An Intelligent GIS-Based Approach to Flood Prediction and Mapping from Multiple Data Sources

Ein intelligenter, GIS-basierter Ansatz zur Hochwasservorhersage und -kartierung aus mehreren Datenquellen

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Accurate flood mapping is essential for disaster risk reduction, especially under increasingly frequent extreme rainfall events. This study presents a methodology that integrates geospatial, hydrometeorological, and remote sensing data with advanced machine learning to generate reliable flood zone maps. The approach combines Digital Elevation Model (DEM) derived indicators such as slope, curvature, and Topographic Wetness Index (TWI) with drainage density, land use, hydrographic networks, infrastructure data, and satellite imagery, along with precipitation and water level time series. The July 2021 flood in Klüsserath, Rhineland-Palatinate (Germany), was used as a case study. The performance of XGBoost, LightGBM, FocalLGBM, and their combinations was compared against the proposed integrated framework. While individual models achieved high accuracy, they showed limitations in delineating flood extents due to class imbalance and fragmented predictions. The integrated methodology achieved superior results, with an accuracy of 0.99, F1-score of 0.89, and IoU of 0.79, outperforming both single algorithms and combined models (e.g., LightGBM + FocalLGBM). Error analysis confirmed that the method maximizes true positives while minimizing false positives and negatives, ensuring greater reliability for decision-making. These results demonstrate that integrating heterogeneous data with spatial post-processing significantly improves the physical consistency of flood mapping and provides a robust tool for risk assessment, evacuation planning, and infrastructure protection.

Keywords: Flood mapping; topographic features; boosting machine learning algorithms; remote sensing imagery

Eine genaue Hochwasserkartierung ist für die Katastrophenvorsorge unerlässlich, insbesondere angesichts immer häufiger auftretender extremer Niederschlagsereignisse. Diese Studie stellt eine Methodik vor, die georäumliche Daten, hydrometeorologische Daten und Fernerkundungsdaten mit fortschrittlichem maschinellem Lernen integriert, um zuverlässige Hochwasserzonenkarten zu erstellen. Der Ansatz kombiniert aus Digitalen Höhenmodellen (DEM) abgeleitete Indikatoren wie Neigung, Krümmung und Topographischer Feuchtigkeitsindex (TWI) mit Entwässerungsdichte, Landnutzung, hydrographischen Netzwerken, Infrastrukturdaten und Satellitenbildern sowie Zeitreihen zu Niederschlag und Wasserstand. Als Fallstudie diente die Überschwemmung im Juli 2021 in Klüsserath, Rheinland-Pfalz (Deutschland). Die Leistung von XGBoost, LightGBM, FocalLGBM und deren Kombinationen wurde mit dem vorgeschlagenen integrierten Rahmen verglichen. Einzelne Modelle erzielten zwar eine hohe Genauigkeit, zeigten jedoch aufgrund von Klassenungleichgewichten und fragmentierten Vorhersagen Einschränkungen bei der Abgrenzung des Ausmaßes von Überschwemmungen. Die integrierte Methodik erzielte mit einer

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Genauigkeit von 0,99, einem F1-Score von 0,89 und einem IoU von 0,79 überlegene Ergebnisse und übertraf damit sowohl einzelne Algorithmen als auch kombinierte Modelle (z. B. LightGBM + FocalLGBM). Die Fehleranalyse bestätigte, dass die Methode die Anzahl der echten Positive maximiert und gleichzeitig die Anzahl der falschen Positive und Negative minimiert, wodurch eine höhere Zuverlässigkeit für die Entscheidungsfindung gewährleistet wird. Diese Ergebnisse zeigen, dass die Integration heterogener Daten mit räumlicher Nachbearbeitung die physikalische Konsistenz der Hochwasserkartierung erheblich verbessert und ein robustes Werkzeug für die Risikobewertung, Evakuierungsplanung und den Schutz der Infrastruktur darstellt.

Schlüsselwörter: Hochwasserkartierung, topographische Merkmale, Boosting-Algorithmen für maschinelles Lernen, Fernerkundungsbilder

1 INTRODUCTION

Floods represent one of the most destructive natural hazards worldwide, causing substantial social, economic, and environmental losses /Belay et al. 2025/. The increasing frequency and intensity of flood events /Kashtan et al. 2024/, /Ivanov et al. 2022/, often linked to climate change /Taye et al. 2024/, /Kwakye et al. 2022/ and rapid urbanization, highlight the urgent need for reliable methods of flood prediction /Hnatushenko et al. 2025/ and risk assessment /Albano et al. 2020/. Accurate delineation of flood-prone areas is essential for disaster management, land-use planning, and the development of adaptive strategies to mitigate adverse impacts on vulnerable communities.

