



Review Article

Use of artificial intelligence and other data-driven technologies for coastal management

Nitin Agarwala

Visiting Faculty, Naval War College, Verem, Goa, India

*Corresponding author's e-mail address: nitindu@yahoo.com

Article information	Abstract
Received: May 30, 2026 Revision: July 28, 2026 Accepted: September 13, 2026 Keywords Artificial intelligence; Coastal management; Deep learning; Machine learning	Biogeochemical cycles occur naturally in coastal regions. Estuaries, wetlands, and tidal creeks assist these cycles. Since increased anthropogenic activities and naturally occurring events act as stressors, they impact physical, chemical, and biological processes in maritime spaces and hence these cycles. This makes existing ecosystems susceptible to trophic imbalance. Resultantly, researchers began monitoring and mapping coastal environments to understand how different stressors impact these biogeochemical processes using numerical and empirical models. With advances in computation infrastructure, use of data-driven techniques such as Artificial Intelligence, Machine Learning, and Deep Learning in different hydrological systems have become commonplace. This has invigorated the use of predictive and decision-making frameworks in coastal management, making habitat conservation more scientific. Such frameworks balance ecological health and human activities through hard and soft engineering, nature-based solutions, and managed retreat. Though substantial literature on the use of Artificial Intelligence and Machine Learning in the coastal environment exists, they focus on independent domains, with limited discussion of their combined impact on coastal management. Accordingly, this desk-based qualitative review discusses recent developments in Artificial Intelligence, Machine Learning, Deep Learning, and other data-driven techniques used for coastal management. In addition, it will identify future directions for such studies, especially with combined stressors.

1. Introduction

Estuaries, wetlands, and tidal creeks are a few highly active biogeochemical ecosystems (Trettin et al., 2024). They occupy less than 1 % of the global surface (Arora & Mishra, 2024), but function as carbon sinks and nutrient processing factories to provide high baseline ecological value (Liu et al., 2024; Bouchoucha et al., 2025; Špoljarić et al., 2021). Studies show that the contribution of coastal wetlands in *sequestering carbon* is nearly 10 times more than that of mature terrestrial forests (Mustafa et al., 2024). Dense vegetation in these wetlands allows fixing of massive amounts of atmospheric carbon dioxide (Serrano et al., 2019). However, waterlogged and oxygen-depleted soil drastically slows organic decomposition, while rising sea levels deposit sediment that bury carbon continuously over millennia. Similarly, due to high salinity, methane-producing microbes that maximize net cooling effects are suppressed, while organic matter washed in from adjacent terrestrial systems is trapped by tidal creeks (Adams et al., 2025). Likewise, in the coastal environment, *nutrient cycling* occurs naturally due to the filtering and transforming of

pollutants and nutrients before they reach the ocean (Kache et al., 2025). Harmful agricultural runoff is converted into harmless nitrogen gas by the action of microbes (Asmala et al., 2017). Tidal sediments store phosphorus by means of adsorption and organic burial (Lønborg et al., 2021). Marsh plants and algae absorb dissolved inorganic nutrients to assist in nutrient cycling (Godfrey et al., 2015). Tidal creeks help move dissolved organic matter to feed offshore marine food webs (Schutte et al., 2019). When these ecosystems are degraded, their ecological value reduces rapidly. Drained wetlands expose buried carbon to oxygen, releasing centuries of stored carbon dioxide (Khan et al., 2025). Loss of ability to filter nutrients triggers toxic algal blooms that destabilize nutrient profiles to compromise fish nurseries and coastal storm buffers (Hayes et al., 2017).

Unfortunately, with human development, anthropogenic activities and climate-driven events that cause coastal degradation have increased. Destabilization of shoreline ecosystems, acceleration of habitat loss, and reduction of biodiversity (Agarwala & Seangsupavanich, 2023; Ghaedi et al., 2026) are some outcomes. This amplifies the high vulnerability of coastal zones to combined stressors, as they interact non-linearly and create disruptions with a potential to dismantle coastal food webs. Unfortunately, traditional linear observation and prediction techniques fail to capture the compound and cascading impacts of such combined stressors, as the dynamic land-sea interface is treated as static and predictable. These linear systems measure (a) pollutants from land, without accounting for their convergence with the marine environment; (b) consider gradual and predictable changes over time, while the actual event occurs differently; (c) do not consider the impact of one stressor on the other; (d) schedule sampling at fixed intervals, even when the marine environment is dynamic, and (e) do not consider coastal species as dynamic, wherein the impact of stressors on their behavioral and physiological change is disregarded.

Such limitations have allowed use of data-driven computational frameworks such as Artificial Intelligence (AI), Machine Learning (ML), and Deep Learning (DL) in place of traditional and simple single-variable linear system. AI is the simulation of human intelligence by machines. These processes include a range of activities, including learning, reasoning, problem-solving, perception, and language understanding. It began as a rule-based system but has evolved to data-driven methods that help automate complex tasks across industries. To train the machine in identifying patterns, and make decisions with minimal human intervention, ML is used. For this, statistical models are used to improve performance with increased exposure to data. To improve learning by mimicking the human brain, artificial neural networks are used. This learning is referred to as DL. Such advances have been possible due to the increasing availability of data, increased computational power, advances in cloud computing, advanced satellite observation, advances in algorithm design, and the urgent need to predict the impact multiple stressors working concurrently. Accordingly, from the late 1980s to the early 1990s, numerous AI algorithms and methods have been developed for a wide range of coastal engineering problems (addressing the physical design of coastal infrastructure) and coastal management issues (addressing the environmental, economic, political strategies required to build resilient coastal communities). These fast-paced developments have been discussed in numerous review papers over the years. Most review papers, however, focus narrowly on standalone fields (e.g., *only* predicting wave heights, *only* mapping mangrove loss, or *only* processing hydrodynamic telemetry) without providing holistic syntheses tying these disparate AI/ML nodes back to integrated coastal management frameworks where decisions between hard and soft engineering is required.

This desk-based qualitative study aims to address these shortcomings. To identify the relevant literature, in the form of peer-reviewed academic papers, a systematic literature mapping using Scopus and Web of Science databases, targeting peer-reviewed studies published between 2006 and 2026, was executed. The search strings used included ('Coast* Manag*' OR 'Shoreline Management' OR 'Coastal Planning' OR 'Coastal Zone Management') AND ('Artificial Intelligence' OR 'Machine Learning' OR 'Predictive Models' OR 'Deep Learning' OR 'Neural Networks'). The period ranging from 2006 to 2026 was selected owing to the time period, when

classical statistical models transitioned to modern deep learning frameworks (2006) till the current year of study (2026). In addition, gray literature, available in the form of books, related documents, and websites, were studied to complement the indexed academic databases. This provided foundational methodologies and industry insights. In doing so, the study will highlight advances in AI, ML, and other data-driven techniques used for coastal management by identifying recent developments and future directions. The study will begin with a literature review of the available statistical frameworks, classical ML, and development of AI and DL techniques. Discussion of how these techniques are used in the efforts of coastal management will follow, afterwards analyzing their use in coastal engineering. The impact of these modern frameworks, their limitations, and the way ahead will be discussed next, before discussing the future of AI/ML for coastal environment issues, and then drawing conclusions.

2. Review of available methods

To address the combined impact of multiple stressors, single-variable linear systems have migrated to highly integrated, data-driven, and multi-physics computational frameworks, duly encouraged by increasing computational power. To understand this migration let us examine the transition from statistical modeling frameworks to classical ML, and then to DL and AI.

2.1 Statistical modeling

Statistical models are used extensively in coastal management as they are considered as fundamental methods for making evidence-based forecast. These models help decision makers make informed decisions by providing them requisite information for creating mitigation strategies. The resulting decisions are grounded on forecasts that consider heterogeneous data from various sensors and platforms and related uncertainties of this data (Vanem et al., 2022; Vanem et al., 2026). Statistical frameworks used for coastal management are summarized in **Table 1**. An analysis of these models shows that these frameworks have gaps and challenges. Most of them are weighted toward physical variables, such as geomorphology and wave regimes, while disregarding geographical boundaries and socioeconomic dependencies. These models fail to update their statistical baseline for shifting climate realities as they assume long-term environmental stability. In addition, statistical modeling suffers from low accuracy of prediction when available field measurements are limited (Vanem et al., 2022). It is to address these limitations that the development of other data-driven methods such as AI/ML/DL models is being encouraged.

2.2 Classical machine learning

Classical machine learning framework is deployed to undertake non-linear regression analysis, spatial clustering, and classification of hazards (Pourzangbar et al., 2023). This framework is a computationally efficient alternative to traditional numerical models in coastal management (Abouhalima et al., 2024; Babati et al., 2025), summarized in **Table 2**. Classical ML algorithms, such as Support Vector Machines (SVM), Random Forests (RF), and Gaussian Process Regression (GPR), are the backbone of coastal engineering due to ease of interpretation, minimum requirement of data, and robust performance with metocean data. These algorithms may either be supervised, an ensemble, or unsupervised (Pourzangbar et al., 2023; Li et al., 2025; Kim & Lee, 2022; Goldstein et al., 2019; Masria & Abouelsaad, 2025).

