International Journal of Science and Research Archive
eISSN: 2582-8185
Cross Ref DOI: 10.30574/ijsra
Journal homepage: https://ijsra.net/

(Research Article)

Coupling environmental chemistry with Artificial Intelligence for coastal hazard risk assessment under climate change

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International Journal of Science and Research Archive, 2025, 16(03), 498–507

Publication history: Received on 30 July 2025; revised on 05 September 2025; accepted on 07 September 2025

Article DOI: https://doi.org/10.30574/ijsra.2025.16.3.2572

Abstract

Climate change represents a big threat to the coastal regions across the world, as they include hazards such as coastal erosion cycles, storm surges, and the increase in sea level, there by affecting people, infrastructure, and the ecosystem. This research paper seeks to design an integrated framework that will utilize the emerging technologies and predictive modeling to evaluate the risks that are caused by climate change in coastal areas. This approach combines machine learning algorithms (Random Forest (RF), Extreme Gradient Boosting (Boost), and K Nearest Neighbor (KNN)) with GIS to thoroughly assess the risks of hazards in coastal areas of United States - taking into account the impact of sea level rise, climate change scenarios, regional climate models and other environmental metrics. Based on ML and ArcGIS, the research will provide hazard predictions and their effects and project a probability map of risks that will establish areas of priority when it comes to interventions and allocation of resources on safety as well as risk mitigation efforts. Finally, the result of this study is a decision support tool that will improve coastal resilience through resource allocation decisions, safety planning, and risk mitigation approaches related to the rising rate of climate change.

Keywords: Climate Change; Coastal Hazards; Risk Assessment; Sea-Level and Predictive Modeling

1. Introduction

Climate change in coastal areas has numerous impacts on the environment, social and economic well-being that come as a result of climatic changes occurring across the world due to the roles of humans and their release of greenhouse gases. These regions that form the land-sea borders are highly vulnerable to climatic imposed pressures making them a significant border of climate studies. Coastal areas tend to be focused on populations, urban infrastructure, ports and economic activity thus being a hot-spot of vulnerability. There is increasing frequency of extreme impacts such as floods, storm surges and shoreline retreats as sea level rise and precipitation patterns alter. Conventional methods to modeling based on hydrology and physical modelling still form the main focus in understanding these dangers. Nevertheless, they are becoming augmented with data-driven and machine-learning approaches, which can ingest large, heterogeneous data, reveal non-linear interactions, and provide spatially resolved, decision-ready hazard maps. The current paper tends to review previous works and delves into recent developments of new technologies in analyzing climate hazards with emphasis on predictive models of artificial intelligence and machine learning into GIS platforms.

It is constantly identified that coastal areas are the most vulnerable areas under climatic change conditions. Dangers like inundation, erosion and instability of the shorelines not only imperil the ecological setup of the place but they dangerously affect the livelihood and settlements. The development of new technological innovations in the form of

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remote sensing, GIS, internet-connected sensors, and the advanced machine learning models offer new possibilities of risk assessment and resilience planning (Jones and Lee, 2021; Patel et al., 2023). The major aim of the current research project is to develop an encompassing framework that evaluates the effects of climate-related hazards along the coast with an integrated system. Particular emphasis is made on the combination of the robust machine learning classifiers (Random Forest: RF, Extreme Gradient Boosting: XGBoost, K-Nearest neighbor; KNN) and GIS mapping for predictive flood risk analysis (Chen et al., 2024, Bello et al., 2023).

While the growing interest in multi-hazard dynamics is another source of innovation. Recent human-caused environmental change and climate variability have resulted in the growing incidence of multiple simultaneous or sequential hazard events, including drought, downstream resurgent flooding, landslides, and wildfires, and flood compounding. This is likely to cause more damage compared to that brought about by isolated events (Wilhite et al., 2014). Their occurrence, intensity and spatial effect are difficult to predict. The study by Wang et al. (2020) admonishes that integrated modeling frameworks that have the capabilities of considering hazard interactions are highly needed to inform adaptation strategy.

