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Spatial Vulnerability Index Modeling for Climate Change Risk Assessment in Indonesia

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Abstract. This study develops a Fuzzy Logic-based Intelligent Decision Support Model (IDSM) to map climate change vulnerability across 34 Indonesian provinces, using 20 variables grouped into four parameters: greenhouse gases, geological factors, anthropological factors, and weather conditions. Data from 2015–2020 were sourced from the Global Atmosphere Watch, LAPAN, BASINS-CAT, BPS, and the DigComp 2.0 framework at the provincial level. The methodology involved data normalization, trend analysis via linear regression, relative value calculation using Euclidean distance, and a two-stage aggregation through a fuzzy inference system to produce a Vulnerability Score. Results indicate Jakarta as the most vulnerable (0.6145), Bali as the least vulnerable (0.498), and West Kalimantan (0.502), Maluku (0.5215), and Papua (0.500) as moderately vulnerable. These variations stem from differing environmental, social, and economic conditions, highlighting the need for location-specific adaptation and mitigation policies. The model offers a valuable tool for prioritizing climate action interventions.

Keywords: Climate change, climate vulnerability, decision support model, fuzzy logic, risk mapping

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1. Introduction

Climate change is one of the greatest challenges, and is the greatest environmental sustainability challenge, facing the world as we know it today and in the foreseeable future [1–4]. It encompasses a massive scope of consequences impacting the social, economic, and environmental aspects of humanity [5,6]. Various scientific studies suggested that Anthropogenic Greenhouse Gas (GHG) emissions produced by economic and social daily activities have significantly affected the environment adversely and became one of the main contributing factors to climate change [7–9].

Waktu Akuisisi : 2020-06-04 04:11:19.000000 UTC
2020-06-03 21:11:19 WIB
Bujur : 136.7529
Lintang : -1.8205
Tingkat Kepercayaan : Sedang
Provinsi : PAPUA
Kabupaten : KAB. KEPULAUAN YAPEN
Kecamatan : YAPEN TIMUR
Satelit : NOAA20

Wilayah	● Rendah	● Sedang	● Tinggi
Sumatera	1	5	0
Kalimantan	0	16	0
Jawa	0	8	0
Papua	1	8	0
Maluku	0	1	0
Sulawesi	1	11	3
Nusa Tenggara	0	4	0

Jumlah titik hotspot : 59

Sumber : Lembaga Penerbangan dan Antariksa Nasional (Lapan)

Figure 1. Map of Hotspot Distribution in Indonesia

Based on monitoring data from the National Institute of Aeronautics and Space (LAPAN) on June 4, 2020, 59 hotspots were detected in various regions of Indonesia using the NOAA20 satellite, with a moderate to high confidence level. The highest concentration of hotspots was found in Kalimantan (16 hotspots, all of moderate category) and Sulawesi (14 hotspots, comprising 11 of moderate category and 3 of high category), while other regions such as Papua, Maluku, Nusa Tenggara, and Sumatra also showed the presence of hotspots, albeit in smaller numbers. This data reflects the real threat of forest and land fires in various provinces, which not only impact environmental degradation and greenhouse gas emissions but also exacerbate the vulnerability of regions to climate change. This situation underscores the importance of comprehensive climate vulnerability mapping to support targeted adaptation and mitigation policies at both the national and regional levels.

Some of the latest groundbreaking innovations in the study of climate system and its changes have sought to assess the impacts of fluctuation in environmental cues such as hurricane occurrences, rising sea levels, droughts, floods, maximum and temperatures, melting ice covers, and other visual as well as non-visual variables as indicators of climate change [10–12]. These observational data make the basis of various model simulations in mapping and forecasting present and future impacts of climate change.

Decision Support Model (DSM) is a computer-based model that helps as a tool to aid the analysis and modelling of these complex and dynamic relationships present between different variables, with the purpose of predicting as well as understanding the patterns and variability of the data provided [13,14]. The components of a DSM include inputs, user knowledge and expertise, outputs, as well as decisions. Inputs mean the attributes of the data which will be analyzed, and it consists of factors, numbers, and characteristics within the attributes. User knowledge and expertise help to analyze the input manually so that the attributes are arranged according to their purpose properly by utilizing the user's expertise on the field. Outputs are the transformed data from which the "decisions" resulting from DSM are generated. Decisions are the results from the DSM which are adjusted to the user criteria and purpose [15–17]. Outputs are gained after running the model in form of transformed data. These outputs generate DSM-based "decisions" in accordance with the user criteria. A DSM which makes extensive use of artificial intelligence (AI) techniques is called an Intelligent Decision Support Model [18–20].

An Intelligent Decision Support Model (IDSM) utilizes the use of AI techniques in the user knowledge and expertise component of building the model, in which the model is programmed to perform complex cognitive tasks without the need of human intervention. These techniques include fuzzy logic-based rules, fuzzy cognitive mapping, maximum likelihood, rough sets as well as supervised and unsupervised learning neural networks. Given set parameters and logic rules, the utilization of AI has produced results whose accuracy and consistency are comparable (and even exceed) the results from human experts [21–23]. However, this advantage depends on the decision parameters given, and high level of uncertainties in the targeted input data can render poor performance. To mitigate this, IDSM usually integrate uncertainty-reduction techniques such as fuzzy logic and rough sets, as well as use different datasets and scenarios to evaluate results.

