

Development of a multi-objective preference analysis (MOPA)-based multicriteria model for assessing the resilience of tourism destinations to flood risk

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ARTICLE INFO	ABSTRACT
Article history: Received Jun 30, 2026 Revised Jul 5, 2026 Accepted Jul 14, 2026 Keywords: Destination Resilience; Flood Risk; MOPA; Multicriteria Analysis. Tourism;	Floods can disrupt the accessibility, facilities, and sustainability of tourism destination activities. This study aims to develop a preliminary model to assess the resilience of tourism destinations to flood risk using a Multi-Objective Preference Analysis (MOPA) approach based on secondary data and openly available digital information. The case study was conducted at the Siombak Lake Tourism Park, Medan City, with five alternative observation periods from 2020-2024. The five indicators used include flood risk, rainfall, area exposure, accessibility, and availability of tourism facilities. Factual data was used when available, while indicators that did not have numerical data were supplemented using proxy scores based on expert judgment. Data were processed through the preparation of a decision matrix, classification of cost and benefit indicators, normalization, weighting, and aggregation of MOPA preference values. Sensitivity testing was conducted by changing the indicator weights by $\pm 5\%$ and $\pm 10\%$. The results showed that alternative A4-2023 obtained the highest preference value of 0.7595, while A5-2024 obtained the lowest value of 0.4000. All sensitivity scenarios produced the same ranking order as the baseline, achieving 100% ranking stability. This research produces a simple, transparent, and replicable initial assessment framework. Future research can develop the model by integrating real-time or near-real-time meteorological, spatial, disaster, and sensor data. <i>This is an open access article under the CC BY-NC license.</i> 

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1. INTRODUCTION

Tourism destinations are complex systems comprised of environmental resources, infrastructure, accessibility, tourism facilities, local communities, economic activities, and management institutions. The interaction between these components makes them vulnerable to external disturbances, particularly hydrometeorological hazards such as flooding and extreme rainfall. Flooding can disrupt transportation, damage tourism facilities, reduce visitor accessibility, halt tourism business activities, and reduce economic benefits for local communities (Alvarez et al., 2022; Dube et al., 2023; Shi et al., 2022). Therefore, destination resilience is an important component in developing sustainable tourism (Awfa et al., 2025; Biardeau et al., 2026; Jayasinghe et al., 2024).

Destination resilience not only indicates the ability to survive when a disaster occurs, but also includes the ability to prepare, maintain primary functions, respond to disruptions, recover from losses, and adapt to changes in the environment and socio-economic conditions (Alvarez et al., 2022; Bethune et al., 2022). Destination resilience is a multidimensional concept that involves physical infrastructure, environmental conditions, social and economic resources, institutional

capacity, stakeholder collaboration, and adaptive governance (Chen et al., 2025; Jiao et al., 2025; Posch et al., 2024; Zhang et al., 2024). Thus, resilience assessment cannot be based solely on hazard intensity or the availability of tourism infrastructure.

Climate change is further increasing the complexity of disaster risks associated with tourism (Dube et al., 2023; Peeters et al., 2024). Changing rainfall patterns, increased extreme weather events, and the interaction between environmental degradation and urban development can increase a destination's exposure to flooding. Therefore, disaster risk reduction needs to be integrated into tourism planning so that risk management is not separated from destination development (Gössling & Scott, 2025; Jayasinghe et al., 2024; Prideaux et al., 2021).

In the Indonesian context, the need for destination resilience assessments is increasingly relevant because many tourist destinations are located in areas exposed to hydrometeorological hazards. Flooding can impact visitor mobility, tourism infrastructure, public facilities, local business activities, and the sustainability of tourism activities. Research on tourism destinations in Indonesia shows that resilience needs to be viewed across multiple dimensions, including environmental conditions, infrastructure, community capacity, institutional support, and economic factors (Awfa et al., 2025; Rahardjo et al., 2025; Rindrasih et al., 2024). Research on coastal tourism vulnerability in Mandalika also shows that a multi-criteria approach can be used to analyze various vulnerability factors in a destination (Rahardjo et al., 2025).

The multidimensional nature of resilience poses methodological challenges because the indicators used can have different units, scales, and directions of influence. In this study, flood risk, rainfall, and regional exposure are treated as cost indicators because higher values indicate greater pressure on destination resilience. Meanwhile, accessibility and availability of tourism facilities are treated as benefit indicators because they can support the destination's operational and response capacity.

