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Climate change-induced vulnerability assessment for the Florida Coast using hybrid machine learning models

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ABSTRACT

Florida's coastal regions are increasingly at risk due to environmental challenges, particularly those stemming from climate change, rising sea levels (SLR), and severe weather events like hurricanes. With a coastline stretching 1,350 miles along the Atlantic and Gulf of Mexico, these coastal areas are vital to the state's economy, generating roughly $102 billion each year and supporting 1.7 million jobs, mainly through tourism, recreational fishing, and boating. However, they face considerable strain from both natural and human-related influences. To evaluate this vulnerability, we employed the InVEST model, which utilizes the Coastal Vulnerability Index (CVI) methodology, considering crucial factors such as coastal shape, water depth, elevation, wave patterns, wind stress, SLR, population density, and natural habitats. Our analysis covered a 30-year period (1992–2022) and revealed that while Florida's northwest coast has a moderate level of exposure, it is highly vulnerable. Similarly, southeastern Florida, including its biggest city, Miami, is also highly vulnerable to climate change and land subsidence. Validation of the InVEST model with machine learning (ML) confirmed its effectiveness in evaluating coastal exposure in various regions. Our results highlighted the importance of natural ecosystems like mangroves and seagrasses in mitigating ecological risks. We also pinpointed the counties most at risk along Florida's coast for focused management efforts and noted dangers to the Everglades, such as saltwater intrusion and the transition of freshwater marshes into mangrove creeks. The study advocates for incorporating "Green-gray" infrastructure, which combines the restoration of natural ecosystems with traditional engineering measures like seawalls, to improve long-term coastal resilience and reduce risks.

1. Introduction

Coastal zones, which include vital ecosystems such as mangroves, salt marshes, and barrier islands, are particularly vulnerable to natural hazards. Despite this vulnerability, they are home to approximately 40 % of the global population (Nicholls et al., 2007). Rising sea levels, increasing storm frequency and intensity, and ecosystem degradation amplify these areas' risks (Cunha et al., 2021). Coastal regions, covering 312,000 km2 and home to 60 % of major cities (Baztan et al., 2015), face severe threats from SLR, land subsidence, and deltaic compaction (Mondal et al., 2024a). Projections suggest sea levels could rise by 0.62–1.11 m by 2100 (Sweet et al., 2024), further increasing the risk of compound flooding, particularly in deltaic and coastal regions (Gavkosh et al., 2021; Mondal et al., 2020). Despite these mounting threats, rapid urbanization, industrialization, and deforestation exacerbate coastal vulnerabilities, with frequent flooding, storm surges, and erosion disrupting communities (Tian et al., 2024). The alarming infrastructure development in high-risk coastal areas intensifies evacuation challenges during catastrophic events (Wei et al., 2022, 2023).

Natural buffers such as stabilized dune fields, mangroves, and salt marshes play a critical role in protecting coastal zones from natural hazards (Mondal et al., 2024b). Mangroves, particularly, are highly

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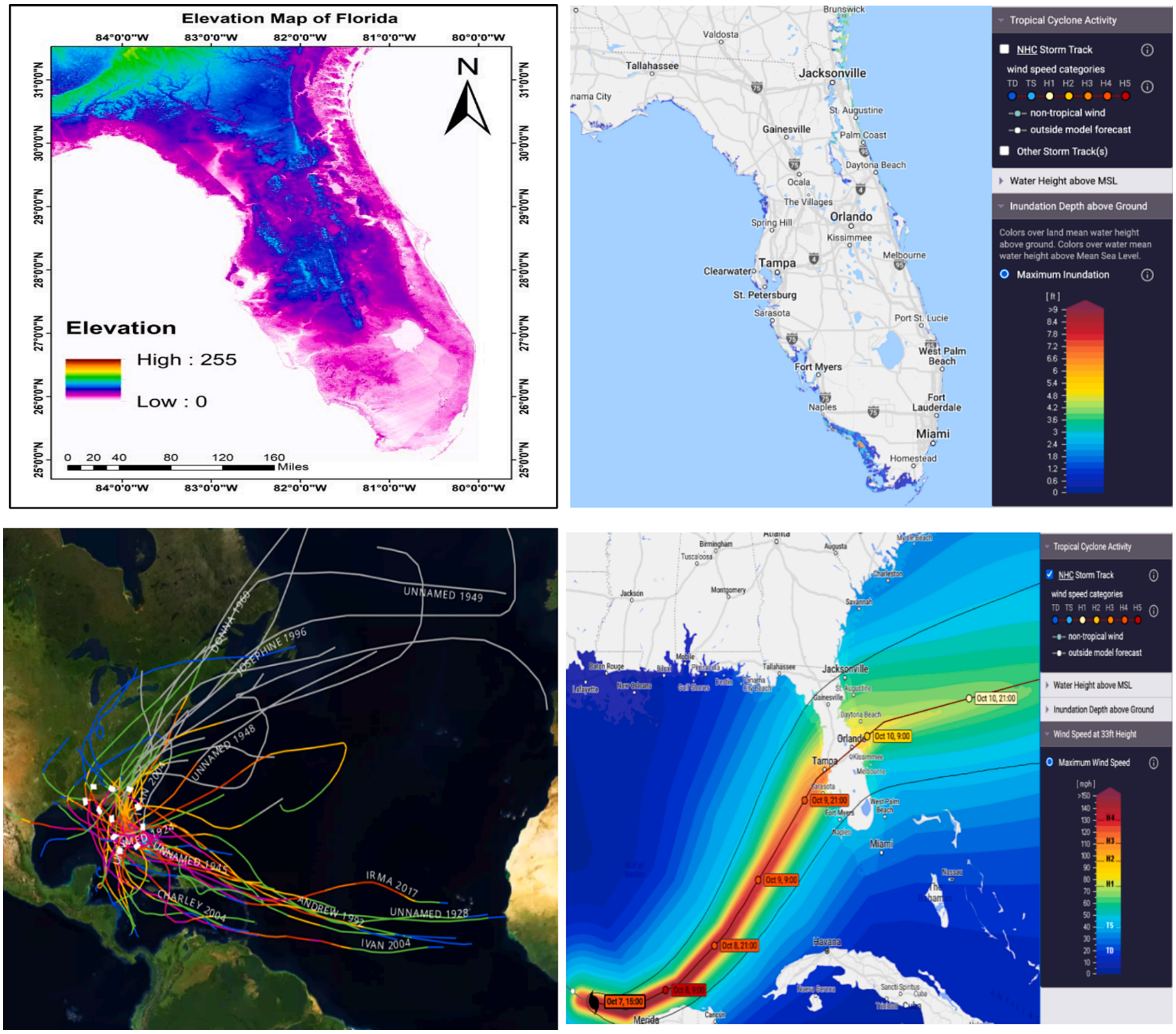

Fig. 1. Location Map of the State of Florida Coastal Stretch, a) Elevation, b) Inundation Depth of the Ground (During Hurricane Milton on10-October-2024), c) Historical hurricane track in categories 4 and 5, and d) Maximum wind speed (Hurricane Milton) it is diverse coastal vulnerability (Source: https://www.climate.gov/maps-data/dataset/historical-hurricane-tracks-gis-map-viewer & https://cera.coastalrisk.live/#).

effective in mitigating risks from storms, tsunamis, waves, and coastal erosion, serving as the first line of defense (Asari et al., 2021; Mondal et al., 2024b). They attenuate up to 66 % of wave energy within the first 100 m of mangrove fringe along the coast (Macivor et al., 2012) and contribute to SLR adaptation through vertical accretion under favorable conditions (Mckee et al., 2007; Krauss et al., 2013; Mondal et al., 2021). Coral reefs, known as the most robust natural defenses, absorb energy from winds and waves, thus reducing shoreline erosion (Qi et al., 2023; Burkett et al., 2005). Coastal zones with these habitats are generally more resilient to natural disasters. Physical factors such as coastal elevation, geomorphology, and bathymetry also shape vulnerability (Hossain et al., 2022a,b). Low-elevation areas, including coral atolls, reef islands, deltaic coasts, and coastal wetlands, are particularly sensitive to accelerated SLR (Bijlsma et al., 1996; IPCC reports, 1998).

Coastal areas, increasingly stressed by global warming and rising sea levels (Mondal et al., 2024a), require robust vulnerability assessments. Coastal vulnerability is defined as the susceptibility of regions to hazards like storms, considering both ecological susceptibility and the capacity to adapt (Bevacqua et al., 2018; Ipcc, 2014; IPCC-SREX, 2012). Florida is highly vulnerable with its extensive coastline, low-lying topography, high population density, and frequent exposure to hurricanes, storm surges, and SLR (DeConcini & Tompkins, 2014). The state's 1,350-mile coastline and population of 22.24 million make it prone to flooding and other hazards, especially in coastal cities like Jacksonville and Miami (Norrell & Fuson, 2023). Florida's waterway system, sinkholes, and ecosystems, such as mangroves and salt marshes, are vulnerable to hurricane damage, with 120 hurricanes, including 36 major ones, recorded since 1851 (Her et al., 2018; NOAA, 2017). Hurricane Milton in 2024 caused significant damage, with over $50 billion in losses (Wee, 2024). Florida's unique geography makes it an ideal location for a comprehensive coastal vulnerability assessment.

Coastal vulnerability is assessed using index-based methodologies, dynamic numerical models, GIS-based platforms, and visual representation (Sekovski et al., 2020; Anfuso et al., 2021; Hossain et al., 2022a, b). The CVI is a widely used method that evaluates coastal areas' susceptibility to rising sea levels, erosion, and flooding. The CVI classifies areas into vulnerability ranks from 1 (very low) to 5 (very high), aiding in prioritizing mitigation efforts (Gornitz, 1990; Hammar-Klose and Thieler, 2001). Other GIS-based methods include DIVA, CSoVI, and CORVI (Mukhopadhyay et al., 2012; Rouleau et al., 2022). As seen in Huu & Thanh's (2018) study of the Mekong Delta, vulnerability indicators assess factors such as tourism, urbanization, and agriculture.

