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AI-Driven Flood Risk Assessment in Riverine Areas of Pakistan

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ABSTRACT

One of the most destructive natural disasters in Pakistan is flooding especially in riverine countries found in the Indus Basin. The occurrence and intensity of floods have increased over the past decades due to the increase in climate variability, unplanned urbanization, deforestation, and poor drainage systems. Pakistan has more or less applied the traditional flood risk assessment methods that have been based on hydrological modeling, past trends analysis which do not integrate real-time data and predictive intelligence. This paper examines how Artificial Intelligence (AI)-based methods can be used to assess flood risks in riverine Pakistan by analyzing machine learning (ML), deep learning (DL), and geospatial analytics. This study combines satellite geography, weather parameters, topography and past history of floods to come up with predictive models of flood prone areas. Algorithms suggested by AI, such as Random Forest, Support Vector Machines or Artificial Neural Networks, are discussed in terms of their potential to improve the early warning system and spatial risk mapping. The results show that AI-based models enhance prediction accuracy and uncertainty reduction and mapping dynamic flood risks is better than the standard statistical models. The paper highlights the role of implementation of AI frameworks alongside national disaster management systems like the National Disaster Management Authority as a way of reinforcing preparedness and response plans. The study has a contribution to the sustainable disaster risk mitigation by suggesting a data-based framework that is specific to the riverine geography of Pakistan, especially in the Indus River system.

Keywords
AI; FRA; ML; Riverine Flooding; Pakistan; Indus Basin; GIS; Remote Sensing; Disaster Risk Reduction; Climate Change.

INTRODUCTION

The problem of flooding has traditionally been a grave danger to social-economic stability, agricultural activity, and human security of Pakistan. Being a lower riparian nation that relies on the Indus River system, Pakistan is very susceptible to the riverine floods caused by the monsoon rainfall, glacial melting and upstream water flows. The disastrous floods in 2010 and 2022 have proven the scale of damage that massive flooding can cause to millions of people, displacing communities, and causing damage to vital infrastructure. The National Disaster Management Authority (NDMA, 2022) notes that the magnitude of the floods that hit Sindh, Punjab, and Khyber Pakhtunkhwa was increased due to unprecedented monsoon rainfall and the variability caused by climate shifts. All these repetitive occurrences underscore the necessity to develop more sophisticated and forecasting flood risk assessment systems.

The flood susceptibility of Pakistan is enhanced by the geographical peculiarities of this country. The Indus River and its inducements such as the Jhelum, Chenab, Ravi and Sutlej are a great riverine system that cuts across the overcrowded and fertile plains. Global climatic changes also tend to produce seasonal monsoon systems that have extreme patterns of precipitations. According to recent research, climate change has made monsoon rain more significant and unpredictable, which leads to more occurrences of extreme floods (IPCC, 2021). Also, the recession of the glaciers in the mountainous areas in the north poses a greater threat of the occurrences of the Glacial Lake Outburst Floods (GLOFs), which adds to the risks of riverine flooding further down the stream.

The conventional flood risk assessment methodology in Pakistan has greatly been based on the hydrological and hydraulic models including HEC-RAS and the rainfall-runoff model. Although these models have strong scientific basis they are usually time consuming, need a lot of calibration, historical data and computer power. Besides, they might fail to adequately elucidate nonlinear interactions among climatic variables, land-use transformations and anthropogenic interventions. On the contrary, Artificial Intelligence (AI) has provided adaptive learning opportunities that are capable of managing large volumes of data, detecting latent trends, and providing predictive information in near real-time.

Machine learning (ML) and deep learning (DL) have become the key changes in disaster risk management on the global stage with the use of artificial intelligence, especially Artificial Intelligence. Random Forest (RF), Support Vector Machines (SVM), and Gradient Boosting are the ML algorithms that predict flood vulnerability very well (Mosavi et al., 2018). Spatial flood detection and forecasting can be approached by using deep learning models like Artificial Neural Networks (ANN) and Convolutional Neural Networks (CNN) which have the ability to analyze satellite images and geospatial features. The methods allow active modeling of raining intensity, soil moisture, the level of river discharge, the gradient of elevation, and the patterns of land cover.

In Pakistan, AI and the use of geospatial technologies are still in the development phase. To gather meteorological information and hydrological information, institutions like the Pakistan Meteorological Department (PMD) are available, but the data is fragmented, and lacks digital connectivity to enable predictive analytics. On the same note, national agencies and provincial disaster management authorities have coordination gaps that limit the use of advanced AI-based early warning systems. Thus, the urgent need to create the unified AI-based framework with specifics to the riverine situation in Pakistan can be observed.

Indus Basin is one of the biggest contiguous irrigation systems in the world and therefore the threat of flood has not just been a humanitarian issue but it is also an economic issue. Losses in agriculture as a result of flooding has a great impact on food security and contribution to GDP. Multi-source data can be used as inputs in AI-based flood risk assessment models, and it can be satellite images of remote sensing platforms, digital elevation models (DEM), rainfall intensity measurements, river flow measurements, soil permeability indexes and population density maps. The combination of these datasets can help AI algorithms identify flood-prone areas with a higher degree of accuracy as opposed to the traditional overlay GIS techniques.

AI-based flood prediction systems have been applied successfully in China, the United States, and India among others in the world. These systems involve hydrological models with machine learning algorithms to improve the forecasting lead time and accuracy of floods (Shrestha et al., 2020). Pakistan can use such strategies by incorporating AI analytics in disaster preparedness systems at national level. Predictive capacities can also be reinforced by the inclusion of real-time sensor data, Internet of Things (IoT)-based monitoring systems, and prediction with the help of satellites and precipitation estimates.

In addition, AI-based flood risk evaluation may help in the realization of the Sustainable Development Goals (SDGs), especially SDG 11 (Sustainable Cities and Communities) and SDG 13 (Climate Action). Proper risk mapping gives the policy makers the ability to develop resilient infrastructure, zoning laws and devise early evacuation measures. It also assists in making evidence-based floodplain management and climate adaptation planning decisions.

