MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 5879-5883

Integrating Spatio-Temporal Data and Machine Learning in Geospatial Decision Support Systems for Flash Flood Prediction: A Systematic Review

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Abstract
Spatiotemporal data and Machine learning are used to analyze complex data among various inputs to produce predictions of flood hazards. Flash floods involve complex and non-linear data such as rainfall, river water level and discharge, and elevation that influence one another in dynamic ways making flash floods and affected areas difficult to predict. This study explores the integration of machine learning models and spatio-temporal datasets into geospatial decision support systems to improve flash flood prediction and early warning functions. Using systematic reviews, preliminary and secondary screening using criteria guided by the PICO framework published studies relevant to integration of spatio temporal data and machine learning models into geospatial decision support systems were examined. There were forty-two initially screened research studies, thirteen of these met the main criteria and examined thoroughly. The results of the review revealed that hybrid and traditional Machine Learning models such as MLP-ANN, BER, and Random Forest demonstrated superior predictive accuracy and reliability for flash flood prediction. Studies revealed that Geospatial, meteorological, and hydrological datasets were the most utilized data, indicating their critical part in spatio-temporal data in flood analysis. ArcGIS, Google Earth Engine and Python are used to improve the processes and analyze these data enabling advanced machine learning model algorithms for accurate flood hazard mapping and flash flood forecasting. MLP-ANN excelled among the machine learning models due to its capability of processing complex and non-linear or spatio temporal data to generate reliable flood maps and forecasts through WebGIS for quick decision-making and fulfill the gaps of the exiting decision support systems. Overall, the integration of Machine Learning and Spatio-temporal data into Decision Support System can significantly enhance predictive capability and data visualization. Integrating machine learning and spatiotemporal data into Geospatial Decision Support Systems using hybrid deep learning and combined models allows real-time and accurate flood forecasting. This study revealed the need for intelligent, real-time Decision support systems integrating spatio-temporal, machine learning, IoT sensors for real-time inputs and GDSS to strengthen community resilience, adaptive planning, and timely early warnings in flood-prone areas.

Keywords: Flash Flood, Spatio-temporal data, Machine Learning, Decision Support System

Introduction

Spatiotemporal data and Machine learning models are used to analyze complex data among various inputs to produce predictions of flood, water depths, or flooded maps hazards essential for early warning systems [1]. Existing approach of utilizing Machine Learning and spatio temporal data in flood prediction presents limitations in achieving real-time, accurate, and physically interrelated flood prediction [2]. This could cause computational bottlenecks resulting in an inadequate early warning [3][4]. Traditional methods relied on largely static or time-average data, failing to capture the non-linear complex interactions and dynamic, short-term temporal changes that are necessary for reliable and precise flood hazard assessments [2][5][6].

Flash floods involve complex, non-linear interactions that vary across locations and time such as rainfll, river water level and discharge, and elevation that influence one another in dynamic ways, making flood intensity and affected areas difficult to predict [7]. Spatio-temporal data can describe how flash floods occur, and how their driving factors vary across both geographical space and time. This concept is crucial for analyzing, modeling, and managing flash flood events[8] particularly within Decision Support Systems (DSS) platforms that integrates and analyze both spatial and non-spatial datasets, applying visual presentation and decision support features that convert these data into practical guidance to support decision-makers in generating strategic plans, or developing recommendations for action for complex and semi-structured problems. Moreover, recent advancements have introduced machine learning into these systems, allowing predictive modeling that learn from historical and real-time datasets[9][10]. With exiting techniques, strategies and technologies, this study intended to explore approaches in integrating Machine Learning models and spatio temporal data into Geospatial Decision Support Systems to provide solutions to the exiting gaps in the traditional flood predictions to improve and provide an improved and robust timely early warning to the community and the related government agencies for actionable insights.

Methodology

This study follows a systematic review process to identify and analyze research studies on the integration of machine learning models and spatio-temporal data into Geospatial Decision Support Systems (GDSS) as shown in Figure 1. The process involves an initial screening based on defined inclusion criteria, followed by a detailed evaluation using the PICO framework to guide the selection and analysis of relevant studies. The results from the reviewed studies were then synthesized to draw conclusions and provide insights for future improvements in GDSS applications.

