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Mapping coastal resilience: a Gis-based Bayesian network approach to coastal hazard identification for Queensland's dynamic shorelines

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Abstract

Coastal regions worldwide face increasing threats from climate change-induced hazards, necessitating more accurate and comprehensive vulnerability assessment tools. This study introduces an innovative approach to coastal vulnerability assessment by integrating Bayesian Networks (BN) with the modern coastal vulnerability (CV) framework. The resulting BN-CV model was applied to Queensland's coastal regions, with a particular focus on tide-modified and tide-dominated beaches, which constitute over 85% of the studied area. The research methodology involved beach classification based on morphodynamic characteristics, spatial subdivision of Queensland's coast into 78 sections, and the application of the BN-CV model to analyze interactions between geomorphological features and oceanic dynamics. This approach achieved over 90% accuracy in correlating beach types with vulnerability factors, significantly outperforming traditional CVI applications. Key findings include the identification of vulnerability hotspots and the creation of detailed exposure and sensitivity maps for Gold Coast City, Redland City, Brisbane City, and the Sunshine Coast Regional area. The study revealed spatial variability in coastal vulnerability, providing crucial insights for targeted management strategies. The BN-CV model demonstrates superior precision and customization capabilities, offering a more nuanced understanding of coastal vulnerability in regions with diverse beach typologies. This research advocates for the adoption of the BN-CV approach to inform tailored coastal planning and management strategies, emphasizing the need for regular reassessments and sustained stakeholder engagement to build resilience against climate change impacts.

Recommendations include prioritizing adaptive infrastructure in high-exposure areas like the Gold Coast, enhancing flood management in Brisbane, improving socio-economic adaptive capacity in Redland, and maintaining natural defences in Moreton Bay. This study contributes significantly to the field of coastal risk management, providing a robust tool for policymakers and coastal managers to develop more effective strategies for building coastal resilience in the face of climate change.

Keywords Managing coastal risk, Coastal vulnerability, Sensitivity, Bayesian networks, Coastal hazard identification, Beach morphology, Resilience

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1 Introduction

Coastal areas are of immense economic, social, and ecological importance, serving as hubs for trade, tourism, fisheries, and biodiversity (Balsas 2024; Ceccacci et al. 2024; Hanafi & Riry 2024; Kurniati et al. 2024; Tur et al. 2021; Ye 2023). Globally, these regions are home to a large proportion of the population and are critical to sustaining livelihoods, economic activities, and ecosystem services. However, coastal regions worldwide are increasingly susceptible to climate change-induced hazards, including sea-level rise, storm surges, and accelerated erosion, which pose significant risks to human settlements, ecosystems, and infrastructure(Sahin et al. 2019; Tür, 2020). The urgency for effective coastal management strategies is growing as these areas experience greater vulnerability to such environmental threats(Durap 2023). Globally, the need to mitigate these risks has led to the widespread use of tools like the Coastal Vulnerability Index (CVI) (Beuzen et al. 2018). However, traditional vulnerability assessments often fail to account for the complex and dynamic nature of coastal systems, particularly variations in beach typologies—such as wave-dominated, tide-modified, and tide-dominated beaches—and the geomorphological features of coastlines. These factors are critical in determining how different coastal regions respond to environmental changes and hazards like storm surges and sea-level rise (Gutierrez et al. 2011). For example, geomorphological variability plays a significant role in the vulnerability of barrier islands and beach systems to erosion and flooding, influencing the effectiveness of risk assessments (Sahin et al. 2019).

. In Queensland, Australia, these challenges are acutely felt due to the region's diverse coastal dynamics, making the need for more advanced risk mitigation strategies particularly urgent. Without proactive efforts, the sustainability of these vital regions is at significant risk, making effective management essential to protect ecosystems, human communities, and economies from the mounting impacts of climate change.

Existing research frequently employs the CVI to assess coastal vulnerability (Perch-Nielsen 2010; Smit & Wandel 2006; Sudha Rani et al. 2015; Tanim & Goharian 2023). However, many studies oversimplify the threats by not incorporating diverse beach classifications and interactions between oceanic dynamics and geomorphological features. For instance, vulnerability assessments often neglect the specific hazards faced by tide-dominated and tide-modified beaches. These gaps in the literature highlight the need for models that better reflect the complexities of coastal ecosystems. Recent advances suggest the integration of Bayesian Networks (BN) into CV frameworks could enhance the predictive accuracy and relevance of vulnerability assessments (Sahin et al. 2019). However, such approaches remain underexplored, particularly in regional contexts like Queensland, where beach typologies significantly influence vulnerability.

Traditional approaches, such as the Coastal Vulnerability Index (CVI), have long been employed to assess the susceptibility of coastal areas to environmental threats (Durap & Balas 2024; Koroglu et al. 2019; Mendoza & Jiménez 2009). While the CVI provides a broad overview of risk factors, it often oversimplifies the complex nature of coastal dynamics, particularly in regions characterized by diverse beach typologies such as wave-dominated, tide-modified, and tide-dominated beaches. This limitation becomes evident in coastal regions like Queensland, Australia, where the geomorphological and oceanic conditions vary significantly across the coastline, necessitating a more nuanced approach to vulnerability assessment.

Recent advancements in coastal risk management suggest the integration of probabilistic models like Bayesian Networks (BN) into the CV framework could enhance the predictive accuracy of vulnerability assessments (Durap et al. 2023; Sahin et al. 2019; Sanuy et al. 2020; Valchev et al. 2017). Bayesian Networks offer a flexible, data-driven approach to model the intricate relationships between various coastal risk factors, providing a more comprehensive understanding of how geomorphological features, oceanic dynamics, and beach characteristics interact to influence vulnerability (Beuzen et al. 2018; Gutierrez et al. 2015). Despite the potential of these advanced models, their application remains underexplored, particularly in regions with complex coastal environments like Queensland.

This study addresses these gaps by introducing an innovative framework that integrates Bayesian Networks with the Coastal Vulnerability Index (BN-CV) to provide a more detailed and accurate assessment of coastal risks. Specifically, the study focuses on Queensland's coastline, which includes over 85% of tide-modified and tide-dominated beaches, to evaluate the interactions between beach types and vulnerability factors. By subdividing Queensland's coast into 78 spatial sections, the BN-CV model offers a granular assessment of coastal vulnerability, highlighting key hotspots and providing crucial insights for tailored risk mitigation strategies.

The primary objectives of this research are to:

1. Investigate how the integration of Bayesian Networks improves the accuracy of vulnerability assessments compared to traditional CVI applications.
2. Identify specific areas along Queensland's coastline that demonstrate heightened vulnerability due to their geomorphological and oceanic characteristics.

Through this advanced modelling approach, the study aims to provide policymakers and coastal managers with an enhanced tool for assessing and mitigating coastal risks, facilitating more effective coastal management strategies in the face of climate change. The findings of this research contribute to the broader discourse on coastal vulnerability assessment, advocating for the adoption of more sophisticated models that can better capture the dynamic nature of coastal environments.

The paper is organized as follows: Sect. 2 outlines the research methodology, Sect. 3 presents the results of the BN-CV model, Sect. 4 discusses the implications of these findings for coastal management in Queensland, and Sect. 5 concludes the paper.