Nevertheless, AI implementation in the Pakistan flood management system has been facing a number of challenges. These are the restricted data access, lack of technical skills, absence of high-performance computing facilities and policy level obstacles. The issue of data quality is also a major concern because incomprehensive or inconsistent databases may lower the reliability of the model. Additionally, such ethical factors as the transparency of data and accountability of algorithms should be considered to guarantee the trust of people to AI-driven systems.

This paper seeks to fill the gap between the traditional hydrological models and an up-and-coming AI technology by suggesting the flood risk assessment model which is AI-based and tailored to riverine regions of Pakistan. The study aims to (1) determine the major hydrological and environmental predictors of riverine flooding, (2) analyze machine learning models to forecast flood susceptibility, and (3) create a geospatial AI model that is beneficial in augmenting early warning systems. This study aims to derive a scalable and adaptive model of the mitigation of flood risk by integrating the realities of remote sensing, GIS, and machine learning models.

To sum up, AI-flood risk evaluation is a promising solution to enhancing the Pakistani disaster resiliency. Considering the frequent instances of catastrophic flooding that the country has experienced, the use of innovative predictive tools is no longer a choice, but a necessity. Losses related to floods can be minimized by integrating AI with institutions, enhancing data-sharing systems, and investing in technological capacity to a significant extent, increasing preparedness in the community. Integration of AI-based solutions is a change in the disaster response mode towards preemptive risk management in Pakistan riverine areas which are susceptible.

