Assessment of the sensitivity of climate risk variables in opposed to climate hazards (study case: Pekalongan City)

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Abstract. This study focusses on assessing the climate risk in Pekalongan City by calculating the exposure, sensitivity, adaptive capacity, and vulnerability by incorporating Principal Component Analysis (PCA) then conceptualize it into climate risk concept by connecting it with their respective climate hazards consist of rainfall and tidal flood. The research aims to develop climate risk index while also identifying the most sensitive risk components to communicate appropriate interventions and adaptation strategies. Weighting of variables method conducted by using PCA and simple sensitivity analysis by using the deficit index of each component's index gained from PCA weighted with the ones that gained from the same weighted. Results exhibit that Northern Pekalongan sub-districts are the one that having high climate risk index, especially sub-districts such as Krapyak and Bandengan, reaching climate risk index almost up to 1. Sensitivity analysis founds that variable including settlement distance to rivers, fisherman families, and clean and healthy behavior families, significantly affect climate risk certainly affect the climate risk levels in a certain sub-district. From the pilot simulation of communicating best adaptation strategies, Krapyak sub-districy should addressed high-weight variables, such as the distance of business districts from the coast and the number of small-medium industries, in addition to addressing the most sensitive variables. Adaptation suggestions such as coastal protection, expanding gender-sensitive resilience programs, and supporting small-medium industries with climate-resilient technologies should be implemented.

1 Introduction

One of the most affected coastal areas by coastal flooding due to climate variabilities and their interaction with socio-economic and geophysical factors is Pekalongan City. Some Pekalongan Sub-districts are vulnerable to tidal floods due to high tides, erosion, and land subsidence [1]. Simultaneous events of waves run-up that cause local sea level rise and medium rain intensity in the coastal area of North Pekalongan District that risen the possibility of pluvial and tidal flooding [2]. Determining the compound drivers of Pekalongan

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local flooding and simulating the flood hazard by considering geo-physics and climatic factors are the initial steps to address the compound flood hazard level, which then serves as a basis to adopt the best disaster mitigation and adaptation efforts.

Mitigation and adaptation options can be determined through climate risk assessment (CRA). Mandatory understanding of climate hazard components across timescales and spaces (e.g, the changes of extreme rainfall likelihood in a certain region), exposures (e.g locations of assets and value chains) and vulnerability as a component of sensitivity and adaptive capacity (e.g the readiness of communities in opposed to climate hazards and the inclusivity of some specific social groups) are needed [3]. Furthermore, this assessment serves as a basis to indicate critical sub-indicators or indicators of vulnerability aspects that are potentially adversely affected by specific climate hazards based on the result.

The importance or weights of climate risk components' variables can be developed through statistical approaches such as Principal Component Analysis (PCA) [4]. Primary PCA is not well-suited for estimating the weights of various socio-economic variables, as it primarily assigns weights to continuous data. However, climate risk assessments often involve categorical variables, which are typically transformed into dummy variables. To address this challenge, the Filmer & Pritchett PCA procedure is applied, allowing for the integration of mixed data types within each component's indicator [4]. This approach involves converting categorical and ordinal variables into binary representations, ensuring compatibility with PCA. The factor loadings of principal components with eigenvalues greater than one serve as weights, highlighting the relative contribution of each variable in explaining climate risk variations. This method enables a more comprehensive assessment of climate risk, particularly in areas where socio-economic and environmental conditions significantly influence vulnerability.

Conducting a sensitivity analysis of the result of PCA-based CRA is crucial to ensure the robustness of the CRA result. Sensitivity analysis aimed to determine which variables have the crucial impact in the model output. In the context of CRA, this analysis was used to inform stakeholders about the reliability of the risk assessments, therefore it served as a ground basis for involved parties to intervene in the most crucial indicators of climate risk components. This study aims to develop a climate risk index using an index-based approach with PCA (i), exhibit the most sensitive indicators and sub-indicators of the climate risk components (adaptive capacity, sensitivity, exposure) (ii), and inform how to address the most critical variables of climate risk components that incorporate the sensitivity analysis result within the resulted climate risk index in Pekalongan City as the pilot project (iii).

2 Method

2.1 Research time and place

This study was conducted within the whole of Pekalongan City from June 2024 until September 2024 (Fig 1). Pekalongan City is a strategic node on the northern coast of Java Island as it is located between Jakarta and Surabaya. Therefore, Pekalongan City is considered a strategic area from an economic perspective. In the Regional Medium-Term Development Plan (RPJMD) of Pekalongan City for 2021-2026, the dynamics of socio-economic and community development are focused on its leading potentials, namely batik and fisheries. In addition, the government is also striving to develop the water tourism sector as another mainstay. However, the development of these leading potentials faces various challenges due to threats related to the impacts of climate change, particularly in all the villages in North Pekalongan District (seven villages) located in the coastal areas of Pekalongan City and one village in West Pekalongan District. These areas are frequently affected by tidal flooding due to sea level rise exacerbated by land subsidence [5].