2.3 Deep learning (DL)

The use of advanced AI techniques such as DL has shifted coastal modeling to spatiotemporal analysis, wherein advanced AI frameworks such as Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, Transformers, and Physics-Informed Neural Networks (PINNs) are used. These frameworks use unstructured data that is made available continuously from satellites, drones, radars, and sensors in the environment. These methods are

used to handle the dynamic nature of coastal environment at a multi-scale level. The use of advanced AI frameworks is possible across three operational domains. These include: (a) computer-vision-driven forecasting, (b) spatiotemporal hydrodynamic forecasting, and (c) physics-informed structural forecasting, and these are discussed in **Table 3**.

Table 1 Summary of statistical frameworks used for coastal management.

Frameworks	Approach	Use	Benefits
Vulnerability and Risk Indexing Frameworks	Coastal Vulnerability Index (CVI)	Aggregates physical variables using geometric mean ranking systems.	Flags risk hot spots.
	Social and Household Vulnerability Frameworks (SVI / HSVI)	Applies principal component analysis (PCA) or factor analysis to weight census data.	Assesses a community's capacity to withstand flooding or climate hazards.
	Circles of Coastal Sustainability (CCS)	Standardizes qualitative and quantitative variables across economic, ecological, political, and cultural scales.	Provides standardization.
Shoreline Change and Morphodynamic Analysis Frameworks	Digital Shoreline Analysis System (DSAS)	Casts perpendicular measurement transects along coastlines.	Calculates rate-of-change statistics.
Probabilistic and Predictive Frameworks	Metocean Clustering and Scenario Frameworks	Implements time-varying clustering algorithms (e.g., K-means, PCA) on historical wave, wind, and tide datasets.	Extracts discrete 'climatic scenarios' to feed into real-time hazard forecasts.
	Extreme Value Theory (EVT)	Applies Generalized Extreme Value (GEV) distributions.	Calculates return periods for structural hard engineering thresholds
	Bayesian Belief Networks (BBN) and Structural Equation Modeling (SEM)	Mathematically map cause-and-effect relationships under deep epistemic uncertainty.	Used for ecosystem and water quality management. Predicts outcomes like algal blooms or pollution.
Decision Support and Policy Evaluation Frameworks	Multi-Criteria Decision Analysis (MCDA) Integration	Incorporates Analytical Hierarchy Process (AHP) to mathematically weight stakeholder preferences alongside geographic risk layers.	Provides optimized Decision Support Indices (DSIs).
	Ecosystem Services Valuation Frameworks	Quantifies monetary or statistical benefits of soft engineering methods versus hard engineering infrastructure.	Explicitly calculates the risk-reduction margins.

Source: Author's compilation

Table 2 Classical machine learning methods, their use areas, and advantages.

ML Type	Algorithm	Primary Applications and Tasks	Key Benefits and Technical Strengths	Mathematical and Environmental Inputs
Supervised Learning	Support Vector Machines (SVM) and Support Vector Regression (SVR)	• Establishes structural boundaries • Forecasts wave heights and wave parameters • Maps non-linear coastal variables • Automated shoreline mapping with Normalized Difference Water Index (NDWI)	• Uses kernel tricks for high-dimensional features • Prevents over-fitting when data is sparse • Reduces error by nearly 74 % compared to empirical equations	• High-dimensional feature spaces • Buoy data • Wave parameters • Existing structural features (of rubble mound breakwaters)
	Shallow Artificial Neural Networks (ANN)	• Emulates tidal predictions • Models water quality indices • Calculates significant wave heights and peak periods • Calculates structural overtopping discharge	• Maps multi-variant inputs for direct, localized outputs • Serves as a fast surrogate model to replace slow, heavy calculations	• Multi-variant inputs • Buoy data • Tidal parameters • Water quality indices
	Gaussian Process Regression (GPR)	• Simulates sandbar migration • Models cross-shore sediment transport rates	• Acts as an emulator to substitute intensive hydrodynamic equations • Provides explicit uncertainty bounds alongside predictions	• Multi-variant inputs • Empirical sediment and morphodynamic data
Ensemble Methods	Random Forest (RF) and Gradient Boosting Method (GBM)	• Classifies dominant environmental drivers • Predicts shoreline position changes • Forecasts storm surge and coastal flooding • Predicts damage levels of rubble mound breakwaters	• Uses decision trees resilient to interdependent ocean parameters • Effectively handles barometric pressure, wind vectors, and satellite indices	• Ocean parameters (Wind vectors, waves, atmospheric/ barometric pressure) • Interdependent environmental variables • Normalized Difference Water Index (NDWI) • Historical satellite indices • Existing structural features
Un-supervised Learning	Principal Component Analysis (PCA) and K-means Clustering	• Regionalizes tasks • Identifies spatial sustainability patterns • Dimensional reduction of multi-spectral datasets	• Facilitates spatial clustering and hazard classification • Simplifies high-dimensional remote sensing data	• Multi-spectral remote sensing datasets • Spatial/ regional sustainability datasets

Source: Author's compilation from various sources

Table 3 DL methods, their use areas, and advantages.

Operational Domain	AI Framework / Architecture	Forecasting Mechanics and Technical Features	Specific Use and Adaptation in Coastal Environments
Computer-Vision-Driven Forecasting	Convolutional Neural Networks (CNNs)	- Classifies every single pixel in an image. - Requires stacked layers to capture long-range dependencies. - Operates via sequential, pixel-by-pixel shift of convolutional windows, making it slower over large areas.	- Considered the gold standard for pixel classification. - Used for mapping shorelines, intertidal wetlands, and classifying coastal land cover.
	U-Net Architecture	- Utilizes a symmetric encoder-decoder framework. - Contracts spatial dimensions via successive 3 X 3 convolutions and 2 X 2 max-pooling layers to extract features. - Expands back to original dimensions using transposed convolution after decoding. - Copies high-resolution feature maps directly from the encoder to the decoder using skip connections.	- Extracts features, such as vegetation, and distinguishes them from water. - Preserves fine spatial gradients when data is down sampled. - Maps accurately to highly dynamic coastal boundaries, such as high-water lines.
	Vision Transformers (ViTs)	- Replaces CNNs when the monitored area is large. - Processes global contextual relationships within satellite tiles simultaneously. - Uses a Self-Attention mechanism that allows all relations to be calculated at the same time, making it much faster.	- Captures large-scale sediment plumes. - Maps long-shore drift patterns across expanded coastal spaces.
Spatiotemporal Hydrodynamic Forecasting	Long Short-Term Memory (LSTM) and Gated Recurrent Units (GRU)	- Models long-term temporal dependencies in metocean parameters. - Overcomes problems of vanishing gradient in shallow networks. - LSTMs resolve standard RNN gradient degradation using a hidden state controlled by a continuous cell state and three mathematical gating mechanisms.	- Ideal for multistep tidal and storm surge forecasting. - Processes multi-step time-series inputs. - Retains a memory of cumulative offshore wave energy over several days. - Effectively models beach recovery cycles and multi-hazard storm tracking.
	Transformers and Self-Attention Mechanisms	- Adopts natural language processing transformers for spatial-temporal forecasting. - Captures non-local interactions across large ocean basins. - Outperforms standard recurrent architectures.	Models large-scale, non-local basin interactions.

Table 3 (continued) DL methods, their use areas, and advantages.

Operational Domain	AI Framework / Architecture	Forecasting Mechanics and Technical Features	Specific Use and Adaptation in Coastal Environments
Physics-Informed Structural Forecasting	Physics-Informed Neural Networks (PINNs)	• Merges laws of physics (e.g., Navier-Stokes, shallow water equations, wave action) with AI/ML/DL. • Ensures mathematical consistency with sparse training data. • Splits objective functions into data-driven error and a physical residual penalty. • Computes partial differential equation derivatives exactly using Automatic Differentiation instead of numerical finite-difference approximations.	• Modeled for propagation of shallow-water waves governed by partial differential equations. • Delivers high accuracy and speed in AI predictions. • Key for coastlines of developing nations with limited data infrastructure. • Ensures high predictive stability and reliable extrapolation for climate-driven scenarios.
	Generative Adversarial Networks (GANs) and Diffusion Models	• Integrates physical laws to synthesize missing environmental data.	• Downscales global climate models to highly localized coastal grids.
Spatial Downscaling	Generative Adversarial Networks (GANs) optimized for Super-Resolution (SRCNNs)	• Operates as a minimizing-maximizing game between two players. • Generator: Ingests coarse, low-resolution bathymetric or wind-field arrays to synthesize highly detailed, downscaled spatial profiles. • Discriminator: Evaluates generated output against real-world data to calculate a validation probability score.	• Bridges the scale mismatch between global climate models (10 - 50 km grids) and near-shore erosion models (sub-meter resolution). • Uses continuous training to synthesize missing local bathymetric configurations and fine topographic features. • Provides a computationally efficient alternative to traditional interpolation methods.