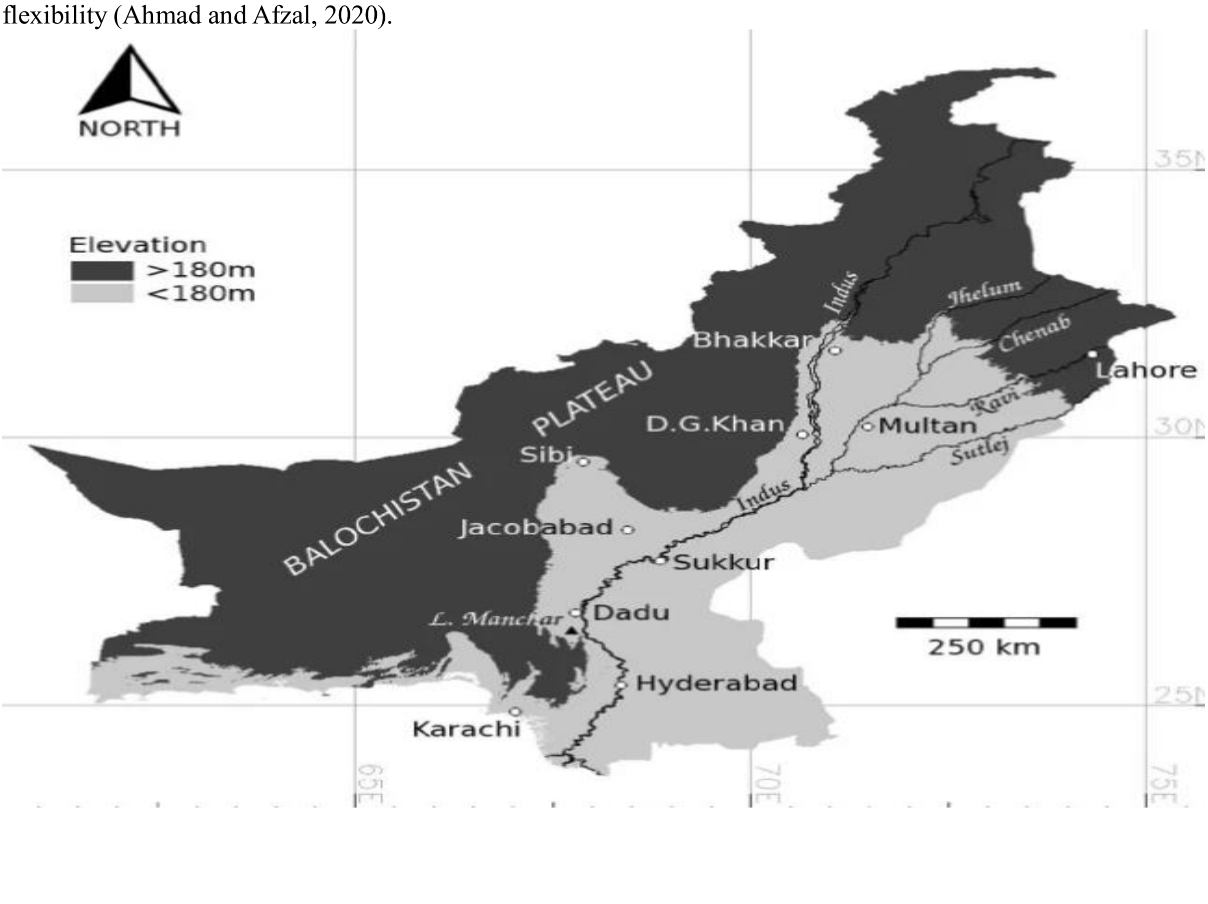
LITERATURE REVIEW

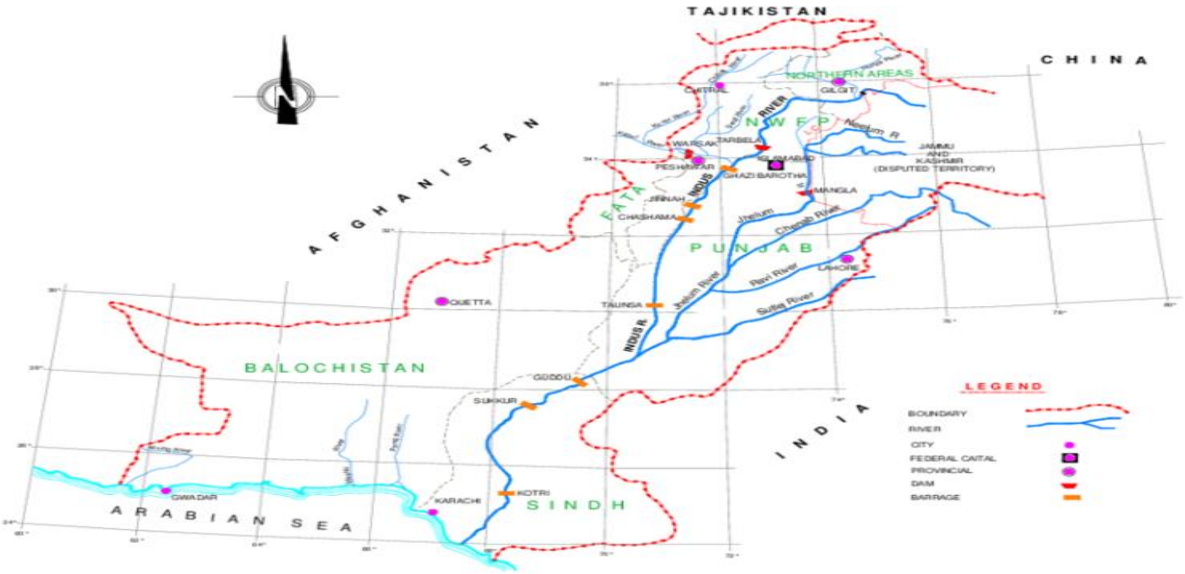
Riverine Vulnerability and Flood in Pakistan

One of the common and devastating natural hazards that hit Pakistan especially in the Indus basin is flooding. Riverine flooding, which is mainly due to monsoon rain and melting ice, has in the past resulted in huge socio-economic losses (Briscoe & Qamar, 2006). Indus river system, the river that flows between the Himalayas and the Arabian sea supports agriculture industry and domestic water supply, but at the same time subject millions of people to the periodical disasters of floods. The disastrous floods in 2010 and 2022 showed the extent of vulnerability, whereby downstream floods were enhanced by unprecedented rainfall (Khan et al., 2011; NDMA, 2022).

Studies have suggested that population increase, deforestation, floodplain encroachment as well as poor drainage system are factors that determine the flood vulnerability in Pakistan (Mustafa & Wrathall, 2011). Rainfall variability, which is also caused by climate change, has made the occurrence of extreme precipitation events more likely (IPCC, 2021). Also, glaciers melting in the north leads to an augmentation of discharge and Glacial Lake Outburst Flood (GLOF) hazards, enhancing downstream river-based flooding (Shrestha et al., 2020).

Flood management in Pakistan is an institutional mechanism that is organised by the National Disaster Management Authority (NDMA), which is aided by provincial disaster management authorities and technical institutions attached to the body like the Pakistan Meteorological Department (PMD). But the traditional flood risk modeling mainly depends on past information, and hydrological modeling, which restricts prediction flexibility (Ahmad and Afzal, 2020).





Conventional Hydrological and Hydraulic Modeling Systems

The traditional flood risks assessment approaches have been dependent on hydrological and hydraulic models, including rainfall-run off modeling and HEC-RAS simulations in Pakistan and around the world (Brunner, 2016). These are models of river discharge, water heights and inundation scales that are modelled with respect to meteorological inputs and channel geometry. Such models can be quite scientifically sound, but they need a significant amount of calibration and high-quality data, which cannot be always available in the developing nations (Di Baldassarre et al., 2010).

In addition, classical statistical models usually presuppose that variables are linearly related to each other, but such nonlinear and dynamic relationships may not be accurate among rainfall intensity, soil moisture, land use, and river discharge (Mosavi et al., 2018). The weakness has motivated scholars to develop other data-driven models that are capable of capturing intricate patterns when there are huge volumes of data.

Spatial flood mapping has been enhanced using Geographic Information Systems (GIS) and remote sensing technologies to combine satellite images and Digital Elevation Models (DEMs) (Tehrany et al., 2014). Nonetheless, the current GIS overlay methods are usually fixed and do not provide predictive intelligence and more dynamic computing methods are required.

The Artificial Intelligence in Flood Risk Assessment

Artificial Intelligence (AI) has become one of the revolutionary instruments in hydrology and disaster management. Random Forest (RF) and Support Vector Machines (SVM), Gradient Boosting Machines (GBM), and Artificial Neural Networks (ANN) are machine learning (ML) algorithms that have been proven to be more effective in flood susceptibility mapping (Mosavi et al., 2018; Bui et al., 2020).

