Multidimensional Vulnerability Mapping Using GIS and Catastrophe Theory

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Abstract
This paper presents a new method for evaluating vulnerability in several dimensions by combining Catastrophe Theory with Geographic Information Systems (GIS). This research investigates vulnerability in three districts in Selangor, Malaysia: Hulu Langat, Sepang, and Kuala Langat. The study analyzes vulnerability across six dimensions, namely social, economic, physical, institutional, environmental, and cultural. The evaluation utilizes ArcGIS 10.8 and a data-driven Multi-Criteria Decision Analysis (MCDA) methodology to generate geographical vulnerability maps. The methodology utilizes Catastrophe Theory, a mathematical framework proficient in understanding abrupt changes in intricate systems, and GIS, a potent tool for studying and visualizing geographic data. These tools work together to help identify important thresholds and tipping points in systems that are prone to disasters, which improves our understanding of how vulnerability changes over time. The studied area contains a historical record of many disasters, encompassing floods, landslides, storms, and forest fires. The 2021 flood, which was the most severe in the area's history, emphasized the necessity for a comprehensive risk assessment. The study's findings demonstrate the heterogeneity in vulnerability across the six categories, offering crucial insights for the management of disaster risk. The results illustrate the efficacy of this integrated approach in comprehending the multifaceted essence of vulnerability. The created multidimensional vulnerability maps provide valuable information for policymakers, planners, and emergency responders. These maps enable focused interventions and enhance resilience. The study emphasizes the significance of improving institutional capacities, economic robustness, and community readiness in order to minimize the effects of disasters. This research makes a substantial contribution to the field of disaster risk management by offering an innovative methodology for assessing vulnerability. This methodology has wide-ranging applications in the areas of disaster prevention and mitigation.

Keywords: Catastrophe Theory, Disaster Risk, GIS, MCDA and Vulnerability

1. Introduction

Today's disaster risk management environment makes it critical to create strong procedures for vulnerability assessment. Vulnerability is characterized by conditions shaped by physical, social, economic, and environmental factors, along with processes that increase the susceptibility of individuals, society, institutions, and systems to the effects of hazards [1] and [2]. One important technique that shows promise is spatial multi-dimensional vulnerability mapping, which provides an advanced method for identifying and measuring vulnerabilities in several dimensions.

Research on vulnerability assessment is typically categorized into two perspectives: social researchers view vulnerability as a combination of socio-economic factors, while other researchers define vulnerability as the extent of potential harm to a specific element at risk [3]. The concept of multidimensional vulnerability assessment (MDVA) aims to address the shortcomings and integrate many aspects of vulnerability assessment into a comprehensive framework [4]. Vulnerability is present in all four key phases of the cycle, namely reaction, recovery, mitigation, and preparedness.

In the context of mitigation, the vulnerability assessment can offer valuable insights into specific areas that require additional research. This knowledge can then be used to develop effective methods for mitigating the impact of future catastrophic events. During another step of the disaster cycle, doing a vulnerability assessment is crucial for obtaining accurate maps and information that can be used for emergency and evacuation planning, rescue operations, and the reinforcing or relocation of buildings. Therefore, the use of MDVA may effectively identify and evaluate the level of susceptibility to disasters. This assessment provides a solid basis for the development and implementation of scientifically informed policies for disaster prevention and mitigation [5].

The MDVA is an integrated approach that would be highly beneficial, suitable and helpful in the disaster risk reduction field [6] and [7]. In this context, the combination of Geographic Information Systems (GIS) and Catastrophe Theory offers a fresh viewpoint that improves the accuracy and comprehensiveness of vulnerability assessments. GIS provides an effective tool for comprehending the spatial attributes of certain features and providing information for decision-making [8]. GIS techniques are essential for developing flood vulnerability maps, which aid in identifying areas that are vulnerable to hazards by integrating diverse data sources such as satellite pictures, soil data, and rainfall data. GIS enables the examination and display of both geographical and attribute data, allowing for efficient decision-making and planning to reduce the impact of floods by identifying areas with varying levels of risk [9]. This article explores the creative use of various technologies with the goal of providing a thorough framework that helps planners, emergency responders, and policymakers lessen the effects of disasters.

Catastrophe Theory, a branch of bifurcation theory in mathematics, provides a valuable lens through which sudden and discontinuous changes can be analyzed. This theoretical framework is particularly suited to understanding complex systems where small changes in parameters can lead to abrupt shifts in system states—a common characteristic in environmental and societal systems affected by disasters. By applying Catastrophe Theory, this study identifies critical thresholds and tipping points in disaster-prone systems, facilitating a deeper understanding of vulnerability dynamics. Catastrophe Theory is a MCDA technique that enhances the understanding and analysis of complex systems where small changes can lead to significant effect [10].

However, geographic information system (GIS) is a powerful tool for geographical data analysis and representation. A multi-dimensional examination of vulnerability is made possible by GIS's ability to combine several data layers, including those related to social-economic, environmental, infrastructure, and demographic issues. This capacity is essential for identifying and displaying spatial patterns and trends that increase susceptibility and provide decision-making processes with a strong factual basis.

A revolutionary method of vulnerability mapping is made possible by the combination of GIS and Catastrophe Theory. This article provides a multidimensional vulnerability analysis by presenting a methodological framework that synthesizes these technologies. The study demonstrates, via case studies and actual data, how this integrated approach may be used to create comprehensive, dynamic, spatially explicit vulnerability maps that capture the complex and ever-changing nature of disaster risks. Previous studies primarily employed traditional normalization calculations based on knowledge-driven approaches to generate vulnerability assessments, whether for spatial or non-spatial vulnerability [6][7] and [11]. The need for enhanced analytical tools in disaster risk management is growing as the globe struggles with an increase in the frequency and intensity of catastrophic occurrences caused by urbanization and climate change. In order to improve resilience and lessen the negative effects of disasters on vulnerable populations, this work makes a significant contribution to this important topic by providing a cutting-edge approach for vulnerability assessment. The present section will delineate the theoretical underpinnings, methodology, case studies, and implications of the findings in a wider context. The emphasis will be on the findings' relevance and use in global catastrophe risk management techniques.

2. Study Area

The study area encompasses three districts in Selangor, namely Hulu Langat, Sepang, and Kuala Langat. These districts are situated within the Langat River Catchment and consist of multiple subdistricts, known locally as mukims. The study area, as depicted in Figure 1, includes a total of 17 mukims, with Hulu Langat and Kuala Langat each containing seven mukims, while Sepang comprises three mukims. In Hulu Langat, the mukims are Ampang, Kajang, Hulu Langat, Cheras, Beranang, Hulu Semenyih, and Semenyih. In Kuala Langat, the mukims include Bandar, Batu, Jugra, Kelanang, Morib, Tanjung Dua Belas, and Telok Panglima Garang.

