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Environmental vulnerability assessment for sustainable mining using GIS based AHP - VIKOR approach: A Case Study of Ha Quang, Cao Bang District, Vietnam

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ABSTRACT

Environmental vulnerability in mining-affected karst regions is difficult to assess due to the interaction between terrain, hydrology, and human activities. This study develops a GIS-based framework to evaluate environmental vulnerability in Ha Quang area, Cao Bang province, Vietnam, using an integrated AHP–VIKOR (Analytic Hierarchy Process - Vise Kriterijumska Optimizacija I Kompromisno Resenje) approach. Ten indicators representing physical, biological, and chemical conditions were selected, including mining proximity, landslide proximity, slope, mass balance index, vegetation indices, and soil heavy metal concentration. Indicator weights were derived using AHP, and vulnerability levels were ranked using VIKOR. The results show a strongly heterogeneous pattern, with high and very high vulnerability zones accounting for over 40% of the study area, mainly located in peripheral regions characterized by steep terrain, intensive mining activity, and elevated contamination. Validation indicates that vulnerability decreases with distance, with mean values dropping from 3.46 within 500m of mining sites to 2.74 beyond 3000m. These findings highlight the critical role of geomorphological and hydrological connectivity in controlling vulnerability patterns and demonstrate the effectiveness of the proposed framework for supporting spatial planning and environmental management.

Keywords: *Environmental vulnerability; AHP–VIKOR; Mining impact; Karst environment; GIS.*

1. Introduction

Mining activities are widely recognized as a major driver of environmental degradation, particularly in mountainous and ecologically sensitive regions. Intensive mineral extraction alters geomorphological structures, accelerates soil erosion, reduces vegetation cover, and increases the occurrence of hazards such as landslides and sediment redistribution (Romańczukiewicz & Górniak-Zimroz, 2025). These impacts are especially pronounced in karst environments, where thin soil layers, strong terrain dissection, and rapid surface–subsurface hydrological connectivity facilitate the propagation of disturbances beyond mining sites. As a result, environmental degradation in such systems is not spatially confined but propagates through geomorphological and hydrological connectivity.

In this study, environmental vulnerability is defined as the spatial susceptibility of environmental systems to degradation under mining-induced disturbances, rather than direct damage or loss. In this study, environmental vulnerability is defined as the spatial susceptibility of environmental systems to degradation under mining-induced disturbances, rather than direct damage or loss estimation. In mining-affected mountainous regions, vulnerability emerges from the interaction between geomorphological processes, ecological responses, and contamination

dynamics (She et al., 2025). This process-based perspective highlights the need to move beyond static, indicator-driven approaches toward integrated frameworks capable of capturing multi-dimensional environmental dynamics.

Recent advances in geographic information systems (GIS) and remote sensing have significantly enhanced the capacity to quantify and map environmental vulnerability using multi-source geospatial datasets. The integration of spatial data with multi-criteria decision-making (MCDM) techniques has become a widely adopted approach for environmental assessment, allowing complex decision problems to be structured and evaluated systematically (Malczewski, 2006; Moradi et al., 2023). Terrain attributes derived from digital elevation models, spectral vegetation indices from multispectral imagery, and environmental monitoring data can be effectively combined within GIS-based frameworks to represent different dimensions of environmental processes. Such integration enables the incorporation of both natural and anthropogenic factors, while supporting spatially explicit analysis of environmental conditions and their interactions (Ratnayake et al., 2022; Singh & Patra, 2025). However, most existing MCDM approaches assume independence among indicators and rely on linear aggregation, which limits their ability to capture non-linear interactions and trade-offs among environmental processes. Among these approaches, the Analytic Hierarchy Process (AHP) has been widely used to derive indicator weights based on expert judgment, while various aggregation techniques, such as weighted linear combination, have been employed to produce composite vulnerability indices.

Despite recent advances, several limitations remain in environmental vulnerability assessment. Many studies treat indicators as independent variables, neglecting interactions among geomorphological processes, ecological responses, and contamination dynamics (Cutter, 2012). This limitation is particularly critical in karst mining environments, where strong hydrological connectivity facilitates the transfer of disturbance and pollutants across spatial scales (Shi et al., 2019; Xiong et al., 2022). In addition, conventional aggregation methods, especially linear weighting approaches, fail to capture trade-offs and non-linear relationships among environmental factors (Greco et al., 2016), while chemical processes are often analyzed separately, leading to fragmented assessments (Tóth et al., 2016).

This leads to a fragmented understanding of environmental vulnerability, particularly in karst mining environments where strong connectivity governs disturbance propagation.

To address this gap, this study develops a GIS-based framework integrating the Analytic Hierarchy Process (AHP) and the VIKOR model within a physical–biological–chemical perspective. Environmental vulnerability is conceptualized as the outcome of interacting processes, where physical conditions define structural drivers, biological indicators represent ecosystem responses, and chemical indicators capture contamination and transport dynamics. AHP is used to derive indicator weights, while VIKOR enables compromise ranking under conflicting criteria.

The framework is implemented at the slope unit scale, providing a geomorphologically meaningful representation of spatial processes. The approach is applied to Ha Quang District, located in the Non Nuoc Cao Bang UNESCO Global Geopark, where complex karst terrain and intensive mining activities create spatially heterogeneous vulnerability patterns.

This study contributes to the literature in three main aspects: (1) proposing a process-oriented framework that links disturbance sources, ecosystem responses, and contamination pathways; (2) integrating AHP and VIKOR to capture trade-offs beyond conventional linear aggregation; (3) highlighting the role of geomorphological and hydrological connectivity in shaping environmental vulnerability in karst mining systems.

2. Material and methods

2.3. Study area

Ha Quang District is located in Cao Bang Province in northern Vietnam, between approximately $22^{\circ}45' - 23^{\circ}05'$ N latitude and $106^{\circ}10' - 106^{\circ}35'$ E longitude in Figure 1. The district covers an area of about 800 km² and had an estimated population of around 59,000 inhabitants in 2022, according to official statistical records. The region lies within the Non Nuoc Cao Bang UNESCO Global Geopark, an area characterized by extensive karst landscapes, steep mountainous terrain, and complex geological formations (UNESCO, 2018).

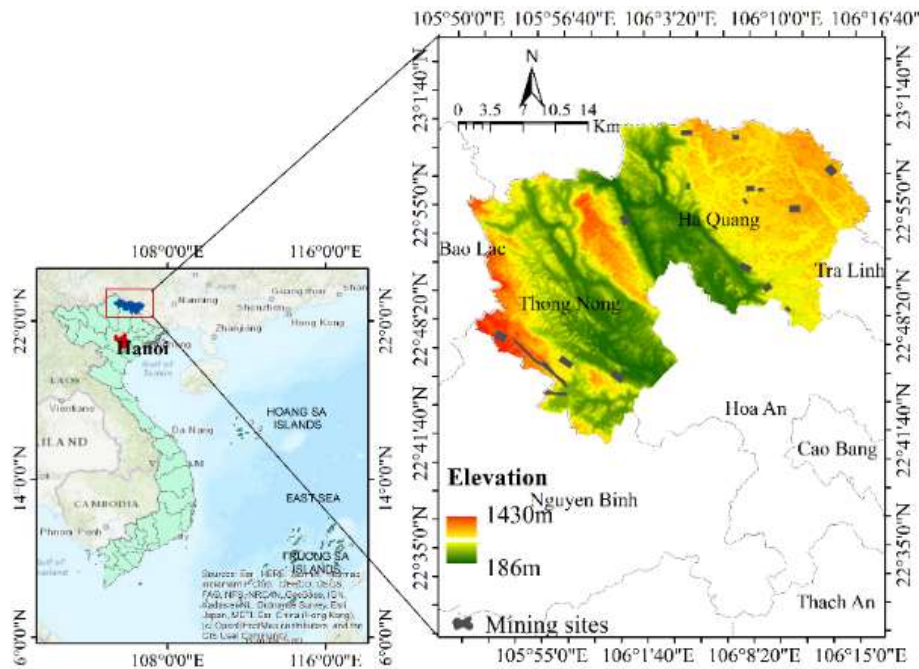


Figure 1. Study area location with distribution of mining sites.

The natural environment of Ha Quang is dominated by limestone mountains, narrow valleys, and highly dissected terrain, making the landscape particularly sensitive to geomorphological hazards and environmental disturbances. In recent decades, the district has experienced increasing mining activities, particularly related to mineral resources such as iron, manganese, and construction materials. While mining contributes to local economic development, intensive extraction can significantly alter landforms, reduce vegetation cover, increase erosion and sediment transport, and introduce heavy metal contamination into surrounding ecosystems (Guo et al., 2025; Sonter et al., 2018).

