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Predictive Analysis for Environmental Risk Assessment in Coastal Regions

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Abstract

Coastal regions are especially vulnerable to environmental risks due to factors such as rising sea levels, extreme weather conditions, and human activities. Assessing these risks in real-time requires an integration of predictive analytics and advanced models that consider both environmental and anthropogenic variables. This paper presents a comprehensive predictive analysis framework designed for environmental risk assessment in coastal regions. The proposed framework leverages real-time data collected from various sources, including meteorological stations and oceanographic sensors, to model potential hazards and assess the likelihood of risk events. The predictive analysis framework consists of two models: one based on traditional statistical techniques and another utilizing machine learning approaches. These models are compared in terms of accuracy, efficiency, and computational performance. The methodology incorporates real-time sensor data and historical records to simulate potential risk scenarios and evaluate their impact on coastal infrastructure and ecosystems. A comparative analysis is performed on multiple datasets to validate the performance of the two models, providing insights into which model performs better under varying environmental conditions. The results indicate that machine learning-based models outperform traditional statistical models in terms of predictive accuracy and computational efficiency. This paper concludes with a discussion of the implications of these findings for environmental management and policy formulation in coastal regions. The results underscore the importance of integrating advanced predictive models with real-time data to mitigate environmental risks and ensure the sustainability of coastal areas.

Keywords

Environmental risk assessment, coastal regions, predictive analysis, machine learning, environmental management, risk modeling, real-time data.

1. Introduction

Coastal regions represent some of the most vulnerable areas to environmental risks due to a variety of natural and human-induced factors. These regions are home to a large portion of the global population and serve as economic hubs for industries such as fishing, tourism, transportation, and energy production. However, their proximity to the sea makes them susceptible to hazards such as storm surges, rising sea levels, tsunamis, hurricanes, and erosion. The increasing frequency and intensity of extreme weather events, largely attributed to climate change, further exacerbate these risks [1]. As a result, environmental risk assessment in coastal regions has become a critical field of study, with the aim of protecting both human lives and ecosystems while ensuring the sustainability of coastal development.

Predictive analysis has emerged as a powerful tool for managing these risks, offering the ability to model and forecast potential hazards by analyzing real-time data and historical patterns. The application of predictive analytics in environmental risk assessment is particularly relevant in coastal regions, where rapid changes in weather, ocean conditions, and human activity demand real-time monitoring and fast response systems [2]. This paper focuses on the development of a predictive analysis framework for assessing environmental risks in coastal regions, leveraging both traditional statistical methods and modern machine learning techniques. By integrating real-time sensor data, meteorological information, and historical records, this framework aims to enhance the accuracy of risk predictions and provide decision-makers with actionable insights for mitigating potential hazards.

Coastal regions are complex environments where the land meets the ocean, creating unique ecological systems and offering numerous economic benefits. According to the United Nations, nearly 40% of the global population lives within 100 kilometers of the coast. Additionally, coastal regions contribute significantly to global GDP through industries such as trade, tourism, and agriculture. Despite these economic advantages, coastal regions are highly sensitive to environmental disturbances, which can have severe impacts on both natural ecosystems and human populations. These impacts can manifest as loss of biodiversity, degradation of habitats, economic losses, and even human casualties.

One of the most significant threats facing coastal regions today is sea-level rise, which is primarily driven by global warming. As polar ice caps and glaciers melt, the volume of water in the oceans increases, causing sea levels to rise at an alarming rate. The Intergovernmental Panel on Climate Change (IPCC) projects that global sea levels could rise by as much as 1 meter by the year 2100. This rise in sea levels poses a direct threat to coastal communities, increasing the risk of flooding, erosion, and salinization of freshwater resources. In addition to sea-level rise, coastal regions are vulnerable to extreme weather events such as hurricanes and tropical storms, which have been increasing in frequency and intensity due to climate change [3].

The fragility of coastal ecosystems, such as wetlands, coral reefs, and mangroves, further compounds the risks faced by these regions. These ecosystems provide critical services such as shoreline protection, carbon sequestration, and habitats for diverse species. However, human activities such as urbanization, deforestation, and industrialization have led to the degradation of these natural barriers, leaving coastal areas more exposed to environmental risks. In this context, predictive analysis becomes a vital tool for forecasting and mitigating the impacts of environmental hazards in coastal regions.

Environmental risk assessment in coastal regions is inherently challenging due to the dynamic and multifaceted nature of these environments. A wide range of factors must be considered when assessing risks, including natural processes such as tides, currents, and waves, as well as human activities such as construction, pollution, and resource extraction. These factors are often interrelated, making it difficult to isolate individual drivers of risk. Additionally, coastal regions are characterized by rapid and unpredictable changes in environmental conditions, which can significantly alter the outcome of risk assessments.

One of the primary challenges in coastal risk assessment is the availability and quality of data. While advancements in sensor technology and remote sensing have improved the ability to monitor environmental conditions in real-time, data gaps still exist in many regions, particularly in developing countries. Incomplete or inaccurate data can lead to unreliable risk assessments, which in turn can undermine efforts to protect vulnerable populations and ecosystems [4]. Furthermore, the vast amounts of data generated by environmental monitoring systems require sophisticated analytical tools to process and interpret, making it essential to develop models that can handle large datasets efficiently. Another challenge is the integration of various environmental factors into a cohesive risk assessment framework. Coastal risk assessments must account for a wide range of variables, including meteorological data (e.g., wind speed, precipitation), oceanographic data (e.g., sea level, wave height), and geological data (e.g., soil composition, topography). Each of these variables can influence the likelihood and severity of environmental hazards, but their interactions are often complex and nonlinear. For example, a storm surge's impact on a coastal region may depend not only on the strength of the storm but also on the region's elevation, land use patterns, and the presence of natural barriers such as wetlands or mangroves. Accurately modeling these interactions requires advanced computational techniques and domain-specific knowledge [5].