In recent years, advances in geospatial technologies, remote sensing /Kashtan et al. 2025/, and machine learning /Bentivoglio et al. 2022/ have opened new opportunities for improving the precision and interpretability of flood mapping. Traditional hydrological and hydraulic models /Pallavi & Ravikumar 2022/, while scientifically robust, are often limited by their computational complexity, dependence on high-quality input data, and challenges in capturing fine-scale spatial variability. Conversely, data-driven approaches, particularly those based on machine, and deep learning, have demonstrated the ability to extract complex patterns from heterogeneous datasets, enabling more efficient integration of topographic, geospatial, and environmental predictors.

State-of-the-art algorithms such as XGBoost, LightGBM, FocalLGBM /Ajin et al. 2025/ have gained increasing attention due to their flexibility, high predictive accuracy, and capacity to handle imbalanced and heterogeneous data. Their application in flood risk studies allows not only the identification of key physical and geomorphological determinants of flooding but also the generation of spatially consistent flood maps that align with established hydrological principles. Importantly, incorporating topographic indicators – such as the Topographic Wetness Index (TWI), Digital Elevation Model (DEM), slope, and drainage network density – enhances the ability to model flood dynamics by explicitly accounting for water flow processes and terrain morphology.

Within this context, the present study develops and evaluates a novel methodology for flood zone mapping that integrates advanced machine learning algorithms with topographic, geospatial, and hydrometeorological predictors. By applying and comparing multiple gradient-boosting approaches, the study demonstrates the scientific validity and practical applicability of the proposed framework for effective flood risk assessment.

2 LITERATURE REVIEW

Flood prediction and mapping have been the subject of extensive research due to the growing frequency and severity of hydrological extremes. Recent advances in geospatial data processing and machine learning have enabled the integration of topographic and geomorphological features into predictive frameworks, improving both accuracy and interpretability. In particular, the Topographic Wetness Index (TWI), Digital Elevation Model (DEM), slope, and drainage density have been consistently identified as strong predictors of flood susceptibility, aligning with established hydrological principles.

Several studies have demonstrated the potential of gradient boosting algorithms for flood risk assessment. The authors in /Abedia et al. 2021/ employed XGBoost to evaluate flash flood risk, showing high predictive performance but also highlighting the issue of fragmented flood polygons that require post-processing for spatial consistency. Similarly, /Avand et al. 2021/ examined the influence of DEM resolution on machine learning performance, concluding that the choice of resolution strongly affects predictor quality but does not always translate into improved model accuracy. /Nguyen et al. 2024/ proposed an integrated framework combining XGBoost, LightGBM, with hydraulic modelling, demonstrating robust results under climate change scenarios, though with significant computational complexity.

Review papers have further systematized emerging methodologies. In /Al-Rawas et al. 2024/ the authors provided a critical overview of recent advances in AI- and IoT-based flash flood early warning, confirming the value of gradient boosting models but also pointing to the lack of standardized evaluation benchmarks. /Liu et al. 2024/ enhanced interpretability through the use of SHAP values with XGBoost, allowing quantification of morphological impacts on urban flood susceptibility; however, their method remained sensitive to sampling design. A technical study by /Winzeler et al. 2022/ focused on the calculation of TWI, emphasizing its reliability as a proxy for soil moisture, while also showing that the choice of computational algorithm significantly influences results.

Beyond methodological refinements, new approaches address data imbalance. In /Hoang et al. 2024/ the authors compared XGBoost, Random Forest, and Boosted Regression Trees, noting that focal loss and resampling strategies improve the detection of small and isolated flood zones often underrepresented in training data. In the context of Central Europe, the catastrophic July 2021 floods in Germany have been extensively analyzed /Thieken et al. 2023/, /Mohr et al. 2023/. These studies underscored that extreme precipitation combined with antecedent soil saturation was the primary driver of devastating impacts, while limitations in early warning and communication amplified damages. Such findings confirm the importance of integrating hydrometeorological indicators with topographic predictors in flood mapping. Recent studies also highlight the potential of ensemble approaches and remote sensing integration. /Reinert et al. 2025/ demonstrated that hindcasts with ensemble meteorological predictions can significantly improve early flood warnings, while /Hajji et al. 2025/ showed that coupling satellite remote sensing with gradient boosting enhances predictive accuracy and spatial consistency.