The three mukims in Sepang are Dengkil, Labu, and Sepang. Historically, this region has experienced various disasters, such as floods, landslides, storms, and forest fires. In 2021, this area faced the worst flooding in its recorded history, affecting 62 locations, with 22 in Hulu Langat, 26 in Sepang, and 14 in Kuala Langat. Between 2014 and 2019, there were 176 flood events, predominantly impacting Hulu Langat (98 occasions), Sepang (51 occasions), and Kuala Langat (27 occasions). In 2011, a major landslide in Mukim Hulu Langat resulted in 16 fatalities. [12] Additionally, several areas within the region, such as Ampang, Cheras, Kajang, Dengkil, Labu, and Sepang, are particularly susceptible to landslides [11] and [13].

The flooding resulted in eight fatalities, with three deaths in Hulu Langat, four in Sepang, and one in Kuala Langat. The estimated total losses from the 2021 floods in Malaysia were approximately USD 1.3 billion. In the study area, the losses were around USD 170.9 million, accounting for 13% of the total losses in Malaysia. In Selangor, the total losses amounted to USD 668 million, with Hulu Langat, Sepang, and Kuala Langat contributing 14%, 5%, and 6%, respectively, to this total [14]. Overall, 11 states and 60 districts were impacted by the floods, with 22 locations affected in Hulu Langat District, 26 in Sepang, and 14 in Kuala Langat.

3. Methods

3.1 Vulnerability Framework

A multidimensional vulnerability assessment that was developed from the MOVE framework by [2] served as the foundation for this study. The conceptual framework for vulnerability used in this study is displayed in Figure 1 along with weighted coefficient values. Six aspects of multidimensional vulnerability—social, economic, physical, institutional, environmental, and cultural—were quantitatively assessed using a variety of subdimensions and indicators. The multivulnerability component was based on multidimensional vulnerability, which considered six dimensions of the vulnerability-based MOVE framework. Each vulnerability dimension had their own indicators. The selection of each indicator was based on expert judgement and analysed using PCA. Overall, multidimensional vulnerability consisted of six dimensions, 16 subdimensions and 54 indicators.

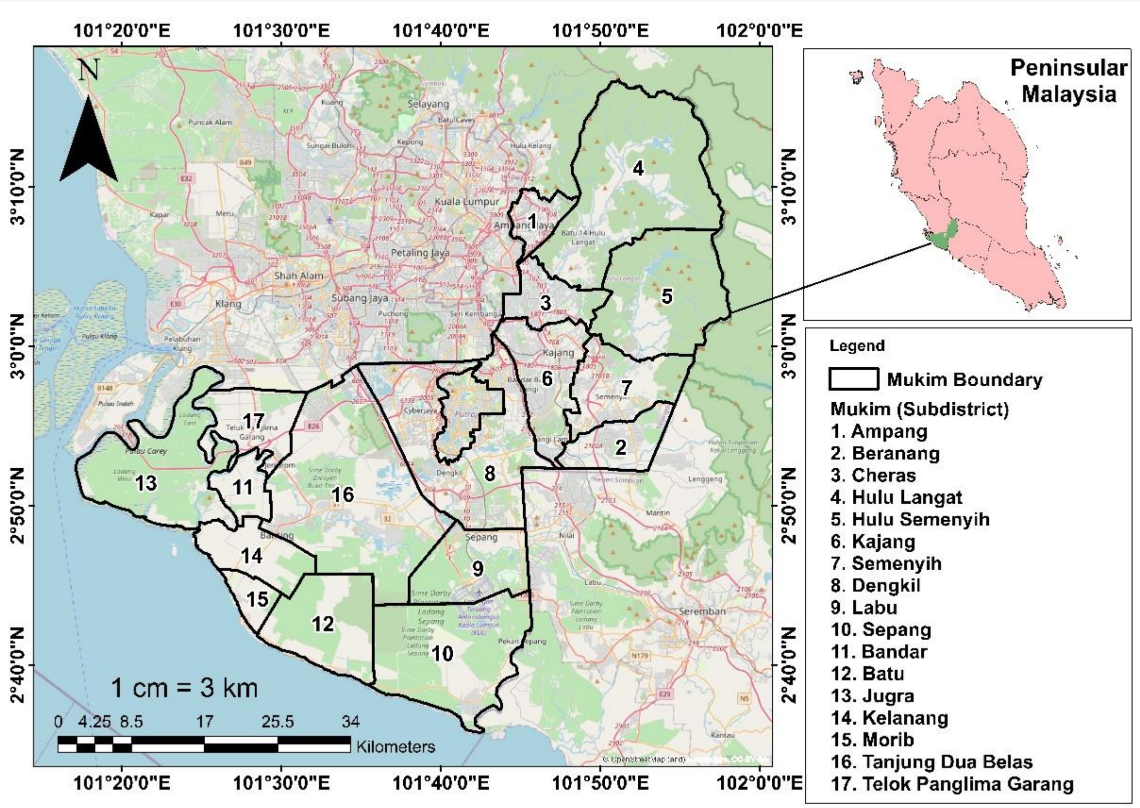

Figure 1: Study area in Selangor, Malaysia

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3.2 GIS Analysis

The analysis in this study used spatial data, so the process of obtaining the results used the geospatial data analysis approach. ArcGIS 10.8 software was used in this study for data processing and to produce the results in the form of maps. Previous studies, such as [15] and [16], have demonstrated the efficacy of these GIS tools in vulnerability mapping. By categorizing areas based on these five classes, we were able to make meaningful comparisons of vulnerability and risk levels, thereby enhancing our understanding of spatial patterns of vulnerability. Several ArcGIS tools were used in this study, such as the data editor, data conversion (rasterization), raster calculator and data classification tools. Data editor tools were used to input the indicator values in the vector data. Data conversion tools or rasterization analysis were used to convert the vector data into raster data for index calculations. Rasterization allows for uniform data processing, enabling spatial analysis across the study area [17]. Raster calculator tools were used for normalizing the data and calculating the multi-hazard index, multidimensional vulnerability index and risk index. Normalization standardizes data values, facilitating accurate comparison across different indicators [18]. Lastly, data classification tools were used to categories the data into five classes, using the natural breaks Jenks method. Therefore, all the areas in this study were categorized based on these five classes so that levels of vulnerability and risk could be compared.