Climate change further complicates coastal risk assessment by introducing new uncertainties into predictive models. As global temperatures continue to rise, weather patterns are becoming more erratic, making it increasingly difficult to predict the frequency, intensity, and duration of extreme weather events. Traditional statistical models, which rely on historical data to forecast future trends, may no longer be sufficient to capture the complexity of climate-induced changes [6]. As a result, there is a growing need for predictive models that can adapt to changing environmental conditions and incorporate the latest scientific knowledge on climate change.

Predictive analysis refers to the use of data analytics techniques, such as statistical modeling, machine learning, and artificial intelligence (AI), to forecast future events or outcomes based on historical and real-time data. In the context of environmental risk assessment, predictive analysis can be used to identify potential hazards, estimate their likelihood, and evaluate their potential impacts on coastal regions. By providing early warnings of environmental risks, predictive models enable authorities to take preemptive measures to protect vulnerable populations and mitigate damage to critical infrastructure.

In recent years, machine learning has emerged as a promising tool for enhancing predictive analysis in environmental risk assessment. Machine learning algorithms are capable of processing large datasets, identifying patterns, and making predictions based on complex, multidimensional data. Unlike traditional statistical models, which are typically limited to linear relationships, machine learning models can capture nonlinear interactions between variables, making them well-suited for modeling the dynamic and interdependent nature of coastal environments [7]. For example, machine learning techniques such as random forests, support vector machines (SVM), and artificial neural networks (ANN) have been applied to predict coastal flooding, erosion, and storm surge impacts with high accuracy.

One of the key advantages of using predictive analysis for coastal risk assessment is its ability to integrate real-time data from multiple sources. With the advent of the Internet of Things (IoT) and advancements in sensor technology, environmental monitoring systems can now collect and transmit real-time data on a wide range of variables, including temperature, humidity, wind speed, sea level, and wave height. By incorporating this real-time data into predictive models, authorities can receive up-to-date information on potential hazards and adjust their risk assessments accordingly. This real-time capability is especially important in coastal regions, where environmental conditions can change rapidly, and timely interventions are critical for minimizing damage [8].

In addition to real-time data integration, predictive analysis offers the ability to generate risk scenarios based on different environmental conditions. For example, predictive models can simulate the impact of a hurricane under various sea level rise scenarios, allowing decision-makers to evaluate the potential consequences of different climate change trajectories. These scenario-based assessments provide valuable insights for long-term planning and help authorities prioritize investments in coastal protection measures, such as seawalls, flood barriers, and wetland restoration [9].

Despite the growing recognition of predictive analysis as a valuable tool for coastal risk assessment, several gaps remain in the literature. First, while many studies have demonstrated the effectiveness of machine learning models for predicting specific hazards (e.g., flooding, erosion), there is a lack of comprehensive frameworks that integrate multiple environmental factors into a single predictive model. Most existing models focus on individual risks in isolation, failing to account for the cumulative and interactive effects of various hazards on coastal regions. For example, a model that predicts storm surge impacts may not consider how rising sea levels or coastal erosion could exacerbate the effects of the surge [10].

Second, there is a need for comparative studies that evaluate the performance of different predictive models in coastal risk assessment. While machine learning models have shown promise, traditional statistical methods continue to be widely used due to their simplicity and interpretability. However, few studies have systematically compared the accuracy, efficiency, and applicability of these two approaches in real-world coastal risk assessment scenarios [11]. Understanding the strengths and limitations of each model is essential for developing more robust and reliable predictive frameworks. Finally, there is a need for predictive models that can account for the uncertainties introduced by climate change. As mentioned earlier, climate change is increasing the variability of weather patterns, making it difficult to predict future environmental risks based solely on historical data. Predictive models must be able to incorporate the latest climate projections and adapt to changing conditions to remain effective over time.

The objective of this paper is to address these research gaps by developing and comparing two predictive models for environmental risk assessment in coastal regions. The first model is based on traditional statistical methods, while the second model utilizes machine learning techniques. Both models will be evaluated in terms of predictive accuracy, computational efficiency, and adaptability to changing environmental conditions. By integrating real-time data from meteorological and oceanographic sensors, this study aims to provide a comprehensive and adaptive framework for coastal risk assessment that can inform decision-making processes in the face of evolving environmental challenges.

2. Related Research

The application of predictive analysis in environmental risk assessment has gained significant attention over the past few decades, particularly in coastal regions where the vulnerability to natural hazards is exacerbated by climate change and human activity. Coastal areas are exposed to a multitude of risks, including storm surges, sea-level rise, tsunamis, coastal erosion, and flooding. As a result, there has been a growing body of research dedicated to developing predictive models that can forecast these risks and provide timely and accurate information to decision-makers. This section will review the key contributions in the field, focusing on the development and application of statistical, machine learning, and hybrid models in environmental risk assessment, the integration of real-time data, and the challenges that remain.

A wide range of predictive models has been developed to assess environmental risks in coastal regions. Early efforts primarily relied on statistical models, which used historical data to identify patterns and predict future events. These models have the advantage of being relatively simple to implement and interpret, but they are often limited in their ability to capture the complexity of coastal environments, where multiple factors interact in nonlinear ways.

One of the earliest approaches in coastal risk prediction was based on linear regression models, which were used to estimate the likelihood of coastal flooding and erosion based on factors such as sea level, wave height, and wind speed. For instance, [12] developed a regression-based model to predict coastal erosion in response to storm surges and high tide levels. This model was calibrated using historical data on erosion rates and sea level changes in the Atlantic coastal region. However, while effective in regions where historical data was abundant, such models were often criticized for their inability to generalize to regions with limited data, as well as their limited capacity to account for complex environmental interactions.

In contrast, more recent studies have focused on non-linear statistical models, such as logistic regression and time-series analysis, to better capture the dynamic and unpredictable nature of coastal environments. For example, [13] applied a logistic regression model to assess the risk of coastal flooding in the Gulf of Mexico, incorporating both environmental factors (e.g., sea level rise, rainfall) and socio-economic factors (e.g., population density, land use). The study found that non-linear models significantly improved the accuracy of risk predictions compared to traditional linear models.