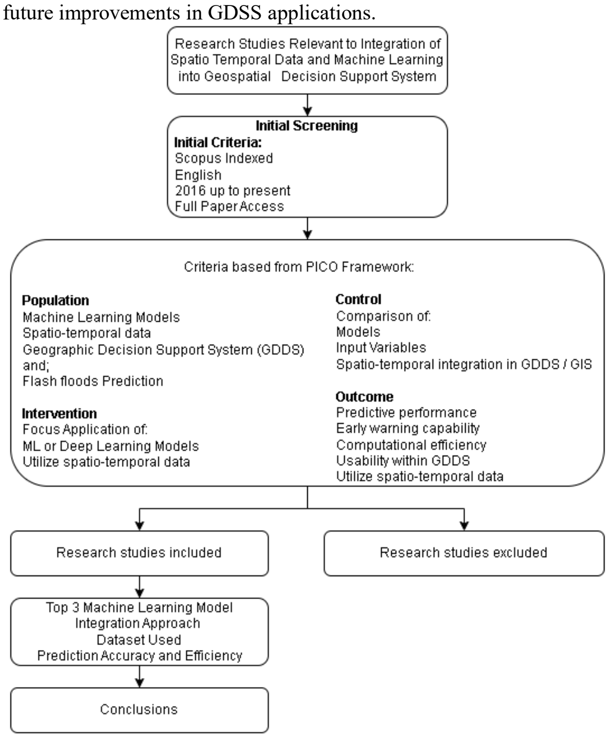

Figure 1. Systematic Review Process

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 5879-5883

Several research articles undergo into two stages of screening which were the primary or initial screening and the secondary or the full review of the research papers. There were Forty-two studies retrieve in the initial screening of research articles in which in this stage, the collected studies were checked using set criteria, such as being Scopus-indexed, published from 2016 to the present, and having full-text access. The titles and abstracts were reviewed to see if they matched the study's focus on utilizing spatio-temporal data and machine learning models in geospatial decision support systems for flash flood prediction. Afterwards, there were thirteen studies in the secondary stage, in which it involves a more detailed examination of the selected papers using the PICO framework because this model is mainly used to make research questions clear, focused, and well-structured. It serves as a guide which helps create specific search terms and use proper keywords. This structured approach improves the accuracy and precision of finding relevant studies and which studies should be included or excluded as shown in table number 1 [11][12][13].Each study was analyzed based on its Population (*machine learning models, spatio-temporal data, and GDSS*, Intervention (use or application of the integration), Comparison (*evaluation methods or existing systems*), and Outcome (*prediction accuracy and early warning capability*) ensuring that only the most relevant and high-quality studies were included in the results.

Population	• Machine Learning Models • Spatio-temporal data • Geographic Decision Support System (GDDS) and; • Flash floods Prediction
Intervention	Focus Application of: • ML or Deep Learning Models • Utilize spatio-temporal data
Control	Comparison of: • Models • Input Variables • Spatio-temporal integration in GDDS / GIS
Outcome	• Integration Approach / Techniques • Predictive performance • Early warning capability • Computational efficiency • Usability within GDDS

Table 1. Systematic Review Criteria using PICO Framework

After the full review of each article, top three Machine Learning models were identified including the development approaches, datasets, and integration techniques to provide flash flood early warnings which shall be the basis in choosing the most suitable for flashflood prediction for future development and implementation.

Results and Discussion

Using the different keywords related to integration of spatio-temporal data and machine learning into geospatial decision support system, the researcher searched across published academic research articles from multiple journals and retrieved research papers related with flood predictions.

There were 42 research related studies included based on the initial screening with the initial criteria that the paper should be published in Scopus index journals, published from the year 2016 up to presents, have fully access, and focus on integration of spatio-temporal data and machine learning into geospatial decision support system.

Out of the 42 related studies, 13 were selected after passing the screening process and were thoroughly reviewed. Table 2 presents the Machine Learning Models used, datasets, prediction metrics outputs and utilized tools of integration into Decision Support system to provide early warnings.

