The multi-criteria decision making for evaluation of vulnerability to climate change: A case study in Vietnam

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Abstract:

Vulnerability to climate change can reflect systemic weakness and, in particular, a susceptibility to severe events such as storms, floods, high temperature, droughts. The Intergovernmental Panel on Climate Change (IPCC) defines vulnerability as a combination of characteristics and magnitudes that express exposure, sensitivity, and adaptive capacity. This paper aims at proposing a multi-criteria decision making (MCDM) approach for the evaluation of vulnerability to climate change in coastal provinces in Vietnam. An integrated approach is performed to achieve the most relevant outcome. The Analytic Hierarchy Process (AHP) and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) are combined to show the most vulnerability in terms of livelihoods in 28 coastal zones in Vietnam. The results, in terms of livelihoods, show that Nghe An, Ha Tinh, and Thai Binh are the most vulnerable to sea level rise as the population density near the coastline significantly contributes to enhanced vulnerability to climate change.

Keywords: **AHP, climate change, multi-criteria decision making, TOPSIS, vulnerability.**

Classification number: **4.1**

Introduction

Climate change is global matter that has extreme influence on global food security and livelihood security of low-income residents not to mention it causes obstacles to hunger eradication and poverty reduction processes. Every year, harmful weather events like global warming, heavy storms, and droughts have increased pressure on the land system causing the risk of desertification, especially in coastal areas, which then has serious consequences on ecosystems and livelihoods. Climate change continues to be complicated and causes serious impacts. For example, according to the McKinsey Global Institute [1], Southeast Asian countries will lose 8-13% of GDP each year to 2050. Vietnam is one of five countries that are extremely influenced by climate change. With a 3200 km long coastline, 70% of the population lives near the coast and low-lying areas.

Negative weather events appear more frequently under the impacts of climate change. Study outcomes of World Bank [2] in developing countries affirm that Vietnam ranks the highest in GDP loss by country. The fact that climate change has already began occurring means these are no longer just predictions. For example, a widespread and severe drought area has formed in the Mekong Delta in 2019 and 2020 in comparison to the same period in 2006. Water resources in the Central and Central Highlands regions were reduced by approximately 35-70% compared to the same period of previous years. Over the past five decades, the southern region has seen more and more 4-level and 5-level storms. For example, Yen Bai (2017) and Thanh Hoa (2018, 2019) experienced flash floods that caused widespread destruction.

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The central provinces suffered from consecutive storms and heavy rains causing extremely serious consequences to people's lives.

The impact of climate change is clearly threatens food security, resident life, and the country's development. The rising sea levels and high temperatures are unavoidable. The Northern Midlands and Mountain areas will be more at risk from flash floods and landslides due to increased rainfall. Meanwhile, the Central and South-Central Coast, the Northeast, and the Central Highlands suffer from drought and lack of water. In the Mekong river delta, compared with the historic flood in 2000, the sea level rose about 30 cm and the flooded area increased by 25% accounting for nearly 90% of the natural area. In addition, these areas are also affected by subsidence due to geology and groundwater exploitation.

Climate change adaptation is an important issue to many fields. Even as reduction plans for greenhouse gas emission are implemented, climate change still emerges as an inevitable event [3]. The assessment of vulnerability to climate change for subjects such as livelihoods (health, habitat, security), economy, or climate-related hazards (heat waves, flood events, rise in sea levels) is a planning task in environmental decision-making. This task helps to identify issues of high vulnerability in the community thereby allocating adaptation resources, monitoring climate change impacts, and proposing solutions [4].

Determination, measurement, and analysis of vulnerability to climate change have successfully attracted many researchers and managements wishing to identify potential risks and threat impacts by climate change [5-7].