3.3 Catastrophe Theory

In 1960, Rene Thom invented catastrophe theory as a mathematical discipline for studying discontinuity occurrences in a non-mechanical way [19] and [20]. Catastrophe theory is a multi-criteria decision-making method (MCDM) that uses the analytics hierarchy, utility function and fuzzy evaluation to obtain the catastrophe fuzzy membership function by normalizing the bifurcation set. According to past research, this method has been used in various fields to define multiple subsystems, each of which could be evaluated using one or more criteria or indicators. There is previous study used this method to assess water model indicators [21], applied it for assessing urban water security [22], conducted groundwater assessment using the catastrophe method [23] and applied this method for flood risk mapping [24].

Before standardizing the data, it was categorized into several classes, either two, three, four or five classes. The data standardization used two equations, the first for the susceptibility data and the second for the capacity data. With susceptibility data, the higher the value, the greater the vulnerability index. The following data standardization Equation 1 was used for the susceptibility data:

$$x_i = \frac{x_i - x_i(\text{min})}{x_i(\text{max}) - x_i(min)}$$

Equation 1

The Equation 2 was used for the capacity data, in which a higher value decreases the vulnerability index in the calculation. The following data standardization equation was used for the capacity data:

$$x_i = 1 - \frac{x_i - x_i(\text{min})}{x_i(\text{max}) - x_i(min)}$$

Equation 2

Where, *i* is the attribute, x_i is the original value of *i*, and $x_i(max)$ and $x_i(min)$ are the maximum and minimum values, respectively.

This study used susceptibility and capacity indicators. The former indicator is fragile or might strongly affect a disaster, while the latter indicator reduces the impact of a hazard on the community, organisation or system. The next step was to normalize the indicator using the catastrophe model. In this study, four types of catastrophe models were used to calculate the indicator normalization. For the indicators classified based on two variables, the catastrophe model used was the Cusp model; for the indicators classified based on two variables, the model used was the Swallowtail model; the Butterfly model was used for indicators with three control variables; and, lastly, the Wigwam model was used to normalize the indicators with five control variables. The catastrophe models and formulas used in this study for the estimation of the sub indicator functions or the rating of each indicator are shown in Table 1. Here, a represents the state variable and *u*, *v*, *w*, *x* and *y* are the control variables. The state variable is related to control variables, based on different catastrophe models. a_i represents the catastrophe fuzzy membership function of the control variable, *i*, where i can be *u*, *v*, *w*, *x* or *y*, depending on the model.

3.3 Multidimensional Vulnerability Mapping

In the multidimensional vulnerability index (MDVI) mapping, the vulnerability was classified into six dimensions, based on the proposed theoretical concept in the MOVE framework. The six dimensions were social, economic, physical, institutional, environmental, and cultural. Each dimension consisted of several subdimensions, which contained several indicators. Producing the MDVI mapping required six main steps, as depicted in Figure 2.

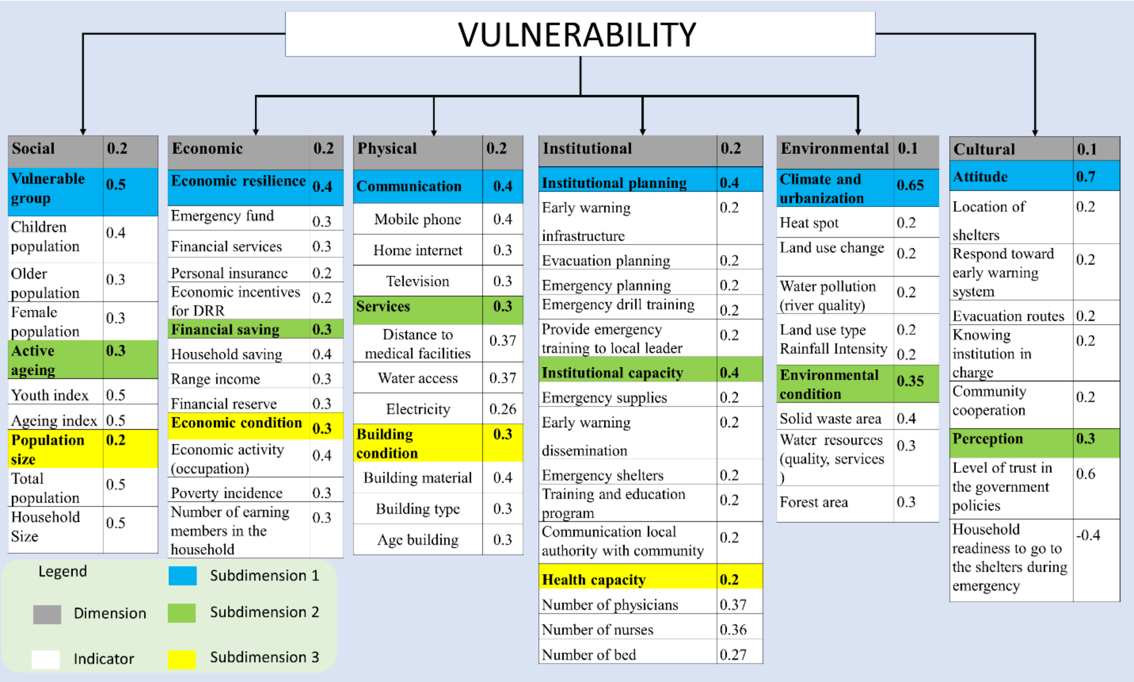

Figure 2: Multidimensional vulnerability index component [2]

Table 1: Different formula based on number of variables [20]

Catastrophe Model	Control Variable	Normalization Formula
Cusp	2	$a_u = u^{0.5}$ and $a_v = v^{0.33}$
Swallowtail	3	$a_u = u^{0.5}$, $a_v = v^{0.33}$, and $w^{0.25}$
Butterfly	4	$a_u = u^{0.5}$, $a_v = v^{0.33}$, $w^{0.25}$, and $a_x = x^{0.20}$
Wigwam	5	$a_u = u^{0.5}$, $a_v = v^{0.33}$, $w^{0.25}$, $a_x = x^{0.20}$, and $a_x = y^{0.17}$

The first step started by inputting all the information into spatial data format based on the available scale. Data was available at the mukim or district scale. The data was collected from government agencies, the community household vulnerability surveys, and the local authority surveys. At the same time, the indicator data classification is based on data range from government agencies and previous study. Next step, the data classification was analyzed using the Catastrophe Theory approach to determine indicator rating. Then data from each mukim was transformed according to the rating values identified from Catastrophe Theory approach. To transform the indicator based on the indicator rating into index values, there are two approaches based on the type of data. For data collected from community survey (fourteen indicators), the data is calculated based on Equation 3. For data from secondary data and local authority surveys, indicators be standardized directly according to the class of data in.