Title	Prediction Metrics	Integration Tools	Model	Percentage
Flood Forecasting System Based on Integrated Big and Crowdsource Data by Using Machine Learning Techniques	AUC: **97.93**. Kappa: **0.89**. MAE: **0.01**. RMSE: **0.10**.	MySQL, PHP, Google Map	MLPANN	97.93%
A Spatiotemporal Deep Learning Approach for Urban Pluvial Flood Forecasting with Multi-Source Data	RMSE **0.028,** CSI **0.768**.	Python, GeoPandas, NetworkX	T-GCN	76.80%
Predicting Eastern Mediterranean Flash Floods Using Support Vector Machines with Precipitable Water Vapor, Pressure, and Lightning Data	Recall: **0.95** F1 score: **0.7917**	NASA's JPL GipsyX software	SVM	95.00%
Boosting vs traditional machine learning models for flood susceptibility mapping - insights from a case study in central Vietnam	ROC_AUC: BER: **0.998**. Testing ROC-AUC: BER (**0.979**), BEG **(0.976).** OA: **0.925 to 0.979.** Kappa: **0.851 to 0.958**	SAGA Software, GEE	BER	97.90%
A Novel Hybrid Swarm Optimized Multilayer Neural Network for Spatial Prediction of Flash Floods	CAR **93.750%**. AUC **0.970**.	ArcGIS	FA-LM-ANN	97.0%
Integrated approaches for flash flood susceptibility mapping: spatial modeling and comparative analysis	AUC: RF (**0.86**), XGBoost (0.85), LR (**0.83**), NB (**0.76**), KNN (**0.75**), FR (**0.72**).	R studio	RF	86.00%
Integrating machine learning and geospatial data analysis for comprehensive flood hazard assessment	AUC: RF (**0.847**) AdaBoost (**0.839**)	GEE, ArcGIS	RF	84.70%
A spatial–temporal deep learning-based warning system against flooding hazards...	RF Accuracy: **0.97486**. F1-score: **0.99752**	Python	RF	97.48%
Modeling Spatial Flood using Novel Ensemble Artificial Intelligence Approaches in Northern Iran	AUC: RSJ48 (**0.931**) RMSE: RSJ48 (**0.30**).	R Studio, ENVI, ArcGIS	RSJ48	93.10%
Flood susceptibility modelling using advanced ensemble machine learning models	ROC: **0.80**	ArcGIS	RS	80.00%
GIS Based Hybrid Computational Approaches for Flash Flood Susceptibility Assessment	AUC (Testing): ABM-CDT (**0.96**). RMSE (Testing): ABM-CDT (**0.291**).	ArcGIS, ENVI, SAGA	ABM-CDT	96.00%
Flash-Flood Susceptibility Assessment Using Multi-Criteria Decision Making and Machine Learning Supported by Remote Sensing and GIS Techniques	AUC: kNN–AHP (Success rate: **0.901**; Prediction rate: **0.896**).	ArcGIS, WEKA, GEE, Excel	KNN-AHP	90.10%
Flash-Flood Potential Mapping Using Deep Learning, Alternating Decision Trees and Data Provided by Remote Sensing Sensors	AUC–ROC: DLNN-WOE (**0.96**). Validating Accuracy: DLNN-WOE (**0.920**).	ArcGIS, GEE, WEKA	SDLNN-WOE	96.00%

Table 2. List of Related Research Studies for Full Review

The researcher screened sources that met the following criteria: Geospatial DSS Focus, Spatio-temporal and ML Integration, System Validation, Technical Methodology, Empirical Evidence, Machine Learning Integration, Spatio-temporal Data Integration, Flood Prediction, and Evidence. Specifically, it focused on studies that addressed geospatial decision support systems (DSS) designed for flash flood prediction, ensuring that both spatio-temporal data and machine learning models were integrated. The studies that included validation or performance evaluation of the prediction system were also prioritized, as were those that described data integration methods and prediction methodologies. It has been also included only the studies with quantitative results, case studies, pilot implementations, proof-of-concepts, those that incorporated machine learning in addition to traditional models and relevant studies that integrated both spatio-temporal data, machine learning and decision support systems.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
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Vol. 36 Issue 1, 2026, Pages 5879-5883

This study presents the machine learning models used by the reviewed studies and their accuracy metrics in flood prediction is shown in figure number 2. The result revealed that MLP-ANN has the most accurate flood predictions with 97.93% accuracy and capable of quick processing complex and non-linear spatiotemporal inputs followed by BER with accuracy output of 97.90%, and 97.48% for Random Forest showing their strong ability to handle complex and dynamic environmental data for flood prediction. The MLP-ANN model proved to be highly effective in learning complex and nonlinear data relationships among flood-related factors such as rainfall, river level, and soil moisture, while the BER demonstrated efficient optimization and training performance due to the combination boosting algorithms and Random Forest in its ensemble method where it displayed robustness and consistency by combining multiple decision trees, making it reliable for diverse environmental conditions.