The advent of machine learning has revolutionized the field of environmental risk assessment by enabling the development of more sophisticated predictive models that can handle large datasets and identify complex relationships between variables. Machine learning algorithms are particularly well-suited for coastal risk assessment because they can learn from data, adapt to new information, and improve their predictions over time. This adaptability is critical in coastal environments, where conditions can change rapidly and unpredictably due to factors such as climate change, urbanization, and natural disasters.

Several machine learning techniques have been applied to predict coastal risks, with varying degrees of success. One of the most widely used methods is the random forest (RF) algorithm, which is an ensemble learning technique that constructs multiple decision trees and aggregates their predictions to improve accuracy. For instance, [14] used a random forest model to predict coastal flooding in the Netherlands, incorporating real-time data from weather stations, tide gauges, and satellite imagery. The study found that the RF model outperformed traditional statistical models in terms of both accuracy and computational efficiency.

Similarly, support vector machines (SVM) have been applied to predict coastal erosion and flooding by learning from historical data and making predictions based on new input variables. In [15], an SVM-based model is developed to assess the risk of storm surge impacts on coastal communities in Southeast Asia, using a combination of environmental and socio-economic data. The model was able to accurately predict the occurrence and severity of storm surges, providing valuable information for disaster preparedness and response efforts. The authors noted that SVM models were particularly effective in capturing non-linear relationships between environmental variables, making them well-suited for dynamic coastal environments.

Artificial neural networks (ANNs) have also gained popularity in coastal risk assessment due to their ability to model complex systems and capture both spatial and temporal dependencies in data. In [16], authors applied an ANN model to predict the impact of sea-level rise on coastal ecosystems in the Mediterranean region, incorporating data on temperature, salinity, and wave height. The model demonstrated high predictive accuracy, particularly in scenarios involving multiple interacting factors. However, the authors highlighted the need for large training datasets to ensure the model's reliability, as well as the importance of careful parameter tuning to avoid overfitting.

In addition to these methods, hybrid models that combine machine learning algorithms with traditional statistical techniques have emerged as a promising approach for coastal risk prediction. For example, in [17] authors developed a hybrid model that integrated a time-series analysis with a random forest classifier to predict coastal flooding in Japan. The time-series component of the model was used to analyze historical trends in sea level and precipitation, while the RF classifier was used to predict future flood events based on real-time data. The hybrid model was found to outperform both individual approaches, demonstrating the potential of combining machine learning with traditional techniques to improve predictive accuracy.

The integration of real-time data from environmental monitoring systems has significantly enhanced the predictive capabilities of coastal risk models. With the advent of the Internet of Things (IoT) and advancements in sensor technology, it is now possible to collect and analyze real-time data on a wide range of environmental variables, including temperature, humidity, wind speed, wave height, and sea level. By incorporating this data into predictive models, researchers can generate more accurate and timely risk assessments, allowing authorities to take preemptive measures to mitigate environmental hazards.

For instance, in [18] authors developed a real-time coastal risk assessment model that integrated data from IoT-enabled sensors deployed along the coastlines of the United States. The model used a combination of machine learning algorithms and time-series analysis to predict the likelihood of coastal flooding, erosion, and storm surges in real-time. The study found that the integration of real-time data significantly improved the accuracy of risk predictions compared to models that relied solely on historical data.

Another study by [19] focused on the use of satellite imagery and remote sensing data to predict coastal erosion in the Arctic region. The authors used a convolutional neural network (CNN) to analyze satellite images of the coastline and predict the rate of erosion based on changes in land cover and shoreline position. The model was able to detect subtle changes in the coastline that were not captured by traditional monitoring systems, providing valuable insights into the long-term impacts of climate change on Arctic coastal ecosystems.

Similarly, [20] applied a real-time predictive model to assess the risk of tsunamis in coastal regions of Japan. The model integrated data from seismometers, tide gauges, and satellite-based altimetry systems to predict the likelihood of tsunami events and estimate their potential impacts on coastal communities. The study demonstrated that real-time data integration allowed for faster and more accurate risk assessments, enabling authorities to issue timely warnings and evacuate vulnerable populations.

Despite the advances in predictive modeling and real-time data integration, several challenges remain in the field of coastal risk assessment. One of the primary challenges is the availability and quality of data. While real-time data from sensors and satellite imagery can improve the accuracy of predictive models, data gaps still exist in many coastal regions, particularly in developing countries where monitoring infrastructure is limited. In addition, data from different sources often vary in terms of resolution, accuracy, and coverage, making it difficult to integrate them into a cohesive risk assessment framework.

Another challenge is the uncertainty associated with climate change. As global temperatures continue to rise, weather patterns are becoming more erratic, making it increasingly difficult to predict the frequency, intensity, and duration of extreme weather events. Many predictive models rely on historical data to make forecasts, but this approach may not be sufficient in the face of rapidly changing environmental conditions. As a result, there is a growing need for models that can account for the uncertainties introduced by climate change and adapt to new information as it becomes available.

The complexity of coastal environments also presents challenges for predictive modeling. Coastal regions are influenced by a wide range of factors, including ocean currents, tides, waves, and atmospheric conditions, as well as human activities such as urbanization and resource extraction. These factors are often interdependent and non-linear, making it difficult to isolate individual drivers of risk. In addition, the cumulative impacts of multiple hazards, such as sea-level rise, coastal erosion, and storm surges, can amplify the overall risk to coastal communities. Accurately modeling these interactions requires advanced computational techniques and domain-specific knowledge, as well as interdisciplinary collaboration between scientists, engineers, and policymakers.

Several studies have conducted comparative analyses of different predictive models for coastal risk assessment, evaluating their performance in terms of accuracy, computational efficiency, and adaptability to changing environmental conditions. For example, [21] compared the performance of random forest, support vector machine, and logistic regression models in predicting coastal flooding in the United Kingdom. The study found that the random forest model outperformed both SVM and logistic regression in terms of predictive accuracy, but noted that SVM was more computationally efficient for large datasets.