Because of the complexity and the use of long-term datasets which fluctuate due to the environmental-altering nature of climate change, this analysis and decision modelling in this study will be done as an

IDSM to map the impacts of climate change and determine the most vulnerable areas (MVAs) in Indonesia. The variables for this study use the five pollutants of air quality as parameters, which are Surface Ozone (O3), Particulate (PM10), Carbon Monoxide (CO), Sulphur Dioxide (SO2), and Nitrogen Dioxide (NO2). These variables are recommended by the Global Atmosphere Watch of Bukit Kototabang, which measures the data of five variables daily. Furthermore, the data of hotspots distribution in Indonesia, from Indonesia's National Institute of Aeronautics and Space's (LAPAN) database, also archived by the Global Atmosphere Watch of Bukit Kototabang, will also be used as a contributing variable to map and analyze the impacts.

The levels of O3, PM10, CO, SO2, and NO2, as well as the status of the hot spots' distribution in the area (none, low, medium, or high) – as seen in Figure I – will determine the rules and decision parameters set which classify the area as an MVA or not. most vulnerable areas are generally defined as those most impacted by climate change. Therefore, while these 5 variables and the hotspot distribution will help calculate the quantitative parameters of the rules, an MVA will also be affected by the conditions of the areas themselves, which may qualify as qualitative-based parameters. In this study, population growth, economic development, and digital literacy will be used as three additional quantifiable qualitative-based parameters. Population growth will be measured by the number of populations in the region. Economic development will be measured by the Gross Domestic Product (GDP) of the region. Digital literacy will be measured using the data from DigComp 2.0 framework [24], that is also used as the officially acknowledged indicators for the Global Framework of Reference on Digital Literacy Skills by the UNESCO [25].

In this study, the *Intelligent Decision Support Model* (IDSM) method based on fuzzy logic was selected for its ability to process quantitative and qualitative data simultaneously, address uncertainty in the data, and model non-linear relationships among variables [26,27]. The indicators used comprise four main parameter groups: greenhouse gases, geological factors, anthropological factors, and weather conditions. The selection of these indicators refers to global literature such as the *Global Atmosphere Watch* [28], the *DigComp 2.0* [29], and climate vulnerability modeling studies in various countries [30,31].

The literature review shows that fuzzy logic-based approaches have been widely applied in climate vulnerability studies in the agricultural sector Bin et al. (2023), urban areas Hanoon et al. (2022), and air quality [34]. However, their application for multi-parameter vulnerability mapping at the national scale in Indonesia remains limited. Furthermore, most previous studies have relied solely on physical or environmental indicators, without integrating socio-economic dimensions and community adaptive capacity.

Based on these gaps, this study aims to develop a fuzzy logic-based intelligent decision support model capable of mapping the most climate-vulnerable areas in Indonesia through the integration of multi-parameter data from 34 provinces. Second, this study seeks to test the model's accuracy in identifying the most vulnerable areas based on a combination of physical, environmental, and socio-economic indicators. Last, it aims to provide priority area recommendations for policymakers in planning climate change mitigation and adaptation strategies.

These objectives are formulated using the SMART criteria (Specific, Measurable, Achievable, Relevant, Time-bound), in which the resulting model is expected to specifically map vulnerability at the provincial level, have performance measures in the form of vulnerability scores, be implementable with the available data resources, be relevant to the national climate change adaptation policy, and be updatable periodically in accordance with the latest data.

Thus, this study is expected not only to contribute to the development of a more accurate and contextual climate vulnerability mapping method for Indonesia but also to enrich the international literature on the application of Intelligent Decision Support Models in climate change risk management in developing countries.

2. **Methods**

2.1. Methodological Framework

This study uses a quantitative approach by developing a fuzzy logic-based Intelligent Decision Support Model (IDSM) to map the areas most vulnerable to climate change in Indonesia. IDSM was chosen because it is capable of integrating heterogeneous multi-parameter data and modeling non-linear relationships between variables while considering data uncertainty. The method used falls under the category of Multi-Criteria Decision Making (MCDM). Weighting was performed using the equal weighting method (weight = 1.0 for all variables) based on expert judgment from literature studies [35,36].

The methodological framework of the study is presented in four main stages:

a. Data Collection (sources, resolution, and time period).
b. Data Preprocessing (normalization, handling of missing data, and variable conversion).
c. IDSM Modeling (standardization, weighting, and aggregation using a fuzzy inference system).
d. Model Validation (technical verification, sensitivity testing, and comparison of results with expert assessments).

2.2. Data Sources and Resolution

The research data covers 34 provinces in Indonesia for the period 2015–2020, with provincial-level spatial resolution. Variables are grouped into four main parameters:

Table 1. Research Parameter

Parameter	Source
Greenhouse Gases (GHG): PM10, O_3, CO, SO_2, NO_2.	*Global Atmosphere Watch* Bukit Kototabang.
Geological Factors (GF): critical soil texture, drainage level, crop yield, biotic damage level, and abiotic damage.	BASINS-CAT dan BPS.
Anthropological Factors (AF): infrastructure density, urbanization density, population size, urban temperature, and socio-economic conditions (GDP per capita).	BPS and *DigComp 2.0 Framework* [29].
Weather Conditions (WC): maximum temperature, minimum temperature, rainfall, solar radiation, and number of hotspots.	LAPAN and Global Atmosphere Watch.