Multi-Criteria Decision Analysis (MCDA) is widely used to support decision-making involving multiple criteria, competing objectives, and limited information. In tourism, MCDA has been applied to sustainable tourism planning, low-carbon tourism, environmental assessment, vulnerability analysis, and destination management (Andria et al., 2021; Khosravi et al., 2019; Manumpil et al., 2023; Withanage et al., 2024). However, MCDA results can be influenced by indicator selection, weighting, normalization techniques, and the sensitivity of rankings to changes in weights (Manumpil et al., 2023; Riandari, Hutagalung, et al., 2026).

The Multi-Objective Preference Analysis (MOPA) method was developed as a multi-criteria decision analysis approach to support tourism planning. Early MOPA research introduced a preference value aggregation process that combined criterion weights and normalized alternative performance values (Riandari et al., 2024). The next study developed MOPA for Islamic tourism planning and tested the effect of weight modification and sensitivity analysis on ranking stability (Riandari, Sihotang, et al., 2026). Other studies also show that normalization techniques are an important component that can influence the results and behavior of MOPA rankings (Riandari, Sihotang, et al., 2026).

While previous research has addressed tourism resilience, disaster risk reduction, destination vulnerability, and MCDA-based planning, there is still a need for simple, transparent, and applicable assessment models using secondary data and openly available digital information. This need is crucial for destinations that lack continuous field measurements, comprehensive sensor networks, or integrated monitoring systems. Data from disaster databases, meteorological services, open spatial data, tourism portals, statistical publications, and government documents can serve as the basis for initial assessments (Camatti et al., 2024).

Based on these gaps, this study developed a preliminary MOPA-based model to assess the resilience of tourism destinations to flood risk using secondary data and digital information. The study was conducted at the Siombak Lake Tourism Park in Medan City with five alternative observation periods, namely 2020–2024. The model integrated indicators of flood risk, rainfall, area exposure, accessibility, and tourist facilities. The study aimed to identify relevant indicators, develop a decision matrix, calculate preference values using MOPA, and test ranking stability through weight changes of $\pm 5\%$ and $\pm 10\%$. The contribution of this study is to provide a transparent and simple initial assessment framework to support destination resilience planning. This model is not intended as a real-time monitoring system, but can be developed through the integration of meteorological, spatial, disaster, infrastructure, and sensor data in future research (Bethune et al., 2022).

2. RESEARCH METHOD

This study used a quantitative approach based on secondary data and online information to assess the resilience of Siombak Lake Tourism Park to flood risk. The research process consisted of five stages: case study determination, indicator determination, data collection, data processing, and model testing.

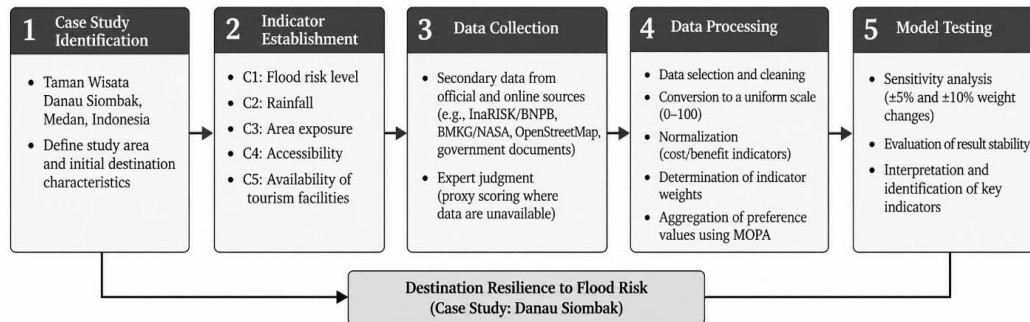


Figure 1. Research Flow of This Study

The case study was conducted at Siombak Lake Tourism Park, Medan, using five indicators: flood risk (C1), rainfall (C2), area exposure (C3), accessibility (C4), and tourism facilities (C5). Data were obtained from BNPB/InaRISK, BMKG/NASA GPM IMERG, OpenStreetMap, Jadesta, BPS, and government documents, with proxy scores based on expert judgment where numerical data were unavailable. Data were standardized and normalized to 0–1, with C1–C3 classified as cost indicators and C4–C5 as benefit indicators. MOPA was applied to construct the decision matrix, assign weights, normalize indicators, and aggregate preference values. Model stability was evaluated through sensitivity analysis using ±5% and ±10% changes in indicator weights.