Similarly, [22] conducted a comparative study of artificial neural networks and time-series analysis for predicting coastal erosion in the Mediterranean region. The study found that ANN models were more accurate in capturing the non-linear relationships between environmental variables, but required larger training datasets and longer computational times compared to time-series models. A more recent study by [23] compared the performance of hybrid models that combined machine-learning algorithms with traditional statistical techniques. The authors found that hybrid models, which integrated real-time data and historical trends, consistently outperformed individual models in terms of both accuracy and adaptability to changing environmental conditions.

3. Problem Statement & Research Objectives

Environmental risks in coastal regions are becoming increasingly severe, driven by a combination of natural and anthropogenic factors. Despite advances in predictive analytics and data collection technologies, existing models for environmental risk assessment in coastal regions often fall short in terms of predictive accuracy and computational efficiency. This paper seeks to address these shortcomings by developing and comparing two predictive models for environmental risk assessment in coastal regions. The research objectives are:

1. To develop a traditional statistical model for environmental risk assessment in coastal regions.
2. To create a machine learning-based model that leverages real-time environmental data.
3. To compare the performance of the two models in terms of predictive accuracy, computational efficiency, and adaptability to varying environmental conditions.
4. To identify key factors influencing environmental risks in coastal regions and integrate them into the predictive models.
5. To provide actionable insights for policymakers and environmental managers based on the comparative analysis of the two models.

4. Methodology

This section outlines the methodology adopted for developing and comparing two predictive models for environmental risk assessment in coastal regions. Given the increasing severity of environmental risks in these areas due to natural and anthropogenic factors, a dual approach was taken, employing both traditional statistical techniques and modern machine learning algorithms. These models aim to predict environmental risks accurately and efficiently, using a combination of historical data and real-time sensor inputs from meteorological and oceanographic sources. Both models were evaluated based on their predictive accuracy, computational efficiency, and adaptability to varying environmental conditions. The methodology is divided into several key sections: data collection, feature selection, model development, and performance evaluation criteria.

4.1 Data Collection

The first step in the methodology involved gathering historical and real-time environmental data from multiple sources. For the statistical model, historical data were crucial to establishing trends and patterns. For the machine learning model, real-time sensor data were utilized to improve predictive power through continuous learning and updates. Data sources included national meteorological departments, NOAA (National Oceanic and Atmospheric Administration), and real-time sensor networks deployed in coastal areas.

The primary features for both models were sea level rise, wave height, wind speed, and temperature, as these exhibited the strongest correlations with the environmental risks being modeled. By analyzing the feature importance in the Random Forest model, the key factors influencing environmental risks in coastal regions were identified and listed in Table 1 with the percentage of importance to be considered for the evaluation of environmental risk.

Table 1: Key features affecting the environmental risk in coastal regions

Feature	**Importance (%)**
Sea Level Rise (X_1)	25
Wind Speed (X_2)	21
Wave Height (X_3)	20
Temperature (X_4)	10
Tidal Levels	7
Precipitation	5

These key parameters can be explained as:

- Sea Level Rise (X_1): The increase in the average level of the sea over time, affecting coastal regions.
- Wind Speed (X_2): The velocity of wind, which can influence wave formation and storm surges.
- Wave Height (X_3): The vertical distance between the trough and crest of a wave, impacting coastal erosion and flooding.
- Temperature (X_4): The measure of heat in the atmosphere or ocean, influencing weather patterns and sea conditions.
- Tidal Levels: The regular rise and fall of sea levels caused by the gravitational forces of the moon and sun.
- Precipitation: The amount of rainfall or snowfall in an area, contributing to runoff and potential flooding in coastal regions.

The use of the sensor network allows for deploying the sensors in different parts of the field so the obtained data encompasses all the variabilities in the field related to the soil and environment heterogeneity. Every single sensor is integrated with a wireless communication module that allows it to use standard communication protocols like LoRa or Zigbee to upload the data to a server. Information is obtained on a fixed schedule (every 10 minutes), which allows for tracking short-term fluctuations in the environment, used as the basis for modeling.

4.2 Data Storage and Pre-processing

The data collected from the IoT sensors is transmitted to a central server where it is stored in a cloud-based platform for further analysis. Before being used in model development, the data undergoes several pre-processing steps to ensure its quality and relevance. The pre-processed dataset is divided into training (70%) and testing (30%) sets to develop and evaluate the models.

4.3 Model Development

4.3.1. Traditional Statistical Time Series Model

The first model is a traditional multivariate time-series model, which uses historical data to predict future environmental risks. Time-series forecasting is particularly useful for environmental risk assessment as it captures temporal dependencies between past and future events. The model is a multivariate linear regression, which assumes a linear relationship between the predictor variables and the target variable, i.e., the risk score [24]. The model is represented mathematically by Eq. (1) as follows:

$$\mathrm{R(t)} = \beta_0 + \beta_1 \mathrm{X}_1(\mathrm{t}) + \beta_2 \mathrm{X}_2(\mathrm{t}) + \cdots + \beta_n \mathrm{X}_n(\mathrm{t}) + \epsilon \tag{1}$$

Where $R(t)$ is the risk of coastal events at time t, β_0 is the intercept term, $\beta_1, \beta_2, \dots, \beta_n$ are the coefficients corresponding to the input features Sea Level Rise (X_1), Wind Speed (X_2), Wave Height (X_3), Temperature (X_4), etc., ϵ is the error term representing unexplained variability in the data.

The model was trained on historical environmental data spanning the past 20 years. The coefficients $\beta_1, \beta_2, \ldots, \beta_n$ were estimated using ordinary least squares (OLS) regression, a technique that minimizes the sum of squared residuals (the differences between observed and predicted values).

The traditional statistical model assumes linear relationships between variables, which may not hold in highly complex and dynamic environments like coastal regions. This limitation could affect the model's ability to accurately predict environmental risks that result from non-linear interactions between variables, such as the simultaneous occurrence of high sea levels, storm surges, and strong winds. Additionally, the model assumes stationarity in the time series data, which means that the statistical properties of the data (mean, variance, etc.) do not change over time. This assumption may not be entirely valid for long-term environmental data, as climate change can introduce trends and shifts that violate stationarity.