2.3. Data Preprocessing

a. Normalization: All numerical variables were normalized using the min–max normalization method to a range of 0–1.
b. Handling Missing Data: Missing data were estimated using linear interpolation (*linear forecasting*).
c. Binary Variable Conversion: Biotic and abiotic damage variables were coded as 1 (present) and 0 (absent).
d. Variable Classification: Variables were categorized as *direct* (high value → high vulnerability) and *inverse* (high value → low vulnerability).

2.4. Standardization, Aggregation, and Fuzzy Modeling

a. Standardization: All variables were standardized using relative values against the national median.
b. First-Stage Aggregation: Variables in each parameter were processed using a *fuzzy inference system* with triangular (*trimf*) and trapezoidal (*trapmf*) membership functions, producing a vulnerability score per parameter (*Vulnerability Degree*).
c. Second-Stage Aggregation: The scores of the four parameters were combined to obtain the provincial *Vulnerability Score*.

d. Categorization:
   - Least Vulnerable: skor < 0,4
   - Moderately Vulnerable: 0,4 ≤ skor ≤ 0,7
   - Most Vulnerable: skor > 0,7

2.5. Data Analysis

The analysis process was carried out in several stages:

a. Data Normalization

All variables were normalized to ensure equal scale using the min–max normalization method so that variables with different units could be analyzed together. Binary variables (biotic/abiotic damage) were excluded from normalization because their values already represented the existence (1) or absence (0) condition.

b. Linear Regression Analysis

Linear regression was used to calculate the slope coefficient of each variable over time (2015–2020) to determine whether there was an increasing or decreasing trend. A positive coefficient indicates an increase in the variable value, while a negative coefficient indicates a decrease.

c. Euclidean Distance and Relative Value Calculation

The Euclidean Distance method was used to measure the relative proximity of each province to the reference value (national median). The results were converted into *relative distance* and *relative value* to be used in fuzzy modeling.

d. Fuzzy Logic Application

Fuzzy logic modeling was performed using MATLAB Fuzzy Toolbox with triangular (*trimf*) and trapezoidal (*trapmf*) membership functions. Each variable was categorized into three vulnerability levels: low, medium, and high. *IF–THEN* rules were developed to combine variables within a parameter and across parameters to produce the final vulnerability score (*Vulnerability Score*).

Data processing was carried out using Python (Jupyter Notebook) for linear regression and Euclidean distance calculations, and MATLAB Fuzzy Logic Toolbox for fuzzy modeling. Vulnerability map visualization was performed using QGIS.

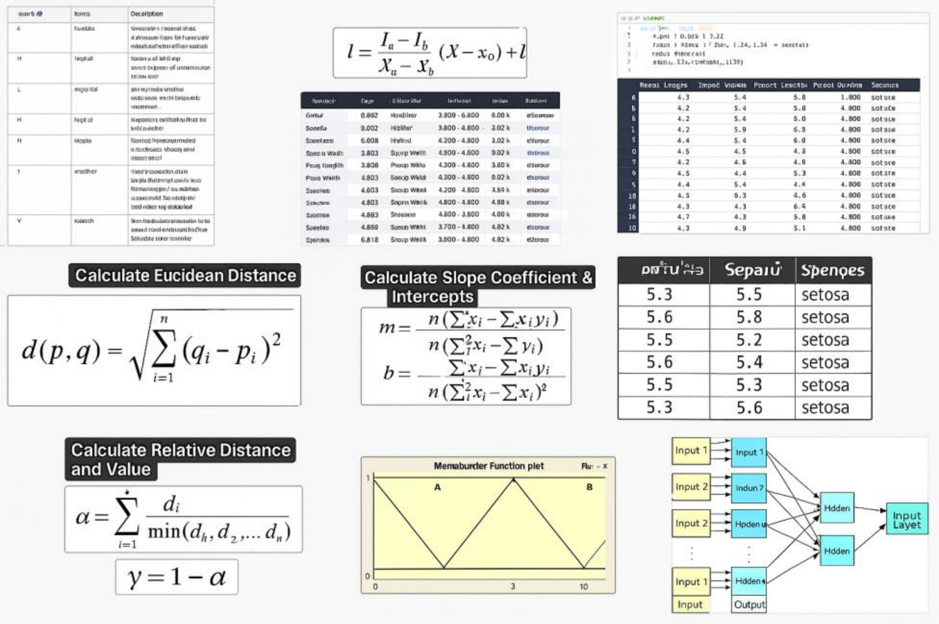


Figure 2. Data Processing Stages

2.6. Model Validation

Validation is carried out through three approaches:

1. Technical Verification: Ensuring that the model runs according to design through code debugging tests and consistency checks of results.
2. Sensitivity Testing: Changing variable weights by ±10% to measure the stability of model output.
3. Comparison with Expert Assessment: Mapping results are compared with studies from climate change experts and Global Climate Risk Index data to ensure the accuracy of regional vulnerability trends.