2.4. Datasets

The methodological workflow consists of four main steps: (i) data acquisition and preprocessing, (ii) indicator construction, (iii) weighting using AHP, and (iv) vulnerability assessment using VIKOR. All procedures were implemented within a GIS environment to ensure spatial consistency and reproducibility.

The indicators were classified into physical, biological, and chemical groups to reflect the main processes governing environmental degradation in mining areas, including terrain instability, ecosystem response, and contaminant accumulation. This grouping reflects the major mechanisms through which mining activities affect the environment and facilitates the subsequent weighting and aggregation of indicators within the AHP–VIKOR decision-making framework.

Proximity indicators capture the spatial influence of mining disturbance and hazard exposure. Areas closer to mining sites are typically subject to more intensive land surface disturbance and ecological degradation due to excavation, vegetation removal, and material redistribution (Sonter et al., 2018). Distance to landslide locations represents exposure to slope instability processes and is widely used to characterize susceptibility to mass movement (Reichenbach et al., 2018). Distance to settlements was used as a proxy for anthropogenic pressure, assuming that areas closer to human activities are subject to more intensive land-use disturbance and environmental stress (Li & Gong, 2016).

Terrain conditions were represented by slope and the Mass Balance Index (MBI), which are key factors controlling erosion, mass movement, and sediment transport processes (P. Zeng et al., 2022). Vegetation and surface conditions were assessed using NDVI, NDMI, and BSI derived from multispectral satellite imagery, which are widely applied indicators for monitoring vegetation health, moisture conditions, and soil exposure (Y. Zeng et al., 2022).

Environmental quality was represented through soil heavy metal concentrations and turbidity-related indicators derived from remote sensing. Heavy metal accumulation in soils and sediments is widely recognized as a major pathway of mining-related environmental contamination, particularly in regions with long-term mineral extraction activities (Lu et al., 2021; Zhou et al., 2024). In addition, the Soil Adjusted Vegetation Index (SAVI) was employed to improve the detection of vegetation conditions by minimizing soil background effects, particularly in sparsely vegetated and disturbed environments. This index is especially suitable for mining-affected areas, where exposed soil surfaces can influence spectral responses and reduce the reliability of conventional vegetation indices (Kocur-Bera & Małek, 2024; Yan et al., 2025). As shown in Table 1, the indicators were derived from multiple geospatial data sources, including satellite imagery, digital elevation models, environmental monitoring data, and spatial proximity analysis. To ensure spatial consistency across datasets obtained from different sources, all indicator layers were resampled to a unified spatial resolution of 30 × 30 m prior to the multi-criteria analysis.

Table 1. Environmental vulnerability indicators and data sources used in the study

Category	Indicator	Data source	Processing approach	Analytical Basis/ Calculation
Physical	Distance to mining sites (DMS)	Mining inventory, provincial mining database	Euclidean distance analysis	Distance (m), normalized
	Distance to landslide locations	Landslide inventory, geological	Euclidean distance analysis	Distance (m), normalized

Category	Indicator	Data source	Processing approach	Analytical Calculation	Basis/
	(DLS)	survey			
	Distance to settlements (DST)	Population dataset	Euclidean distance analysis	Distance (m), normalized	
	Slope	DEM	Terrain analysis from DEM	Degrees (°), normalized	
	Mass Balance Index (MBI)	DEM	Derived from DEM-based terrain analysis	Dimensionless index	
Biological	NDVI	Landsat satellite imagery	8 Spectral index calculation	NDVI = (NIR – Red) / (NIR + Red) (Survey, 2023)	
	NDMI	Landsat satellite imagery	8 Spectral index calculation	NDMI = (NIR – SWIR) / (NIR + SWIR) (Gao, 1996)	
	SAVI	Landsat satellite imagery	8 Spectral index calculation	SAVI = (NIR - RED) / (NIR + RED + L)x (1+L). L is a soil adjustment factor, commonly set to 0.5 under intermediate vegetation conditions (Kocur-Bera & Małek, 2024)	
	BSI	Landsat satellite imagery	8 Spectral index calculation	BSI = ((SWIR + Red) – (NIR + Blue)) / ((SWIR + Red) + (NIR + Blue))(AbdelRahman et al., 2023; Javed et al., 2021)	
Chemical	Soil heavy metal concentration (SHMC)	Field sampling; environmental monitoring	Spatial interpolation (kriging)	See contamination index below	

Soil heavy metal contamination was evaluated using six elements (As, Cd, Cr, Hg, Ni, and Pb), which are commonly reported in mining affected environments due to their persistence, toxicity, and bioaccumulation potential (Han et al., 2023; Mustapha et al., 2025). For each metal, a contamination factor (CF) was calculated as the ratio between the measured concentration and the corresponding background or regulatory threshold value. To account for the combined effect of multiple metals, an integrated pollution index (IPI) was computed as the average of all CF values. The resulting index was subsequently normalized to ensure comparability with other indicators within the VIKOR framework.

2.3. Data normalization and weighting

Because the selected indicators differ in units and value ranges, all variables were standardized prior to the multi-criteria analysis to ensure comparability across datasets. A min–max normalization approach was applied to transform the indicator values into a dimensionless scale ranging from 0 to 1 (Malczewski, 2006). Beneficial indicators, such as distance-based variables, NDVI, SAVI and NDMI, were normalized so that higher values indicate lower environmental vulnerability. In contrast, non-beneficial indicators, including slope, the Mass Balance Index (MBI), BSI and soil heavy metal concentration, were normalized so that higher values reflect greater environmental stress.

The relative importance of the indicators was determined using the Analytic Hierarchy Process (AHP) (Saaty, 2013). In this approach, pairwise comparisons were performed to evaluate the relative contribution of each indicator to environmental vulnerability. The comparison matrix was constructed based on expert knowledge and relevant literature on mining-related environmental impacts. Pairwise comparisons were conducted based on expert judgment ($n = 6$). The principal eigenvector method was used to derive weights. The consistency of the judgment matrix was evaluated using the Consistency Ratio (CR), and only matrices with $CR < 0.1$ were accepted, ensuring the reliability of the weighting process.

2.4. VIKOR multi-criteria decision model

The VIKOR (Vise Kriterijumska Optimizacija I Kompromisno Resenje) method was applied to evaluate environmental vulnerability by addressing trade-offs among multiple, potentially conflicting indicators representing physical, biological, and chemical processes. In this study, weights derived from the AHP procedure were incorporated into the VIKOR framework to ensure a consistent representation of indicator importance while allowing compromise ranking among spatial units (Opricovic & Tzeng, 2004).

To implement the model in a spatial context, the analysis was conducted at the slope unit (SU) scale. Slope units were delineated using hydrological segmentation based on flow direction and watershed boundaries derived from the DEM. Each slope unit was treated as an independent spatial entity, allowing the model to better capture terrain-controlled processes compared to pixel-based approaches.

For each spatial unit i , the utility measure S_i and the regret measure R_i were calculated as:

$$S_i = \sum_{j=1}^n w_j \frac{f_j^* - x_{ij}}{f_j^* - f_j^-} \quad (1)$$

$$R_i = \max_j \left[w_j \frac{f_j^* - x_{ij}}{f_j^* - f_j^-} \right] \quad (2)$$

Where: x_{ij} represents the normalized value of criterion j for spatial unit i , w_j is the weight derived from the AHP procedure, and f_j^* and f_j^- denote the best and worst values of criterion j , respectively. In this formulation, S_i reflects the aggregated environmental pressure across all indicators, whereas R_i identifies the influence of the most critical factor affecting each spatial unit.

The compromise index Q_i was then calculated as:

$$Q_i = v \frac{S_i - S^*}{S^- - S^*} + (1 - v) \frac{R_i - R^*}{R^- - R^*} \quad (3)$$

Where S^* and S^- are the minimum and maximum values of S_i , R^* and R^- represent the minimum and maximum values of R_i . The parameter v expresses the decision strategy weight and was set to 0.5 to balance overall system conditions and the influence of dominant local factors (Opricovic & Tzeng, 2004).

Lower values of Q_i indicate lower environmental vulnerability, while higher values correspond to areas under greater environmental pressure. The resulting Q_i values were mapped within a GIS environment to generate a spatially explicit environmental vulnerability index.

To improve interpretability, the continuous Q_i values were classified into five categories (very low, low, moderate, high, and very high) using the Jenks natural breaks method. The Jenks method was selected because it minimizes intra-class variance and maximizes inter-class differences, making it suitable for heterogeneous environmental data (Chen et al., 2013).