Pekalongan City is one of the cities in Central Java located between Batang Regency and Pekalongan Regency. Geographically, Pekalongan City is located between 6º 50’ 42" - 6º 55’ 44” South Latitude and 109º 37’ 55” - 109º 42’ 19” East Longitude. Administratively, Pekalongan City is divided into four districts and 27 villages with a total area of 46.42 km² or 0.14% of the total area of Central Java. Topographically, Pekalongan City is located in the lowlands of the northern coast of Java Island with an elevation ranging from 1 meter above sea level (masl) in the northern part to 6 masl in the southern part. Pekalongan City has a coastline of approximately 6 to 7 km stretching from west to east, facing directly towards the Java Sea. Morphologically, its coastline is characterized by gentle slopes dominated by sandy expanses, not rocky, with open waters, not a bay, and relatively low wave strength. The western coastal area has fine sand and tends to be mixed with vegetation such as shrubs or fields, while the eastern coastal area tends to have muddy sand. The coastline consists of a long sandy beach with a coastal plain extending inland. The river system flowing into this coast has low energy, so during high tide, seawater can flow far inland through the river channels. Pekalongan City is dominated by very flat areas with a slope ranging between 0-8%. The difference in elevation between places is minimal. Certain areas have been identified to be below sea level, such as in the Pabean area of Padukuhan Kraton Village in North Pekalongan District. As a result, this area experiences permanent inundation [6].

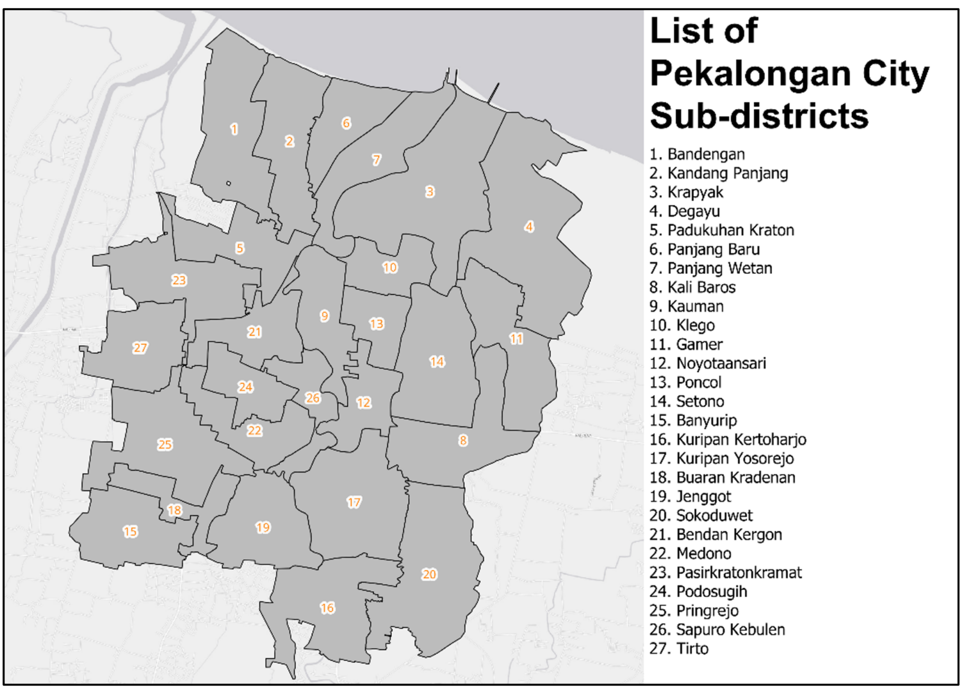

Fig. 1. Pekalongan City administrative map.

2.2 Tools and materials

This research utilized MS Excel, Python for climate analysis, indicator weighting, and statistical analysis, and QGIS 2.34 for mapping climate risk components. Climate data on ocean climatology and biophysics were sourced from Indonesia’s Geospatial Information Agency (BIG), while rainfall data came from the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPs). Socio-economic data were gathered from Village

Potency, BPS, and other institutions. Data requirements were based on the concept and elements of each climate risk component. Following a literature review and recommendations from a Focus Group Discussion (FGD) with LGUs, ministries, and NGOs, the study categorized risk components into indicators, sub-indicators, and data sources, which are detailed below.

Table 1. Factors, indicators, variable data used for comparison and assessment of climate risk in Pekalongan City.

Component	Initiate Indicators	Variable (variable type)	Source and Period
Exposure	Exposed Socio-Economic Aspect	Population Density (People/Ha) (Numeric)	Podes 2021
		Settlement Density (Houses/Ha) (Numeric)	Podes 2021
	Biophysics	Average Elevation (m) (Numeric)	Podes 2021
		Landuse_Settlement (Binary)	Podes 2021
		Landuse_Agricultural Field (Binary)	Podes 2021
		Landuse_Fish Pond (Binary)	Podes 2021
	Livelihood and Settlement Distance	Settlement Distance to Coastal Areas (Km) (Numeric)	Geospatial Information Agency 2020
		Business District Distance from Coastal Areas (Km) (Numeric)	Geospatial Information Agency 2020
		Settlement Distance to River (Km) (Numeric)	Geospatial Information Agency 2020
		Business District Distance from River (Km) (Numeric)	Geospatial Information Agency 2020
Sensitivity	Main Livelihoods	Main Income Sources_Agriculture Forestry and Fisheries (Binary)	Indonesian Statistical Bureau 2023
		Main Income Sources_Manufactoring Industries (Binary)	Indonesian Statistical Bureau 2023
	Unhygiene Waste Disposal Facilities	Industrial waste disposal to the river (Binary)	Podes 2021
	Vulnerable Groups	Number of Women (Numeric)	Health Profile 2020
		Number of Children (0-14) (Numeric)	Health Profile 2020
		Number of Elder Group People (usia 65+) (Numeric)	Health Profile 2020
		Number of People with Disabilities (Numeric)	Podes 2021
		Fisherman Families (Numeric)	Podes 2021

Table 2. Factors, indicators, variable data used for comparison and assessment of climate risk in Pekalongan City (*continue*).