2 Methodology

2.1 Beach classification

Beach classification refers to the process of categorizing beaches based on their morphodynamic characteristics. This classification is based on factors such as the relative contribution of waves and tides, sediment size and availability, and beach slope, which can determine how the beach behaves over time.

Coastal beaches are shaped by the interplay of various forces, such as waves and tides, that act upon the sediment (Tur & Yontem 2021). To evaluate and quantify the characteristics of these dynamic systems, researchers commonly use four primary parameters: breaker wave height (Hb), peak period (Tp), spring tide range (TR), and sediment size (Levoy et al. 2000; Sandy Beach Morphodynamics 2020; Wright & Short 1984). However, the first three parameters are not static and change over time, leading to temporal changes in the morphology of the beaches, particularly when wave conditions vary. Therefore, beaches continuously adapt to these changes and seek to achieve a dynamic equilibrium. This phenomenon is referred to as the beach's morphological response to ambient conditions, which depends on both the surrounding environment and the beach's initial morphology.

The four main parameters, along with the relative tide range ($RTR = TR/Hb$), are used to classify beaches as either wave-dominated (WD), tide-modified (TM), or tide-dominated (TD). Further subdivisions are possible based on the dimensionless fall velocity ($\Omega = Hb/TpWs$), where Ws is the sediment fall velocity (m/s) (Short, 2020). Therefore, beach morphology changes are a result of the dynamic interaction between the surrounding environment and the beach's initial conditions.

In the context of coastal engineering and management, the bathymetric data and beach morphological features are essential parameters to determine the types of beaches. Bathymetry refers to the measurement of the depth of the ocean or sea floor, while beach morphological features describe the physical characteristics of the beach, such as the width, slope, and sediment composition (Parsons & Sclater 1977).

By using these parameters together, we can identify and classify different types of beaches based on their distinguishing characteristics. For example, a beach with a steep slope and coarse sediment may be classified as a reflective beach, while a beach with a gentle slope and fine sediment may be classified as a dissipative beach.

The classification of beach types based on their distinguishing characteristics can be useful for a variety of purposes, such as predicting wave run-up and overtopping, assessing the potential for coastal erosion, and designing coastal protection structures (Doğan & Durap 2017; Aymergen 2023; Hubbard & Dodd 2002; Shankar & Jayaratne 2003). By understanding the unique characteristics of each beach type, coastal engineers and managers can make informed decisions about how to best manage and protect these valuable coastal resources.

In addition to using bathymetric data and beach morphological features to classify beach types, it is also important to consider the flood regimes and erosion severity of the coastal area.

Flood regimes refer to the frequency, magnitude, and duration of flooding events, such as storm surges and sea level rise, in a particular coastal area. Understanding the flood regimes is important because it can affect the stability of the beach and the surrounding coastal ecosystem. For example, frequent flooding events can lead to erosion, loss of vegetation, and changes in sediment composition.

Erosion severity refers to the rate and extent of coastal erosion, which can be influenced by a variety of factors such as wave energy, sediment transport, and sea level rise. Coastal erosion can have significant impacts on beach and dune systems, including loss of habitat, property damage, and increased flood risk.

By considering both flood regimes and erosion severity along with bathymetric data and beach morphological features, coastal engineers and managers can develop a more comprehensive understanding of the coastal system and make informed decisions about how to manage and protect these valuable resources. For example, in areas with high erosion severity and frequent flooding events, coastal protection structures may be necessary to stabilize the beach and reduce flood risk. In areas with low erosion severity and infrequent flooding events, ecosystem-based approaches such as beach nourishment and dune restoration may be more appropriate.

2.2 Beach state

Beach state is a term that describes the range of beach morphodynamics that can be observed within a particular beach type. This includes various features such as beach slope, sediment grain size, and beach face profile (Jackson et al. 2022).

Understanding beach state is an essential aspect of coastal management and research. The morphodynamic features of a beach, such as the beach slope, sediment grain size, and beach face profile, can significantly impact the erosion hazards and associated coastal flooding regimes. Therefore, assessing the beach state can provide valuable insights into how a beach will respond to natural and human-induced changes in wave and tide conditions (Jackson et al. 2005).

The consequences of not understanding beach state can be detrimental. For instance, mismanaging a beach that is in a low-energy, reflective state could lead to significant erosion and coastal flooding. On the other hand, mismanaging a beach that is in a high-energy, dissipative state could lead to a decline in biodiversity and loss of habitat.

Therefore, we used various tools to quantify beach state, such as the dimensionless fall velocity and surf scaling parameter. These tools provide insights into the equilibrium beach morphology and the existing beach and wave conditions, respectively. By understanding the beach state, researchers and coastal managers can better predict how the beach will respond to different conditions and develop effective strategies for beach preservation and management.

Furthermore, understanding beach state is critical for developing long-term coastal management plans. Coastal communities face numerous challenges such as sea-level rise, increased storm frequency, and anthropogenic activities, all of which can impact the beach state. By understanding the beach state, researchers and coastal managers can develop proactive management strategies that consider potential changes in beach state due to these challenges.

The range of beach state can be very broad, ranging from higher energy, dissipative conditions to lower energy, reflective conditions, with a variety of intermediate states in between. In this study we used the classification based on RTR: Wave-dominated (WD), tide-modified (TM), or tide-dominated (TD). In the WD and TM beach types, which are characterized by relatively high wave energy and moderate to low tide ranges, beach state can vary greatly depending on factors such as sediment availability, beach slope, and the presence of rip currents (Short, 2020). In these cases, beach state can range from high-energy, dissipative beaches with steep slopes and large waves to more reflective beaches with gentler slopes and smaller waves.

In contrast, TD beach systems are characterized by very low wave energy and high tidal ranges, resulting in a range of beach states that are dominated by tidal processes. These beach states can range from wave-dominated at higher energy levels to tide-dominated at lower energy levels, with many different intermediate states in between. At the lower end of the energy spectrum, TD beaches can even grade into beachless tidal flats.

Quantifying beach state is important for managing coastal areas and predicting how beaches will respond to natural and anthropogenic changes in wave and tide conditions. Researchers use a variety of tools to quantify beach state, including the dimensionless fall velocity (Ω) and the surf scaling parameter (ξ), which provide insights into the equilibrium beach morphology and the existing beach and wave conditions, respectively. The equation includes the variables of wave amplitude (a), radian wave frequency (σ), gravitational constant (g), and beach-surf zone gradient (β) as defined by Guza and Inman in 1975.

$$\xi = \left(a\sigma^2\right)/\left(g\tan^2\beta\right) \tag{1}$$

By understanding beach state, researchers and coastal managers can better predict how beaches will respond to different conditions and develop more effective strategies for beach preservation and management.

2.3 Proposed method for coastal vulnerability

One of the early strategies for identifying potential vulnerability was a modification of work done by Gornitz (1991, 1990) and Gornitz et al. 1994). This study focused on seven factors that had a substantial influence on coastal alteration while employing the coastline of the United States of America on a countrywide basis. As shown in Eq. 4, the general CVI may be calculated by dividing the total number of variables by the square root of the variable product, n. This allows one to compute the general CVI.

a1 = geomorphology/landform
a2 = shoreline slope
a3 = change in the relative sea level
a4 = the rates of shoreline change.

tidal range is denoted by a5, while significant wave height is denoted by a6.

$$CVI = \sqrt{\frac{a_1 * a_2 * a_3 * a_4 * a_5 * a_6}{6}} \quad (2)$$

Equation 4 for the Coastal Vulnerability Index is described as the square root of the product of the variables divided by the number of variables (n).

