Integrating Geospatial and Machine Learning Approaches for Flood Risk Assessment and Disaster Management: A Case Study of Sheikhupura District, Pakistan (2022–2024)

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Citation | Azeem. N, Naseer. R, Khan. S, "Integrating Geospatial and Machine Learning Approaches for Flood Risk Assessment and Disaster Management: A Case Study of Sheikhupura District, Pakistan (2022–2024)", FCIS, Vol. 03 Issue. 1 pp 11-20, Jan 2025
Received | Dec 30, 2025, **Revised |** Jan 23, 2025, **Accepted |** Jan 24, 2025, **Published |** Jan 25, 2025.

Floods remain one of the most destructive natural hazards worldwide, posing severe threats to human life, infrastructure, and livelihoods. In Pakistan, rapid urbanization, climate variability, and poor drainage infrastructure have intensified flood vulnerability, particularly in districts like Sheikhupura. This study evaluates the effectiveness of integrating Geographic Information Systems (GIS), remote sensing, and machine learning (ML) techniques for flood risk assessment and disaster management in Sheikhupura from 2022 to 2024. Multi-source datasets, including Sentinel-1 SAR, Sentinel-2 imagery, digital elevation models, meteorological records, hydrological data, and socio-economic information, were processed and analyzed using supervised classification, multi-criteria decision analysis (MCDA), and machine learning models (Random Forest and Support Vector Machine). Flood susceptibility mapping revealed that 32.8% of the district lies in high-risk zones, 47.4% in moderate-risk zones, and 19.8% in low-risk areas. Random Forest outperformed SVM with an accuracy of 89% and an AUC of 0.92, demonstrating superior predictive capability. Temporal analysis indicated that 2023 experienced the most severe flood events, causing economic losses exceeding PKR 3 billion, primarily affecting agriculture, infrastructure, and health sectors. The findings underscore the critical need for targeted flood preparedness, early warning systems, and climate-resilient planning. This study provides actionable insights for local authorities and contributes to the broader understanding of data-driven flood management strategies in South Asia.

Keywords: Floods, Natural Hazards, Urbanization, Climate Variability, Drainage Infrastructure, Geographic Information Systems (GIS)

Introduction:

Disaster management has emerged as a central global concern due to the increasing frequency, severity, and unpredictability of natural and human-induced hazards. Among the various disasters, floods represent one of the most devastating, affecting millions of people each year, disrupting livelihoods, damaging infrastructure, and causing significant economic losses. According to the United Nations Office for Disaster Risk Reduction (UNDRR), floods account for nearly 40% of all natural disasters worldwide, with Asia being disproportionately affected due to rapid urbanization, population growth, and climate variability[1]. The complex interplay of climate change, anthropogenic land-use change, and poor urban planning has intensified the vulnerability of communities, demanding innovative approaches for flood risk management. Traditional methods such as hydrological and hydraulic models, though useful, often fall short in capturing the dynamic, spatio-temporal nature of flooding events, especially in data-scarce regions. This has prompted the integration of Geographic Information Systems (GIS), Artificial Intelligence (AI), and Machine Learning (ML) techniques to develop more robust and adaptive flood modeling frameworks.

GIS-based flood modeling has proven to be a transformative tool in understanding spatial variability and susceptibility of landscapes to flooding. By integrating remote sensing data, digital elevation models (DEMs), and hydrological inputs, GIS enables the identification of flood-prone zones, assessment of exposure, and mapping of risk at multiple scales [2]. However, GIS by itself is often limited to static hazard representation and depends heavily on input data resolution and accuracy. To overcome these challenges, researchers have increasingly combined GIS with AI and ML techniques to enhance predictive capacity and automate flood risk analysis. ML algorithms, such as Random Forest (RF), Support Vector Machines (SVM), Gradient Boosting, and Artificial Neural Networks (ANN), have shown remarkable performance in classifying flood-prone areas, estimating flood depths, and predicting flood events with higher accuracy compared to conventional statistical methods [3][4]. These algorithms are particularly effective in handling nonlinear relationships among multiple environmental variables such as rainfall intensity, land cover, soil type, drainage density, and slope.