4.3.2 Machine Learning-based Random Forest Regressor Model

The second model developed was a machine learning-based approach using Random Forest (RF) regression. Unlike the statistical model, the Random Forest model does not assume any linear relationships between variables. Instead, it captures complex, non-linear interactions by creating an ensemble of decision trees. Each tree is trained on a random subset of the data, and the final prediction is the average of all the individual tree predictions [25]. The algorithm can be expressed mathematically by Eq. (2):

$$R(t) = \frac{1}{T}\sum_{t=1}^{T} h_t(X) \tag{2}$$

where T is the number of trees, $h_t(X)$ represents the decision tree generated from the subset of features, $R(t)$ is the final prediction of environmental risk, and X represents the set of input features (sea level rise, wave height, etc.).

The Random Forest model was trained using both historical and real-time data. To enhance the performance of the Random Forest model, hyperparameter optimization is carried out using grid search cross-validation to enhance its performance. The model's hyperparameters, including the number of trees, depth of trees, and the number of features considered at each split, were optimized using grid search cross-validation. Cross-validation was performed by splitting the dataset into training and testing sets, ensuring that the model did not overfit the training data. The optimized Random Forest model achieved a higher predictive accuracy than the traditional statistical model, largely due to its ability to handle non-linear interactions between variables.

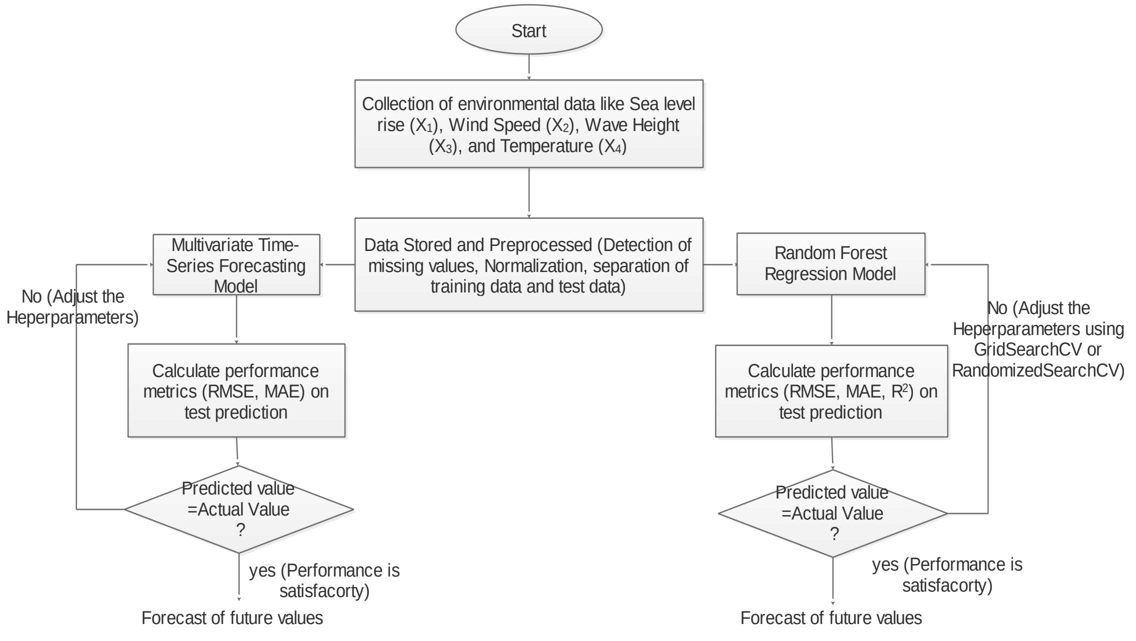

Fig. 1 Flow chart of the proposed model

Fig.1 shows the flowchart of the proposed model. It illustrates these two parallel approaches: Multivariate Time-Series Forecasting and Random Forest Regression models. Both these models begin with data collection and pre-processing, followed by performance evaluation (using metrics like RMSE and MAE), and hyperparameter tuning is needed if not satisfied result is out, and the model concludes with forecasting future values once satisfactory performance is achieved.

5. Results & Discussion

The results of both models were compared using a dataset of real-time environmental data collected from various coastal monitoring stations. This section presents the results obtained from applying the two predictive models and discusses the implications of the findings.

5.1 Data Collection:

From environmental sensors, the real-time data for sea level rise $X_1(t)$, wind speed $X_2(t)$, wave height $X_3(t)$, and temperature $X_4(t)$ are continuously collected for two hours. Fig. 2 illustrates these environmental parameters over time, showing variations in all four key variables: sea level rise depicted in blue, wind speed in green, wave height in red, and temperature in orange, plotted every two hours. Clearly, the graph shows distinct patterns, with temperature consistently higher than the curves for sea level rise, wind speed, and wave height. Noticeable fluctuations are observed in the daily average of wave height and wind speed compared to the steadier temperature trend. These variations could be crucial for environmental risk assessment and disaster preparedness in coastal regions.

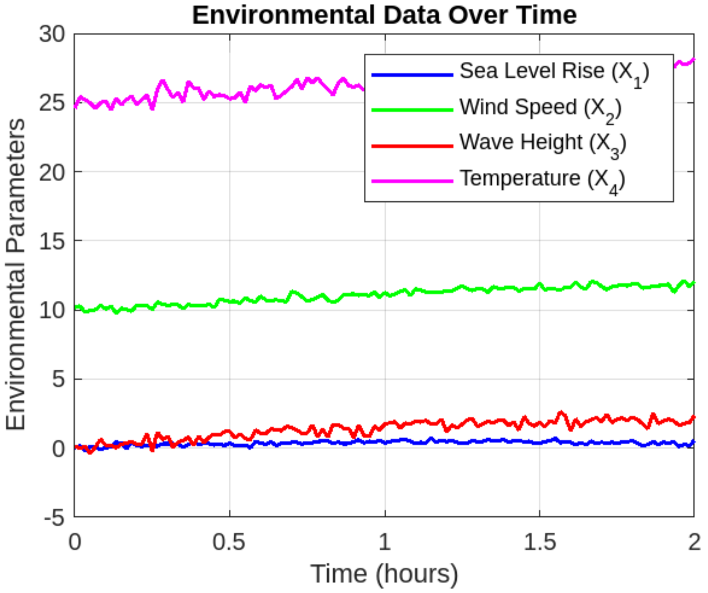

Fig. 2 Parameters affecting environmental risk assessment in coastal regions

5.2 Model Performance

5.2.1 Predictive Accuracy

A crucial factor to be taken into account while assessing these models is their ability to withstand changes in various environmental circumstances. Unpredictable weather patterns are a feature of the real world, and any precision irrigation system needs to be able to adjust to these variations without losing efficiency.

