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Coastal Hazard Risk Assessment in a Changing Climate: A Review of Predictive Models and Emerging Technologies

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Abstract: *Climate change is one of the most significant problems facing the coastal regions throughout the entire world, exposing communities, infrastructure, and ecosystems to the risks of erosion, storm surges, floods, and sea level rise. Traditional risk assessment of coastal hazards using statistics-based techniques and deterministic models has been found useful, but is typically insufficient to capture a non-stationary climate regime and compound events. The paper establishes a coherent system to apply predictive analytics and new technologies to evaluate the risks associated with climate-induced events in the United States' coastal communities. Probability hazard maps from sea level rise, regional climate model, socioeconomics, and environmental features are developed using GIS and Random Forest, Extreme Gradient Boosting, and K-Nearest Neighbour. Due to the development of early warning systems, digital twins, the Internet of Things, next-generation monitoring satellite systems, and big data analytics, coastal management can become more proactive. In addition to providing a decision-making tool for resource distribution, treatment prioritization, and long-term adaptation planning, the resulting projection was more accurate with the system. In bringing together machine learning, geospatial analysis, and technology advances, the study provides a compelling window for resilience-building, adaptive management, and sustainable coastal risk management under accelerated climate change.*

Keywords: *Climate change, Coastal hazard, risk assessment, Predictive modeling, Machine learning, GIS, Remote sensing, Coastal resilience.*

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1.0 Introduction

Coastal areas are dynamic ecosystems of great importance in human livelihood, economic development, and ecological sustainability. Currently, more than 600 million people are living in low-lying coastal areas, and the number is expected to increase substantially by

2050 (Neumann *et al*., 2015). However, these areas are increasingly threatened by the adverse effects of climate change, such as sea-level rise, more intense storm surges, frequent flooding, loss of shorelines, and saline intrusion (Nicholls & Cazenave, 2010; Oppenheimer *et al*., 2019). Global mean sea level has accelerated from 1980 to 2010 at a rate of 3.3 mm yr^{-1} as a result of thermal expansion and melting of glaciers and ice sheets (Nerem *et al*., 2018). This sea-level rise, in addition to extreme weather events, dramatically increases the frequency of coastal flooding events and thus poses considerable risks to infrastructure, ecosystems, and human lives (Sweet *et al*., 2022).

The United States is especially susceptible to these climate-related coastal hazards because of its long shorelines on the Atlantic, Pacific, and Gulf coasts. Coastal flooding already causes billions of dollars of damage annually, and the figure is expected to rise if mitigation and adaptation efforts are not exponentially strengthened (Hauer *et al*., 2016; Tebaldi *et al*., 2012). Moreover, the effects of compound flooding—when several drivers coincide, such as storm surge, heavy rainfall, and river overflow—are projected to become more pronounced due to climate change and related multidimensional risk scenarios in which people reside along coastlines (Wahl *et al*., 2015).

The nature of these risks has created the need to invest in highly developed predictive modelling and decision support systems that use in-situ socio-environmental data in combination with climate forecasts. Traditional risk appraisal methods rely largely on deterministic or statistical approaches that are useful but limited, as they cannot fully capture the non-linear and multi-dimensional interactions among coastal risk factors (Vousdoukas *et al*., 2018). For example, conventional regression-based models often assume linearity, which reduces their ability to represent thresholds, feedback loops, or cascading failures in coastal systems.

Recent advances in artificial intelligence (AI), machine learning (ML), and geospatial technologies have opened up opportunities for more accurate and spatially explicit hazard forecasting. A variety of ML algorithms—including Random Forest (RF), XGBoost, and K-Nearest Neighbour (KNN)—have been applied to coastal hazard mapping, showing promise in handling complex interactions among climatic, geomorphological, and socio-economic variables (Mosavi *et al*., 2020). These algorithms can also be integrated with Geographic Information Systems (GIS) and Remote Sensing (RS) data, providing powerful platforms for vulnerability mapping and flood-prone zone prediction (Shirzabi *et al*., 2019; Khosrowi *et al*., 2018; Ademola *et al*., 2021). In addition, hybrid approaches that combine physical process-based models with data-driven ML systems are gaining attention for their ability to balance physical interpretability with predictive accuracy.

Despite these advancements, current predictive frameworks still face limitations. First, most studies emphasize physical hazard projections while giving insufficient attention to the integration of socio-economic exposure and adaptive capacity. Second, cross-comparisons of different ML algorithms for coastal flood risk are relatively scarce, making it difficult to establish best practices for model selection. Finally, the incorporation of explainable AI (XAI) techniques into predictive models remains underexplored, raising concerns about model transparency and stakeholder trust.

It is against this background that the current study seeks to develop a unified construct that integrates predictive models and emerging geospatial technologies to assess and mitigate climate change-induced coastal hazards in the United States**.** These models will combine sea-level rise projections, regional circulation patterns, geospatial environmental variables, and socio-economic datasets to estimate human vulnerability and exposure. The hazard maps produced through this approach will employ ML algorithms such as RF, XGBoost, and KNN, integrated with GIS, to support evidence-based ranking of at-risk areas and guide the prioritization of adaptive interventions.

The aim of this study is to evaluate and refine general predictive modelling frameworks that combine machine learning algorithms, geospatial tools, and socio-environmental datasets for coastal hazard assessment. Specifically, the study examines how integrated modelling approaches can enhance forecasting accuracy, capture non-linear interactions, and improve transparency in decision-making.

The significance of the study lies in its potential to contribute to resilience planning by providing stakeholders with reliable, transparent, and spatially explicit hazard maps. Such outputs can support coastal managers, urban planners, and policymakers in prioritizing adaptation strategies, allocating resources effectively, and safeguarding vulnerable populations. By integrating both physical and socio-economic dimensions, the study also advances the discourse on climate adaptation, bridging the gap between environmental modelling and human-centered resilience frameworks.