Overall, the integration of AHP-derived weights with the VIKOR model at the slope unit scale enables a balanced assessment of environmental vulnerability, accounting for both cumulative effects and dominant local factors while preserving the spatial structure of terrain-driven processes.

2.5. Consistency assessment with mining distribution

Consistency assessment was conducted to evaluate the spatial agreement between modeled environmental vulnerability and mining activities using GIS-based overlay and distance analysis. This approach is widely applied in spatial modeling studies to examine whether model outputs reflect the distribution of key driving factors (Reichenbach et al., 2018; Roccati et al., 2021).

Mining locations were overlaid with the vulnerability map, and the proportion of mining sites within each vulnerability class was calculated. Buffer zones (0–500 m to >3000 m) were generated to analyze the variation of vulnerability with distance, and mean Q_i values were computed for each zone. Local consistency was further examined by comparing environmental indicators (NDVI, NDMI, BSI, and SAVI) in areas where mining sites did not correspond to high vulnerability (Yan et al., 2021).

3. Results and discussion

3.1 Spatial distribution of environmental vulnerability indicators

The spatial distribution of physical indicators demonstrates that environmental vulnerability is structurally controlled by the interaction between mining disturbance and terrain instability. Low values of distance to mining sites (DMS) in Figure 2b are predominantly distributed in the eastern, northeastern, and southern parts of the study area, indicating zones of intensive anthropogenic pressure. These areas are associated with increased land surface disturbance, vegetation removal, and enhanced susceptibility to environmental degradation.

Terrain-related indicators further reinforce this pattern (Figure 2c and Figure 2d). High slope gradients ($>30^\circ$) and elevated Mass Balance Index (MBI) values are concentrated in the central and southwestern regions, where geomorphological conditions promote erosion and slope instability. In addition, proximity to landslide locations (low DLS values) highlights areas with a higher likelihood of slope reactivation under continued disturbance.

These results indicate that the physical dimension defines the structural framework of environmental vulnerability. Areas where steep terrain coincides with intensive mining activity

represent zones of compounded instability, where disturbance generation and propagation processes are both intensified.

Biological indicators reveal a clear spatial gradient reflecting variations in vegetation condition and moisture availability (Figure 2f and Figure 2g. High NDVI (>0.4) and NDMI (>0.2) values are mainly observed in northern mountainous areas, where dense vegetation cover contributes to higher ecological stability. In contrast, lower values dominate in central and southern regions, indicating vegetation degradation associated with agricultural expansion and mining-related disturbance.

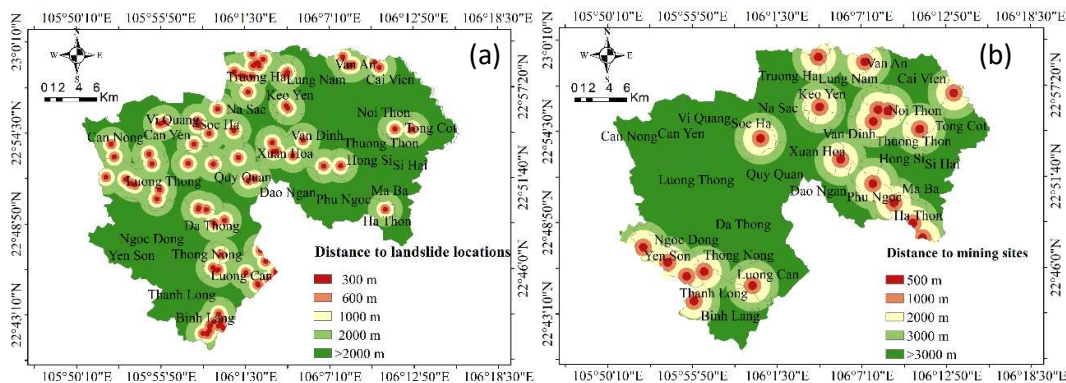
Elevated BSI values in these areas indicate increased exposure of bare soil surfaces, which enhances susceptibility to erosion and surface runoff (Figure 2i). The inclusion of SAVI further refines this pattern by reducing soil background effects, highlighting zones where vegetation cover is insufficient to mitigate environmental stress (Figure 2h).

These patterns demonstrate that biological indicators primarily represent ecosystem responses to underlying physical and anthropogenic drivers. Vegetation degradation acts as an amplifying mechanism, reducing surface protection and increasing the sensitivity of the system to terrain instability and external disturbance.

Chemical indicators reflect the spatial distribution of contamination and sediment transport processes associated with mining activities. High soil heavy metal concentrations (SHMC) (Figure 2j) are concentrated in areas where mining operations overlap with steep terrain and strong weathering conditions, particularly in Lung Nam, Van An, and Si Hai. These zones represent critical hotspots of contamination accumulation.

These results demonstrate that chemical impacts are not spatially isolated but propagate through geomorphological and hydrological pathways. Consequently, contamination processes act as secondary but critical mechanisms that extend environmental vulnerability across the landscape.

Overall, the spatial patterns of physical, biological, and chemical indicators demonstrate strong interdependencies, providing the basis for their integration within the AHP–VIKOR framework to assess overall environmental vulnerability.



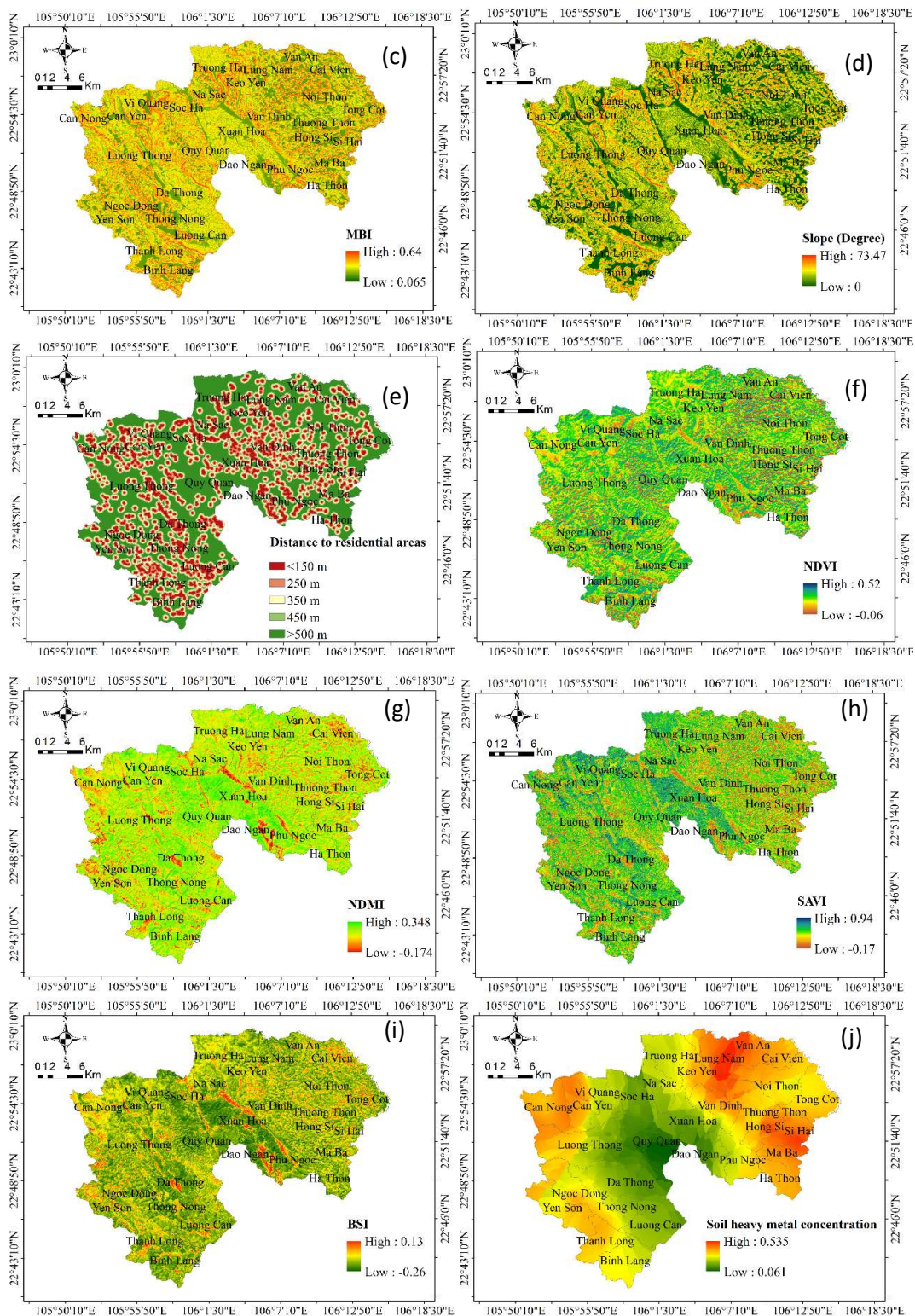


Figure 2. Spatial distribution of indicators (a) DLS, (b) DMS, (c) MBI, (d) Slope, (e) DST, (f) NDVI, (g) NDMI, (h) SAVI, (i) BSI, (j) SHMC used in the environmental vulnerability assessment.