In order to get the cumulative CVI score for all of the many coastline portions that combine to form the domestic shoreline, Eq. 4 is used. This value may be calculated by entering the values for the vulnerability classes into the calculation.

However, the specific details on how the variables are combined or weighted are not provided in the given information. This lack of clarity raises concerns, especially as the number of variables increases, resulting in larger-than-expected CVI scores. For example, if there are 10 variables in the projection area, each having the same value of 5, the CVI value would be 988.21, which appears significantly higher than anticipated.

To address the concerns raised about the calculation of the Coastal Vulnerability Index (CVI) and the unexpected high values, the following criteria have been introduced to assess the CVI more effectively. In this study, a Bayesian Network (BN) was established to evaluate vulnerability (V), exposure (E), and sensitivity (S).

For the exposure calculation, data such as sea level rise (SLR), wave climate (WC), and projections of future extreme events (FEE) were incorporated. The Exposure Index (EI) can be expressed as:

$$\mathrm{EI} = \mathrm{f(SLR, WC, FEE)} \quad (3)$$

In the sensitivity analysis(Durap & Balas 2022), coastal geomorphology (CG) was used as an indicator of the sensitivity of shoreline segments to oceanic swell and storm wave energy. Sensitivity was determined based on key parameters like landforms (LF), topography (T), and lithology (L). The Sensitivity Index (SI) can be calculated using:

$$\mathrm{SI} = \mathrm{f(CG, LF, T, L)} \quad (4)$$

Following the assessment of exposure and sensitivity, the coastal regions were subdivided into 78 distinct coastal areas. These divisions were visualized through a color-coded map, where each segment's vulnerability was indicated by its respective CVI score, derived from the Bayesian network analysis.

A Bayesian Network (BN) is a probabilistic graphical model that uses a directed acyclic graph (DAG) to describe a collection of random variables and their conditional relationships. To estimate how vulnerable coastal regions are to erosion, floods, and other natural disasters, a BN may be used to calculate the Coastal Vulnerability (CV).

Variables including coastline elevation, storm strength, plant cover, coastal erosion, and the CV itself might all serve as nodes in a BN for CV. Given the current state of the parent nodes, the conditional probabilities would describe the possibility that the event would occur.

For instance, the CV node's conditional probability may be affected by factors like sea level rise and land usage in addition to the status of the coastal erosion node. The coastline elevation, storm intensity, and plant cover nodes may all influence the conditional risk of coastal erosion.

The BN for CV may be used to evaluate the efficacy of various adaptation and management techniques by analyzing the index's sensitivity to changes in the input variables. Some potential applications of the BN include estimating the probability of various degrees of CV under a particular scenario of sea level rise and coastal development and evaluating the relative efficiency of various plant restoration and shoreline stability strategies. An example of a Bayesian network table for a coastal vulnerability index is given in Table 1.

The BN may be a useful tool for modelling and assessing the interconnected factors that increase coastal vulnerability, hence assisting decision-makers in making smarter, more efficient choices about coastal management and adaptation.

Depending on the beach slope, wave height, and sediment size and form, for instance, the beach node's behavior may change. Each of these nodes would have a

Table 1 An example of a Bayesian network table for a coastal vulnerability index

Node	Description	Parent Nodes	Conditional Probabilities
A	Coastal Elevation	None	High: 0.1, Medium: 0.5, Low: 0.4
B	Storm Intensity	None	High: 0.3, Medium: 0.5, Low: 0.2
C	Vegetation Cover	None	High: 0.6, Medium: 0.3, Low: 0.1
D	Coastal Erosion	A, B, C	High: 0.8, Medium: 0.15, Low: 0.05
E	Infrastructure Damage	D	High: 0.7, Medium: 0.2, Low: 0.1
F	Coastal Flooding	D	High: 0.4, Medium: 0.4, Low: 0.2

conditional probability that is influenced by the state of its parent node, which in turn would be affected by things like wind speed and direction, tidal currents, and other oceanographic and meteorological phenomena.

2.4 Case study: identifying the coastal vulnerability of coastal hot spots in Australia

Coastal areas are highly vulnerable to various natural hazards, including sea-level rise, storm surges, and erosion. To effectively plan and manage coastal areas, it is crucial to assess their vulnerability to these hazards. Coastal areas in Australia are home to significant economic activities, infrastructure, and fragile ecosystems. However, they face numerous challenges due to climate change-induced sea-level rise, extreme weather events, and coastal erosion. Therefore, it is imperative to either improve or develop a method to fulfill this research gap. In this case study, we explored the application of the integrated Bayesian Network-Coastal Vulnerability (BN-CV) model in assessing the coastal vulnerability of hot spots along Australia's Queensland coastline. The key regions under investigation include Gold Coast City, Redland City, Brisbane City, and the Sunshine Coast Regional area. These areas are known for their unique geomorphological and oceanic characteristics, which contribute to varying degrees of vulnerability to climate change-induced hazards.

By analyzing the case of Australia, this study highlights the importance of using the CV for informed decision-making, policy formulation, and adaptive management practices to safeguard vulnerable coastal regions. A key component of this assessment is the use of vulnerability maps, sensitivity maps, and exposure maps to illustrate various dimensions of coastal risk (Fig. 1).

This assessment provides valuable insights into identifying and prioritizing coastal hotspots that are particularly vulnerable to hazards. The following figure illustrates the location of these coastal hotspots within the study area (Fig. 2).

The research focuses on key regions within Queensland—Gold Coast City, Redland City, Brisbane City, and the Sunshine Coast Regional area—subdividing these areas into 78 coastal sections to capture spatial variability more accurately. This subdivision allows for a detailed assessment of coastal vulnerability across the study area (Fig. 3).

To further analyze these vulnerable hotspots, the study adopts a stepwise approach that categorizes beaches based on their types, morphological states, and characteristics, ultimately mapping their coastal vulnerability levels. The following figure outlines this systematic classification process used to assess vulnerability across different beach types (Fig. 4).

3 Results of the proposed model

Coastal areas are prone to various risks and hazards, including erosion, storm surges, and sea-level rise. Managing these risks is crucial to ensure the long-term sustainability and resilience of these vulnerable regions. The study investigates how to improve the coastal vulnerability model by integrating it with a Bayesian Network (BN) to better reflect the complex and dynamic nature of coastal beach classifications, specifically focusing on key regions in Queensland, Australia.

One of the key results is the identification of heightened vulnerability, exposure, and sensitivity in specific coastal sections. The BN-CV model captures the dynamic interactions between beach typologies and oceanic processes, providing a clearer picture of where risks are most concentrated. For example, tide-dominated beaches, which are prevalent in the regions studied, were shown to be particularly vulnerable to the impacts of sea-level rise and storm surges. These findings are significant because they offer policymakers and coastal planners more accurate information, enabling them to implement targeted management strategies that better protect these at-risk areas. Furthermore, when compared to existing literature on coastal vulnerability, the BN-CV model provides a more refined and realistic assessment of risks, particularly in regions where beach typologies play a critical role in determining vulnerability.