The Integrated Valuation of Ecosystem Services and Trade-offs (InVEST) model is also widely used to assess coastal vulnerability (InVEST, 2023). It evaluates environmental factors like geomorphology, bathymetry, and natural habitats and considers the density of coastal

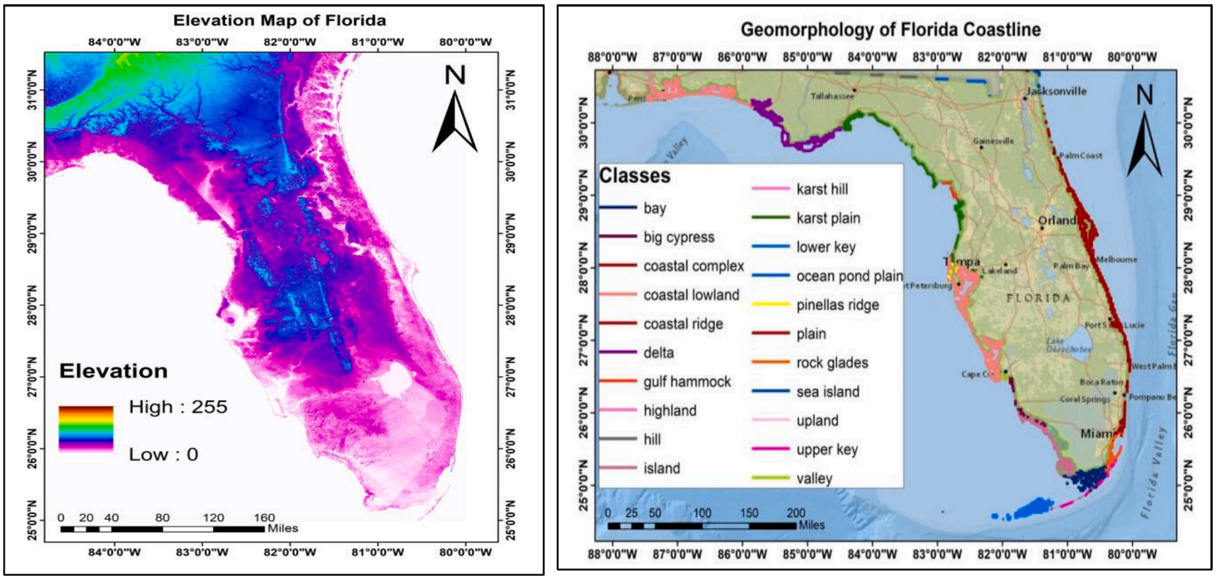

Fig. 2. Elevation (a) and Geomorphologic (b) classification of the Florida coastline.

populations. The model generates exposure indices (1 to 5), similar to CVI ranks, and integrates factors like population density and SLR to determine overall vulnerability. The accuracy of the InVEST coastal vulnerability model is assessed using machine learning techniques such as Artificial Neural Networks (ANN), K-Nearest Neighbor (KNN), Support Vector Machines (SVM), and Random Forest (RF) (Mondal et al., 2024a,b; Tian et al., 2023). These techniques estimate correlations and errors to evaluate the model's precision and adaptability to the specific study area. Regression analysis is used to forecast future coastal vulnerability. The exposure data is divided into training data, which enhances the model's predictive capabilities, and testing data, which verifies the model's accuracy and performance (Schölkopf & Smola, 2002; Cutler et al., 2007; Mao et al., 2024; Azarafza et al., 2021).

Our study analyzed the coastal vulnerability of the Florida Coast over the past three decades (1992–2022). In situ data and Satellite data were gathered for analyzing SLR, coastal erosion, storm surge impacts, and other critical factors, from multiple sources. Our analysis period captures significant upward trends in climate-related changes, including rising sea level and increasing hurricane activity, which are critical for understanding coastal vulnerability in the region. Our primary objective was to assess the evolving vulnerability landscape of the Florida coast over this three-decade time frame. Specifically, we scrutinized the influence of rising sea levels and escalating human activities on coastal susceptibility. By examining the presence and health of natural habitats, we explored their role in mitigating natural disasters and projected future outcomes without their presence. Furthermore, we conducted a comparative assessment of diverse environmental variables and unraveled their varying impacts on coastal vulnerability. These factors played a pivotal role in affecting the state of vulnerability along the coastline. Conclusively, our study extended its focus to social implications arising from potential risks from nature. We identified conceivable avenues for mitigating these impacts, contributing to proactive coastal management strategies.

2. Materials and method

2.1. Study area

Along the southeastern United States, Florida lies between 25° 0́0 N to 31° 0́0 N latitudes and 80° 2́3 W to 84° 0́0 W longitudes (Fig. 1). The Atlantic Ocean to the east and the Gulf of Mexico to the west border this third most populous state, boasting a coastline spanning over 2,170 km (1,350 miles, NOAA). Florida's geography, characterized by low-lying terrain and extensive coastlines, makes it highly vulnerable to storm surges, hurricanes, and rising sea levels.

Florida is an ecologically rich state, home to diverse natural habitats. Its mangrove forests, comprising red mangroves (Rhizophora mangle), black mangroves (Avicennia germinans), white mangroves (Laguncularia racemosa), and buttonwood mangroves (Conocarpus erectus), are vital ecosystems (Mondal et al., 2024a). Additionally, the shallow estuaries host one of the world's most extensive seagrass beds, which stabilize the seafloor, maintain water clarity, and provide crucial habitats for fish, turtles, manatees, and invertebrates (NOAA, 2023). Florida's biodiversity includes over 700 terrestrial animal species, more than 200 freshwater fish, and over 1,000 marine fish, along with a thriving coral reef community in the Florida Keys. The Florida Keys National Marine Sanctuary contains the only coral barrier reef in the continental United States, providing habitats for marine life, protecting coastlines from storms, and offering significant pharmaceutical and tourism benefits (Florida Museum) (Florida Fish, 2022). However, these reefs face severe threats, with climate change and ocean warming causing annual thermal stress and coral degradation (McIvor et al., 2016; McKee, 2011).

The state is also at high risk of SLR. Projections suggest a rise of 3 to 8 feet by 2100 (Her et al., 2018), affecting over 7.2 million people who live within six feet of tidally influenced areas. Impacts include road submergence during King Tides, saltwater intrusion into aquifers, and intensified hurricane effects, particularly in Miami-Dade and Monroe counties (Ocean Conservancy). Florida's flat topography exacerbates hurricane impacts, allowing wind to travel across the state with minimal speed loss (Florida Climate Centre, 2023). On average, the state experiences a hurricane every 1.38 years, with damages totaling approximately $526 billion since 1900 (Pielke et al., 2008).

2.2. Model input parameters and their sources

Developing a robust coastal vulnerability assessment model requires incorporating various geophysical and meteorological parameters. Bathymetry and coastal morphology are crucial as they influence a coastline's resilience to natural hazards. Elevated terrains with dune fields show greater resistance to erosion, while low-lying, erosion-prone areas are highly susceptible to SLR and storm surges (Sweet et al., 2017). Bathymetric data was sourced from the GEBCO global database, and elevation data from the SRTM DEM 30 m dataset, using a 500-meter averaging radius for precision. Florida's elevation map is illustrated in

Table 1
Geomorphological features of Florida coastline along with their respective ranks.

Geomorphology class	Rank	Geomorphology class	Rank
Bay	5	Island	4
Coastal complex	5	Karst hill	1
Coastal lowland	5	Karst plain	5
Big Cypress	3	Lower key	5
Coastal ridge	4	Ocean pond plain	5
Delta	5	Pinellas ridge	4
Gulf hammock	2	Plain land	5
Highland	2	Rock glades	1
Hill	1	Sea island	5
Upland	3	Upper key	2
Valley	2	–	–

Table 2
Various coastal habitats of Florida, along with their respective ranks and protective distances.

Habitat	Rank	Protective Distance (m)
Mangrove Forest	1	1000
Crop Land	2	1000
Swampy Tidal Vegetation	3	1000
Built area	5	500
Bare land	5	500
Rangeland	4	500
Water body	5	1000

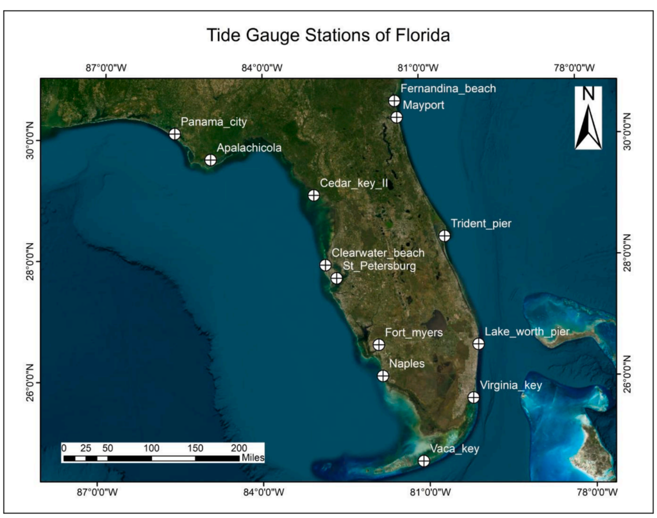

Fig. 3. Tide gauge stations are distributed around Florida, from which the sea level data is estimated.

Fig. 2(a).

The width and slope of the continental shelf significantly affect storm surges during hurricane landfall. A narrow, steep shelf reduces surge effects, whereas a wide, gentle shelf amplifies them like the ~ 250 km-wide West Florida Shelf. Data on Florida's continental shelf morphology were obtained from the Marine Regions' IFREMER-COMARGE database (https://www.marineregions.org/downloads.php).

The geomorphology of a region also dictates vulnerability, with sandy beaches and low-lying areas being highly exposed to storms and flooding. In contrast, rocky terrains and elevated features offer natural protection. These features were mapped using Sentinel-2 satellite imagery from January 2022 and processed through ArcGIS 10.8 using the artificial vectorization tool (Fig. 2(a, b)).

Table 1 provides different geomorphology classes identified along the Florida coast using remote sensing techniques. The geomorphic features were then ranked according to their vulnerability using the methodology proposed by Hammar-Klose and Thieler (2001), where a rank of 1 denotes very low vulnerability, and a rank of 5 indicates very high vulnerability. A summary of the geomorphic classes and their corresponding ranks is provided in Table 5.

Natural habitats, such as mangroves and coral reefs, act as buffers, reducing stressors, while human-built areas and water bodies increase vulnerability. Built-up regions and water bodies were classified as "No Habitat" with the highest vulnerability rank (5). A detailed list of habitat types, ranks, and protective distances is provided in Table 2.

Table 3
Mean Sea Level in different locations of Florida as collected from PSMSL.

Station name	Tide gauge data (Mean Sea Level) in mm			
	1992	2002	2012	2022
Panama City	6972	6970	7000	6970
Apalachicola	6930	6908	6998	6908
Cedar key II	7037	7009	7136	7009
Clearwater beach	7012	7055	7146	7055
St. Petersburg	7119	7138	7236	7138
Naples	7031	7056	7138	7056
Vaca key	7059	7098	7161	7098
Fort Myers	6987	7034	7102	7034
Virginia Key	5939	5950	6017	5950
Lake worth pier	7012	7000	7091	7000
Trident pier	7000	7063	7115	7063
Mayport	6980	7032	7069	7032
Fernandina beach	7284	7248	7235	7248

Table 4
Input Variables and their respective sources.

Input variable	Data type	Requirement	Source	Period
Landmass	Vector (.shp)	Compulsory	GADM	1992, 2002, 2012, 2022
Area of Interest	Vector (.shp)	Compulsory	Manually created using ArcGIS 10.8	2022
Bathymetry	Raster (.tif)	Compulsory	GEBCO	2022
Relief [DEM]	Raster (.tif)	Compulsory	SRTM [30 m resolution]	2022
Geomorphology	Vector (.shp)	Optional	Artificial vectorisation, Using Arc map and Satellite data (Sentinel 2 and Landsat TM).	1992, 2002, 2012, 2022
Continental Shelf Contour	Vector (.shp)	Compulsory	Natural Capital Project (2021) [Provided in the model data alongwith the InVEST coastal vulnerability model]	1992, 2002, 2012, 2022
Wind and Wave Effect	Vector (.shp)	Compulsory	Natural Capital Project (2021), WaveWatchIII. (Provided in the model data along with the InVEST coastal vulnerability model	1992, 2002, 2012, 2022
Sea level Rise	Vector (.shp)	Optional	PSMSL	1992, 2002, 2012, 2022
Natural Habitat	CSV file (.csv)	Compulsory	Satellite data [Sentinel 2, and Landsat TM], Google earth,	1992, 2002, 2012, 2022
Human population	Raster (.tif)	Optional	NASA (GPW, V3 & V4)	1992, 2002, 2012, 2022

Table 5
Ranks associated with variables of different Coastal hazards as proposed by Gornitz (1990) and Hammar-Klose and Thieler (2001).