Component	Initiate Indicators	Variable (variable type)	Source and Period
Adaptive Capacity	Social and Institutional Modalities	PKH Recipients (Numeric)	Podes 2021
		Number of Farmer Groups (Numeric)	Podes 2021
		Number of Small-Medium size Industries (Numeric)	Podes 2021
		Number of Societal Groups (Numeric)	Podes 2021
	Health and Well-being	Number of Hospitals (Numeric)	Podes 2021
		Clean and Healthy Behavior Families (Numeric)	Podes 2021
	Environmental and Ecological	Green Space Area (Numeric)	Podes 2021
		Climate Village Program/Proklim (Binary)	Podes 2021
	Disaster Resilince Program	Disaster-Resilient Villages (Binary)	Podes 2021

2.3 Overall research procedures

The production of climate risk products is conducted through several steps consisting of Literature Review, Climate Risk Products, and Sensitivity Analysis. Several literature materials from IPCC AR5th, vulnerability sourcebook published by The German Embassy, and technical guidelines to determine climate change actions for regional action plan from Government Regulations were necessary to synthesize Conceptual Climate Risk Framework that considers acceptable climate risk terminologies [7,8]. This synthesized Conceptual Framework serves as a basis to select appropriate climate risk variables that could describe the local climate risk in Pekalongan City. PCA from variables level were conducted to determine the weight of each variable and principal component groups to the corresponding climate risk product. Lastly, sensitivity analysis is conducted by defining the deficit between the index gained from the equal weighted analysis and from the stepwise PCA. This result serves to inform which variables influence the most to the final climate risk index.

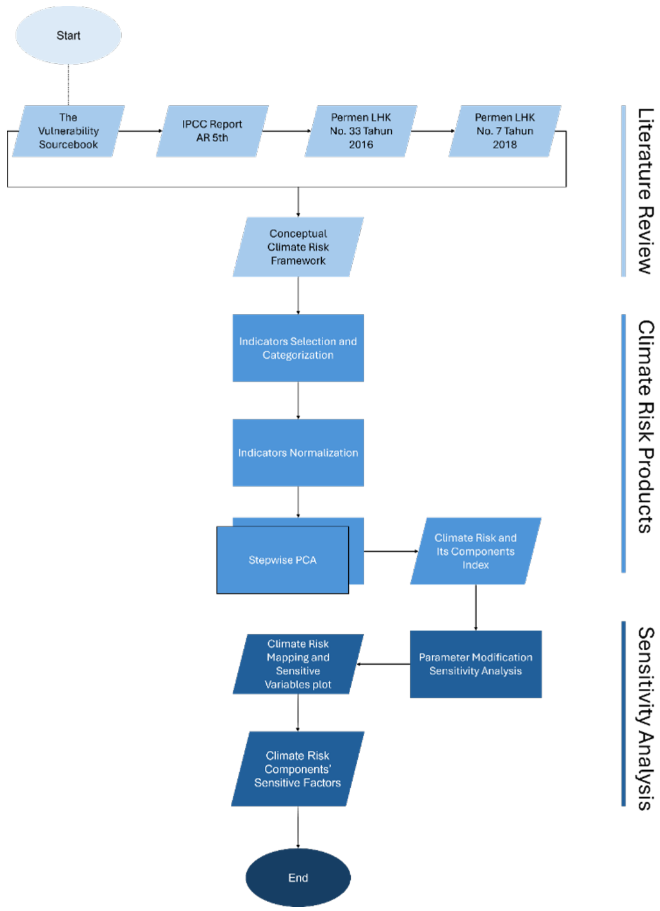

Fig. 2. Workflow diagram to produce climate risk products and sensitivity analysis.

2.4 Data analysis

2.4.1 Rainfall return period Hazard Analysis

Pekalongan City, classified as Type B based on the Schmidt-Ferguson Classification, experiences high annual rainfall with minimal dry periods. A lump model approach was used to calculate rainfall return periods of 2, 10, 15, and 25 years, essential for assessing climate-induced hydrometeorological hazards. Historical rainfall data were analyzed by ranking values to determine the corresponding rainfall levels for each return period. The equation for estimating the ranking of certain rainfall return period value is provided below [9]:

$$Rank = \frac{N+1}{T}$$

Information:
Rank= Rank of rainfall value for a specific return period
Rsorted= Number of observations (non-zero rainfall data points) in the time series for the current grid point.
T = Rainfall return period

Then, the equation proceeds to estimate the rainfall value for a specific return period using equation below:

$$RT = Rsorted[k - 1]$$

Information:
RT= Rainfall value for a given return period T.
Rsorted= Rainfall values sorted in descending order.
k = ⌊T/N+1⌋: The rank corresponding to the return period T, where N is the total number of observations, and T is the return period.