Overall, the literature indicates that gradient boosting algorithms (XGBoost, LightGBM and FocalLGBM) consistently outperform traditional statistical approaches in flood susceptibility mapping. Their strengths lie in handling heterogeneous data and capturing nonlinear relationships, while limitations remain in spatial consistency, class imbalance, and dependence on high-quality input datasets. Lessons from the German floods highlight the need for models that not only achieve high predictive performance but also integrate hydrological realism and operational applicability.

This study aims to develop and test a comprehensive methodology for flood zone mapping that integrates heterogeneous geospatial, hydrometeorological, and multi-temporal remote sensing data using advanced machine learning algorithms. By combining topographic indicators, e.g., Digital Elevation Model (DEM), slope, Topographic Wetness Index (TWI), drainage density, infrastructure and land-use data, satellite imagery, and hydrometeorological time series, the framework seeks to generate reliable and physically consistent flood maps. The methodology is applied to a case study in Rhineland-Palatinate, Germany, focusing on the July 2021 flood in Klüsserath, to evaluate its effectiveness in capturing spatial and temporal dynamics of flood formation. Lessons from similar catastrophic floods /Petry & Becker 2022/ highlight the importance of integrating hydrological realism with predictive performance.

3 METHODOLOGY FOR MAPPING FLOOD ZONES

The proposed methodology, presented in *Fig. 1*, is based on integrating heterogeneous geospatial, hydrometeorological, and remote sensing data using machine learning methods. This approach enables flood maps to capture both spatial and temporal dynamics of flood formation.

The input data reflect the territory's physio-geographic characteristics and hydrometeorological processes. The primary source is the DEM, which provides the basis for calculating surface morphometric parameters such as slope, aspect, curvature, and the TWI. Additionally, flow density was considered, characterizing the structure of the drainage network and the degree of surface runoff accumulation. Vector data were also incorporated, including the hydrographic network (rivers and streams), infrastructure objects (buildings and roads), land use maps, and historical flood polygons. This information makes it possible to combine the topographic properties of the terrain with the spatial distribution of elements sensitive to flood processes and enables spatial-contextual analysis. A separate category is represented by time series of hydrometeorological parameters, particularly precipitation over time, water levels in watercourses, and historical records of flood events. Such dynamic indicators allow for accounting of the temporal patterns of flood formation and linking them with the spatial characteristics of the terrain. For flood zone mapping, it is proposed to use satellite data, represented by both high-resolution optical imagery and radar (SAR) data. Optical