In the MOPA stage, the data is arranged in a decision matrix, indicating the value of the i th alternative for the j th indicator. Because each indicator has a different unit and direction of assessment, a normalization process is carried out into the range 0–1. $X = [x_{ij}]$

For benefit type indicators, the equation used is:

$$r_{ij} = \frac{x_{ij} - x_{\min j}}{x_{\max j} - x_{\min j}}$$

Meanwhile, for cost type indicators, the equation used is:

$$r_{ij} = \frac{x_{\max j} - x_{ij}}{x_{\max j} - x_{\min j}}$$

Information:

r_{ij} is the normalization value of the i -th alternative on the j -th indicator ij ;

x_{ij} is the initial value of the alternative i ;

$x_{\max j}$ is the maximum value of the indicator j ;

$x_{\min j}$ is the minimum value of the indicator j ;

The preference value of each alternative is calculated using weighted aggregation:

$$S_i = \sum_{j=1}^n w_j r_{ij}$$

with S_i as the preference value of the i -th alternative, w_j as the weight of the j -th indicator, and r_{ij} as the normalization value. The indicator weight is determined by the following provisions:

$$\sum_{j=1}^n w_j = 1$$

Alternatives with higher values indicate a better relative level of resilience based on the indicators and weights used S_i . Sensitivity analysis is performed by changing the weight of each indicator individually by $\pm 5\%$ and $\pm 10\%$. The resulting weight changes are calculated using $w_j' = w_j(1 \pm \delta)$

with a δ value of 0.05 or 0.10. Since changing the weights can cause the sum of the weights to no longer equal one, the weights are renormalized using:

$$w_j^* = \frac{w_j'}{\sum_{j=1}^n w_j'}$$

The preference values for each sensitivity scenario are then recalculated using:

$$S_i^{(s)} = \sum_{j=1}^n w_j^* r_{ij}$$

The change in preference value is calculated by:

$$\Delta S_i = S_i^{(s)} - S_i^{(0)}$$

with $S_i^{(s)}$ as the preference value in the sensitivity scenario and $S_i^{(0)}$ as the preference value in the baseline condition. The ranking change is calculated by:

$$\Delta R_i = R_i^{(s)} - R_i^{(0)}$$

The stability of the model is then calculated based on the percentage of scenarios that do not result in a change in the ranking order:

$$SR = \frac{N_{\text{stabil}}}{N_{\text{total}}} \times 100\%$$

with SR as the percentage of ranking stability, N_{stabil} as the number of scenarios with no ranking change, and N_{total} as the total number of test scenarios. The higher the SR value, the more stable the model results are to changes in indicator weights.

3. RESULTS AND DISCUSSIONS

Research Results

3.1 Preparation of Initial Data Matrix

The resilience assessment of Siombak Lake Tourism Park used five indicators: flood risk, rainfall, area exposure, accessibility, and tourism facilities. The 2020–2024 observation years were treated as alternatives in the MOPA analysis. Initial data were standardized to a 0–100 scale to enable comparison across indicators with different units.

Table 4. Initial Data Matrix

Alternative	C1 Flood risk	C2 Rainfall	C3 Exposure	C4 Accessibility	C5 Facilities
A1 – 2020	55	60	50	45	45
A2 – 2021	50	50	50	45	45
A3 – 2022	60	55	55	50	50
A4 – 2023	65	45	60	55	55
A5 – 2024	85	65	80	55	60

C1, C3, C4, and C5 are initial proxy scores based on secondary information and expert judgment, while C2 uses a temporary standardized score. These scores should be replaced with actual measurements in future data collection. Overall, C1 and C3 indicate increased risk and exposure in 2024, while C4 and C5 show relative improvements in accessibility and facility availability.

3.2 Determination of Indicator Weights

Initial weights were assigned based on the indicators' importance to destination resilience, with higher weights given to flood risk and exposure due to their direct impacts, while accessibility and tourism facilities support tourism continuity and service capacity.

Table 5. Indicator Weights

Code	Indicator	Type	Weight
C1	Flood risk level	Cost	0.25
C2	Rainfall	Cost	0.15
C3	Regional exposure	Cost	0.20
C4	Accessibility	Benefits	0.20
C5	Availability of facilities	Benefits	0.20
Total			1.00

Indicators C1, C2, and C3 are cost indicators, so higher values indicate conditions that are less conducive to resilience. Indicators C4 and C5 are benefit indicators, so higher values indicate conditions that are more conducive to resilience.