Within the field of flood prediction in particular, much of the early research was based upon deterministic or physics-based hydrological and hydraulic modeling. As an example, Schumann et al. (2013) used measurement data and the modified VIC model to perform flood forecasting in 1-km resolution, in both gauged and ungauged basins. These methods featured good physical re-presentation of hydrological processes but were more computation-extensive and constrained by the quality of input data. Machine learning and deep learning have gained in prominence over the past decade. However, their flexible, data-driven framework can learn patterns across a variety of input variables. In contrast to the classical models of hydrology, data-driven algorithms may be used to fit local data and identify non-linear relationships that can be otherwise missed due to the inability of a traditional model to capture those relationships.

Machine learning algorithm, including support vectors machines (SVMs), decision trees (DTs) and artificial neural networks (ANNs) have been used in hazard classification. Equivalently, the classification of drought severity using SVMs, ANNs, and KNN models is developed in Khan et al. (2020), and susceptibility to wildfire in protected landscapes is predicted based on Bayesian Networks, Naïve Bayes, DTs, and logistic regression (Pham et al., 2018). Recent progress in deep learning including LSTM networks, CNNs and DNNs have been proposed to train sequential modelling and high-resolution flood susceptibility maps (Fang et al., 2021). These methods have great prospects in finding spatial-temporal hazard patterns. Nevertheless, the issues of data needs and computational requirements, as well as the interpretability of the model are still there. In contrast, the traditional models may have difficulty with high-dimensional spatiotemporal data sets whereas deep learning models are opaque, which can be a perceived problem. An attempt to correct these problems will be to combine the different types of data, architectures that are easier to interpret and practice hybrid machine learning which combines both scientifically and statistically rigorous work and physical knowledge (Antzoulatos et al., 2022).

The present paper suggests the implementation of ensemble machine learning models- Random Forest, K-Nearest Neighbour, and Extreme Gradient Boosting-and uses them to forecast the multi-hazard in coasts. Such models are appropriate to process complex environmental data because it is robust, has the capacity to work with high-dimensional variable, and it discourages overfitting. Simplicity is reflected in the addition of K-Nearest Neighbor that gives an understanding of the difference in classifiers. With a GIS infrastructure the algorithms can create 2-dimensional grid-based damage susceptibility maps which provide local decision-makers with a visual representation of the spatial distribution of hazard probabilities as a basis to support zoning, evacuation planning and infrastructure development.

The value of this review is that it has a multidimensional outlook. As opposed to describing hazards in a silo, it designs models to accommodate the compound character of climate risks. Second, it places more emphasis on predictive power through the use of various inputs that include climatic records and characteristics, land-use data and climate indices. Third, it is more interpretable in that the outcome is presented in formats that can be understood and used easily by policymakers and coastal stakeholders. The given contributions resonate with growing need in comprehensive, information-based, and humanity-oriented methods to climate adaptation.

The need to act with regard to coast climate threats is highlighted by crisis statistics in the recent past. In the United States, 2023 experienced 28 singular climatic and weather events that were individually valued at billion-dollars, such as severe storms, floods, cyclones, wildfires, winter storms, and heatwaves causing damages of almost 93 billion dollars (NCEI, 2024). There were more than a million dollars in disaster expenses between 2017 and 2023, and when inflation is not factored in since 1980, the total amount amounted to more than 2.7 trillion dollars (NCEI, 2024). All these statistics reveal the growing social, economic, and environmental threat of extreme weather conditions and reflect the ways climate change forms the role of the so-called disaster multiplier, stimulating the frequency and magnitude of the hazards, along with an increase in exposure and vulnerability in highly populated coastal areas. Against this background, the aims of this study are as follows: (i) to design an integrated framework in which machine learning algorithms, GIS, and environmental datasets could be used to evaluate and reduce climate-related risks along the coasts and, in particular, to mitigate flood hazards along the U.S. coasts; (ii) to apply Random Forest, Extreme Gradient Boosting, and K-Nearest Neighbor and to combine these machine learning algorithms with GIS and remote sensing in order to isolate high-risk flood zones and determine the current extent of coastal flood vulnerability This research methodology enhancement empowers not only scholarly research work but also its application into practice by policymakers, urban planners, and local people.

This paper tends to adds to the growing body of literature on the perspective of how climate change is affecting the coast by integrating new data-driven technologies into the learnings. The results are not only relevant to academia as a methodological approach but also to decision-makers, who have to manage risks in some of the most fragile and vulnerable environments throughout the world.