3. Results and Discussion

3.1. Linear Regression Analysis

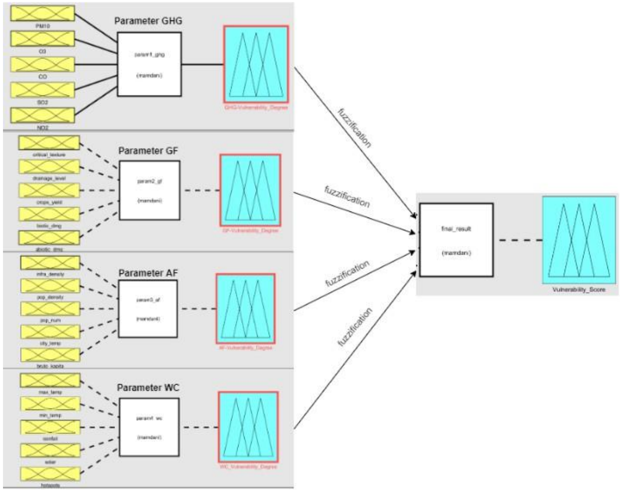
The data for each of the 12 variables used are collected and normalized so that the attributes for all data are equalized in relations to each other. This is done with the purpose of equalizing each variable to prepare them as equal input with the weighted value = 1. Table 2 explains all the detailed initial calculations done to equalize and adjust each variable in their respective group of parameters. Because variable biotic damage and abiotic damage are binary (0,1), these two variables are the only ones not processed in this stage as their meaning and contribution are already clear: 0 for non-existing variable, and 1 for existing variable.

Table 2. Environmental Variables And Their Contributions (%) To The Species Habitats

Parameter	Variable	Data Processing
GHG	PM10 (ghg_pm10)	$I = \frac{I_a - I_b}{X_a - X_b}(X_x - X_b) + I_b$ where, I is the resulting Indeks Standar Pencemar Udara (ISPU) / Air Pollution Index (API), I_a is the maximum value of I while I_b is the minimum value of I. X_a is the maximum ambient concentration of the variable (in µg/m3), X_b is the minimum ambient concentration of the variable (µg/m3), and X_x is the real value of ambient concentration of the measured variable. ISPU / Air Pollution Index is calculated based on averages of all pollutant concentrations measured in a full hour, a full 8 hours, or a full day
	SO2 (ghg_so2)	
	CO (ghg_co)	
	O3 (ghg_o3)	
	NO2 (ghg_no2)	
GF	Critical Texture (gf_critical_texture)	Missing values are calculated using step-value projected linear series.
	Drainage Level (gf_drainage_level)	$= FORECAST.LINEAR(x, known\_y's, known\_x's)$ Where, x is the numeric x-value for which we want
	Crops Yield (gf_crops_yield)	to forecast a new y-value, known_y's is the dependent array or range of data, and known_x's is
AF	Infrastructure Density (af_infra_density)	the independent array or range of data that is known. Using linear trendline by calculating the step value /
	Population	slope: y = αx + β

	Density (af_pop_density)	
	Population Number (af_pop_num)	where, step value (β) is calculated using: $\beta = \frac{\sum y - \alpha \sum xn}{n}$
	Urban Temperatures (af_city_temp)	y is the projected value, α is a constant and x is the
	SES Condition (af_bruto_capita)	available/independent data/value. β is the step value or more commonly known as the regression
WC	Maximum Temperature (wc_max_temp)	coefficient.
	Minimum Temperature (wc_min_temp)	
	Rainfall (wc_rainfall)	
	Solar Radiation Exposure (wc_solar)	
	Hotspots (wc_hotspots)	

The next step after all the data has been processed is to calculate the slope coefficient of each variable for each area input. The slope coefficient signifies whether there is a positive or negative correlation between each independent variable and the dependent variable. In this thesis, a positive coefficient indicates the increase of the variable's value as the x-value (year) goes up one-unit at a time for 6 times (2015- 2020). The greater the positive number shows the greater the increase of the variable's value, which will determine the variable's impact on the vulnerability scoring, depending on which variable it is. Meanwhile, a negative coefficient indicates the decrease of the variable's value for each time the x-value (year) goes up one-unit. The greater the negative number shows the greater the decrease of the variable's value. The calculations for linear regression analysis for this research are done using Phyton in Jupyter Notebook.