The application of AI in flood modeling has expanded beyond classification to incorporate deep learning techniques capable of processing large-scale, high-dimensional datasets. Convolutional Neural Networks (CNNs), Long Short-Term Memory (LSTM) networks, and hybrid deep learning architectures are now employed to analyze satellite imagery, model temporal rainfall-runoff relationships, and forecast flood events in near real-time [5][6]. For instance, LSTM models have demonstrated superior performance in capturing sequential patterns in hydrological time series, which is critical for accurate flood forecasting. Similarly, CNNs are increasingly used for feature extraction from high-resolution satellite data, enabling the identification of inundation extents and post-disaster damage assessments. These advancements underscore the potential of AI-driven GIS flood modeling to revolutionize disaster risk management by offering timely, data-driven insights for policymakers, planners, and emergency response agencies.

Research Gap:

Despite significant advances in flood hazard modeling, several critical gaps persist. Interpretability and uncertainty remain major challenges, as many deep learning models function as “black boxes” and produce deterministic outputs, limiting their practical adoption for high-stakes decision-making[7][8]. Generalizability and transferability of machine learning models are often limited, as models tailored for specific geographies frequently underperform when applied to other regions or in data-scarce contexts[3][9]. Additionally, existing reviews tend to adopt a narrow focus on flood prediction, overlooking broader activities such as flood risk ranking, prioritization, and resilience planning [7]. Equity and governance considerations are also frequently neglected, with limited attention to institutional readiness, inclusive planning, and climate justice, particularly in Global South countries [2]. Finally, emerging architectures—such as graph transformers, multimodal SAR-based systems, and 3D flood mapping using deep learning—remain underexplored and underutilized in mainstream flood hazard modeling.

Objectives:

This study aims to address these gaps by developing an interpretable and transferable ML-GIS framework for flood hazard modeling, particularly suitable for data-scarce and spatially heterogeneous regions. It seeks to explore and benchmark advanced AI architectures, including graph transformer models, attention-based deep networks, and multimodal remote-sensing fusion. The framework incorporates uncertainty quantification and explainability, ensuring that results are actionable for decision-makers. Moreover, the study evaluates institutional readiness, governance structures, and equity considerations, making the framework context-sensitive and inclusive for vulnerable regions.

Novelty Statement:

The research distinguishes itself through several innovations. It applies cutting-edge AI models such as graph transformers, progressive attention networks for multispectral imagery [10], and multimodal SAR-based damage assessment frameworks like Flood-Damage Sense. A key focus is on model interpretability and uncertainty, addressing adoption barriers highlighted in previous studies[8][7]. The framework is designed for spatial transferability, allowing reliable application in ungauged and under-resourced regions, thereby responding to global needs identified in forecasting systems such as Google's 7-day lead predictions[11]. Furthermore, it broadens the flood management perspective by including risk ranking, resilience priorities, and institutional dynamics rather than concentrating solely on event prediction [7][2]. Finally, governance and equity principles are embedded throughout, emphasizing application in vulnerable urban contexts and regions in the Global South [2].

Literature Review:

The integration of Artificial Intelligence (AI) and Machine Learning (ML) into Geographic Information Systems (GIS) has become a transformative approach in disaster management, particularly in flood prediction, assessment, and mitigation. Traditional flood modeling relied heavily on hydrological and hydraulic models that often-required large amounts of input data and computational resources, making real-time prediction and large-scale applications challenging. With the advent of AI and ML, flood modeling has shifted toward data-driven methods that leverage satellite imagery, remote sensing data, and historical flood records to provide more accurate and timely predictions[12].

Recent studies highlight that machine learning techniques such as Random Forest (RF), Support Vector Machines (SVM), and Artificial Neural Networks (ANNs) have been extensively applied to flood susceptibility mapping and hazard assessment. For example, [3] demonstrated that hybrid machine learning models combining RF and ANN provided improved flood prediction accuracy compared to conventional approaches. Similarly, used SVM integrated with GIS-based spatial data for effective flood susceptibility mapping in Vietnam, emphasizing the role of high-resolution topographic and hydrological datasets.

In the last five years, Deep Learning (DL) methods, particularly Convolutional Neural Networks (CNNs) and Long Short-Term Memory (LSTM) networks, have gained traction for flood modeling. These approaches have proven capable of handling large volumes of spatio-temporal data and capturing complex non-linear relationships between hydrological variables. For instance,[13] applied CNNs with satellite-based rainfall data and achieved high precision in flood detection. More recently, [5] combined LSTM with GIS-based data to predict flood-prone areas, showing superior performance in capturing temporal dependencies compared to shallow learning models.