Initially, the trends in this research varied from an impact-based approach to vulnerability-led evaluation. The latter approach focuses on the socioeconomic and environmental factors that will influence how to deal with climate hazards [8]. The concept of vulnerability is understood in a variety of ways due to studied communications. The IPCC [9] believed that vulnerability is the degree to which a system susceptible to or unable to respond to negative impacts of climate change. Vulnerability combines external and internal impacts including exposure, sensitivity, and adaptive capacity [10]. The evaluation of vulnerability plays a prioritized role in climate change response plans. It is necessary to consider many aspects during an evaluation of the vulnerability to climate change so that it can be viewed as a MCDM related to the determination of an optimal solution among alternatives under conflict criteria.

MCDM models have been successfully utilized to determine optimal alternatives in vulnerability evaluation [7, 11-13]. G. Lee, et al. (2013) [12] proposed a procedure of spatial tools vulnerability analytics, which integrate the Delphi model and the Technique for Order of TOPSIS. E.S. Chung, et al. (2017) [14] generalized a MCDM method to evaluate water resource vulnerability of the Han river basin using TOPSIS. D.M. Runfola, et al. (2017) [15] implemented the multi-criteria weighted ordered weighted average model to measure the flood vulnerability to climate change in the United States. P.M. Tam, et al. [7] (2019) measured the vulnerable level of 28 zones using AHP and vulnerable indicator. The mentioned approaches have advantages and disadvantages in the decision-making process. Therefore, this study combines two methods, which enhances the outcome validity. This paper aims at building a model to evaluate the vulnerability to climate change in terms of livelihoods of coastal zones in Vietnam. The AHP is employed to determine the weights of attributes that influence the vulnerability. The TOPSIS ranks the vulnerability of zones using the weights of criteria and collected data.

Materials and methods

Materials

In this paper, the vulnerability framework used is based on IPCC. The vulnerability of a system at any scale integrates three components: sensitivity, exposure, and adaptation to deal with effects of conditions. Climate exposure reflects extreme phenomenon such as rise in level, high temperatures, floods, storms, heat waves, and droughts. Sensitivity shows how system is influenced by impacts. Adaptive capacity (AC) expresses the ability to respond to risks and environmental hazards. The vulnerability index is defined as:

$VI=w_E E+w_S S+w_{AC} AC$ [13].

After careful consideration, literature reviews, and expert advice, the criteria are defined as presented in Table 1. The data is acquired from authority agencies such as the General Statistic Office, annually synthesized reports from 28 provinces, and the National Centre for Hydro in 2019, which are shown in the Appendix. The data is different from quantitative scales, thus, it is standardized to fit the model. A survey is formed for identifying the importance of criteria. Respondents are experts in socio-economic fields with experiences in evaluation assessment and aggregation annual outcome.

Methods

In a MCDM process, determining the importance of attributes and ranking alternatives are two important issues. AHP and TOPSIS are two frequency used methods for these tasks. AHP was suggested by L.T. Saaty (2008) [24], which has been confirmed as an effective method in various fields such as selection suppliers [25] and agile manufacturing [26]. AHP is meaningful to achieve goal priorities of alternatives or weights of attributes. It integrates the intangible perspectives involving decision makers by creating pairwise comparisons. In this paper, the model is used to construct a hierarchy system of criteria and sub-criteria to evaluate the relative important of attributes via pairwise comparisons following Saaty's scale. The process includes the following steps:

Table 1. Description of vulnerability criteria.

Criteria		Description	References
Exposure (E)	Storms (E_1)	The number of storms per year	[7], [16], [17]
	Sea level rise (E_2) (cm)	Reflects the rising of water levels in the world's oceans	[16], [18], [19]
	Precipitation (E_3) (mm)	Average precipitation per year from monitoring station	[16], [20]
Sensitivity (S)	Population density (S_1) (people/km^2)	Population per unit area	[16], [21]
	Population density near coastline (S_2) (people/km^2)	Population ratio in the coastline area	[18], [22]
	Coastline (S_3) (km)	Length of coastline	[18], [21]
Adaptive capacity (AC)	Gross domestic product (AC_1) (billions VND)	Total value of final products and services by present price in considered year	[16], [22]
	Industrial production value (AC_2) (billions VND)	The industrial production value in GDP	[16], [22]
	Agriculture production value (AC_3) (billions VND)	Agriculture production value in GDP	Expert suggestions
	Poor household (AC_4) (%)	The ration of poor households in area	[16], [23]
	Unemployment ratio (AC_5) (%)	Unemployment ratio in labour age	Expert suggestions
	Average income (AC_6) (millions VND)	The average income of households in area	Expert suggestions