2. Related works

Recent literature has helped add importance to machine learning and new technology in coastal climate adaptation and mitigation of floods. Although a number of studies have been conducted on implementing ML to flood susceptibility analysis in coastal areas, the major challenge has been the inability to incorporate all-inclusive environmental data to bring out more detailed results regarding susceptibility (Ali et al., 2019; Park and Lee, 2020; Al-Hinai and Abdalla, 2021). Whatever is needed to fill in this gap is the innovative models that can accommodate a variety of geospatial and climatic factors.

Machine learning techniques that have been tested in the application of hydrological and climate related predictions are quite diverse. Sarzaeim et al. (2018) used support vector machine (SVM), genetic programming (GP), and neural networks artificial (ANN) to predict runoffs in Iran, and the model performance showed that SVM models are 7 and 5 percent better than GP and ANN, respectively. This was also the case in other studies by Modaresi et al. (2018) where they compared K-nearest neighbor (KNN), ANN, least-square support vector regression (LS-SVR), and generalized regression neural networks (GRNN) in dam inflow prediction and ANN was found best performing. Kim et al. (2019) concluded that MLP had a better performance in comparison to MARS, SVM, and ANFIS methods to estimate runoff in the U.S. Wu et al. (2019) did a study in China and found that tree-based models including extreme gradient boosting (XGBoost), random forest (RF), and gradient boosting decision trees (GBDT) are more accurate compared to kernel-based or shallow models. Ni et al. (2024) later confirmed this but gave mixed results than XGBoost performed better than SVM at Hankou station but worse than SVM at Cuntan station, indicating possible site-specific performance.

In flood forecasting, Thapa et al. (2019) used simulation results to compare SVM, KNN, Naive Bayes and deep neural networks (DNNs) on Indian river basins, which showed that DNNs demonstrated a high level of accuracy. Besides flood-centered tasks, Kaur et al. (2019) also evaluated ensemble models, including AdaBoost, GBM, XGBoost, and RF in power load scheduling with XGBoost and AdaBoost being slightly better. For mineralogical modeling, AdaBoost, MLP, and SVM had the highest R 2 scores (0.9 and above) (Oliveira and Carneiro 2019), which was also used in Brazil, although RF and AdaBoost showed the best result with R 2 equal to 0.99 (Zhu et al. 2019).

Ren et al. (2020) applied ANN, SVM, RF, and linear regression to downscaling temperature in Tibet and concluded that RF is the most efficient. Some other ensemble comparisons include Ahmed et al. (2020), who utilize ANN, KNN, relevance vector machines (RVM), and SVM over 36 GCMs in Pakistan with the best results obtained by RVM and KNN. Hosseini et al. (2020) also showed that all three ANN, ANFIS, and KNN models had satisfactory results when downscaling precipitation in Iran. These findings point out that there is still no clear algorithm that can be considered as the best algorithm and that the selection should be made according to the targeted process, the input data, and the area.

Chen, et al. (2024) improved on this existing literature by using RF together with GIS when determining multi-hazard susceptibility in coastal regions. Their methodology also showed that RF can process a wide range of geospatial data- elevation, slope, rainfall, land use, distance to shoreline, among others- and make those parameters interpretable by ranking the relative importance of those parameters, a key feature in such risk-reduction efforts. On a larger scale, this was the scope of Rolnick et al. (2019) who described the applications of ML in addressing climate change in the context of renewable energy forecasting, transportation, agriculture, and disaster risk management. They also demonstrate the opportunities and challenges of ML, specifically data availability, interpretability, and energy costs they provide a taxonomy that sets ML in its context.

The real-time Flood Alert System (FAS) presented by Ghimire et al. (2020) used an Extreme Gradient Boosting (XGBoost) model to predict river stage levels by the five-minute interval and will allow the authors to apply it to an Austin, Texas watershed. By feeding a model with time-series hydro-meteorological data of precipitation, and upstream water level, the model develops short-term predictions at a highly resolved time scale. The FAS was accordingly compared to historical flooding intensities according to which, the model exhibited high performances regarding accuracy criteria, such as, RMSE and Kling-Gupta Efficiency (KGE). This system can show how machine learning can address shortfalls in traditional hydrological models-such as the lack of lead time and processor requirements to give timely warnings. In a coastal environment such as the U.S. Gulf Coast, a system such as this could be optimized to include surge data allowing improved operational flood forecasting and response.