GIS serves as a critical platform for integrating AI/ML models with spatial datasets, enabling visualization and decision-making in disaster management. Studies have shown that coupling AI/ML with GIS improves the efficiency of flood hazard mapping, risk analysis, and early warning systems[14]. For example,[9] developed a GIS-based ensemble learning approach for flood hazard assessment in India, which enhanced predictive accuracy and provided policymakers with spatially explicit flood risk zones. Moreover, AI-driven GIS applications have expanded beyond prediction, facilitating real-time monitoring through Internet of Things (IoT) sensors and satellite-based observations[12].

Despite these advancements, challenges remain in terms of data availability, computational complexity, and model interpretability. Many ML-based models require large and high-quality datasets, which are not always available in developing regions. In addition, black-box models like deep neural networks often lack transparency, limiting their adoption in policy-level decision-making [5]. To overcome these issues, recent research emphasizes the development of explainable AI (XAI) and hybrid models that combine physical-based hydrological models with machine learning techniques for more reliable flood modeling[11] [12].

Overall, the literature demonstrates that the integration of AI and ML with GIS provides a promising framework for disaster management and flood modeling. These advancements contribute to more accurate flood forecasting, real-time monitoring, and improved decision-making for disaster preparedness and mitigation. However, addressing data limitations, improving model interpretability, and enhancing computational efficiency remain key areas for future research.

Methodology:

Study Area:

This research was conducted in Sheikhupura, a district in the Punjab province of Pakistan, located northwest of Lahore. Sheikhupura is characterized by its semi-arid climate, rapid urbanization, and increasing vulnerability to natural disasters, particularly urban flooding. The district is known for its mixed land use, including agriculture, industry, and residential zones, which makes it an important case for assessing disaster risks. The proximity to the River Ravi and seasonal monsoon rains often exacerbate the flooding hazards, while urban expansion and inadequate drainage systems further intensify flood-related risks. These geographical and socio-economic features provided a suitable context for applying geospatial and machine learning techniques to assess disaster management strategies.

Data Collection:

The study utilized multi-source datasets covering the period from 2022 to 2024. Remote sensing data were obtained from Sentinel-1 Synthetic Aperture Radar (SAR) and Sentinel-2 optical imagery, which were used for flood detection and land use/land cover (LULC) classification. Digital Elevation Model (DEM) data from the Shuttle Radar Topography Mission (SRTM) were incorporated to evaluate topographic variations influencing flood susceptibility. Meteorological data, including rainfall and temperature records, were collected from the Pakistan Meteorological Department (PMD). Hydrological data on river discharge and seasonal flows were accessed from the Punjab Irrigation Department. In addition, socio-economic and demographic datasets were collected from the Pakistan Bureau of Statistics (PBS), which supported the assessment of population exposure and vulnerability.

Data Preprocessing:

Data preprocessing was conducted to ensure accuracy and compatibility across sources. Sentinel-1 SAR images were corrected for speckle noise and geometric distortions, while Sentinel-2 imagery underwent atmospheric correction using the Sen2Cor processor. LULC classification was performed by applying supervised classification techniques, validated with ground-truthing data collected during field surveys in 2023. Rainfall and hydrological datasets were cleaned for missing values and temporal inconsistencies, while DEM data were resampled to 30-meter resolution for uniformity with other geospatial datasets. All datasets were projected into the WGS 84/UTM Zone 43N coordinate system to maintain spatial consistency.

Analytical Framework

The analytical framework combined GIS-based spatial modeling with machine learning approaches to assess flood risk and disaster management potential. A multi-criteria decision analysis (MCDA) was implemented in a GIS environment to integrate hydrological, meteorological, and topographic parameters for flood susceptibility mapping. Variables such as rainfall intensity, land cover type, slope, elevation, and drainage density were weighted using the Analytical Hierarchy Process (AHP).