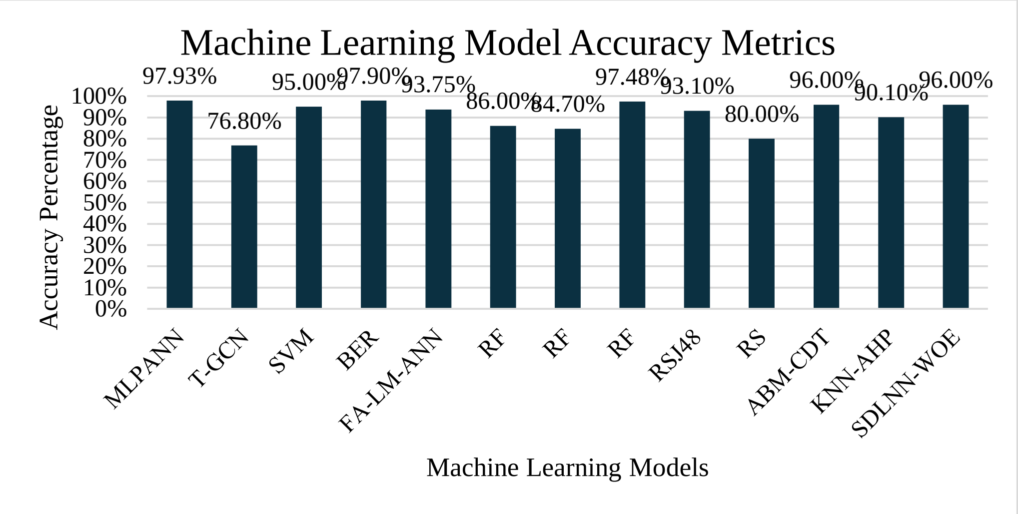

Figure 2. Machine Learning Model Accuracy Metrics.

The findings in the different data sets used to train the machine learning models and analyze data in each study were categorized and shown in figure 3. It illustrates how may does each category were used in all the studies. The review of related studies revealed that Geospatial data was the most frequently used having a 28.95%, followed by Meteorological with 26.32% and Hydrological data with 23.68%. Geological data with 15.79% and was moderately used, while Anthropogenic and Crowdsourced data were the least applied in the studies which represented only 2.63% of the total. These results indicate that most flood prediction models depend heavily on datasets particularly geospatial, meteorological, and hydrological inputs to robust the flash flood prediction accuracy and spatial analysis. However, the limited integration of crowdsource data suggests the need to expand current models to include real-time and socio-environmental factors. With this, it can improve early warning systems, risk mapping, and decision support for flood management and disaster preparedness of the concerned agencies and the community.

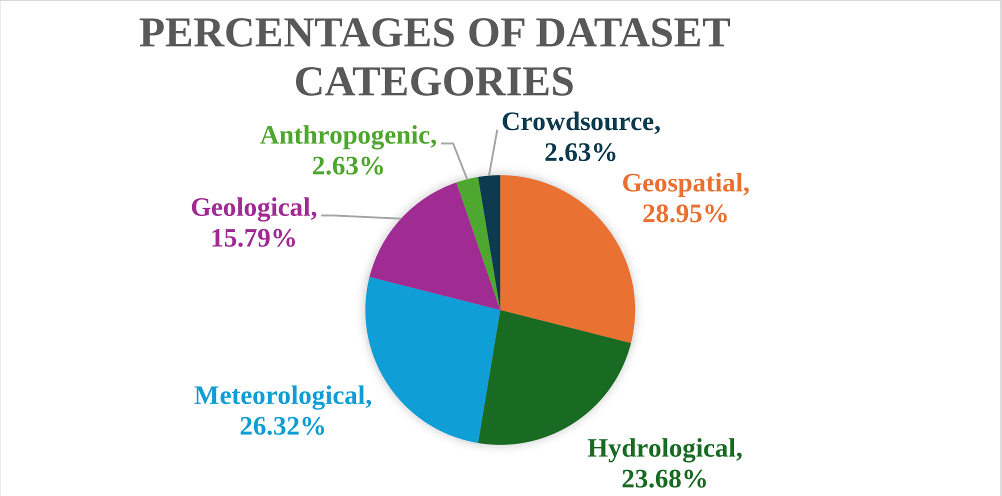

Figure 3. Datasets Categories

In the integration of machine learning and spatio-temporal data into a decision support system, comprehensive review was conducted to clearly identify the technology and approach in the integration. The result revealed as shown in figure 4, that ArcGIS was the most dominant tool, appearing in 7 out of 13 studies. Its frequent use presents its reliability for spatial data visualization, hydrological modeling, and flood risk mapping. Next on this is the Google Earth Engine (GEE) which appeared in 4 studies reflecting its growing usage in cloud-based geospatial processing and real-time remote sensing analysis. Other tools such as Python, R Studio, ENVI, WEKA, and SAGA Software which appeared in multiple studies, indicating that their supplemental roles in data analysis, statistical modeling, and image processing. Meanwhile, MySQL, PHP, and Google Maps were integrated into some systems to facilitate data storage, web-based visualization, and user interaction. Specialized software such as NASA's JPL GipsyX, GeoPandas, and NetworkX appeared in studies employing satellite-based positioning and network-based spatial modeling techniques.