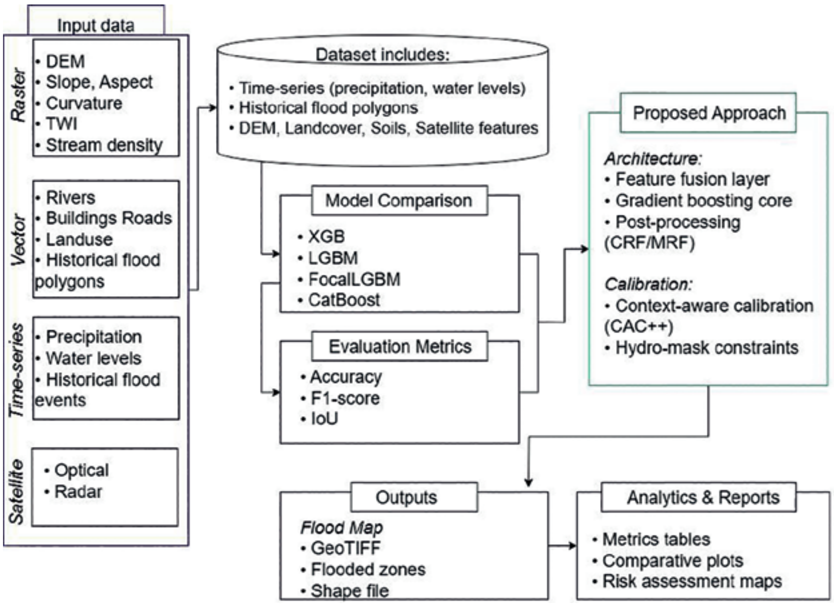

Fig. 1 | The flowchart of the methodology for mapping flood zones imagery makes it possible to identify surface changes and land cover types. In contrast, radar imagery ensures the robustness of analysis under cloud cover conditions and poor visibility, which is critical in the case of floods. The methodology is designed to incorporate multi-temporal remote sensing data, allowing the integration of images acquired at different dates to capture temporal changes in flood dynamics. Thus, the assembled input dataset integrates topographic characteristics, spatial infrastructure information, temporal hydrometeorological series, and satellite observations. This comprehensive approach provides a more complete description of flood processes and creates the prerequisites for developing reliable and physically consistent mapping models.

An integrated dataset was constructed from the data, comprising three main blocks: static spatial characteristics (relief, land use, infrastructure), dynamic time series (precipitation, water levels, flood events), and multi-temporal satellite imagery. Actual flood polygons were used as the input data, serving as reference samples for model training. The developed dataset combines a multidimensional spatio-temporal representation of the territory. It enables implementing a methodological approach based on applying machine learning methods for flood mapping and detecting complex interrelationships between natural and anthropogenic factors. Historical flood data is considered reliable, which allows the model to be trained to capture complex relationships between natural and anthropogenic factors.

The constructed dataset serves as the basis for developing a model capable of reproducing hydrological processes and their consequences, as represented in the input data, and mapping flooded areas. For this purpose, a core based on gradient boosting algorithms was selected: XGBoost (XGB), LightGBM (LGBM) and FocalLGBM. Each of these algorithms enables the accurate representation of complex spatio-temporal relationships between the input features and the target variable, which is essential for reliable flood mapping. The algorithms are integrated into a unified ensemble approach within the proposed methodology to improve mapping accuracy and reduce overfitting. The model is trained on a dataset where the input features are geospatial and temporal characteristics, while the outputs are binary indicators of flood presence or absence. The training sample (Y_i, Y_i) is considered, where $i = 1, \ldots, N$. The initial model $F_0(x)$ is defined as one that minimises the empirical risk /Airlangga & Liu 2025/:

$$F_0(x) = \arg\min_c \sum_{i=1}^{N} L(y_i, c), \tag{1}$$

where y_i is the target value for the i-th object, c is the initialisation constant, and the loss function L measures the difference between the predicted and actual values.

At each step of the iterative learning process (boosting iteration), a new base model $h_m(x)$ is formed, which learns from the residual errors of previous models /Taye & Dyer 2024/:

$$F_M(x) = F_0(x) + \sum_{m=1}^{M} v\, h_m(x), \tag{2}$$

where v is the learning rate coefficient, $h_m(x)$ is the decision tree at iteration m.

A generalised representation of the gradient boosting ensemble can be written as:

$$\hat{Y}(x) = \sum_{m=1}^{M} \gamma_m\, h_m(x), \tag{3}$$

where $h_m(x)$ is the decision tree at iteration m, γ_m is its weight.

Every subsequent tree $h_m(x)$ is constructed based on the residual errors of the previous ones:

$$r_i^{(m)} = -\left[\frac{\partial L\left(\hat{Y}^{(m-1)}(x_i)\right)}{\partial \hat{Y}^{(m-1)}(x_i)}\right], \tag{4}$$

where L is the loss function.

FocalLGBM uses a focal loss function that allows for class imbalance:

$$L_{\text{focal}}(p_t) = -\alpha\,(1 - p_t)^{\gamma} \log(p_t), \tag{5}$$

where p_t is the predicted probability of the correct class, γ is the focus parameter, and α is the weight coefficient.

Conditional random fields and Markov random fields are used for spatial smoothing of results, taking into account the spatial dependence between neighbouring pixels:

$$E(y) = \sum_{i} \psi_{\text{u}}(y_i) + \sum_{i,j} \psi_{\text{p}}(y_i, y_i), \tag{6}$$

where ψ_{u} is the unitary potential (probability from the model), ψ_{p} is the paired potential (smoothing between neighbours).