3.2. Integrated vulnerability assessment (AHP–VIKOR)

The relative importance of the ten indicators was determined using the Analytic Hierarchy Process (AHP). Pairwise comparisons were conducted following Saaty's 1–9 scale,

and the resulting weights reflect the environmental conditions of Ha Quang, where mining activities and terrain instability represent dominant controlling factors in Table 2.

The integration of normalized indicators and AHP-derived weights within the VIKOR framework enables a comprehensive evaluation of environmental vulnerability. The weighting results indicate that physical indicators exert the strongest influence, with distance to mining sites (0.180), landslide proximity (0.155), and slope (0.145) identified as dominant factors.

This result confirms that anthropogenic disturbance and geomorphological instability are the primary drivers of environmental vulnerability. In contrast, vegetation-related indicators (NDVI, NDMI, BSI, SAVI) exhibit moderate weights, indicating their role as response variables, while chemical indicators such as SHMC capture the spatial extent of impact propagation rather than initial disturbance.

Table 2. Pair-wise comparison matrix and Final criterion weights

Indicators	DM S	DL S	DS T	Slope	MB I	NDVI	NDMI	BSI	SAVI	SHMC	Weighted
DMS	1	1	3	1	2	2	3	3	4	2	0.180
DLS	1	1	2	1	2	2	2	2	3	2	0.155
DST	0.33	0.5	1	0.5	0.5	1	1	1	1	1	0.067
Slope	1	1	2	1	1	2	2	2	3	2	0.145
MBI	0.5	0.5	2	1	1	1	2	2	2	1	0.107
NDVI	0.5	0.5	1	0.5	1	1	1	1	2	1	0.080
NDMI	0.33	0.5	1	0.5	0.5	1	1	1	1	1	0.067
BSI	0.33	0.5	1	0.5	0.5	1	1	1	1	0.5	0.063
SAVI	0.25	0.33	1	0.33	0.5	0.5	1	1	1	1	0.056
SHMC	0.5	0.5	1	0.5	1	1	1	2	1	1	0.081

The consistency ratio (CR = 0.012) is well below the acceptable threshold of 0.1, indicating a high level of consistency in the weighting process.

The derived weights were subsequently incorporated into the VIKOR model to compute the environmental vulnerability index (Q_i), which integrates both cumulative environmental stress (S_i) and the influence of dominant limiting factors (R_i). The statistical distribution of these components across all spatial units is summarized in Figure 3, showing consistent variability patterns among S_i , R_i , and Q_i values.

The resulting VIKOR index (Q_i) reveals a strongly heterogeneous spatial pattern in Figure 5. Low and very low vulnerability classes are mainly concentrated in central areas characterized by gentle terrain, greater distance from mining activities, and relatively stable vegetation cover. Moderate vulnerability zones form transitional areas surrounding these stable regions, where environmental conditions are sensitive to changes in land use and disturbance intensity.

High and very high vulnerability zones are predominantly distributed in peripheral areas, particularly in northern and northeastern regions. These areas correspond to zones where multiple adverse factors converge, including steep slopes, intensive mining activity, high landslide susceptibility, and elevated contamination levels.

The areal distribution indicates that high and very high vulnerability classes together account for more than 40% of the total study area, highlighting substantial environmental pressure associated with mining activities (Figure 4). This spatial imbalance reflects the concentration of stable conditions in limited central zones, while large peripheral areas experience intensified environmental stress.

Within the VIKOR framework, the Q_i index effectively captures both cumulative environmental pressure and the influence of dominant local constraints. The results demonstrate that environmental vulnerability is not controlled by a single factor but emerges from the interaction between physical, biological, and chemical processes.

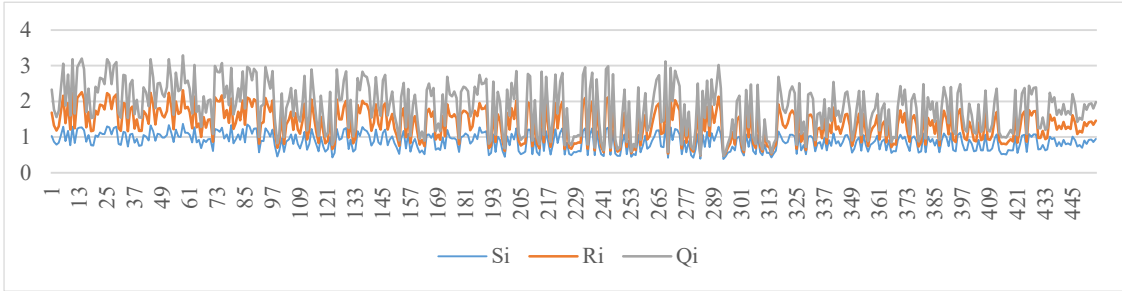


Figure 3. Summary statistics of VIKOR components (S_i , R_i , and Q_i) across spatial units

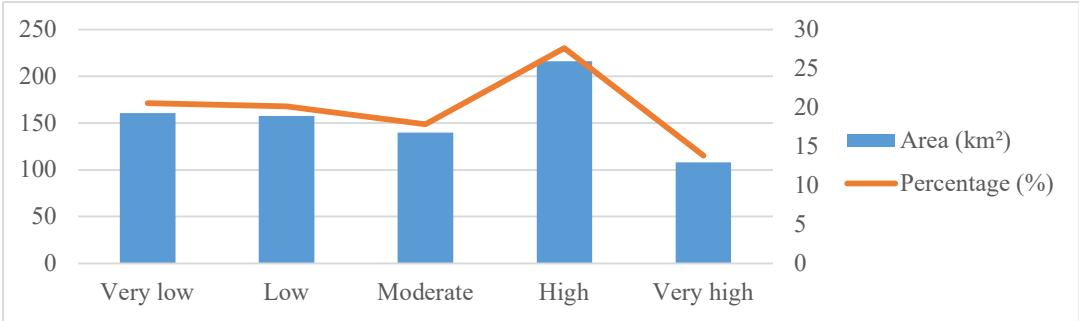


Figure 4. Statistical distribution of environmental vulnerability classes in Ha Quang area

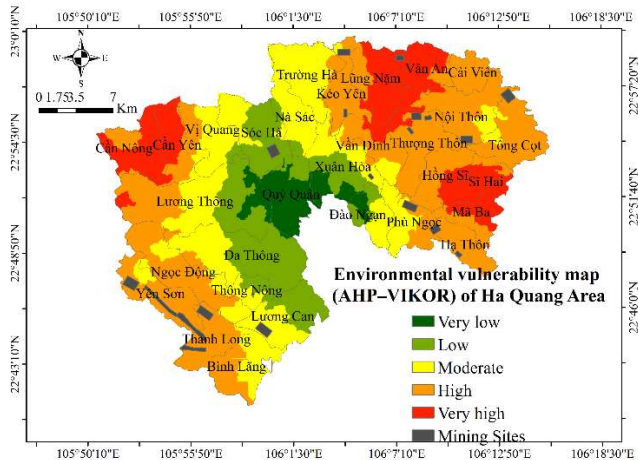


Figure 5. Environmental vulnerability zoning for sustainable mining management in Ha Quang area

A consistency assessment was conducted to evaluate the spatial agreement between the modeled environmental vulnerability and mining activities using GIS-based overlay and

distance analysis. This approach has been widely applied in spatial modeling studies to examine whether model outputs correspond to the distribution of key driving factors and disturbance sources (Pourghasemi et al., 2018; Xiao et al., 2019). By analyzing the spatial relationship between vulnerability patterns and mining locations, this method provides an indirect validation of the model by assessing its ability to capture the influence of anthropogenic drivers.