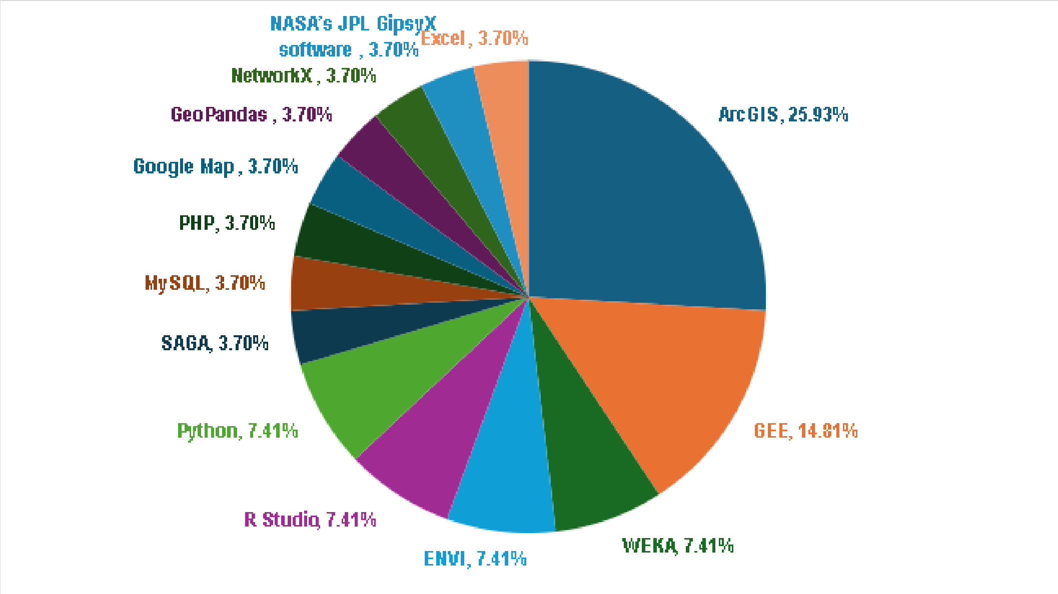

Figure 4. Related Study Integration Tools

Studies revealed that the methods and techniques in integrating machine learning and spatiotemporal data into a Geospatial Decision Support System are through Geospatial Artificial Intelligence frameworks that utilize a hybrid deep learning architecture and combination of Machine Learning models to fuse multi-source data that provides real-time and interpretable hazard assessments. These mixed data such as meteorological, hydrological, geospatial, and remote sensing information where Machine learning models act as an efficient tool that transforms complex spatio temporal inputs into clear, location-based prediction, efficient processing and enables real-time forecasting of flash floods.

Analyzing spatiotemporal data such as river water level, River water discharge, rainfall, elevation and other factors that influence flash floods through algorithms like MLP-ANN model to forecast flash floods and integrating into Geospatial Decision Support Systems that will equipped the system with the capability of capturing non-linear, complex, time-dependent, and will reveal hidden layers to enhance the flood forecasting making it more reliable for dynamic and real-time flood prediction. Therefore, the MLP-ANN model is considered the most suitable for integration that employs a deep learning model architecture that involves processing multiple variables and can include real-time data from IoT sensors to predict flash floods and identify the most likely flood areas Furthermore, configuring MLP-ANN as a core component of combined models for highly accurate flood vulnerability mapping or hybridizing these top 3 models with multiple statistical models or integration tools such as GEE and Python to enhance prediction when geospatial data are used. Outputs from the MLP-ANN-driven process, such as flood severity classifications, water level forecasts, or susceptibility maps, are then disseminated and visualized through geospatial interfaces like Web Application GIS that enable decision-makers and the public to take timely preventive actions in flood events.