According to the proposed methodology, additional refinement of flood zone boundaries is performed, considering local contextual features such as morphometric characteristics of the relief, spatial distribution of vegetation, and distance to elements of the river network. The results obtained are superimposed on a hydrological mask, which ensures the physical and geographical consistency of the map and excludes forecast zones in areas that are geographically inaccessible for flooding. The model's effectiveness was assessed using standard forecast accuracy indicators, particularly accuracy, F1-measure, and Intersection over Union (IoU) similarity coefficient.

Implementing the methodology results in constructing a flood zone map with clearly defined flooded areas. Additionally, analytical reports, comparative graphs, and risk assessment maps are generated, providing the possibility of a comprehensive analysis of the spatial and temporal patterns of flood events.

4 EXPERIMENTAL RESULTS

In the current study, satellite data from 2021 were used as an illustrative case. The data were processed for a case study conducted in the Rhineland-Palatinate region of Germany, where intense rainfall on 13 July 2021 led to the expectation of a severe flood along the Moselle River. This event prompted the German Joint Information and Situation Centre to activate the Copernicus Emergency Management Service Rapid Mapping to monitor the situation's development. The study focused on the town of Klüsserath and its surroundings, which were directly affected by the flood, the applied modeling methods aimed to produce detailed flood maps for this region. A visualization of the study area is presented in *Fig. 2*.

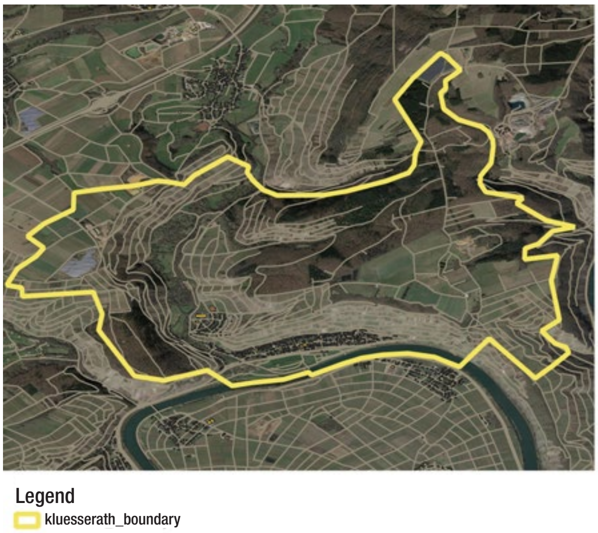

Fig. 2 | The territory of Klüsserath, Germany

The influence of topographic and geospatial features on flood prediction, as presented in *Fig. 3*, highlights that the proposed methodology demonstrates high quantitative performance and is scientifically grounded and interpretable. The relative importance of features was computed using the feature importance scores provided by the gradient boosting algorithms (XGBoost, LightGBM), which quantify each predictor's contribution to reducing the model's loss function during training. The results indicate that the TWI and the DEM are the most significant predictors, contributing the most to flood forecasting. It confirms that physical and geomorphological characteristics of the terrain are the primary determinants of flooding, consistent with established hydrological principles. Other topographic indicators, such as slope and drainage network density, also play a substantial role, demonstrating that the model effectively accounts for water flow dynamics and proximity to watercourses.

Fig. 4 shows the boundaries of flooded areas according to the proposed methodology, including the Moselle River floodplains and infrastructure close to the riverbed. Visualization and spatial data analysis confirm the camping areas are in the predicted flooded area. It indicates a high risk of flooding damaging these facilities. The results confirm the need to develop risk reduction strategies, including structural and non-structural adaptation measures, to protect vulnerable infrastructure from the potential effects of flooding. Thanks to post-processing based on Conditional Random Fields, the final map shows smooth and logical boundaries of flood zones that correspond to hydrological processes, rather than a collection of individual pixels. This approach minimizes "noise" in the data and ensures high spatial coherence of the results. On the flood map obtained using the proposed methodology, the identified flooded areas (marked in purple polygons) correlate with historical flood data (light blue polygons) and also allow for the assessment of potential risks to the recreational use of coastal areas and provide a basis for planning preventive safety measures during flood events.