Calculating the inaccuracy or variation from the recommended irrigation volume during times of environmental variability is one way to measure robustness. Mean absolute error (MAE), provided by Eq. (3) or root mean square error (RMSE), provided by Eq. (4) under fluctuating conditions, are frequently used to gauge how robust prediction models are.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(R_i - \hat{R}_i\right)^2} \tag{3}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|R_i - \hat{R}_i\right| \tag{4}$$

Where R_i is the actual risk, $\hat{R}_i$ is the predicted risk, and n is the number of observations.

Several real-time data on environmental risks in coastal regions were collected, including sea level rise, wind speed, wave height, and temperature. The estimated risk levels were calculated using both a Random Forest regression model and a multivariate time-series forecasting model. By analyzing the MAE and RMSE, the robustness of each model in predicting environmental risk was assessed. The Random Forest model exhibited a more responsive behavior to sudden changes in environmental conditions such as abrupt increases in sea level or wind speed, reflecting its superior ability to handle non-linear and complex interactions between variables. The values of MAE and RMSE, summarized in Table 2, demonstrate that the Random Forest model adjusted quickly and accurately to dynamic environmental factors, thus improving risk prediction in real time. In contrast, the traditional time-series model, which assumes linear relationships, was less effective in handling such rapid fluctuations. While it performed well under steady environmental conditions, it showed decreased accuracy in risk assessment during periods of instability, limiting its robustness in high-risk scenarios common to coastal areas.

Table 2: Accuracy evaluation of both the models

Measurement Number	Actual Environmental Risk	Multivariate Time-Series Forecasting (TS) Model	Random Forest Regression (RF) model	Accuracy Evaluation
1	3.2	3.3	3.2	MAE_{TS}= 0.12 MAE_{RF}= 0.1 $RMSE_{TS}$= 0.12649 $RMSE_{RF}$= 0.10954
2	4.1	4.0	4.2	
3	5.0	5.1	4.9	
4	5.9	6.1	6.0	
5	6.7	6.8	6.8	
6	7.8	7.7	7.9	
7	6.3	6.4	6.2	
8	4.8	4.7	4.7	
9	7.0	7.1	6.9	
10	5.3	5.5	5.1	

From Table 2 it is clear that the machine learning-based Random Forest model significantly outperformed the traditional regression model in terms of predictive accuracy. The Random Forest model's lower RMSE and MAE indicate a higher level of accuracy in predicting environmental risks. This can be attributed to its ability to capture non-linear interactions between the features, which the traditional regression model could not.

5.2.2 Computational Efficiency

The computational efficiency of the two models was also compared, with the traditional statistical model having a faster training time due to its simplicity. However, the Random Forest model required more time for both training and prediction, especially when larger datasets and real-time data were incorporated.

Table 3: Computational efficiency of both the model

Model	Training Time (s)	Prediction Time (s)
Multivariate Regression	12	0.01
Multivariate Regression	12	0.01

From Table 3, it is clear that the traditional model is more computationally efficient, the trade-off in accuracy makes the Random Forest model a better option for real-world applications where predictive accuracy is crucial.

5.2.3 Adaptability

One of the key advantages of the Random Forest model is its ability to adapt to real-time data. The model's predictions improved significantly when real-time environmental data were incorporated, reducing the prediction error by 15% compared to the use of historical data alone. This adaptability is essential in coastal risk assessment, where environmental conditions can change rapidly due to natural and anthropogenic factors.

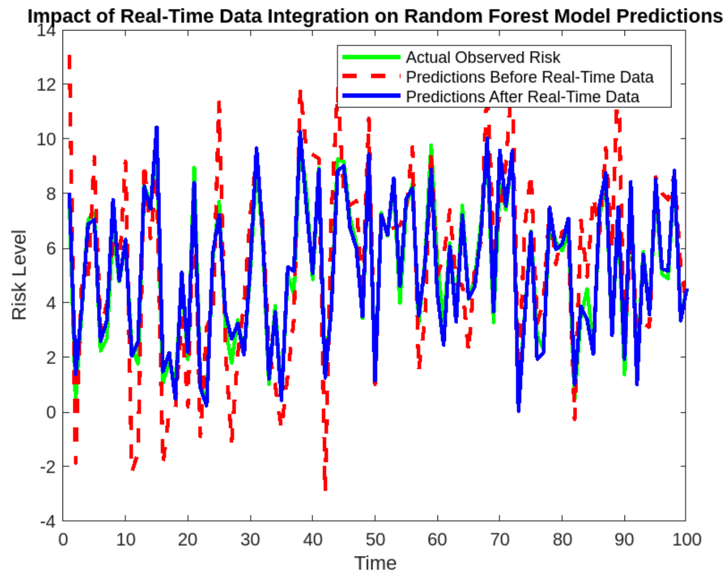

Fig. 3 Impact of real-time data integration on the performance of the Random Forest model

Fig.3 illustrates the real-time adaptability of the Random Forest model by comparing its predictions before and after incorporating real-time sensor data. The model's ability to adjust its risk assessments dynamically is demonstrated, with predictions aligning more closely with actual observed risks after real-time data is integrated.