Table 3. Distribution of environmental vulnerability classes across distance to mining zones

Environmental vulnerability classes Distance to mining zones (m)	Very low	Low	Moderate	High	Very high
0–500	5.5	11.3	23.2	51.6	8.4
500–1000	7.5	12.1	21.7	47.9	10.7
1000–2000	10.8	13.4	24.0	41.4	10.4
200–3000	15.5	15.5	24.8	28.6	15.6
>3000	28.5	23.2	13.0	16.2	19.2

The results reveal a clear distance–decay relationship. Areas located closest to mining sites (0–500 m) exhibit the highest mean vulnerability ($Q_i = 3.46$), which gradually decreases with distance to 2.74 in areas beyond 3000 m. This trend indicates a progressive reduction in environmental stress away from mining activities.

In terms of class distribution, high vulnerability dominates in near-mining zones, accounting for 51.6% within 0–500 m and 47.9% within 500–1000 m. In contrast, its proportion decreases significantly to 16.2% in areas beyond 3000 m. Conversely, very low vulnerability increases with distance, rising from 5.5% (0–500 m) to 28.6% (>3000 m), reflecting improved environmental stability in more distant areas in Table 3.

These findings confirm that environmental vulnerability is strongly controlled by proximity to mining activities. The observed spatial gradient reflects the combined effects of excavation, vegetation removal, and terrain disturbance, which intensify environmental degradation in near-field zones.

Overall, the strong correspondence between vulnerability patterns and distance to mining provides robust independent validation of the AHP–VIKOR model, demonstrating its ability to capture the spatial influence of anthropogenic drivers in the study area.

3.3. Discussion

Environmental vulnerability in the study area emerges from the interaction between physical conditions, ecological responses, and contamination processes rather than from isolated factors. The dominant influence of physical indicators, particularly mining proximity, slope, and landslide susceptibility, indicates that geomorphological instability and anthropogenic disturbance jointly control the spatial structure of vulnerability. Steep terrain enhances erosion and mass movement, while mining activities act as primary disturbance sources, creating conditions for the initiation and propagation of environmental degradation (Reichenbach et al., 2018).

Biological indicators (NDVI, NDMI, BSI, SAVI) primarily reflect ecosystem responses to these drivers. Reduced vegetation cover in high-vulnerability areas indicates diminished

ecological resilience, which further increases surface instability and facilitates runoff and sediment transport. In turn, chemical indicators, particularly soil heavy metal concentration (SHMC), represent the propagation of impacts, controlled by terrain-driven transport processes and hydrological pathways (Tóth et al., 2016). This confirms that environmental vulnerability is governed by a process-based system linking disturbance sources, transport pathways, and landscape conditions.

The integration of AHP and VIKOR provides a more robust framework than weighted linear combination by incorporating expert-based weighting and accounting for trade-offs among conflicting criteria (Brans et al., 2005). This is particularly relevant in mining environments, where multiple processes interact. A key finding is the dominant role of geomorphological and hydrological connectivity, with high-vulnerability zones extending along slope and drainage pathways. In karst systems, strong connectivity facilitates the transfer of water, sediment, and contaminants, amplifying environmental degradation (Goldscheider et al., 2020).

Despite these strengths, several limitations should be acknowledged. The AHP weighting process introduces subjectivity, although consistency checks reduce this effect. Uncertainties in remote sensing data and spatial interpolation, particularly for soil contamination, may influence the results. In addition, the analysis represents a static assessment and does not capture temporal dynamics of environmental processes. Future studies should incorporate time-series data and advanced modeling approaches to improve the robustness and predictive capability of vulnerability assessments.

4. Conclusion

This study developed a GIS-based environmental vulnerability framework by integrating AHP and VIKOR within a physical–biological–chemical perspective. The results reveal a heterogeneous spatial pattern in Ha Quang District, where high and very high vulnerability zones account for over 40% of the area and are concentrated in peripheral regions characterized by steep terrain, intensive mining activity, and elevated contamination.

Environmental vulnerability is primarily controlled by the interaction between geomorphological instability and anthropogenic disturbance. Physical factors dominate as key drivers, while biological and chemical indicators reflect ecosystem responses and impact propagation, confirming that vulnerability emerges from a coupled process system.

Methodologically, the AHP–VIKOR integration provides a robust alternative to linear aggregation by incorporating expert-based weighting and capturing trade-offs among conflicting criteria. The use of slope units further enhances the geomorphological relevance of the assessment.

A key contribution is the identification of geomorphological and hydrological connectivity as a fundamental control, with vulnerability extending along slope and drainage pathways beyond mining sites. This highlights the importance of a landscape-scale perspective in environmental assessment.

From a practical perspective, the results support targeted management in high-vulnerability zones through slope stabilization, vegetation restoration, and monitoring of contaminant transport. However, the framework is subject to uncertainties related to expert-based weighting and data limitations and represents a static assessment. Future research should

incorporate time-series data and dynamic modeling to improve predictive capability.

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Assessment of Hydrodynamic Changes Induced by Dredging and Sand Mining in Tra Ly Estuary for Sustainable Resource Management

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ABSTRACT

The combined effects of dredging and sand mining in estuarine systems remain insufficiently quantified, despite their widespread application for both navigation improvement and material extraction. This study investigates hydrodynamic responses to dredging coupled with sand extraction in the Tra Ly estuary, northern Vietnam, using a coupled MIKE21 modeling system. The model integrates hydrodynamic and wave modules and is calibrated against field observations to ensure reliable simulation of water levels, flow velocity, and tidal dynamics. Two scenarios were simulated, representing pre- and post-intervention bathymetric conditions under identical boundary forcing. Results show that channel deepening leads to a reduction in flow velocity within the range of 0.1–0.6 m/s, accompanied by a decrease in upstream water levels of up to 0.08 m and an increase in tidal discharge reaching 400–600 m³/s. These findings indicate that dredging combined with sand mining enhances channel conveyance while only moderately altering the hydrodynamic regime. Although the impacts remain limited under normal conditions, changes in flow structure may influence sediment transport and system behavior under extreme events. The results provide quantitative evidence for evaluating combined dredging–mining impacts and support sustainable management of estuarine systems.

Keywords: *Hydrodynamics; sand mining; MIKE21; Tidal dynamics; Channel deepening.*

1. Introduction

Estuaries are highly dynamic transitional environments where fluvial and marine processes interact to control hydrodynamics, sediment transport, and morphological evolution. These systems are governed by the combined effects of river discharge, tidal forcing, wave action, and sediment dynamics, which regulate energy distribution and material fluxes across the land–sea interface (Dalrymple et al., 2012; Ma et al., 2010). Recent studies further emphasize that estuarine responses to external forcing are increasingly influenced by human interventions, particularly under conditions of intensified resource exploitation and climate variability (Dunn et al., 2023; Wang, 2024).

Among anthropogenic activities, dredging and sand mining are widely implemented to maintain navigation channels and supply construction materials. In many estuaries, these activities are conducted simultaneously, leading to coupled alterations in channel morphology and sediment budgets. However, such combined interventions may disturb the hydrodynamic equilibrium by modifying flow structure, tidal asymmetry, and sediment transport pathways (Cox et al., 2022; Jia et al., 2024; Tran et al., 2022). Recent studies indicate that channel deepening associated with sand extraction can reduce flow resistance, redistribute hydrodynamic energy, and alter current velocity and water level gradients (Bendô et al., 2023; Winterwerp & Wang, 2021). In addition, increased water depth may enhance wave propagation

toward nearshore zones, potentially intensifying coastal erosion and affecting shoreline stability, particularly under extreme conditions such as storms and floods (Sohrt et al., 2021; Yang et al., 2019).

Numerical modeling has become an essential tool for investigating hydrodynamic processes and quantifying the impacts of human-induced changes in estuarine environments. Process-based models, such as the MIKE21 system developed by the Danish Hydraulic Institute, enable the simulation of depth-averaged flow, wave dynamics, and sediment transport within a coupled framework. The hydrodynamic module is based on the shallow water equations and is solved using a finite-volume approach on an unstructured mesh, allowing accurate representation of complex coastal and estuarine geometries (Xu et al., 2023; Yan et al., 2022).

The integration of hydrodynamic (HD) and spectral wave (SW) modules allows for explicit representation of wave–current interactions through radiation stress gradients, which are essential for understanding energy transfer and sediment mobility in shallow environments (Warren & Bach, 1992). Such coupled modeling approaches have been widely applied in recent studies to assess hydrodynamic responses and sediment transport under dredging and coastal engineering interventions (Ngo & Nguyen, 2023).

The Tra Ly estuary in northern Vietnam is a tide-dominated system characterized by strong interactions between river discharge and marine forcing. The area plays a key role in inland waterway transportation and regional development. A dredging project combined with sand mining has been proposed to improve navigation and provide construction materials. While these activities bring economic benefits, their combined hydrodynamic impacts remain insufficiently quantified, particularly in terms of flow velocity, water level variation, and tidal exchange.