When combined with the existing literature's on ML applications on flood and climate-related prediction, this body of works demonstrates the developing maturity of the ML methods in that realm, yet simultaneously shows significant gaps: the older works are still strongly focused on model benchmarking with little connection to overall environmental datasets, whereas works focusing on coastal zones in particular (Chen et al., 2024) are much closer to being used as part of an operational risk mapping. The issue here is that, in spite of these methodological improvements there are still no easily scaled, ecologically substantial models that would enable adaptive management response to coastal communities exposed to climatically-driven hazards.

3. Methodology and Methods

The research design in this paper combines the information on climate change and flood hazards with peer-reviewed articles to form a generalized guideline about analyzing flood vulnerability in the coastal areas of the United States. Information has been collected by many sources of authority, and the National Centers for Environmental Information (NCEI) will act as the major source of records over severe weather and climatic events from previous studies (Dey et al., 2024; NCEI, 2024; Ni et al., 2020; Rolnick, 2019). NCEI serves as an authoritative source of standardized data on all kinds of weather and climate extremes with large economic and societal effects over time 1980-2024 (NCEI, 2024). The analysis is supported by these datasets, which are long-term indicators of the frequency, intensity, and geographic occurrences of hazardous events in U.S. coastal zones.

A systematic review of peer-reviewed literature was additionally completed in order to complement the empirical data. The literature research covered researches released between 2000 and 2020. Open-source portals were also put to screening and the last search was done in December, 2024. This review seeks to synthesize past and current flood susceptibility applications of emerging technologies, especially machine learning (ML).

Although various studies have been conducted to indicate the usefulness of ML techniques in service of flood susceptibility analysis within the coastal setting, still, some drawbacks remain. As an example, Chen et al. (2024) used Random Forest to determine the multi-hazard susceptibility of the coastal areas in GIS setting and produced a good predictive output, but with a heavy emphasis on the physical complexes of the hazards and little concern toward the social-economic vulnerability layers. In their turn, Rolnick et al. (2019) provided an extensive description of how ML can be utilized to address climate-relevant issues, such as flood prediction, although the work did not include in-depth empirical application in different regions. The methodological framework for this study is illustrated in Fig 1 which outlines the process of data collection, processing and application of machine learning models

Although a few studies have established the usefulness of ML methods in the evaluation of flood susceptibility in coastal setting, there are pertinent gaps of knowledge. Specifically, Chen et al. (2024) have utilized Random Forest in combination with GIS to map multi-hazard coastal susceptibility, as it yielded excellent predictive performance, but the critical part was that they did not sufficiently integrate the socioeconomic vulnerability variables. In a comparable manner, Rolnick et al. (2019) have presented a holistic picture of the implementation of ML solutions to various problems in climate-related issues, such as forecasting floods, but their work has stayed at a high level, and so has not offered a regional and empirical implementation.

The research relates to these efforts and adds to them by making deliberate use of a range of environmental information (geomorphological, climatic and socioeconomic factors) within ML-based models of U.S. coastal regions. In doing so, it mediates the divide between the hazard-based modeling Chen et al. (2020) and the conceptual framework Rolnick et al. (2019), leading in the direction of more practical assessment of flood risks that can be directly translated into adaptive management practices.

