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THE ROLE OF EXPLAINABLE AI IN FLOOD MODELLING AND RISK ASSESSMENT IN THE ERA OF CLIMATE CHANGE: A SYSTEMATIC REVIEW

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Abstract: *Flood risk is intensifying under climate change, making accurate and transparent prediction tools a global priority. While artificial intelligence (AI), machine learning (ML) and deep learning (DL) have shown strong performance in flood forecasting and susceptibility mapping. Hence, their black-box nature limits stakeholder trust and operational use. This review systematically examines the emerging role of explainable AI (XAI) in flood analysis under changing climate conditions. A structured search was conducted across Scopus, Web of Science, IEEE, Springer, and ScienceDirect, followed by PRISMA screening. Sixty-four eligible studies were analysed and grouped into four thematic domains: (i) flood forecasting, (ii) hazard and susceptibility mapping, (iii) integration with climate projections, and (iv) decision support systems. Across these domains, SHAP, LIME and attention mechanisms emerged as the most widely applied XAI techniques, improving model interpretability and stakeholder engagement. However, some key gaps persist, which includes weak operational adoption, limited integration with climate change scenarios, data scarcity in developing regions and a lack of user-oriented visualisation tools. This review concludes that XAI provides a promising pathway toward more trustworthy and actionable flood risk assessment but calls for standardised frameworks, stronger linkage with climate projections, and policy-friendly outputs to bridge research and practice.*

Key words: Explainable Artificial Intelligence, Flood Risk, Climate Change, Hydrology, SHAP

1 Introduction

Floods are among the most frequent and destructive hydroclimatic disasters, accounted for nearly one-third of global economic losses attributed to natural hazards (Kumar *et al*., 2023). Their impacts extend from loss of human life and displacement to damages in agriculture, infrastructure and ecosystems (Hirabayashi *et al*., 2021). Recent assessments by the Intergovernmental Panel on Climate Change (IPCC, 2022) indicate that the frequency, severity and spatial distribution of flood events are expected to intensify under a changing climate, primarily due to shifts in extreme precipitation, snowmelt dynamics and sea-level rise. This growing uncertainty underscores the urgent need for improved flood risk assessment and early warning systems. Traditionally, flood modelling has been dominated by physically based hydrological and hydraulic models, which rely on process representations of rainfall-runoff and river routing dynamics (Teng *et al*., 2017). Though, scientifically robust, these models face limitations under non-stationary climatic conditions, as parameter calibration often assumes stable historical relationships that may no longer be valid in future scenarios (Cosmo *et al*., 2015). Moreover, data scarcity in many regions particularly in the Global South restricts the accuracy of conventional models.

Artificial intelligence, ML and DL have emerged as powerful alternatives, capable of learning complex, nonlinear relationships from large datasets without strict assumptions about underlying processes (Adekunle *et al*., 2024). Applications include short-term flood forecasting using deep learning (Kratzert *et al*., 2019), flood susceptibility mapping with ensemble ML (Towfiqul-Islam *et al*., 2021) and integration of remote sensing and climate projections for flood hazard assessments (Lyu *et al*.,2019). Despite demonstrated predictive success, these models often operate as black boxes, providing little or no explanation of how inputs influence outputs. This lack of interpretability limits their adoption in operational flood management where transparency is essential for stakeholder trust and policy acceptance (Samek *et al*., 2019). XAI has recently emerged as a paradigm to address this challenge by enhancing transparency and interpretability in AI-driven predictions (Arrieta *et al.,* 2020). XAI techniques such as Shapley Additive Explanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME) and attention mechanisms offer insights into variable importance, sensitivity analysis and causal relationships within a model. In the context of flood risk, XAI enables domain experts to answer key questions: Which climatic or hydrological variables drive a forecast? How do land-use or topographical changes alter susceptibility maps? How robust are the predictions under uncertainty?

This systematic review uniquely (i) maps and synthesizes explainable AI (XAI) methods specifically applied to flood analysis under climate change, (ii) evaluates the suitability and limitations of XAI strategies across four application areas forecasting, hazard mapping, climate-projection integration and decision support and (iii) proposes an operational XAI framework and policy recommendations to accelerate adoption in practice. Unlike prior reviews that address AI in hydrology more broadly, this work explicitly links XAI methods to climate drivers and to stakeholder needs, offering practical guidance for model selection, interpretability assessment and governance.