So, each class in indicator data standardized into index values based on indicator rating values.

$$Index\ Values = \frac{Indicator\ Rating\ \times Data}{100}$$

Equation 3

Where the *Indicator Rating* represents the values for each class in the indicator as determined from the Catastrophe Theory. The *data* is the indicator data collected from the community surveys. Next, the weightage was assigned to each indicator, subdimension and dimension using the values identified based on previous study shown in Figure 2. The data was classified into five groups: very low, low, medium, high and very high vulnerability. All the areas in this study were classified in this way to compare their levels of vulnerability.

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4. Result and Discussion

4.1 Indicator Rating

The rating of the sub-indicator classes was determined using the catastrophe theory function. Every indicator was separated into two, three, four, or five classes, each having a distinct value. Three distinct catastrophe models were applied in this study: the Cusp model was applied to indicators with two classes, the Swallow model was applied to indicators with three classes, the Butterfly model was applied to indicators with four classes, and the Wigwam model was applied to indicators with five classes. Table 2 displays sample results for each class's rating in the social vulnerability indicators. For the social dimension indicator, the data range (column 4) was based on the data collected from the Department of Statistical Malaysia (DOSM) for the overall number of mukims or districts in Malaysia. Some of the indicator ranges are based on previous study. Although the assessment conducted in this study only applied to three districts in Selangor, for the indicator rating, the data range was based on the local conditions in Malaysia overall. The data range for each indicator was not restricted to the study area, except for the data required from the community questionnaires and local authority surveys.

Table 2: Data standardization using Catastrophe theory

Dimension	Subdimension	Indicator	Range	Normalize Value	Rating
Social	Vulnerable Group	Female Population	8 - 7,992	0.00	0.00
			7,993 - 30,280	0.06	0.40
			30,281 - 87,911	0.23	0.69
			87,912 - 171,736	0.52	0.88
			171,737- 322,026	1.00	1.00
		Child Population (0 -15)	4 - 6,459	0.00	0.00
			6,460 - 19,824	0.08	0.44
			19,825 - 48,570	0.25	0.71
			48,571 - 99,261	0.57	0.89
			99,262 - 155,034	1.00	1.00
		Older Population (> 60)	1 - 2408	0.00	0.00
			2,409 - 7563	0.10	0.47
			7,564 - 17534	0.30	0.74
			17,535 - 34280	0.64	0.92
			34,281 - 78276	1.00	1.00
	Active Ageing	Ageing Index	2.2471 - 31.214	0.00	0.00
			31.2141 - 45.04	0.10	0.47
			45.041 - 60.32	0.17	0.64
			60.321 - 96.79	0.28	0.78
			96.791 - 370.73	1.00	1.00
		Youth Index	53.95 - 317.38	1.00	1.00
			317.381 - 579.33	0.90	0.97
			579.331 - 1103.21	0.76	0.93
			1103.211 -1904.45	0.52	0.88
			1,904.451 - 4,000	0.00	0.00
	Population size	Total population	22 – 23,275	0.00	0.00
			23,276 - 73,411	0.08	0.43
			73,412 - 177,105	0.23	0.69
			177,106 - 360,642	0.53	0.88
			360,643 - 639,512	1.00	1.00
		Household size	2.70 - 3.50	0.00	0.00
			3.51 - 4.00	0.22	0.60
			4.01 - 4.50	0.38	0.79
			4.51 - 5.40	0.62	0.91
			5.41 - 6.80	1.00	1.00

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The data range in column four describes the class in the indicator, while the initial values were identified from the mean of the data from each class. The lowest initial value in the indicator was the minimum value and the highest was the maximum value. These were used to determine the normalized values, as presented in column 5. Then, the normalized values from each indicator class were calculated using the formula, depending on the catastrophe model used. The last column presents the ratings from each class of each indicator. Then, all the classified values were used to calculate each vulnerability dimension for the multidimensional vulnerability index.

4.2 Vulnerability Assessment

Three subdimensions comprised social vulnerability: population size, the active ageing index, and vulnerable groups. Each of the three subdimensions of social vulnerability has its own set of indicators. Three indicators made up vulnerable groups: the proportion of women, children, and older people. While the population size included two indicators—household size and total population—the active ageing index contained two indicators: youth and the aging index indicator. Utilizing these three subdimensions, the research area's vulnerability levels were examined. As can be seen in Figure 3, overall, the lowest index value was 0.140 and the largest index value was 0.772. The variance, divergence, and differences with regard to the social component of vulnerability in the research area were calculated using the ranges between the minimum and greatest values in the area. The mukims in Hulu Langat District showed higher index values than those in Sepang and Kuala Langat, as the map shows. The degree of social vulnerability for each of the three research area districts housing the 17 mukims is depicted in Figure 3(a). As a result, Figure 3(a) illustrates that Ampang, Cheras, Kajang, Semenyih, and Tanjung Dua Belas were the five mukims classified as having very high vulnerability; Hulu Langat, Beranang, Dengkil, and Telok Panglima Garang were the five mukims classified as having high vulnerability; and Batu was the only mukim in the medium vulnerability class. Two mukims, Hulu Semenyih and Jugra, were in the very low vulnerability class, while four mukims, Labu, Bandar, Kelanang, and Morib, were in the low vulnerability class. Due to their larger populations than those of the other mukims, these five mukims - Ampang, Cheras, Kajang, Semenyih, and Tanjung Dua Belas - were classified as having extremely high potential for vulnerability. Therefore, the social vulnerability dimension should be the primary emphasis of these five mukims when assessing the risk of disaster. These five mukims have indices ranging from 0.604 to 0.772.

The term "economic vulnerability" describes the possibility of financial loss for a person or an organization. This dimension includes the financial resources available to local organizations to anticipate and address possible risks, as well as the preparation, financial capability, and protection of individuals and groups [23] and [24]. Three economic subdimensions were considered in this study's analysis of economic vulnerability. Financial services, emergency funds, personal insurance, and financial incentives for disaster risk reduction made up the first indicator, economic resilience. Three subdimensions make up the following subdimension, financial saving: income range, household savings, and financial reserves. Three variables make up the final subdimension, which is economic conditions: the number of wage workers in the home, poverty, and economic activity. The findings are displayed as an economic vulnerability map in Figure 3. Mukims Morib, Beranang and Batu were classified as having very high economic vulnerability. Compared to the other mukims, Hulu Semenyih and Beranang had very high vulnerability in two subdimensions, economic resilience and economic conditions, while Mukim Batu had two subdimensions of very high vulnerability, financial savings and economic conditions. This explains why these three Mukims were in the “very high” economic vulnerability class. All these three subdimensions have different index ranges in terms of their minimum to maximum values. The economic resilience subdimension index ranged from 0.86 to 0.93, the financial savings subdimension index ranged from 0.640 to 0.813 and the economic conditions subdimension had an index range of 0.280 to 0.506.