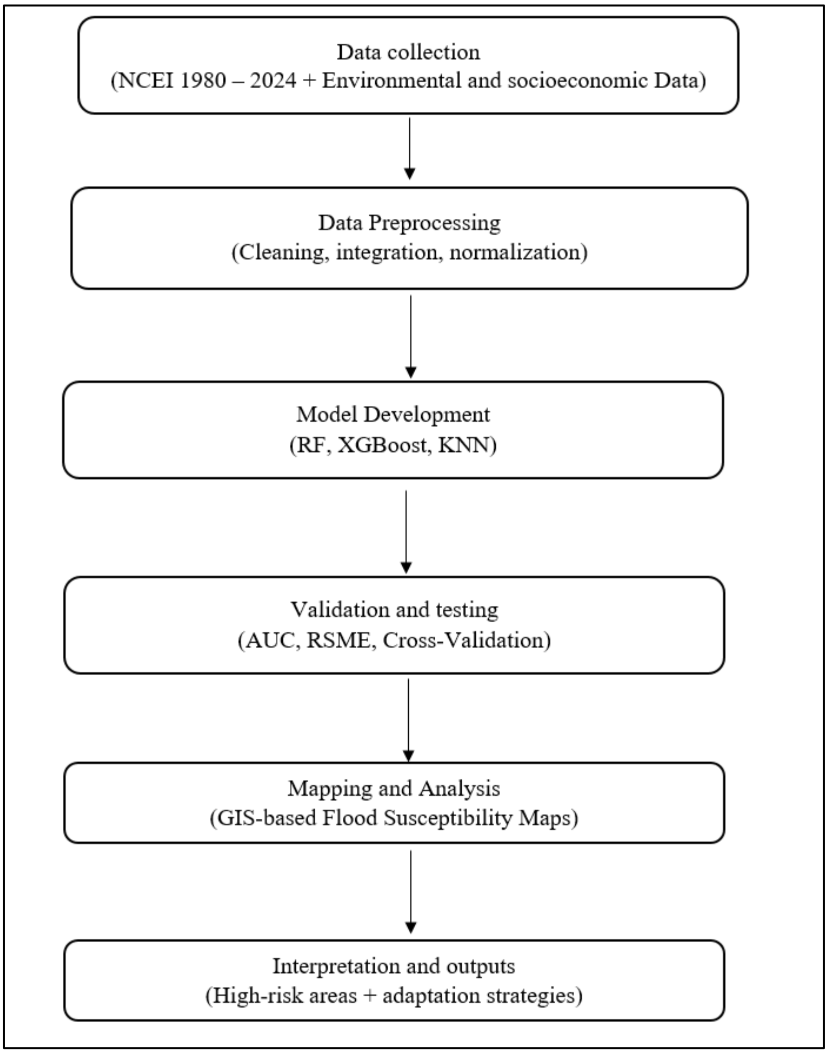

Figure 1 Methodology framework (modified after Dey et al., 2024)

As a measure to operationalize the research objectives, various machine learning (ML) algorithms were applied with an aim of comparing their effectiveness at predicting susceptibility to floods based on the modeling of floods. The choice of algorithms includes

- Random Forest (RF): RF is an ensemble learning technique that constructs a multitude of decision trees and uses them to increase impact and reduce overfitting is Random Forest. Each tree is also fit on a random sample of the data and features and the final prediction is (e.g., by a majority vote in the classification case or an average in the regression case). it has been commonly employed on flood susceptibly due to its ability to manage large size data, non-linear relationships, relative importance of variables. Its capability to provide ranking of variances of importance also provides assistance to find the most important drivers of coastal flooding. In this study, we expand the use of RF by including, in addition to physical indications, socioeconomic and infrastructural factors.
- Extreme Gradient Boosting (XGBoost): XGBoost is a more advanced version of a boosting algorithm that constructs trees in a sequence, each of them addressing the mistakes made by the previous tree. It is very strong in its power to carry out predictive modeling since it balances both speed and accuracy through gradient descent and regularization. XGBoost can be well-suited to flood hazard studies because of the ability to exploit the complicated relationships among variables.
- K-Nearest Neighbor (KNN): A simple, instance-based learning algorithm KNN provides classifications or predicts the value based on the "k" nearest data points in the feature space. On flood susceptibility mapping KNN uses pattern recognition comparisons of an area of unknown flooding characteristics against already known flood and non-flood patterns. It can be easily applied, though quite difficult to achieve an accurate result, due to the selection of k and the quality of input information.

These models were trained and validated on historical climate event datasets provided by NCEI and complemented by geospatial datasets (e.g., elevation, slope, proximity to the shoreline, land use, and socioeconomic data). Standard accuracy metrics, such as Area Under the Curve (AUC), Root Mean Square Error (RMSE) and F1-score were used to measure Model performance. By combining various environmental layers and using various ML algorithms, the current research does not only comply but also advances the theoretical principles invented in Rolnick et al. (2019) into the realm of applied, data-intensive flood forecasting throughout the U.S. coastline.

4. Results and Discussions

This paper discusses flood susceptibility in the United States but specifically set the discussion in a coastal environment. Topographical and geographical diversity and a history of extreme weather events that are more likely to aggravate the prevalence of floods. We evaluated various environmental and socio-economic predictors of flooding using machine learning (ML) models including Random Forest (RF), Extreme Gradient Boosting (XGBoost), and K Nearest Neighbor (KNN). Although the RF and XGBoost have repeatedly worked well in the prediction of flood-prone areas (Fig. 2), it cannot be assumed that the models will always outwork others in other areas of the globe (Dey et al., 2024, Fig 2). Their success hinges on the peculiarities of the datasets at disposal at each geographical site and thus, landform, hydrology, and settlement density are factors that will highly impact the accuracy of their predictions as stated in Dey et al. (2024).