2.4.2 Tidal flood inundation hazard

Tidal flood inundation in this analysis was determined using the Mean Sea Level (MSL) and Highest High-Water Level (HHWL) deficit, calculated using the Admiralty Method for the period of May to June 2024. A DEM-based approach was employed to assess sea level inundation by removing sinks from the deficit between MSL and HHWL [10]. Subsequently, a standard deviation normalization method was applied to generate an index from the inundation raster, providing a comprehensive understanding of tidal flood and erosion dynamics. Neighbouring raster analysis was conducted to limit the extent of the tidal flood inundation by assessing the between adjacent raster cells. This approach conducted to ensure the inundation is limited within to the surrounding topography.

2.4.3 Overall Hazard Analysis

While all others components supposedly group by their principal components, hazard variables were group manually according to their initiate indicators. Simple ranking method were conducted to determine the weight of each rainfall hazard, so that 25-year rainfall return periods was among the highest rank above 10, 15, and 5 years. From Table 1, the weight of intiate indicators of Rainfall Return Period Value and Sea Level Inundation are supposedly the same. All the hazard variables were standardized using z-score method.

2.4.4 Exposure, sensitivity, and adaptive capacity analysis

Standard deviation normalization method was conducted to convert each numerical exposure, adaptive capacity, sensitivity, and hazards variables that are numeric. Detailed formula is detailed below [11]:

$$Normalized\ value : \frac{Observed\ value - Mean}{Standard\ Deviation}$$

Information:
Observed value = Real value from the data
Mean = Data variable’s average
Standard Deviation = Standar deviation for each numerical variable

2.4.5 Assigning variables, sub-indicators, and indicators’ weight

Climate risk components can be defined using Principal Component Analysis (PCA), which is commonly applied in multi-criteria analysis involving numerical and categorical data [11]. While numeric variables can be normalized, to handle ordinal variables, the Filmer and Pritchett procedure can be used, transforming them into binary (dummy) variables through one-hot encoding [12]. Each ordinal category is represented as a separate binary variable, indicating its presence (1) or absence (0). This method ensures that the ordinal nature of the data is respected in analyses like PCA without assuming linearity between categories

The weighting of variables and indicators was based on their factor loadings within each climate risk component. Variables with factor loadings of 0.3 or higher within one principal component were grouped []13. The number of principal components retained was determined by eigenvalues greater than 1. The weight of each variable within climate risk component was calculated by squaring its factor loading, for those that passed the 0.3 threshold, and dividing by the sum of squared loadings of all qualifying variables. Below is the detailed breakdown of the variable weights within the climate risk components [11]:

$$Weight = \frac{(Factor\ loading_{kj})^2}{Sum\ of\ \text{the}\ Factor\ loading}$$

Where factor_loading$_{kj}$ is the value of the factor loading of indicator k in the principal component j and eigenvalue$_j$ is the eigenvalue of the jth principal component. Finally, the climate risk index can be calculated as a weighted aggregation of the defined variables and indicators aggregation.

Furthermore, to obtain the weight for each climate risk components (exposure, sensitivity, and adaptive capacity), the percentage of variance from each principal component was divided by the accumulated variance explained as below [11]:

$$\text{Wc} = \frac{\%variance\ explained}{Total\%Varianceexplained}$$

2.4.6 Risk assessment with IPCC Assessment Report 5th (AR-5) framework

Climate risk in this assessment is defined through the integration of numerous mathematical conceptualizations of the IPCC AR-5 framework that have been proposed by multiple researchers(4,7,8,14). The IPCC AR-5 suggests that climate risk is the function of how vulnerable the exposed system is to climate hazards. The climate risk conceptualization lies in the linearity between exposure, vulnerability, and hazard that is exhibited through the report of IPCC AR-5 framework in Fig. 1, this framework was initially conceptualized by researchers into simple multiplication formula [8]:

$$R = H\ x\ V\ x\ E$$

Information:
R = Climate risk (probability)
V = Vulnerability (as a function of sensitivity and adaptive capacity; represent in probability)
E = Exposure (exposure)

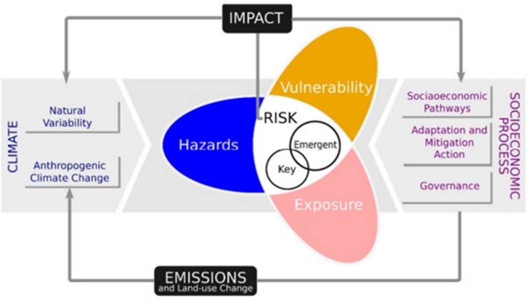

Fig. 3. Climate risk framework AR-5 framework.

This linearity was based on the definition of each climate risk component. Exposure refers to the presence of people, livelihoods, species, and other aspects that could be adversely affected. While sensitivity defines the system's susceptibility to harm. On the other hand, adaptive capacity is defined as the internal capacity of the system ability to recover from the anticipated climate hazards. Vulnerability in the context of climate risk could be interpreted as the residual value between sensitivity and adaptive capacity. Therefore, the conceptual formula above could be reformulated into another simple multiplication formula that maintained the same linearity:

$$Risk = \frac{(H * Wh + (S * Ws - AC * Wac) + E * We)}{3}$$

Information:
H = Hazard
Wh = Hazard weights or loadings
S = Sensitivity
Ws = Sensitivity weights or loadings
AC = Adaptive Capacity weights or loadings
Wac = Adaptive Capacity weights or loadings
E = Exposure
We = Exposure weights or loadings

2.4.7 Sensitivity analysis to determine the most sensitive indicators within the climate risk components

A sensitivity analysis was conducted to identify the most sensitive climate risk variables by comparing PCA-weighted and mean-weighted indices [15]. PCA reduced dimensionality, retaining key variations, while the mean-weighted index treated all variables equally. The sensitivity of each variable was assessed by calculating the absolute difference between the two indices, with higher standard deviation indicating greater sensitivity. Variables with a larger standard deviation are more volatile and influential in the climate risk index, while those with a smaller standard deviation are more stable.