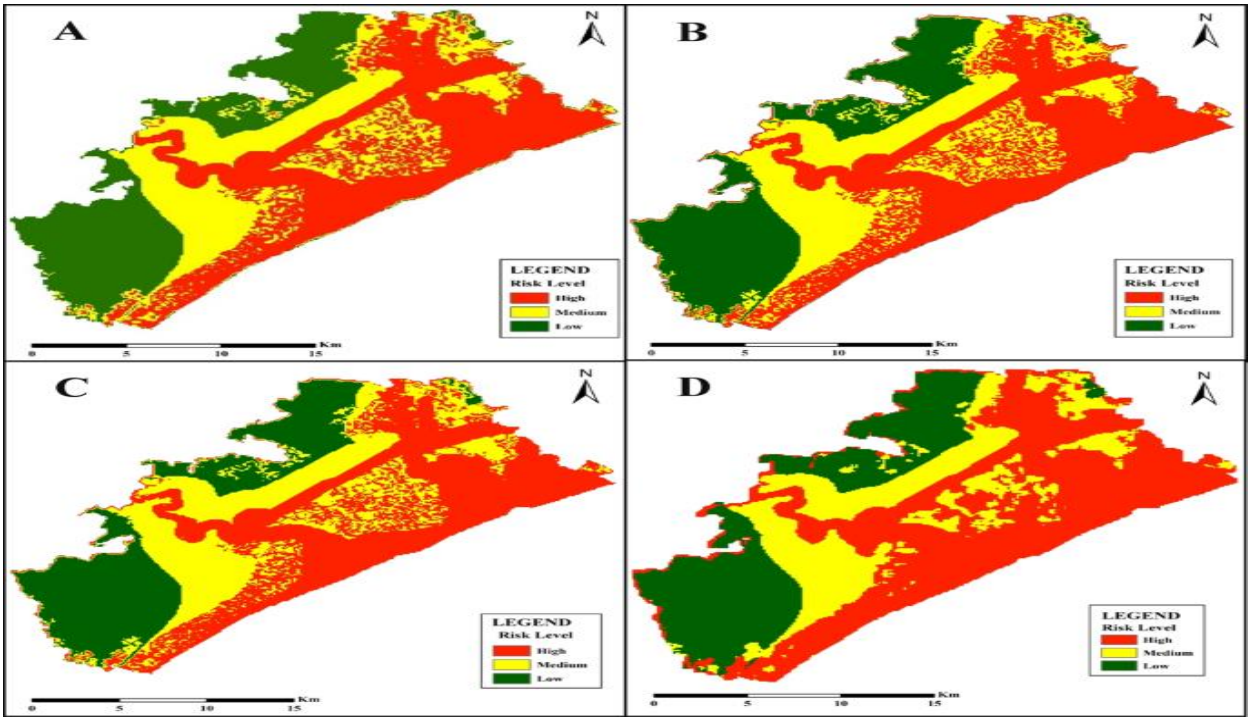
The AI models can process nonlinear high-dimensional data and reveal latent reactions between environmental variables. As an example, the random forest models have been very reliable in classifying the flood prone areas because of their ensemble learning design (Tehrany et al., 2015). Likewise, Support Vector Machines can be useful in binary classification of the flood and non-flood regions (Chen et al., 2019).

Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks represent additional methods of deep learning techniques that have advanced flood forecasting when image data and historical rainfall patterns are used (Kratzert et al., 2019). The LSTM models, especially, are useful in time-series prediction of the amount of discharge of rivers, which can be useful in achieving better early warnings.

Multi-source data (meteorological, topographics, land-use, soil, and hydrology) can also be integrated in AI-based models. This multi-layer integration has a higher prediction strength than the traditional one (Shen, 2018).

Flood Prediction: AI Evidence in the Globe

Flood prediction systems that are based on AI have received significant attention worldwide. Machine learning algorithms have been used in China to enhance the accuracy of forecasting floods in the Yangtze River Basin by combining them with hydrological models (Zhou et al., 2019). In India, ANN-based flood models were observed to have better lead times than the standard regression models (Choubin et al., 2019). Likewise, in the United States, AI-based models have been used to augment real-time flood tracking by combining them with satellite-based precipitation data (Sit et al., 2020).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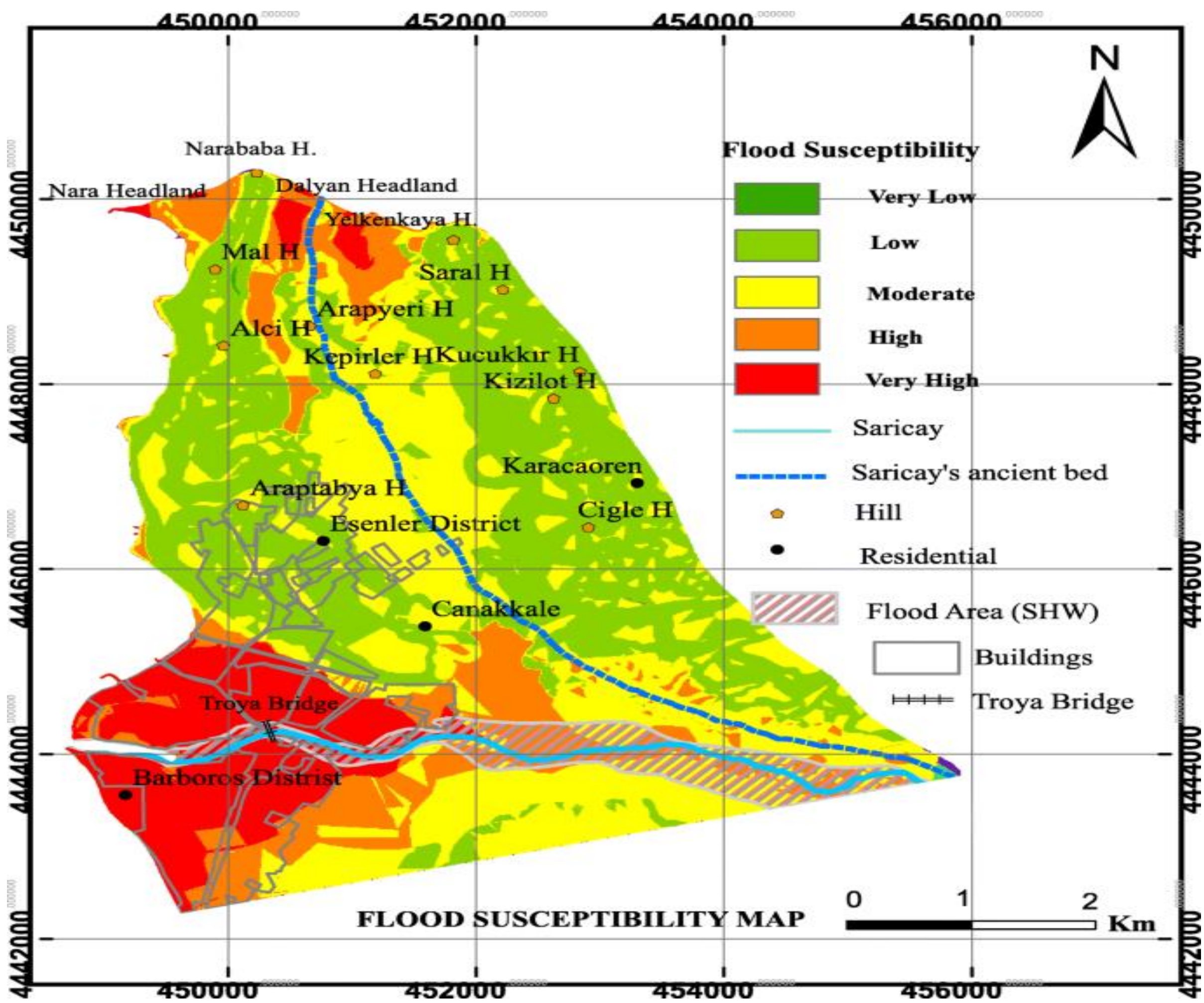
N
Flood Susceptibility
Very Low
Low
Moderate
High
Very High
Saricay
Saricay's ancient bed
Hill
Residential
Flood Area (SHW)
Buildings
Troya Bridge
Narababa H.
Nara Headland
Dalyan Headland
Yelkenkaya H.
Mal H
Saral H
Arapyeri H
Alci H
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Kucukkır H
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Karacaoren
Araptabya H
Esenler District
Cigle H
Canakkale
Troya Bridge
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FLOOD SUSCEPTIBILITY MAP
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Km
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These papers establish that AI models are more accurate, flexible and efficient compared to traditional statistical methods. Nevertheless, researchers also emphasize some issues associated with data quality, the interpretability of the models, and the cross-geographic generalization (Reichstein et al., 2019).