This study aims to assess hydrodynamic changes induced by dredging and sand mining in the Tra Ly estuary using a coupled MIKE21 model. The model is calibrated and validated against field observations to ensure reliable representation of key hydrodynamic variables. The objectives are to: (i) quantify changes in flow velocity and tidal dynamics; (ii) evaluate variations in water levels and tidal discharge; and (iii) discuss implications for sustainable resource management. The results provide a quantitative basis for understanding the combined effects of dredging and sand mining and support evidence-based decision-making in estuarine systems.

2. Material and methods

2.1. Case study

The study focuses on the Tra Ly estuary located in Thai Binh Province, northern Vietnam, which is a typical tide-dominated river mouth influenced by both fluvial discharge and marine processes. The estuary plays an important role in inland waterway transportation and sediment exchange between the Red River system and the coastal zone.



Figure 1. Boundary of the proposed dredging and sand mining area at the Tra Ly estuary.

The investigated area extends from the upstream river section to the nearshore coastal zone, covering approximately 4.6 km along the navigation channel and extending offshore to capture wave–current interactions (Figure 1). The bathymetry is characterized by a gently sloping riverbed transitioning into a shallow coastal shelf, where tidal dynamics and wave action strongly influence flow patterns.

2.2. Hydrodynamic modeling

Hydrodynamic processes were simulated using the MIKE21 FM system developed by the Danish Hydraulic Institute. The model solves the depth-integrated two-dimensional shallow water equations on an unstructured mesh using a finite-volume approach. A coupled configuration between the hydrodynamic (HD) and spectral wave (SW) modules was applied to account for wave–current interactions, while sediment-related outputs were used for interpretation.

The HD module solves the depth-integrated shallow water equations, including the continuity equation (DHI, 2009):

$$\frac{\partial h}{\partial t} + \frac{\partial hU}{\partial x} + \frac{\partial hV}{\partial y} = hS \quad (1)$$

Where U and V are the depth-averaged velocity components corresponding to the velocity components u and v in the x and y directions, defined as follows:

$$U = \frac{1}{h} \int_{-d}^{\eta} u dz, \quad V = \frac{1}{h} \int_{-d}^{\eta} v dz \quad (2)$$

Where $h = \eta + d$ is the total water depth, defined as the sum of the water surface elevation (η) and the bed depth (d).

And the momentum equations as following (DHI, 2009):

$$\begin{aligned} \frac{\partial hU}{\partial t} + \frac{\partial hU^2}{\partial x} + \frac{\partial hUV}{\partial y} = fVh - gh \frac{\partial \eta}{\partial x} - \frac{h}{\rho_0} \frac{\partial p_a}{\partial x} - \frac{gh^2}{2\rho_0} \frac{\partial \rho}{\partial x} + \\ \frac{\tau_{sx}}{\rho_0} - \frac{\tau_{bx}}{\rho_0} - \frac{1}{\rho_0} \left(\frac{\partial S_{xx}}{\partial x} + \frac{\partial S_{xy}}{\partial x} \right) + \frac{\partial}{\partial x} (hT_{xx}) + \frac{\partial}{\partial y} (hT_{xy}) + hU_s S \end{aligned} \quad (3)$$

$$\begin{aligned} \frac{\partial hV}{\partial t} + \frac{\partial hV^2}{\partial x} + \frac{\partial hUV}{\partial y} = fUh - gh \frac{\partial \eta}{\partial y} - \frac{h}{\rho_0} \frac{\partial p_a}{\partial y} - \frac{gh^2}{2\rho_0} \frac{\partial \rho}{\partial y} + \\ \frac{\tau_{sy}}{\rho_0} - \frac{\tau_{by}}{\rho_0} - \frac{1}{\rho_0} \left(\frac{\partial S_{xx}}{\partial x} + \frac{\partial S_{xy}}{\partial x} \right) + \frac{\partial}{\partial x} (hT_{xy}) + \frac{\partial}{\partial y} (hT_{yy}) + hV_s S \end{aligned} \quad (4)$$

The terms T_{xx} , T_{yy} and T_{xy} represent the components of the total viscous stresses, which are calculated based on the horizontal velocity gradients.

The spectral wave module (SW) is based on the wave action conservation equation and simulates wave generation, propagation, and dissipation processes, including wind input, whitecapping, bottom friction, and depth-induced breaking. The coupling between HD and SW allows the model to account for wave–current interactions through radiation stress gradients.

The computational domain was discretized using an unstructured mesh with approximately 30,000 elements. Grid resolution ranges from 10–50 m in the navigation channel and nearshore areas to 300–500 m offshore, allowing accurate representation of bathymetry and shoreline geometry.

2.3. Data and boundary conditions

The model integrates multiple data sources. Bathymetry was constructed from project surveys at a scale of 1:5,000 combined with regional datasets ranging from 1:10,000 to 1:50,000. Offshore wave and wind conditions were derived from the ERA5 reanalysis dataset, while river discharge and upstream water levels were used to represent fluvial forcing. Tidal forcing was obtained from the global tidal toolbox integrated within MIKE21.

The computational domain includes three open sea boundaries located in the northeast, east, and southwest, and one upstream river boundary. Along the sea boundaries, spatially and temporally varying water levels and wave parameters were prescribed, whereas river boundaries were assigned discharge and water level conditions.

A constant time step of 30 s was applied with a Courant–Friedrichs–Lewy (CFL) number of 0.8 to ensure numerical stability. Additional hydraulic settings include a Smagorinsky eddy viscosity formulation with a coefficient of 0.28, a drying depth of 0.005 m, a flooding depth of 0.05 m, and a wetting depth of 0.1 m.

2.4. Model calibration and validation

Model calibration was performed by adjusting bed roughness coefficients. Manning values were assigned in the range of 28–35 m/s, varying by bathymetric zone. Calibration was based on comparison between simulated and observed data, including water levels, wave characteristics, flow velocity, and suspended sediment concentration.

The Nash–Sutcliffe efficiency coefficient is used to evaluate model performance, where values closer to 1 indicate higher agreement between observed and simulated data.

$$\text{Nash} = 1 - \frac{\sum (X_{o,i} - X_{s,i})^2}{\sum (X_{o,i} - \bar{X}_o)^2} \quad (5)$$

Where $X_{o,i}$ is the observed value, $X_{s,i}$ is the simulated value, and $\bar{X}_o$ is the mean of observed values.

The Nash value close to 1 indicates a strong agreement between observed and simulated water levels.

2.5. Scenario design

Two scenarios were simulated to assess the impacts of dredging and sand mining. The baseline scenario represents existing bathymetry, while the intervention scenario reflects channel deepening to approximately 7.8 m. Both scenarios were run under identical boundaries and forcing conditions to isolate the effects of bathymetric modification.

The analysis focuses on three key indicators: flow velocity, water level variation, and tidal discharge. Simulations were conducted under northeast and southwest monsoon conditions, as well as representative extreme events, including storm and flood scenarios. This approach allows direct comparison of hydrodynamic responses before and after dredging.

3. Results and Discussion

Prior to scenario analysis, model performance was evaluated to ensure reliability. The model reproduced observed water levels with high accuracy (Nash $\approx$ 0.97) and showed acceptable agreement for wave and flow parameters, providing a reliable basis for subsequent hydrodynamic analysis.

3.1 Hydrodynamic changes

Dredging combined with sand mining results in a consistent but moderate reduction in

flow velocity across the study area. Depth-averaged velocities generally range from 0.1 to 0.6 m/s under existing conditions and decrease slightly after channel deepening, with mean reductions of approximately 0.01–0.04 m/s depending on location (Table 1 and Table 2).

Spatial patterns of flow are clearly modified, as shown in Figure 2. Under northeast monsoon conditions, flow fields become more uniform after dredging, with reduced lateral variability and stronger alignment along the main channel axis. This effect is observed during both flood and ebb tides, indicating a systematic reorganization of the flow structure rather than localized changes.

Figure 3 presents the schematic distribution of sampling locations (P1–P8) used for data extraction and quantitative analysis, forming the basis for evaluating changes in flow velocity, water level, and tidal discharge between baseline and dredged scenarios.

Temporal variations further confirm these trends. As illustrated in Figure 4, flow velocity and direction exhibit reduced fluctuations after dredging, particularly during peak tidal phases. The main current becomes more stable and concentrated, while directional variability decreases. These changes indicate reduced turbulence and more efficient flow conveyance within the channel.