Source: Author's compilation from various sources

2.4 Comparison of modeling frameworks

Each framework discussed in the preceding sub-sections has its own advantages and disadvantages. The development of modeling techniques has evolved over the years, as seen in **Figure 1**. Subsequent frameworks have addressed limitations of previous frameworks. This has led to the availability of numerous frameworks, which make understanding and their utility difficult. Accordingly, these frameworks have been compared in **Table 4** for better appreciation. This effort

is not intended to provide the best framework, but to provide an idea of the bounds over which each framework is effective.

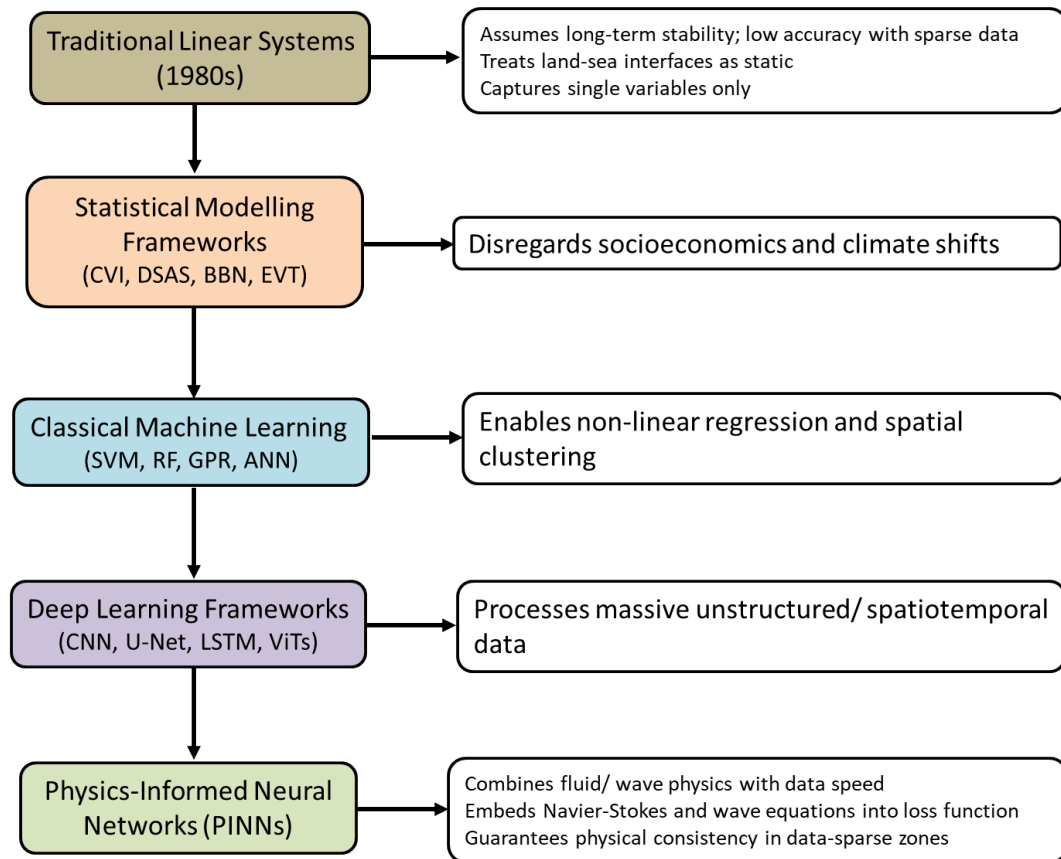


Figure 1 Development of numerical methods for coastal management over the years.

Source: Author

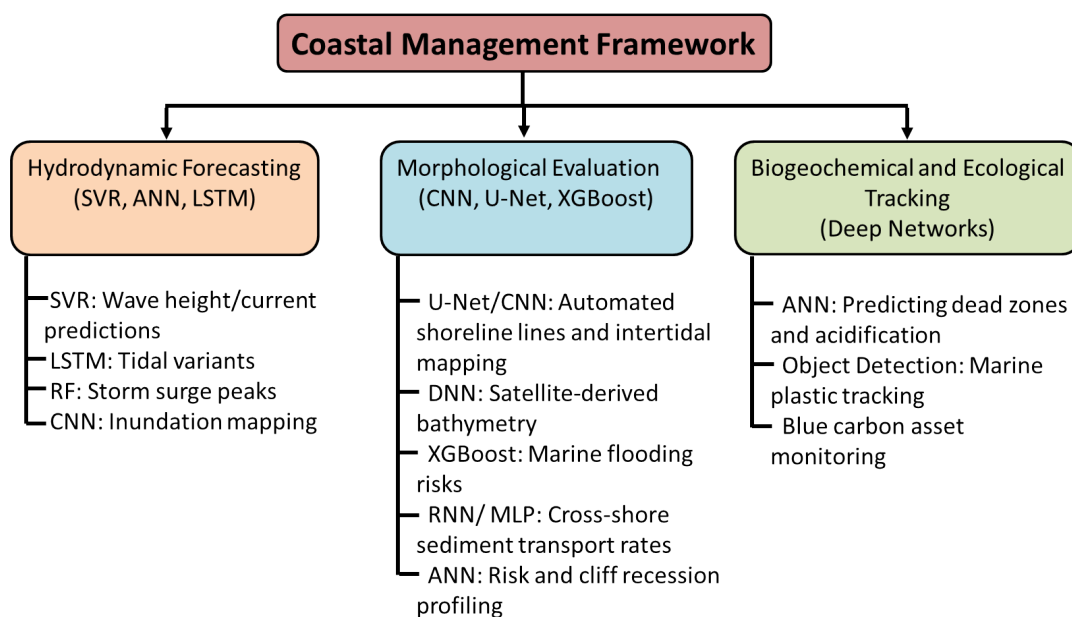


Figure 2 Focus areas of AI/ML in coastal management.

Source: Author

Table 4 Comparative assessment of numerical models for coastal management.

Metric	Traditional Numerical Models (e.g., Delft3D)	Classical Machine Learning (e.g., RF, SVM)	Deep Learning Frameworks (e.g., LSTM, CNN)	Physics-Informed AI (e.g., PINNs)
Computational Efficiency	Low: High CPU-hours needed for real-time operations.	High: Execution happens in milliseconds post-training.	Medium-High: Intense training required; quick inference.	Very high: Intense training time (complex loss functions); fast inference.
Data Requirements	Deterministic: Needs precise bathymetry, boundary conditions.	Medium: Relies on a modest set of high-quality historical logs.	Very High: Demands massive unstructured/spatio-temporal data.	Moderate: Physical constraints guide the model with less data.
Interpretability	High: Grounded directly in physical conservation laws.	Medium: Features can be ranked via Gini importance / SHAP.	Low: Black-box nature makes validation challenging.	Good: In theory but limited in practice
Handling Non-linearity	Moderate: Constrained by idealized mathematical simplifications.	High: Superb at resolving complex, multivariate non-linear trends.	Extremely High: Excels at complex structural/temporal patterns.	Excellent: At representing highly complex, non-linear functions, but struggle to accurately train, converge, and resolve sharp non-linear features due to multi-objective loss landscape.
Physical Constraints	Strictly enforced (mass/momentum conservation).	Completely absent.	Completely absent.	Strictly enforced (mass/momentum conservation).
Out-of-Distribution Generalization	Poor; Do not learn from historical data	Poor; fails outside the bounds of historical data.	Very poor; easily suffers from hallucinations or unphysical outputs.	Excellent; physical laws guide predictions in uncharted scenarios.
Primary Input Modality	Quantitative numerical data	Station-based tables (buoys, gauges).	Gridded fields, satellite arrays, continuous videos.	Spatial-temporal coordinate grids

Source: Author's compilation

3. Application of AI/ML in coastal management

Since coastal data is extremely messy, developing unified multimodal coastal foundation models that can be self-trained on the diverse oceanographic data is the primary objective for current AI research. The present focus is on three themes, viz. hazard mitigation and hydrodynamics; morphological and geomorphological evolution; and biogeochemical cycles and ecological health, as seen in **Figure 2**. To understand the importance of each, each of them are discussed individually.