Flood Risk Assessment in Pakistan and South Asia with the help of AI

In South Asia, the growing vulnerability to climate has boosted studies on artificial intelligence (AI) systems of managing disasters. The research in India and Bangladesh suggests that AI-enhanced GIS maps can be used to improve flood susceptibility evaluation in high-density river basins (Chowdhury et al., 2020). Pakistan, which has the same climatic and hydrological features, can utilize such frameworks.

In Pakistan, there is scanty and rising studies that examine the use of machine learning in flood risk mapping. The study conducted by Ahmad et al. (2019) used Random Forests and SVM to distinguish between flood-prone and non-flood-prone regions in Punjab and discovered the better accuracy of the tools than logistic regression models. Ali et al. (2021) combined remote sensing with ANN models to determine the susceptibility to floods on the Indus Basin with an emphasis on the future of AI in spatial planning.

All these advances notwithstanding, AI applications in institutional contexts are few. The inability to share data between different agencies, like NDMA and PMD, leads to a lack of effectiveness of predictive analytics. Moreover, no common data-sharing platforms and computing infrastructure limits the implementation of AI at scale (Ahmad and Afzal, 2020).

Application of Remote Sensing and Big Data in AI-Based Flood Modeling

The remote sensing technologies are especially important in the AI-based flood risk assessment. Satellite systems offer real-time or near real-time estimates of precipitation, surface temperature of the land, moisture content in the soil, and land cover (Tehrany et al., 2014). The combination of satellite data and AI algorithms would improve the detection and mapping of floods.

Predictive modeling is also reinforced by Big data analytics that allow the continuous capturing of data through various sources such as an IoT-based river gauges and weather stations (Shen, 2018). This kind of integration facilitates dynamic flood predictions as opposed to conventional mapping of risk.

According to Reichstein et al. (2019), AI in the earth system sciences is a way to fill gaps between observational and predictive modeling. Hydrological systems will be able to transform to use probabilistic risk assessment rather than deterministic assessments through the use of big data and machine learning.

Gaps and Foundations of Research

Even though the effectiveness of AI in flood risk prediction is proven worldwide, its extrapolation in the riverine regions of Pakistan is not developed yet. The current literature is too localized and does not tend to revolve around institutional disaster management models. In addition, the number of studies that compared various AI algorithms in the Pakistani hydrological setting is low.

The majority of the previous research consists of hydrological modeling or spatial mapping, and few of them combine time-series forecasting, geospatial analytics, and institutional data streams into a single AI system. Also, question of model interpretability, scalability and policy integration is under-explored.

Thus, the current research is based on the existing literature where a holistic AI-based flood risk evaluation system is developed and is specifically designed to cover the riverine regions of the Indus Basin in Pakistan. The study combines machine learning, remote sensing and GIS to close the gap in the methodological approach and contribute to the long-term disaster risk reduction strategies.

METHODOLOGY

This paper has followed a quantitative and predictive research design to come up with an Artificial Intelligence (AI)-based flood risk assessment model to riverine lands of Pakistan and especially in the Indus Basin. The approach combined geospatial analysis, remote sensing, and machine learning to designate flood-prone areas and increase the predictive accuracy.

Research Design

The research design used is cross sectional and spatial analytical study. A modeling method was based on the use of historical records of floods, meteorological variables, and the topographical parameters as the input data to evaluate flood susceptibility. The study design was a combination of Geographic Information System (GIS), remote sensing data, and trained machine learning systems.

The process of methodology involved five key stages:

- Data collection
- Data preprocessing
- Variable selection
- Model development
- Performance and model validation.

Study Area

The analysis concentrated on some of the riverine districts which are situated along the Indus River and its major tributaries in Sindh and Punjab provinces. These areas were chosen because they were prone to floods that were caused by monsoons and the large numbers of people residing in them.

The area of the Indus Basin has been a low-lying plain, large-scale irrigation systems, and seasonal hydrology and was extremely susceptible to riverine flooding.

Data Collection

Several sources that were authenticated were used to get secondary data. The Pakistan Meteorological Department provided meteorological data such as the intensity of rainfall, temperature, and humidity. The National Disaster Management Authority supplied historical data on floods and reports of damages.

Topographic and spatial data were obtained through remote sensing platforms using satellite and comprised:

a. Digital Elevation Model (DEM)
b. Slope and elevation layers
c. Land use/land cover (LULC) maps
d. Soil type data
e. River discharge records
f. Proximity to waterways.