2.0 Traditional Approaches to Coastal Hazard Risk Assessment

2.1 Overview of Conventional Statistical and Deterministic Models

The primary tools in conventional assessment of the risks of coastal hazards have been historical observations and deterministic or process-based models used to evaluate the dynamics and probabilities of hazard occurrence. Statistical models rely on long-term records of tides, storm surge databases, and precipitation or storm frequency data to derive predictive relationships. To estimate the likelihood and magnitude of rare events, extreme value theory (EVT) is commonly applied (Coles, 2001). Two widely used EVT methods include the Generalized Extreme Value (GEV) distribution, often applied to annual maxima of sea levels, and the peaks-over-threshold (POT) approach, which is useful in modeling occurrences that exceed defined thresholds of interest (Arns *et al*., 2013; Wahl *et al*., 2017). These models remain important for establishing design parameters, such as return-period flood levels, for seawalls, dikes, and port facilities (Menendez & Woodworth, 2010).

Deterministic or process-based models, on the other hand, simulate the physical processes that generate coastal hazards (Chukwudi & Oladunjoye, 2023; Baba Aminu et al., 2025). Tide- and surge-based hydrodynamic models compute water-level evolution due to tides, waves, and meteorological drivers by solving the governing fluid dynamics equations. Examples include the Advanced Circulation (ADCIRC) model, widely used for storm surge, tidal waves, and nearshore currents (Luettich *et al*., 1992), and the Delft3D modelling suite, which simulates nearshore hydrodynamics and sediment transport (Deltares, 2014). Morphological changes associated with extreme storms, such as dune erosion and overwash, have also been represented with models like XBeach (Roelvink *et al*., 2009). These deterministic models are especially advantageous in scenario-based studies, where process-level descriptions are needed to assess localized impacts and guide engineering design.

Together, statistical and deterministic approaches provided the foundation of coastal hazard assessment in the late 20th century and continue to inform present-day engineering and policy. They offer probabilistic hazard estimates and physics-based forecasts that remain indispensable for infrastructure design, floodplain mapping, and disaster preparedness. For instance, FEMA in the United States and similar agencies globally continue to rely on these methods for regulatory flood risk mapping and long-term adaptation planning.

2.2 Strengths and Limitations in Capturing Complex Climate Hazard Interactions

Statistical methods provide significant benefits due to their simplicity and computational efficiency. EVT-based methods are especially appealing because they can express risk in probabilistic terms (e.g., 1-in-100-year or 1-in-500-year floods), making them directly applicable to planning frameworks (Coles, 2001; Menendez & Woodworth, 2010). Such models have been particularly successful in data-rich regions with long tide-gauge records, such as Europe and North America (Haigh *et al*., 2014).

Deterministic models, by contrast, generate physically realistic simulations of storm surge and wave dynamics, with high spatial and temporal resolution. These outputs can be coupled with land-surface and floodplain models to assess inundation risk. For example, the ADCIRC model is routinely employed by NOAA and FEMA in real-time operational storm surge forecasting (Dietrich *et al*., 2011). Delft3D and XBeach provide valuable insights into morphodynamic change during extreme events, including dune erosion, barrier island breaching, and overwash processes, which are crucial for coastal management and emergency planning (Splinter *et al*., 2014; Roelvink *et al*., 2018). Such physically based models are also valuable for assessing adaptation options, including the design performance of levees, breakwaters, and natural defenses like dunes and wetlands.

Despite these strengths, both statistical and deterministic models face critical limitations under non-stationary climate conditions. Statistical models generally assume stationarity—that the probability distribution of past hazards will remain valid in the future (Milly *et al*., 2008). This assumption is increasingly invalid as sea levels rise and storm patterns change, leading to systematic underestimation of future risks (Wahl *et al*., 2015). Moreover, the availability and continuity of long-term observations are often insufficient to characterize low-frequency, high-impact events such as compound flooding from storm surge and intense precipitation (Bevacqua *et al*., 2019).

Deterministic models, though physically grounded, are computationally demanding and require extensive calibration and validation against observed data (Resio & Westerink, 2008). Their process-specific design also makes them limited in capturing multi-hazard interactions. For example, while storm surge models can simulate surge dynamics, they often do not account for simultaneous rainfall-induced flooding or river discharge effects unless explicitly coupled with hydrological models**.** As a result, compound and cascading events—such as the simultaneous occurrence of high tides, extreme rainfall, and strong surges—remain difficult to capture (Moftakhari *et al*., 2017). These compounding effects are increasingly recognized as the hallmark of climate-driven risk (Zscheischler *et al*., 2018).

Generally, traditional approaches remain indispensable for engineering and policy, but they are constrained by assumptions of stationarity, single-hazard representation, and computational intensity. This creates a growing need for next-generation modelling frameworks that integrate statistical, process-based, and data-driven methods, while also accounting for uncertainty and multi-hazard interactions.

3.0 Predictive Modeling Techniques under Climate Change Scenarios

3.1 Machine Learning and AI-Based Approaches

Machine Learning (ML) and Artificial Intelligence (AI) have emerged as transformative tools across disciplines, offering robust solutions for data interpretation, real-time decision-making, self-navigation, and coastal hazard risk assessment (Akinsanya *et al*., 2022; 2023; Ufomba & Ndibe, 2023;

Ademilua & Areghan, 2025a; 2025b; Ndibe & Ufomba, 2024; Adjei, 2025a; 2025b; 2025c; Abolade, 2023; Okolo, 2023; Ademilua & Areghan, 2022; Dada *et al*., 2024; Abolade & Zhao, 2024; Utomi *et al*., 2024; Ndibe, 2025a; 2025b; Okolo *et al*., 2025; Umoren *et al*., 2025; Areghan, 2025; Adeusi *et al*., 2024). Unlike traditional statistical or deterministic models, which are often constrained by assumptions of linearity or computational intensity, ML-based approaches can process vast, heterogeneous datasets and uncover complex nonlinear interactions among hazard drivers.