The physical vulnerability analysis consisted of a specific and detailed household spatial data scale for the building condition subdimension. The other data indicators were based on the mukim or district spatial scale. Besides the building condition subdimension, two other subdimensions featured in physical vulnerability: communications and services. In total, there were nine indicators of physical vulnerability, with each subdimension having three indicators. Figure 3(c) shows the physical vulnerability map with all three subdimensions in all 17 mukims in the study area. In this research area, the physical vulnerability index varied from 0 to 0.573. As a result, the index value fell outside of the range of 0 to 1. This is because the area's communications and service index values were also low.

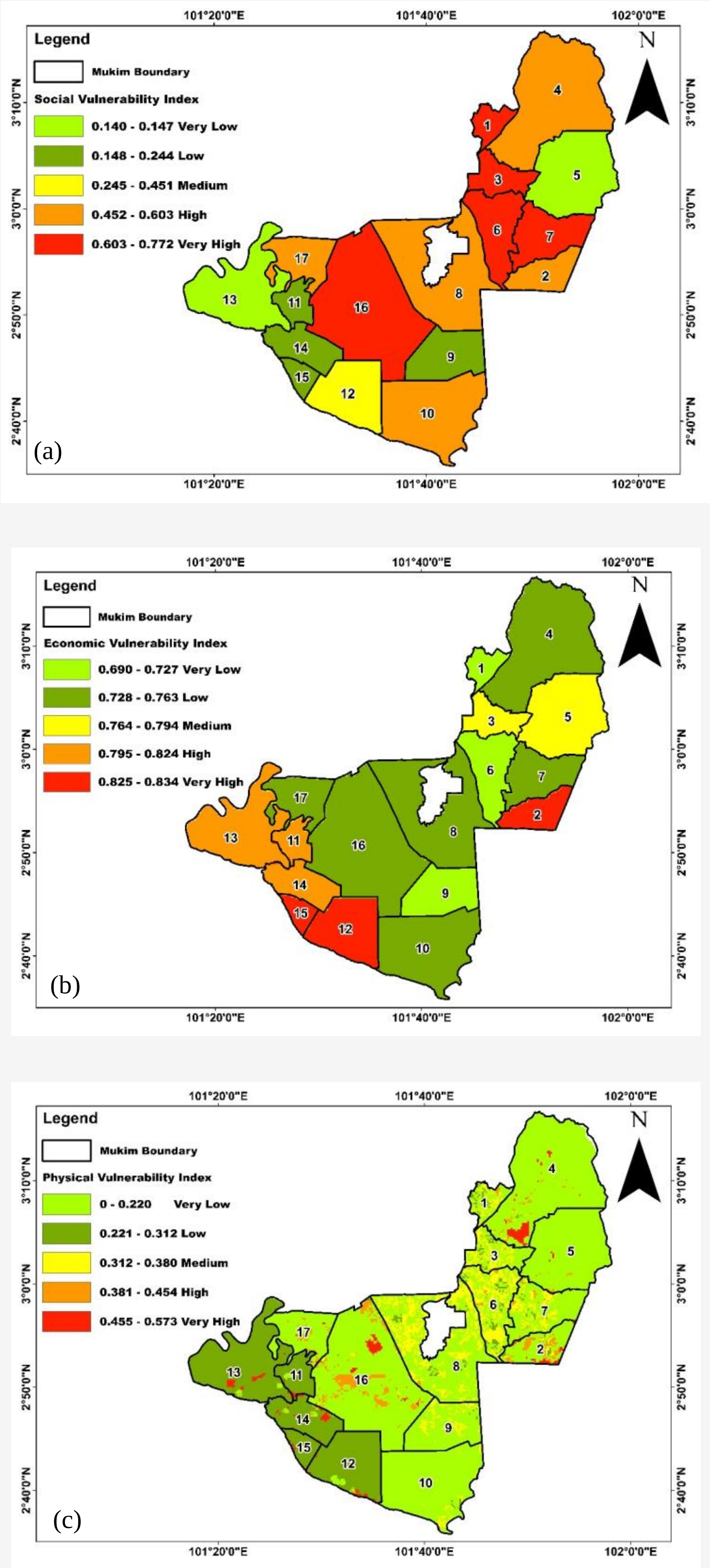
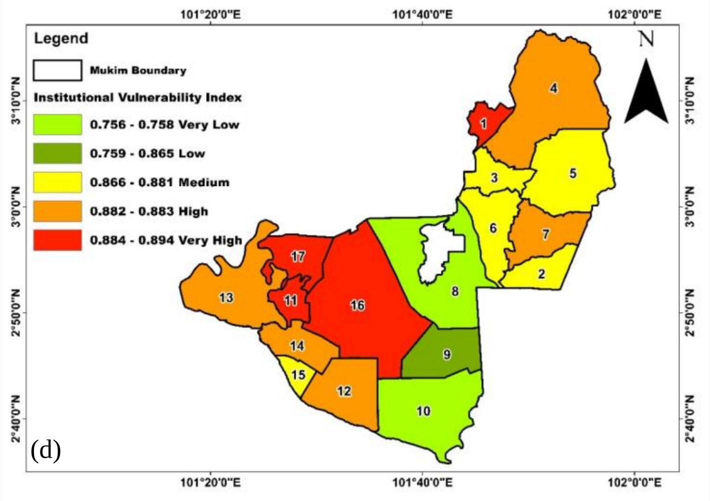
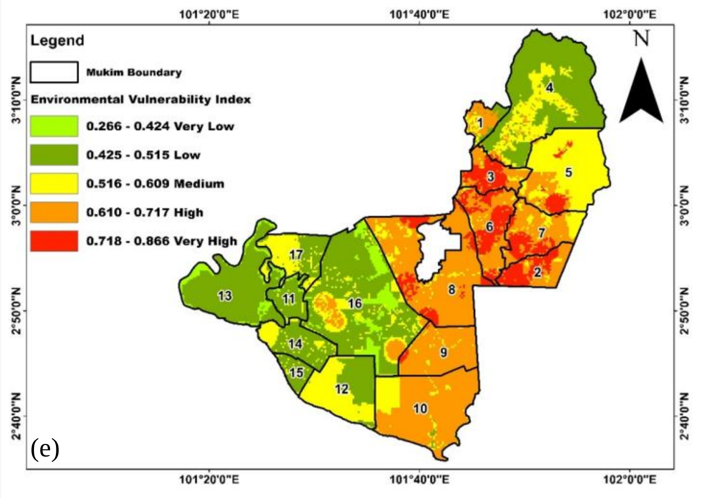


Figure 3: Vulnerability mapping: (a) Social vulnerability map, (b) Economic vulnerability map, (c) Physical vulnerability map (Continue next page)