Conclusion

The integration of Machine Learning (ML) and spatiotemporal data into Geographic Decision Support Systems (GDSS) is essential for advancing flood forecasting from computationally expensive, limited-interpretability models to robust, real-time, and highly accurate warning systems. By leveraging GeoAI techniques, GDSS can effectively harness large volumes of multi-source, multi-scale geospatial and temporal data, addressing the non-linear, complex interactions among hydrologic, topographic, and built environmental features that traditional models often struggle with. Successful integration with machine learning models such as MLP-ANN, BER, and Random Forest have demonstrated superior predictive capabilities, making them highly suitable for dynamic and data-driven flood forecasting demonstrates superior performance in capturing both spatial dependencies and temporal trends which are critical for effective disaster mitigation and timely response. Platforms such as ArcGIS and Google Earth Engine further enhance GDSS which can provide geospatial visualization and cloud-based analytics, facilitating better data interpretation and model integration. Overall, the study concludes that combining advanced ML approaches with spatio-temporal data within GDSS strengthens data-driven decision-making, supports timely interventions, and improves disaster preparedness and risk reduction of flash floods.

Future developments in flash flood prediction may be fully integrated, adaptive, and intelligent Decision Support Systems that can process real-time and spatio-temporal data utilizing new technologies to further improve their capabilities. Additional datasets by including IoT sensor data can also strengthen early warning accuracy and community engagement. Integrating these kinds of systems into a cloud-based platform provides efficient data sharing, visualization, and decision making among related government agencies, and to local community. Combining data-driven forecasting and geospatial analytics, future decision support systems for flash floods can deliver actionable insights in near real-time, ultimately improving resilience, preparedness and reliable actions in flood events.

References

[1] A. D. L. Zanchetta and P. Coulibaly, "Hybrid Surrogate Model for Timely Prediction of Flash Flood Inundation Maps Caused by Rapid River Overflow," *Forecasting*, vol. 4, no. 1, pp. 126–148, Oct. 2022, doi: 10.3390/forecast4010007.

[2] P. Chaimook, N. Khamsemanan, C. Nattee, and A. Sharp, "Spatiotemporal Flood Hazard Classification in Bangkok Using Graph Convolutional Network and Temporal Fusion Transformer," *IEEE Access*, vol. 13, pp. 140816–140829, 2025, doi: 10.1109/ACCESS.2025.3597328.

[3] A. D. L. Zanchetta and P. Coulibaly, "Recent advances in real-time pluvial flash flood forecasting," Feb. 01, 2020, *MDPI AG*. doi: 10.3390/w12020570.

[4] J. H. Lee, G. M. Yuk, H. T. Moon, and Y. Il Moon, "Integrated flood forecasting and warning system against flash rainfall in the small-scaled urban stream," *Atmosphere (Basel)*, vol. 11, no. 9, Sep. 2020, doi: 10.3390/ATMOS11090971.

[5] N. H. Quang, L. N. Hanh, and N. Van An, "Boosting vs. traditional machine learning models for flood susceptibility mapping: insights from a case study in central Vietnam," *Advances in Space Research*, Nov. 2025, doi: 10.1016/j.asr.2025.07.105.

[6] K. H. Chang, Y. T. Chiu, W. R. Su, Y. C. Yu, and C. H. Chang, "A spatial–temporal deep learning-based warning system against flooding hazards with an empirical study in Taiwan," *International Journal of Disaster Risk Reduction*, vol. 102, Feb. 2024, doi: 10.1016/j.ijdrr.2024.104263.

[7] P. T. T. Ngo *et al.*, "A novel hybrid swarm optimized multilayer neural network for spatial prediction of flash floods in tropical areas using sentinel-1 SAR imagery and geospatial data," *Sensors (Switzerland)*, vol. 18, no. 11, Nov. 2018, doi: 10.3390/s18113704.

[8] J. Hurtado-Pidal, J. S. A. Triana, E. Espitia-Sarmiento, and F. Jarrín-Pérez, "Flood hazard assessment in data-scarce watersheds using model coupling, event sampling, and survey data," *Water (Switzerland)*, vol. 12, no. 10, 2020, doi: 10.3390/w12102768.

[9] P. B. Keenan and P. Jankowski, "Spatial Decision Support Systems: Three decades on," *Decis Support Syst*, vol. 116, 2019, doi: 10.1016/j.dss.2018.10.010.

[10] A. Aljohani, "Predictive Analytics and Machine Learning for Real-Time Supply Chain Risk Mitigation and Agility," *Sustainability (Switzerland)*, vol. 15, no. 20, 2023, doi: 10.3390/su152015088.

[11] Lindexer, "Using the PICO framework in your systematic literature review."