A comparative analysis of the results obtained using the XGBoost, LightGBM, FocalLGBM algorithms was performed to evaluate the effectiveness of the proposed methodology for mapping flood zones. In *Fig. 5*, each algorithm is marked with a separate colour, which allows us to identify significant differences in the mapping of flood zones clearly. The XGBoost and LightGBM algorithms map flood zones based on historical data, but they form fragmented polygons that do not always reflect physically justified boundaries of flood areas. It highlights the need for additional processing of the results to improve the spatial consistency of flood polygons with the physical and geographical features of the territory. By optimizing the loss function for unbalanced data, FocalLGBM more effectively reproduces small and isolated flood zones, which XGBoost and LightGBM predict less accurately due to the limited number of observations in the corresponding classes of the training sample. FocalLGBM demonstrates high mapping accuracy in areas where categorical features (e.g., land use types) influence the formation of flooded areas. By

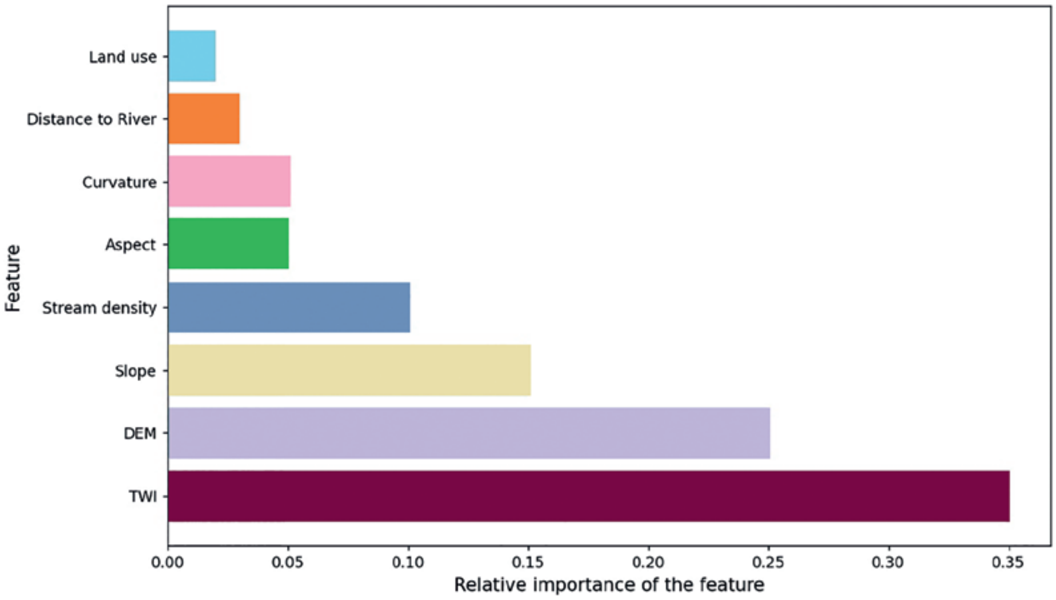

Fig. 3 | Topographic and geospatial features

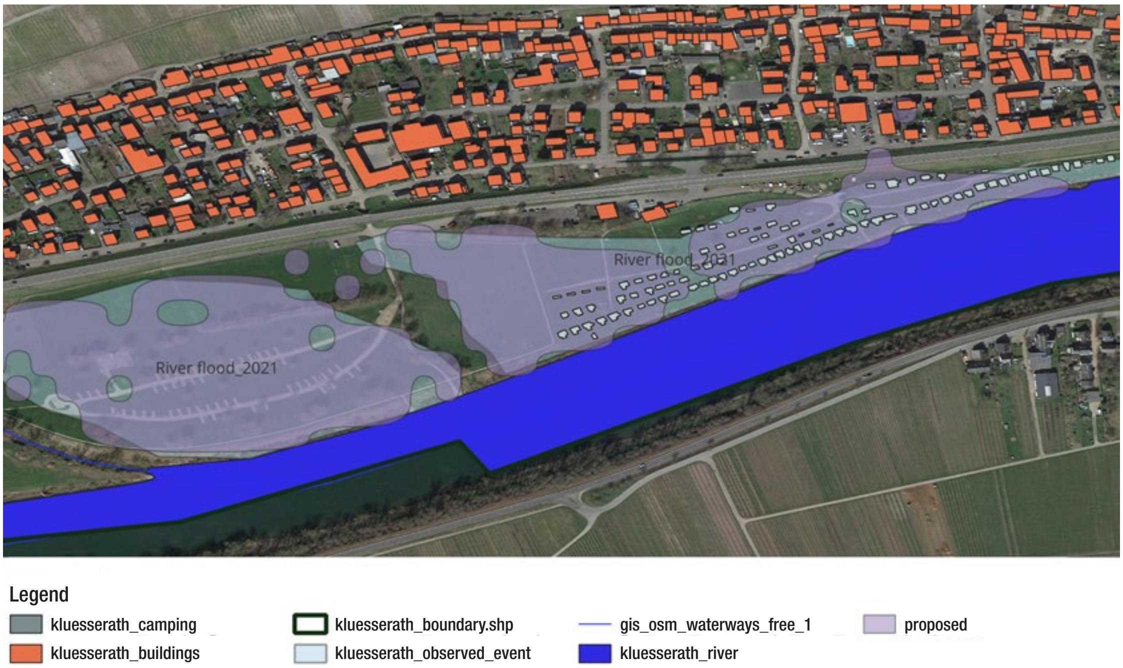

Fig. 4 | Result of mapping flood zones in the coastal area of the Moselle River

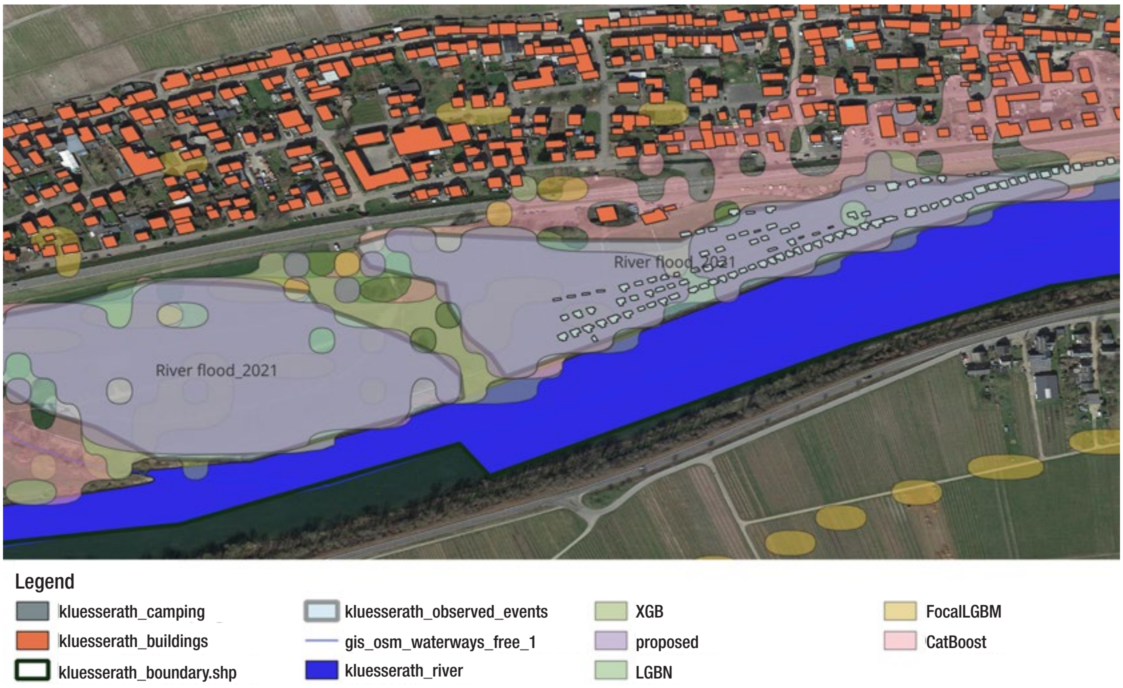

Fig. 5 | Flood mapping obtained using different machine learning models

Model	Accuracy	F1-score	IoU
Proposed methodology	0.99	0.89	0.79
XGB	0.79	0.71	0.56
LGBM	0.79	0.64	0.47
FocalLGBM	0.79	0.66	0.50
LGBM + FocalLGBM	0.89	0.85	0.64

Tab. 1 | Flood mapping model metrics

effectively accounting for these features, the model reproduces flood boundaries consistent with actual hydrological processes and topographical features of the terrain.

To quantitatively evaluate the effectiveness of the proposed methodology, the following metrics were used: Accuracy, F1-score, and Intersection over Union (IoU) /Ajin et al. 2025/. The results of comparing the model developed within the proposed approach with other gradient boosting models (XGBoost, LightGBM, FocalLGBM) are presented in *Tab. 1*.