2. 0 Methodology of Review

This review followed a structured protocol to ensure transparency and reproducibility. Five major databases were searched: Scopus, Web of Science, IEEE Xplore, SpringerLink and ScienceDirect. The search combined keywords related to explainable artificial intelligence ("XAI," "interpretable machine learning," "SHAP," "LIME," "attention mechanism") with flood-related terms ("flood forecasting," "flood risk," "flood susceptibility," "hydrology," "climate change"). The search period was restricted to 2015–2025, as explainable machine learning methods relevant to hydrology like SHAP and LIME only began to appear meaningfully in the literature after 2015.The initial search retrieved 327 records. After removing duplicates, 112 articles remained for screening. Titles and abstracts were screened for relevance, leaving 87 full-text studies. Of these, 24 were excluded because they either lacked an XAI component or were not focused on floods, resulting in a final set of 64 studies included in the review. Figure 1 presents the PRISMA flow diagram of the screening process. It shows systematic and structured approach followed to identify, evaluate and subsequently synthesises relevant literature on the application of XAI in flood analysis under climate change. Stepwise search techniques were employed along with screening and thematic categorisation in order to ensure comprehensive coverage of the subject. Though, a total of 64 studies were included after screening. To maintain readability, 28 representative studies were extensively summarised therein, while the rest were highlighted in Appendix A.

Records identified through database searching (n = 327)

Duplicates removed (n = 215)

Records screened (n = 112)

Excluded as irrelevant (n = 25)

Full-text articles assessed for eligibility (n = 87)

Excluded (n = 24: not flood-related or no XAI focus)

Studies included in review (n = 64)

Figure 1: PRISMA flow diagram for Screening Process

2.1 Inclusion and Exclusion Criteria

1. Inclusion: Peer-reviewed journal articles, conference proceedings and book chapters that applied or discussed XAI in flood-related contexts, studies integrating AI/ML/DL for flood modelling under climate variability or change and relevant English language publications.
2. Exclusion: Studies that (i) addressed other hazards (droughts and landslides) (ii) used purely black-box models without interpretability, or (iii) secondary reviews without systematic analysis were excluded.

Table 1 summarises the databases search strings and screening criteria applied. The protocol highlighted in the table was used to ensure transparency and reproducibility. This is somewhat consistent with PRISMA guidelines highlighted earlier. The searching algorithm was tilted towards five major world databases with a combination of keywords related to explainable artificial intelligence verse flood analysis and climate change. In addition, the boolean query as shown in Table 1 combined three thematic blocks: (flood* OR inundation OR "flood hazard" OR "flood risk" OR "flash flood" OR pluvial OR fluvial) AND ("explainable AI" OR "explainable artificial intelligence" OR XAI OR interpretab* OR explainab* OR SHAP OR LIME OR "local interpretable model-agnostic explanations" OR attention OR "feature importance" OR saliency OR "surrogate model") AND ("climate change" OR "climate projection*" OR "global warming" OR CMIP6 OR "climatic change"). Quotation marks were used for multi-word phrases ("machine learning") and wildcards (model*) to capture spelling variants. Equivalent queries were adapted for Web of Science (TS=) and IEEE Xplore. In the overall Table 1 gives a condensed overview of the searching techniques and selection criteria employed.

Table 1: Search strategy and criteria

Search Protocol	Details
Databases searched	Scopus, Web of Science, IEEE Xplore, SpringerLink and ScienceDirect
Search strings	(“Explainable AI” OR “XAI” OR “interpretable machine learning” OR SHAP OR LIME OR “attention mechanism”) AND (“flood forecasting” OR “flood risk” OR “flood susceptibility” OR “hydrology” OR “climate change”)
Timeframe	2015 – March 2025
Reason for cut-off (2015)	XAI methods (SHAP, LIME, attention models) only emerged and gained traction post-2015 in hydrology and climate sciences
Inclusion criteria	Peer-reviewed journal/conference papers; studies applying AI/ML to flood risk with interpretability or XAI component; written in English
Exclusion criteria	Studies unrelated to floods or climate, purely black-box ML with no interpretability, reviews without systematic analysis and duplicates