3.3 Normalization of Decision Matrix

Normalization is performed to convert all indicator values into a range of 0–1. Because the indicators have different assessment directions, two equation forms are used.

For cost indicators:

$$r_{ij} = \frac{x_{\max} - x_{ij}}{x_{\max} - x_{\min}}$$

For benefit indicators:

$$r_{ij} = \frac{x_{ij} - x_{\min}}{x_{\max} - x_{\min}}$$

Information:

- x_{ij} is the initial value of the i th alternative on the j th indicator;
- $x_{\max}$ is the maximum value of the indicator;
- $x_{\min}$ is the minimum value of the indicator;
- r_{ij} is the normalized value.

Example of calculating C1 on A1

The C1 score is 55, with a minimum score of 50 and a maximum of 85.

$$r_{11} = \frac{85 - 55}{85 - 50} = \frac{30}{35} = 0,8571$$

Thus, the normalized value of C1 for A1 is 0.8571.

Example of C4 calculation on A3

The C4 score is 50, with a minimum score of 45 and a maximum of 55.

$$r_{34} = \frac{50 - 45}{55 - 45} = \frac{5}{10} = 0,5000$$

The normalized value of C4 for A3 is 0.5000.

Table 6. Normalization Result Matrix

Alternative	C1	C2	C3	C4	C5
A1 – 2020	0.8571	0.2500	10,000	0.0000	0.0000
A2 – 2021	10,000	0.7500	10,000	0.0000	0.0000
A3 – 2022	0.7143	0.5000	0.8333	0.5000	0.3333
A4 – 2023	0.5714	10,000	0.6667	10,000	0.6667
A5 – 2024	0.0000	0.0000	0.0000	10,000	10,000

The normalization results show that A1 and A2 have relatively high values for the risk and exposure indicators due to their lower initial values. Meanwhile, A5 received a score of 0 for C1, C2, and C3 due to its highest initial values for all three cost indicators. For the benefit indicator, A5 received the maximum score due to its highest accessibility and facility values.

3.4 Calculation of MOPA Preference Value

The preference value of each alternative is calculated by multiplying the normalized value by the indicator weight, then adding up all the multiplication results.

$$S_i = \sum_{j=1}^n r_{ij} w_j$$

Information:

S_i = preference value of the alternative i ;

r_{ij} = normalization value;

w_j = indicator weight.

Alternative calculation A1

$$S_1 = (0.8571 \times 0.25) + (0.2500 \times 0.15) + (1.0000 \times 0.20) + (0.0000 \times 0.20) + (0.0000 \times 0.20)$$

$$S_1 = 0.2143 + 0.0375 + 0.2000 + 0 + 0$$

$$S_1 = 0.4518$$

Alternative calculation A4

$$S_4 = (0.5714 \times 0.25) + (1.0000 \times 0.15) + (0.6667 \times 0.20) + (1.0000 \times 0.20) + (0.6667 \times 0.20)$$

$$S_4 = 0.1429 + 0.1500 + 0.1333 + 0.2000 + 0.1333$$

$$S_4 = 0.7595$$

3.5 Final Grade and Alternative Rankings

Table 7. MOPA Preference Values

Ranking	Alternative	Period	Preference value
1	A4	2023	0.7595
2	A3	2022	0.5869
3	A2	2021	0.5625
4	A1	2020	0.4518
5	A5	2024	0.4000

The preference value is calculated by multiplying normalized scores by indicator weights. A4 (2023) achieved the highest value (0.7595), while A5 (2024) recorded the lowest (0.4000). A4 was mainly supported by its high normalized C2, C4, and C5 values, whereas A5 scored zero on C1, C2, and C3. Although A5 had the highest C4 and C5 values, these contributions were insufficient to offset its higher risk and exposure scores.