One of the central advantages of ML is its ability to integrate diverse geospatial, climatic, and socio-environmental variables (e.g., elevation, land use, precipitation, soil type, distance from the coastline, population density) into predictive frameworks. This integration allows the creation of hazard susceptibility maps and vulnerability indices with high predictive accuracy, which are essential for planning under climate uncertainty**.** Recent studies have demonstrated that ML models are particularly effective in handling incomplete, noisy, or multi-scale datasets, a common challenge in coastal hazard research (Rolnick *et al*., 2019; Mosavi *et al*., 2020; Ololade *et al*., 2025).

Several ML algorithms have been applied in hydrological and flood forecasting. For example, Hadi and Tombul (2018) employed Support Vector Machines (SVM), Genetic Programming (GP), and Artificial Neural Networks (ANN) to predict runoff in Iran, with SVM outperforming both GP and ANN. Similarly, Zhao *et al*. (2024) reported that tree-based ensemble models such as Random Forest (RF), Gradient Boosting Decision Trees (GBDT), and Extreme Gradient Boosting (XGBoost) outperformed kernel-based algorithms in hydrological predictions. They also noted that the performance of these models varies depending on geographic and hydrological conditions, highlighting the need for site-specific calibration. This observation underscores a critical point: while ML models are powerful, their generalizability across different coastal regions may be limited without proper adaptation and retraining.

Recent developments further highlight the potential of ML for real-time flood forecasting. Dey *et al*. (2024) designed a machine learning framework capable of simulating flood risks in near real-time, enabling early warning systems that can reduce damage and save lives. Other studies have applied deep learning models, such as Long Short-Term Memory (LSTM) networks and Convolutional Neural Networks (CNNs), to capture temporal and spatial dependencies in flood dynamics, improving lead-time forecasts and enhancing disaster preparedness (Zhang *et al*., 2023).

Beyond predictive accuracy, ML models are increasingly being paired with Explainable Artificial Intelligence (XAI) techniques such as SHAP (SHapley Additive Explanations) and LIME (Local Interpretable Model-agnostic Explanations). This integration ensures that predictions are not “black-box” outputs but are transparent and interpretable to policymakers, engineers, and communities. Such transparency is vital for building stakeholder trust and facilitating the adoption of ML-driven hazard assessments in real-world decision-making**.**

Despite their promise, ML and AI approaches face challenges. They require large, high-quality datasets, which may be scarce in many coastal regions of the Global South. In addition, model interpretability, computational requirements for training deep models, and the potential for overfitting remain barriers to widespread operationalization. Furthermore, while ML models excel in capturing correlations, they may struggle to embed physical causality unless explicitly combined with process-based models.

Therefore, the future of ML in coastal hazard risk assessment likely lies in hybrid frameworks that integrate process-based simulations with data-driven models, ensuring both physical interpretability and predictive accuracy. Such integration will enable more resilient forecasting systems capable of addressing the non-stationarity and complexity of climate change impacts.

Tampa Bay, Florida, based on historical history of damages and 16 predictors. They compared five ML models (Random Forest and XGBoost) and made a detailed risk map with low altitude, close to water, and large infrastructure as the most significant risk groups (Fig 1).

Fig. 1 provides a clear, side-by-side comparison of the flood risk predictions from the Random Forest and XGBoost models. Both models show similar overall patterns, with higher-risk areas (orange and red) concentrated along the coastlines and within low-lying inland areas, which are likely river estuaries and floodplains. However, a closer look reveals subtle yet significant differences. The XGBoost model appears to show a more concentrated and slightly more extensive area of high and very high risk (the orange and red areas) compared to the Random Forest model. This difference is particularly noticeable in the zoomed-in sections (a) and (b), where the XGBoost map (b) seems to delineate the high-risk zones with greater precision and a slightly wider spread, especially in the intricate coastal waterways. This might indicate that the XGBoost model is better at capturing the complex, non-linear relationships between various predictors, such as elevation, land use, and proximity to water, which are crucial for accurate flood risk mapping. The paper's text notes that XGBoost often outperforms other models in hydrological predictions, and this figure visually supports that claim.

The figure also reinforces the study's core argument that machine learning models offer a significant advantage over traditional, stationarity-based methods. By processing a large number of predictors and identifying complex interactions, these models can produce detailed and accurate risk assessments. The maps provide a granular view of hazard susceptibility, allowing for targeted and evidence-based decision-making. For example, local planners could use these maps to identify specific neighborhoods or critical infrastructure (e.g., roads, hospitals, power plants) at the highest risk and prioritize mitigation efforts, such as building seawalls or elevating structures. The ability to generate such a detailed risk map is a key contribution to resilience planning and resource allocation. The visual differences between the two models also underscore the importance of model selection and cross-comparison, a point the paper emphasizes as a current gap in research. While both models are effective, their outputs are not identical, highlighting that the choice of algorithm can impact the final risk assessment and, consequently, the planning and policy decisions that follow. This approach is also useful in generating non-linear relationships to present a scaling assessment tool, and will become the tool that will prove useful to policymakers once they start undertaking specific flood mitigation and planning measures. Moreover, RF is combined with GIS to evaluate multi-hazard vulnerable areas in coastal areas where Yu *et al*. (2024) have already shown RF to be able not only to attain a better predictive power but also to provide an interpretable variable importance ranking. This will be particularly helpful in the decision making of coastal risk management where all the environmental driver contribution is required. Although these have been successfully achieved, scalability, environmental datasets interpretability, and integration still remain a challenge, and one gap in this regard is hybrid frameworks that can combine ML with real-world models and spatial models.