3 Flood Risk Analysis in the Presence of Climate Change

Flood risk is inherently shaped by the interaction between hazard, exposure and vulnerability. In recent decades, climate change has emerged as a major driver that exacerbates flood hazards by altering precipitation regimes, increasing the frequency of extreme rainfall events, accelerating glacier and snowmelt and contributing to sea-level rise (IPCC, 2022). Projections from Coupled Model Intercomparison Project Phase 6 (CMIP6) indicate that many regions, particularly in Asia, Africa and coastal megacities are likely to experience more intense pluvial and fluvial floods under high-emission scenarios (Hirabayashi *et al.,* 2021). The non-stationarity of hydrological processes under climate change poses a significant challenge to conventional flood analysis. Historically, flood risk assessment relied on the assumption that hydrological extremes follow stationary statistical distributions (Milly *et al*., 2008). However, increasing evidence shows that these assumptions are no longer valid in many basins worldwide, where flood frequencies and magnitudes are shifting outside historical bounds (Blöschl *et al*., 2019). As a result, traditional hydrological models and statistical approaches may underestimate risks and may fail to capture emerging compound patterns and cascading flood events. In addition, to climate drivers, anthropogenic factors such as urbanisation, deforestation and land-use change may amplify flood risk by altering surface runoff, infiltration and drainage pathways (Winsemius *et al*., 2016). The combined impact of climate and land-use pressures has led to heightened uncertainty in flood hazard mapping and forecasting, particularly in rapidly growing regions of the Global South where observational networks are sparse. These evolving challenges underscore the need for advanced flood modelling approaches that integrate multiple drivers of risk, hence, accounts for uncertainties and provide actionable outputs for disaster risk reduction. In this context, AI, ML and DL are increasingly being used as complementary or alternative tools to physically based hydrological models. By learning directly from observational and remote sensing datasets, AI models can capture complex, nonlinear relationships in flood-generating processes under changing climate conditions (Adekunle *et al*., 2024).

However, while AI models have improved flood forecasting accuracy, their lack of transparency limits their usability in policy and planning. To bridge this gap, Explainable AI (XAI) is gaining traction as a framework for enhancing interpretability in climate-related flood analysis, thereby addressing the critical trust deficit that often hinders adoption of AI-driven tools in operational flood management.

4 AI and Machine Learning in Flood Studies

This section synthesizes evidence across studies to evaluate where specific algorithmic classes (tree-based ensembles, deep learning, hybrid hydrological and ML models) perform well and where they systematically fail as well as their interpretability though differ by application. Key patterns emerge: (i) tree-based ensembles (RF, XGBoost) dominate susceptibility mapping because of their robustness to mixed predictors and readily compatibility with feature-attribution methods (ii) deep learning (CNN, LSTM and CNN–LSTM) is commonly applied for large-scale remote sensing and sequence forecasting tasks but tends to require XAI tools specifically adapted to time-series and spatial inputs and (iii) hybrid models that couple process-based hydrology with ML show promise for climate-change attribution yet remain under-used because of integration complexity and calibration need (Ouyang *et al.,* 2021).

4.1. Applications in Flood Forecasting

One of the most widely studied areas is short to medium-term flood forecasting, where ML models leverage rainfall, streamflow, soil moisture and meteorological data to predict river discharge and inundation. Recurrent neural networks (RNNs) and Long Short-Term Memory (LSTM) models have demonstrated superior performance in capturing temporal dependencies in hydrological time series (Kratzert *et al*., 2019). Hybrid approaches that combine physical models with ML techniques are also gaining popularity, as they integrate process-based understanding with data-driven adaptability.

4.2. Flood Susceptibility and Hazard Mapping

Machine learning has been extensively applied in flood susceptibility mapping, particularly in data-scarce regions where physically based modelling is infeasible. Ensemble methods such as Random Forests (RF), Gradient Boosting Machines (GBM) and Support Vector Machines (SVM) are often employed to identify flood-prone areas based on topographical, land-use and climatic variables (Tehrany *et al*., 2015; Towfiqul-Islam *et al*., 2021). Deep learning approaches, especially Convolutional Neural Networks (CNNs), have further advanced flood mapping by integrating satellite imagery and digital elevation models.