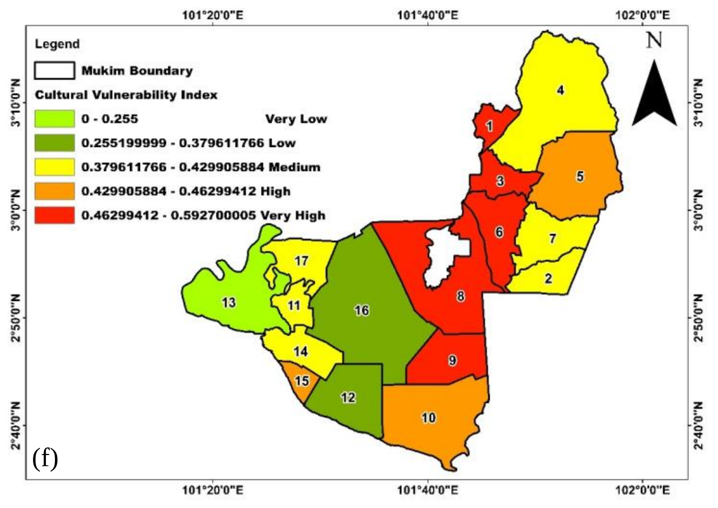


Figure 3: Vulnerability mapping: (d) Institutional vulnerability map, (e) Environmental vulnerability map and (f) Cultural vulnerability map (Continue from previous page)

The majority of mukims in this region are urban, and since Selangor is Malaysia's most developed state, it offers superior physical infrastructure for services and communications. Low index values were observed for the communications and services subdimensions, ranging from 0 to 0.465 and 0 to 0.380, respectively. In contrast, a number of mukims in the research region were categorized as having extremely high physical vulnerability, including Ampang, Hulu Langat, Cheras, Kajang, Beranang, Semenyih, Tanjung Dua Belas, Jugra, Telok Panglima Garang, and Morib. The index ranges for each of these places with extremely high physical vulnerability were 0.455 to 0.573. Because of their higher population density, these subdimensions have an impact on the locations with extremely high physical vulnerability. There are a lot of buildings in populated regions, and some of them are very vulnerable due to their age, type, and material characteristics. Some locations, such plantations, open spaces, or forests, had very low and low physical vulnerability since they were devoid of buildings.

In disaster risk assessments, institutional vulnerability is rarely considered or used as a vulnerability component. Institutional vulnerability is a function of how resilient and equipped local institutions, governance frameworks, and organizational structures are to withstand a future crisis [27]. Thirteen indicators of institutional vulnerability were used in this study and were divided into three subdimensions. The first, institutional planning, had five indicators: early warning infrastructure, disaster drill preparation, evacuation planning, emergency drill training for community leaders, and emergency drill preparation. Five variables were also included in the following subdimension, institutional capability: emergency supplies, early warning system dissemination, emergency shelter capacity, training and education programs, and community communications with the local government. Health capacity, which is comprised of three indicators: the number of physicians, nurses, and hospital beds, was the final subdimension of institutional vulnerability. The findings of the institutional vulnerability index map for this research area are displayed in Figure 3(d). The analysis's findings showed that there was an index range of 0.756 to 0.864 across the 17 mukims. Due to the three mukims (Bandar, Tanjung Dua Belas, and Telok Panglima Garang) classified as very high institutional vulnerability and the three classified as high institutional vulnerability (Jugra, Kelanang, and Batu) combined, there was extremely high institutional vulnerability in Kuala Langat District. Consequently, Kuala Langat's range index fell between 0.867 and 0.894. When comparing the three districts, Sepang had one mukim in the low vulnerability class and two in the very low vulnerability class (Dengkil and Sepang). In Sepang District, the index ranged from 0.756 to 0.78. Because Sepang District had a lower health capacity vulnerability index than the other two districts, it had a lower vulnerability index. In Hulu Langat, the final district, there was one mukim (Ampang) classified as extremely vulnerable, one mukim (Semenyih) classified as highly vulnerable, and five mukims (Beranang, Cheras, Hulu Langat, Kajang, and Hulu Semenyih) classified as mediumly vulnerable.

The degree of ecosystem degradation is known as environmental vulnerability, and the impacted region's vulnerability may be influenced by environmental factors [25]. Two subdimensions—environmental conditions and climate and urbanization—formed the basis of the discussion of environmental vulnerability in this study. There were five indicators for the climate and urbanization subdimension: land-use types, heat spots, rainfall intensity, river quality, and land-use change. Forest areas, water resources, and solid waste areas made up the environmental conditions subdimension. The results of the environmental vulnerability map are shown in detail in Figure 3(e). The entire environmental vulnerability index fell between 0.266 and 0.866 in the index range. The more urbanized areas of Cheras, Kajang, Dengkil, Beranang, and Semenyih are typically included in the very high vulnerability index. The very high score of environmental vulnerability varied from 0.450 to 0.566. Consequently, regions classified as very high or high susceptibility typically had higher population densities or had undergone significant land use changes. Nonetheless, the majority of the regions in the very low and low vulnerability classes were protected or forested, with some having little to no inhabitants. In addition, there are palm oil plantations in a few places in Mukims Jugra, Kelanang, Bandar, and Sepang, for example. These regions, which contained more plantations and forests, had extremely low index values, ranging from 0.252 to 0.492. In the research area, urbanization seems to be a significant factor in the increase in the environmental vulnerability index. Cultural vulnerability was the study's final dimension. In comparison to the other dimensions, the cultural vulnerability component has received less attention from researchers, discussions, and analyses. The intangible aspects of the attitude and perception subdimensions were the main emphasis of this study's investigation of cultural vulnerability.

The attitude subdimension assessed household and community attitudes and responses to disasters using five indicators. The five indicators were as follows: (1) Do people know where the evacuation shelters are located in their community? (2) Do people react to the early warning system in the event of a disaster? (3) Do people know the routes to the safest location during an evacuation? (4) Do they know the name of the organization in charge during a disaster? and (5) Does the community cooperate in their area? Two factors comprised the second subdimension, perception: the degree of faith in government DDR programs and the preparedness of households to utilize the emergency shelters offered by local authorities. The results of the Cultural Vulnerability Index are displayed in Figure 3(f), which includes the attitude and perception subdimensions. The lowest vulnerability index value was 0.255, and the highest value was 0.593, according to the findings of the cultural vulnerability index map. The only mukim categorized as having extremely low cultural vulnerability was Mukim Jugra. Compared to other mukims in the research area, households in Mukim Jugra responded better to disasters and had greater faith in the government and local authority's disaster recovery efforts since this mukim had the lowest vulnerability in the attitude and perception subdimensions. Ampang, Cheras, and Labu were the three mukims categorized as having extremely high vulnerability, nevertheless. These three mukims' respective index ranges were 0.4901 and 0.5649. Overall, six mukims (Hulu Semenyih, Beranang, Sepang, Bandar, Morib, and Telok Panglima Garang) were in the medium vulnerability class, four were in the low vulnerability class, and three mukims (Semenyih, Kajang, and Dengkil) were in the high vulnerability class.