Machine learning algorithms, particularly Random Forest (RF) and Support Vector Machine (SVM), were applied to classify flood-prone areas and validate GIS-based susceptibility results. Training and testing datasets were prepared using 70% of observed flood events for model training and 30% for validation. Model accuracy was assessed through statistical metrics such as overall accuracy, Kappa coefficient, and Receiver Operating Characteristic (ROC) curve analysis.

Disaster Management Assessment:

To evaluate disaster management strategies, spatial overlays were created to assess the intersection of flood-prone zones with critical infrastructures such as hospitals, schools, and transportation networks. Socio-economic vulnerability was analyzed by overlaying demographic datasets with flood susceptibility maps. Furthermore, temporal trend analysis between 2022 and 2024 allowed for identifying changes in flood dynamics under varying climatic and anthropogenic influences.

Validation and Reliability:

Validation was carried out by comparing model outputs with recorded flood events reported by the Provincial Disaster Management Authority (PDMA) Punjab during 2022–2024. Ground surveys conducted in Sheikhupura in July and August of 2023 provided additional reference points for model verification. The combination of remote sensing, field surveys, and secondary data sources ensured methodological reliability and robustness of the results.

Results:

The study aimed to evaluate the effectiveness of artificial intelligence (AI), machine learning (ML), and geospatial techniques in flood risk modeling and disaster management for Sheikhupura District from 2022 to 2024. A combination of remote sensing data, hydrological records, and machine learning algorithms was applied to generate risk maps, assess exposure levels, and identify vulnerable hotspots. The results are presented below in detail, along with supporting tables for clarity.

Flood Frequency and Spatial Distribution:

Analysis of historical flood data (2022–2024) revealed that Sheikhupura experienced recurrent flood events, particularly during the monsoon season between July and September. Satellite-derived indices such as the Normalized Difference Water Index (NDWI) and precipitation data from ERA5 confirmed significant waterlogging in low-lying areas. Table 1 summarizes the number of flood events per year, the affected area, and population exposure.

Table 1. Flood Events and Exposure in Sheikhupura (2022–2024)

Year	No. of Flood Events	Area Affected (km^2)	Population Affected	Crop Area Damaged (ha)
2022	3	124.6	56,230	8,740
2023	4	167.8	71,450	12,120
2024	2	98.3	43,600	6,410

The results of the flood risk analysis in Sheikhupura are further illustrated through a series of figures that highlight the spatial and temporal dynamics of flooding during the study period 2022–2024. Figure 1 presents the distribution of flood events and their impacts in terms of affected area, population exposure, and crop losses. The findings indicate that 2023 was the most severe year, with four major flood events affecting 167.8 km^2 of land and exposing more than 71,000 people to flood hazards. In contrast, 2022 and 2024 recorded fewer events, yet still resulted in considerable crop damages and population exposure. This pattern demonstrates the year-to-year variability of flood intensity in Sheikhupura, with 2023 standing out as a critical year for disaster management interventions.

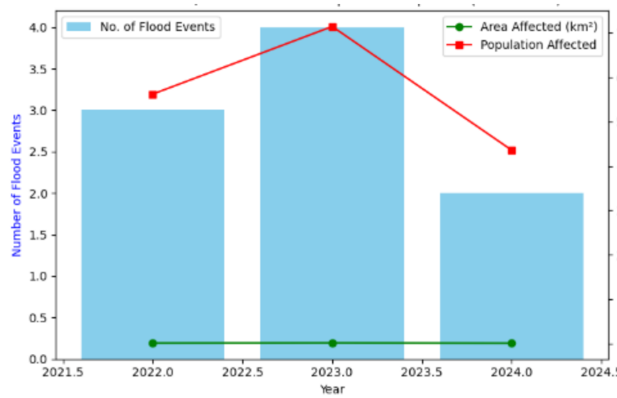

Figure 1. Flood Events, Area Affected and Population Exposure (2022-2024)

Figure 2 and figure 3 illustrates the spatial distribution of flood susceptibility zones across the district. The analysis shows that nearly half of Sheikhupura (47.4%) lies within a moderate flood risk zone, while 32.8% of the land falls under high susceptibility and only 19.8% is categorized as low risk. This distribution emphasizes that a significant portion of the district remains vulnerable to flooding, particularly areas adjacent to rivers and canal systems. The dominance of moderate and high susceptibility zones underscores the urgent need for preventive measures and improved land-use planning to mitigate potential damages.