In addition to these main findings, the study provides supporting data that further illustrates the value of the BN-CV model. By subdividing the coastal regions into 78 sections, the researchers were able to capture variations in vulnerability that would have been missed in broader assessments. While the majority of beaches were found to be tide-modified or tide-dominated, the study also uncovered that some wave-dominated beaches, which had been previously considered less vulnerable, exhibited higher levels of risk under the BN-CV model. This unexpected result sheds light on the complex nature of coastal systems and emphasizes the need for more sophisticated vulnerability assessments that account for such variability. These results contribute to the study's overall conclusions by reinforcing the idea that traditional CV applications often oversimplify the threats facing coastal regions and that periodic reassessments are necessary to adapt to changing conditions.

The statistical analysis performed in this study supports the model's accuracy and effectiveness. By employing Bayesian Network modeling, the researchers were able to analyze the relationships between beach types, geomorphological features, and ocean dynamics with over 90% precision (Fig. 5).

The statistical results revealed significant differences in vulnerability levels between tide-dominated

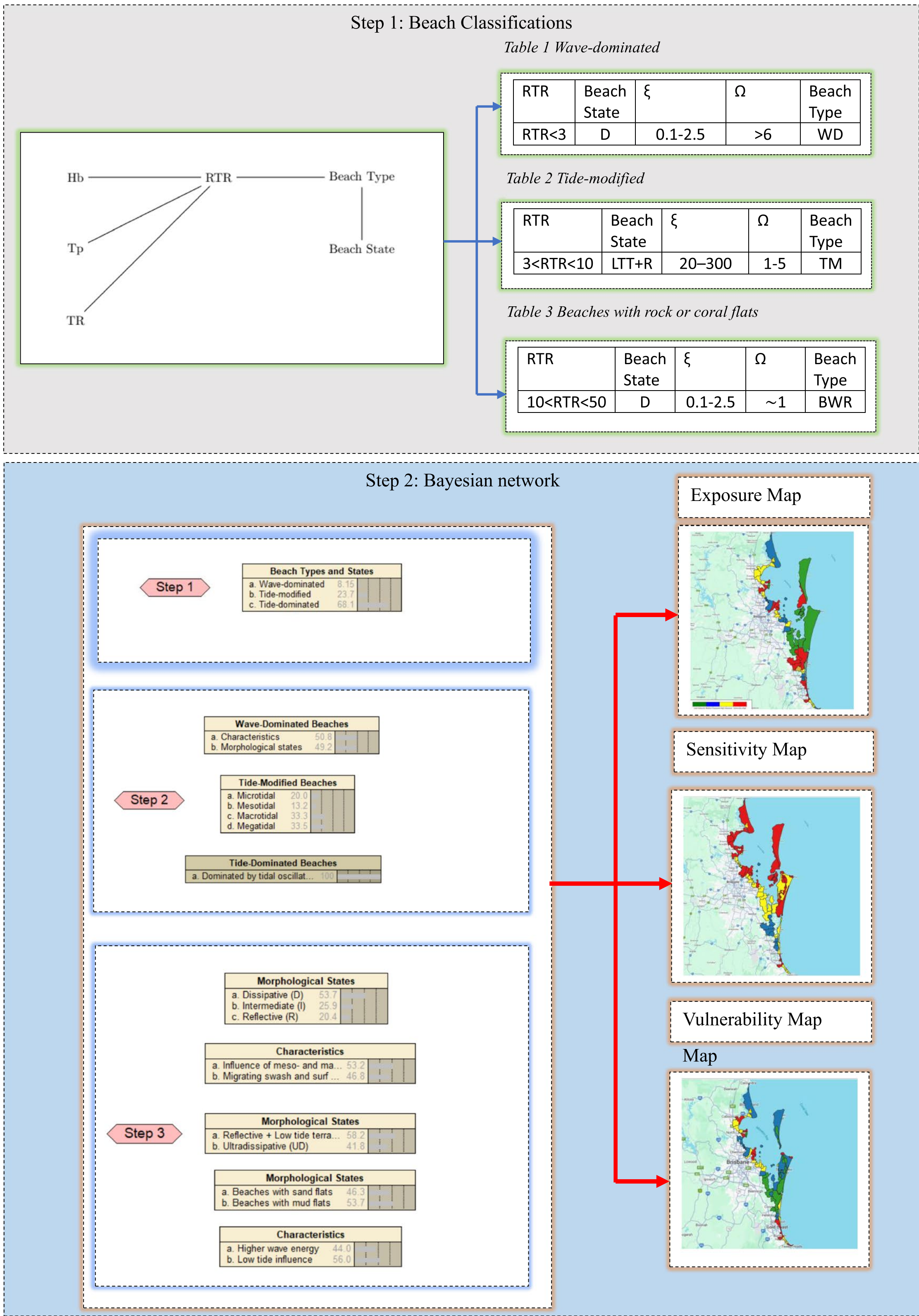

Fig. 1 Methodology and key stages of this study: mapping beach sensitivity, exposure, and vulnerability