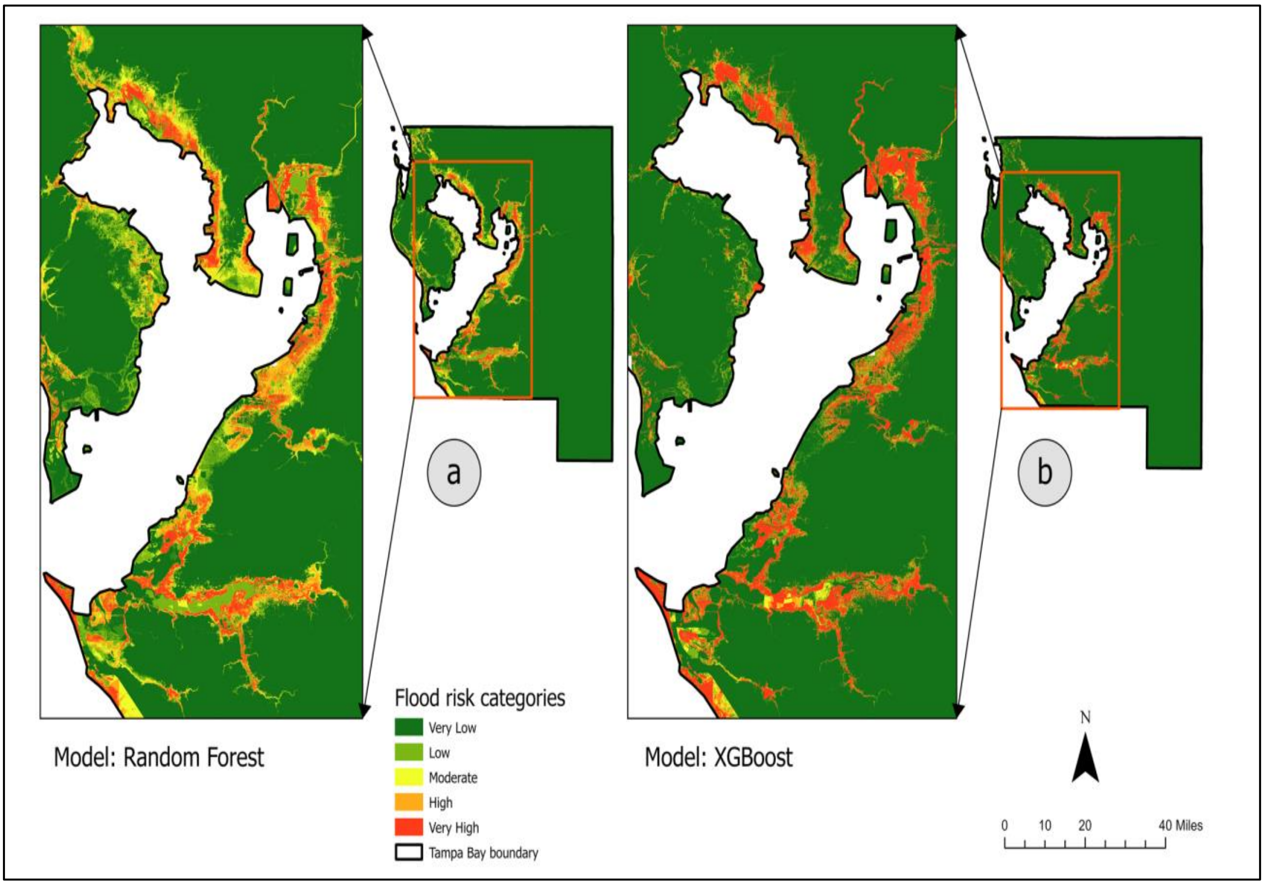

Figure 2 A Modeled flood risk distribution in Tampa Bay adapted from Dey et al. (2024)