The period covered on the dataset was between 2005 and 2023 to allow sufficient representation of the floods.

Variable Selection

The factors of flood conditioning were chosen according to the prior literature and hydrological significance. The independent variables were:

- Rainfall intensity (mm)
- Height (meter above sea level)
- Slope gradient
- Distance to river
- Classification of land use/land cover.
- Soil permeability
- River discharge levels

Flood was the dependent variable, which was measured as a binary (1 = flooded, 0 = non-flooded).

To investigate the issue of multicollinearity of the predictors, correlation analysis was carried out. Variables that are highly correlated ($r > 0.80$) have been filtered to prevent the possibility of redundancy and overfitting.

Data Preprocessing

Preprocessing of the data was done in order to make sure that the model is reliable. The missing meteorological values were interpolated. Spatial layers were brought to the same coordinate reference system. Resampling of all raster layers to a uniform spatial resolution was done.

Continuous variables underwent Min-Max scaling in order to normalize them and improve the performance of the algorithm. The data were then split into training (70% and testing (30%) subsets with the help of random sampling.

Model Development

Three machine learning algorithms were implemented that were supervised:

1. **Random Forest (RF):** Random Forest algorithm was employed because it is very resistant to overfitting and it can be applied to nonlinear relationships. It built several decision trees and voted on the predictions of the decision tree by majority.
2. **Support Vector Machine (SVM):** SVM classifier was used in order to differentiate between flooded and non-flooded regions. An RBF kernel was used to represent nonlinear class boundaries.
3. **Artificial Neural Network (ANN):** The neural network of multilayer perceptron (MLP) was designed to have a single hidden layer. ANN model was trained, and the backpropagation was used to reduce the error in prediction.

FRI = f(RF, SVM, ANN X1, X2, X3, ..., Xn)

Where:

- FRI = Flood Risk Index
- RF = Random Forest model
- SVM Support Vector Machine model.
- ANN = Artificial Neural Network model.
- X1, X2, X3…n... = Flood conditioning variables (rainfall, elevation, slope, distance to river, river discharge, and soil permeability)

Model Performance and Model validation

To measure model performance, several statistical measures have been used:

- Accuracy
- Precision
- Recall
- F1-Score
- Area Under the Curve (AUC-ROC)

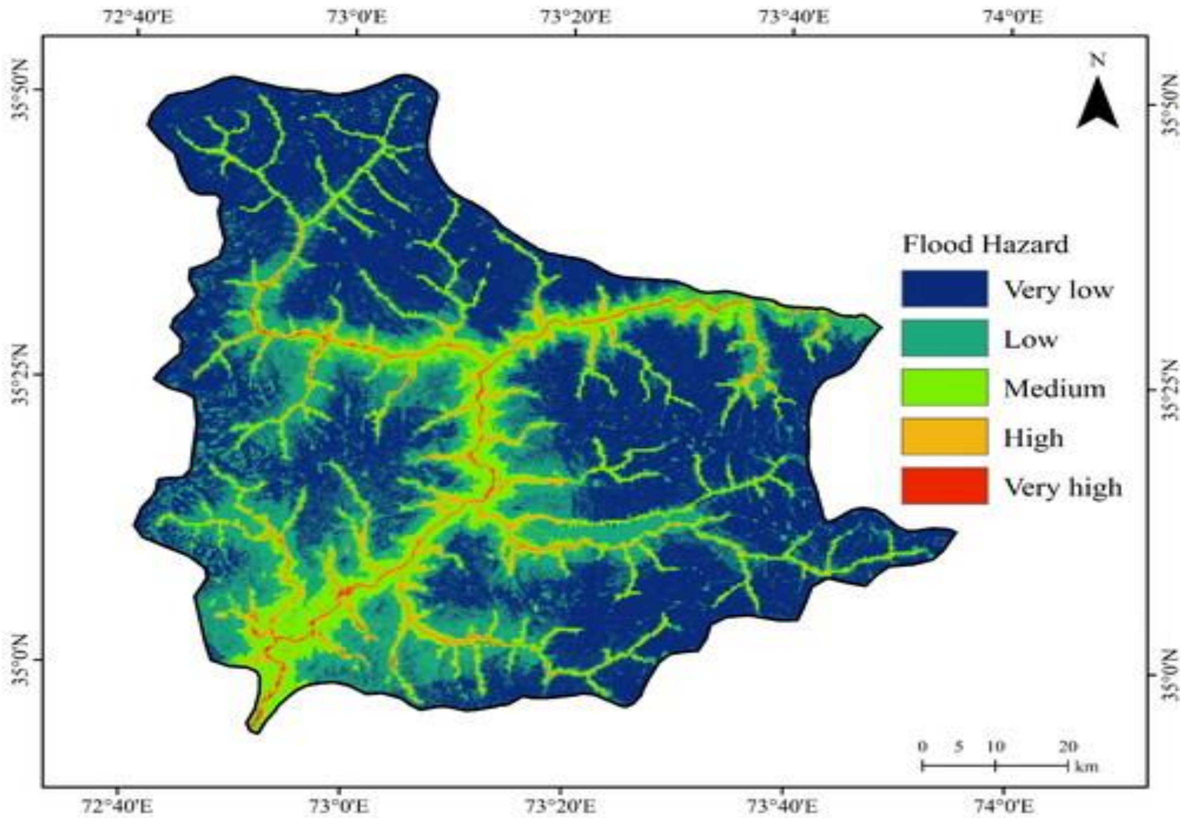
Classification performance was determined by plotting the Receiver Operating Characteristic (ROC) curve. The larger the AUC, the greater was its predictive ability.