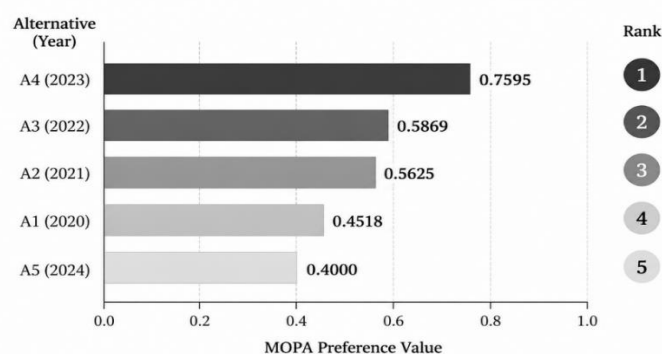


Figure 2. MOPA preference values and ranking of alternatives (2020-2024)

3.6 Analysis of the Contribution of Each Indicator

The contribution value of each indicator is calculated using the equation:

$$K_{ij} = r_{ij} \times w_j$$

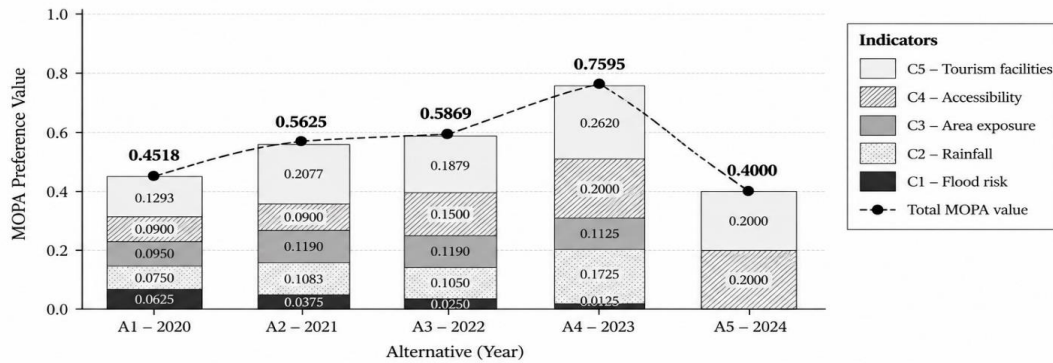


Table 3. Contribution of Indicators to Preference Values

The contribution value shows that A4 received a high contribution from C4 of 0.2000, C2 of 0.1500, and C5 of 0.1333. This condition causes the total value of A4 to be the highest. In A5, the contributions of C4 and C5 are each 0.2000. However, the three cost indicators do not contribute because their normalized values are 0. This condition explains why A5's total value remains the lowest despite having the highest values for the accessibility and facilities indicators.

3.8 Initial Sensitivity Analysis

A sensitivity analysis was conducted to test the stability of MOPA results against changes in indicator weights. The initial weights were used as the baseline scenario, and then each indicator was individually increased and decreased by 5% and 10%.

Weight changes are made relatively:

$$w_j' = w_j(1 \pm p)$$

Next, the weights are renormalized so that the sum of all weights remains equal to one:

$$w_j^* = \frac{w_j'}{\sum_{j=1}^n w_j'}$$

The preference value of each alternative is recalculated using:

$$S_i = \sum_{j=1}^n n_{ij} w_j^*$$

Basic Scenario

The initial weights used are:

Table 9. Baseline Scenario: Indicator Weights and MOPA Results

(a) Initial Indicator Weights			
Indicator		Weight	
C1		0.25	
C2		0.15	
C3		0.2	
C4		0.2	
C5		0.2	
Total		1	
(b) Baseline MOPA Preference Values and Rankings			
Alternative	Year	MOPA Value	Ranking
A1	2020	0.451775	4
A2	2021	0.5625	3
A3	2022	0.586895	2
A4	2023	0.75953	1
A5	2024	0.4	5

Weight Change Scenario $\pm 5\%$

In the following table, the weight order is written as:

(C1, C2, C3, C4, C5)

values are written in the following order:

(A1, A2, A3, A4, A5)

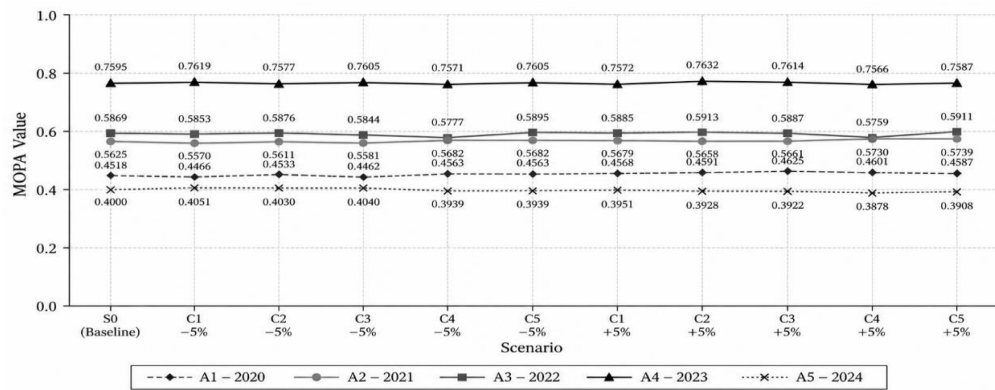


Figure 4. MOPA Sensitivity Analysis under $\pm 5\%$ Weight Changes

All weight change scenarios of $\pm 5\%$ maintain the same ranking order.