4.3. Integration with Climate Change Projections

Recent efforts have explored the coupling of ML models with downscaled climate projections to assess future flood hazards under scenarios from CMIP6 and CORDEX (Hosseini-Moghari and Tang, 2022). These integrations allow probabilistic risk assessments under varying emission pathways, although uncertainties remain in model downscaling and scenario selection.

4.4. Limitations of Black-Box Models

Despite their predictive success AI, ML and DL models face a fundamental limitation, basically interpretability issue. Most of these models operate as black boxes, thus offered a limited insights on the relative contribution of climatic drivers, hydrological processes or land-use changes to predictability of climatic extremes (Samek *et al*., 2019). For instance, while an LSTM may accurately predict river discharge peaks, it may not thoroughly explain precipitation intensity, antecedent soil moisture or land cover which may have a strong dominant influence in the face of climate change. This opacity reduces stakeholder trust and constrains the translation of ML outputs into actionable flood management strategies. In this context, Figure 2 highlighted the basic attribute of XAI, at such emerged as a critical complement to ML-based flood modelling. By providing interpretability and transparency thereby, bridge the gap between high-performing predictive models and the need for accountable decision-support in climate change adaptation.

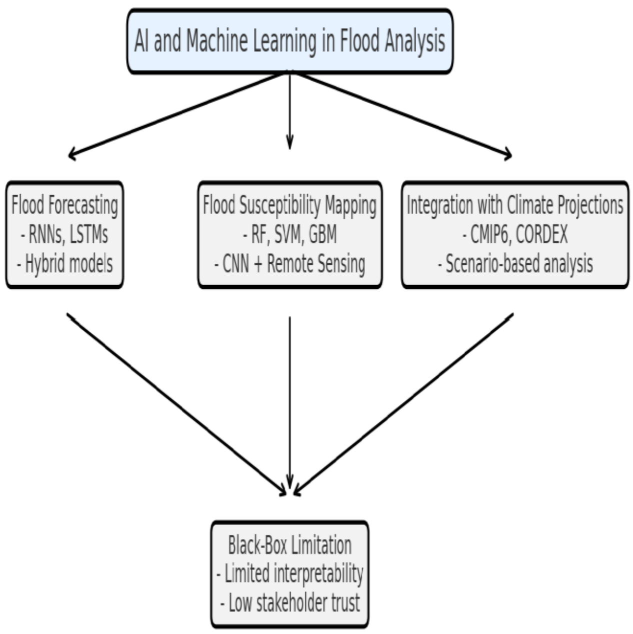

Figure 2: Application of AI and ML in flood analysis and the Black Box

5 Explainable AI Approaches in Flood Analysis

The increasing application of AI in flood analysis has heightened concerns regarding the opacity of black-box models. Explainable Artificial Intelligence (XAI) has therefore emerged as a critical framework to enhance transparency, interpretability and accountability in hydrological applications. XAI enables stakeholders including scientists, policymakers and water resource managers saddled not only to access accurate flood predictions but also to understand why models produce particular outcomes. This section reviews key XAI approaches applied in flood-related studies and highlights their potential under changing climate conditions.

5.1. Feature Attribution Methods

Feature attribution methods explain model predictions by quantifying the relative importance of input variables.

1. Shapley Additive Explanations (SHAP): Based on cooperative game theory, SHAP values provide a consistent measure of each feature contribution to a model output (Lundberg and Lee, 2017). In flood modelling, SHAP has been applied to identify dominant predictors such as rainfall intensity, soil moisture and topography in susceptibility mapping (Conrad *et al*., 2023).
2. Local Interpretable Model-agnostic Explanations (LIME): LIME approximates complex models locally with simpler interpretable models. In hydrology, it has been used to explain CNN-based flood susceptibility maps by highlighting local landscape features driving high flood probability (Bui *et al.,* 2021).

5.2. Visualisation-Based Approaches

Visualisation techniques provide intuitive insights into model decision-making

1. Saliency Maps and Heatmaps**:** Applied in convolutional neural networks (CNNs), these highlight spatial regions of satellite imagery most influential in flood detection and mapping (Li *et al*., 2020).
2. Partial Dependence Plots (PDPs): Commonly used to visualise marginal effects of climatic drivers (rainfall and temperature) on flood probability, offering interpretable trends across different input ranges.