The contributing factors relating to flood susceptibility in the study area in the United State is summarized in Table 1. The most significant finding in this research study was the realization that elevation stood out as the most influential factor affecting the risk of flooding with a result of approximated 39% of the predictive capacity of the model. This was also shown in Fig 3 (Dey et al., 2024) which highlighted elevation as the main influential factor affecting flooding. This is in line with the findings across the world. As described by published research in Ethiopia by Desalegn, and Mulu (2021), in Malaysia by Ziarh et al. (2021), in Bangladesh by Hoque et al. (2019), in Slovakia Vojtek and Vojtekova (2019), and in the U.S. by Dey et al. (2024) and Mukherjee (2020). Their study revealed that elevation as the main variable that affects flood vulnerability. Along with that, the second most crucial factor was the presence of rivers or coasts (25%), the trend that was confirmed in the past studies (Vafakhah et al., 2020). The communities that are situated along the rivers or coastal areas are more prone since the combination of the storm surge and heavy rainfall add arterial importance to the flood riskiness in the times of extreme weather (Torresan et al., 2012).

Density attributed to built-up intensity was also an important factor in the analysis especially in highly urbanized regions like the Tampa Bay. Dense infrastructure- road networks and clusters of buildings- were found to be linked to high flood risk as a result of the destruction of natural drainage areas and the minimization of the water infiltration into the ground. This fact supports the perception that flood hazards can be heightened by human-made alterations to a terrain, hence exposing susceptible settlements.