RANK	VERY LOW (RANK = 1)	LOW (RANK = 2)	MODERATE (RANK = 3)	HIGH (RANK = 4)	VERY HIGH (RANK = 5)
Geomorphology	Rocky; high cliffs; fjords; fiards; sea walls	Medium cliff; indented coasts; bulkheads and small seawalls	Low cliff; glacial drift; revetments; rip-rap walls	Cobble beach; lagoon; bluff	Mud flats; sandy beach; delta; intertidal area
Relief	81 to 100 percentile	61 to 80 percentile	41 to 60 percentile	21 to 40 percentile	0 to 20 percentile
Natural Habitats	Coral reefs; Mangroves; Coastal Forests	High Dune; marsh	Low dune; swamps	Seagrass; kelp	No habitat
Sea level change	0 to 20 percentile	21 to 40 percentile	41 to 60 percentile	61 to 80 percentile	81 to 100 percentile
Wave exposure	0 to 20 percentile	21 to 40 percentile	41 to 60 percentile	61 to 80 percentile	81 to 100 percentile
Surge Potential	0 to 20 percentile	21 to 40 percentile	41 to 60 percentile	61 to 80 percentile	81 to 100 percentile

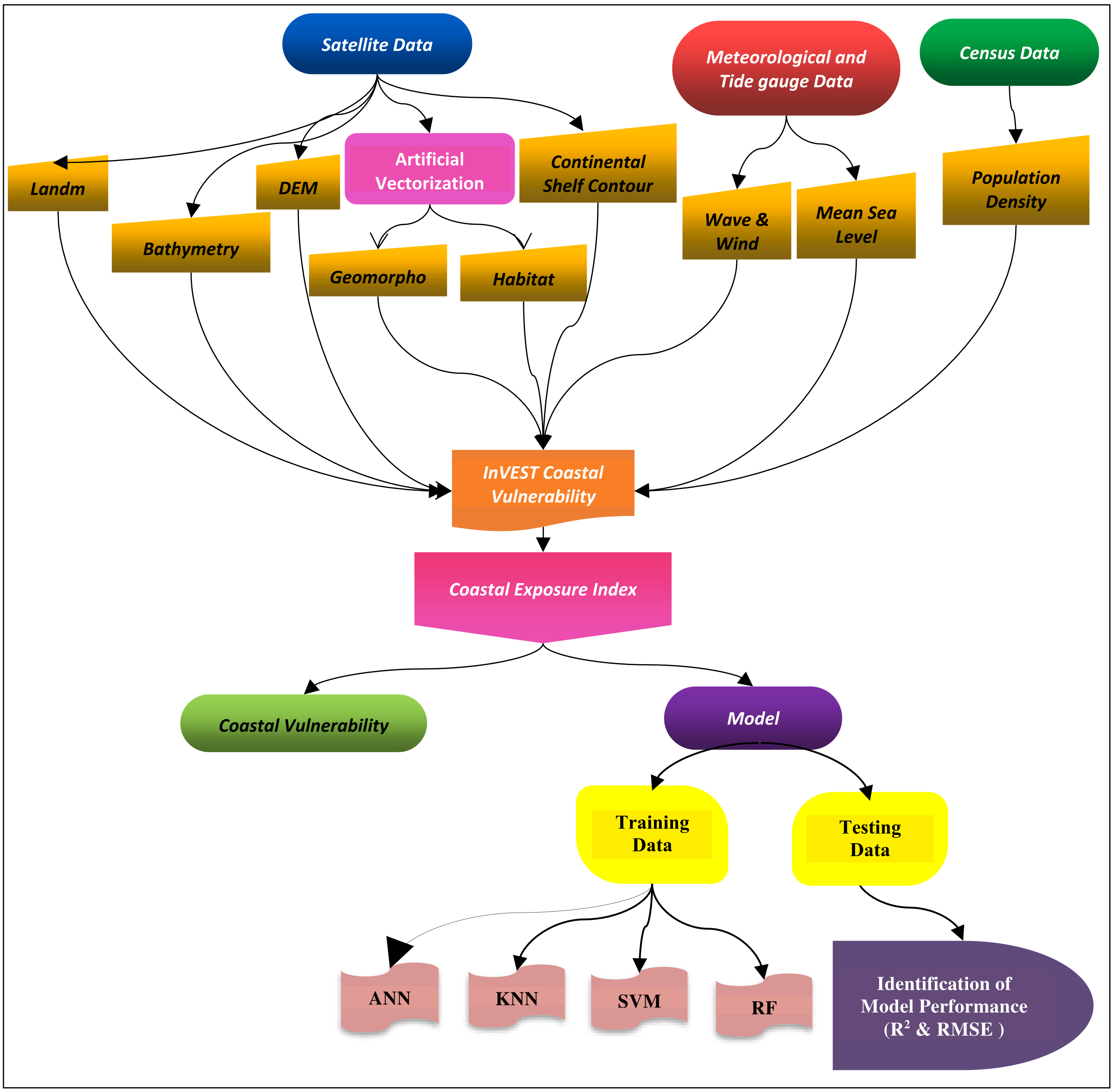

Fig. 4. Methodological Framework for Coastal Vulnerability Analysis using InVEST Modeling suit.

Anthropogenic stress, indicated by population density, adds to vulnerability. Population data for Florida were obtained from NASA's GPW datasets (GPW 3 for 1992; GPW 4 for 2002, 2012, and 2020), highlighting the impact of urbanization on coastal resilience.

SLR data from 1992 to 2022 was retrieved from the PSMSL database and analyzed using 13 tide gauge stations around Florida (Fig. 3). The processed data, summarized in Table 3, provides insights into the region's response to rising sea level.

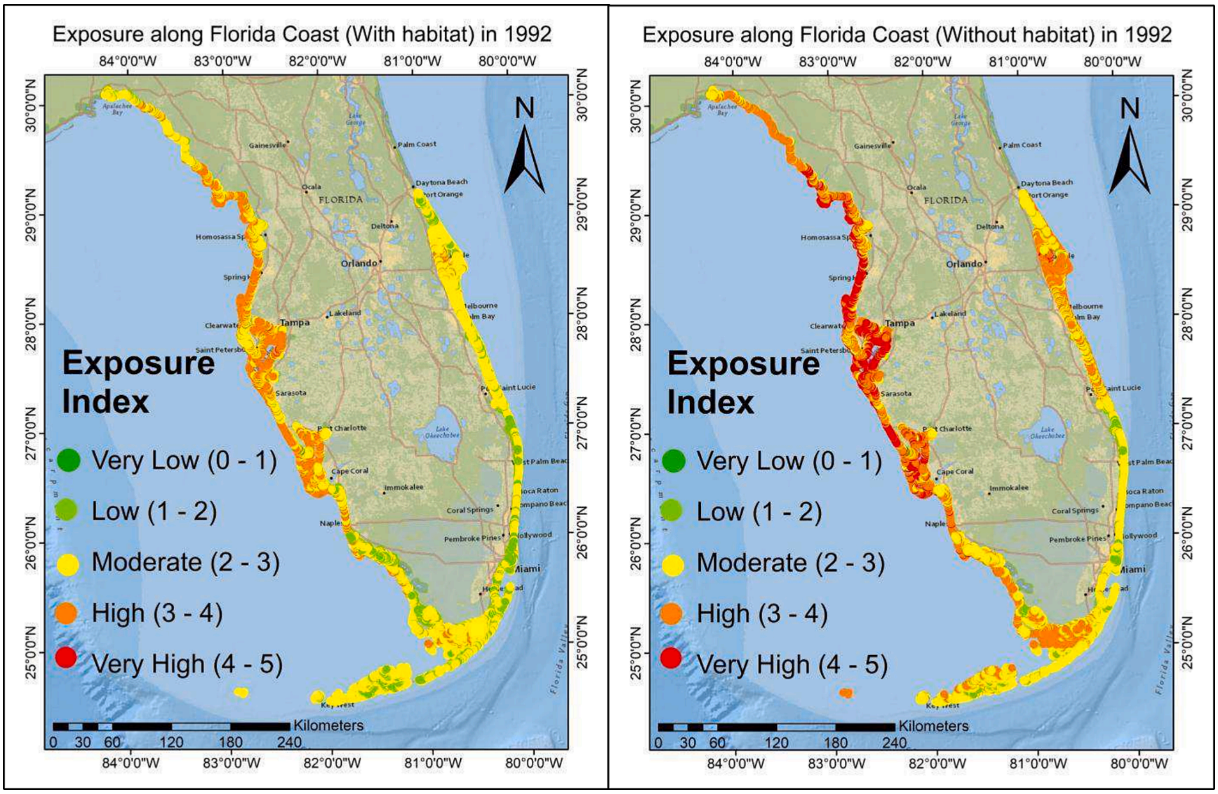

Fig. 5. (a,b). Coastal exposure map – with habitat & without habitat: in 1992.

Meteorological parameters, including wind speed, direction, and wave height (S1-3), were sourced from InVEST (2023). These factors are critical in determining storm surge and erosion impacts during extreme weather events.

Lastly, the shoreline location was defined using the landmass of the continental United States, with the Florida peninsula clipped as the study area via ArcGIS. Table 4 summarizes the input parameters, sources, and processing methods, forming the basis for assessing Florida's coastal vulnerability.

2.3. Methodology

To execute the InVEST model, seven biophysical variables were specified, along with the peninsular landmass and the designated area of interest. Three optional input parameters (as outlined in Table 4) were also included to enhance the model's performance accuracy. All ten parameters were defined using reliable data sources. The ranking mechanism for variable significance was implemented following the approach proposed by Gornitz (1990) and Hammar-Klose and Thieler (2001), as detailed in Table 5. For geomorphology and natural habitat, ranks were assigned manually based on the defined methodology.

The coastal exposure index (CEI) was calculated to assess vulnerability, with CEI values reflecting the degree of exposure to stressors such as SLR, erosion, and hurricanes. CEI, a continuous variable ranging from 1 to 5, was derived using the algorithm in Eq. (1). Here, n represents the number of input variables (excluding landmass and area of interest), and R_i is the rank of the i^{th} variable.

$$CEI = (R_{Geomorphology} R_{Relief} R_{Habitat} R_{SLR} R_{WindExposure} R_{WaveExposure} R_{Surge})^{1/7}$$

Or, in more general terms:

$$CEI = \left(\prod_{i=1}^{n} R_i\right)^{1/n} \quad (1)$$

The vulnerability assessment was conducted at a spatial resolution of 500 m. While a finer spatial resolution could offer a more detailed analysis of exposure conditions, the expansive study area led to notable overlap between shore points when presented as a mosaic map. Vulnerability assessments were performed for four specific years: 1992, 2002, 2012, and 2022. Static variables such as geomorphology, bathymetry, relief, and continental shelf contour were held constant, with data from 2022 used for these variables. Dynamic variables, including habitat distribution, human population density, and sea level, were assessed individually for each year. Landmass data also varied due to changes resulting from erosion and accretion scenarios, requiring unique datasets for each of the four years. The methodology followed for this assessment is summarized in Fig. 4.

2.3.1. Model validation

The model validation process involved the application of four machine-learning algorithms to assess coastal vulnerability: ANN, KNN, SVM, and RF. Each algorithm was selected for its specific strengths in analyzing coastal vulnerability. The ANN model was implemented with a structure comprising three layers: the input layer, two hidden layers with ten neurons each, and the output layer. The hidden layers performed complex mathematical operations to capture non-linear relationships between input features and coastal vulnerability (Mondal et al., 2024a; Ram et al., 2018; Mao et al., 2024). This configuration was chosen to ensure robust training and precise predictions of vulnerability factors.