This analysis aims to prioritize internal variables of each risk component that have negligible impact on the final climate risk index. Hence, this procedure was only conducted for exposure, sensitivity, and adaptive capacity variables because, in the IPCC framework, hazard refers to the physical climate event or trend (e.g., temperature rise, extreme weather) that could cause harm, and is typically treated as an exogenous factor in risk assessments. In contrast, exposure represents the degree to which a system is exposed to a climate hazard, sensitivity reflects how sensitive the system is to that exposure, and adaptive capacity denotes the ability of the system to adjust to these stresses. Since hazard is not influenced by the system's internal variables, its inclusion would not contribute to the analysis of sensitivity, which is focused on how system attributes respond to the changing climate risks.

2.4.8 Communicating the most sensitive variables to intervene within the climate risk components

The step to determine action or intervention to reduce the climate risk in a specific sub-district could be broken down into:

1. Choosing sub-district with considerably the highest risk index, then assess the sensitive variables index within the sub-districts, check whether the adaptive capacity is under the threshold of 0 for numeric variables or below 1 for binary variables. While for the other components (sensitivity and exposure) the reasoning is vice versa.

2. If the indices were not far enough from the step (1) threshold, then the proposed actions and interventions should focus only on variables and principal components that have high weight
3. If they are, then the proposed action shoul focusses on both with further emphasis on the sensitive variable ones.

3 Results and discussion

3.1 PCA resulted weights

Three principal components with eigenvalue higher than 1 for each component was extracted (Table 2). The table showed that the extracted components explain a substantial portion of the variation in the data, with the first component of Exposure accounting for 32% of the variance, the second component for 30%, and the third for 20%, accumulatively 82% for all three variances. For Sensitivity, the first component accounts for 32% of the variance, the second for 29%, and the third for 19%, reaching to 80% of cumulative variance. In Adaptive Capacity, the first component explains 25% of the variance, the second component accounts for 23%, and the third for 19%, with a cumulative variance of 67%. These results indicate that the first few components are the most significant in explaining the variation within each component of climate risk, with the Exposure and Sensitivity components showing the highest cumulative variances.

Table 2. Eigenvalues and variance explained for each principal component

Components	Principal Components	Eigenvalues	Variance Explained (%)	Accumulation of Variance Explained (%)
Exposure	1	2.15	0.32	0.32
	2	2	0.3	0.62
	3	1.32	0.2	0.82
Sensitivity	1	3.95	0.32	0.32
	2	1.49	0.29	0.61
	3	1.06	0.19	0.8
Adaptive Capacity	1	1.94	0.25	0.25
	2	1.74	0.23	0.48
	3	1.46	0.19	0.67

All the variables that passed the factor loadings threshold of 0.3 for each component's PC were determined to be grouped as one PC for each climate risk components (Table 3) as it substantially contributed to the PCA's principal components. The PCA analysis exhibited that exposure was highly influenced by PC1 (0.62) with variables consisting of Settlement Distance to Coastal Areas (0.34) and Business District Distance from Coastal Areas (0.66), which indicates the exposed coastal hazard to the climate risk. The second component, PC2 having weight almost 0.48 defined the assets exposed to the river induced climate hazards. PC2 was defined by Settlement Distance to River (0.26) and Business District Distance from River (0.74).

While for sensitivity, the first PC was considerably influenced by Vulnerable Group such as Number of Female (0.61), Number of Children with age zero to fourteen (0.24), and number of Elderly People (0.24). While the second PC emphasizes on marginalized people as part of the vulnerable group, with Certified Poor People (0.59) and Fisherman Families

(0.41). The third components from sensitivity solely defined by the Number of People with Disabilities (1.00).

Furthermore, the first PC of adaptive capacity (0.53) are defined by the importance of Small-Medium size Industries (0.60) and Societal Groups (0.40), serves as a sub-district capacity basis to adapt, while the second component (PC2) highlighted the role of Clean and Healthy Behavior Families (0.32) and Number of Hospitals (0.68), highlighting the healthcare role on adaptive capacity.

Table 3. Principal Component Analysis (PCA) weight calculations

Components	Variables	Variables Weight	Principal Components	Principal Components Weight
Exposure	Settlement Distance to Coastal Areas (Km)	0.34	1	0.62
	Business District Distance from Coastal Areas (Km)	0.66		
	Settlement Distance to River (Km)	0.26	2	0.48
	Business District Distance from River (Km)	0.74		
Sensitivity	Number of Female	0.27	1	0.61
	Number of Children (0-14)	0.24		
	Number of Elder Group People (usia 65+)	0.24		
	Number of Female Head of Household	0.26		
	Certified Poor People (SKTM) (People)	0.59	2	0.23
	Fisherman Families	0.41		
	Number of People with Disabilities	1.00	3	0.16

Table 3. Principal Component Analysis (PCA) weight calculations (*continue*)