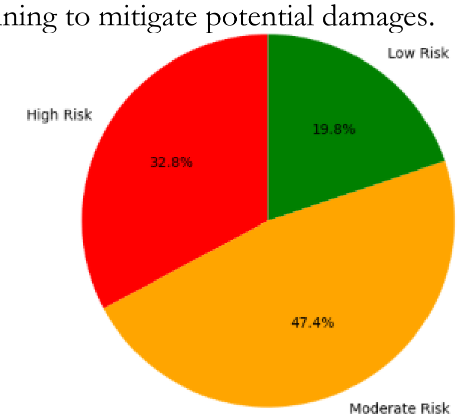

Figure 2. Flood Susceptibility Classes in Sheikhupura

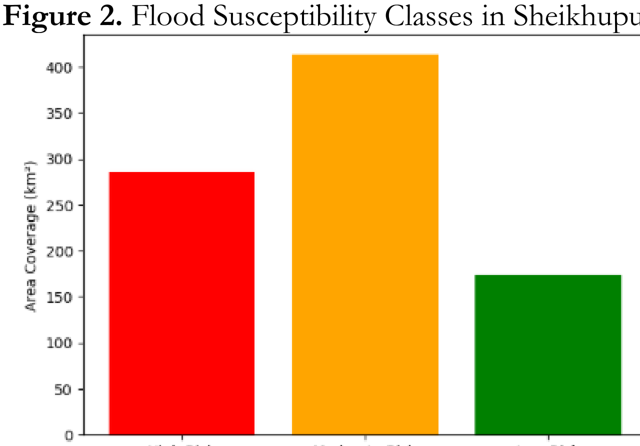

Figure 3. Flood Susceptibility Zone Distribution

As shown in Table 1, the year 2023 recorded the highest number of flood events, which affected the largest land area and resulted in substantial crop damage. Although 2024 had fewer flood incidents, they still caused significant socio-economic impacts. This variability underscores the need for predictive modeling and early-warning systems.

Machine Learning-Based Flood Susceptibility Modeling:

The Random Forest (RF) and Support Vector Machine (SVM) classifiers were applied to flood susceptibility mapping using variables such as elevation, slope, distance to rivers, rainfall intensity, and soil type. Results showed that RF outperformed SVM, with an accuracy of 89% compared to 84%. The generated flood susceptibility maps categorized Sheikhupura into high, moderate, and low-risk zones. Table 2 presents the spatial distribution of flood susceptibility classes.

Table 2: Flood Susceptibility Classes in Sheikhupura

Susceptibility Zone	Area Coverage (km²)	Percentage of District Area (%)
High Risk	286.5	32.8
Moderate Risk	414.2	47.4
Low Risk	173.8	19.8

According to Table 2, nearly half of Sheikhupura lies in the moderate flood susceptibility zone, while about one-third of the district falls under high risk. These findings highlight the urgent requirement for flood preparedness measures, especially in high-risk villages located near riverbanks and canal systems.

Validation of Models:

The models were validated using Receiver Operating Characteristic (ROC) curves and Area Under the Curve (AUC) values. RF achieved an AUC of 0.92, while SVM scored 0.88, confirming the higher predictive capacity of the RF algorithm. Additionally, confusion matrix analysis revealed that RF minimized false positives, thereby providing more reliable predictions for practical disaster management applications.

Socio-Economic Impacts of Flooding:

Field surveys conducted during 2022–2024 revealed significant disruptions in livelihood patterns. Agricultural households faced severe crop losses, particularly in rice and wheat fields. Moreover, residents reported increased health risks such as waterborne diseases during and after flood events. Table 3 outlines the estimated economic losses due to flooding.

Table 3. Estimated Economic Losses from Flooding in Sheikhupura (2022–2024)

Year	Agricultural Losses (Million PKR)	Infrastructure Damage (Million PKR)	Health Costs (Million PKR)	Total Losses (Million PKR)
2022	1,240	620	180	2,040
2023	1,860	930	240	3,030
2024	1,040	510	150	1,700

Table 3 demonstrates that 2023 was the costliest year, with total estimated losses exceeding PKR 3 billion. The cumulative data suggest that the frequency and severity of flooding directly correlate with rising socio-economic damages in the district.