3.2 Simulation and Scenario-Based Modeling

Alongside data-driven techniques such as ML, simulation and scenario-based modeling remain indispensable in predictive coastal hazard assessments. Physics-based numerical models such as ADCIRC (Luettich *et al*., 1992) and Delft3D (Deltares, 2014), illustrated in Fig. 2, are widely adopted for simulating storm surges, tidal dynamics, and inundation patterns under variable boundary conditions.

These models allow researchers to reconstruct past extreme events and to explore "what-if" scenarios, such as the projected impacts of sea-level rise on coastal flooding, estuarine hydrodynamics, or barrier island erosion (Dietrich *et al*., 2011; Roelvink *et al*., 2009). When combined with Geographic Information Systems (GIS), simulation outputs can be spatially integrated to enhance hazard visualization and vulnerability mapping, thereby improving risk communication and planning strategies. GIS-based flood modeling has been particularly useful for delineating flood-prone areas in coastal cities and identifying hotspots of socio-economic and infrastructural exposure (Wahl *et al*., 2015).

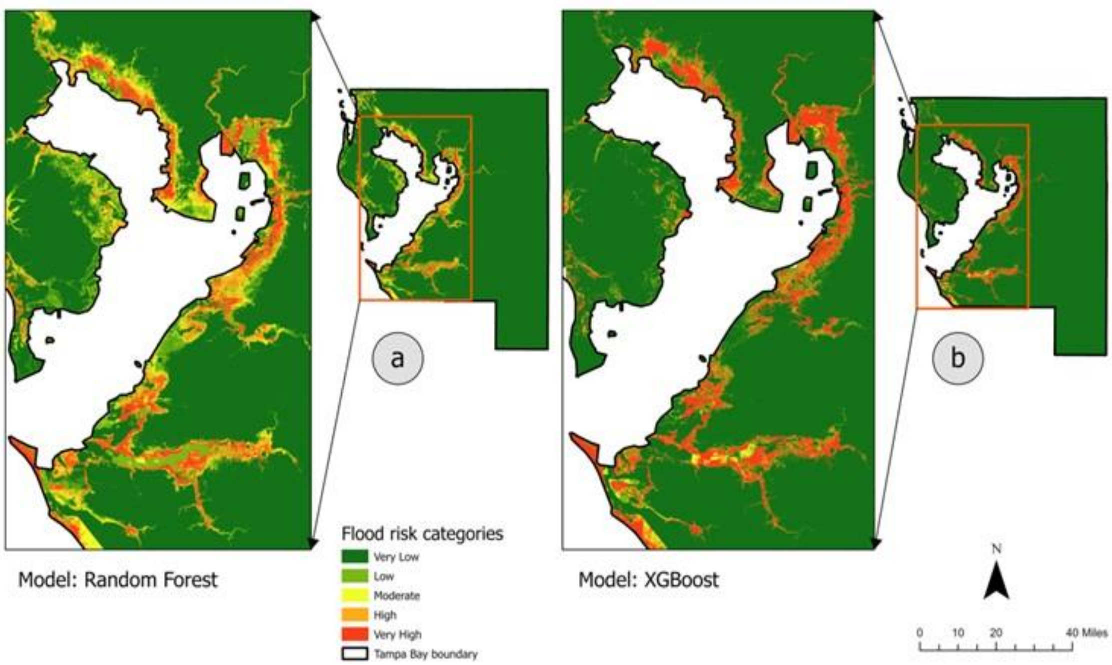

Fig 1: A modeled flood risk distribution in Tampa Bay (Adapted from Dey *et al*., 2024).

Scenario-based approaches also provide a flexible framework for adaptive planning. By testing alternative adaptation strategies—such as flood defense structures, wetland restoration, or land-use zoning—under multiple climate futures, planners can better evaluate trade-offs and design robust interventions**.** This ability to simulate a range of plausible outcomes is crucial in the context of uncertainty associated with climate change, where deterministic predictions are often insufficient for policy-making.

Despite their strengths, hydrodynamic and scenario-based models present notable challenges. They are computationally intensive, often requiring high-performance computing resources for large-scale

simulations, and rely on significant simplifications to make problems tractable (Resio & Westerink, 2008). Such simplifications may limit their capacity to accurately capture nonlinear feedbacks and compound events (e.g., simultaneous storm surge and heavy rainfall). Moreover, these models are sensitive to input quality, boundary conditions, and parameterization choices, which can propagate uncertainty into the final outputs.

As a result, recent research emphasizes coupling scenario-based models with data-driven methods, including machine learning and data assimilation techniques, to enhance predictive accuracy while reducing computational demands. This hybridization not only improves real-time forecasting capabilities but also provides greater transparency and adaptability for decision support in coastal risk management.