5.3. Model-Specific Interpretability

Certain AI architectures incorporate interpretability directly into their design, examples are:

1. Attention Mechanisms: Widely used in recurrent neural networks (RNNs) and LSTMs, attention layers assign weights to time steps, highlighting critical periods (antecedent rainfall or seasonal signals) driving flood peaks.
2. Interpretable Rule-Based Models**:** Ensemble models such as Explainable Boosting Machines (EBMs) provide inherently interpretable outputs by constructing additive functions with clear variable contributions.

5.4. Uncertainty-Aware Explanations

Climate change introduces deep uncertainties in hydrological extremes. Recent studies combine XAI with probabilistic modelling to improve decision-making under uncertainty. For instance, Bayesian deep learning integrated with SHAP has been used to quantify both prediction intervals and feature importance in flood forecasting (Sun *et al*., 2022). This dual approach strengthens the credibility of climate-informed flood risk assessments.

5.5. Implications for Flood Risk Management

The integration of XAI into flood analysis offers several advantages as follows:

1. Improved Trust and Adoption: Transparent models facilitate uptake by disaster management agencies and communities.
2. Policy-Relevant Insights: By linking predictions to interpretable drivers, XAI supports evidence-based policy and adaptation planning.
3. Bridging Data Gaps: In data-scarce regions, interpretable models help validate AI predictions against expert knowledge.
4. Climate Adaptation: XAI enables clearer attribution of climate-related drivers (extreme rainfall, land-use change) in shaping future flood risks.

Despite these advances, the application of XAI in flood analysis remains in its infancy. Most studies are exploratory and focus on localized case studies, with limited integration into operational flood forecasting systems

6 Comparative Analysis of Existing Studies

As summarised in Table 2, SHAP (Lundberg and Lee, 2017) remains the most widely used framework because of its consistent local and global feature attributions, especially when combined with tree-based or ensemble models for flood-susceptibility mapping (Zhao *et al*., 2024). LIME (Ribeiro *et al*., 2016) is preferred when fast, local interpretability is required, such as in early-warning or operational decision systems, though its explanations can vary across perturbations. Attention mechanisms and saliency-map approaches are better suited for deep learning architectures (CNN-LSTM) that handle

Table 2: Comparative analysis of basic XAI techniques

Method	Type	Strengths	Weaknesses	Best fit for flood tasks	Representative refs
SHAP	Post-hoc, additive feature attribution	Theoretically grounded; local and global explanations; consistent attributions for tree models	Computational cost for large DL; baseline choice matters	Susceptibility mapping, feature ranking for forecasting	Lundberg and Lee (2017); Zhao *et al.* (2024)
LIME	Local surrogate	Quick local explanations; model-agnostic	Instability; sensitive to sampling	Local explanation checks, model debugging	Ribeiro *et al.* (2016)
Permutation / Feature importance	Global, model-agnostic	Fast, intuitive	May confound correlated predictors	Global ranking in mapping tasks	Tehrany *et al.*, (2019)
Attention / Saliency	Internal to DL (sequence/vision)	Natural for spatio-temporal inputs; highlights time/space regions	Hard to translate to physical drivers; less stable	Remote sensing inundation mapping; LSTM forecasting	Kratzert *et al*., (2019); Li *et al.* (2020)
Surrogate models (trees, rules)	Approximation	Human-readable rules; policy friendly	Loss of fidelity; approximations may mislead	Decision-support visualization for stakeholders	Arrieta *et al*. (2020)

Note: This table presents a representative selection of studies (n = 28) from the 64 included in the systematic review. The comprehensive list, included additional metadata (region, methods, data sources and outcomes) are provided in Appendix A.