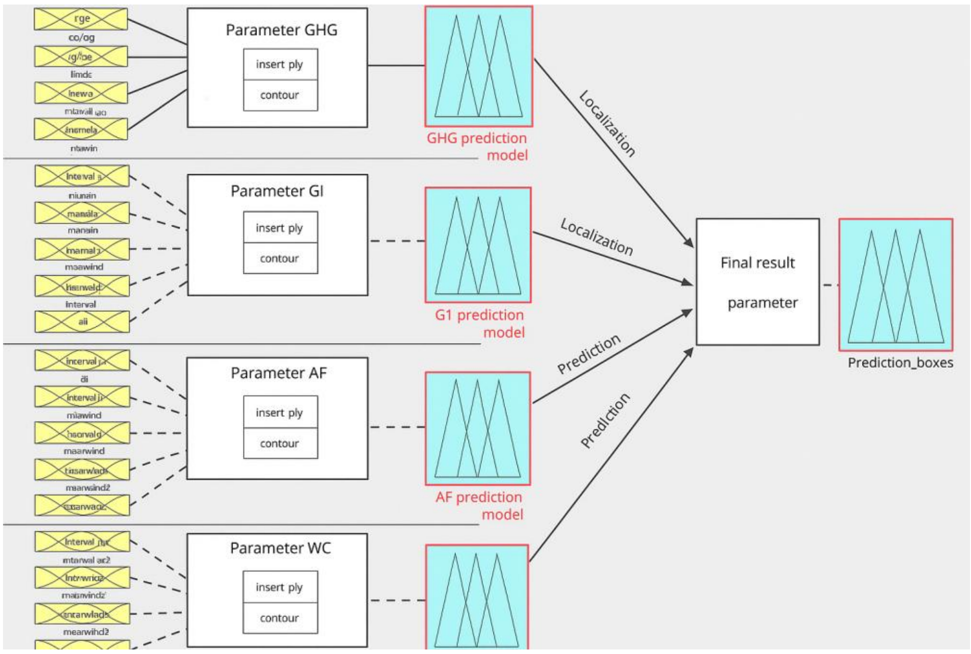


Figure 3. Structure of Fuzzy Input and Output

3.2. *Euclidean Distance*

After the coefficient values are calculated, the next step is to find the Euclidean Distance, Relative Distance, and Relative Point of each variable. The goal of this method is to be able to sort the relative point between all 35 data areas (34 provinces + the median "Indonesia"), before aggregating all the sorted relative points into a model using fuzzy logic. Euclidean distance is the length of a line segment between two points; in this case, the line segment is drawn between the previously-calculated coefficient value, and the relative minimum value (for positive correlation variables) or the relative maximum value (for negative correlation variables). The purpose of using Euclidean distance in this equation is because there are two real-valued vectors with differing scales that are acquired after the coefficient values are calculated. The first of the two vectors is the coefficient value itself and the other is the relative point (minimum or maximum depending on whether the correlation is negative or positive). Afterwards, a relative distance and relative point are measured from comparing all the values of the Euclidean distances.

3.3. *Fuzzy Logic Membership Functions*

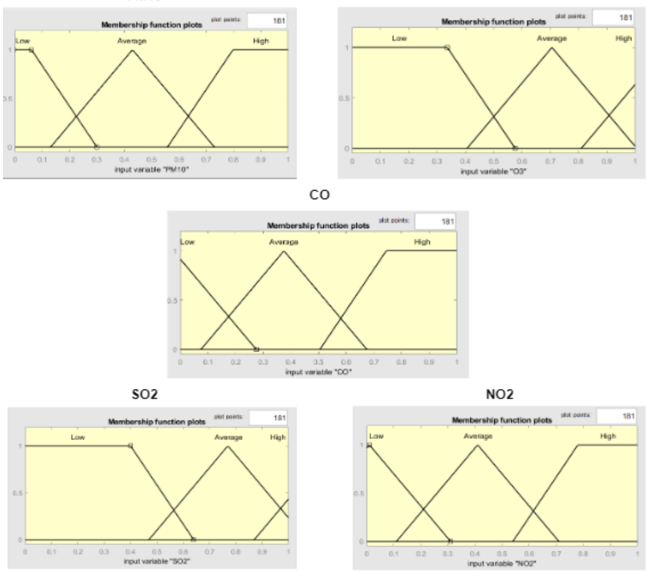
Using expert judgment from literature study, this thesis has utilized 20 variables that are categorized into 4 groups of parameters. For the purpose of simplifying the fuzzy calculation, this thesis assigns equal weight to all variables with the value of 1,0. The fuzzy logic calculations will be done using MATLAB's fuzzy logic toolbox with the distribution of parameters and variables as represented in Figure 3.

Membership Function (MF) represents the degree of truth as an extension of valuation, which explains the condition level for every fuzzy parameter that is calculated (Goguen, 1967). It is usually represented by the notation of $\mu(x)$, with variable x as the value of the parameter. Language Variable (LV) is the graph that represents the value of the membership function for every value of parameter in the input that is between the interval of 0 and 1. MF fuzzy in this thesis uses both trimf (triangular membership function) and trapmf (trapezoidal membership function) to represent the fuzzy parameters. Some of the trapmf functions used also invoke the use of R-function and L-function special cases, which are defined when the trapezoidal function has parameter of $a = b = -\infty$.

During the process of building a fuzzy inference system, there is a lot of flexibility in characterizing fuzziness via graphically depicting the MF’s intervals and numbers. For this research, it is important to find a model and distribution of MF that is representative to the data; hence, this research uses relativity as the basis for deciding the distribution and configuration of membership function. First, the area “Indonesia” is chosen as the relative point for all 25 compiled relative points, as the data for Indonesia tends to be the aggregate of all provinces. However, there are some data in the parameter in which Indonesia’s relative point is not able to represent fairly. For these sets of data, this research uses median values as the substitute. Second, the Language Variable configuration is counted by subtracting -0.3 and adding +0.3 from the peak value in the graph. Last is the configuration of the overlap points, in which subtracting and adding the value of 0.2 is used from the farthest point of the middle graph. At this stage of processing, the negative and positive correlation classification for each parameter no longer has impact since the values have been equalized using relative points.