[12] T. F. Frandsen, M. F. Bruun Nielsen, C. L. Lindhardt, and M. B. Eriksen, "Using the full PICO model as a search tool for systematic reviews resulted in lower recall for some PICO elements," *J Clin Epidemiol*, vol. 127, 2020, doi: 10.1016/j.jclinepi.2020.07.005.

[13] A. De Cassai, B. Dost, S. Tulgar, and A. Boscolo, "Methodological Standards for Conducting High-Quality Systematic Reviews," Aug. 01, 2025, *Multidisciplinary Digital Publishing Institute (MDPI)*. doi: 10.3390/biology14080973.

MSW MANAGEMENT -Multidisciplinary, Scientific Work and Management Journal
ISSN: 1053-7899
Vol. 36 Issue 1, 2026, Pages 5879-5883

[14.] Dimara Kusuma Hakim, Rahmat Gernowo, and Anang Widhi Nirwansyah, "Flood prediction with time series data mining: Systematic review," Natural Hazards Research, Oct. 2023, doi: https://doi.org/10.1016/j.nhres.2023.10.001.
[15.] M. R. Perdana Putra, Rama Ashari, Muhirin, Azib Widad Zuhaily Imam, and Kusrini, "Flood Prediction Using Machine Learning Model Integrated with Geographical Information System," *Khazanah Informatika : Jurnal Ilmu Komputer dan Informatika*, vol. 10, no. 2, pp. 121–126, Mar. 2025, doi: https://doi.org/10.23917/khif.v10i2.3723.
[16.] S. Puttinaovarat and P. Horkaew, "Flood Forecasting System Based on Integrated Big and Crowdsource Data by Using Machine Learning Techniques," *IEEE Access*, vol. 8, pp. 5885–5905, 2020, doi: https://doi.org/10.1109/access.2019.2963819.
[17.] P. C. Oddo, J. D. Bolten, S. V. Kumar, and B. Cleary, "Deep Convolutional LSTM for improved flash flood prediction," *Frontiers in water*, vol. 6, Feb. 2024, doi: https://doi.org/10.3389/frwa.2024.1346104.
[18.] Z. Liu, T. Felton, and A. Mostafavi, "Interpretable machine learning for predicting urban flash flood hotspots using intertwined land and built-environment features," *Computers, environment and urban systems*, vol. 110, pp. 102096–102096, Jun. 2024, doi: https://doi.org/10.1016/j.compenvurbsys.2024.102096.
[19.] B. Burrichter, J. Hofmann, J. Koltermann, A. Niemann, and M. Quirmbach, "A Spatiotemporal Deep Learning Approach for Urban Pluvial Flood Forecasting with Multi-Source Data," *Water*, vol. 15, no. 9, pp. 1760–1760, May 2023, doi: https://doi.org/10.3390/w15091760.
[20.] Saed Asaly, L.-A. Gottlieb, Yoav Yair, C. Price, and Yuval Reuveni, "Predicting Eastern Mediterranean Flash Floods Using Support Vector Machines with Precipitable Water Vapor, Pressure, and Lightning Data," *Remote Sensing*, vol. 15, no. 11, pp. 2916–2916, Jun. 2023, doi: https://doi.org/10.3390/rs15112916.
[21.] C. Liu and A. Mostafavi, "FloodGenome: interpretable machine learning for decoding features shaping property flood risk predisposition in cities," *Environmental Research: Infrastructure and Sustainability*, vol. 5, no. 1, p. 015018, Mar. 2025, doi: https://doi.org/10.1088/2634-4505/adb800.
[22.] F. Yeboah, E. K. Ackom, Sandow Mark Yidana, and A. Awotwi, "Hydrologic Modelling for Flood Threshold and Hazard Prediction in the Black Volta River Basin, West Africa," *Environmental Modeling & Assessment*, vol. 29, no. 2, pp. 375–394, Dec. 2023, doi: https://doi.org/10.1007/s10666-023-09946-6.
[23.] C. Cattoën *et al.*, "Integrating Prediction of Precipitation and Hydrology for Early Actions: The InPRHA Project within the World Weather Research Programme," *Bulletin of the American Meteorological Society*, vol. 106, no. 7, pp. E1303–E1318, Jul. 2025, doi: https://doi.org/10.1175/bams-d-24-0332.1.
[24.] Z. Fang, Y. Wang, L. Peng, and H. Hong, "Predicting flood susceptibility using long short-term memory (LSTM) neural network model," *Journal of Hydrology*, p. 125734, Nov. 2020, doi: https://doi.org/10.1016/j.jhydrol.2020.125734.