The KNN algorithm classified coastal vulnerability by analyzing the proximity of data points, relying on the outcomes of nearby locations to predict vulnerability (Mondal et al., 2024a; Sun et al., 2018; Uddin et al., 2022). Its simplicity and efficiency in handling classification tasks made it suitable for identifying patterns in coastal exposure (Yan et al., 2023; Zhou et al., 2022a). The SVM algorithm was employed to classify vulnerability categories by identifying the optimal hyperplane that separates classes within the dataset (Cortes & Vapnik, 1995). This algorithm was particularly advantageous for datasets with numerous

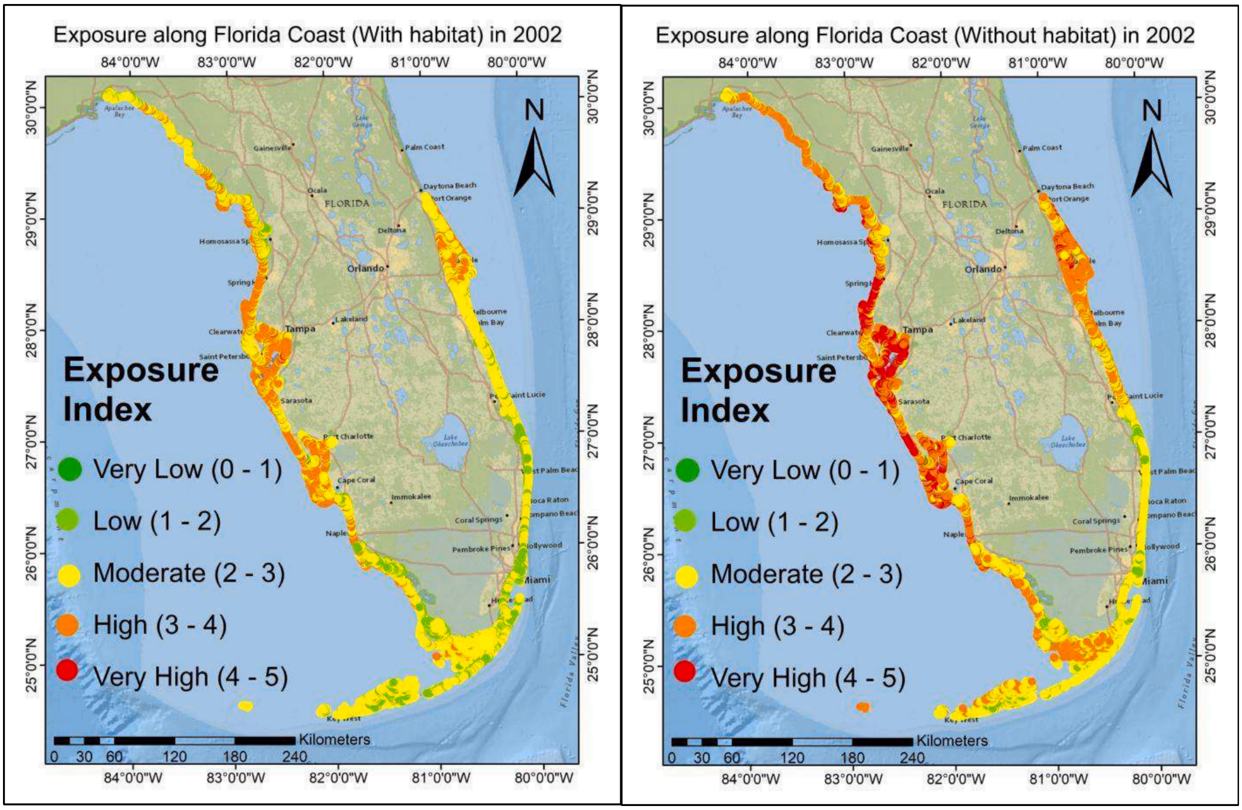

Fig. 6. (a, b). Coastal exposure map – with habitat & without habitat: in 2002.

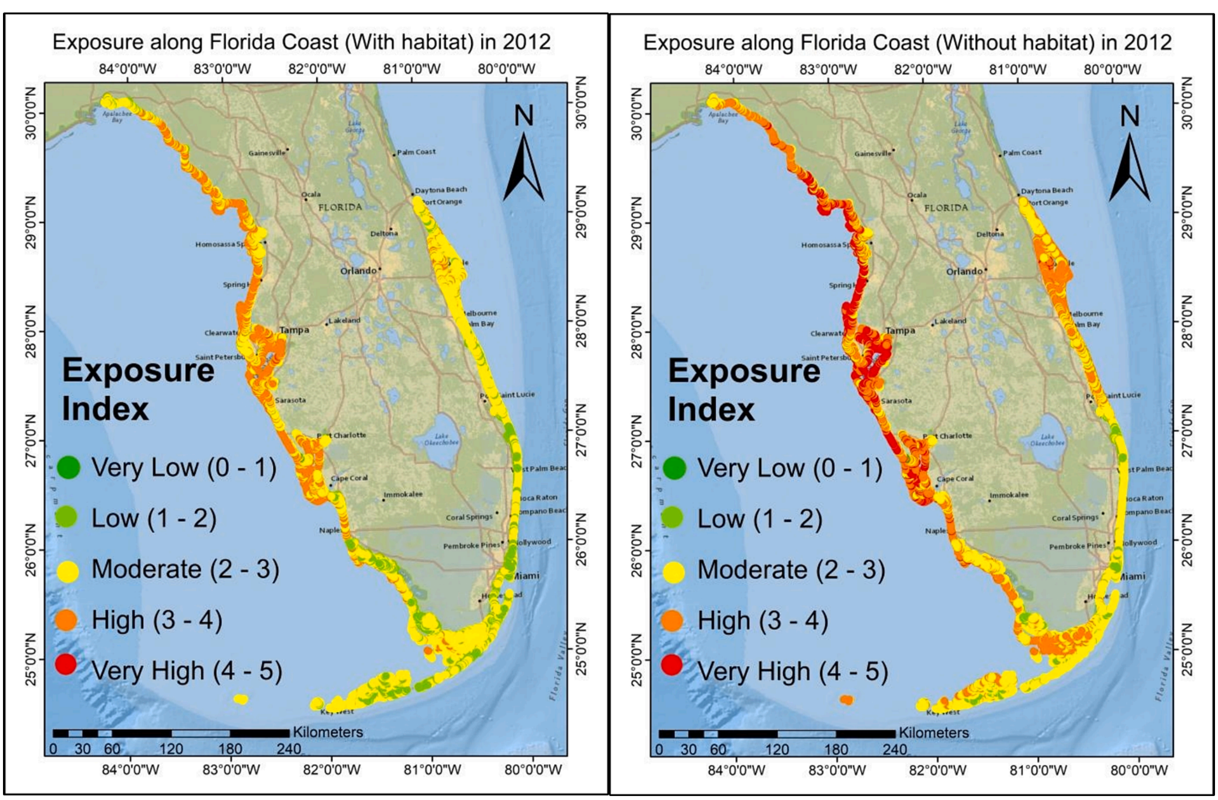

Fig. 7. (a,b). Coastal exposure map – with habitat & without habitat: in 2012.

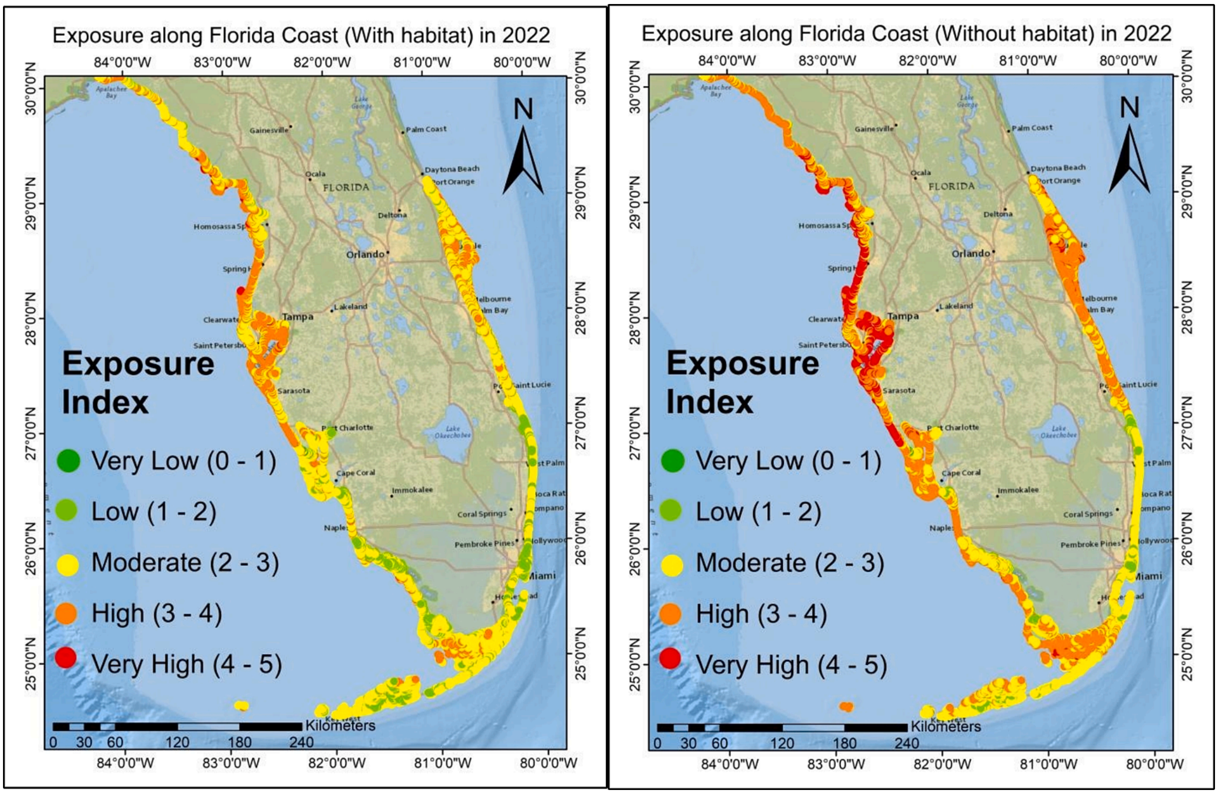

Fig. 8. (a, b). Coastal exposure map – with habitat & without habitat: in 2022.