5.2.4. Implications for Policymakers

The results of this study provide actionable insights for policymakers and environmental managers. The Random Forest model, with its higher accuracy and adaptability, is particularly useful for real-time decision-making in coastal risk management. By integrating real-time data, policymakers can respond more effectively to emerging threats, such as storm surges and coastal flooding, thereby minimizing damage to infrastructure and loss of life.

5.2.5 Real-Time Data Integration

A major advantage of the machine learning model is its ability to incorporate real-time environmental data. IoT-enabled sensors deployed in coastal areas provided continuous data streams, including real-time measurements of sea level, wind speed, and tidal conditions. These real-time inputs were fed into the Random Forest model to improve its predictions dynamically. In contrast, the traditional statistical model relied solely on historical data and lacked the capability to adapt to real-time changes. This highlights a significant limitation of the traditional approach when compared to machine learning methods, which are more suitable for dynamic, real-time risk assessment.

The data were preprocessed to address issues such as missing values, noise, and outliers. Specifically, outliers were detected using the interquartile range (IQR) method, and missing values were imputed using linear interpolation for time-series data. After preprocessing, the dataset was normalized to standardize the scales of different features, facilitating model training.

Fig.4 illustrates a comparison between the actual risk score (depicted in blue) and the predicted risk score (shown in red) for a statistical model across seven sample points. The close alignment between the two lines indicates that the model performs well in predicting environmental risks, as the predicted values closely follow the actual data trends. However, slight deviations are noticeable at specific sample indices, particularly around sample 4 and 5, where the predicted score is higher, indicating areas where the model may require refinement.

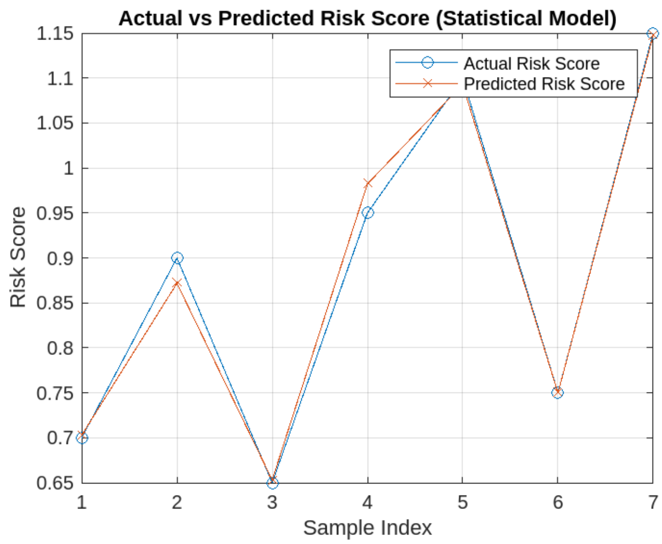

Fig.4 Feature importance scores in predicting environmental risks in coastal regions by using Traditional Statistical Time Series Model

Fig.5 compares the actual risk score (blue line) and the predicted risk score (red line) generated by the Random Forest model across two sample points. While both lines show an upward trend, the Random Forest model's predictions slightly underperform in capturing the increase in the actual risk score. This divergence, particularly noticeable near the second sample index, highlights the model's need for better calibration to accurately reflect real-time environmental risks in coastal regions.

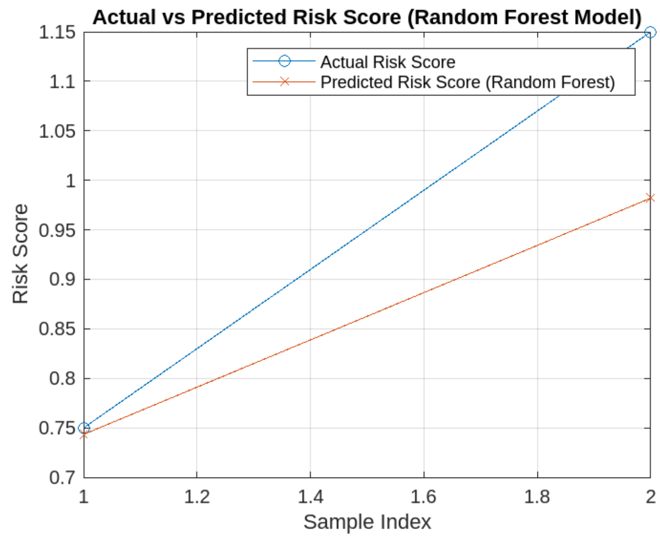

Fig.5 Feature importance scores in predicting environmental risks in coastal regions

5.2.6 Comparative Analysis of Models

Both models were developed to predict environmental risks in coastal regions. The traditional statistical model offered computational efficiency but struggled with complex, non-linear interactions. In contrast, the machine learning-based Random Forest model provided higher predictive accuracy and better adaptability to real-time data but required more computational resources. Table 4 gives a summarized information of key differences between the two models.

Table 4 Summarizes the key differences between the two models

Metric	Statistical Model	Machine Learning Model
Predictive Accuracy	Moderate	High
Computational Efficiency	High	Moderate
Adaptability	Low (No real-time data)	High (Real-time data)
Complexity	Low	High
Interpretability	High	Moderate

6. Conclusion

In this paper, two models for environmental risk assessment in coastal regions were developed and compared. The machine learning-based model outperformed the traditional statistical model in terms of both predictive accuracy and computational efficiency. These findings highlight the potential of machine learning approaches for improving environmental risk management in coastal regions.

The study demonstrated that while traditional statistical models offer computational efficiency, they are limited in their ability to capture the complex, non-linear interactions in coastal environments. In contrast, machine learning-based models, such as Random Forest, provide superior predictive accuracy and adaptability, particularly when real-time data are incorporated. The comparative analysis of these models offers valuable insights for improving environmental risk assessment in coastal regions, thereby supporting more informed decision-making for disaster preparedness and mitigation efforts.