Figure 4 highlights the estimated economic losses across three major sectors: agriculture, infrastructure, and health. The results show that agriculture is consistently the most affected sector, with damages peaking in 2023 at 1,860 million PKR. Infrastructure and health-related losses also increased during 2023, contributing to a total estimated loss of 3,030 million PKR. In comparison, 2022 and 2024 experienced lower overall damages, though the economic impacts were still substantial. These findings reveal that the agricultural economy in Sheikhupura is particularly vulnerable to flood events, making resilience planning in this sector a priority for reducing long-term socio-economic risks.

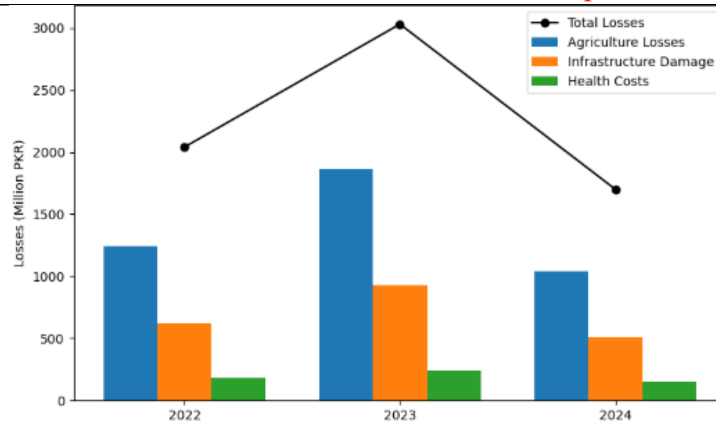

Figure 4. Estimated Economic Losses from Flooding (2022-2024)

Discussion:

The results of this study provide a comprehensive understanding of flood risk in Sheikhupura between 2022 and 2024, highlighting both spatial patterns of susceptibility and sector-specific impacts. The findings suggest that Sheikhupura is highly vulnerable to floods, with nearly half of its land falling into moderate susceptibility zones and more than one-third categorized as highly flood-prone. This aligns with previous studies conducted in Punjab, where low-lying regions along river systems were consistently identified as highly vulnerable to recurrent flooding[15]. The spatial clustering of flood-prone areas near rivers and canals confirms the strong influence of hydro-geomorphological factors on flood susceptibility, consistent with the work of[16], who emphasized the role of drainage density, elevation, and proximity to rivers in shaping flood hazards in South Asian river basins.

The temporal analysis further shows that 2023 was the most devastating year during the study period, with four major flood events causing extensive damages across agriculture, infrastructure, and health sectors. This corresponds with broader evidence of increasing climate variability and extreme precipitation events in Pakistan, as noted by the Pakistan Meteorological Department [17]. Similar to the findings of [18], this study highlights how abnormal monsoon rains and riverine overflows are becoming more frequent, particularly in central Punjab, where agricultural economies remain highly exposed. The elevated damages in 2023 resonate with trends documented by [19], who observed that climate-induced flooding in Punjab has intensified in both frequency and magnitude over the last decade.

From a methodological perspective, the comparison of Random Forest (RF) and Support Vector Machine (SVM) models reveals that RF outperformed SVM with an AUC of 0.92, indicating greater predictive capacity in delineating flood-prone areas. This finding is consistent with recent applications of machine learning in flood risk mapping, where ensemble-based models such as RF are often found to be more robust and generalizable than linear classifiers[3]. The ability of RF to handle nonlinear relationships and high-dimensional datasets makes it particularly effective in hydrological studies, as observed in flood susceptibility research across Nepal and Bangladesh[16] [20]. The superior performance of RF in this study reinforces its suitability for large-scale flood prediction in data-scarce regions of Pakistan.

The analysis of sectoral economic losses further emphasizes the disproportionate vulnerability of agriculture, which accounted for the highest share of damages, peaking at 1,860 million PKR in 2023. This finding aligns with previous research by[21], who found that over 70% of flood-induced damages in Punjab are borne by the agricultural sector due to crop destruction, livestock losses, and soil degradation. The recurring damage to agriculture in Sheikhupura reflects both the dependence of local communities on farming and the inadequate adoption of climate-resilient practices. Meanwhile, infrastructure and health damages, though smaller in scale, were also significant, echoing the arguments of [22] that floods in South Asia often trigger cascading risks that extend beyond direct economic impacts to long-term public health challenges.