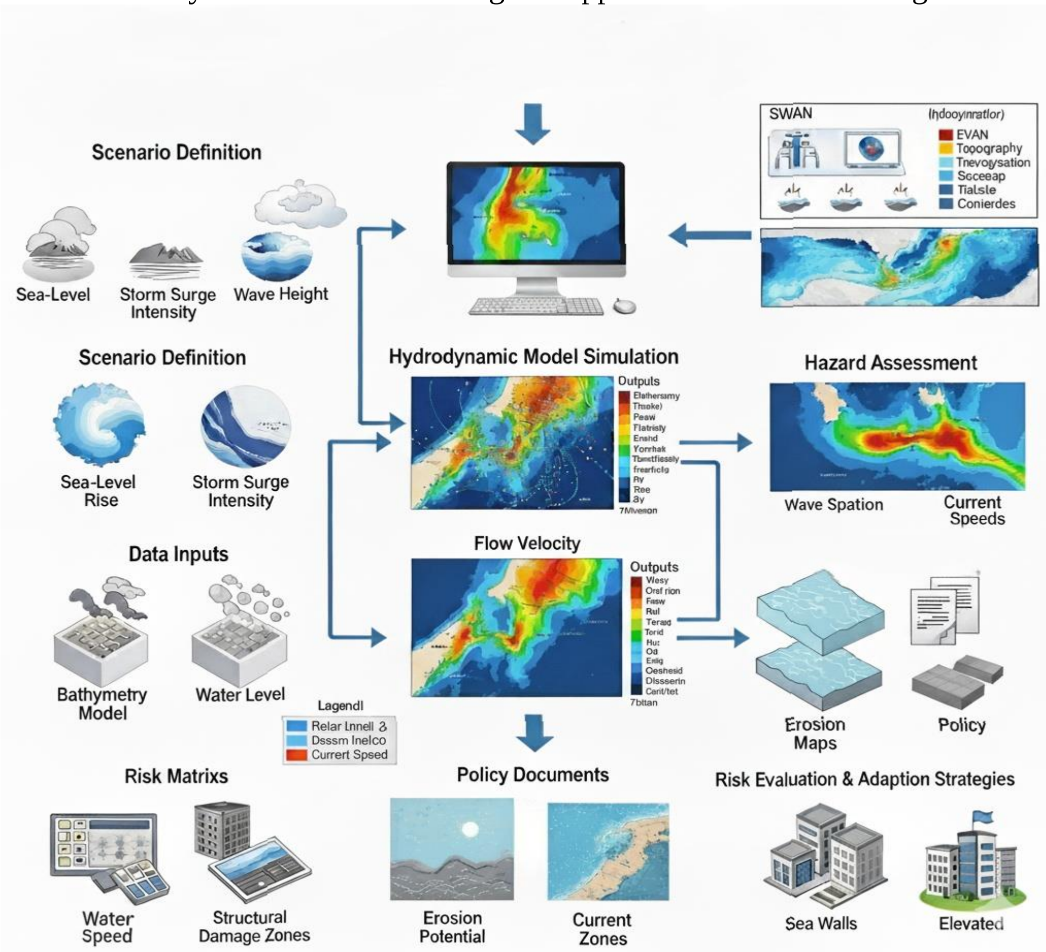

Fig 2: A Workflow for Coastal Hazard Assessment Using Hydrodynamic Models

3.3 Integration of Climate Projections into Predictive Hazard Models

In recent years, there has been growing emphasis on integrating climate projections into predictive hazard models to enable forward-looking risk assessments that account for the non-stationarity of hazard regimes. Global Climate Models (GCMs) and Regional Climate Models (RCMs) provide scenario-based projections of future climate conditions under Representative Concentration Pathways (RCPs) and Shared Socioeconomic Pathways (SSPs). These outputs can be downscaled and incorporated into hydrodynamic, machine learning, or hybrid models to evaluate long-term shifts in flood frequency, storm intensity, and spatial hazard distribution (Hinkel *et al*., 2014). By linking climate scenarios with predictive modeling, it becomes possible to explore how sea-level rise, precipitation variability, and changing storm regimes will alter coastal risk profiles over time.

Applications of this approach are increasingly evident. For example, Asadollah *et al*. (2022) demonstrated that downscaling precipitation using Artificial Neural Networks (ANN), Adaptive Neuro-Fuzzy Inference Systems (ANFIS), and K-Nearest Neighbors (KNN) provided effective results for local-scale hazard modeling in Iran. Similarly, Yu *et al*. (2024) showed that integrating ML-GIS frameworks with sea-level rise and precipitation projections significantly improves multi-hazard susceptibility mapping, offering more comprehensive insights into compound coastal risks.

However, the incorporation of climate projections into hazard modeling is not without challenges. Uncertainties arise from multiple sources, including the spread of GCM outputs, the downscaling methods applied, and the aggregation of inter-model errors (Hawkins & Sutton, 2009). These uncertainties complicate the task of translating climate projections into actionable information for coastal planners and policymakers. Nevertheless, the combined use of climate projections with machine learning and hydrodynamic tools represents one of the most promising pathways toward anticipatory, adaptive risk assessment frameworks that are aligned with resilience planning and long-term coastal management strategies.

Table 1 presents an overview of predictive models and emerging technologies currently applied in coastal hazard assessments, highlighting their strengths, limitations, and application contexts. The Table summarizes the major predictive modeling approaches and emerging technologies currently applied in coastal hazard assessment, with a focus on their relative strengths, limitations, and application contexts. The comparison reveals that no single modeling approach is universally sufficient; rather, each offers unique contributions that are most effective when combined within an integrated risk assessment framework.

Table 1: Predictive Models and Emerging Technologies for Coastal Hazard Assessment

Model / Technology	Description	Strengths	Limitations	Example Applications	References
Statistical Models	Use historical hazard/climate data to predict the probability of future events (e.g., regression, time-series).	Simple, transparent, effective for short-term trends.	Limited in capturing nonlinear and complex climate–hazard feedbacks.	Flood frequency analysis for coastal cities.	Wahl *et al*., 2017; Vousdoukas *et al*., 2018
Deterministic / Process-Based Models	Physics-based models simulating ocean–atmosphere–land interactions (e.g., hydrodynamic, wave and erosion models).	High accuracy, can model physical processes and extreme scenarios.	Data-intensive, computationally expensive, requires calibration.	Delft3D for storm surge and coastal flooding in Europe.	Nicholls *et al*., 2007; Lowe *et al*., 2009
Machine Learning Models	Use AI/ML algorithms (e.g., Random Forest, Neural Networks) to capture	Can learn complex interactions, adaptive with more data.	Require large datasets, risk of overfitting, lack of interpretability.	Predicting coastal flood susceptibility and shoreline change.	Dey *et al*., 2024