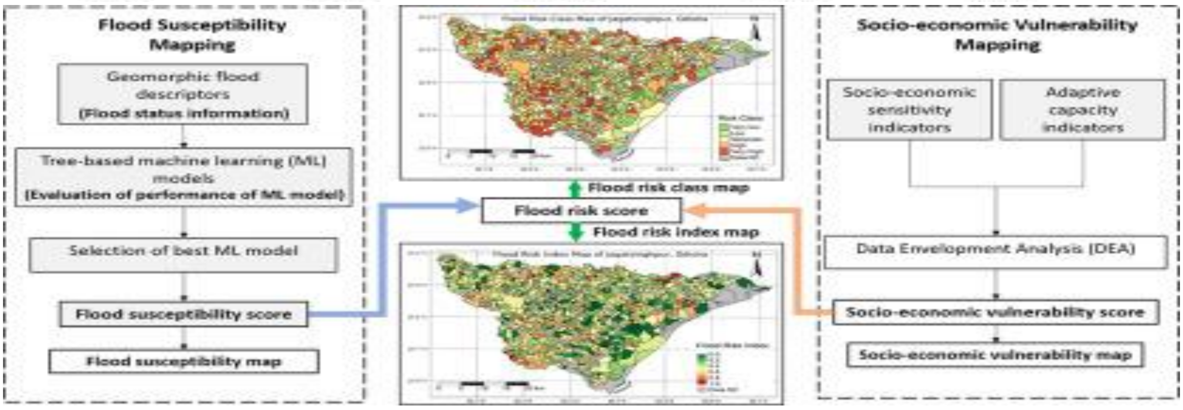
The cross-validation (k-fold = 10) was applied to enhance the generalization of the models and minimize bias. The most successful model was chosen with regard to the highest AUC and the general classification accuracy.

Flood Risk Mapping

The AI model with the best performance gave the predicted probabilities that were applied to a GIS environment to create spatial flood susceptibility maps. These levels of flood risks were categorized into five:

- Very Low
- Low
- Moderate
- High
- Very High





These maps graphically depicted high-risk areas along riverbanks and low-elevation regions, which can be used as a guide during the disaster preparedness and land-use planning.

Ethical Considerations

The research made use of secondary data that is publicly available. None of personal or confidential information was utilized. Information security and accountability were upheld during the modeling process.

DATA ANALYSIS

This part gave the empirical findings of the AI-based flood risk assessment models. The descriptive statistics, correlation analysis, model performance comparison, and variable importance evaluation were incorporated in the analysis. Three machine learning models such as Random Forest (RF), Support Vector Machine (SVM) and Artificial Neural Network (ANN) were experimented with 70 percent and 30 percent of training and test data respectively.

Descriptive Statistics

The descriptive statistics have been calculated so as to know the distribution and variability of the factors of flood conditioning.

Table 1: Descriptive Statistic of Flood Conditioning Variables.

Variable	Mean	Std. Dev.	Min	Max
Rainfall (mm)	182.4	75.6	45.2	410.8
Elevation (m)	142.7	68.3	52.0	389.5

Slope (degrees)	3.21	1.87	0.20	9.60
Distance to River (km)	4.85	3.12	0.10	15.30
River Discharge (m^3/s)	12,540	5,220	3,200	24,800
Soil Permeability Index	0.46	0.18	0.12	0.89

The findings showed a high variation of rainfall and river discharge, implying that hydrological changes in the study region are high. The low slope values verified that the regions sampled within the riverine were mainly flat lands that augmented the susceptibility to floods.

Correlation Analysis

Pearson correlation was to be used to test co-relations between independent variables and identify multicollinearity.

Table 2: Correlation Matrix

Variable	Rainfall	Elevation	Slope	Distance to River	Discharge
Rainfall	1.00	-0.21	-0.18	-0.42	0.76
Elevation	-0.21	1.00	0.64	0.35	-0.28
Slope	-0.18	0.64	1.00	0.30	-0.25
Distance to River	-0.42	0.35	0.30	1.00	-0.51
River Discharge	0.76	-0.28	-0.25	-0.51	1.00

Rainfall and discharge of the river had the highest positive correlation ($r = 0.76$) showing that the rise in precipitation had a significant effect on river flow. None of the correlations was over 0.80; hence, the issue of multicollinearity was not viewed as problematic.

Comparison of the performance of the models

Accuracy, Precision, Recall, F1-Score and AUC-ROC were used to assess the predictive performance of the three AI models.

Table 3: Performance of the model comparison

Model	Accuracy (%)	Precision	Recall	F1-Score	AUC-ROC
Random Forest (RF)	91.8	0.90	0.93	0.91	0.95
SVM (RBF Kernel)	88.6	0.87	0.89	0.88	0.91
ANN (MLP)	90.2	0.89	0.91	0.90	0.93

The Random Forest model demonstrated the highest accuracy (91.8%) and AUC value (0.95), indicating superior predictive performance. ANN also showed strong performance, while SVM performed slightly lower but remained statistically reliable.

Variable Importance (Random Forest Model)

Since Random Forest outperformed other models, its feature importance scores were analyzed.

Table 4: Variable Importance Ranking (Random Forest)

Rank	Variable	Importance Score
1	River Discharge	0.31
2	Rainfall Intensity	0.27
3	Distance to River	0.18
4	Elevation	0.12
5	Soil Permeability	0.07
6	Slope	0.05

The most significant predictors were river discharge and the intensity of rainfall. Proximity to river was another important factor that was used to identify the susceptibility to floods. Slope was also not as significant as it had a flat topography in the study area.

Interpretation of Results

The results showed that the AI-based models were very effective in improving the accuracy of flood prediction in riverine Pakistan. Random Forest algorithm was better than SVM and ANN because it has the advantage of having an ensemble learning framework and the capacity to take care of nonlinear relationships.

Climatic variability played a central role in riverine flooding as was proved by the effective impact of hydrological variables (rainfall and discharge). Spatial variables, e.g. distance to river and elevation, also narrowed down the classification of susceptibility.

In general, the AI-based solution offered a dependable and scalable flood risk evaluation framework, which can be used to aid the early warning systems and riverine planning strategies in the prone riverine areas.