Using a sample parameter of GHG / Greenhouse Gas Parameter (coded as param1_ghg) in Figure 4, the configuration has 5 variables configured as the input with GHG-Vulnerability_Degree as the output. The LVs for each variable are Low, Average, and High. A sample of the fuzzy calculations used for a sample variable of PM10 are calculated using equations (1), (2) and (3). The language variable calculations for the membership function of variable PM10 are in equation (1) for “low”, equation (2) for “average”, and equation (3) for “high

These IF-THEN fuzzy rules are used for all 20 variables categorized into 4 groups of parameters. The calculations produce input fuzzy values which is the result of the process of fuzzification, which are next processed again to the fuzzy rules that are configured. In order to calculate the final results, which are in the form of Vulnerability_Score, the resulting calculations from the initial fuzzification of the parameters and variables are fuzzified again together. There are 4 Vulnerability_Degrees that have been calculated from 4 groups of parameters. These degrees are then aggregated into the final score, which will be symbolized with Zi for the next process of defuzzification. The value Zi contains the final defuzzification value for each parameter, which are then summed together. Next, the value is multiplied with the weight of each parameter which is symbolized by Wi which can be seen in equation (4). One data area is consisted of 4 parameters and 5 variables for each parameter.



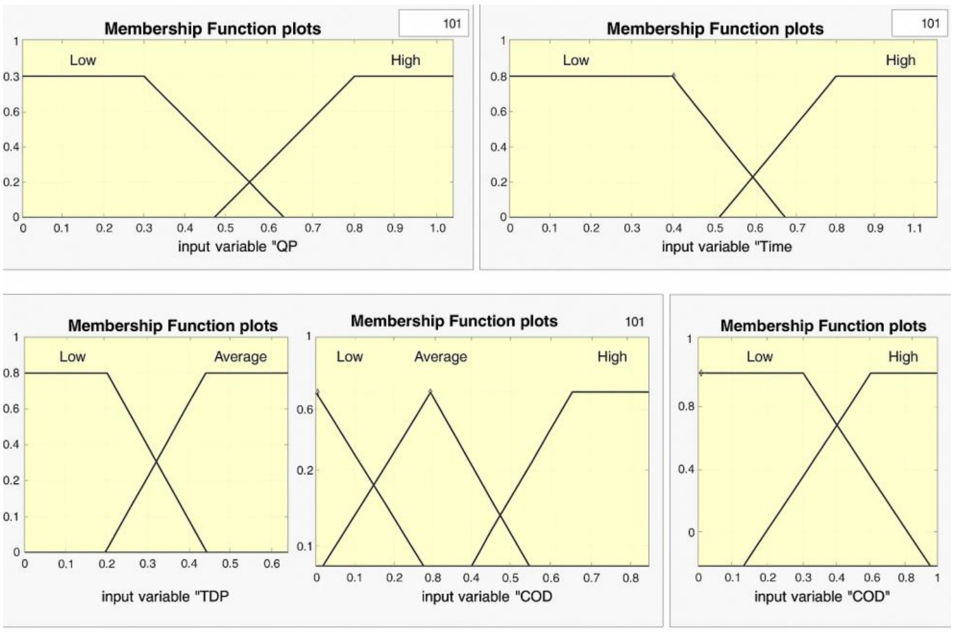


Figure 4. Membership Functions for GHG Parameter

The fuzzy rules that are used to calculate the Vulnerability Degree from the groups of parameters consisting of variables is the fuzzy rules for each parameter. After acquiring the values of Vulnerability_Degree from 4 parameters in each area datasets, the next and last step is to calculate the final score of Vulnerability Score, which will require its own fuzzy rules. There are three final decisions that will be produced: 1) If the score is below 0.4, then the area is LEAST VULNERABLE, 2) If the score is between 0.4 and 0.7, then the area is MODERATELY VULNERABLE; 3) If the score is above 0.7, then the area is MOST VULNERABLE. The final scoring result has membership functions which are depicted in Figure 5. The fuzzy rule base for final vulnerability score is shown in Table 3.

3.4. Fuzzy modelling for mapping variables and most vulnerable areas

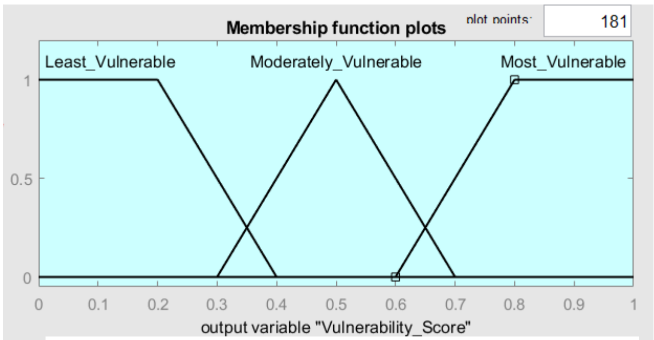


Figure 5. Membership Function for Final Scoring

The mathematical, statistical, and fuzzy rules calculations are applied to the datasets from 35 areas from 34 provinces of Indonesia with the addition of Indonesia's dataset from the aggregated values of 34 provinces. This study depicts 5 sample area datasets of relative values that will be fuzzified using the established fuzzy rules. These data for relative values have undergone the process of mathematical and statistical methods. The sample datasets are fuzzified using the calculations according to the fuzzy rules as follows:

Table 3. Fuzzy Rules for Final Scoring

	Vulnerability Degree							
Sample Datasets	GHG		GF		AF		WC	
Jakarta	0,518	Moderate_Risk	0,711	High_Risk	0,5	Moderate_Risk	0,711	High_Risk
Bali	0,289	Low_Risk	0,5	Moderate_Risk	0,496	Moderate_Risk	0,527	Moderate_Risk
Kalimantan Barat	0,503	Moderate_Risk	0,5	Moderate_Risk	0,557	Moderate_Risk	0,501	Moderate_Risk
Maluku	0,289	Low_Risk	0,5	Moderate_Risk	0,543	Moderate_Risk	0,593	Moderate_Risk
Papua	0,289	Low_Risk	0,5	Moderate Risk	0,5	Moderate_Risk	0,711	High_Risk

Rule 1	IF Vulnerability_Degree (LOW) THEN Least Vulnerable
Rule 2	F Vulnerability_Degree (LOW) AND Vulnerability_Degree (MID) THEN Least Vulnerable

Afterwards, the fuzzy results from the aggregation of variables are fuzzified again in order to find the final result, which is the final vulnerability score for the area dataset. The final vulnerability score is shown in Table 5 alongside with the decision produced.

The fuzzy results from the sample area datasets reveal the final vulnerability scores, which determine the decision on what area is most vulnerable to the impacts of climate change and thus, requires the most attention. From Table 4.11, the fuzzification score for area Jakarta is 0.6145, the score for area Bali is 0.498, the score for area Kalimantan Barat is 0.502, the score for Maluku is 0.5215, and the score for Papua is 0.5. The defuzzification process using equation (4.40) multiplies all the scores by the weight of the variable (Wi) = 1. In the final resulting vulnerability score, it is now known that area Jakarta is the most vulnerable area while Bali is the least vulnerable area.

Table 4. Fuzzy Results for Variables

Rule 3	F Vulnerability_Degree (MID) THEN Moderately Vulnerable
Rule 4	F Vulnerability_Degree (LOW) AND Vulnerability_Degree (MID) AND Vulnerability_Degree (MID) THEN Moderately Vulnerable
Rule 5	F Vulnerability_Degree (MID) AND Vulnerability_Degree (HIGH) THEN Most Vulnerable
Rule 6	F Vulnerability_Degree (HIGH) THEN Most Vulnerable

The results of the Vulnerability Degree analysis in Table 4 show variations in vulnerability levels in the five sample provinces based on four main parameters. Jakarta has a GHG score of 0.518 (Moderate Risk), GF 0.711 (High Risk), AF 0.500 (Moderate Risk), and WC 0.711 (High Risk), indicating that geological factors and weather conditions are the main contributors to the high vulnerability of this region. Bali shows a GHG score of 0.289 (Low Risk) and the other three parameters are in the Moderate Risk category, indicating relatively balanced vulnerability across all dimensions. West Kalimantan has consistent scores in the Moderate Risk category for all parameters, indicating evenly distributed vulnerability without any dominant factor. Maluku shows a low GHG value (0.289; Low Risk) but the other three parameters are in the Moderate Risk category, indicating that the primary influence comes from non-GHG factors. Meanwhile, Papua has a low GHG score (0.289; Low Risk), GF and AF at the Moderate Risk level, and WC is quite high (0.711; High Risk), indicating that extreme weather conditions are the most significant factor in determining the vulnerability of this region.

Table 5. Final Fuzzy Results and Decision

Sample Datasets	Fuzzy Parameters	Vulnerability Score	Decision
Jakarta	[0.518;0.711;0.5;0.711]	0,6145	Most Vulnerable

Bali	[0.289;0.5;0.496;0.527]	0,498	Least Vulnerable
Kalimantan Barat	[0.503;0.5;0.557;0.501]	0,502	Moderately Vulnerable
Maluku	[0.289;0.5;0.543;0.593]	0,5215	Moderately Vulnerable
Papua	[0.289;0.5;0.5;0.711]	0,5	Moderately Vulnerable

The final results of the fuzzy logic calculations in Table 5 show that Jakarta has the highest vulnerability score of 0.6145, categorizing it as Most Vulnerable, with significant contributions from geological factors and weather conditions. Bali has the lowest score of 0.498 and is categorized as Least Vulnerable, reflecting relatively stable conditions across all parameters. West Kalimantan with a score of 0.502, Maluku with 0.5215, and Papua with 0.500 are all in the Moderately Vulnerable category. This indicates that these three provinces have moderate vulnerability levels, although Papua shows a higher risk tendency in weather condition parameters, while Maluku and West Kalimantan exhibit a more even distribution of vulnerability across parameters.