Components	Variables	Variables Weight	Principal Components	Principal Components Weight
Adaptive Capacity	Number of Small-Medium size Industries	0.60	1	0.53
	Number of Societal Groups	0.40		
	Clean and Healthy Behavior Families	0.32	2	0.47
	Number of Hospital	0.68		

3.2 Hazard, exposure, sensitivity, adaptive capacity, and vulnerability

The hazard index in Pekalongan city shows distinguishable pattern with the northern areas specifically, Bandengan, Kandang Panjang, Krapyak, Panjang Baru, and Degayu—showing a high hazard classification, approaching a value of 1. This high value is attributed to the doubling hazard of tidal flood inundation and return period rainfall induced hazard, which is evidence by the redness of the scattered raster near the coastal areas of Pekalongan. The usage of DEM-based tidal flood inundation also highlights that sub-districts located in the northern part of Pekalongan are considerably submerge as the difference between HHWL and MSL rises. Since these areas are positioned along the coast, they experience frequent tidal flooding due to the rising sea levels, which, when combined with rainfall from heavy storms (as indicated by the ranking of rainfall return periods), result in a compounded risk.

On the other hand, north-eastern of Pekalongan, which appears to have a lower rainfall hazard index, can be explained by its geographical positioning and topography. The north-eastern part of Pekalongan exhibits a lower rainfall hazard index primarily due to its geographical positioning and topography. This area is farther from the coastline, which means it is less exposed to the immediate impacts of coastal storms and tidal surges that could amplify rainfall and flooding risks. Additionally, this region experiences lower return periods for rainfall events, meaning the rainfall events here are less frequent or intense compared to the coastal areas.

The southern part of Pekalongan displays moderate to high hazard levels, with hazard indices nearing 0.5. This area's hazard classification is primarily influenced by high return periods of rainfall, which indicate that significant rainfall events, such as those with return periods of 25, 15, or 10 years, occur more frequently and with greater intensity in this region compared to other parts of the city.

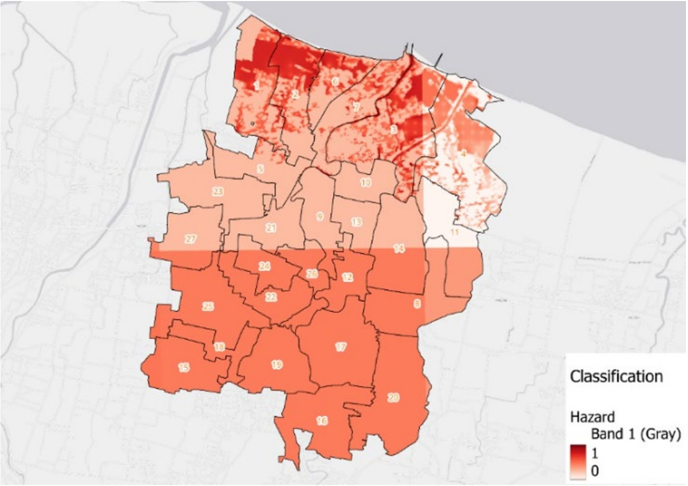

Fig. 3. Pekalongan sub-districts' climate hazard.

Fig.4 suggests the visible difference between the Exposure, Sensitivity, Adaptive Capacity, and Vulnerability indices for Pekalongan City based for PCA-weighted and same-weight methods. To begin with, consistent exposure index was shown in the northern areas of Pekalongan, including Bandengan, Krapyak, and Panjang Wetan, except Panjang Wetan. This suggests that most northern areas are similarly exposed to climate hazards like coastal flooding and high rainfall [2], but Panjang Wetan has unique characteristics, such as its proximity to coastal areas or specific demographic vulnerabilities, that affect its classification differently under the PCA-weighted method.

However, in the middle of the Pekalongan, the exposure index is considerably similar for both methods, although there are some exceptions for Kauman, Poncol, and Noyo Bansari sub-districts. Moreover, the sensitivity index in those sub-districts were also higher with the PCA-weighted approach, indicating these areas are sensitive to the increase or decrease of index from specific sensitivity variables. This higher sensitivity is likely linked to socio-economic factors, such as higher poverty rates or more vulnerable populations in these areas.

The Adaptive Capacity index shows that a few sub-districts, including Bandengan and Krapyak, are classified differently between the PCA-weighted and same-weight methods. The PCA method suggests a higher adaptive capacity in these areas, likely because it better captures the influence of local infrastructure or resource availability that reduces vulnerability. These differences in adaptive capacity result in variations in the Vulnerability index, particularly in the middle part of the city. Where adaptive capacity is higher, the vulnerability index is lower, demonstrating the critical role of local resilience factors in determining overall vulnerability.

To further understand the root causes of these differences, the Sensitivity Analysis in section 3.3 will identify the key variables contributing to the variations between the two methods. This analysis will highlight the most influential factors for each component, offering valuable insights for improving climate resilience and guiding targeted interventions in Pekalongan City.