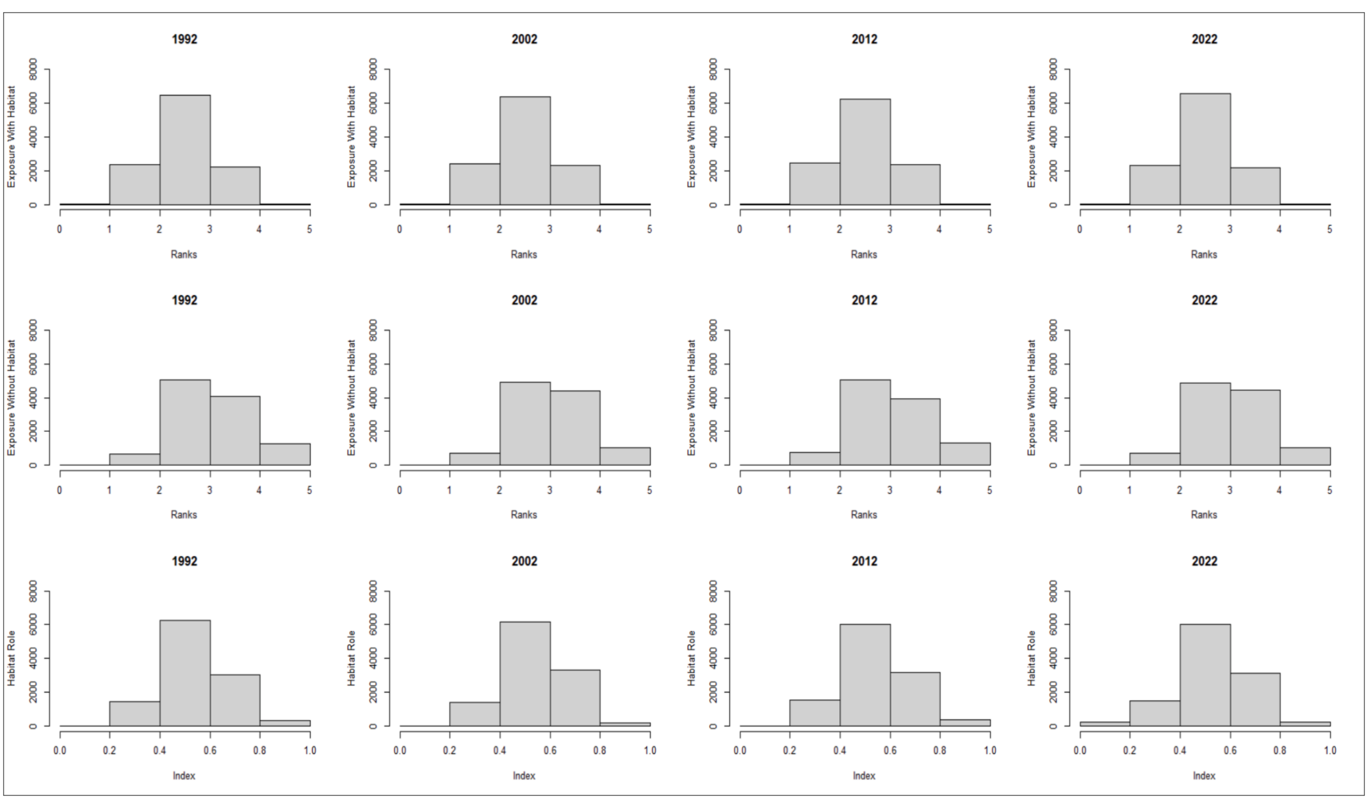

Fig. 9. Histogram plot of comparison of Exposure indices (with and without habitat) and their habitat roles for 1992, 2002, 2012, and 2022 (e.g., Very Low (1),“ ”Low (2),“ ”Moderate (3),“ ”High (4),“ and ”Very High (5).

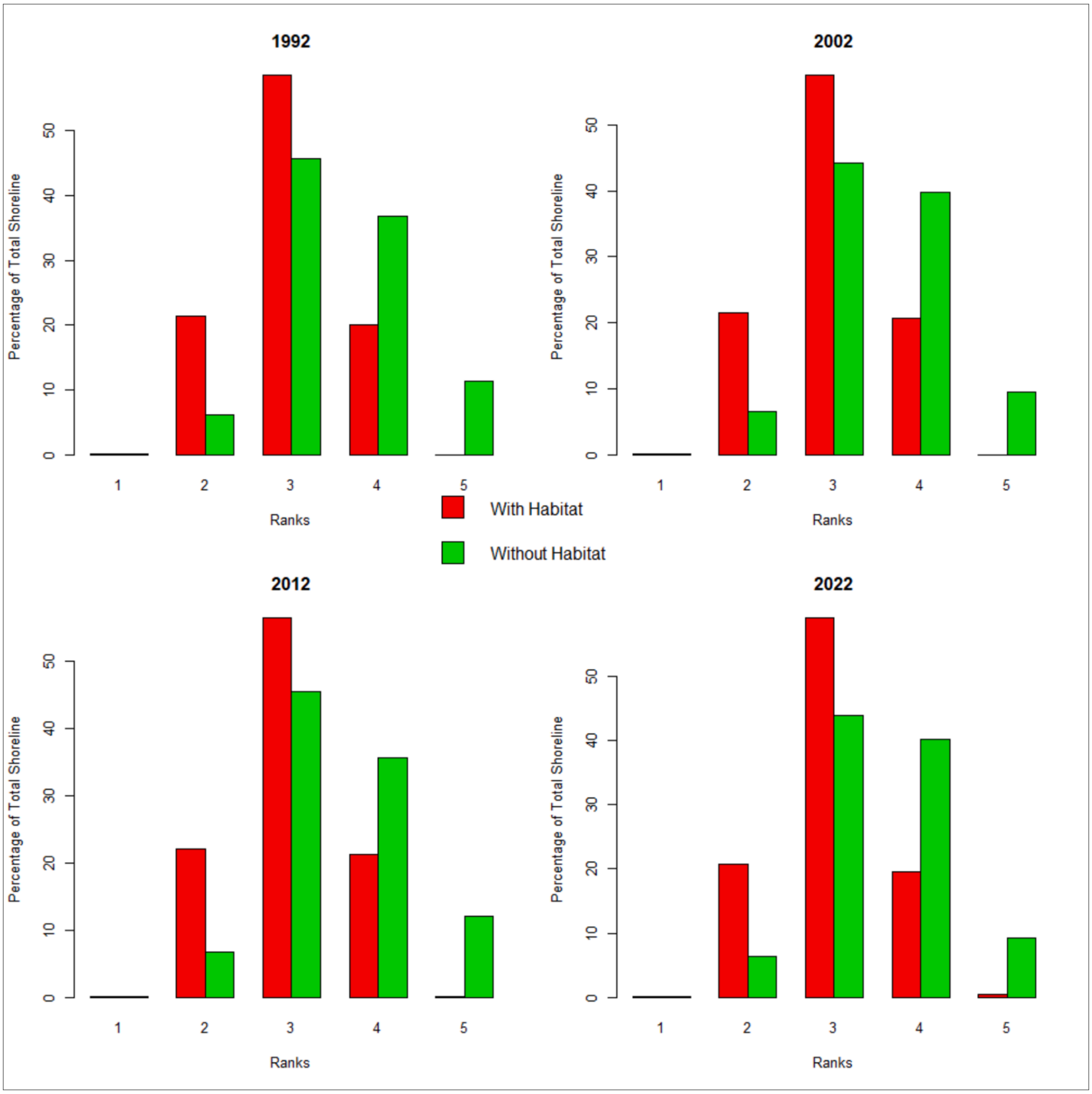

Fig. 10. Bar plots comparing the vulnerability conditions in presence and absence of natural habitat (as the percentage of a total length of the shoreline) in 1992, 2002, 2012, and 2022 (e.g., Very Low (1),“ ”Low (2),“ ”Moderate (3),“ ”High (4),“ and ”Very High (5).

features, allowing for both linear and non-linear classification (Chen et al., 2024a,b; Zhao et al., 2024). The RF algorithm was utilized for its ability to handle regression and classification tasks with high accuracy (Breiman, 2001). By aggregating predictions from multiple decision trees, RF comprehensively understood variable interactions and feature importance (Li et al., 2024; Jiao et al., 2024). The feature importance metric offered insights into the relative significance of different factors influencing coastal vulnerability (Zhou et al., 2022b; Zhou and Liu, 2022).

The dataset was stratified and divided into training (70 %) and testing (30 %) subsets to ensure rigorous evaluation. This partitioning approach allowed the algorithms to learn underlying patterns during training while preserving a separate subset for unbiased performance testing. Model performance was evaluated using two key metrics: R2 (coefficient of determination) and RMSE (root mean square error). The R2 metric quantified the alignment between input features and predicted coastal exposure, with values nearing 1 indicating strong predictive accuracy. RMSE measured the average magnitude of errors between observed values from the InVEST model and predictions made by the machine learning algorithms. A low RMSE value, close to 0, confirmed the reliability of the predictions and highlighted the model’s effectiveness in replicating real-world vulnerability scenarios. The entire model validation process was conducted using Python 3, leveraging its computational capabilities for efficient algorithm implementation and performance evaluation.

3. Results

The InVEST coastal vulnerability model was applied to estimate the Coastal Exposure Index (CEI) for each shore point along Florida’s coastline, each representing an area of 500 square meters. Based on CEI values, the coastline was classified into five distinct exposure zones: Very low exposure zone (CEI: 0–1), Low exposure zone (CEI: 1–2), Moderate exposure zone (CEI: 2–3), High exposure zone (CEI: 3–4) and very high exposure zone (CEI: 4–5).

Two scenarios were evaluated to analyze the vulnerability of

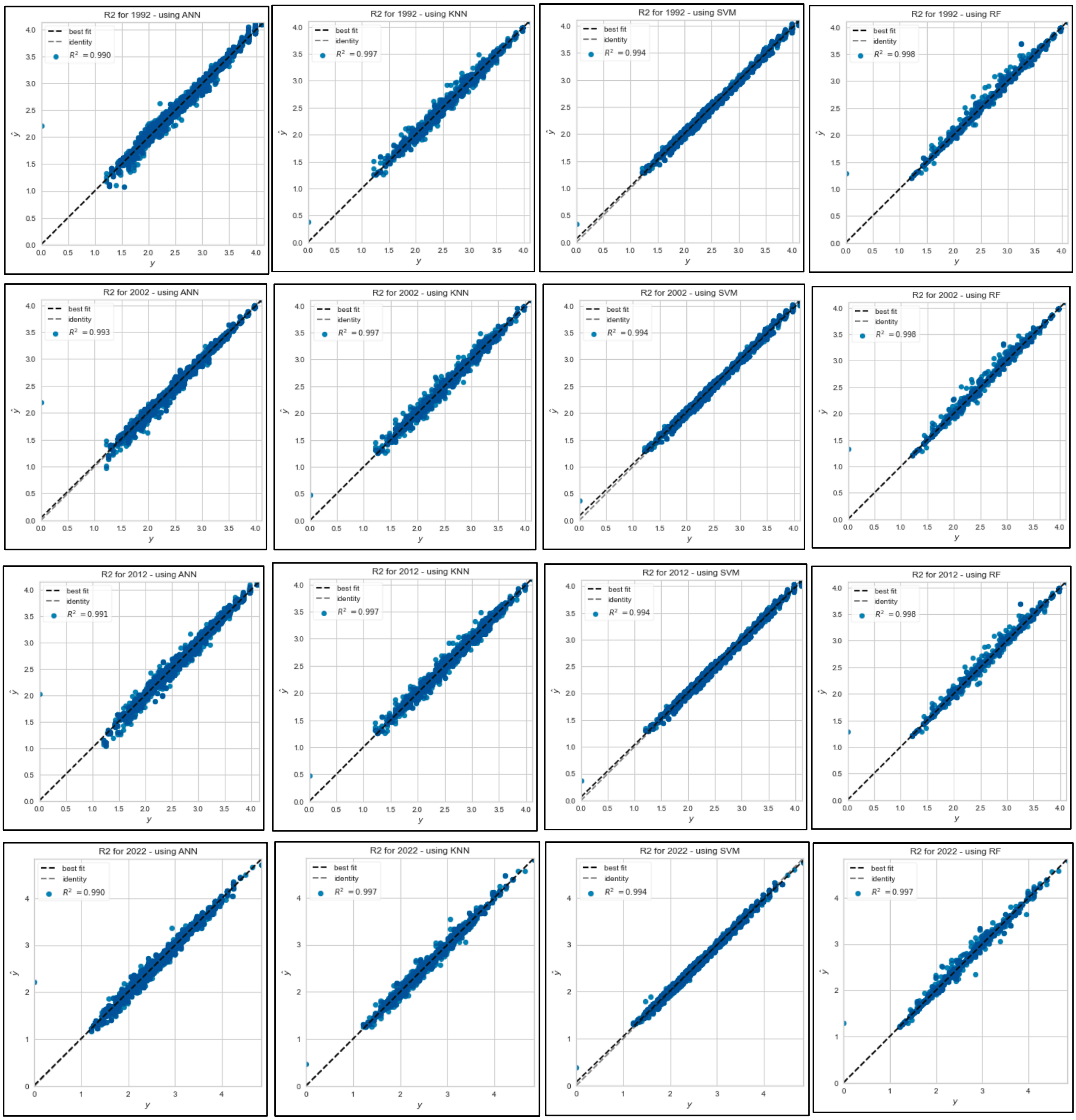

Fig. 11. Regression lines for 1992, 2002, 2012, and 2022 using ANN, KNN, SVM, and RF.