5 DISCUSSION AND CONCLUSION

The accuracy values for all models are high, which can be explained by the characteristics of tasks with imbalanced classes, where the area of non-flooded territories significantly exceeds that of flooded zones. The accuracy score by the proposed approach (0.99) demonstrates precise classification, made possible by the effective integration of multidimensional data and a post-processing application. The F1-score and Intersection over Union for the proposed methodology (0.88 and 0.79, respectively) exceed the results of individual models. It confirms that the proposed method minimizes the overall number of errors and ensures high precision in delineating the boundaries of flooded areas. The XGBoost, LightGBM, and FocalLGBM algorithms show comparable performance across the main metrics but exhibit lower ability to reproduce flooded zones accurately. Using the LGBM + FocalLGBM combination (F1-score 0.85, IoU 0.64) improves individual models, but still falls short of the performance achieved by the integrated methodology. It highlights the importance of applying specialized calibration methods and spatial post-processing to enhance flood mapping accuracy

To evaluate the accuracy of flood mapping, the components of classification errors, namely True Positive (TP), False Positive (FP), False Negative (FN), and True Negative (TN), were analyzed for different machine learning models (*Fig. 6*). The proposed methodology achieves the highest proportion of true positive predictions while minimizing both false positives and false negatives. This performance is significant for flood risk assessment, as false negative predictions may lead to inadequate evacuation decisions and insufficient critical infrastructure protection. Although the method may produce some false positives, these are less critical in flood prediction because overestimating flood-prone areas is generally safer than missing actual flooded zones. The balance between reduced FP and FN rates highlights the robustness of the methodology in capturing actual flood events with higher reliability compared to individual gradient boosting models.

This study demonstrates the effectiveness of integrating heterogeneous geospatial, hydrometeorological, and remote sensing data with advanced machine learning to improve flood zone mapping. By combining topographic indicators (DEM, slope, curvature, TWI, drainage density), land use and infrastructure data, satellite observations, and hydrometeorological time series, the proposed methodology achieves reliable and physically consistent predictions of flood extents. The results show that the integrated approach substantially outperforms individual gradient boosting models (XGBoost, LightGBM, FocalLGBM) and their combinations, achieving the highest accuracy, F1-score, and IoU while minimizing false positives and false negatives. These improvements are particularly significant for flood risk management, as they ensure more precise delineation of hazardous areas, support timely evacuation planning, and strengthen the protection of critical infrastructure. The case study of the July 2021 flood in Klüsserath, Germany, confirms the robustness of the methodology in capturing both spatial and temporal dynamics of flood processes. Future research should focus on scaling the approach to larger regions, incorporating near-real-time satellite data, and further enhancing model calibration to support operational flood monitoring and early warning systems.

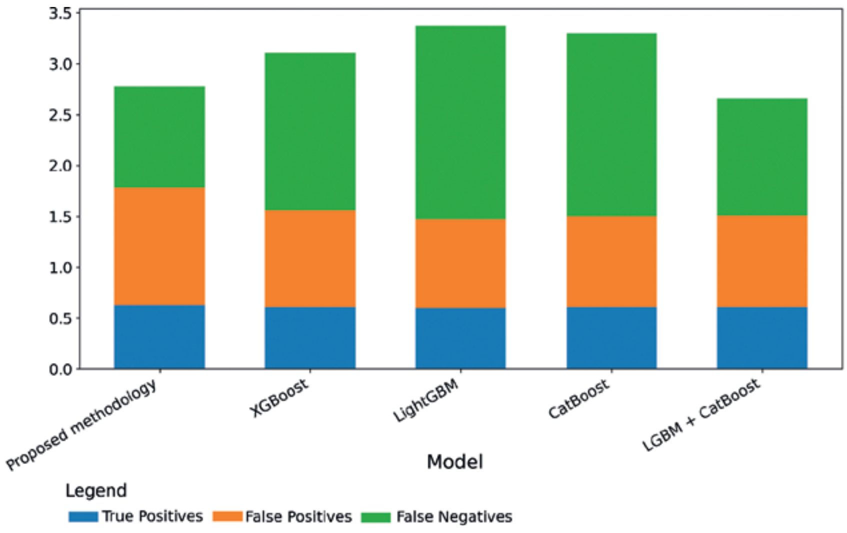

Fig. 6 | Classification error components for different machine learning models in flood mapping

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