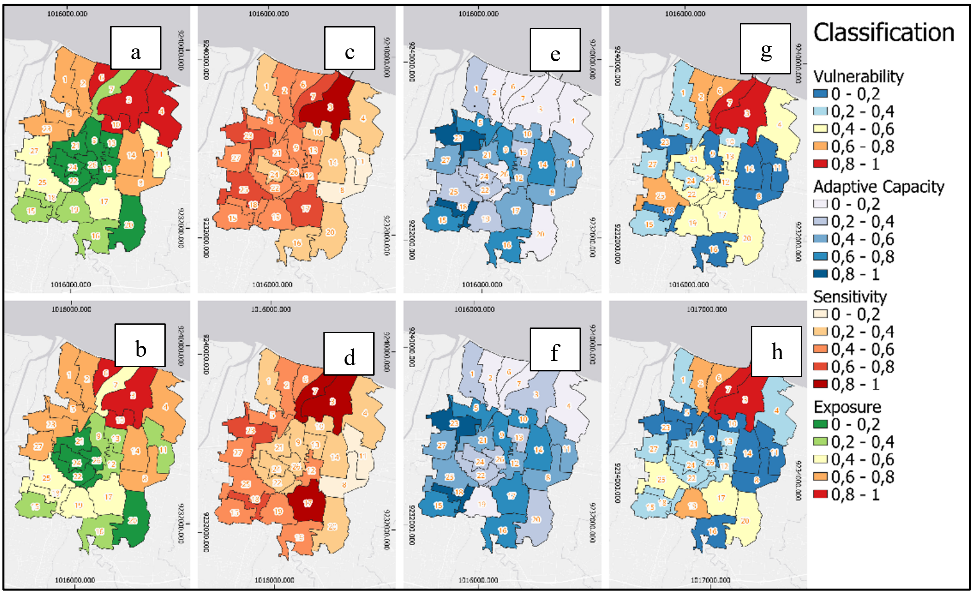

Fig. 4. Pekalongan sub-districts' exposure, sensitivity, adaptive capacity, and vulnerability from PCA-weighted and same-weighted methods: Exposure (a): PCA-weighted (b): Same-weighted, Sensitivity (c): PCA-weighted (d): Same-weighted, Adaptive Capacity (e): PCA-weighted (f): Same-weighted method, Vulnerability (g): PCA-weighted method, Vulnerability (h): Same-weighted.

3.3 Communicating the most sensitive variables to intervene within the climate risk components

To communicate the resulted sensitivity analysis for prioritizing considerably the riskiest sub-district within Pekalongan, the standard deviation of the variables index change was considered as a basis of intervention. From Table 4, we can conclude that the most sensitive variables from the weight changes is Settlement Distance to River. While for sensitivity fisherman families were the one that are sensitive to the weight changes. On the other hand, Clean and Healthy Behaviour Families was the one that are sensitive among other adaptive capacity variables.

The fluctuate value of standard deviation of the index changes among variables considered; there are indices with high value ranges across sub-districts (zero to one for binary variables, lower or higher than 0 for numeric variables). For example, for only several sub-districts such as Bendan Kergon, Podosugih, and Medono that are approximately far from the river, while North Pekalongan sub-districts, particularly Bandengan and Krapyak, are rather close to the coastal areas. As an addition, Clean and Healthy Behavior Families were only located in Pasirkratonkramat and Krapyak. Fisherman families with high z-score values were concentrated in Bendan Kergon and Banyurip, as these sub-districts have positively distinct values for the Fisherman Families indicator. Specifically, Bendan Kergon has a value of 1 for Fisherman Families, while Banyurip has a z-score of 2.759. These values reflect a significantly higher concentration of fisherman families compared to other sub-districts in the dataset.

This pattern of fisherman families is consistent with research on coastal communities in Indonesia, where regions dependent on the fishing industry, such as Bendan Kergon and Banyurip, have a higher concentration of families engaged in fisheries. Similarly, flood vulnerability and exposure to climate risks proposed that coastal proximity in sub-districts like Bandengan and Krapyak increases their exposure to tidal and flood hazards, a finding mirrored in the higher Exposure indices observed in these areas. As a conclusion, to fully addressed the strategic issues of climate risk in a specific Pekalongan sub-district by adaptation efforts, variables that we prioritized to intervene are Settlement Distance to River for the exposure component, Fisherman Families for sensitivity component, and Clean and Healthy Behaviour family for adaptive capacity component.

Table 4. Climate risk variables sensitivity.

Variables	Min. Index Changes	Max. Index Changes	Standard Deviation Index Changes
Settlement Distance to Coastal Areas (Km)	0.012	0.302	0.093
Business District Distance from Coastal Areas (Km)	0.013	0.268	0.071
Settlement Distance to River (Km)	0.003	0.487	0.119
Business District Distance from River (Km)	0.039	0.303	0.074
Number of Women	0.000	0.043	0.013
Number of Children (0-14)	0.000	0.029	0.008
Number of Elder Group People (usia 65+)	0.001	0.027	0.008
Number of Female Head of Household	0.001	0.014	0.004
Certified Poor People (SKTM) (People)	0.007	0.241	0.055
Fisherman Families	0.001	0.303	0.070
Number of People with Disabilities	0.000	0.000	0.000
Number of Small-Medium size Industries	0.003	0.248	0.050
Number of Societal Groups	0.027	0.296	0.067
Clean and Healthy Behavior Families	0.018	0.597	0.123
Number of Hospital	0.118	0.519	0.082

To communicate the most sensitive variables to intervene within the climate risk components from the method in sub-sub section 2.4.8, first we should choose sub-district that have the highest climate risk index.The overall climate risk index in the north of Pekalongan city are high, while southern part of Pekalongan are moderately low, regardless of the weighting methods. To put into practical example of how to prioritize climate adaptation and intervention based on the results of the climate risk index and sensitivity analis, Krapyak sub-district are chosen as it had the highest risk index among all sub-district, while also having considerably high risk index changes (See Fig 5). After doing the first step, we assess the choosen sensitive variables for exposure (Settlement Distance to River), sensitivity (Fisherman Families), and adaptive capacity (Clean and Healthy Behavior Family). The assessment suggest that Krapyak does not having any sensitive variables to intervene, because the index of the aforementioned choosen variables are not having far ranges from the threshold, therefore proposed actions and interventions should focusses on variables with high weight for each components (Business District Distance from Coastal Areas, Number of Females, and Number of Small-Medium Industries).