3.1 Hazard mitigation and hydrodynamics

Using data-driven predictions, there is higher understanding of coastal flooding, storm surge inundation levels, and wave hydrodynamics that allow early warning and, hence, real-time decision-making for disaster response and long-term climate adaptation (Masria & Abouelsaad, 2025; Duiker et al., 2025). This notwithstanding, the process has limitations due to data scarcity of high-quality historical data for extreme and rare hazard events, making predictions for such events difficult and unreliable. Sometimes, due to lack of physical constraints, the results obtained are illogical, such as negative wave heights. Such limitations and more are pushing the industry to use Physics-Informed Neural Networks (PINNs) that account for laws of physics in AI training (Eddamiri et al., 2025; Issakov et al., 2025; Qin et al., 2023).

3.1.1 Hydrodynamic and wave modeling

To address the immense computational power requirement of traditional numerical models like SWAN or ADCIRC, AI/ML use data synthesis (Jörges et al., 2023). With AI/ML, the following are feasible.

(a) *Wave heights and ocean current predictions*. For this surrogate, modeling that uses neural networks acting as emulators for physics-based models is employed. By using a CNN based surrogate model in the real-world for Automated Regional Wind-Wave Forecasting and Typhoon Warning Systems for Hurricane Lorenzo in the Azores Archipelago (Campos et al., 2022) a relative error of less than 5 %, compared to actual SWAN outputs, was possible. It also increased execution speeds by over 300,000 times, enabling real-time marine safety warnings (Jörges et al., 2023).

(b) *Tidal prediction* can be made. For this, Long Short-Term Memory (LSTM) networks that analyze historical gauge data to forecast tidal variations and harmonic patterns are employed. When a LSTM/ GRU framework is used in the real-world for multi-step ahead sea-level and tidal prediction in High-Risk waterways (e.g., the Gulf of Finland / US Territorial Seas) (Immas et al., 2021), deep recurrent networks achieve high mathematical precision (R^2 correlation score of 0.93 and Root Mean Square Error limited to ± 5 cm) for real-time Automated Underwater Vehicle (AUV) navigation and port flood warnings (Rajabi-Kiasari et al., 2025).

(c) *Run-up and overtopping predictions* can be made. For this, Random Forests (RF) and Support Vector Machines (SVM) are employed (Liu & Yuen, 2025). When costal run-up and overtopping predictions are undertaken using RF and SVM in the real-world, such as for Flash Inundation mapping and Seawall Structural Risk assessment, an architectural accuracy of 96 % and a processing latency of just 1.9 seconds are achieved. The ML system undertakes flood-depth overtopping calculations using 1.5 to 4 % of the operational runtime demanded by standard 2D hydrodynamic codes. This provides disaster management teams with additional hours to execute emergency evacuations (Sasanapuri et al., 2025; Zarbipour et al., 2026).

3.1.2 Coastal hazard mitigation

Using AI/ML and processing multi-modal environmental data, early warnings can be made. These warnings can help protect vulnerable coastal communities (Gao et al., 2026). Some other costal hazards that can be mitigated using AI/ML are discussed here for completeness.

3.1.3 Data assimilation and processing

Since coastal environments suffer from sparse, noisy data, ML is used to optimize the integration of disparate data streams and hence improve data availability (Drakopoulou et al., 2026; Masria, 2024).

(a) Using DL, the extraction of shorelines, bathymetry, and benthic habitats from optical and radar satellite imagery can be automated (Christofi et al., 2025). This method can be applied to Automated Continuous Shoreline Delineation and Benthic Habitat Classification in the real-world. The method successfully delineates changing shoreline boundaries and extracts Satellite-Derived Bathymetry (SDB) till the coastal shelves. It classifies localized seafloor signatures, mapping vulnerable coral-reef systems and benthic marine habitats without requiring intensive field campaigns (Erasmus et al., 2026).

(b) ML algorithms can be used to clean data received from live oceanographic buoys and radar systems and help improve quality of data for processing. When using for High-Fidelity Coastal Water Quality and Hydrodynamic Feature Calibration in the real-world, these networks enhance data quality, lowering the Mean Absolute Percentage Error (MAPE) of complex coastal metrics such as chlorophyll-a concentration and wave parameters by 12.4 to 19.8 %, ensuring clean inputs for downstream warning models (Zeng et al., 2025).

(c) Generative Adversarial Networks (GANs) reconstruct missing spatial or temporal data gaps in historical climate records, making the data complete and providing improved analysis (Mabula et al., 2023). Climate data reconstruction in the real-world has been tried for sequence-to-sequence gap filling and reconstruction of sparse marine records to provide high perceptual alignment with real physical observations and to provide a reliable baseline for long-term climate trend analysis (Gonzalez-Calabuig et al., 2025; Wang et al., 2023).

3.2 Morphological and geomorphological evaluation

Traditional modeling techniques are computationally expensive while finding it difficult to handle non-linear, multi-scale, dynamic problems. AI/ML overcome these limitations by identifying complex patterns in datasets and optimizing coastal protection to permit real-time decision-making (Dammak et al., 2025). Such studies are critical for shoreline monitoring, bathymetric studies, and vulnerability assessment of coastal hazards. Though **Table 5** provides a summary of morphological and geomorphological evaluation of the coastal environment using AI/ML, each one of them are discussed for greater understanding and clarity.

3.2.1 Change in shorelines

The mapping of shorelines is essential for current and future coastal projects. Accordingly, AI/ML models extract and analyze shorelines from massive remote sensing datasets to help make decisions (Tsiakos and Chalkias, 2023).

(a) *Automated shoreline extraction*: By using Convolutional Neural Networks (CNNs), sub-meter satellite imagery, and UAV data, high-water lines, vegetation lines, and intertidal zones can be mapped (Christofi et al., 2025; Palanikkumar et al., 2025). When used on the Mediterranean and European coastlines, the benefits of resource reduction, sub-pixel extraction, and standardized inter-sector data allow multi-spectral bands to isolate high-water lines, vegetation lines, and dynamic intertidal zones (Christofi et al., 2025).

(b) *Long-term trend analysis*: Using SVM and Random Forests, decades of historical satellite data from satellites such as Landsat and Sentinel is analyzed. The resulting analysis helps establish erosion or accretion patterns across large spatial scales, allowing changes in shoreline to be predicted. The method has been used on the Campeche coastal region and the Indian Ocean infrastructure to identify cyclical erosion and accretion patterns to forecast exact coastal retreat profiles many years before they occur (Palanikkumar et al., 2025).

(c) *Post-storm impact assessment*: Through DL, rapid pixel-level changes can be detected immediately after extreme weather events. Such studies allow sediment volume loss and dune breaching to be quantified. In the real-world the method has been used for safeguarding coastal dunes and megacusp tracking to evaluate multi-temporal imagery. This has allowed the study of highly dynamic environments, the tracking of megacusp undulations, and the safeguarding of coastal dunes from structural collapse (Binetti et al., 2024). The process delivers rapid response, volumetric dune loss metrics, and an objective insurance appraisal for insurance agencies.

3.2.2 Bathymetric and beach modeling

Knowing the changes in beach profile and bathymetry is essential for coastal infrastructure safety and the creation of new structures. For this, AI/ML is used in various ways, as discussed here (Asborn et al., 2023).

(a) *Satellite-derived bathymetry*: For shallow water bathymetry, Multi-Layer Perceptron (MLPs) and deep neural network are used. Using the existing relationship between reflectance and depth of the water column allows AI/ML to predict depth in shallow waters. SDB has been used in the turbid and dynamic environment of El Burullus Lake and its coastal zones. The model achieved high correlation of R^2 of approximately 0.97 and root mean square error of under 0.85 m. This allowed the elimination of field hazards and achieved cost saving (Hany et al., 2022).

(b) *Cross-shore sediment transport*: Recurrent Neural Networks (RNNs) and LSTM networks can help predict profile changes, sand-bar mitigation, and beach recovery cycles. For this, they use time-series data of wave height, period, angle, and tidal stages. This method has been used for DL shoreline and sandbar evolution on the Tuvaluan Coast in the real-world. The advantages achieved are the capture of non-linearity, optimized beach nourishment, and mitigation of infrastructure risks (Kim and Aoki., 2021).

(c) *Estuarine and deltaic morphodynamics*: AI models can be used to predict shift in deltas. These predictions allow the impact of discharge of rivers, increasing sea-level, and anthropogenic activities that impact the coastal environment to be understood better. The method has been used in the Minho River Estuary and high-frequency tidal systems. The benefits achieved include proactive flooding, seiche mitigation, the safeguarding of navigational channels, and wetland conservation (Weber et al., 2022).

(d) *Surrogate modeling*: Neural networks replace slow Computational Fluid Dynamics (CFD) simulations, predicting wave-structure interactions in milliseconds for predictive action to be initiated and to avoid the erosion of coastline. Surrogate modeling has been used in Macao to predict real-time flooding. The process allowed achieving millisecond level predictive velocity, early failure intervention, and the possibility of running numerous virtual iterations for structures and varying significant wave height with minimum expenses (Xu & Gao, 2024).