Table 6
Results of model performance using different ML algorithms.

Machine Learning Model	Years 1992 R^2	RMSE	2002 R^2	RMSE	2012 R^2	RMSE	2022 R^2	RMSE
ANN	0.990	0.062	0.993	0.052	0.991	0.059	0.990	0.064
KNN	0.997	0.032	0.997	0.032	0.997	0.032	0.997	0.033
SVM	0.994	0.048	0.994	0.049	0.994	0.049	0.994	0.051
RF	0.998	0.028	0.998	0.029	0.998	0.028	0.997	0.032

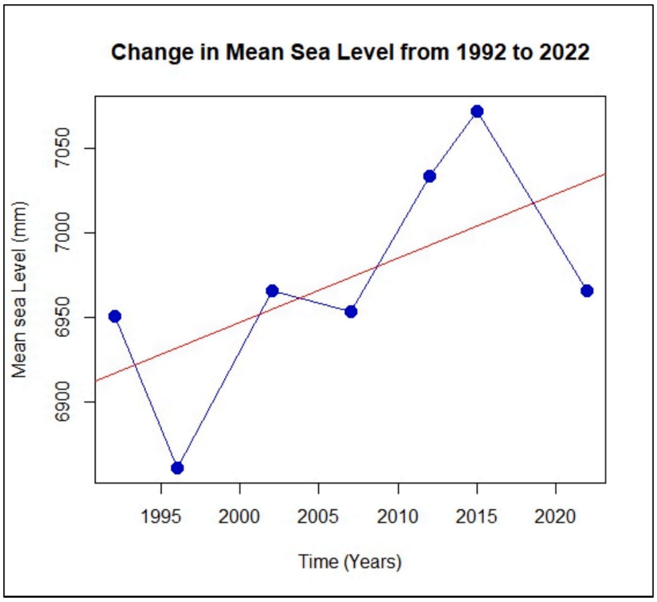

Fig. 12. Time Series Analysis of Mean Sea Level from 1992 to 2022 (Data collected from Permanent Service Mean Sea Level official site,

Florida's coastline: (i) the current state, which considers the presence of natural habitats, and (ii) a hypothetical scenario, where natural habitats were entirely removed or naturally absent.

3.1. Temporal and spatial patterns in coastal vulnerability

Detailed exposure maps are provided in Figs. 5(a,b) (for 1992), Fig. 6 (a,b) (for 2002), Fig. 7 (a,b) (for 2012), and Fig. 8 (a,b) (for 2022; present scenario). These maps reveal significant spatial variability in coastal vulnerability across Florida. Regions on the west coast consistently showed higher CEI values compared to the southeastern coast. Notably, all timeframes identified Tampa and its surrounding areas as highly vulnerable, particularly without natural habitats.

The vulnerability trends derived from histograms (Fig. 9) indicate relatively minor temporal differences in CEI values over the years. However, a clear pattern emerges when comparing scenarios with and without natural habitats. The absence of habitats results in a significant increase in highly vulnerable regions, with 30 % of Florida's coastline categorized as highly vulnerable in 2022 compared to only 10 % in the presence of habitats. Furthermore, the presence of habitats increases the proportion of low-vulnerability zones, rising from 20 % to 40 %.

3.2. Role of natural habitats in reducing vulnerability

The results highlight the vital role of natural habitats in mitigating coastal vulnerability (S-4). Highly vulnerable zones dominate in the absence of habitats, particularly in the west coast regions. However, the presence of habitats eliminates very high vulnerability zones and significantly reduces the overall exposure index.

The comparative analysis of the two scenarios underscores the protective influence of habitats. For example, areas such as West Palm Beach, Coral Springs, and Pompano Beach exhibit low CEI values under the current state, but their vulnerability escalates dramatically without natural habitats.

Bar plots in Fig. 10 visually demonstrate the contrast between the two scenarios across all four-time frames. These plots reveal that while the distribution of CEI values remained consistent over the decades, the presence of habitats consistently reduced exposure levels, reinforcing their critical role in coastal resilience.

3.3. Decadal trends in vulnerability

Temporal trends in vulnerability indicate that the west coast of Florida remains the most exposed region throughout the study period. The presence of natural habitats significantly influenced these improvements, even though the overall extent of highly vulnerable areas decreased slightly between 1992 and 2022.

The 2022 results are particularly noteworthy, as they highlight the dynamic role of habitats in reducing vulnerability. Without habitats, regions with very low vulnerability cease to exist, and highly vulnerable zones dominate the coastline. Conversely, habitats reduce the extent of highly vulnerable regions and increase the proportion of low- and moderately vulnerable areas.

4. Discussion

According to the IPCC-SREX report, vulnerability is a generic term indicating the inclination or susceptibility to experience adverse effects. This inclination forms an inherent attribute of the impacted entity. Many factors, including historical, social, economic, political, cultural, institutional, natural resource, and environmental conditions and processes, collectively contribute to the emergence of vulnerability. Vulnerability emerges as a complex outcome resulting from these diverse elements' interplay. Conversely, exposure refers to the presence or location of individuals, livelihoods, environmental services, resources, infrastructure, and economic, social, or cultural assets in these regions vulnerable to adverse impacts from physical events. Consequently, these areas risk potential future harm, loss, or damage.

This comprehensive study meticulously analyzed coastal vulnerability along the Florida coastline. The investigation spanned four distinct years – 1992, 2002, 2012, and 2022, with the latter considered the present case. Our assessment utilized the InVEST CVI model, a robust tool developed under the auspices of the Natural Capital Project. This model is designed to evaluate the impacts of critical biophysical variables, encompassing geomorphology, elevation, natural habitats, SLR, wind-wave exposure, surge potential, and population density, as Ai et al. (2022) outlined. While our primary focus is on studying vulnerability, we present the results as exposure indices. Our investigation introduces a novel approach to presenting results, utilizing exposure indices categorized into five distinct levels: "Very Low (0–1)," "Low (1–2)," "Moderate (2–3)," "High (3–4)," and "Very High (4–5)." These categories offer a transparent and interpretable representation of the varying degrees of susceptibility observed along the Florida coastline, and its aim to enhance the accessibility and practical utility of our findings for a broad audience. Policymakers, coastal managers, and stakeholders can readily interpret and act upon the categorized vulnerability levels, thus contributing to informed decision-making in the realm of coastal management and conservation.

We investigated the effect of eight biophysical parameters on the susceptibility of the Florida coastline. Some factors, notably the SLR, population density, wind and wave heights, and surge potential, highly impact coastal exposure. The natural environment is the most significant component influencing the coastline's vulnerability.

The InVEST approach has yielded relatively few vulnerability studies worldwide. Al Ruheili and Boluwade (2023) conducted comparable research on Oman using the InVEST model. The most influential elements in evaluating vulnerability were natural habitat, coastal type, relief, wave exposure, surge potential, and sea level change. China conducted a similar survey in 2022. Among the input factors employed by Ai et al. are bathymetry, climatic forcing, DEM, contour of the continental shelf, natural habitat, geomorphology, landmass, and sea level change. Hopper and Meixier assessed the vulnerability of New York's Jamaica Bay. Additionally, they employed comparable input parameters for their investigation. They also computed an erosion index by considering wave exposure, habitat, and geomorphology.

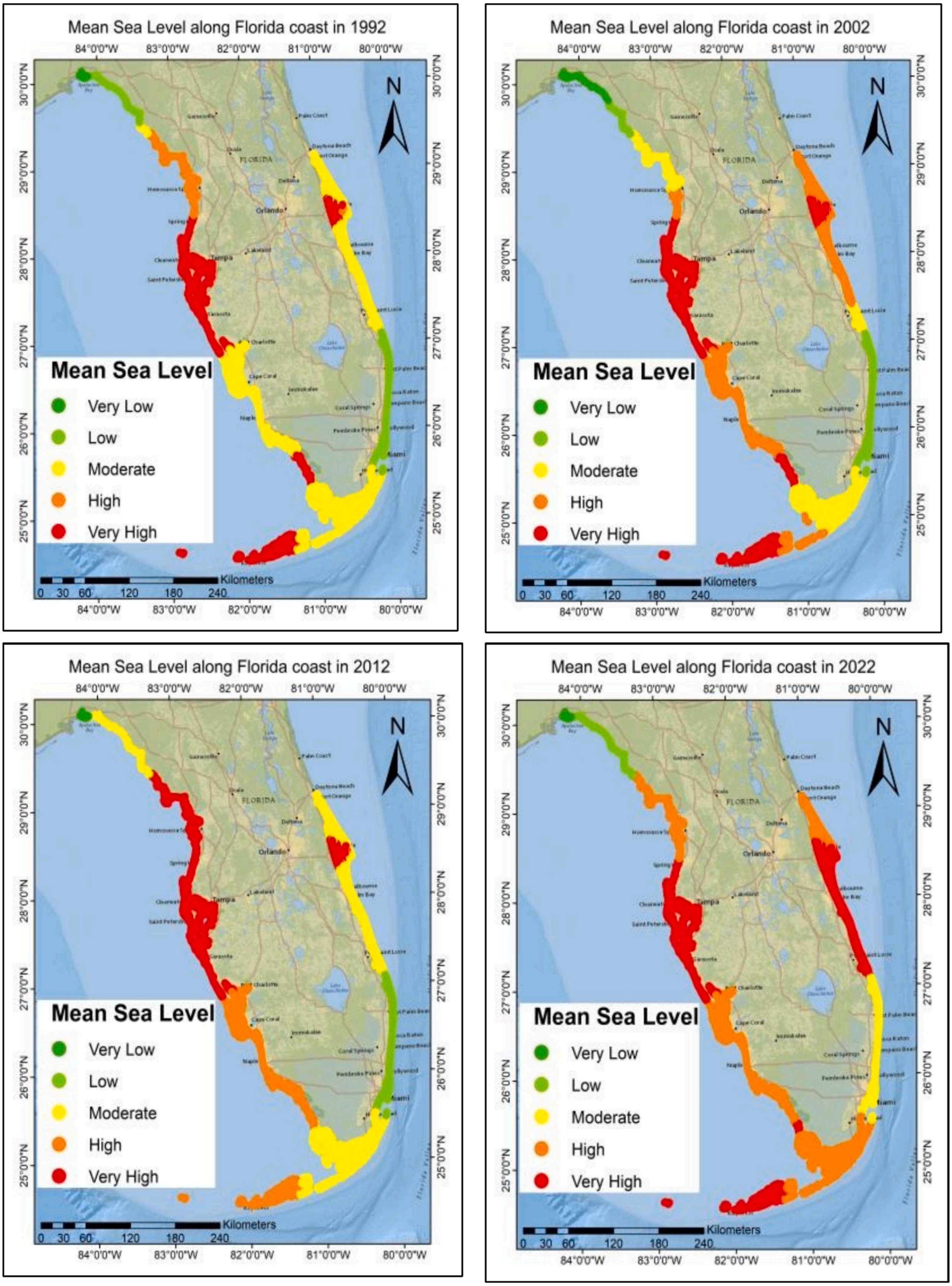

Fig. 13. Mean Sea Level along the Shoreline of Florida (1992–2022).