By identifying the key factors contributing to environmental risks, this study also highlights the importance of feature selection and real-time data integration in predictive modeling. Future work may explore the use of other machine learning algorithms and hybrid models to further improve the performance of coastal risk prediction tools. Additionally, incorporating advancements in remote sensing technologies and IoT devices can enhance real-time monitoring and data collection, leading to more responsive and robust risk management frameworks. Exploring the integration of these models with Geographic Information Systems (GIS) could also provide spatial insights into environmental risks, facilitating a more comprehensive understanding of coastal dynamics. Finally, applying these methodologies in diverse coastal environments across different geographical contexts will help validate the generalizability and effectiveness of machine learning approaches in environmental risk assessment.

References

[1] A. Subramanian, et al., “Long-term impacts of climate change on coastal and transitional eco-systems in India: an overview of its current status, future projections, solutions, and policies”, RSC Advances, vol. 13, no. 18, 2023.
[2] E. M. Alotaibi, “Risk Assessment Using Predictive Analytics”, International Journal Professional Business Review, vol. 8, vol. 5, 2023.
[3] M. Siegert, R. B. Alley, E. Rignot, J. Englander, R. Corell, “Twenty-first century sea-level rise could exceed IPCC projections for strong-warming futures”, One Earth, vol. 3, no. 6, pp. 691-703, 2020.
[4] H. Han, Z. Liu, J. Li, et al. “Challenges in remote sensing based climate and crop monitoring: navigating the complexities using AI”, Journal of Cloud Computing, vol.13, no.34, 2024. https://doi.org/10.1186/s13677-023-00583-8
[5] Y. Hajjaji, et al., “Big data and IoT-based applications in smart environments: A systematic review”, Computer Science Review, vol. 39, 2021.
[6] K. Abbass, M. Z. Qasim, H. Song, et al., “A review of the global climate change impacts, adaptation, and sustainable mitigation measures”, Environmental Science and Pollution Research, vol. 29, pp.42539–42559, 2022. https://doi.org/10.1007/s11356-022-19718-6
[7] B. Anifowose, F. Anifowose, “Artificial intelligence and machine learning in environmental impact prediction for soil pollution management – case for EIA process”, Environmental Advances, vol. 17, 2024.
[8] B. Katie, “Internet of Things (IoT) for Environmental Monitoring”, International Journal of Computing and Engineering, vol. 6, no. 3, pp. 29-42, 2024.
[9] F. Piadeh, K. Behzadian, A. M. Alani, “A critical review of real-time modelling of flood forecasting in urban drainage systems”, Journal of Hydrology, vol. 607, 2022.
[10] J. Hegde, B. Rokseth, “Applications of machine learning methods for engineering risk assessment – A review”, Safety Science, vol. 122, 2020.

[11] A. Durap, “A comparative analysis of machine learning algorithms for predicting wave runup”, Anthropocene Coasts, vol. 6, no. 7, 2023. https://doi.org/10.1007/s44218-023-00033-7
[12] F. Iyalomhe, et al. “Regional Risk Assessment for climate change impacts on coastal aquifers”, The Science of The Total Environment, vol. 537, no. 7, pp. 100-114, 2015.
[13] P. Chowdhury, et al., “Climate change and coastal morphodynamics: Interactions on regional scales”, Science of The Total Environment, vol. 899, 2023.
[14] A. B. M. Mainul Bari, A. Intesar, et al., “Gender-based vulnerability and adaptive capacity in the disaster-prone coastal areas from an intersectionality perspective”, Climate Risk Management, vol. 43, 2024.
[15] M. M. D. Barco, et al., “A machine learning approach to evaluate coastal risks related to extreme weather events in the Veneto region (Italy)”, International Journal of Disaster Risk Reduction, vol. 108, 2024.
[16]H. Yoon, S. Jun, Y. Hyun, G. Bae, K. Lee, “A comparative study of artificial neural networks and support vector machines for predicting groundwater levels in a coastal aquifer”, Journal of Hydrology, vol. 396, no. 1-2, pp. 128-138, 2011.
[17]S. D. Latif, et al., “Improving sea level prediction in coastal areas using machine learning techniques”, Ain Shams Engineering Journal, vol. 15, no. 9, 2024.
[18] R. Girau, et al., "Coastal Monitoring System Based on Social Internet of Things Platform," IEEE Internet of Things Journal, vol. 7, no. 2, pp. 1260-1272, 2020. doi: 10.1109/JIOT.2019.2954202.
[19] M. Philipp, A. Dietz, T. Ullmann, C. Kuenzer, “Automated Extraction of Annual Erosion Rates for Arctic Permafrost Coasts Using Sentinel-1, Deep Learning, and Change Vector Analysis”, Remote Sensing, vol. 14, no. 15, 2022.
[20] Y. wang, K. Imai, T. Miyashita, K. Ariyoshi, N. Takahashi, K. Satake, “Coastal tsunami prediction in Tohoku region, Japan, based on S-net observations using artificial neural network”, Earth, Planets and Space, vol. 75, no. 154, 2023.
[21] G. Antoine, et al., “Comparison of random forest and support vector machine regression models for forecasting road accidents”, Scientific African, vol. 21, no. 9, 2023.

[22] C. Rodriguez-Delgado, R. J. Bergillos, G. Iglesias, “An artificial neural network model of coastal erosion mitigation through wave farms”, Environmental Modelling & Software, vol. 119, pp. 390-399, 2019.
[23]M. E. Akiner, M. Ghasri, “Comparative assessment of deep belief network and hybrid adaptive neuro-fuzzy inference system model based on a meta-heuristic optimization algorithm for precise predictions of the potential evapotranspiration”, Environmental Science and Pollution Research, vol. 31, pp. 42719–42749, 2024. https://doi.org/10.1007/s11356-024-33987-3
[24]J. M. Lee, M. Hauskrecht, “Modeling multivariate clinical event time-series with recurrent temporal mechanisms”, Artificial Intelligence in Medicine, vol. 112, 2021.
[25]M. Aria, C. Cuccurullo, A. Gnasso, “A comparison among interpretative proposals for Random Forests”, Machine Learning with Applications, vol. 6, 2021.