3.2.3 Coastal hazard assessment

The need for vulnerability assessment for coastal infrastructure cannot be overlooked. With numerous variables making assessment difficult, ML is used to map risk and vulnerability profiles by synthesizing heterogeneous geographic and hydrodynamic datasets (Olivatto & Di Lollo, 2026).

(a) *Overwash and inundation mapping*: Using Gradient Boosting Machines (XGBoost, LightGBM), susceptibility of the coast to wave overtopping and marine flooding is evaluated. The digital elevation models (DEMs) are fused with hydrodynamic forcing data when undertaking such analysis. A real-world case study of this method is the Mid-Adriatic Sea Coast and Urban Flood Management to model severe storm surge vulnerabilities. The study showed near real-time hazard zoning, micro-scale elevation accuracy, and data-driven defense adaptations (Baldoni et al., 2025).

(b) *Erosion risk*: Artificial Neural Networks (ANNs) can assess the rate at which cliffs are receding. This is undertaken by accessing geology features, wave energy, rainfall data, and toe-erosion history. Such an assessment allows flagging imminent failure zones. The method has been

used in the real-world on soft rock and clay stiff systems between Portonovo and the Trave Cliffs (Ancona, Italy). Early failure intervention was achieved by using this method (Fullin et al., 2024).

(c) *Vulnerability indices*: To protect coastlines, they need to be provided with vulnerability indices. Such indices will allow focused attention for their protection and allow government funding to be sought. These indices can be predicted by using unsupervised ML techniques such as K-means clustering and Self-Organizing Maps. Using vulnerability indices in Latin America, the Caribbean, and Global Coastal risk indices, comprehensive multidisciplinary risk indices were constructed. The approach has allowed researchers to reduce highly disparate variables into a unified local marine hazard (Theocharidis et al., 2024).

Table 5 Summary of using AI/ML for morphological and geomorphological evaluation.

Area of Use	AI/ML Framework used	Input Data	Benefits Achieved
Shoreline Mapping	CNNs, U-Net, Random Forest	Data from satellites, drones, LiDAR, and photos is used for analysis	Replaces digitization to track shoreline for present and future coastal projects.
Evolution of coast profile	LSTM, RNNs, GRUs	Data made available from wave gauges, tide metrics, and historical profiles	Allows understand changes in structural beach volume ahead of storm seasons.
Bathymetry Retrieval	Deep Neural Networks (DNN), RF	Data made available from multispectral imagery, echo-sounder calibration points	Provides a cost-effective depth mapping for navigation and sediment budgets.
Mapping of risks	XGBoost, SVM, K-means	Data made available from DEMs, tidal ranges, storm surge history, and geology	Helps to identify high-risk erosion zones for creating setback zoning policies.
Surrogate Modeling	PINNs, Autoencoders	Data made available from output of numerical model such as Delft3D and XBeach	Scales up real-time forecasting capacities for emergency responses.

Source: Author's compilation

3.3 Biogeochemical cycles and ecological health

Biogeochemical cycles are active in coastal environments and, hence, tracking nutrient flow becomes critical to ensure the protection of marine life and the maintenance of these biogeochemical cycles. Since traditional monitoring is slow and expensive, AI/ML is used to overcome these limitations by monitoring biogeochemical cycles, ecological health, and water quality.

3.3.1 Biogeochemical cycles

To ensure that biogeochemical cycles are preserved in the coastal environment, AI/ML models are used to predict dead zones with low oxygen. Such predictions can be made by analyzing the water temperature, condition of runoff, and existing nutrient load in the water. Using data from satellites, drones, and ocean buoys, AI/ML can help access blue carbon storage in mangroves and

salt marshes while neural networks can simulate runoff of agricultural nutrient into coastal estuaries. Similarly, by tracking pH and measurement of dissolved inorganic carbon, ocean acidification can be predicted (Pruseth et al., 2026). Study of carbon fluxes, nitrogen loading, and eutrophication has been undertaken in the Sundarbans, India (Mondal et al., 2025).

3.3.2 Ecological health

Today, using AI/ML techniques, toxic algae bloom can be detected far before they actually becomes visible; seagrass beds, coral reefs, and kelp forests can be classified; fish species can be tracked for migration using data from underwater sensors; plastic debris and chemical spill can be identified to be likely entry points, while pollutants can be cleaned from the ocean (Agarwala, 2021). Such predictions allow the ecological health of ocean systems to be monitored and for corrective actions to be initiated to improve them. This method has been used in various applications to map mangroves and wetland in South Asia and Australia. Mapping the coastal lagoon of Chilka is one such example (Lemenkova, 2024).

4. Use of AI in coastal engineering

As for coastal management, AI can be used for coastal engineering by refining the design, lifespan, and risk modeling of gray infrastructure and by the deployment of soft engineering structures such as Nature Based Solutions (NBS) as seen in **Figure 3**.

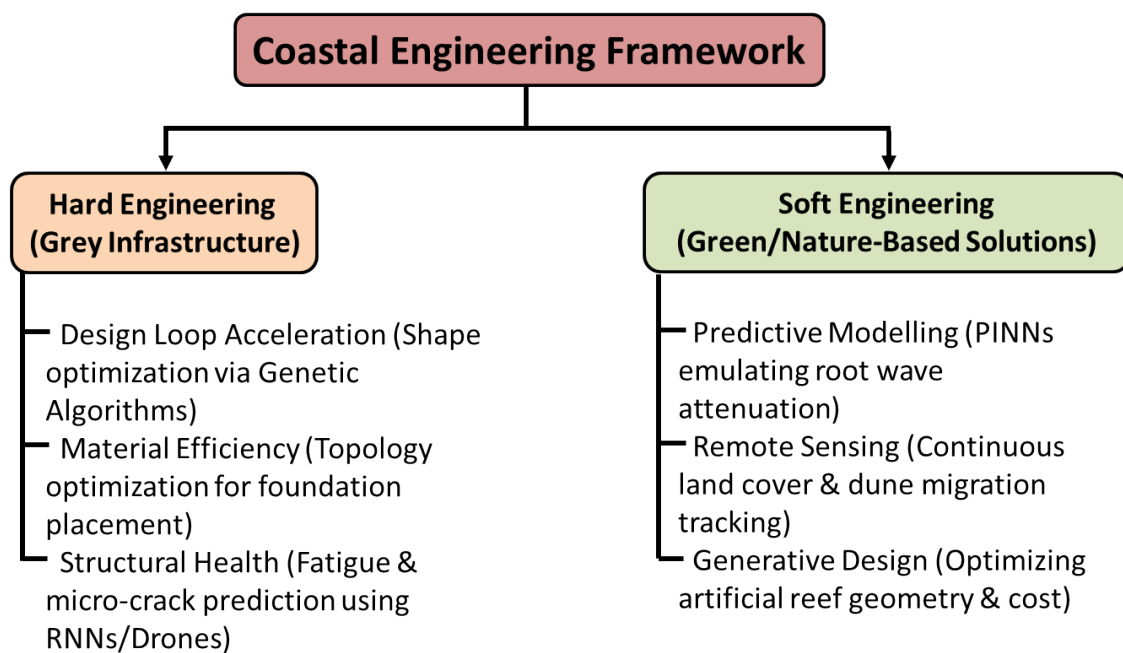


Figure 3 Use of AI in coastal engineering.

4.1 Hard engineering

Hard engineering, in the form of seawalls, breakwater, groins, and revetments, has been used to minimize the impact of waves and, hence, protect coastlines from erosion. To optimize these hard engineered structures, AI is used. Optimization of these structures will help move away from traditional designs that are based on empirical formulae to designs that are driven by dynamic data from the environment. This is critical, as these coastal structures demand very high capital investment, where structural failure needs to be minimized.

4.1.1 Optimized design

By using AI, the design loop can be accelerated as CAD tools can be coupled with hydrodynamic solvers to obtain an optimized design. This coupling may use one of the following methods.

(a) *Surrogate modeling*: In this, neural networks predict wave-structure interaction and allow faster design decisions. In the real-world, this method has been used in regional studies for New York City, Tyndall Air Force Base in Florida, Ho Chi Minh City in Vietnam (Dang et al., 2024), and Tianjin in China (Bian et al., 2025). These data-driven emulators replace or accelerate expensive hydrodynamic simulations.

(b) *Shape optimization*: Genetic algorithms and reinforced learning modify the shape of breakwater armor units to ensure maximization of wave energy dissipation. The method has been applied in the Port of Valencia in Spain, in which adaptation measures for the head and trunk section of the breaker water were evaluated. This helped to optimize and change the size of the breakwater specific to Valencia for improved effectiveness (Portillo et al., 2026) and to optimize hybrid floating breakwaters for Port Said in Egypt (Hamed et al., 2026).