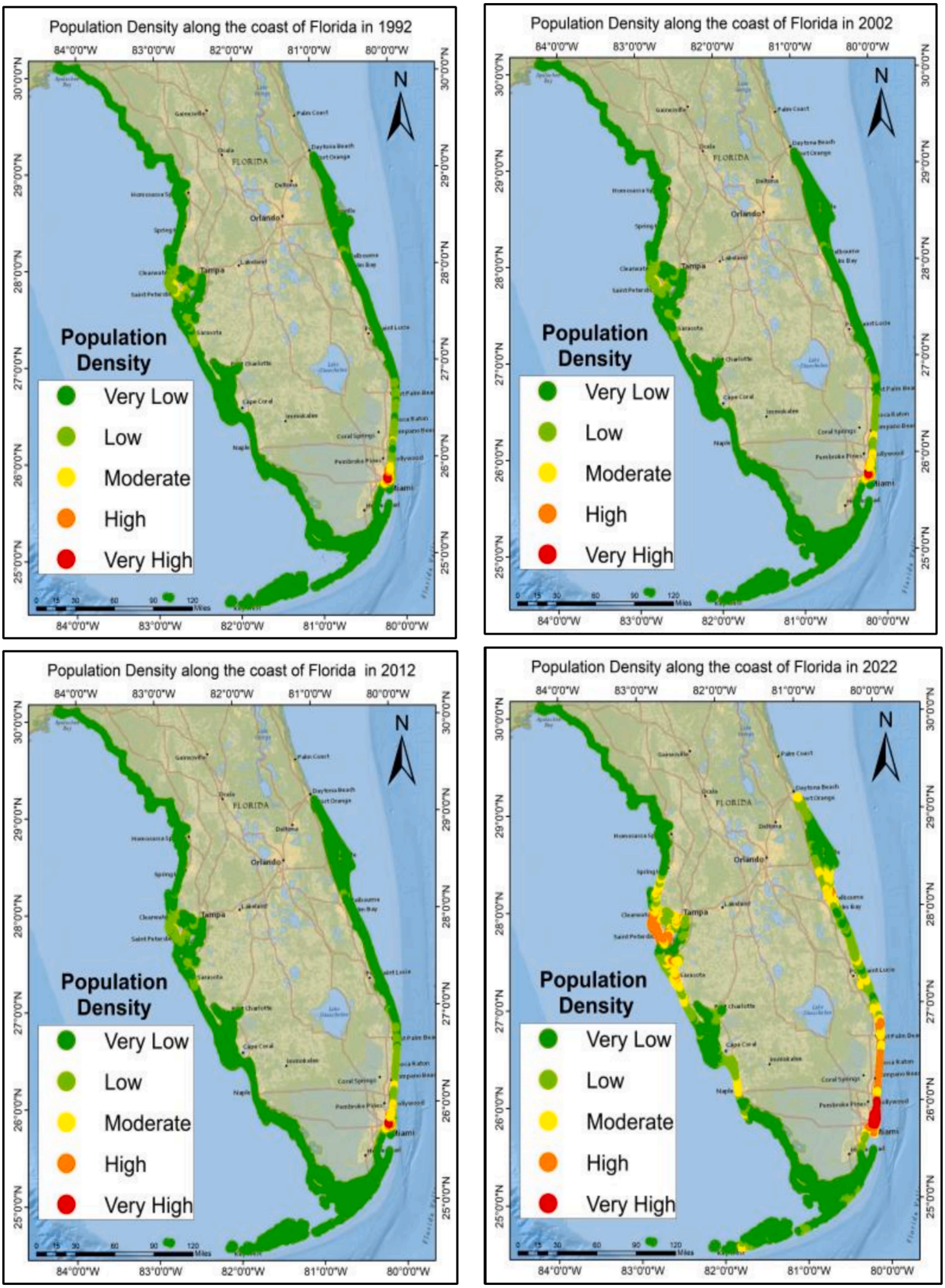

Fig. 14. Population density along the coastline of Florida in 1992, 2002, 2012, and 2022.

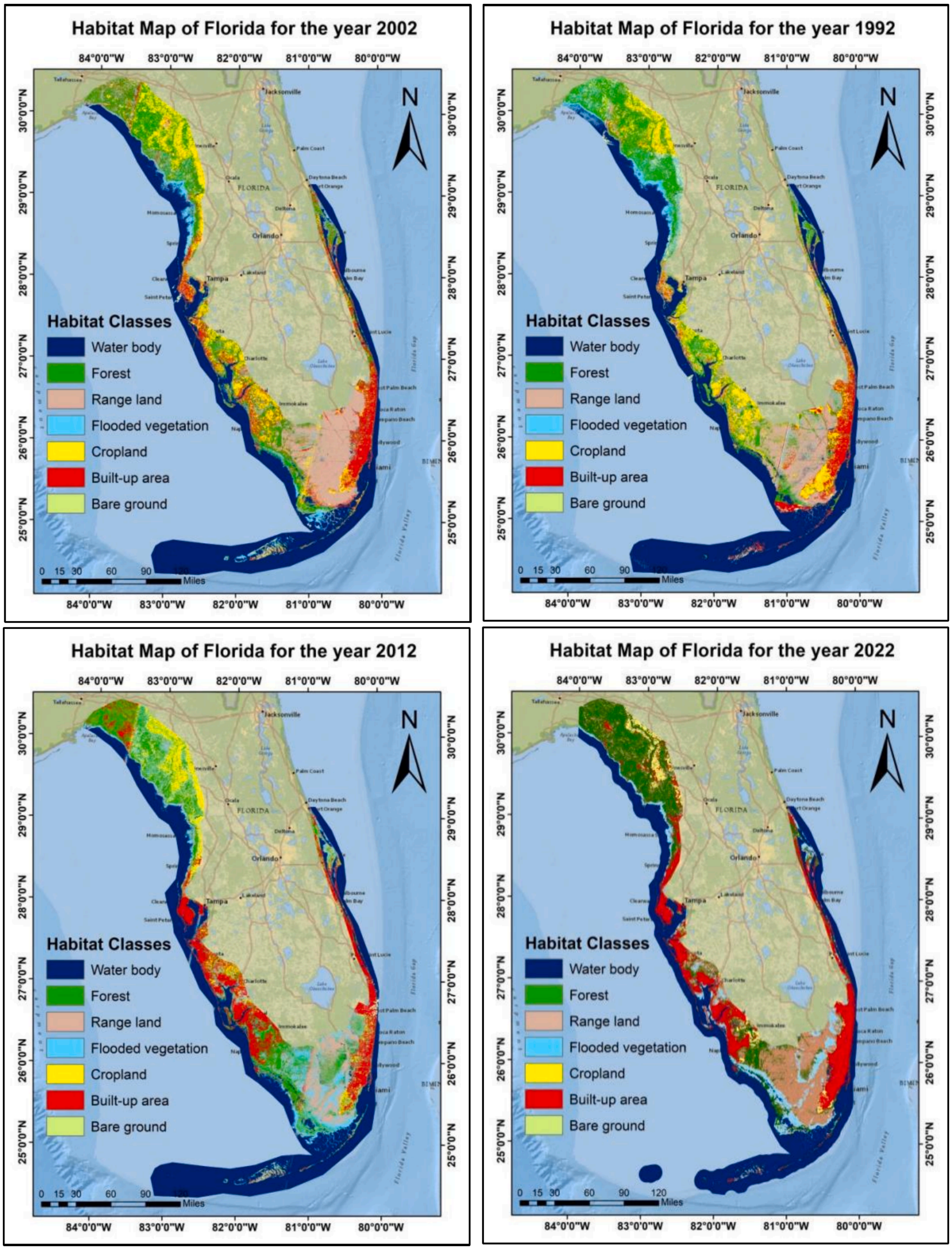

Fig. 15. Land Cover map of the study area on the Florida coast in 1992, 2002, 2012 and 2022.

4.1. Validation of model performance

The model's performance was validated using ML algorithms, including ANN, KNN, SVM, and RF. These techniques aid in optimizing model performance by adjusting hyperparameters and identifying discrepancies or issues in the data produced by the InVEST model. They assist in identifying both overfitting and underfitting. Overfitting transpires when a model excels on training data but falters with novel data due to excessive focus on certain patterns. Underfitting occurs when a model is too simplistic, failing to identify significant patterns, leading to inadequate training and fresh data performance. To achieve reliable results, it is crucial to balance these two extremes.

Model performance was assessed using R^2 and RMSE values alongside correlation coefficients and regression lines for each year. Fig. 11 presents the best fits from each ML algorithm across all years. The graphs indicate an excellent model fit with a high positive correlation, suggesting that the biophysical parameters accurately describe the exposure. A positive correlation indicates that changes in factors like geomorphology, natural habitat presence, and population density directly affect the exposure index, thereby influencing vulnerability. This reinforces the model's ability to capture the complex dynamics of coastal vulnerability.

Table 6 quantifies the results of model performance using different ML algorithms. R^2 values range from 0.990 to 0.998, with an ideal value of 1 (values greater than 0.6 are acceptable), and RMSE values range from 0.028 to 0.064, with 0 being ideal. Lower RMSE values signify greater accuracy, reflecting minimal differences between model outputs and original InVEST data. Higher R^2 values indicate better model fit, as shown in Fig. 11. Among the algorithms tested, RF produced the most accurate predictions.

The model's ability to closely align with historical coastal hazard records and perform consistently across various validation metrics

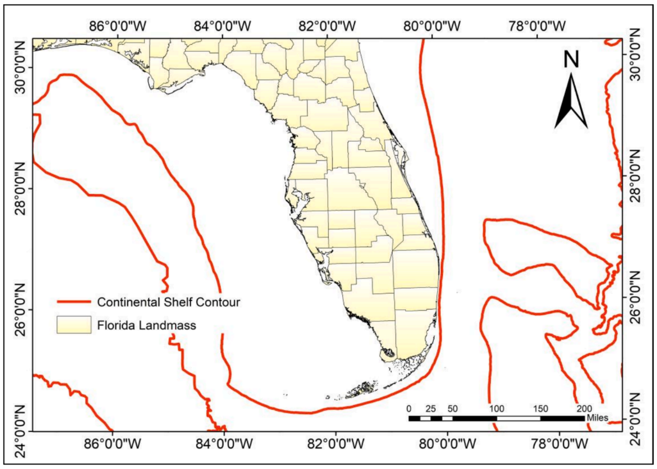

Fig. 16. Position of the continental shelf with respect to the Florida coast.

strengthens its reliability. This validation highlights the value of using advanced machine learning techniques to understand the complex dynamics of coastal vulnerability better.