Spatial and temporal data, offering insights into which pixels or time windows influence flood predictions. Table 2 further highlighted that Surrogate or rule-based models provide easily communicable, human-readable rules that are useful for stakeholder engagement, but they risk reduced fidelity when simplifying complex non-linear relationships. In the overall, the comparative assessment underscores that no single XAI method is universally optimal. The choice depends on the modelling goal, data dimensionality, computational budget, and interpretability needs of end-users. Combining complementary XAI techniques such as pairing SHAP global attributions with LIME local explanations or coupling attention visualization with SHAP feature ranking has proven most effective for transparent, stakeholder-trustworthy flood analyses under climate change. Figure 3 gives an overview of XAI as applied in flood studies.

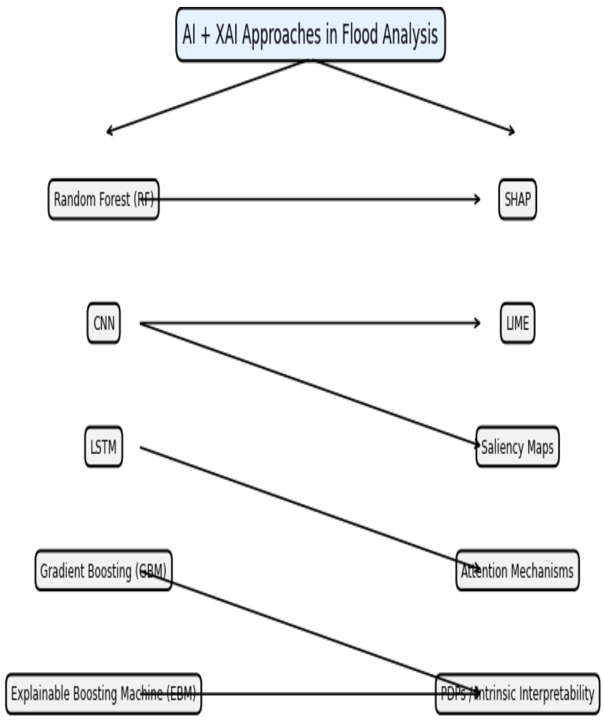

Figure 3: AI Models and XAI Methods in Flood Analysis

7 Research Gaps and Future Directions

Despite significant progress in applying AI and XAI techniques to flood analysis, several research and practical gaps remain that hinder their full integration into operational hydrological systems. Addressing these gaps is critical to enhance the reliability, interpretability and policy relevance of AI-driven flood models particularly under the uncertainties of climate change.

7.1. Limited Operational Adoption

While numerous case studies demonstrate the feasibility of XAI in flood forecasting and susceptibility mapping, very few applications have been integrated into national or regional early warning systems (Kumar *et al.,* 2023). The absence of standardized frameworks for embedding XAI outputs into decision-support platforms, reduces their utility for practitioners and policymakers.

7.2 Data Scarcity and Quality Issues

Flood-prone regions in the Global South often face data limitations, including sparse hydrological records, inconsistent climate datasets, and limited high-resolution remote sensing. These challenges restrict the training of data-intensive AI models and undermine the generalizability of XAI insights (Wang *et al.,*2023). Developing data-efficient algorithms and leveraging transfer learning remain open research priorities.

7.3. Model Generalisability and Scalability

Most XAI-based flood studies remain localized and cannot be directly generalized to other catchments or climatic zones (Hirabayashi *et al.,* 2021). There is a pressing need for multi-basin comparative studies and scalable AI–XAI frameworks that can adapt to diverse hydrological, topographic and climatic settings.

7.4. Computational and Methodological Challenges

The deployment of SHAP, LIME, or Bayesian deep learning methods in real-time flood forecasting is often computationally expensive (Conrad *et al*., 2023). Research should prioritize lightweight interpretability methods and hybrid modelling approaches that balance accuracy, interpretability and efficiency.

7.5. Integration with Climate Change Projections

Current applications of XAI in flood analysis often neglect the uncertainty of climate change scenarios. Few studies explicitly link interpretability methods with outputs from CMIP6 or CORDEX climate models. Future work should focus on climate-informed XAI frameworks to disentangle the contributions of extreme rainfall, land-use change and temperature variability to future flood risks (Adrian *et al*., 2020).

7.6 Human-Centred and Policy-Oriented XAI

Most XAI tools are designed for technical users, while non-expert stakeholders (disaster managers, local communities) require more intuitive interfaces and explanation formats. Research should explore human-centred XAI (visual narratives and dashboard integration) that can bridge the science policy gap and strengthen adaptive capacity at community levels (Doshi-Velez and Kim, 2017).