(c) *Overtopping reduction*: By using AI, seawall crest height and its curved profile can be optimized for minimum wave overtopping while reducing the material used, thereby achieving an optimum and cheaper product. Some projects and applications for this method include the CLASH and EurOTop Project of Europe (Habib et al., 2022), the SLASH project of UK (McGlade et al., 2025), and Eco-Engineered Seawalls for lab to field testing (Habib et al., 2025).

4.1.2 Higher material efficiency

By using AI for such designs, human bias can be removed for certain structural layouts. This allows more efficient use of construction material, thereby optimizing their cost. The optimization can be done for mass, scouring, or foundation placement.

(a) *Optimizing mass*: Using AI, the lightest structural topology that can withstand maximum wave and tidal pressure can be identified. A real-world use of this methodology is in the Port of Valencia in Spain, wherein the breakwater was optimized in shape, size, and material used (Portillo et al., 2026). Additionally, precast elements for marine infrastructure and cast-in-place elements were optimized using this technique (Gindy et al., 2025).

(b) *Minimize scouring*: Scouring and erosion of built structures can be minimized if their position with regard to the waves and the coastline can be optimized. Since empirical methods cannot cater for dynamic ocean conditions, to prevent scouring and erosion AI/ML methods, such as reinforced learning models, need to be used. This method has been used in Italy, Tunisia, and Egypt, with success, and by various engineering hubs in the UK and Europe (Habib et al., 2024).

(c) *Foundation placement*: ML helps classify seabed soil that helps to optimize the pile depth and spacing required for offshore barriers, thereby optimizing their use. This has allowed optimization and predictive analysis for structural asset placement in the Monaco and Ibiza marinas (Ioras et al., 2025) and Tolo harbor in Hong Kong (Deng et al., 2021).

4.1.3 Structural health

To move from reactive repairs to predictive repairs, IoT data can be used to monitor structural health of coastal infrastructure.

(a) *Anomaly detection*: Computer vision algorithms use aerial footage from drones and LiDAR to identify breakwater armor blocks that may have shifted and to identify micro-cracks in concrete. Timely repairs can help ensure the health of the coastline. In the real-world, this has been used in South Korean ports (Lee et al., 2025) and North Sea marine and offshore infrastructure (Mahajan et al., 2026), to name a few.

(b) *Fatigue prediction*: Seawalls can undergo structural fatigue due to the cyclic nature of waves impacting them. To predict their structural integrity, and to allow timely maintenance,

Recurrent Neural Networks (RNNs) can be used. This is done by analyzing sensor data from seawalls to predict likely structural fatigue. This has been used to predict metal fatigue in bridges of Sydney (Nott, 2018) and to predict structural instability under tides and weather events along the coastlines of Nigeria and Germany (Hake et al., 2022).

(c) *Failure forecasting*: By using AI models alongside tidal gauges and storm surge data, the risk of structural breaching during extreme weather events can be forecast, allowing preventive measures to be taken in a timely manner. The key deployment of this method has been at the Hong Kong-Zhuhai-Macau Bridge (Sharma et al., 2025), along the coast of China's Pearl River Delta (Wang et al., 2025), and in the Gulf of Guinea (Babati et al., 2025).

4.2 Soft engineering

Traditional defense mechanisms for coastlines rely on hard structures like seawalls and breakwaters. However, soft engineering, such as nature-based solutions, can also be employed to encourage environmental sustainability. Natural processes that dissipate wave energy and climate change adaptation are encouraged. For this, the growth of roots, mangroves, and oyster reefs is recommended to bind sediments and to make the shoreline active, while beaches and dunes can be protected by planting native vegetation. For bridging the gap between the high complexity of natural systems and the precision required for engineering design through soft engineering, AI can be used (Alenezi & Akour, 2025). Some AI/ML methods used are discussed.

4.2.1 Predictive modeling

By using predictive models, one can access where natural fauna can be planted and how they can act as wave attenuation barriers (Figueroa-Alfaro et al., 2022). This, when run alongside erosion forecasting, will help encourage sediment transport and avoid loss of coastline.

(a) *Physics-Informed Neural Networks (PINNs)*: Traditional numerical models such as SWAN and Delft3D are computationally heavy. AI emulates these physics models, predicting how complex mangrove roots or kelp forests attenuate wave energy in milliseconds instead of hours. The methodology has been successfully used in Bohai Bay of China to evaluate coastal vulnerability and decipher management options (Zhu et al., 2025), in Northern Oman coastal aquifers to understand saltwater intrusion (Al Jabri et al., 2026), and in Syrdarya river and Shardara River basin in Kazakhstan to study the sediment deposit dynamics (Baydaulet et al., 2025).

(b) *Erosion forecasting*: By using RNNs and LSTM, erosion forecasting can be done. Using historical wave data, tidal shifts, and sediment transportation, likely changes to the shoreline can be predicted. This process has been used in Norderney Coast, Germany (Khan et al., 2024), Ogu/ Bolo, Nigeria (Osondu et al., 2025), and Valencia Coast, Spain (Kumar & Leonardi, 2023).

4.2.2 Remote sensing

By maintaining a continuous monitoring and predictive analysis using data from remote sensors, coastlines and coastal bottoms can be preserved.

(a) *Image analysis*: AI/ML can monitor coastal geometry, land cover, migration of dunes, and health of salt marshes. This is possible by analyzing images from satellites and drones using AI/ML tools such as CNNs. Erosion hot spots have been measured at La Paz, Mexico (Arasi et al., 2025), Central Vietnam (Kinh, 2024), and the Greek coastline (Drakopoulou et al., 2026) using this method.

(b) *Bathymetry mapping*: Near-shore water depth can be derived by AI from optical satellite imagery and wave kinematics, thereby eliminating the requirement of expensive boat surveys (O'Dea et al., 2025). Using this method, fast-changing seabed topographies have been mapped in Hasaki Coast, Japan (Hao et al., 2025), California (Kalkan et al., 2021), and Natuna Sea (Napitupulu et al., 2026), to name a few.

4.2.3 Generative design

Generative designs created with the help of AI can help optimize placement, density, and geometry of artificial reefs and where vegetation is to be developed to ensure maximization of flood mitigation and minimization of associated cost. The method has been used successfully in Norfolk, Virginia, for urban coastal zones facing rising groundwater and severe storm surges (Zhang & Bowes, 2019), and in the Mediterranean, to optimize and upgrade coastal protection structures (Portillo et al., 2026).

5. Impact on AI/ML frameworks

Over the years, studies in coastal management have seen the use of data driven AI/ML methods as against traditional methods that were used extensively earlier. This has allowed forecasting to become proactive, with reliance on data, rather than being reactive as earlier. As a result, it is possible to implement economic, preservation, and mitigation activities, such as spatial planning hazard mitigation, and marine operations simultaneously in coastal regions with greater ease. Despite this, data bias and the high cost of infrastructure are some challenges that disallow the full utilization of AI/ML in coastal management. This notwithstanding, it is important to appreciate how ML models allow managers and policymakers to make decisions through a dashboard. Hence, the use of decision support systems (DSS) and trade-offs by planners to preserve vulnerable ecosystems and to sustain vital maritime economic activities based on the outcomes provided by AI/ML needs to be understood.

5.1 Decision support systems (DSS)

In most cases, the data available to AI/ML is fragmented, not continuous, the latter of which is desired for a sound decision. To overcome this limitation, decision support systems (DSS) are required to transform humungous heterogeneous data into predictive and actionable strategies. Such a system requires specialized algorithms. These include LSTM Networks, RF, SVM, and CNNs. To translate these predictions into actionable decisions, the framework needs to integrate ML models with Geographical Information Systems (GIS) and Multi-Criteria Decision Analysis (MCDA) techniques (Barzehkar et al., 2021; Sebastian et al., 2025). This integration yields localized Decision Support Indices (DSIs). An explainability layer is added to the framework using SHAP (SHapley Additive exPlanations) along with a probabilistic uncertainty module. This transparency ensures that policy recommendations remain accountable, interpretable, and scientifically sound for coastal engineers. Additionally, incorporating multi-agent systems allows planners to model diverse stakeholder interactions to evaluate long-term socioeconomic trade-offs of natural versus hard infrastructure. By embedding continuous feedback loops, these adaptive systems continuously refine their algorithms based on actual ecological outcomes. Ultimately, an AI/ML-driven DSS shifts coastal defense from a reactive posture to a proactive, resilient management model. However, since the presented results must translate data into actionable insights, and not merely provide raw probabilities or complex outputs, economic impact maps, safety margins for specific areas, and what-if simulation models need to be provided on the dashboard (Kumar & Leonardi, 2025).