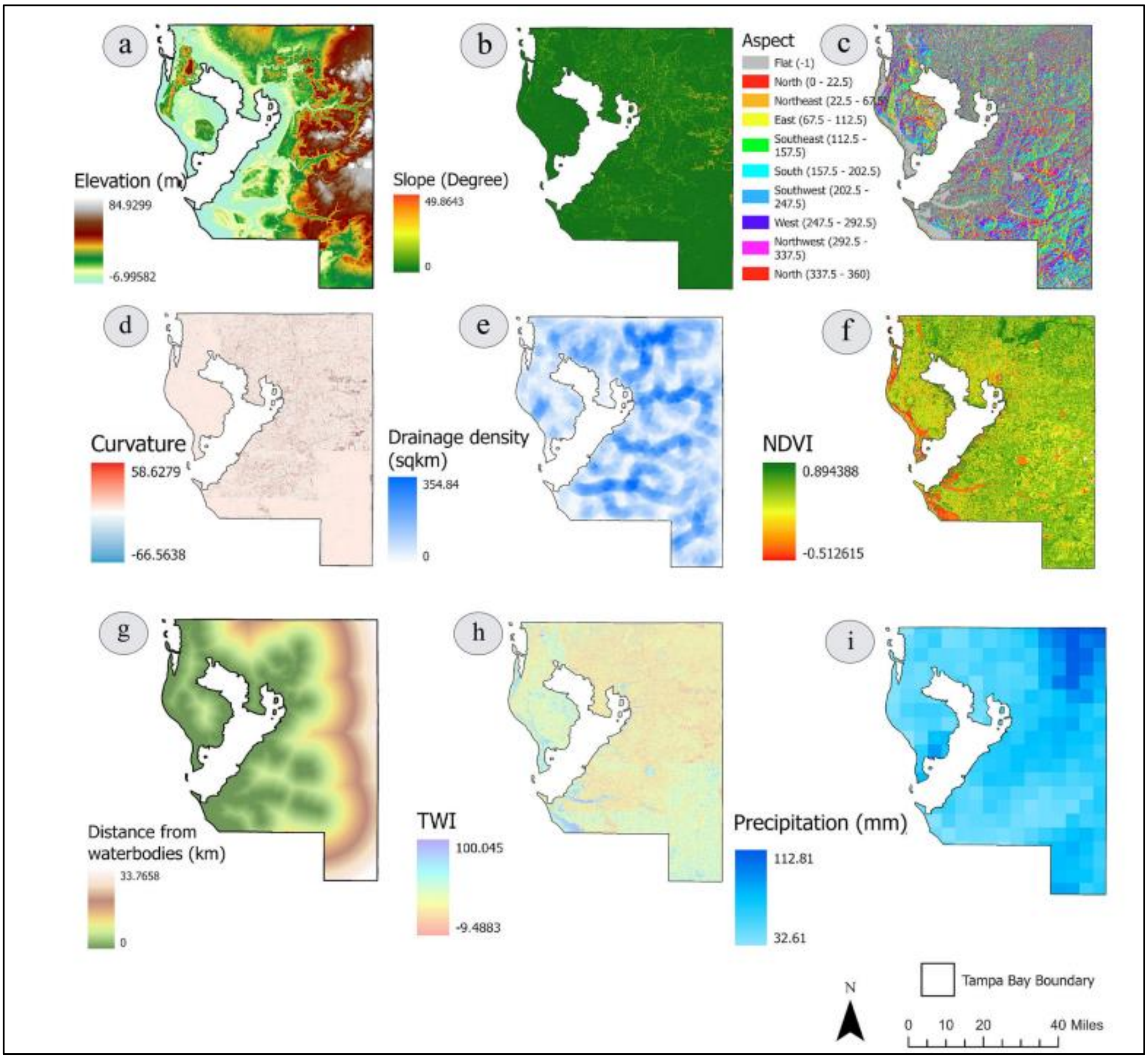

Figure 3 Spatial representation of flood-related hazards by Dey et al. (2024)

In general, the results indicate that flood risk is mainly conditioned by risk-related parameters (table 1), i.e., slope, and water bodies and proximity or exposure parameters, i.e., infrastructure density. In comparison, lower predictive outcome contribution was attributed to variables that indicated vulnerability, i.e., socioeconomic variables. This certainly underscores the necessity of coordinated planning measures that take into consideration both the physical roots of floods and infrastructural vulnerability of endangered communities.

The proposed line of risk areas, especially the thickly populated infrastructure on the coastal fringe, is useful information in flood control governance. With scant management, these societies will become more exposed to extreme flooding events and especially due to the compounding stressors of climate change, sea-level rise and increasing storm-intensity. These findings firmly indicate that resilience-building, in terms of infrastructural gains, the social and economic safety nets, and institutional strategies should be made a priority in flood risk mitigation strategies.

Table 1 Key contributing factors to flood susceptibility in the United States

Factor	Relative Contribution (%)	Supporting Studies
Elevation	39%	Desalegn and Mulu (2021); Ziarh et al. (2021); Hoque et al. (2019); Vojtek and Vojteková (2019); Dey et al. (2024); Mukherjee (2020)
Proximity to River/Coast	25%	Vafakhah et al. (2020); Torresan et al. (2012)
Built-up Density (Infrastructure)	20%	This study was consistent with urban flood risk studies
Road Network Density	9%	This study reinforces built-up area influence
Socioeconomic Vulnerability	6%	Found to have lesser impact in this study

The findings, both scientific and policy-wise, will improve the knowledge on flood susceptibility and lead to practice flood mitigation strategies. When combining machine learning techniques and geographic information system (GIS) methods, this investigation not only determines flood risk priority areas of focus but also offers a decision-making tool that can help the policymakers develop area-specific adaptive flood management plans in the United States and possibly other locations.

5. Conclusion

This paper presents the transformative capacity of machine learning and emerging technologies in developing flood risk evaluation and management. The application of random forest, Boost, and KNN models to the flood-prone areas in the U.S. reveal that physical conditions, especially altitude and closeness to rivers and the sea, are the prevailing factors in the assessment of flood susceptibility. These results match those conducted internationally, and it has been established that elevation as a driver of flood risk is universal. Urbanization drivers, such as high-density infrastructure networks, are also known to increase exposure, and thus community vulnerability, hence the need to incorporate built environment in flood modeling.

The findings indicate that hazard- and exposure-related factors have a higher impact than socioeconomic conditions implying that carefully engineered infrastructural and land-use interventions will play a large role in reduction of risk in high exposure areas. Most significantly, the study establishes that despite the strengths of both RF and XGBoost in terms of predictive capacity in the context of the U.S., no single model can work across different geographic and environmental variables without considerations.

These results are useful to guide policymakers, planners, and researchers in view of the increasing risks of climate change, rising sea levels, and social vulnerability that are intensifying. The additional of these powerful machine learning methods within the field of flood risk assessment can only serve to further our scientific comprehension, as well as provide appropriate decision-making where resilience planning and adaptive management are concerned. Ultimately, optimizing the connection between data-driven modeling and decisions will be critical towards protecting at-risk communities, ensuring sustainable land use, and spearheading resilience globally to flood-related disasters.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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