8 Future Research Priorities

To overcome these gaps, future research should:

1. Develop standardized XAI frameworks for operational flood forecasting systems.
2. Advance data-efficient and transfer learning approaches to address data scarcity.
3. Conduct multi-basin comparative studies to test scalability and generalizability.
4. Optimize computational efficiency of interpretability techniques for real-time applications.
5. Integrate climate projections into XAI-driven flood risk models for robust adaptation planning.
6. Design stakeholder-oriented interfaces that translate complex model explanations into actionable insights.

By addressing these gaps, XAI can evolve from an exploratory tool into a mainstream component of climate-resilient flood risk management systems, thereby enhancing both scientific understanding and societal preparedness.

9 Conclusion

Recent literatures have shown that feature attribution methods (SHAP and LIME), visualisation-based approaches (saliency maps and PDPs), model-specific interpretability techniques (attention mechanisms and EBMs) and uncertainty-aware explanations are emerging as robust strategies to enhance model interpretability. These approaches not only demystify model decisions but also bridge the gap between scientific innovation and disaster risk management. Nevertheless, this analysis revealed key research gaps; for example, limited operational adoption, data scarcity in vulnerable regions, computational challenges and inadequate integration with climate change projections. Addressing these limitations requires the development of standardized frameworks, data-efficient models and human-centred explanation tools that will empower both technical and non-technical stakeholders. Looking ahead, Explainable AI offers a transformative pathway for climate-resilient flood management. By enhancing transparency, trust and usability, XAI can strengthen early warning systems, support evidence-based policymaking and improve community preparedness in the face of growing hydrological extremes. Thus, XAI is not merely a technical enhancement but a critical enabler of sustainable adaptation in the era of climate uncertainty.

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Appendix A. Full list of studies included in the systematic review (2015–2025)

No.	Author(s), Year	Region / Case Study	AI/ML Model(s)	XAI Method(s)	Application Area
1	Kratzert *et al.,* 2019	Large-sample catchments (Europe and US	Entity-Aware-LSTM (EA-LSTM)	Attention mechanisms	Streamflow / flood forecasting
2	Adekunle *et al*., 2024	Global (review)	ANN, SVM, ensemble methods	-	Flood prediction review
3	Lundberg & Lee, 2017	Methodological	Model-agnostic	SHAP	Interpretability method
4	Arrieta *et al.,* 2020	Conceptual review	Various ML/DL	SHAP, LIME, counterfactuals	XAI taxonomy
5	Samek *et al*., 2019	Conceptual / XAI	DL interpretability	Layer-wise relevance, visualization	Explainable AI
6	Tehrany *et al*., 2015	Malaysia	SVM, RF	Feature ranking	Flood susceptibility mapping
7	Li *et al*., 2020	Bangladesh	CNN	Saliency maps	Remote-sensing flood detection
8	Winsemius *et al*., 2016	Global	GLOFRIS framework	-	Global drivers of river flood risk
9	Blöschl *et al*., 2019	Europe	Statistical analysis	-	Changing flood regimes
10	Teng *et al*., 2017	Review	Hydrodynamic + models	-	Flood inundation methods & uncertainty
11	Hirabayashi *et al*., 2021	Global (CMIP6)	Climate–hydrology coupling	-	Flood exposure projections
12	Milly *et al.,* 2008	Conceptual	-	-	Non-stationarity in hydrology
13	Rajendran, *et al*., 2022	Case study (e.g., Nile region)	Feature Selection and Ensemble Boosting Machine Learning	-	Climate impact on floods
14	Wang *et al*., 2023	Urban (data-scarce)	Graph Attention Network (GAT)	-	Pluvial flood susceptibility
15	Lyu et al., 2019	Topľa river basin, Slovakia	boosted regression trees and feature selection	-	Flood susceptibility mapping
16	Towfiqul-Islam *et al*., 2021	Iran	Ensemble ML (RF, SVM, ANN)	Feature importance	Flood susceptibility mapping
17	Kumar *et al.,* 2023	Review	Deep learning (LSTM, CNN)	-	Review of DL in flood forecasting
18	Pham *et al*., 2019	SE Asia region	Ensemble ML (RF, GBM)	Feature importance	Susceptibility mapping
19	Anderson and Radic, 2022	SW Canada	CNN + climate projection integration	Sensitivity analysis	Flood hazard assessments
20	Sun *et al*., 2023	Europe (example)	Probabilistic DL / Bayesian DL	SHAP	Probabilistic flood forecasting
21	Bahram *et al.,* 2025	South Asia	XGBoost, RF	SHAP	Flood susceptibility analysis
22	Xia *et al*., 2022	Hun River Basin, Chain	LSTM	Attention mechanisms	Flood prediction
23	Abdelkader *et al.,* 2024	Wadi El Harrach Algeria	CNN + DEM	Saliency / visualization	Flood susceptibility mapping
24	Luna *et al*., 2022	Global Focus	Review	-	Review