5.2 Trade-offs

Data-driven predictions balance ecological preservation with maritime economics by using spatial-temporal optimization algorithms to identify ‘dynamic zoning windows’. However, to make such a balanced decision that meets economic requirements without compromising on environmental conservation, an understanding of how planners make decisions and strike a balance is considered essential. Hence, based on historical and live data, the algorithm divides the ocean space for human use and protection, while AI models help identify regions where habitat restoration can help achieve commercial fishing and coastal protection simultaneously. To explain the required

trade-off, let us consider the need to dredge shipping channels for the safe movement of deep-draft cargo ships (Wang et al., 2024). When dredging is undertaken, the channel water becomes turbid. This turbid water blocks sunlight, killing living organisms, such as seagrass meadows, in the channel. Since this seagrass is considered critical for coastline protection and local fishes, their destruction is detrimental to the health of the channel. To achieve the economic goal of an accessible shipping channel, without compromising on the ecological health of the channel, requires a trade-off. Hence, using ML driven information using data from fixed sensors, satellite, seagrass growth pattern, and waves, a dynamic window can be established to define when dredging should be undertaken without harming the health of the channel. Thus, an informed trade-off that allows both sustainability and economic growth is feasible. Some other competing priorities between ecological risks and quantifiable economic variables that can be handled in the maritime domain using AI/ML are summarized in **Table 6**, while the entire process of data analysis using AI/ML is seen in **Figure 4**.

6. Known limitations

Use of AI/ML faces some basic concerns. These arise from data scarcity, sensor drift, missing historical baselines, trust barrier of results presented, and AI models being non-stationary. These concerns are more relevant to developing nations, where limited infrastructure and human resources disallow algorithms to generalize, thereby producing highly skewed risk predictions. Planners overcome these structural challenges by substituting missing local data with global satellite constellations, using ML to self-calibrate drifting sensors, and establishing synthetic baselines via physics-informed neural networks (Gizachew, 2026). Owing to their importance, these limitations need to be examined individually.

6.1 Data scarcity

Training of AI models in the developing nations is usually done using manually collected sparse data due to lack of ground infrastructure for data collection (Ames, 2026; Katende, 2026). This forces them to use the available network of ocean buoys, tidal gauges, and regular LiDAR to train DL models. Though DL models in the developed nations are comprehensively trained with better data, they cannot be used in the developing world due to different climate patterns, ecological dynamics, different coastlines, and different geomorphology (Li et al., 2026). This demands the learning of developed nations to be transferred to developing nations by using pre-training models on data-rich regions and then fine-tuning them on small, localized datasets of developing nations (Yadav et al., 2024). To address the lack of infrastructure, data from Earth observation satellites such as Sentinel-1 and 2 or Landsat can be made available (Mai, 2025). In addition, citizens can be encouraged to use mobile apps to upload geotagged photos of erosion or flooding to provide the missing dataset (Tareke et al., 2026).

6.2 Sensor drift

Corrosive environment in coastal regions can degrade hardware, introducing silent errors and, hence, sensor drifting into ML (Terrados-Cristos et al., 2025). Since corrosion causes minor changes, such errors are considered as environmental changes by ML to either provide incorrect results or by missing out critical ecological tipping points. Hence, unsupervised neural networks that continuously monitor sensor cross-relations need to be used (Wang et al., 2025). If one sensor reports rising temperatures, which are not validated by adjacent sensors, the system flags the anomalous sensor for drift, thereby avoiding an error. Similarly, using AI to dynamically recalibrate drifting sensors by predicting what the true values should be based on surrounding environmental variables and satellite readings can help correct the drift in the data pipeline (Wang et al., 2023).

Table 6 Summary of ecological risks and economic gains for trade-off decisions.

Concern Area	Ecological Goal	Economic Goal	Trade-off
Complete Closure of Offshore Wind Farms	Recovery of habitat.	Causes loss of revenue and disruption of supply chain.	Create predictive corridors: AI identified closure zones by identifying high-risk zones.
Speed Cap on Ships in Shipping Channels	Reduction of marine mammal mortality by ship collision.	Causes loss of revenue due to increased fuel consumption and delays in delivery.	Selective speed reduction: Reduces ship speeds during migration period only.
Defining Fish Catch Quotas	Stabilization of productivity of fishes.	Reduces fish catch; reduces profitability for fishermen.	Define fish quota: AI based predictive modeling can define fish quotas.

Source: Author's compilation

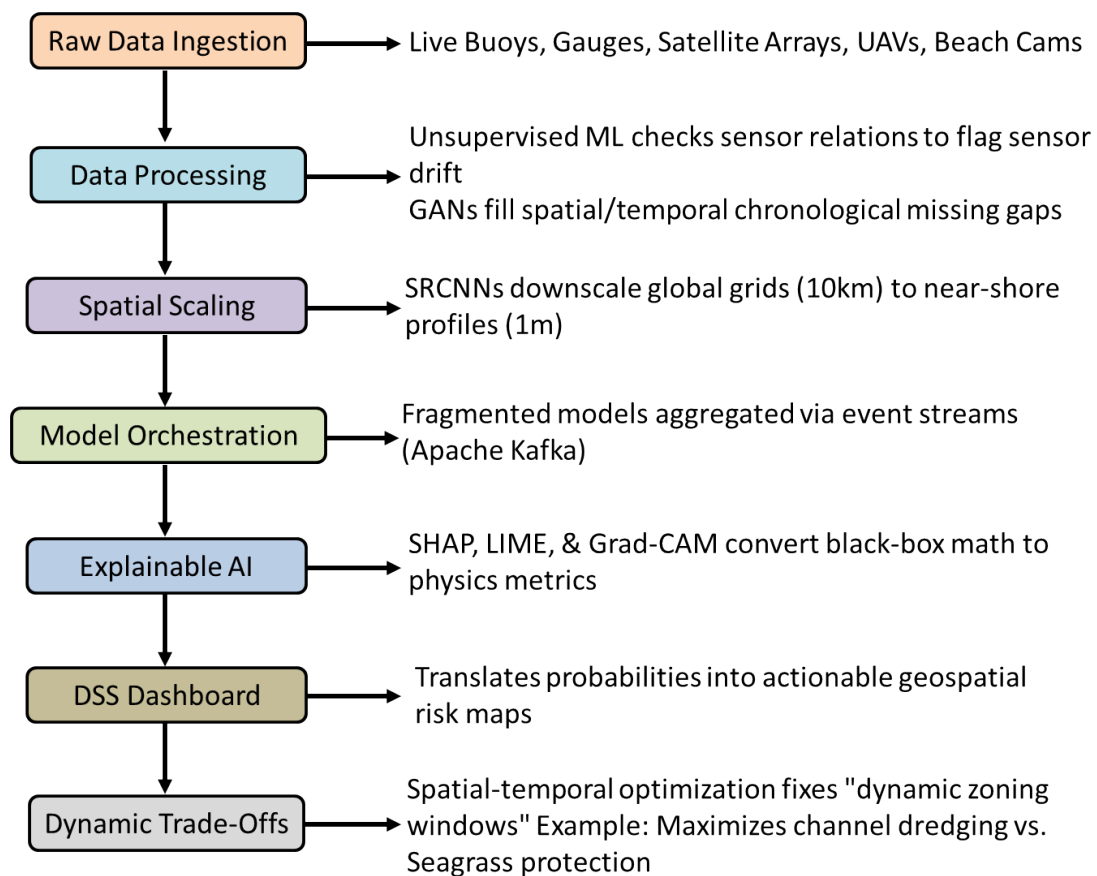


Figure 4 Process of data analysis.

Source: Author

6.3 Missing historical baselines

ML models need high-resolution historical data to make long-term predictions of natural events. Unfortunately, since the interest and focus on environmental monitoring is a recent development, sufficient historical data for such predictions is not available. As a result, the learning of such ML models is limited, so that it disallows long-term predictive forecasting speculative (Hsieh, 2022). To ensure that AI predictions remain bound by the laws of physics, use of Physics-Informed Neural Networks (PINNs) that embed laws of physics (such as fluid dynamics or sediment transport equations) directly into the loss function of the ML model is a possible way ahead (Kashinath et al., 2021). Such methods disallow statistical guesses, ensuring that the predictions are more reliable (Tipu et al., 2025). Another method to address this concern is hindcasting, wherein numerical climate models are used to simulate past environmental conditions (hindcasting) (Pais et al., 2023). This creates synthetic historical training sets that fill the chronological gaps for the AI to analyze.

6.4 Trust issues

The trust barrier in coastal engineering stems from a fundamental shift from physics-bound numerical models like Delft3D or SWAN, that are highly interpretable, to a deep neural network (DNN) that offers higher predictive accuracy but lacks physical guarantees (as it acts as a black-box without explaining the physics behind the decisions made). To bridge this gap, explainable AI (XAI) is used, which converts complex neural activations into human-readable visual attributions and sensitivity metrics (Mukonza et al., 2023; Mihailov et al., 2025). This allows engineers to verify that predictions made by AI are actually grounded in fluid mechanics and not statistical noise (Minuzzi & Farina, 2024). Other techniques used are Integrated Gradients, SHAP (SHapley Additive exPlanations), Grad-CAM, and Local Surrogate Models such as Local Interpretable Model-agnostic Explanations (LIME) that provide engineers a local ‘physics-like’ formula explaining the decision of the AI.