4.2. Factors shaping the coastal vulnerability

Rising sea levels are a significant factor in shaping coastal vulnerability. The SLR rate has risen to 3 mm/year since 1993, according to recent tidal gauge data (Church & White, 2006; FitzGerald et al., 2008). The IPCC (2022) report highlights the impacts of SLR on U.S. coasts, emphasizing the need to understand its socioeconomic, physical, and ecological effects. Our study on Florida's sea level trend from 1992 to 2022 (Fig. 12) reveals an average increase of 2.73 mm per year. The mean sea level conditions along Florida's shoreline (Fig. 13) show periodic changes, with regions experiencing high mean sea levels being particularly vulnerable (Figs. 5–8). The last decade has seen a significant increase in mean sea levels, especially along Miami's coast, which is more exposed to storm surges and flooding. On the other hand, with its dense mangrove forests, northwest Florida faces lower sea levels, which naturally reduce exposure to SLR. These forests help buffer against storm surges and slow tidal movement, protecting the coastline.

Increasing human population density compounds the vulnerability to coastal hazards. In Florida, the population grew significantly along the west coast, especially in Miami and its surroundings (Fig. 14). According to the 2020 census, Florida's population reached ~ 21 million, with a density of 406 people per square mile. Tourism is a major industry, with an influx of 106.3 million tourists in 2015, contributing significantly to the state's economy (Harrington et al., 2015). However, tourism also intensifies coastal pressure.

Although threatened by SLR (Fakhruddin et al., 2018), Mangrove forests are key in mitigating coastal vulnerability. These habitats act as natural defenses, reducing the impact of erosion and storm surges. Fig. 15 highlights the changing landcover along the Florida coast over the last two decades. Our study highlights an increase in mangrove coverage along Florida's northwest coast, significantly decreasing coastal exposure in these regions (Figs. 7 and 8). Jiaozhou Bay, China (Ai et al., 2022) has observed similar patterns where natural habitats reduce coastal vulnerability. In Oman, a study by Al Ruheili and Boluwade (2023) demonstrated that natural habitats can mitigate coastal risks, with habitats covering 41 % of coastal communities under intermediate exposure and 59 % under the highest exposure category. These results highlight how crucial protecting natural ecosystems is to boosting coastal resilience.

4.2.1. Effects of the geophysical parameters

Geophysical factors such as geomorphology, elevation, and bathymetry play a critical role in determining a coastal zone's vulnerability. Low-lying areas are generally more susceptible to coastal hazards compared to uplands and hilly terrains. In contrast, steep coastlines tend to be less prone to inundation from storm surges and rising sea levels. Underwater bathymetry is also significant, with the continental shelf's slope influencing storm surge and wave height impacts. As shown in Fig. 16, Florida's continental shelf is relatively close to the southeast coast, which helps reduce the exposure to storm surges and large waves.

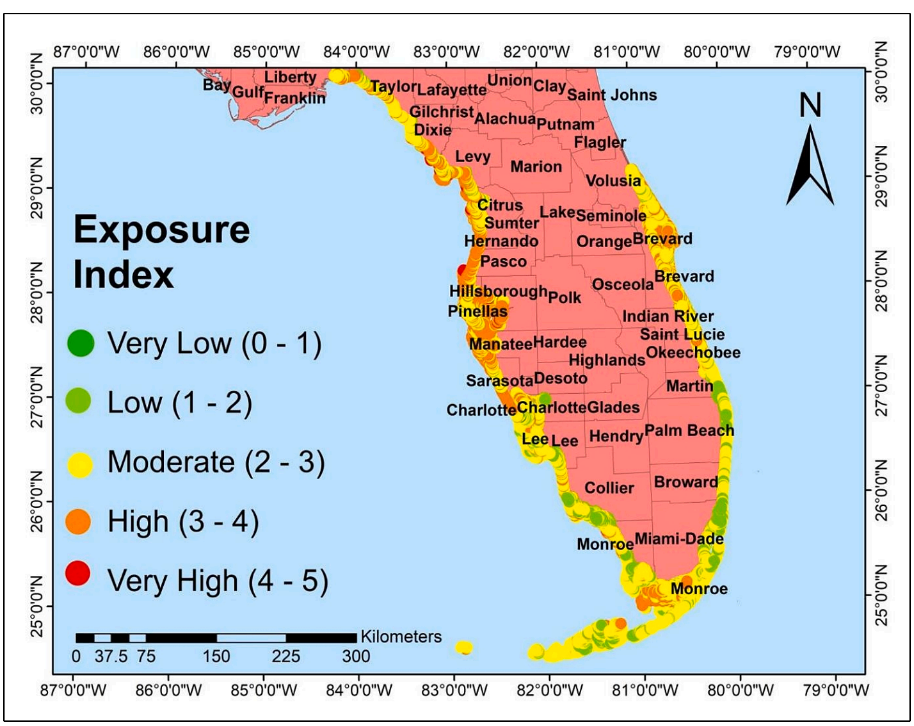

Fig. 17. Sub-level distribution of coastal exposure in recent times.

However, the shelf break is farther from the West Coast, making those areas more vulnerable to flooding and storm surge events. Florida's coastline includes both high and low-elevation regions, with the low-elevation areas facing greater risks from stronger winds, larger waves, and higher tides (Fig. 2b).

4.2.2. Sub-level distribution of vulnerability

Fig. 17 illustrates the recent exposure conditions of various county shorelines in Florida, focusing on 2022. The results show that counties like Pasco, Hillsborough, Pinellas, Sarasota, and Charlotte are highly exposed to coastal hazards, indicating significant vulnerability. Hernando Beach also falls within this high-vulnerability category. Areas like Taylor, Dixie, and Levy show moderate to high vulnerability, while Monroe, Lee, and Miami-Dade are vulnerable to hurricane landfalls. In contrast, Palm Beach, Martin, and Seminole exhibit low vulnerability. The southern and northeast coasts, including Volusia, Brevard, Broward, and Collier, report low to very low vulnerability, with many other regions in the moderately vulnerable range.

This study also benefits other coastal areas, such as the Maryland and Texas coasts, which face similar risks like rising sea levels and storm surges. The methods applied here could help assess their vulnerability and inform region-specific management strategies. Additionally, exploring the climate change impacts on Lake Michigan and Chesapeake Bay could provide insights into inland coastal zones' risks, such as storm surges and water level changes. Extending the InVEST model to these areas can enhance vulnerability assessments and guide adaptive strategies for Florida and other U.S. coastlines. Future work could broaden the model's application, incorporating climate projections for better predictive accuracy.

4.2.3. Requirement of vulnerability assessment and measures for sustainable development

According to Malone et al. (2010), vulnerability assessments are essential for land-use planning, habitat restoration, and understanding the impacts of SLR and coastal inundation on ecosystem services. These assessments require adaptive sampling to document ecological impacts, evaluate recovery, and track changes over time, focusing on coastal infrastructure, habitats, and living marine resources.

Effective coastal hazard management demands sustainable adaptations, including urban planning that anticipates long-term environmental changes. Chen et al. (2023) and Hurlimann et al. (2014) emphasize the need for resilient urban design and zoning regulations that restrict construction in high-risk areas. Green infrastructure, such as mangrove forests, plays a crucial role in enhancing coastal resilience. Protecting natural habitats is key to sustainable development (Munasinghe & Wells, 1992). Our study found that rising sea levels, high population density, and mangrove forests are key factors influencing coastal vulnerability in Florida. In high-tourism areas like Miami, it's important to focus on resilient coastal structures and eco-tourism. Additionally, strategies like living shorelines, beach nourishment, and mangrove restoration align with broader goals of sustainable coastal management and conservation in Florida.

5. Conclusion, limitations and recommendations

Coastal areas are highly vulnerable to natural calamities, necessitating regular assessments for sustainability. A robust framework of routine, interdisciplinary observations and modeling is crucial for providing the data needed for informed evaluations. Adaptive, ecosystem-based approaches to climate risk management are essential to address evolving challenges. The study emphasizes the need for high-resolution, geospatial nowcasts and 5–10-year forecasts for assessing vulnerability, with updates every 1 to 10 years based on coastal geomorphology and human impacts.

This study, focusing on Florida from 1992 to 2022, highlights the impact of SLR, population growth, and the protective role of mangrove forests. Areas with natural habitats, such as mangroves, show significantly reduced vulnerability compared to those without. Low-lying regions and softer slopes are more prone to inundation, with southeast Florida less sensitive than northwest Florida. The InVEST and ML models used for vulnerability evaluation demonstrated strong accuracy, validating their effectiveness. The study predicts increased vulnerability as global warming and rising sea levels continue. It suggests mitigation strategies such as mangrove preservation, reforestation, protective infrastructure, strategic relocation, and early warning systems to reduce coastal disaster impacts.

This study offers significant insights on Florida's coastal vulnerability; however, important limitations must be recognized. The analysis is limited by data availability, especially in documenting localized geomorphological alterations and small-scale hydrodynamic processes that substantially affect vulnerability. The dependence on historical datasets and model assumptions creates difficulties in projections, particularly in regions experiencing rapid coastal changes as a result of urbanization or catastrophic weather phenomena. While the combined approach of InVEST and machine learning models proficiently evaluates vulnerability, their applicability to different coastal areas with unique geomorphological and socio-economic traits necessitates additional validation. The research predominantly employed Landsat TM and Sentinel-2 satellite data for geomorphological and natural habitat evaluations, in conjunction with datasets from GADM, GEBCO, SRTM, Wave Watch III, and PSMSL. Although these datasets were crucial inputs, using higher-resolution data, such as hyperspectral photography or LiDAR-derived elevation models, could improve the reliability of coastal vulnerability mapping. Future studies need to integrate high-resolution datasets, utilize more dynamic climate forecasts, and investigate region-specific calibrations to enhance the robustness and applicability of the suggested methodology beyond Florida. Extending the research to additional coastal regions with varied environmental conditions would enhance the validation and refinement of the methodology for comprehensive coastal resilience planning.

Finally, we suggest that "Green-gray" infrastructure integrates the maintenance and restoration of natural ecosystems, including coastal buffers like mangroves and seagrasses, with traditional methods such as constructing offshore ecological breakwaters, dikes with integrated foreshores, artificial reefs, sandy foreshores with integrated natural dune systems and wetland restoration become essential for enhancing coastal resilience to protecting natural habitats which are pivotal for sustainable global development and local development. The study of Florida and Everglades coastal areas are economically protected against erosion and floods due to hurricanes by including green components as well. It can protect against potential hazards, including rising sea levels, and is more resilient than conventional grey infrastructures. Nature-based solutions may be less expensive to maintain and repair because they can readily adapt to changing environmental circumstances.

CRediT authorship contribution statement

Ismail Mondal: Writing – original draft, Visualization, Validation, Software, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Anirjita Das:** Writing – review & editing, Validation, Methodology, Investigation, Data curation. **SK Ariful Hossain:** Writing – review & editing, Validation, Methodology, Investigation, Data curation, Conceptualization. **Felix Jose:** Writing – review & editing, Validation, Supervision, Methodology, Formal analysis. **Hamad Ahmed Altuwaijri:** Writing – review & editing, Validation, Investigation, Formal analysis, Data curation.

Declaration of competing interest

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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Data availability

Data will be made available on request.

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