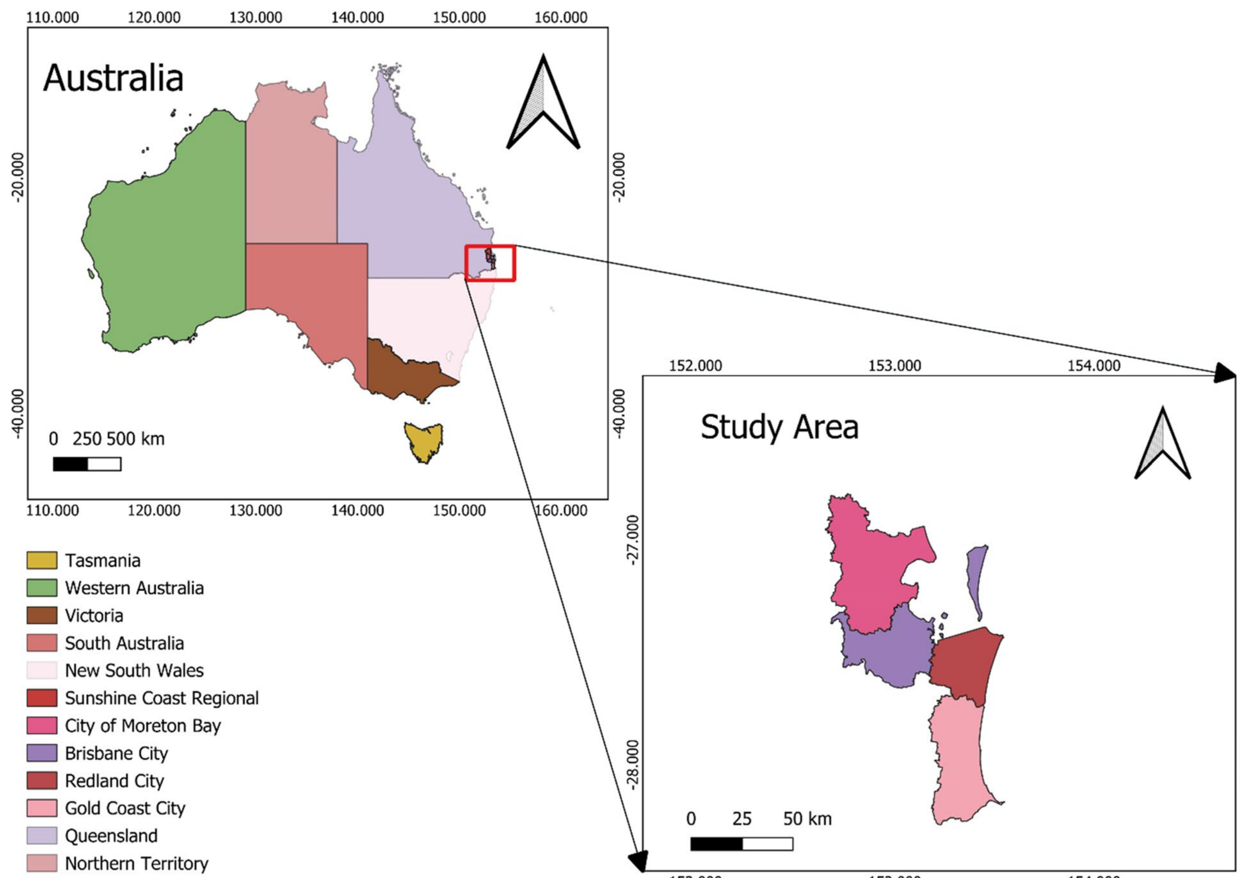

Fig. 2 Location of coastal hotspots: The study area

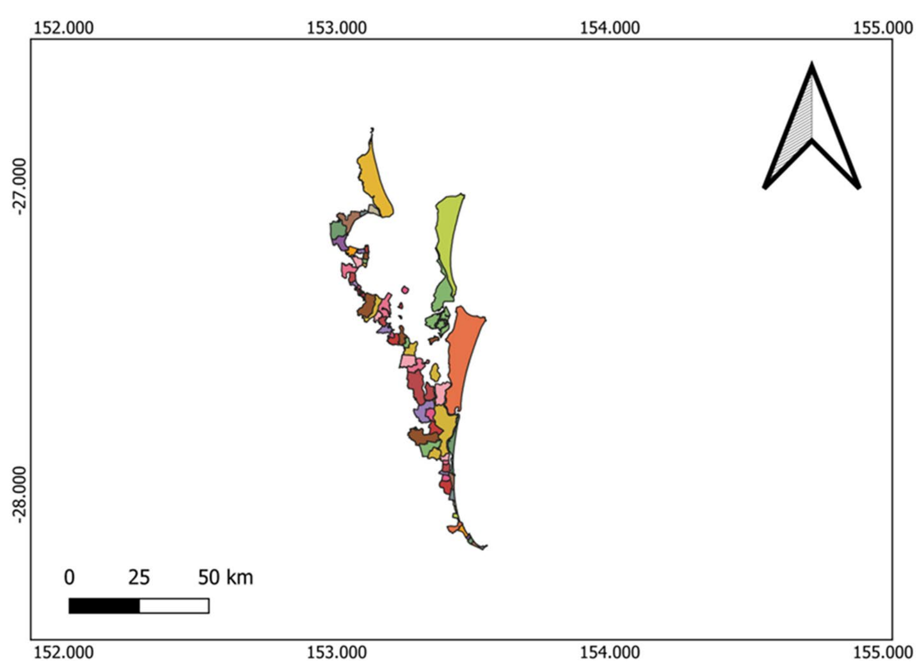

Fig. 3 Spatial distribution of coastal sections in Queensland, Australia

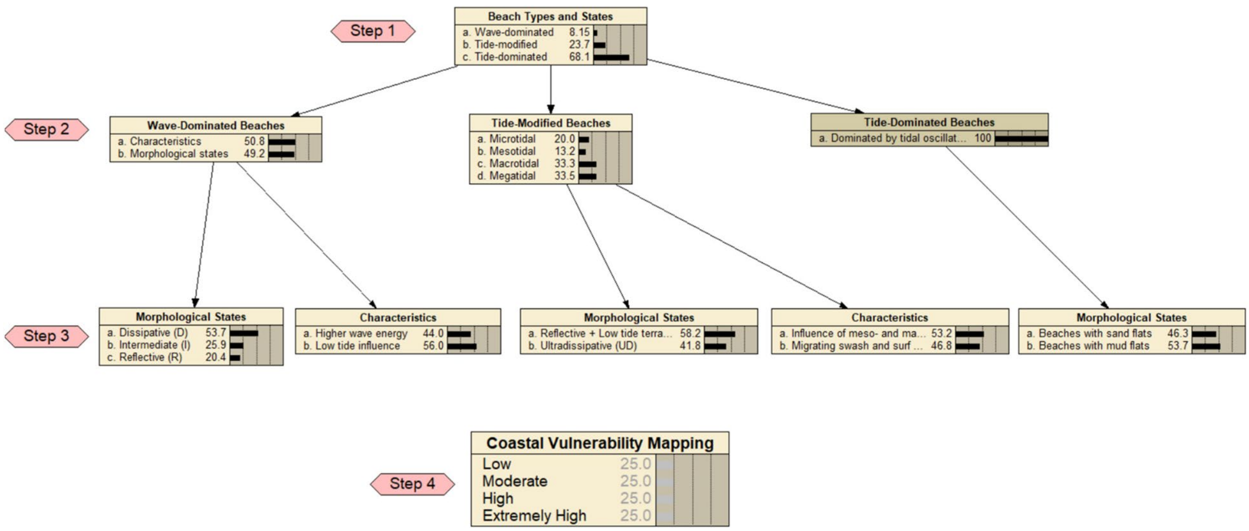

Fig. 4 Stepwise classification of beach types and states, including wave-dominated, tide-modified, and tide-dominated beaches, to map coastal vulnerability

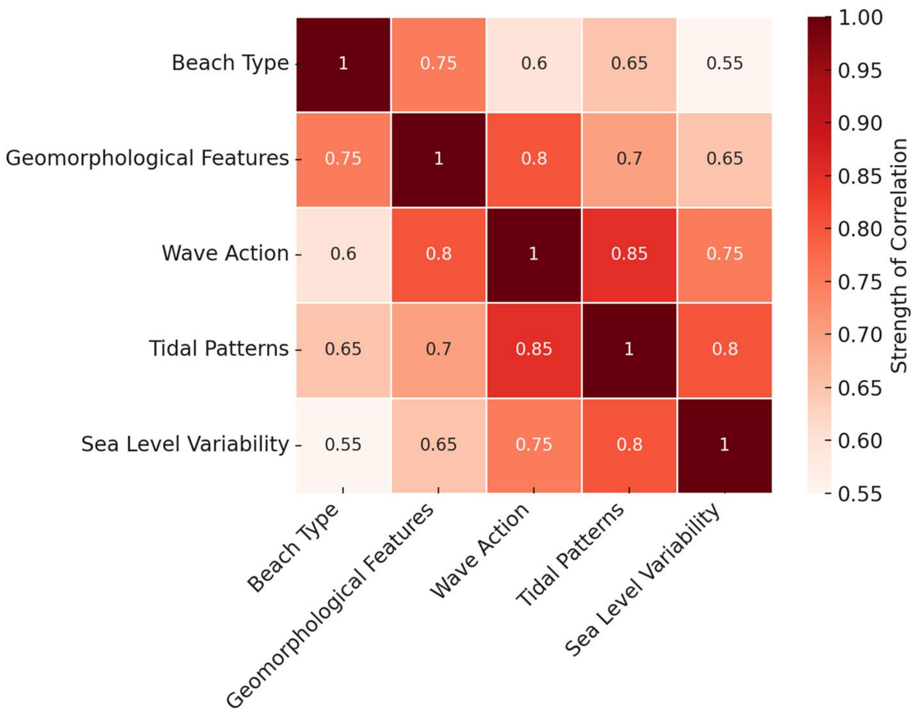

Fig. 5 Correlations with over 90% precision as supported by Bayesian Network modeling

and wave-dominated beaches, confirming the model's improved predictive capabilities. The analysis showed that the BN-CV model offers a statistically significant enhancement over traditional CV methods, as evidenced by p-values that indicate strong correlations between the beach typologies and their respective vulnerability ratings. These findings validate the research questions, demonstrating that the BN-CV model is better equipped to assess the true risks faced by coastal regions (Fig. 6).