6.5 Non-stationary climate

AI models are trained to existing sea-level (Zanotti, 2025). In a climate-driven accelerated sea-level rise, these models would need to be re-trained to achieve correct predictions (Martin & White, 2024). Since re-training of AI models is expensive and time consuming, this is a challenge, especially in a future IPCC climate projection scenario (Vaghefi et al., 2023).

7. Discussion and way ahead

Coastal zones are biogeochemically active zones that have displayed high vulnerability to stressors, both individual and combined. So far, due to limitations of traditional numerical computational methods, most studies have been undertaken for individual stressors. With time, studies showed that, when anthropogenic and climate-change stressors act together, the interaction is usually non-linear, and the resulting disruptions have the potential to dismantle coastal food webs. To study such non-linear conditions, coastal modeling has evolved from a linear system that considers only a single-variable to a framework that undertakes multi-physics computations and is driven by data. This evolution, which began in the late 1980s and early 1990s, has been feasible due to the increase in computational power, advances made in satellite observation, and the need to predict the impact of multiple stressors working at the same time on the coastal environment. As a result, the use of AI algorithms for the coastal environment has become common to address a wide range of coastal engineering problems and coastal management issues. The ability to handle non-linear problems with ease, process terabytes of images and data near instantaneously, and accurately estimate missing data points for an informed decision makes AI a versatile tool for predictions in the coastal environment. Though numerous review papers have been written on the use of AI/ML

on issues of coastal environment, they have mostly focused on standalone fields without providing a holistic synthesis of tying AI/ML nodes back to integrated coastal management frameworks (hard vs. soft engineering decisions) which has been addressed here.

One may note that AI/ML have been experimented with successfully in various coastal environment problems and have been found to be faster and much more reliable than traditional numerical methods of predictions. However, these methods face numerous challenges that disallow extensive use of classical ML by coastal agencies. Challenges such as *data scarcity* for model training, especially for extreme events caused by climate change, and *non-adherence of conservation laws* result in physical anomalies in the results by making unrealistic and physically impossible predictions. Though hybrid frameworks are being encouraged to address these shortcomings, they remain a work-in-progress. On the acceptance side, even though AI models are considered the state-of-the-art techniques, their deployment is met with resistance, especially in life-safety applications and high-liability civil engineering problems, due to a *lack of interpretability*. This demands integration of Explainable AI (XAI) frameworks, such as the Integrated Gradients and attention maps, to show how deep networks address meteorological inputs. It is presumed that, with changing sea levels due to climate change, AI models would need to be *re-trained*, as the present training is for existing sea levels. With such unpredictable requirements for the future, the use of generative AI for simulations with PINNs to address missing data is possibly the best available mechanism for resilient coastal planning.

Though some concern areas exist, the use of AI/ML is here to stay, as it provides a tool that is flexible and versatile with an ability to provide predictions that were not possible previously using traditional methods of analysis. If AI is to be developed for effective use for coastal environment issues, there is a need for the coastal authorities and engineering firms to adopt a structured deployment methodology. Such a deployment requires the use of IoT sensors in wave level gauges, wave buoys, and other ocean sensors, along with automated satellites, such that real-time data is available continuously for AI models. Building digital twins would help simulate what-if scenarios to improve understanding and decision making in a dynamic coastal environment. To ensure that AI/ML predictions are reliable, automated triggers, to retrain AI models whenever new bathymetric data or extreme weather patterns are logged, are considered essential. In doing so, one needs to ensure that AI/ML predictions do not violate conservation laws of mass and momentum. To achieve this compliance, one possible means is the use of hybrid frameworks, such as Physics-Informed Neural Networks (PINNs) and surrogate modeling using Computational Acceleration.

Hybrid modeling and the use of digital twins can assist in bridging the gap between physics and speed by embedding ML inside traditional numerical solvers. This allows planners to run high-resolution, yet physically consistent, coastal simulations in milliseconds instead of days. This shift can help move coastal management from a reactive to a predictive process, where preventive decisions can be made as extreme weather events unfold. Such techniques are already helping shape resilience in low-lying coastlines of the Netherlands, Singapore, and vulnerable delta regions globally. Tools such as digital twins are able to predict the erosion of beaches by seasonal currents, thereby allowing engineers to place dredged sand that can be distributed optimally by the natural wave energy. Similarly, hybrid models can assist ports in forecasting drafts available, such that cargo vessel throughput can be maximized without risking grounding incidents. Other possible applications of these techniques are discussed here.

7.1 Hybrid modeling

Traditional numerical models such as Delft3D and SWAN are highly accurate but computationally expensive, as against ML models that are quick but prone to errors. By using hybrid modeling, individual weaknesses of the two methods can be eliminated. Such modeling may be undertaken in any of the following ways.

7.1.1 Accelerate parameterization

In some cases where the problem is complex, such as the calculation of bottom friction over complex surfaces or wave breaking at the micro scale, numerical calculations can become expensive. Such calculations can be undertaken using deep neural networks that are trained on high-fidelity simulation data to reduce cost of computation.

7.1.2 Physics-informed surrogates

For problems such as predicting wave run-up at the coast, where the laws of physics have to be adhered to, neural networks are used as ‘surrogate models’, while open-ocean propagation is left to the numerical model, cutting down total computation time by several orders of magnitude.

7.1.3 Error correction twinning

A numerical model runs a coarse, low-resolution simulation to guarantee physical consistency, while a coupled ML model scales down the output to 1-meter resolution and corrects systemic model biases in real-time.

7.2 Real-time digital twins

Digital twins are mathematical models prepared to create a virtual mirror of the target to be studied. These mathematical models for coastline are continuously updated and can be used by AI to simulate possible scenarios for informed decision-making. Though the use of such digital twins is recommended, one should not underestimate the infrastructure required, associated computation costs, and edge-computing latencies required to process multi-modal satellite images and live buoy networks simultaneously in a real-world scenario that allow such digital twins to be created. It is hence essential to understand that such options though possible, must be exercised with extreme care and caution.

7.2.1 Continuous data assimilation

Digital twins leverage edge-computing, IoT ocean buoys, X-band marine radars, and automated satellite feeds to constantly update the initial boundary conditions of the coastal state.

7.2.2 Providing what-if projections

AI can simulate permutations of storm-tracks on a digital twin to predict possible areas at risk to flooding.

7.2.3 Closed-loop automation

Digital twins can be used analyze possible dangers during a storm to autonomously trigger closure of storm surge barriers or send out evacuation messages based on the set thresholds.

8. Conclusions

This study demonstrates that data-driven technologies like Artificial Intelligence (AI) and Machine Learning (ML) provide a powerful predictive tool to overcome the existing limitations of traditional coastal observation models. Such methods and models help in making real-time decisions in coastal engineering by capturing non-linear interactions of various stressors. The study underscores the importance of hybrid computational frameworks and how, by using fundamental laws of physics along with deep learning, such hybrid frameworks eliminate anomalies such as negative wave heights and provide physically consistent simulations in real-time rather than in days. Resultantly, issues of data scarcity can be overcome while improving the model generalization for unknown climate scenarios. Such generalized models are considered beneficial for developing nations.

Quality of data for training and explainable artificial intelligence (XAI) is yet another area

discussed and considered critical for improved trust. By using unsupervised anomaly detection, black-box predictions can be verified against laws of physics and converted into actionable insights. Since climate change alters the sea-level, thereby changing the coastal baselines, model validation and automated re-training on a near continuous basis is considered essential. Such limitations can be overcome by using digital twins and integrating it with automated data collection to ensure that the model remains updated and relevant for changing environmental conditions. Deploying data-driven technologies will assist authorities to achieve an optimal and sustainable balance between economic exploitation and sustainable preservation leading to improved coastal management.

Disclaimer

The views expressed in the paper are that of the author. They do not reflect the views or policies of the Government of India or the Indian Navy.

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Declaration of generative AI in scientific writing

The author used Gemini (OpenAI) for refinement of the manuscript. With or without AI applications, the authors are fully accountable for every process of the work and manuscript writing. All final edits, interpretations, and conclusions are the sole responsibility of the authors. The authors academically and ethically confirm that the stated AI statements are true, and the authors are ultimately responsible and accountable for the contents of the published work, including the correctness of the references in the reference list.

CRedit contribution statement

Nitin Agarwala: Conceptualization, Methodology, Formal analysis, Investigation, Writing – original draft, Visualization.

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