Overall, the results demonstrate that dredging primarily affects flow distribution and stability, rather than significantly altering the magnitude of velocity.

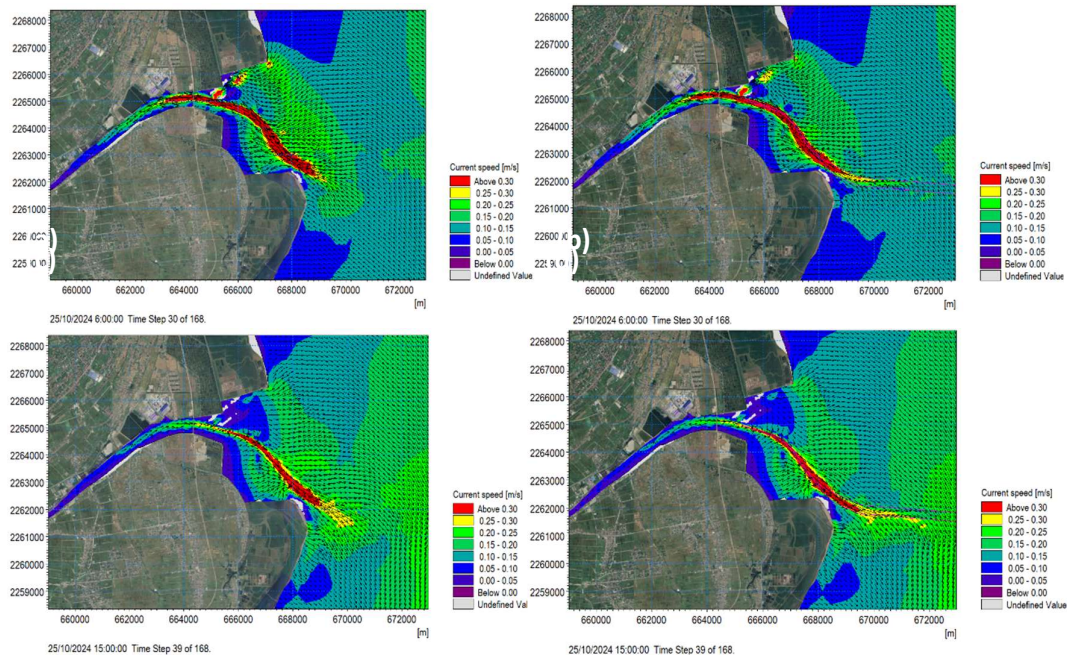


Figure 2. Flow velocity fields under northeast monsoon conditions: (a) flood tide and (b) ebb tide for existing bathymetry; (c) flood tide and (d) ebb tide for dredged bathymetry (-1 m).

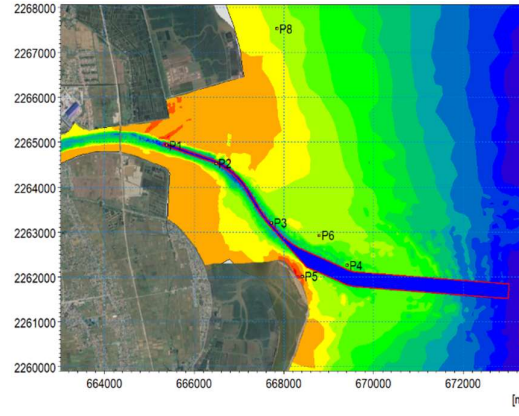


Figure 3. Schematic map showing sampling locations (P1–P8) used for data extraction and hydrodynamic assessment.

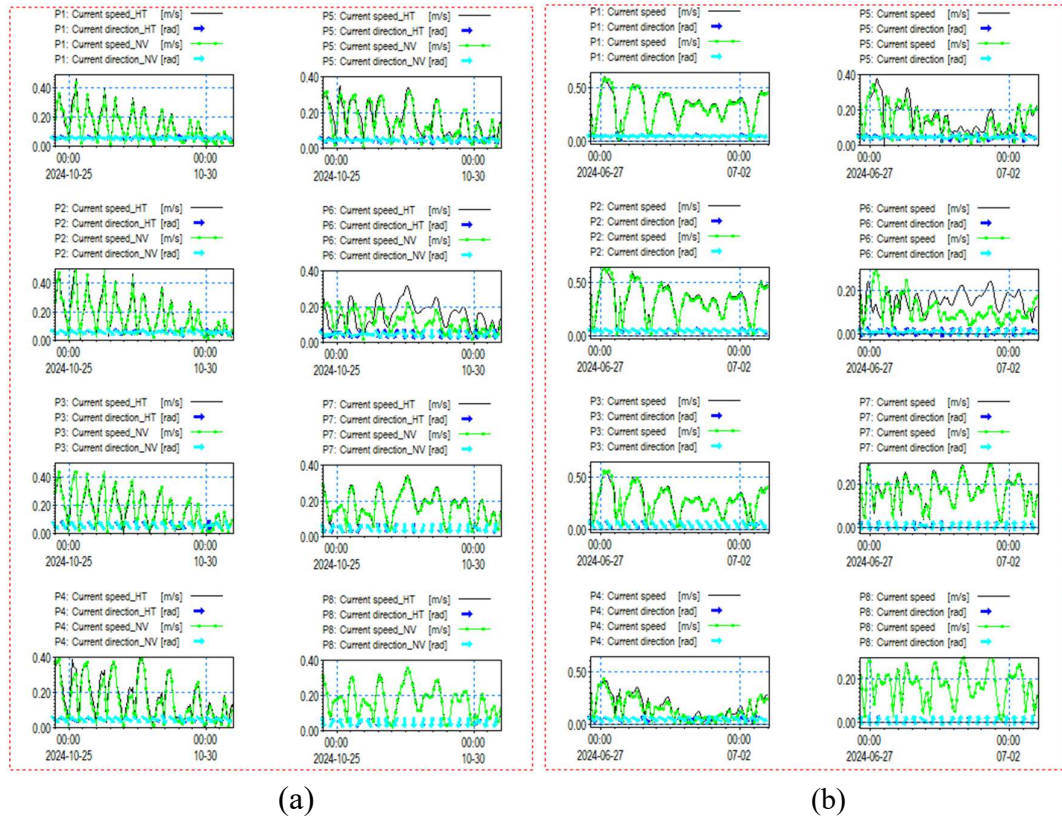


Figure 4. Comparison of flow velocity and direction before and after dredging (−1 m): (a) northeast monsoon and (b) southwest monsoon conditions.

3.2. Water level changes

Changes in water level are relatively small but spatially systematic. Under northeast monsoon conditions, tidal water levels range from approximately -1.6 m to $+1.8$ m, with a maximum reduction of about **0.08 m** observed in upstream sections after dredging (Table 1).

The magnitude of water level changes decreases gradually from upstream to the estuary mouth, indicating that dredging impacts are more pronounced in confined river sections. In most locations, mean water level differences remain within **0.00–0.01 m**, confirming that the overall tidal range is largely preserved.

A similar pattern is observed under southwest monsoon conditions (Table 2), although slightly larger variations occur at some locations due to combined river discharge and tidal forcing. Despite these variations, the overall change remains limited.

These results indicate that dredging induces a minor lowering of water levels without significantly modifying tidal dynamics, and its influence is primarily local rather than system wide.

Table 1. Variation of hydrodynamic parameters after dredging under northeast monsoon conditions.

Parameter	Location	Existing condition			Dredged condition			Difference (Existing – Dredged)		
		Min	Max	Mean	Min	Max	Mean	Min	Max	Mean
Velocity (m/s)	P1	-1.53	1.61	0.00	-1.61	1.60	-0.01	0.08	0.00	0.01
	P2	-1.53	1.59	-0.01	-1.61	1.58	-0.01	0.08	0.01	0.01
	P3	-1.53	1.58	-0.01	-1.59	1.57	-0.01	0.06	0.00	0.01
	P4	-1.52	1.57	0.00	-1.56	1.56	-0.01	0.04	0.00	0.00
	P5	-1.51	1.57	0.00	-1.55	1.56	-0.01	0.04	0.00	0.00
	P6	-1.52	1.57	-0.01	-1.53	1.57	-0.01	0.01	0.00	0.00
	P7	-1.52	1.57	-0.01	-1.52	1.57	-0.01	0.00	0.00	0.00
	P8	-1.52	1.57	-0.01	-1.52	1.57	-0.01	0.00	0.00	0.00
Velocity (m/s)	P1	0.01	0.46	0.14	0.01	0.44	0.13	0.00	0.03	0.01
	P2	0.01	0.56	0.17	0.01	0.53	0.17	0.00	0.03	0.01
	P3	0.01	0.43	0.17	0.00	0.44	0.17	0.00	-0.01	0.00
	P4	0.00	0.40	0.18	0.00	0.39	0.16	0.00	0.01	0.02
	P5	0.02	0.35	0.16	0.00	0.32	0.15	0.01	0.03	0.02
	P6	0.02	0.32	0.15	0.02	0.23	0.12	0.00	0.09	0.04
	P7	0.03	0.35	0.17	0.02	0.33	0.16	0.00	0.01	0.00
	P8	0.01	0.36	0.17	0.01	0.35	0.16	0.00	0.00	0.00
Flow direction (°)	P1	74	307	181	62	309	178	12	-2	3
	P2	110	300	193	105	299	189	5	2	4
	P3	107	341	229	23	336	233	84	5	-4
	P4	121	306	186	123	308	188	-1	-2	-2
	P5	107	317	177	91	307	174	16	10	3
	P6	20	354	186	26	341	171	-5	13	15
	P7	2	359	185	1	360	186	1	-1	-1
	P8	2	357	182	1	359	183	1	-2	-1

Table 2. Variation of hydrodynamic parameters after dredging under southwest monsoon conditions.