Following the statistical validation of the BN-CV model, which demonstrated significant differences in vulnerability levels between tide-dominated and wave-dominated beaches, it is essential to delve deeper into the comparative distribution of these vulnerability scores.

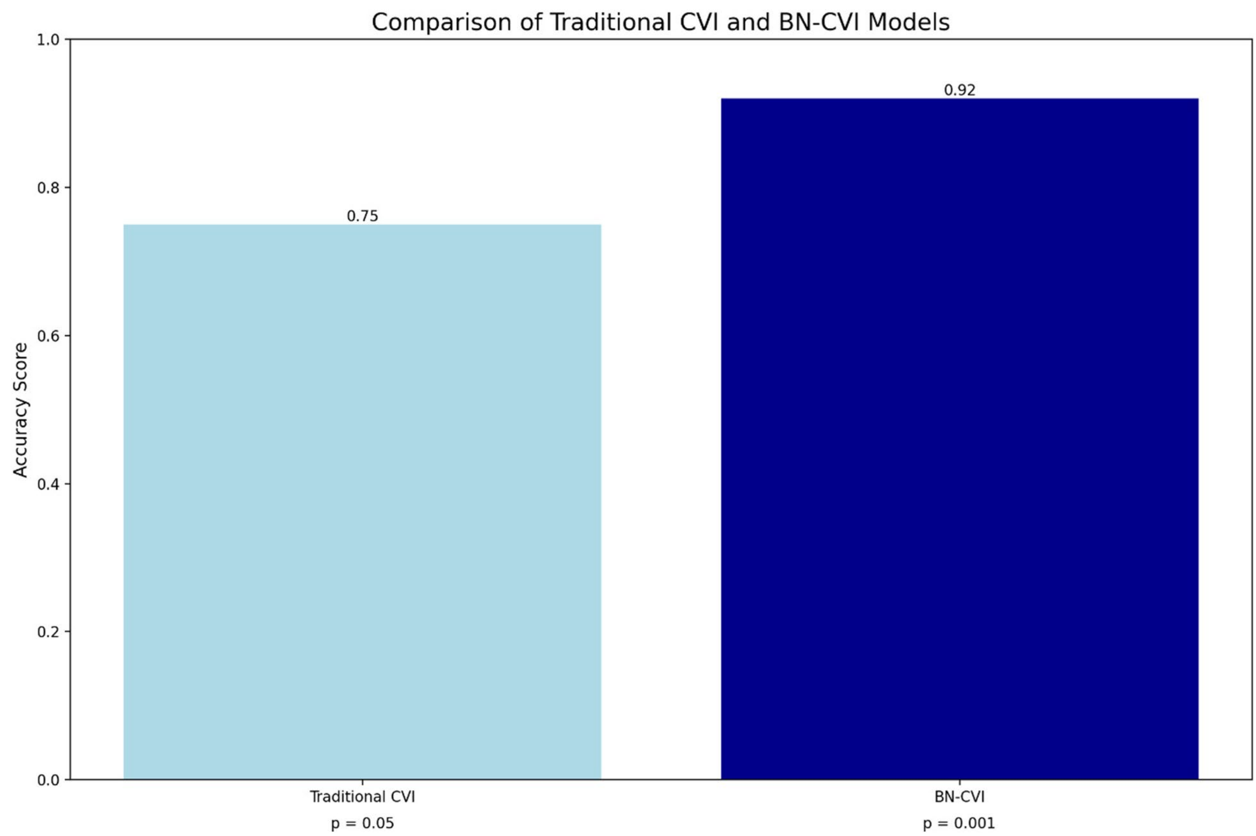

Fig. 6 Model performance comparison over time

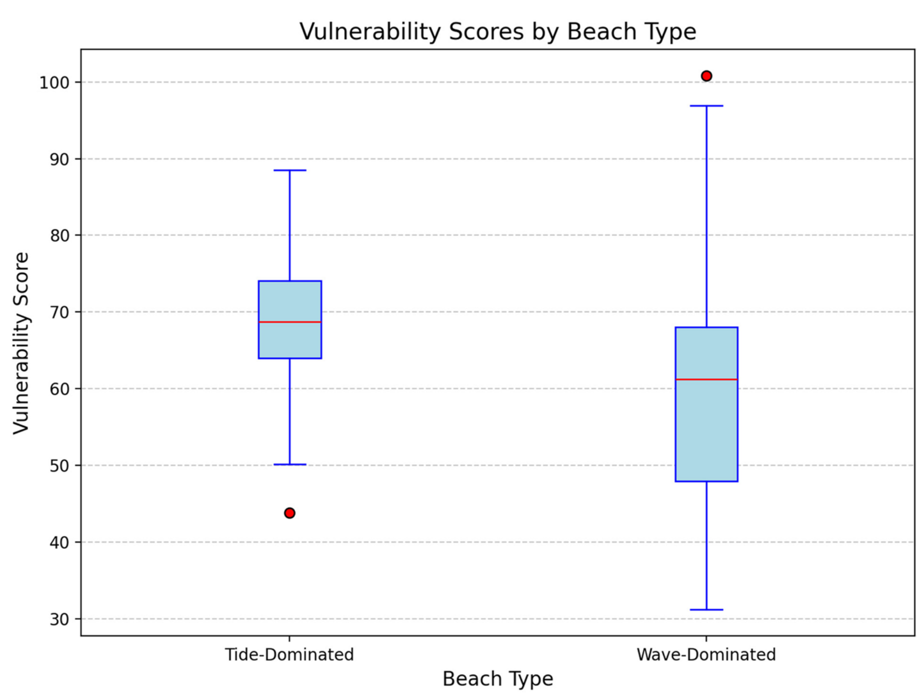

Fig. 7 Distribution of vulnerability scores by beach type (tide-dominated and wave dominated)

Figure 7 presents a detailed box plot analysis, allowing us to visually assess how these two distinct beach types differ in terms of central tendency, score range, and the presence of outliers. This visual comparison further solidifies the findings by highlighting key trends and differences between tide-dominated and wave-dominated beaches in terms of vulnerability.