Weight Change Scenario $\pm 10\%$

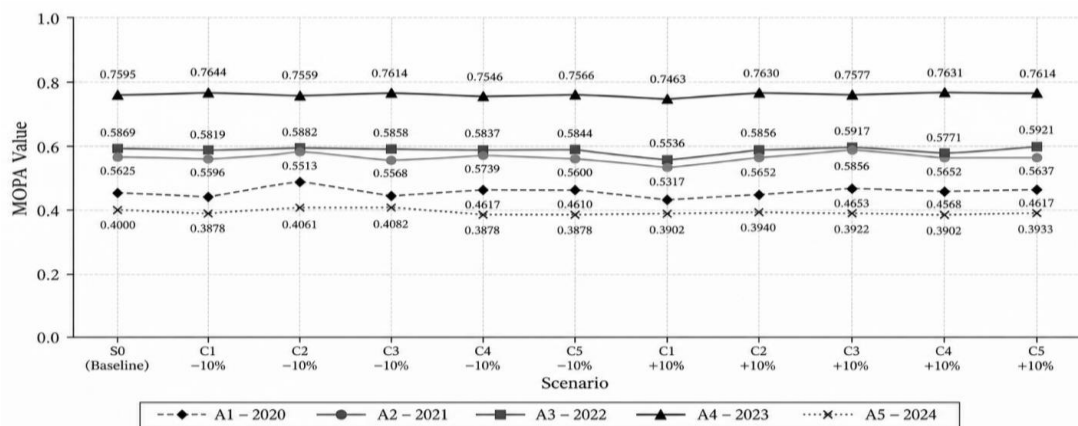


Figure 5. MOPA Sensitivity Analysis under $\pm 10\%$ Weight Changes

Figure 5 shows the MOPA preference values for all alternatives under individual $\pm 10\%$ changes in indicator weights. Although the preference values vary across scenarios, the ranking order remains unchanged, with A4-2023 consistently ranked first and A5-2024 last.

All weight change scenarios of $\pm 10\%$ also maintain the same ranking order.

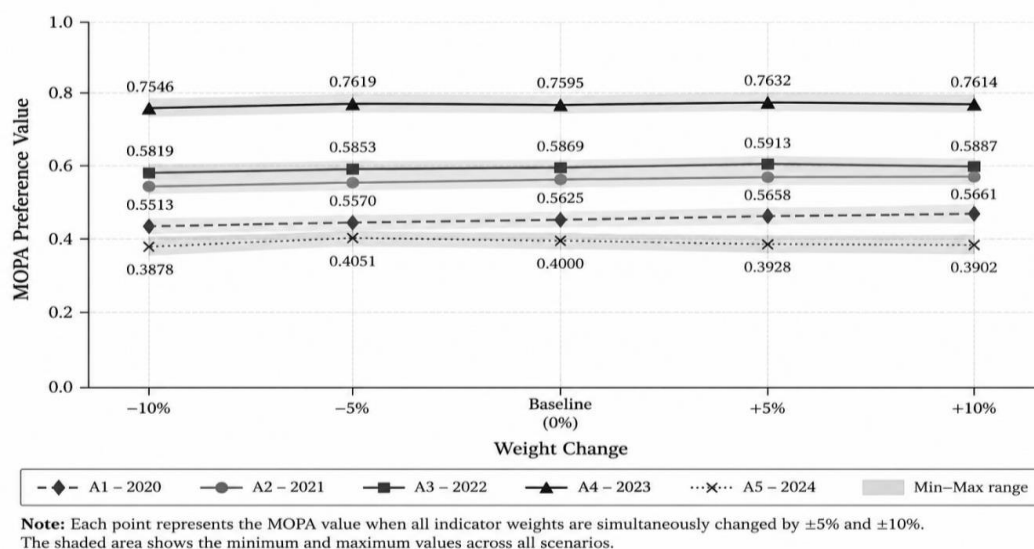


Figure 6. Sensitivity of MOPA preference values to changes in indicator weights (±5% and ±10%)

Figure 6 summarizes the preference-value changes under -10%, -5%, baseline, +5%, and +10% weight changes. The relatively narrow variation in preference values and consistent ranking indicate that the model remains stable under the tested weight perturbations.