	nonlinear hazard–climate relationships.				
Bayesian Networks	Probabilistic graphical models linking climate drivers and hazards with uncertainty quantification.	Incorporates uncertainty, suitable for risk assessment with incomplete data.	Requires expert input, results can be sensitive to prior assumptions.	Risk assessment of storm surges and flooding in deltas.	Oliver *et al*., 2019
Remote Sensing & GIS	Satellite/drone-based data integrated with GIS for mapping hazards and exposure.	Wide spatial coverage, real-time monitoring, cost-effective.	Limited temporal resolution for some hazards, requires ground-truthing.	Shoreline erosion mapping, flood extent monitoring.	Luijendijk *et al*., 2018; Chukwudi, 2025
Climate–Hydrodynamic Coupled Models	Combine global/regional climate models with coastal hydrodynamics.	Captures future climate-driven hazard projections, including sea-level rise.	Computationally demanding, uncertainties from climate models.	Sea-level rise and coastal flood risk projections for small islands.	Vousdoukas *et al*., 2017
Internet of Things (IoT) & Sensor Networks	Deploy sensors for real-time monitoring of tides, waves, and erosion.	High-frequency, local-scale hazard monitoring, supports early warning.	Limited coverage, maintenance and connectivity issues.	Real-time tide and flood monitoring in urban coasts.	Cemiloglu *et al*., 2025
Big Data & Cloud Computing Platforms	Integrate large-scale hazard datasets with scalable computing for prediction.	Handles massive datasets, supports decision-making platforms.	Requires infrastructure, technical expertise, and data governance.	Coastal risk dashboards and early warning systems.	Balica *et al*., 2012; Muis *et al*., 2016

4. 0 Emerging Technological Approaches in Coastal Risk Assessment

Coastal environments are highly dynamic and at risk to hazards like flooding, storm surge, erosion, and sea level rise. Traditional monitoring techniques, though valuable, do not often have the resolution, frequency of observation, and integration inherent in timely and accurate risk assessment. Recent technological developments in remote sensing, drones, IoT, digital twins, geospatial platforms, and big data analytics cloud-based platforms (Fig. 3) have opened up new possibilities for integrated and real-time coastal hazard monitoring and forecasting. The section focuses on these emerging approaches and how they interact in constructing a sound coastal hazard risk management system.

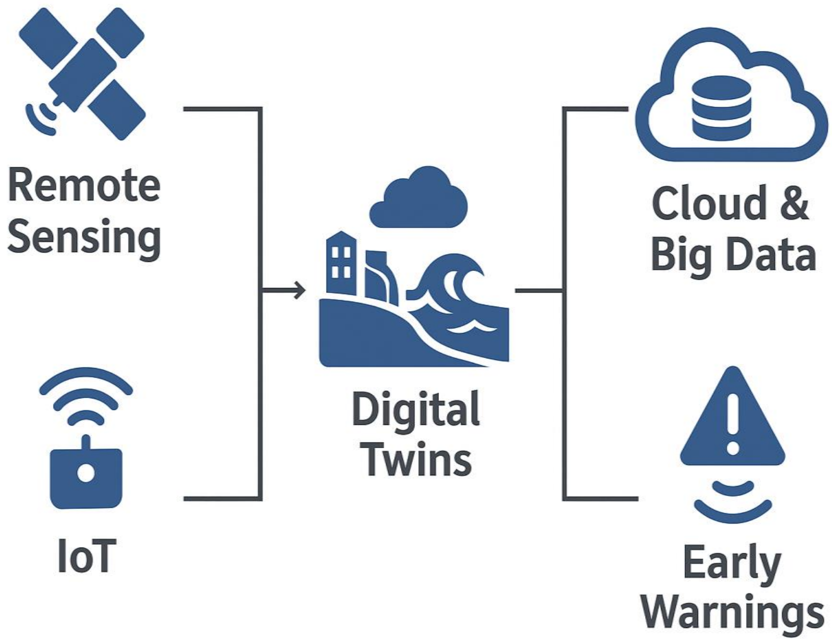

Fig 3: Emerging Technological Approaches in Coastal Risk Assessment

4.1 Remote Sensing, Drones (UAVs), and IoT for Data Collection

Remote sensing provides large-scale, repeatable, synoptic-based observations of coastlines as required for the detection of shoreline retreat, sediment transport, and post-disaster quantification (Klemas, 2015). For example, shoreline products derived from satellites can provide long-term trend data, whereas radar (e.g., Sentinel-1) and optical (e.g., Landsat, Sentinel-2) imagery enable monitoring of intertidal areas and mangrove degradation (Gorelick *et al*., 2017). Unmanned Aerial Vehicles (UAVs) or drones make possible high-resolution site-specific monitoring, which far exceeds the spatial detail of satellite-derived data (Table 2). UAV photogrammetry can be used to create digital elevation model (DEM) and orthomosaic data with centimeter accuracy to support dune monitoring, floodplain mapping, and embankment inspection (James & Robson, 2014; Klemas, 2015). IoT sensor networks support these aerial and satellite systems by recording the actual conditions of the hydrological, meteorological, and oceanographic parameters in situ. Oceanographic wave buoys, water level loggers and weather nodes have been employed to supply continuous data series for model calibration and validation of remotely sensed data (Hart & Martinez, 2006; Gubbi *et al*., 2013). Recently, these data streams are usually sent through low-power networks such as

LoRaWAN, and hence large-scale, distributed deployments are possible in the coastal catchment (Zakaria *et al*., 2023).