Parameter	Location	Existing condition			Dredged condition			Difference (Existing – Dredged)		
		Min	Max	Mean	Min	Min	Max	Mean	Max	Min
Velocity (m/s)	P1	-1.22	1.80	0.08	-1.57	1.79	0.05	0.36	0.01	0.03
	P2	-1.25	1.77	0.06	-1.61	1.77	0.03	0.36	0.01	0.03
	P3	-1.27	1.76	0.04	-1.63	1.75	0.02	0.36	0.00	0.02
	P4	-1.29	1.75	0.03	-1.62	1.75	0.02	0.33	0.00	0.02
	P5	-1.31	1.75	0.03	-1.62	1.75	0.02	0.31	0.00	0.01
	P6	-1.60	1.75	0.02	-1.61	1.75	0.02	0.01	0.00	0.00
	P7	-1.60	1.76	0.02	-1.60	1.76	0.02	0.00	0.00	0.00
	P8	-1.60	1.76	0.02	-1.61	1.76	0.02	0.00	0.00	0.00

Parameter	Location	Existing condition			Dredged condition			Difference (Existing – Dredged)		
		Min	Max	Mean	Min	Min	Max	Mean	Max	Min
Velocity (m/s)	P1	0.01	0.60	0.32	0.02	0.58	0.31	-0.01	0.02	0.01
	P2	0.01	0.67	0.34	0.01	0.67	0.33	0.00	0.00	0.01
	P3	0.01	0.57	0.28	0.01	0.56	0.27	0.00	0.01	0.01
	P4	0.01	0.42	0.17	0.01	0.43	0.15	0.00	-0.01	0.02
	P5	0.00	0.38	0.16	0.01	0.34	0.13	-0.01	0.04	0.02
	P6	0.04	0.25	0.15	0.03	0.30	0.12	0.01	-0.05	0.04
	P7	0.02	0.30	0.17	0.03	0.29	0.17	0.00	0.01	0.00
	P8	0.00	0.32	0.18	0.00	0.32	0.18	0.00	0.00	0.00
Flow direction (°)	P1	103	290	118	94	298	117	9	-7	1
	P2	56	314	136	91	303	135	-35	11	1
	P3	95	340	164	105	337	167	-10	3	-3
	P4	39	319	168	18	337	178	21	-18	-9
	P5	2	359	167	10	342	168	-8	17	-1
	P6	1	359	104	7	356	147	-6	3	-42
	P7	0	360	114	0	360	119	0	0	-6
	P8	1	359	121	1	358	123	0	1	-2

3.3. Tidal discharge

Tidal discharge through the estuary increases slightly after dredging, reflecting improved channel conveyance. Peak ebb discharge ranges from approximately 400 to 600 m³/s under existing conditions and shows a consistent increase after channel deepening.

As shown in Figure 5a (northeast monsoon) and Figure 5b (southwest monsoon), the discharge curve under dredged conditions is consistently higher than that of the baseline scenario, particularly during ebb phases. This indicates enhanced drainage capacity and reduces hydraulic resistance.

However, the magnitude of change remains moderate, suggesting that dredging primarily affects flow efficiency and redistribution, rather than inducing major changes in the tidal regime.

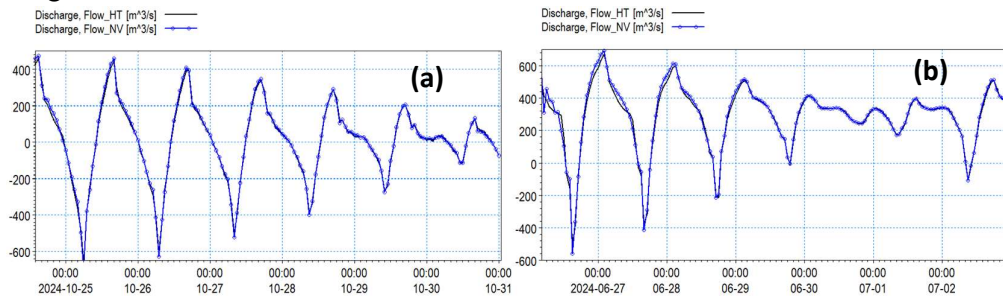


Figure 5. Comparison of tidal discharge at the estuary before and after dredging and sand mining under (a) northeast monsoon and (b) southwest monsoon conditions.

3.4. Discussion

The results indicate that dredging combined with sand mining primarily modifies channel geometry, leading to moderate changes in hydrodynamic conditions. The observed reduction in flow velocity is consistent with hydraulic responses to channel deepening, where an increase in cross-sectional area reduces flow resistance and redistributes discharge. Similar behavior has been widely reported in estuarine systems, where dredging can weaken residual circulation and reorganize velocity fields (van Maren, 2015; Winterwerp, 2013). The

concentration of flow along the main channel observed in this study reflects hydrodynamic adjustment to bathymetric modification, which is consistent with morphodynamic responses reported in engineered estuaries (Guo, 2014; Zhang et al., 2026).

The slight decrease in water level, particularly in upstream sections, can be attributed to bed lowering and associated changes in hydraulic gradients. Channel deepening is known to reduce bottom friction and alter tidal wave propagation, thereby affecting water level distribution along estuaries (Friedrichs, 2010; Winterwerp, 2013). More recent studies confirm that dredging can modify tidal amplitude and phase, although the magnitude of change is often limited in tide-dominated systems (Cox et al., 2022; van Maren, 2015). The relatively small variation observed in this study indicates that tidal forcing remains the dominant control, and the impacts of dredging and sand mining are mainly localized under normal conditions.

The increase in tidal discharge reflects enhanced channel conveyance capacity following dredging and sediment removal. This mechanism is consistent with studies showing that bathymetric deepening can increase tidal exchange and influence ebb–flood dynamics without fundamentally altering the overall hydrodynamic regime (Purkiani et al., 2021; Venancio et al., 2020). These findings suggest that combined dredging–mining activities primarily affect flow redistribution rather than inducing large-scale system shifts.

From a management perspective, reduced flow velocity and increased discharge capacity improve navigation conditions and hydraulic efficiency, which are key objectives of dredging and sand mining projects. However, the redistribution of flow may also alter sediment transport pathways. Recent studies highlight that sand mining can significantly modify sediment budgets, leading to localized erosion or deposition and affecting channel stability (Kennish, 2023). In addition, increased water depth may facilitate wave propagation toward nearshore areas, particularly under extreme conditions, thereby increasing the risk of coastal erosion and shoreline instability (Gou et al., 2023).

Overall, dredging combined with sand mining provides clear benefits for navigation and resource utilization but introduces potential environmental implications related to sediment dynamics and coastal processes. These results emphasize the need for integrated assessment approaches that consider both hydrodynamic and sediment responses, supporting sustainable resource management in estuarine systems.

4. Conclusion

This study assessed hydrodynamic changes induced by dredging combined with sand mining in the Tra Ly estuary using a coupled MIKE21 model. The results indicate a slight reduction in flow velocity, a minor decrease in upstream water levels (approximately 0.08 m), and a moderate increase in tidal discharge. These changes are mainly associated with channel deepening and expansion of the wetted cross-section, which enhance flow conveyance without significantly altering the overall tidal regime. Although the impacts remain limited under normal conditions, modifications in flow structure and tidal propagation suggest potential sensitivity under extreme events. The findings provide a quantitative basis for evaluating combined dredging–mining impacts and support sustainable resource management in estuarine systems.

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