Percentage of Rank Stability

The stability percentage is calculated using the equation:

$$SR = \frac{\text{Number of scenarios with no change in ranking}}{\text{Total number of scenarios}} \times 100\%$$

The number of scenarios tested is:

- 1 basic scenario;
- 10 scenarios of change ±5%;
- 10 scenarios of change ±10%.

Total scenarios:

$$N = 21$$

All 21 scenarios yield the same ranking order. Therefore:

$$SR = \frac{21}{21} \times 100\% = 100\%$$

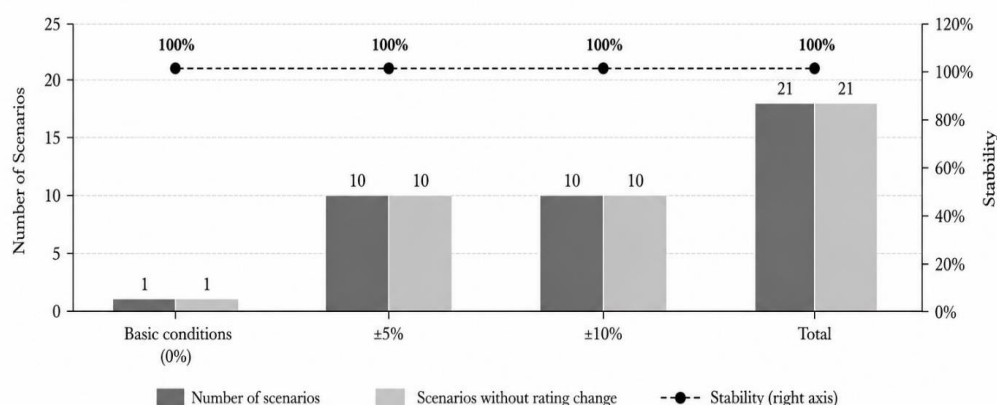


Figure 7. Model Stability Summary

The sensitivity analysis demonstrates 100% ranking stability across all 21 tested scenarios. The baseline ranking order was maintained under both $\pm 5\%$ and $\pm 10\%$ indicator-weight changes, indicating that the MOPA ranking was relatively insensitive to the tested weight perturbations.

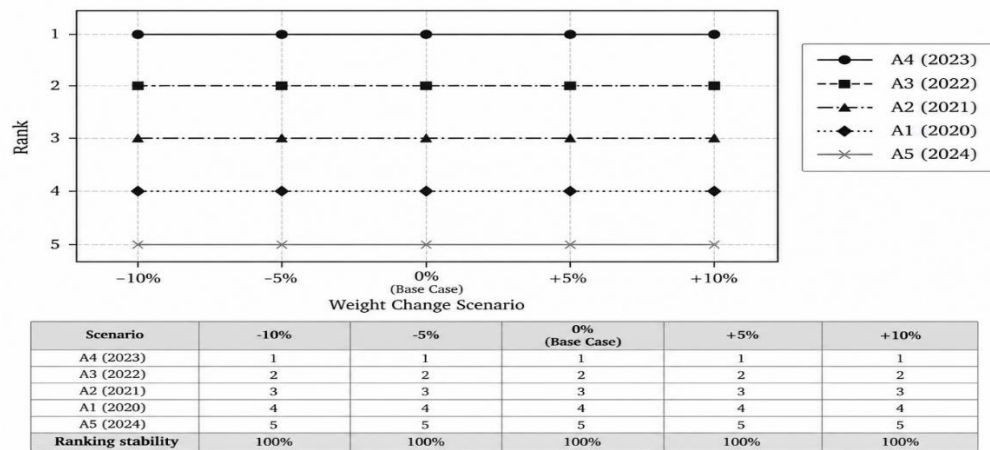


Figure 8. Ranking stability of alternatives under weight perturbation scenarios ($\pm 5\%$ and $\pm 10\%$)

Sensitivity analysis showed that $\pm 5\%$ and $\pm 10\%$ changes in indicator weights did not alter the ranking order. A4–2023 remained first, followed by A3–2022, A2–2021, A1–2020, and A5–2024. However, preference values changed, with A4 ranging from 0.754622 to 0.764354 and A5 from 0.387755 to 0.411765. Increasing C1 tended to reduce A4's value, while increasing C4 and C5 benefited alternatives with higher accessibility and facility scores. Changes in C3 affected preference values but not the ranking. Overall, A4 and A5 remained consistently first and last across all scenarios.