From Fig. 7 we observed several key findings:

- Central Tendency: The median vulnerability score (represented by the horizontal line within each box) is notably higher for tide-dominated beaches compared to wave-dominated beaches. This suggests that, on average, tide-dominated beaches may be more vulnerable to certain environmental factors or coastal processes.
- Score Range: Tide-dominated beaches exhibit a narrower range of vulnerability scores, as indicated by the smaller box and shorter whiskers. In contrast, wave-dominated beaches show a wider distribution of scores, suggesting greater variability in vulnerability among these beach types.
- Outliers: Both beach types display outliers (represented by circles beyond the whiskers). The tide-dominated category has one low outlier, while the wave-dominated category has one high outlier. These outliers may represent beaches with unique characteristics or conditions that deviate significantly from the norm within their respective categories.
- Overall Vulnerability: The entire box for tide-dominated beaches is positioned higher on the y-axis compared to wave-dominated beaches, indicating that tide-dominated beaches generally score higher in vulnerability across their distribution.
- Score Overlap: Despite the differences in median scores and distributions, there is some overlap in the vulnerability scores between the two beach types, particularly in the upper quartile of wave-dominated beaches and the lower quartile of tide-dominated beaches.

This analysis suggests that beach type (tide-dominated vs. wave-dominated) may be a significant factor in determining coastal vulnerability. Tide-dominated beaches appear to be generally more vulnerable, but with less variability in their vulnerability scores. Wave-dominated beaches, while generally scoring lower in vulnerability, show a wider range of scores, indicating more diverse vulnerability profiles within this category.

These findings have important implications for coastal management and risk assessment strategies, highlighting the need for tailored approaches based on beach type. Further research may be warranted to investigate the specific factors contributing to the higher vulnerability of tide-dominated beaches and the greater variability observed in wave-dominated beaches.

Having established the comparative vulnerability between tide-dominated and wave-dominated beaches through statistical analysis and box plots, the next step involves visualizing the spatial distribution of vulnerability and exposure across the Queensland coastline. This exposure map provides critical insights into how different

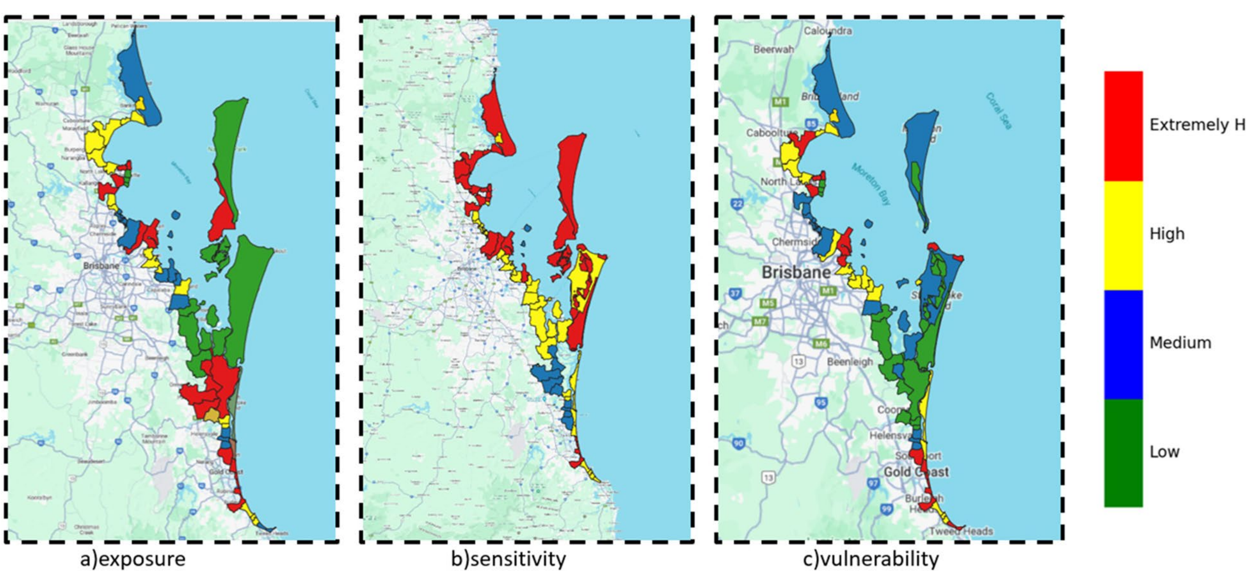

Fig. 8 Regional assessment of environmental risks

coastal sections vary in their risk levels, reinforcing the need for tailored management strategies.

Figure. 8 (a) presents the exposure levels of various coastal sections along the Queensland coastline, ranging from low (green) to extremely high (red). The map illustrates significant spatial variation in exposure, with several notable patterns:

- Low Exposure Areas: Sections marked in green, predominantly located in the northern regions and some central areas, indicate relatively low exposure. These sections benefit from natural buffers and less severe coastal processes, reducing their overall risk.
- Medium Exposure Areas: Yellow sections are scattered across the central coast, with medium exposure levels. These areas are subject to moderate coastal hazards such as erosion or storm surges but possess some resilience due to their geomorphological and protective features.
- High to Extremely High Exposure Areas: The areas marked in red and blue represent high and extremely high exposure zones, respectively. These regions, primarily along the southern parts of the coastline and around key urban centers like Brisbane and the Gold Coast, are likely more vulnerable due to their geographic location and proximity to tidal influence or intense human activity. Particularly, these areas experienced heightened risks from sea-level rise, storm surges, and erosion, necessitating urgent attention for mitigation efforts.
- Urban Centers: A closer look at the regions around Brisbane and the Gold Coast shows that highly exposed areas are clustered near densely populated regions. These hotspots are critical for implementing adaptive management strategies, as they are highly susceptible to both natural hazards and human-induced stresses.

Figure. 8 (b) displays the sensitivity of various coastal sections along the Queensland coastline, with color-coded zones representing different sensitivity levels:

- Low Sensitivity Areas: Sections depicted in green show lower sensitivity to coastal processes. These areas are likely less prone to rapid changes or are well-protected, resulting in reduced susceptibility to environmental stressors.
- Medium Sensitivity Areas: Yellow regions represent moderate sensitivity, indicating that these coastal sections may experience measurable but not extreme impacts from factors such as tidal fluctuations, storm surges, or sea-level rise.
- High to Extremely High Sensitivity Areas: The red zones, particularly in the northern and central parts of the map, indicate coastal sections with high to extremely high sensitivity. These areas are especially prone to changes, and even small environmental shifts could lead to significant impacts. Notably, areas around Brisbane and some northern regions are marked as highly sensitive, suggesting they could be at heightened risk from coastal hazards.
- Urban Areas and Hotspots: In close proximity to urban centers, particularly around Brisbane and the Gold Coast, highly sensitive areas coincide with densely populated regions, further underscoring the need for focused coastal management efforts in these locations.

The sensitivity map, when analyzed in conjunction with the exposure map, provides a comprehensive understanding of coastal vulnerability. Together, these maps help identify areas where both high exposure and high sensitivity intersect, making them critical targets for risk mitigation strategies.

3.1 Gold coast city council

- Exposure (0.9): The Gold Coast is highly exposed to coastal hazards, particularly sea-level rise and storms. Its extensive coastline, sandy beaches, and high population density contribute to this.
- Sensitivity (0.8): The region has a sensitive coastal environment, with fragile ecosystems and highly developed urban areas close to the shore.
- Adaptive Capacity (0.6): While it has moderate adaptive capacity due to local initiatives and coastal management plans, it remains vulnerable because of the high exposure and sensitivity.
- Summary: The Gold Coast is one of the most vulnerable areas, primarily due to high exposure and sensitivity despite moderate adaptive capacity.