For Krapyak, interventions should prioritize coastal protection measures such as the construction of seawalls and mangrove restoration, given the sub-district's vulnerability to tidal flooding due to its proximity to the coast. Coastal defense infrastructure is important, and such interventions would help reduce the risk of coastal erosion and flooding, enhancing the resilience of Krapyak. As of now, Krapyak has begun incorporating these strategies through mangrove restoration efforts supported by local government and environmental organizations. However, the implementation of seawalls and further coastal infrastructure could be accelerated to improve long-term protection.

Additionally, gender-sensitive programs must be a focal point in the adaptation strategy. According to, disaster preparedness and empowerment initiatives for women are critical to improving resilience, particularly in coastal communities [15]. Krapyak has made progress in this area with the Clean and Healthy Behavior Families programs, which engage women in community health initiatives and disaster preparedness training. However, further programs that focus specifically on women's empowerment, including leadership training and financial support for women-headed households, are needed to enhance their capacity to cope with climate impacts.

Moreover, supporting local small-medium industries (SMIs) by promoting climate-resilient technologies and business adaptation strategies is crucial for long-term sustainability. SMIs in vulnerable communities need access to resources that help them adapt to climate risks. In Krapyak, there have been efforts to support SMIs through government grants and training programs on sustainable practices. However, these initiatives could be expanded to include access to low-carbon technologies, climate insurance, and market diversification strategies to enhance the economic resilience of small businesses.

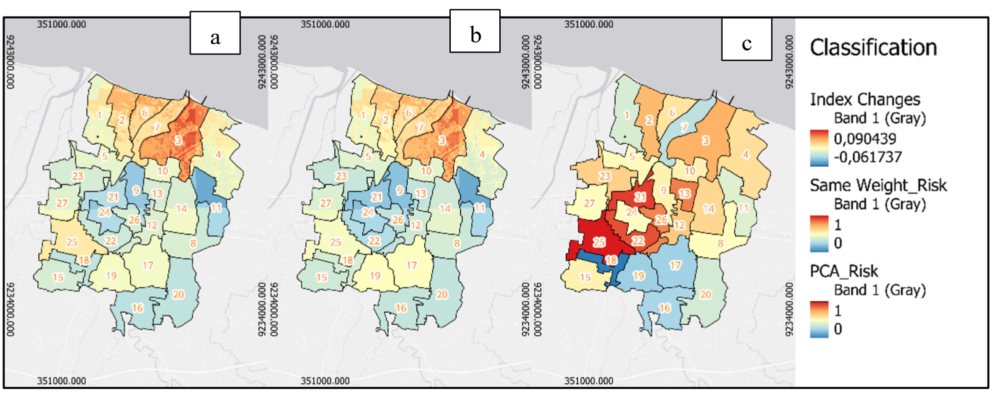

Fig. 5. Pekalongan sub-districts' risk level (a) from PCA-weighted and same-weighted methods (b), with their index differences (c).

4 Conclusions and recommendation

4.1 Conclusions

This study analysed climate induced risk in Pekalongan City by using exposure, sensitivity and adaptive capacity that builds vulnerability components using Principal Component Analysis (PCA). From the index value of the contributing variables of each risk component, the finding exhibits that Northern Pekalongan sub-districts such as Krapyak and Bandengan sub-districts have the highest climate risk index due to their asset's proximity to coast (exposure component, PC1 indicator) and double hazards (rainfall and tidal flooding) occurrences.

Due to their high indices varianve, Settlement Distance to River, Fisherman Families, and Clean and Healthy Behavior Families are considered as the most sensitive risk variables amongst all. From these findings, climate adaptation and intervention could be determined by also considering the weight of each risk component and prioritizing interventions based on the most sensitive variables identified through sensitivity analysis. If the indices are significantly below the threshold, interventions should focus on both high-weight variables and the most sensitive one. Therefore, the research suggests the importance of targeted adaptation strategies to address climate risks effectively. Coastal defence infrastructure, gender-sensitive resilience programs, and support for small-medium industries were identified as key interventions.

4.2 Recommendation

To implement methods for communicating sensitive climate risk variables, stakeholders' participation is necessary in tuning the multi-criteria analysis model's assumptions and variable weightings. This effort can be done by integrating data that exhibits local vulnerabilities to a specific climate hazard, such as climate patterns and their socio-economic potentially impacted factors. Furthermore, sensitivity analysis is implemented by tuning the variable weight based on numerous stakeholders' opinions input, including local communities' input. This tuning interactive should be dynamically looped, allowing stakeholders to iteratively update the multi-criteria analysis model as new insights are considered. Lastly, to communicate the results interactively, cascading impacts from specific hazards and their response capacity could be communicated through GIS story maps.

Acknowledgement

We extend our gratitude to the unknown reviewers for their substantial input to this paper that critically improved the manuscript.

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