4.3 Multidimensional Vulnerability Mapping

This study examined and observed the six comprehensive dimensions of vulnerability in the 17 mukims across three districts. Figure 4 displays the chart representing the average six-dimensional index for the study area, serving as a point of comparison. According to the chart, the majority of mukims in the study area exhibited greater vulnerability in the institutional component as compared to the other dimensions. In this study area, the first emphasis should be placed on addressing the institutional dimension in order to decrease the vulnerability of the area to disasters. Subsequently, attention should be directed towards the economic dimension. The government and local authorities continue to demonstrate insufficient commitment and capability in terms of disaster preparation and mitigating disaster risk. This study aligns with the conclusions given by [28], who highlighted that the effects of hurricanes Katrina and Rina on the United States were worsened by institutional factors, including insufficient reaction, communication, and coordination among the respective institutions. Previous study emphasized that the importance of institutional vulnerability was evident in a series of past disasters, such as Hurricane Katrina (2005), Nepal Earthquake (2015), and the more recent Cyclone Idai (2019) [29]. The local authorities should enhance their Disaster Risk Reduction (DDR) procedures and educate the public to enhance their attitudes, knowledge, and perceptions of disaster management.

Despite the fact that this study area is urban and has the highest income population in Malaysia, it has a high economic vulnerability due to a lack of budget and funding for disaster risk mitigation initiatives. Even though the area is urban and its citizens have high salaries and assets, they cannot increase the economic capacity of a location if not enough funds has been set aside for disaster preparedness [30]. However, the result also shows that the areas, on average, had lower vulnerability in the physical dimension compared to the other five dimensions. This is because some areas feature better physical facilities in terms of communications and access to basic services like electricity and water. The economic dimension is a further cause for concern in this study area because, based on the results, many mukims displayed the highest vulnerability in this dimension. The economic dimension is important, especially in how it reflects the capacity of people, organisations, and the local authorities to recover after a disaster event.

The results from the combination of six dimensions show that the index range for MDVI was between 0.450 and 0.690. For the very low MDVI, the classes are between 0.450 and 0.515, with most very low vulnerability areas being in the Dengkil, Labu, Sepang and Jugra Mukims. However, in three mukims - Ampang, Cheras and Kajang - most of the areas were classified as very high or high. The index range for the very high class was between 0.622 and 0.690, while the high-class index values ranged from 0.584 to 0.621. Several other mukims contained areas classified as very high vulnerability, but these areas were small. For example, Mukim Tanjung Dua Belas fitted into all five classes, but most areas were in the medium vulnerability class. The detailed results are presented in the MDVI map shown in Figure 5.

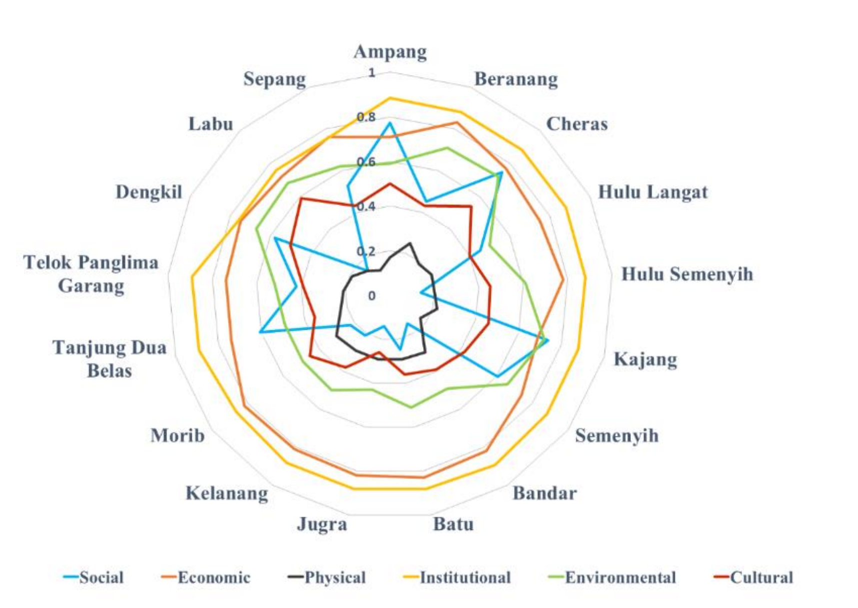


Figure 4: Multidimensional vulnerability index chart

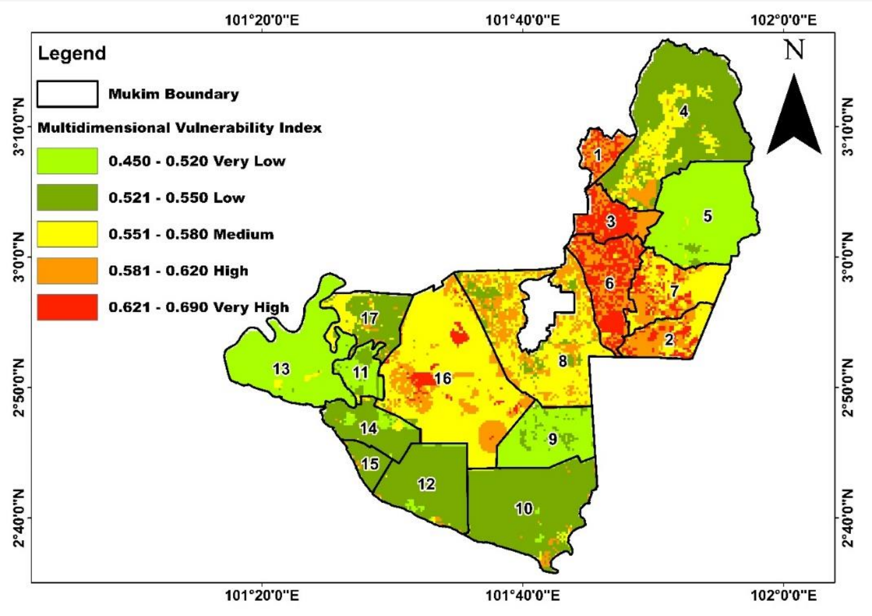
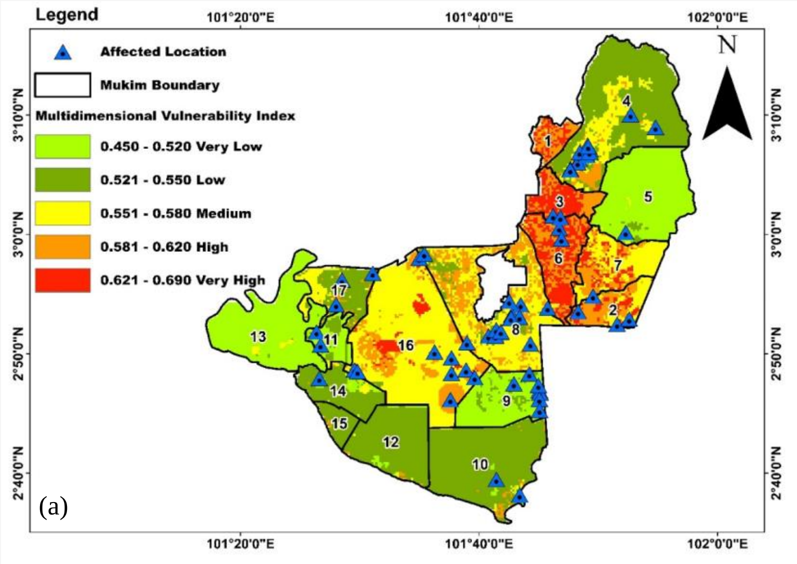