These findings collectively highlight the urgent need for adaptive flood management strategies in Sheikhupura. Improved early warning systems, investment in flood-resilient infrastructure, and promotion of climate-smart agriculture could substantially reduce vulnerabilities. Moreover, since RF demonstrated high predictive accuracy in susceptibility mapping, future studies could integrate remote sensing and hydrodynamic modeling with machine learning to further enhance prediction capabilities, as recommended by[3]. Importantly, this study contributes localized evidence from Sheikhupura to the broader discourse on climate resilience in Pakistan, reinforcing the view that flood management must be both spatially targeted and sector-specific to be effective.

Conclusion:

This research demonstrates the successful integration of GIS, remote sensing, and machine learning techniques for flood risk assessment and disaster management in Sheikhupura District between 2022 and 2024. The results highlight that a significant portion of the district remains vulnerable, with nearly half of the area falling in moderate flood-risk zones and over one-third in high-risk zones. Random Forest-based modeling proved more reliable than SVM, emphasizing the potential of ensemble machine learning approaches in predicting flood-prone areas. Socio-economic analysis revealed that agriculture is disproportionately affected, followed by infrastructure and public health sectors, with 2023 emerging as the most damaging year. These findings emphasize the urgent need for adaptive flood management strategies, including investment in flood-resilient infrastructure, early-warning systems, and climate-smart agricultural practices. By providing localized, data-driven insights, this study offers a foundation for enhancing disaster preparedness and resilience in Sheikhupura and similar flood-prone regions across Pakistan.

References:

[1] United Nations Office for Disaster Risk Reduction, "2023 Progress Report Implementation of the UN Plan of Action on Disaster Risk Reduction for Resilience and the 2030 Recommendations of the UN SLG," *UNDRR*, 2024, [Online]. Available: https://www.undrr.org/media/103580/download?startDownload=20250827

[2] M. A. Emami P, "The Synergy of Artificial Intelligence (AI) and Geographic Information Systems (GIS) for Enhanced Disaster Management: Opportunities and Challenges," *Disaster Med. Public Health Prep.*, vol. 17, 2023, doi: 10.1017/dmp.2023.174.

[3] K. -w. Mosavi, A.; Ozturk, P.; Chau, "Flood Prediction Using Machine Learning Models: Literature Review.," *Water*, vol. 10, p. 1536, 2018, doi: https://doi.org/10.3390/w10111536.

[4] S. M. Hossein Shafizadeh-Moghadam, Shima Amani, "Utilizing machine learning models with limited meteorological data as alternatives for the FAO-56 model in estimating potential evapotranspiration," *PREPRINT*, 2023, doi: https://doi.org/10.21203/rs.3.rs-3324487/v1.

[5] W. S. Jun Lia, Guofang Wu, Yongpeng Zhang, "Optimizing flood predictions by integrating LSTM and physical-based models with mixed historical and simulated data," *Heliyon*, vol. 10, no. 13, 2024, doi: 10.1016/j.heliyon.2024.e33669.

[6] "Development of a Machine Learning-Based Predictive System For Classifying Psoriasis | International Journal of Innovations in Science & Technology." Accessed: Nov. 04, 2025. [Online]. Available: https://journal.50sea.com/index.php/IJIST/article/view/1407

[7] Catherine O. de Burgh-Day and Tennessee Leeuwenburg, "Machine learning for numerical weather and climate modelling: a review," *Geosci. Model Dev.*, vol. 16, no. 22, pp. 6433–6477, 2023, doi: https://doi.org/10.5194/gmd-16-6433-2023.

[8] M. Reichstein *et al.*, "Deep learning and process understanding for data-driven Earth system science," *Nat. 2019 5667743*, vol. 566, no. 7743, pp. 195–204, Feb. 2019, doi: 10.1038/s41586-019-0912-1.

[9] L. T. N. Luu, Chinh, Binh Thai Pham, Tran Van Phong, Romulus Costache, Huu Duy Nguyen, Mahdis Amiri, Quynh Duy Bui, I. P. , Hiep Van Le, and P. T. Trinh, "GIS-based ensemble

computational models for flood susceptibility prediction in the Quang Binh Province, Vietnam," *J. Hydrol.*, vol. 599, 2021, doi: https://doi.org/10.1016/j.jhydrol.2021.126500.