Table 2: Comparison of Remote Sensing, UAVs, and IoT in Coastal Risk Assessment

Technology	Spatial Coverage	Temporal Frequency	Resolution	Main Applications	Limitations	References
Remote Sensing (satellite)	Regional to global	Days to weeks (depending on sensor)	10–30 m typical (Sentinel/Landsat)	Shoreline change, mangrove monitoring, land cover mapping	Cloud cover, coarse resolution	Klemas (2015); Gorelick *et al*. (2017)
UAVs (drones)	Local to site-specific	On-demand (hours to days)	Centimeter-scale	DEM creation, dune monitoring, embankment inspection	Weather-dependent, limited endurance	James & Robson (2014); Klemas (2015)
IoT Sensors	Point to catchment scale	Continuous, real-time	High-frequency (seconds–minutes)	Flood monitoring, water level, storm surge detection	Sensor maintenance, communication	Hart & Martinez (2006); Zakaria *et al*. (2023)

4.2 Digital Twins and Geospatial Platforms

A digital twin (DT) is defined as a virtual representation of the real-world system that brings together real-time data, simulation models, and analytics to forecast future states (Tzachor *et al*., 2023). DTs can be applied to coastal processes, storm surge, shoreline change, sea level rise scenarios, and infrastructure vulnerability (Table 3). For example, Yu *et al*. (2024a) have developed a Coastal Zone Information Model (CZIM) that uses data, models, and expert knowledge in a digital twin to support adaptive management. Data across vast areas can be processed using geospatial tools, such as Google Earth Engine (GEE) and GIS-based systems as DT enablers, and interactive hazard maps created for planners and decision makers (Gorelick *et al*., 2017). Lagap & Ghaffarian (2024) highlighted that DTs are used as a tool to improve the post-disaster recovery planning by providing predictive scenario testing. planning by offering predictive scenario testing.

4.3 Synthesis and Integrated Framework

These technological advances are additive rather than independently stand-alone solutions. Remote sensing and UAVs provide spatial context, IoT provides temporal continuity, digital twins and GIS platforms provide simulation and visualization, and cloud/big data infrastructures provide scalability, speed, and integration. Together, they present a complete framework for anticipatory coastal risk assessment and rapid response (Tzachor *et al*., 2023; Yu *et al*., 2024b; Basher, 2006). The main point is that the assessment of coastal hazard risk is shifting from reactive evaluation after the event, to proactive and continuous, and predictive management. The combination of these technologies has the potential to deliver not only scientific progress but also improved community resilience - systems should be co-designed with stakeholders to make sure outputs are actionable.

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5.0 Challenges and Future Directions

Uncertainty is one of the most significant obstacles to integrating predictive modeling and new technological approaches to coastal hazard risk assessment. Uncertainty has several sources, including incomplete information, model assumptions, and the intrinsic variability of coastal processes influenced by climate change (Hedden-Nicely, 2022). For example, projections of sea-level rise are highly sensitive to global greenhouse gas emission scenarios and the dynamics of the ice sheets, and long-term projections are therefore less specific (Oppenheimer *et al*., 2019). This uncertainty can erode trust in model estimates by stakeholders, which can limit their usefulness in informing decisions.

Table 3. Applications of Digital Twins in Coastal Risk Management

Application	Example Use Case	Benefits	References
Flood Simulation	Virtual flood models of estuarine cities	Early warning, evacuation planning	Yu *et al*. (2024b)
Shoreline Change Monitoring	Coastal erosion management in sandy beaches	Predictive shoreline evolution	Tzachor *et al*. (2023)
Infrastructure Resilience	Protection of ports and embankments	Identify vulnerabilities under climate scenarios	Lagap & Ghaffarian (2024)
Ecosystem Service Mapping	Mangrove and reef protection DTs	Incorporates ecological feedbacks into hazard models	Yu *et al*. (2024b)

Data quality and availability: Data from terrestrial, aerial, and spaceborne remote sensing, as well as IoT sensors, provide ample data, but these are usually fragmented, inconsistent, or limited by spatial and temporal resolution (Wahl *et al*., 2017). For example, high-resolution satellite data may not always be available due to financial constraints, and a sensor network may experience calibration or maintenance issues in a hostile coastal environment (Wahl *et al*., 2017). Incomplete or low-quality data can result in biased training of models and reduced accuracy of predictions.

Scalability: This is also difficult. While pilot studies and site-specific digital twin implementations have demonstrated their value, such models are computationally expensive and require synthesis of heterogeneous datasets if they are to be extended spatially across the coast (Gorelick *et al*., 2017). For example, the deployment of digital twins at a national or continental scale requires the integration of massive volumes of satellite data, IoT feeds, and simulation models simultaneously, which necessitates powerful cloud infrastructure and substantial financial investment.

5.1 Operational AI for Forecasting, Explainability, and Uncertainty Quantification

Artificial intelligence is a powerful tool in coastal hazard prediction, but moving from research experiments to operational forecasting systems is still a significant challenge (McGlade *et al*., 2025). Predictive models are trained on historical data, or physics-informed machine learning frameworks can generate rapid forecasts of storm surge, coastal flooding, or shoreline change. However, emergency managers and local planners are often hesitant to rely on AI if they cannot understand why a model gives a particular prediction. This is where explainable AI (XAI) comes in as techniques such as feature attribution, surrogate interpretation models, and visualization tools allow forecasters to trace which factors (e.g., wind speed, tidal stage, or sea-level anomalies) most influenced the output.

Another crucial frontier is uncertainty quantification (UQ). Unlike deterministic models that produce a single "best guess," AI-driven systems must also communicate the confidence level of their predictions. For example, a forecast that coastal flooding has a 70% probability of exceeding a certain threshold provides decision-makers with much richer information than a binary "flood/no flood" output. The challenge is that uncertainty itself is complex: it can stem from data gaps, model assumptions, or unpredictable climate drivers. Translating that uncertainty into formats usable by non-technical stakeholders remains one of the biggest obstacles.