Figure 5: Multidimensional vulnerability index map

4.4 Comparison of MDVI Map

After completing producing the map using the Catastrophe Theory and GIS, the map produced was compared with the MDVI map produced using the Standard Normalization approach. Each map was overlay with the affected flood location based on the occurrences in 2021 as shown in Figure 6. Overall, there were 61 locations identified based on the information provided by DOSM. Based on Figure 6(a) and Figure 6(b) shown that both maps have different class range of vulnerability. As shown in Figure 6, the MDVI produce by using the Catastrophe Theory and GIS are higher compared to the MDVI map produced using the standard normalization approach. The flood occurrences within each MDVI class for both Catastrophe Theory and Standard Normalisation approaches are summarised in Table 3 for the purpose of comparison.



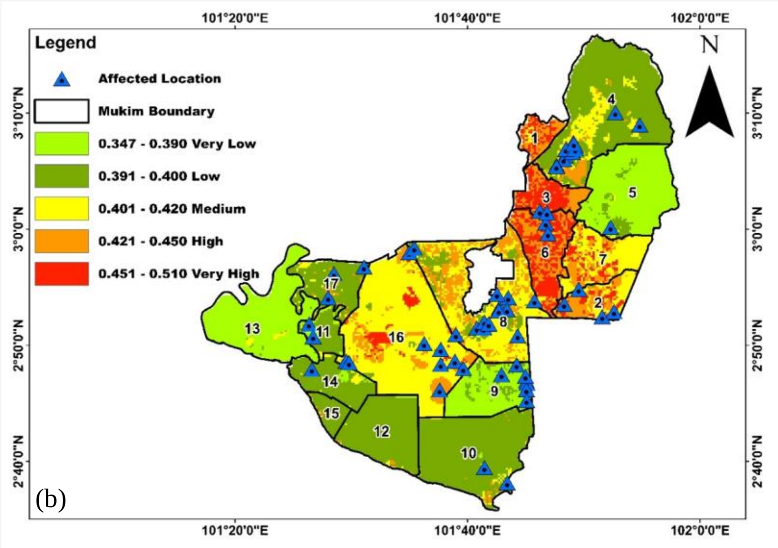


Figure 6: MDVI map:
(a) Produced using the Catastrophe theory and (b) Produced using the standard normalisation

Table 3: Comparison MDVI using Catastrophe theory and standard normalization

MDVI Class	Flood Occurrences (Catastrophe Theory)	Flood Occurrences (Standard Normalization)	Total Flood Occurrences	Percentage % (Catastrophe Theory)	Percentage % (Standard Normalization)
Very High	6	4	10	60.0	40.0
High	8	5	13	61.5	38.5
Medium	28	13	41	68.3	31.7
Low	9	12	21	42.9	57.1
Very Low	10	27	37	27.0	63.0

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The Catastrophe Theory method identifies a greater percentage of flood events in the categories of very high and high vulnerability, compared to the Standard Normalisation method. This suggests that the Catastrophe Theory approach would be more efficient in identifying the most vulnerable areas. In contrast, the Standard Normalisation approach identifies a considerably larger proportion of flood events in the categories of very low and low vulnerability. This implies that it can incorrectly categorise safer areas as vulnerable, resulting in a decrease in its accuracy. In general, the Catastrophe Theory method seems to be more efficient in identifying areas with high and medium vulnerability. It captures a higher proportion of real flood events in these zones compared to the Standard Normalisation method.

5. Conclusion

This study proposed the development of multidimensional vulnerability mapping assessment at the local level in Malaysia by considering six different dimension social, economic, physical, institutional, environmental and cultural using Catastrophe Theory and GIS. As a pilot study area, three districts in Selangor (Hulu Langat, Sepang and Kuala Langat) were selected as the study area in which to conduct the multidimensional vulnerability index assessment based on the proposed index model. This study's main contribution is to conduct an assessment multidimensional vulnerability mapping assessment at the local level based on new MCDA approach with GIS. This study is an improvement from the previous approach used for a multidimensional vulnerability index. This new approach incorporates GIS, the new data driven MCDA approach and six different vulnerability dimensions. The findings prove Catastrophe Theory's applicability as a tool for categorizing vulnerability indicators in the context of multidimensional vulnerability assessment using index approach. However, this approach has advantages if indicators have larger dataset, so indicator index values are balanced in each range. In this study, some of indicators have greater margin between one class to another class. The generated multidimensional vulnerability map proposed in the study area (Hulu Langat, Sepang and Kuala Langat) shows that the proposed model can present vulnerability at the local level. The map was generated by using the six vulnerability dimensions to map and classify the areas from very low to very high vulnerability.

In conclusion, this research contributes significantly to the field of disaster risk management by providing a sophisticated approach to vulnerability assessment. The Catastrophe Theory method is more suitable for identifying and prioritizing high-risk areas for immediate intervention and resource allocation. Further studies could explore hybrid models that incorporate strengths from both methods to enhance overall predictive performance. The findings underscore the need for targeted interventions based on specific vulnerability dimensions, offering a solid foundation for scientifically informed policies and strategies for disaster prevention and mitigation. The study's integrated approach is highly beneficial for disaster risk reduction, emphasizing the importance of enhancing institutional capabilities, economic resilience, and community preparedness to improve overall resilience and reduce the impacts of future catastrophic events on vulnerable populations. The study's methodological framework, combining GIS and Catastrophe Theory, offers a valuable tool for developing dynamic, spatially explicit vulnerability maps that capture the evolving nature of disaster risks.

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