To obtain the weights of criteria, experts are responsible to evaluate the importance degree by Saaty's seven-point scale, which is given in Table 2. The weights of criteria are determined from an evaluated matrix. The evaluated results of experts are tested using the consistency ratio (CR) where 0.1 is an acceptable degree [24]. This means that if CR is larger than 0.1, then the responses are inconsistent with the evaluation, therefore, the assessment should be eliminated or revised.

Table 2. Saaty's seven-point scale.

Number pairwise value	Definition	Explanation
1	Equally important	Two attributes have the same importance
3 or 1/3	Weakly important	The attribute is slightly more important than another one
5 or 1/5	Strongly important	The attribute is more important than another one
7 or 1/7	Very strongly important	The attribute is much more important than another one
2, 4, 6	Intermediate values between two evaluations	

TOPSIS was proposed by C.L. Huang and K. Yoon (1981) [27], which has been applied to deal with choosing the best value for all alternatives. The fundamental framework is to determine the alternative that is simultaneously nearest to the ideal solution and farthest from the negative solution. TOPSIS takes advantage when representing the human choice. It is a simple calculation process that can handle both the best and the worst aspects simultaneously. TOPSIS has been efficiently proven in many fields [11, 12, 28, 29]. The procedure is expressed as follows:

Let x_{ij} be the value of object A_i under criterion C_j. The criterion has different scales, therefore, it needs to be normalized in forms of r_{ij} by

$$r_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \quad (1)$$

Denote the normalized performance matrix by $V = [r_{ij}]$, then the overall weighted values of obtained alternatives under criteria is calculated by $R = [\omega_{ij}], \omega_{ij} = w_j r_{ij}$. In order to select the most appropriate solution with respect to criteria, each alternative is compared to the positive ideal solution (PIS) and negative ideal solution (NIS), which are the maximal and minimal weighted values, respectively, that rely on the benefit or cost criterion and determined as follows:

$$A^+ = (\omega_1^+, \omega_2^+, ..., \omega_n^+), A^- = (\omega_1^-, \omega_2^-, ..., \omega_n^-), \ \omega_j^+ = \max_i \omega_{ij}, \omega_j^- = \min_i \omega_{ij} \quad (2)$$

The distance of alternative A_i to A^+, A^- is the Euclidean distanc:

$$d_i^+ = \sqrt{\sum_{j=1}^{m} (\omega_{ij} - \omega_j^+)^2}, d_i^- = \sqrt{\sum_{j=1}^{m} (\omega_{ij} - \omega_j^-)^2} \quad (3)$$

The preferred alternative is the one with smallest relative closeness:

$$Rc_i = \frac{d_i^-}{d_i^- + d_i^+} \quad (4)$$

To measure the vulnerability level of climate change, the integrated vulnerability index is determined by:

$$VI = w_E E + w_S S + w_{AC} AC = \sum_{i=1}^{3} \mathrm{w}_{E_i} E_i + \sum_{i=1}^{3} \mathrm{w}_{S_i} S_i + \sum_{i=1}^{6} \mathrm{w}_{AC_i} AC_i \quad (5)$$