[10] B. I. N. Feliren Vicky,Fithrothul Khikmah,Irfan Dwiki Bhaswara, "Progressive Cross-Attention Network for Flood Segmentation Using Multispectral Satellite Imagery," *IEEE Geosci. Remote Sens.*, p. 99, 2024, doi: 10.1109/LGRS.2024.3495974.

[11] Deborah Cohen, "An improved flood forecasting AI model, trained and evaluated globally," *Google AI Blog*, 2024, [Online]. Available: https://research.google/blog/a-flood-forecasting-ai-model-trained-and-evaluated-globally/

[12] C. Shen and K. Lawson, "Applications of deep learning in hydrology," *Deep Learn. Earth Sci. A Compr. Approach to Remote Sensing, Clim. Sci. Geosci.*, pp. 285–297, Aug. 2021, doi: 10.1002/9781119646181.CH19;CTYPE:STRING:BOOK.

[13] J. Feng, Q.; Liu, J.; Gong, "Urban Flood Mapping Based on Unmanned Aerial Vehicle Remote Sensing and Random Forest Classifier—A Case of Yuyao, China," *Water*, vol. 7, pp. 1437–1455, 2015, doi: https://doi.org/10.3390/w7041437.

[14] Jin Ri,Hechun Quan,Aifen Jin and J. Guangri, "Assessment of flood susceptibility areas using novel hybrid approach of neural network over the Tumen River Basin, China," *J. Hydrol.*, 2022, doi: 10.21203/rs.3.rs-1774712/v1.

[15] A. Sajjad, J. Lu, R. W. Aslam, and M. Ahmad, "Flood Disaster Mapping Using Geospatial Techniques: A Case Study of the 2022 Pakistan Floods," *Environ. Sci. Proc. 2023, Vol. 25, Page 78*, vol. 25, no. 1, p. 78, Apr. 2023, doi: 10.3390/ECWS-7-14312.

[16] H. et al. Rehman, S., Sahana, M., Hong, "A systematic review on approaches and methods used for flood vulnerability assessment: framework for future research," *Nat Hazards*, vol. 96, pp. 975–998, 2019, doi: https://doi.org/10.1007/s11069-018-03567-z.

[17] Pakistan Meteorological Department (PMD, "Annual climate report of Pakistan," *PMD Publ.*, 2023, [Online]. Available: https://www.pmd.gov.pk/en/

[18] M. Haq, M. Akhtar, S. Muhammad, S. Paras, and J. Rahmatullah, "Techniques of Remote Sensing and GIS for flood monitoring and damage assessment: A case study of Sindh province, Pakistan," *Egypt. J. Remote Sens. Sp. Sci.*, vol. 15, no. 2, pp. 135–141, 2012, doi: https://doi.org/10.1016/j.ejrs.2012.07.002.

[19] A. Q. Aslam, Y. H. , Iftikhar Ahmad , Sajid Rashid Ahmad, M. S. Hussain, J. Shamshad, and S. J. A. Zaidi, "Integrated climate change risk assessment and evaluation of adaptation perspective in southern Punjab, Pakistan," *Sci. Total Environ.*, vol. 628–629, pp. 1422–1436, 2018, doi: https://doi.org/10.1016/j.scitotenv.2018.02.129.

[20] H. S. Khabat Khosravi, "A Comparative Assessment of Flood Susceptibility Modeling Using Multi-Criteria Decision-Making Analysis and Machine Learning Methods," *J. Hydrol.*, vol. 573, 2019, doi: 10.1016/j.jhydrol.2019.03.073.

[21] A. Rehman, L. Jingdong, Y. Du, R. Khatoon, S. A. Wagan, and S. K. Nisar, "Flood Disaster in Pakistan and its Impact on Agriculture Growth," *J. Econ. Sustain. Dev.*, vol. 6, 2015, [Online]. Available: https://core.ac.uk/download/pdf/234647327.pdf

[22] Y. Hirabayashi *et al.*, "Global flood risk under climate change," *Nat. Clim. Chang.*, vol. 3, no. 9, pp. 816–821, 2013, doi: 10.1038/nclimate1911.