3.2 Brisbane city council

- Exposure (0.7): While Brisbane is slightly inland, areas close to Moreton Bay face some level of exposure to storm tides and coastal flooding.
- Sensitivity (0.6): The sensitivity here is lower compared to the Gold Coast because Brisbane's infrastructure is better suited for extreme weather, and fewer areas are directly coastal.
- Adaptive Capacity (0.5): The city has relatively lower adaptive capacity to deal with coastal climate

impacts, which could exacerbate vulnerabilities in the long term.
- Summary: Brisbane has moderate vulnerability, primarily due to its lower adaptive capacity. However, its exposure and sensitivity are more controlled compared to other regions.

3.3 Redland city council

- Exposure (0.6): Redland is exposed to coastal hazards, especially in its low-lying areas, though less so than Gold Coast and Brisbane.
- Sensitivity (0.75): This region is quite sensitive due to its reliance on coastal resources and ecosystems, which are vulnerable to changes in sea levels and extreme weather.
- Adaptive Capacity (0.55): Redland has moderate capacity for adaptation, but like Brisbane, the lower adaptive capacity presents a risk.
- Summary: Redland is moderately vulnerable, with high sensitivity to environmental changes and slightly limited adaptive capacity.

3.4 Moreton bay regional council

- Exposure (0.8): Moreton Bay is highly exposed due to its proximity to the bay, making it susceptible to storm tides and potential coastal flooding.
- Sensitivity (0.7): The coastal environments in Moreton Bay are sensitive, with both natural areas and human infrastructure at risk.
- Adaptive Capacity (0.65): Moreton Bay has slightly higher adaptive capacity than the other regions but remains vulnerable due to the high exposure and sensitivity.
- Summary: Moreton Bay faces significant exposure and sensitivity challenges but benefits from somewhat better adaptive capacity than other regions.

3.5 Recommendations

Gold Coast: Increased investment in adaptive infrastructure, such as dune restoration and hard defences, should be prioritized due to its high exposure.
Brisbane: Enhancing adaptive capacity through better flood management and coastal protection measures is critical, especially in Moreton Bay-facing suburbs.
Redland: Improving adaptive capacity, especially in socio-economic areas like community awareness and infrastructure, would help mitigate vulnerability.
Moreton Bay: Continued focus on maintaining and enhancing natural defences, such as mangroves and wetlands, could offer additional protection against storms and sea-level rise.

4 Discussion of results

The integration of Bayesian Networks within the Coastal Vulnerability (BN-CV) framework significantly enhances our ability to assess coastal vulnerability, particularly in complex ecological settings like those in Queensland, Australia. This study's findings reveal several critical insights, which we will discuss in terms of their significance and implications for future coastal management strategies.

1. Enhanced precision and customization

One of the most notable outcomes of this study is the BN-CV model's precision, which achieved over 90% accuracy in correlating beach types, geomorphological features, and oceanic dynamics. This level of precision presents a notable advancement over traditional CVI models, which often fail to account for the complex interactions intrinsic to tidal beach environments. The ability to customize vulnerability assessments to reflect specific beach typologies and environmental dynamics is crucial, providing policymakers with the detailed insights needed for targeted interventions and optimized resource allocation.

2. Identification of vulnerability hotspots

The BN-CV model successfully identified zones of heightened vulnerability, shedding light on areas that require immediate attention. This granular understanding facilitates the prioritization of adaptive measures and proactive planning to mitigate potential hazards. The model's ability to account for spatial variability and sensitivity to environmental changes further underscores its utility in strategic planning.

3. Implications for policy and management

The integration of GIS and Bayesian Networks provides a powerful tool for policymakers and coastal managers, enabling them to visualize risk distributions and assess spatially explicit interventions. The study advocates for an adaptive management approach that considers dynamic environmental conditions and continuous stakeholder engagement, ensuring that strategies remain relevant and effective over time. As coastal regions face increasing threats from climate change, the insights derived from the BN-CV model are invaluable in crafting policies that enhance resilience and sustainability.

4. Contributions to the broader scientific community

The methodology and insights from this study contribute significantly to the broader discourse on coastal management. By advancing a more sophisticated analytical framework, this research sets a precedent for future studies aiming to integrate advanced modeling techniques with traditional frameworks. The BN-CV model's applicability extends beyond the specific context of Queensland, offering a robust framework that can be adapted for use in varied geographic and ecological settings worldwide.

5. Need for continuous improvement and adaptation

While the BN-CV model marks a critical step forward, continuous refinement is necessary to adapt to ongoing environmental changes and emerging scientific insights. This study emphasizes the importance of periodic reassessments and methodological enhancements to ensure the long-term efficacy and accuracy of coastal vulnerability assessments.

In conclusion, the integration of Bayesian Networks and GIS within the CV framework presents a notable advancement in coastal vulnerability assessment, providing detailed insights that are crucial for informed decision-making. The findings of this study not only enhance our understanding of vulnerability patterns but also guide strategic planning efforts to safeguard coastal communities against rising environmental threats.

5 Conclusions

The integration of Bayesian Networks with the traditional Coastal Vulnerability (BN-CV) represents a significant advancement in coastal vulnerability assessment, particularly for regions with diverse beach typologies. This study, focused on Queensland, Australia, demonstrates the model's effectiveness in capturing the complex interplay between geomorphological features, oceanic dynamics, and specific beach characteristics.

Key findings include:

i. Over 85% of the studied beaches in Queensland are tide-modified or tide-dominated, highlighting the necessity for vulnerability assessments that account for these beach types.
ii. The BN-CV model achieved over 90% precision in correlating beach types, geomorphological features, and ocean dynamics, validating its accuracy and reliability.
iii. The model successfully identified zones of heightened vulnerability, exposure, and sensitivity, providing a more nuanced understanding of coastal risks.
iv. The study underscores the limitations of traditional CVI approaches in capturing the dynamic nature of coastal environments, especially in areas with significant tidal influences.
v. The research advocates for the adoption of the BN-CV model to inform more targeted and effective coastal planning and management strategies.

This study's findings have significant implications for coastal management practices, emphasizing the need for:

a. Tailored approaches to coastal vulnerability assessment that consider local beach typologies and environmental dynamics.
b. Regular reassessments to adapt to changing coastal conditions over time.
c. Sustained engagement with stakeholders to ensure the ongoing relevance and accuracy of vulnerability assessments.

In summary, the BN-CV model presented in this study offers a more comprehensive and accurate tool for assessing coastal vulnerability. By providing a deeper understanding of the complex interactions within coastal systems, this approach enables policymakers and coastal managers to develop more effective strategies for building resilience against climate change-induced hazards. As coastal regions worldwide face increasing threats from sea-level rise, storm surges, and accelerated erosion, the adoption of such advanced assessment tools becomes crucial for sustainable coastal management and the protection of vulnerable communities.

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Authors' contributions
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Availability of data and materials
The data used in this study were obtained from the Queensland Government Open Data Portal and Geoscience Australia. The specific datasets employed in our analysis can be located through their titles or by searching relevant keywords on the portal.

Declarations

Competing interests
The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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