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25	Mohamed *et al*., 2024	Japan	RF and GIS	Attention	Flood forecasting with remote sensing
26	Conrad, *et al*., 2023	Australia	XGBoost	SHAP	Coastal flood vulnerability
27	Chenmin *et al.*, 2024	China	CNN, BiLSTM, CNN–BiLSTM	Attention mechanisms	Flood susceptibility mapping
28	Bentivoglio *et al.,* 2021	Global focus	Review		Review
29	Islam *et al.,* 2022	Zimbabwe	CNN, RNN, LSTM	SHAP	Flood risk mapping
30	Nguyen, 2023	Vietnam	SVM, ANN	-	Flood Susceptibility Mapping
31		Iran	GLMbayesian, RF	-	Flood Susceptibility Mapping
32	Yogesh, 2020	Pakistan	CNN, RNN, LSTM	Attention mechanisms	Susceptibility mapping
33	Ri *et al.,* 2022	China	GA	-	Susceptibility mapping
34	Gessang and Umboro, 2020	Indonesia	ANN	Feature importance	Flood susceptibility
35	Zelalem *et al.,* 2024	USA	RF, SVM, XGB	-	Flood susceptibility mapping
36	Abu et al., 2021	Bangladesh	RF, SVM		Flood forecasting
37	Aman *et al*., 2025	India	ANN, Random subspace	-	Flood susceptibility zonation
39	Abedi *et al*, 2022	Romania	RF, XGBoos, BRT	-	Flash-flood susceptibility mapping
40	Zahid *et al.,* 2025	Pakistan	XGBoost, ANN, RF	-	Flood susceptibility Mapping
41	Chapi, *et al*., 2017	Iran	RF, XGB, SVM	Feature importance	Flood hazard assessment
42	Debnath, *et al.,* 2023	Chain	RF, SVM	-	Flood susceptibility Mapping
43	Lai *et al.,* 2025	China	LSTM, RNN, RF	SHAP	Flood forecasting
44	Andaleeb *et al*., 2022	Pakistan	SVM, RF	-	Flood risk modelling
45	Khabat *et al*., 2018	Mexico	ANN	-	River flood forecasting
46	Xu *et al*., 2020	China	RF	SHAP	Flood susceptibility under land-use chang
47	Yuan *et al*., 2019	China	CNN	Saliency	Rapid flood mapping

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48	Patel *et al*., 2024	Panam River Basin	Hybrid ML + hydrological models	-	Flood inundation forecasting
49	Rahebe *et al*., 2021	Vietnam	XGBoost	SHAP	Storm flood susceptibility
50	Lopez and Frances, 2015	Spanish	Statistical + ML	-	Flood frequency analysis
51	Xuan-Hien *et al*., 2019	China	LSTM	-	River flow forecasting
52	Mohammadtaghi *et al.,* 2020	Iran	RF	Feature importance	Flood mapping
53	Ahmed *et al*., 2022	Colombia	FR, LR, SVM	-	Flood vulnerability mapping
54	Aryan *et al*., 2023	Egypt	SVR	-	Nile Basin flood susceptibility
55	Ibrahim *et al.,* 2023	Nigeria	RF and FR	-	Urban flood susceptibility
56	Jin et al., 2020	China	CNN	Saliency	Inundation extent mapping
57	Vijendra et al., 2017	Germany	RF	-	Flood hazard mapping