where, $w_E, w_S, w_{AC}, \mathrm{w}_{E_i}, \mathrm{w}_{S_i}, \mathrm{w}_{AC_i}$ are the weights of criteria and overall weights of sub-criteria and E_i, S_i, AC_i are the normalized values of provinces under sub-criteria. The normalized data is used to identify the vulnerability degree, and they are used for classification into three groups following interval of the distance:

$$\Delta_{VI} = \frac{VI_{\max} - VI_{\min}}{3} \quad (6)$$

Findings

An experts group was asked to evaluate the role of criteria and their crucial level by Saaty's seven-point scale as in Table 2. They drive the pair comparison matrix between criteria and sub-criteria. The assessments of respondents are aggregated by Microsoft Excel to explore the weights of criteria and the consistency ratio of each evaluation. After shifting and eliminating inconsistent evaluations, the aggregated values were used to calculate the weights of criteria and sub-criteria. The outcomes are expressed in Table 3. The selected data is normalized by Eq. (1) and considered as a performance matrix for achievement of the overall weighted values. The PIS and NIS are determined using Eq. (2). Table 4 represents the distances of alternatives of the PIS and NIS and the relative closeness following Eqs. (3) and (4). The rank of vulnerability of each province is given in the last column.

Table 3. Local weights and overall weights of criteria and sub-criteria.

Weight of criteria		Sub-criteria	Local weights	Overall weights
E	0.557	E_1	0.122	0.068
		E_2	0.648	0.360
		E_3	0.230	0.128
S	0.32	S_1	0.198	0.063
		S_2	0.490	0.157
		S_3	0.312	0.1
AC	0.123	AC_1	0.370	0.046
		AC_2	0.232	0.029
		AC_3	0.195	0.024
		AC_4	0.099	0.012
		AC_5	0.060	0.007
		AC_6	0.044	0.005

The findings in Table 3 show that exposure has the highest weight followed by sensitivity and AC. This expresses that exposure significantly causes the vulnerability in terms of livelihoods. The explanation for this is storms, sea level rise, precipitation, and temperature directly affect and lead to adverse consequences on lives and livelihoods. In overall weights, the sea level rise and population density near coastline account for the most weight, which confirms the remarkable impact these factors have on the vulnerability to climate change.

Table 4. The rank of vulnerability.

Province	d_i^+	d_i^-	Rc_i	Rank of vulnerability
Ho Chi Minh city	0.193	0.118	0.379	13
Nghe An	0.169	0.164	0.491	2
Thai Binh	0.169	0.152	0.473	3
Quang Nam	0.179	0.157	0.467	4
Nam Dinh	0.166	0.141	0.458	5
Kien Giang	0.228	0.062	0.213	22
Ha Tinh	0.152	0.147	0.492	1
Da Nang	0.129	0.092	0.432	8
Thanh Hoa	0.170	0.135	0.442	6
Ca Mau	0.169	0.125	0.4252	9
Bac Lieu	0.209	0.056	0.210	24
Tien Giang	0.214	0.059	0.215	21
Ba Ria - Vung Tau	0.165	0.115	0.410	12
Ninh Binh	0.181	0.139	0.435	7
Tra Vinh	0.217	0.044	0.169	28
Soc Trang	0.216	0.049	0.184	27
Ben Tre	0.212	0.057	0.212	23
Hai Phong	0.165	0.118	0.417	11
Binh Dinh	0.185	0.102	0.356	16
Khanh Hoa	0.183	0.132	0.419	10
Quang Ngai	0.189	0.086	0.312	18
Quang Tri	0.212	0.053	0.201	25
Quang Ninh	0.188	0.113	0.377	14
Quang Binh	0.214	0.053	0.198	26
Phu Yen	0.185	0.105	0.363	15
Ninh Thuan	0.201	0.070	0.258	20
Hue	0.189	0.092	0.327	17
Binh Thuan	0.206	0.074	0.264	19

To measure vulnerability level of climate change, the vulnerability index of each province is given in Table 5. The range of VI is split into three levels, high, medium, and low, which correspond to red, yellow, and green colour, respectively, with domains of less than 0.267, from 0.267 to 0.3, and larger 0.3, respectively.