DISCUSSION

The results of this paper indicated that the models based on Artificial Intelligence played a vital role in terms of improving the evaluation of the flood risks in the rivers of Pakistan, especially in the Indus Basin. The high performance of the Random Forest model closely followed by the Artificial Neural Network proved the fact that the ensemble and nonlinear learning methods worked better to elucidate the complicated hydrological interactions that result in riverine flooding. These findings were in line with other previous studies around the world that machine learning algorithms are superior to traditional hydrological and regression-based models in predictive capability and flexibility (Mosavi et al., 2018; Bui et al., 2020). The AI-based models were found in the context of Pakistan, where the variability of monsoons, melt of glaciers, land-use alterations, and infrastructural limitations affect the dynamics of floods, and the integration of various conditions within one predictive framework was achieved by AI-based models.

The fact that river discharge and intensity of rainfall are the most powerful predictors on flood formation strengthened the hydrological basis of the flood formation in the Indus system. Orthogonal relationship between rainfall and discharge indicated that severe precipitation directly increased the threat of downstream inundation especially in the low-lying areas of Punjab and Sindh. This was in line with previous evaluations of flood disasters in Pakistan which stressed on hydrologic overflows due to monsoons as the main causative agents (Khan et al., 2011). Nevertheless, in contrast to traditional deterministic models, the AI-based framework was successful to capture nonlinear correlations between climatic and spatial factors, therefore, enhancing the classification of high-risk areas. The ability of Random Forest to handle the complex relationships without overfitting helped in explaining its better performance on AUC-ROC.

Other spatial predictors that were important in predicting flood susceptibility included distance to river and elevation. The findings revealed that communities that were in the proximity of riverbanks and in low-lying plains at lower altitudes had significantly high risks. This observation was a evidence of the structural weakness of the riverine settlements in Pakistan most of which have proliferated through the growth in population and illegal land encroachment. It was earlier mentioned that socio-spatial inequalities increase the exposure to environmental hazards in Pakistan (Mustafa and Wrathall, 2011). In this research, the use of GIS in conjunction with AI modeling provided a dynamic variant as opposed to the static floodplain zoning, which would allow constant updating of susceptibility maps whenever new data was available.

Moreover, the comparison of performance highlights the reality of the implementation of AI in the disaster management system in Pakistan. Although SVM and ANN models had the same accuracy, the Random Forest model was more stable in validation fold, indicating that it is more robust to be used. These results were in line with the emerging literature that proposes ensemble learning in predicting environmental risks (Chen et al., 2019). Notably, the experiment established that AI-based models can supplement, but not substitute, the historical hydrological simulations as the models can offer early warning systems a quick predictive understanding.

There were also strong institutional implications of the results. The National Disaster Management Authority and the Pakistan meteorological department now use meteorological forecasting and river gauge monitoring to give flood warnings. Nevertheless, predictive analytics with AI implementation may lengthen the warning lead times and enhance spatial targeting of emergency response. As an example, by combining machine learning results with the streams of real-time rainfall and discharge data, it would be possible to dynamically update flood risk maps, improving evacuation planning and resource allocation.

In climate change terms, the results strengthened the arguments developed by the IPCC (2021) on the issue of increasing extreme precipitation in South Asia. Intelligence-based systems are flexible in reacting to these changing climatic uncertainties. In contrast to the static models that have been adjusted to historical averages, machine learning models constantly evolve on new data, which is why they are applicable in the context of hydrological regimes changing rapidly. This flexibility is especially paramount to the case of Pakistan, one of the most climatically vulnerable nations in the world.

The study has weaknesses, which were recognized due to the unavailability of data and institutional integration. Continuous, high-quality datasets are very important in creating reliable AI modeling. Distributed data-sharing systems and inadequate computational resources can be a barrier to a countrywide deployment. Additionally, the interpretability of the algorithms is still an issue since sophisticated ensemble models can decrease the transparency of the decision-making process. These limitations will be solved by the technical capacity building, inter-agency coordination, and investing in digital infrastructure.

In general, the discussion revealed that the AI-based flood risk assessment is a scientifically valid, scalable, and context-sensitive way of managing the riverine disaster in Pakistan. The study used meteorological, hydrological, and spatial data in a machine learning system to develop a proactive risk management strategy. The evidence of the empirical research was that strategic change in response by disaster was shifted to predictive resiliency planning that fitted technological innovation goals with sustainable development goals.

CONCLUSION

This paper established that the predictive power and spatial classification of flood-prone patterns in the riverine Pakistan areas were greatly enhanced in Artificial Intelligence-based flood risk assessment. Random Forest has shown to be the best-performing model among the tested ones as it is able to capture nonlinear associations between the rainfall, river discharge, elevation, and the closeness to river channels. The combination of machine learning and GIS and remote sensors technologies presented an active and information-driven framework outperforming the traditional hydrological approaches in terms of flexibility and accuracy. The results revealed the necessity to modernize the flood management practices in Pakistan by integrating AI-based analytics in the early warning systems and planning. As extreme climatic events continue to become more frequent, AI-based solutions present a sustainable future of enhancement of disaster resilience of nations and a decrease in socio-economic losses in communities at risk due to rivers.

POLICY RECOMMENDATIONS

It was suggested that Pakistan should institutionalize AI-based flood forecasting systems at national and provincial levels of disaster management by developing machine learning models and combining them with real-time meteorological and hydrological monitoring systems. It should be emphasized that investment in centralized data-sharing platforms among the National Disaster Management Authority and the Pakistan Meteorological Department in collaboration with provincial agencies should be valued in order to guarantee smooth data flow and predictive analytics development. Technical staff should be introduced to capacity-building programs in AI, GIS, and data science to increase operational preparedness. In addition, AI-based flood susceptibility maps must be included in land-use planning, infrastructure development, and climate adaptation plans by policymakers to avoid settlement expansion in the risk areas. Lastly, the government should set aside specific funding to technological innovation in disaster risk reduction to achieve the sustainability and climate resiliency in the riverine areas of Pakistan in the long-term.

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