The results of this study reveal variations in the level of climate change vulnerability between provinces in Indonesia, with differences in the contribution of factors in each region. Based on the Vulnerability Degree score, it is evident that Jakarta has the highest value for the geological factor parameter (0.711; High Risk) and weather conditions (0.711; High Risk), while the greenhouse gas factor (0.518) and anthropological factor (0.500) are categorized as Moderate Risk. This indicates that Jakarta's vulnerability risk is triggered by a combination of limited geological capacity to absorb the impacts of climate change, such as low absorption areas and high land conversion, as well as increasingly frequent extreme weather conditions. This finding is consistent with Kazak's (2018) study, which shows that densely populated urban areas with low environmental adaptation capacity tend to have high vulnerability, particularly to heatwaves and tidal flooding.

In contrast, Bali has a relatively low Vulnerability Degree score for greenhouse gas parameters (0.289; Low Risk) and moderate scores for the other three parameters, resulting in a total Vulnerability Score of 0.498, categorizing it as Least Vulnerable. The low GHG score in Bali can be attributed to relatively good air quality, spatial distribution that still preserves green open spaces, and environmental management based on local wisdom. However, Bali's geological parameters and weather conditions still show moderate vulnerability, which needs to be anticipated through the strengthening of hydrometeorological disaster mitigation.

West Kalimantan, Maluku, and Papua are in the Moderately Vulnerable category with final scores of 0.502, 0.5215, and 0.500, respectively. In West Kalimantan, all parameters indicate moderate vulnerability, which indicates a relative balance between physical and socioeconomic risk factors. Maluku shows a low score for GHG (0.289) but moderate vulnerability in other parameters, likely influenced by the vulnerability of coastal ecosystems to sea level rise. Meanwhile, Papua has a low GHG score but a high weather condition score (0.711), indicating that extreme weather is the dominant threat to this region, consistent with the IPCC (2022) report highlighting the high sensitivity of tropical regions to weather variability.

The results of this study are in line with Kazak (2018) findings, which show that urban areas with high density and low environmental adaptation capacity tend to have high vulnerability levels, as seen in Jakarta in this study. However, unlike Kazak, who only used environmental and thermal comfort indicators, this study integrated socioeconomic indicators to provide a more comprehensive picture. Hanoon et al. (2022) also applied fuzzy logic to assess the vulnerability of urban areas, but their scope was limited to the city scale, whereas this study analyzed 34 provinces in Indonesia. Meanwhile,Czimber & Gálos (2016) focused on the forestry and agriculture sectors with biophysical indicators, without considering the adaptive capacity of communities.

The dominant factors influencing differences in vulnerability levels between provinces include: (1) air pollutant concentrations, particularly PM10 and NO_2, which contribute significantly to GHG parameters; (2) geological capacity to absorb water runoff and maintain land productivity; (3)

urbanization levels and infrastructure density that influence anthropological factors; and (4) the intensity of extreme rainfall, maximum temperatures, and the number of hotspots in weather condition parameters. The combination of these factors forms a unique vulnerability profile for each province.

The policy implications of this research are the need for location-specific climate change adaptation strategies. For provinces with high vulnerability scores such as Jakarta, priority policies can focus on increasing geological capacity through the expansion of green open spaces, revitalization of river basins, and control of land conversion. For regions with high weather vulnerability, such as Papua, adaptation strategies should emphasize early warning systems, improving infrastructure resilience to extreme weather, and diversifying community livelihoods. Meanwhile, for regions in the Least Vulnerable category, such as Bali, policy approaches should be directed at maintaining current positive conditions through strengthening community-based environmental governance and sustainable tourism.

From a technical perspective, the use of equal weighting in the model provides an initial objective overview. However, for future policy implementation, weights can be further developed based on expert judgment or the Analytic Hierarchy Process (AHP) method to provide more proportional priorities according to the local context. In addition, this method can be expanded by integrating higher-resolution spatial data (e.g., Sentinel or Landsat satellite data) to identify variations in vulnerability within a province.

Nevertheless, this study has several limitations. First, the data resolution used is at the provincial level, so it does not capture vulnerability at the regency/city level. Second, some of the data are derived from secondary sources and climate models, which may introduce data bias and result uncertainties. Third, model validation was conducted by comparing trends with expert assessments and global indices, without direct field testing or in-depth case studies. In the future, field validation and collaboration with local governments and communities will strengthen the accuracy and relevance of this model.

4. Conclusion

The conclusion of this study is that the development of a Fuzzy Logic-based Intelligent Decision Support Model (IDSM) is capable of mapping climate change vulnerability across 34 provinces in Indonesia more comprehensively by integrating four main parameter groups, namely greenhouse gases, geological factors, anthropogenic factors, and weather conditions encompassing 20 variables. The analysis results indicate that Jakarta falls into the Most Vulnerable category, with high vulnerability in geological and weather factors; Bali is in the Least Vulnerable category; while West Kalimantan, Maluku, and Papua are classified as Moderately Vulnerable. These findings confirm that the vulnerability profile of each province is influenced by a different combination of environmental, social, and economic factors, meaning that climate adaptation and mitigation strategies need to be tailored to the local characteristics of each region. This model can serve as a relevant decision-support tool for policymakers in setting intervention priorities and allocating resources to effectively reduce climate change risks.

Declaration of AI and AI assisted technologies in the writing process

The authors used ChatGPT to support the writing and editing process of this manuscript. All content was reviewed and approved by the authors.

Declaration of Competing Interest

The authors confirm that there are no conflicts of interest related to this research and publication.

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