Based on 21 test scenarios, the model achieved 100% ranking stability, indicating that the baseline MOPA results were relatively insensitive to weight changes within $\pm 10\%$. The model can therefore serve as a baseline for comparing resilience across periods, although the results should be revalidated using actual data from InaRISK, BMKG/GPM IMERG, OpenStreetMap, and official tourism facility sources.

3.9 Discussion

The research results show that the Multi-Objective Preference Analysis (MOPA) approach can be used to integrate several indicators with different characteristics to assess the resilience of tourism destinations to flood risk. Flood risk, rainfall, and exposure are treated as cost indicators, while accessibility and facilities are treated as benefit indicators. This arrangement allows the model to distinguish between factors that increase risk and those that support a destination's ability to cope with flooding.

Based on the calculation results, alternative A4–2023 obtained the highest preference score of 0.7595, while A5–2024 obtained the lowest score of 0.4000. These results indicate that resilience is determined not only by the availability of facilities and accessibility, but also by the level of flood risk, rainfall, and regional exposure. In A5–2024, the increase in accessibility and facility scores was not enough to offset the high scores on the risk and exposure indicators. This finding demonstrates the importance of a multi-criteria approach in assessing destination resilience.

Sensitivity analysis showed that weight changes of $\pm 5\%$ and $\pm 10\%$ did not alter the ranking order of the alternatives. All 21 scenarios produced the same ranking as the baseline, resulting in a ranking stability rate of 100%. These results indicate that the model is relatively stable to weight changes within the testing range. However, changes in preference values still occurred, indicating that each indicator still influences the final outcome.

From a practical perspective, research findings indicate that increasing destination resilience should primarily focus on reducing flood risk and regional exposure. Improving tourism facilities and accessibility remains crucial, but should be combined with strengthening drainage

systems, managing flood-prone areas, providing evacuation routes, and enhancing disaster preparedness.

This study still has limitations because some indicator values use proxy scores based on expert judgment. Therefore, the results obtained should be understood as an initial assessment based on secondary data, not as a final measurement of field conditions. The use of actual rainfall data, flood occurrence data, spatial exposure data, and a more measurable facility inventory are needed to increase the validity of the results in further research.

4. CONCLUSION

This study developed a preliminary model for assessing the resilience of tourism destinations to flood risk using the Multi-Objective Preference Analysis (MOPA) approach. The model integrates five indicators: flood risk, rainfall, area exposure, accessibility, and tourism facilities. Data were analyzed through the development of a decision matrix, normalization of cost and benefit indicators, weighting, calculation of preference values, and sensitivity analysis. The test results show that alternative A4–2023 obtained the highest preference value of 0.7595, while A5–2024 obtained the lowest value of 0.4000. This finding indicates that high accessibility and availability of facilities are not sufficient to produce a high resilience value if the risk of flooding, rainfall, and regional exposure are still high. Sensitivity analysis to weight changes of $\pm 5\%$ and $\pm 10\%$ resulted in a ranking stability of 100% in all tested scenarios.

This research contributes to providing a simple, transparent, multi-criteria assessment framework that can be used as an initial step in evaluating destination resilience based on secondary data and digital information. Practically, the research findings can support the identification of priority indicators, particularly for flood risk reduction and regional exposure. Further research will focus on developing real-time or near-real-time data-based models to enhance the ability to dynamically monitor and assess destination resilience. Data on rainfall, water levels, inundation intensity, and flooding events can be obtained periodically from environmental sensors, the Meteorology, Climatology, and Geophysics Agency (BMKG), the National Disaster Management Agency (BNPB)/InaRISK, satellite imagery, and other digital sources. Furthermore, further research is needed to develop automated data processing mechanisms, indicator weight or value updates, and risk threshold-based early warnings. Testing at multiple destinations, expert validation, and broader sensitivity analysis are needed to assess the reliability, responsiveness, and generalizability of real-time models.

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