Model interpretability: Most of the leading prediction models, particularly those based on machine learning and deep learning, are 'black boxes' that are difficult for stakeholders who are not technically minded to understand (Rudin, 2019). Also, when the predictive systems are described without transparency, this may be a reason for domestic ill will, as it may detract from confidence in a predictive system when policymakers and local populations desire actionable input as opposed to black box statistical output.

Equity and social justice considerations: Many models insufficiently incorporate measures of social vulnerability, such as income, race, or community capacity, which results in resilience strategies that may inadvertently privilege well-resourced populations. Marginalized groups in coastal zones often face disproportionate exposure and limited adaptive capacity, underscoring the need for predictive assessments that explicitly embed equity indicators (Michel *et al.*, 2024; Johnson *et al.*, 2023; Okamoto & Doyon, 2024).

Interdisciplinary integration remains underdeveloped: While predictive modeling has advanced rapidly in the domains of machine learning, climate science, and geospatial technologies, the incorporation of insights from the social sciences, economics, law, and local knowledge systems is comparatively limited (Niamir & Pachauri, 2023). This creates a disconnect between highly technical models and their human-centered applicability for decision-making.

5.2 Future Directions

Despite these challenges, there will continue to be opportunities to develop risk assessments for coastal hazards in the future—one suggestion that looks promising is the integration of adaptive management and predictive modelling. According to Marchau *et al*. (2019), adaptive management (AM) is an iterative decision-making process in which, after initial decisions, policies and management practices are adjusted based on new data and model output results. Unlike deterministic systems, a combination of predictive models and adaptive organizational design may allow coastal managers to adapt to uncertainties and to adjust resilience strategies on the fly as they encounter new or greater effects. These opportunities also serve as an implementation activity for resilience-based measures. As also for nature-based solutions, predictive models could be applied to determine vulnerability and resilience functions, as well as disaster prediction (e.g. mangrove restoration, dune stabilization; Temmerman *et al*, 2013). By simulating the different adaptation scenarios, digital twins and big data platforms will facilitate the delivery of insights into long-term sustainability that consider engineering versus ecosystem-based adaptation trade-offs. Big data analytics coupled with cloud computing will also enable the ability to process larger and increasingly complex datasets. To increase accuracy and reliability, novel systems will combine the outcomes of global climate models with information streams from Internet of Things sensors and crowdsourced data collected by citizens to a single platform (Gorelick *et al.*, 2017). Such integrated platforms would enable better institutionalised mechanisms to react more effectively, facilitating better anticipation and early warning at every level of government.

Traditionally, coastal hazard models often focus on a single event driver. In recent times, coastal hazards have frequently been acknowledged to occur together. For instance, a hurricane can trigger river flooding, storm surge, and rainfall. These compound events are more damaging than single hazards yet challenging to model as they require linking multiple systems (Xu *et al*., 2022; Sun *et al*., 2024). The impacts also extend beyond flooding and, in some cases, Industrial spills, mold growth, wildfire smoke, and debris burning can all degrade air quality in the aftermath. Future work should integrate coastal hazard and air quality models to capture these cascading risks and their health implications.

Advances in hybrid explainable models represent another frontier. By coupling process-based simulations with interpretable machine learning (XAI), it will be possible to maintain scientific rigor while enhancing stakeholder trust in predictive outputs (Slater, 2022; Camps-Valls *et al*., 2025). Equally important is the expansion of nature-based and hybrid adaptation modeling. By explicitly incorporating the protective functions of ecosystems such as mangroves, coral reefs, dunes, and wetlands, predictive frameworks can evaluate trade-offs between engineered and ecological adaptation strategies (Lakku *et al*., 2024; Mao *et al*., 2025; Adeli *et al*., 2025). Finally, reasoning via explainable artificial intelligence (XAI) paves a pathway to confidence for greater adoption of prediction models. While the knowledge, data quality, scalability, and interpretability of these systems are up for debate, the three concepts of resilience planning, adaptive management, and Cloud-based data infrastructure linked to explainable AI do provide a framework in which predictive models can be both robust and future-proof. This evolution will not only enhance resource resilience in risk assessment, but it will also build resilience within coastal communities.

6.0 Conclusion

This review explored new technical approaches and prediction modeling tools for estimating risk of coastal hazards under climate change. Statistical and deterministic models were among classical tools that have proved useful in shedding light upon the aspects of flood frequency and storm surge yet have failed to provide the data regarding non-stationary climates and compound events to explain why more adaptive tools are required. Combined with remote sensing, GIS, IoT, and digital twins, new methods such as machine learning, Bayesian networks, climate-hydrodynamic coupled models offer a new ability to capture nonlinear interactions, process heterogeneous data sets, and provide spatially explicit, real-time risk assessments. Nevertheless, the challenges related to uncertainty in climate prediction, data quality, scalability, and interpretability of models persist. Cooperation of adaptive management systems, explainable artificial intelligence (XAI), and resilience-driven systems integrating engineering solutions with nature-based interventions will be needed to overcome these limitations. The trend away from reactive, event-based coastal hazard management towards continuous, integrated, and proactive management to improve preparation, reduce vulnerabilities, and increase adaptive capacity in response to changing climate change is influencing our future practices of coastal hazard risk management.

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Declaration

Consent for publication

Not Applicable

Availability of data and materials

The publisher has the right to make the data public

Ethical Considerations

The authors declare that all research and development described in this manuscript were conducted with the highest standards of integrity. The project was carried out as a collaborative effort, and all authors involved in the physical construction were voluntary participants who have been appropriately acknowledged.

Competing interest

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O.E.O. conceived and supervised the study, while A.O. conducted the literature review and methodology development. J.N. analyzed the data and interpreted the results, and O.S.A. managed visualization, references, and proofreading. Together, they contributed to writing, reviewing, and finalizing the manuscript, ensuring accuracy, coherence, and scholarly quality.