risk management. Although the ppp values are estimates rather than actual surveyed values, they may be useful in estimating the distribution characteristics of the population in the country and, in particular, the proportion of the population potentially exposed to flood damage.

This analysis focuses on the level of exposure of the population in each administrative area, with an emphasis on vulnerable populations experiencing poverty and low levels of education. However, it is important to recognize that sensitivity to flooding varies among

different demographic groups. Factors such as age, health conditions, and cultural nuances can significantly influence how residents experience and respond to flooding. Recognizing these variations in sensitivity is crucial to tailoring disaster management strategies to the diverse needs of the population. Further research and analysis on the sensitivity of different demographic groups will contribute to a better understanding of the social dynamics associated with flood exposure.

From the limitations and uncertainties encountered, further research is needed that has the potential to develop this research. This could include longitudinal analysis, which involves repeated observations of the same variables over a period of time, observing changes in vulnerability of socioeconomics and exposure of poor people and economic over time. A multi-hazard analysis of the area concerned can extend the assessment to multiple hazards, as Indonesia is known for its many natural hazards other than floods, such as volcanic eruptions, earthquakes, tsunamis, and landslides. Climate change adaptation can assess the impact of climate change on flood risk in the region, given that flood hazard areas may change as climate change increases due to global warming. And policy evaluation can assess the effectiveness of policies in reducing vulnerability and exposure. Social diversity in Indonesia is related to local wisdom that has the potential to be effective and efficient to be applied to flood risk reduction policies. Cost-benefit analysis can be performed.

To apply the results of this study to comprehensive flood risk management strategies, we will focus on the characteristics of each measure in existing strategies and the relationship between the measure's implementers. Table 5 provides a comparative analysis of the advantages and weaknesses of each strategy, allowing for a nuanced understanding of their applicability in the context of Central Java, Indonesia.

Table 5. Comparative Analysis of Flood Risk Management Strategies.

Strategy	Advantage	Weakness
Early Warning Systems	Timely alerts, Potential for reducing casualties.	Dependence on infrastructure, False alarms.
Infrastructure Development	Enhanced resilience, Protection of assets.	High cost, Environmental impact.
Community Engagement and Preparedness	Empowering communities, Local knowledge.	Variable community response, Resource constraints.
Land Use Planning and Zoning	Mitigation of exposure, Sustainable development.	Implementation challenges, Resistance.
Insurance and Risk Transfer Mechanisms	Financial protection, Incentive for risk reduction.	Limited coverage, Affordability.
Ecosystem-Based Approaches	Natural flood defenses, Ecological benefits.	Time-intensive, Potential conflicts.

Considering the research findings, significant policy implications arise for various stakeholders, including development organizations (NGOs, INGOs, CBOs) and disaster management agencies. The comparative analysis of flood risk management strategies, particularly in early warning systems, underscores the need for a multi-faceted approach to enhance resilience. Development organizations can align their strategies with identified advantages and weaknesses, fostering collaboration with local communities and investing in infrastructure for early warning capabilities. To ensure effective dissemination to those in need, a targeted and inclusive communication strategy is essential, leveraging traditional and modern channels. The National Disaster Management Agency (*Badan Nasional Penanggulangan Bencana*—BNPB) and Regional Disaster Management Agency (*Badan Penanggulangan Bencana Daerah*—BPBD), including relevant national ministries/institutions, educational institutions, community organizations and companies, can benefit by tailoring policies to address specific challenges and opportunities. The incorporation of indigenous local knowledge (ILK) into early warning strategies is a key recommendation, involving the

integration of traditional weather forecasting methods and community-based observations. ILK contributes to community resilience by promoting sustainable land use practices and ecosystem-based approaches, tapping into generations of local wisdom. By effectively channeling this information and leveraging ILK, policymakers can enhance the resilience of Central Java, Indonesia, actively engaging communities in sustainable strategies to mitigate the impact of flooding events.

5. Conclusions

This research paper introduces a method for analyzing flood-prone communities using open data, as exemplified by a case study in Central Java, Indonesia. The findings show that most of the region's population lives in low-lying areas, placing them at great risk of flooding, with vulnerability exacerbated by low levels of education and poverty. This underlines the importance of considering socio-economic factors in flood risk assessment. While our study provides valuable insights into flood risk assessment, it is imperative to acknowledge the sensitivity of different populations in the study area to floods. Future research endeavors should delve deeper into understanding the unique challenges faced by various demographic groups, including considerations of age, health, and cultural factors. This will enable more targeted and effective disaster management strategies that account for the diverse sensitivities within the population. By utilizing GIS-based analysis, this study offers a comprehensive view of flood risk, thereby assisting policymakers in efficient resource allocation. However, limited data, dynamic socio-economic conditions, and the absence of land use data pose challenges. Some of the issues with this method could be improved by taking land use into account, but this is a subject for future work.

Author Contributions: Conceptualization, A.S. and M.H.; methodology, A.S. and M.H.; writing—original draft preparation, A.S.; writing—review and editing, M.H. and M.K.; visualization, A.S.; supervision, M.K. and M.H. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partly funded by JSPS KAKENHI Grant Number 20H00256.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The sources of the open data used in this study are explained in the methodology section and are listed in the references.

Acknowledgments: The authors thank to Shinichiro Nakamura, Nagoya University for his important suggestions in the preparation of this study.

Conflicts of Interest: The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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