Table 5. The vulnerability index.

Provinces	VI	Colour display	Explanation
Ha Tinh	0.345		High risk of vulnerability
Nghe An	0.340		
Thai Binh	0.315		
Nam Dinh	0.300		The risk degree is medium in terms of vulnerability to climate change
Quang Ninh	0.295		
Da Nang	0.293		
Thanh Hoa	0.292		
Ca Mau	0.291		
Quang Tri	0.291		
Soc Trang	0.288		
Binh Thuan	0.287		
Ben Tre	0.284		
Khanh Hoa	0.280		
Ninh Thuan	0.280		
Ninh Binh	0.280		
Hai Phong	0.280		
Quang Nam	0.275		
Ho Chi Minh	0.275		
Ba Ria - Vung Tau	0.274		
Quang Binh	0.260		Areas have low vulnerability
Tra Vinh	0.260		
Kien Giang	0.255		
Tien Giang	0.255		
Bac Lieu	0.254		
Quang Ngai	0.249		
Hue	0.237		
Binh Dinh	0.235		
Phu Yen	0.234		

A comparison of the outcomes of TOPSIS and the vulnerability index show they were significantly consistent. As seen in Table 4 and Table 5, Ha Tinh, Nghe An, and Thai Binh are classified into the first group with highly vulnerability to climate change. The VI for Ha Tinh and Nghe An are 0.345 and 0.340, respectively, followed by Thai Binh at 0.315. These provinces frequently suffer more from various extreme weather events such as strong storms, floods during the rainy season, and droughts in the dry season compared to the other 28 provinces. This bad weather greatly affects agriculture production and the livelihood of local people. In of 28 considering provinces, the given data for Nghe An and Ha Tinh reflect high poor rate and low average income, which make it difficult to allocate resources and leads to vulnerability to climate change. Therefore, Nghe An and Ha Tinh have high exposure and low adaptive capacity, which cause high vulnerability. Quang Binh, Tra Vinh, Kien Giang, Tien Giang, Bac Lieu, Quang Ngai, Hue, Binh Dinh, and Phu Yen belong to the third group with low vulnerability. Although they are not as high as the last groups in terms of GDP or income, they are less susceptible to extreme weather and low population densities, and their sensitivity degree is also low, which lead to low vulnerability to climate change in terms of livelihoods. The second group of 16 provinces have medium vulnerability, and their VI scores ranged from 0.274 to 0.3.

Conclusions

Human activities have caused an increase of global warming. Countries need to reflect on all aspects of climate change to act and gain clear indications of action. Global greenhouse gas emissions are considerably high degree when compared to minimal requirements. Countries must boost the urgency of action in the carbon dioxide emissions reduction plan. Vietnam is one of the countries that are most seriously influenced by climate change with extreme weather events that directly cause the difficulty in the lives and livelihoods of residents.

This study assesses the vulnerability associated with the coastal zones of Vietnam. To evaluate the weights of the attributes, expert survey and AHP methods are employed. The TOPSIS model releases the vulnerability raking of provinces. To check the robustness of outcome, the vulnerable indicator is performed to release the vulnerable level. The results show that both results are consistent. In terms of livelihoods, the findings confirm that

Nghe An, Ha Tinh, and Thai Binh have the highest vulnerability followed by Nam Dinh, Da Nang, Thanh Hoa, and Ca Mau. The exposure factor causes the highest risk zones to climate change. The sea level rise, temperature, and population density near the coastline cause great impacts on vulnerability.

This study provides useful information about the climate change vulnerability ranking and suggests how to evaluate the vulnerability degree of zones. These points will help managers proposing adaptive solutions for the high-risk zones in Vietnam.

COMPETING INTERESTS

The author declares that there is no conflict of interest regarding the publication of this article.

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