[25.] Pakpoom Chaimook, Nirattaya Khamsemanan, Cholwich Nattee, and A. Sharp, "Spatiotemporal Flood Hazard Classification in Bangkok Using Graph Convolutional Network and Temporal Fusion Transformer," *IEEE Access*, pp. 1–1, Jan. 2025, doi: https://doi.org/10.1109/access.2025.3597328.
[26.] D. Raynaud, J. Thielen, P. Salamon, P. Burek, S. Anquetin, and L. Alfieri, "A dynamic runoff co-efficient to improve flash flood early warning in Europe: evaluation on the 2013 central European floods in Germany," *Meteorological Applications*, vol. 22, no. 3, pp. 410–418, Aug. 2014, doi: https://doi.org/10.1002/met.1469.
[27.] V.-N. Nguyen *et al.*, "A New Modeling Approach for Spatial Prediction of Flash Flood with Biogeography Optimized CHAID Tree Ensemble and Remote Sensing Data," *Remote Sensing*, vol. 12, no. 9, p. 1373, Apr. 2020, doi: https://doi.org/10.3390/rs12091373.
[28.] T. V. Hoang *et al.*, "A Robust Early Warning System for Preventing Flash Floods in Mountainous Area in Vietnam," *ISPRS International Journal of Geo-Information*, vol. 8, no. 5, p. 228, May 2019, doi: https://doi.org/10.3390/ijgi8050228.
[29.] C. Corral, M. Berenguer, D. Sempere-Torres, L. Poletti, F. Silvestro, and N. Rebora, "Comparison of two early warning systems for regional flash flood hazard forecasting," *Journal of Hydrology*, vol. 572, pp. 603–619, May 2019, doi: https://doi.org/10.1016/j.jhydrol.2019.03.026.
[30.] H. T. Nguyen *et al.*, "Development of a Spatial Decision Support System for Real-Time Flood Early Warning in the Vu Gia-Thu Bon River Basin, Quang Nam Province, Vietnam," *Sensors*, vol. 20, no. 6, p. 1667, Mar. 2020, doi: https://doi.org/10.3390/s20061667.
[31.] Koji Ikeuchi *et al.*, "Development of Flash Flood Forecasting System for Small and Medium-Sized Rivers," *Journal of Flood Risk Management*, vol. 18, no. 1, Mar. 2025, doi: https://doi.org/10.1111/jfr3.70026.
[32.] C. Prakash, A. Barthwal, and D. Acharya, "FLOODWALL: A Real-Time Flash Flood Monitoring and Forecasting System Using IoT," *IEEE Sensors Journal*, vol. 23, no. 1, pp. 787–799, Jan. 2023, doi: https://doi.org/10.1109/jsen.2022.3223671.
[33.] A. A. Soebroto, L. M. Limantara, Ery Suhartanto, and Moh. Sholichin, "Modelling of Flood Hazard Early Warning Group Decision Support System," *Civil Engineering Journal*, vol. 10, no. 2, pp. 614–627, Feb. 2024, doi: https://doi.org/10.28991/cej-2024-010-02-018.
[34.] Hamid Mirfenderesk *et al.*, "New generation flood forecasting and decision support system for emergency management," *Australian Journal of Emergency Management*, vol. 31, no. 2, pp. 31–37, Apr. 2016.
[35.] M. Acosta-Coll, F. Ballester-Merelo, M. Martinez-Peiró, and E. De la Hoz-Franco, "Real-Time Early Warning System Design for Pluvial Flash Floods—A Review," *Sensors*, vol. 18, no. 7, p. 2255, Jul. 2018, doi: https://doi.org/10.3390/s18072255.
[36.] Joško Trošelj, S. Nayak, L. Hobohm, and Tetsuya Takemi, "Real-time flash flood forecasting approach for development of early warning systems: integrated hydrological and meteorological application," *Geomatics, Natural Hazards and Risk*, vol. 14, no. 1, Oct. 2023, doi: https://doi.org/10.1080/19475705.2023.2269295.
[37.] A. D. L. Zanchetta and P. Coulibaly, "Recent Advances in Real-Time Pluvial Flash Flood Forecasting," *Water*, vol. 12, no. 2, p. 570, Feb. 2020, doi: https://doi.org/10.3390/w12020570.
[38.] E. M. Marouane, "Towards a Real Time Distributed Flood Early Warning System," *International Journal of Advanced Computer Science and Applications*, vol. 12, no. 1, 2021, doi: https://doi.org/10.14569/ijacsa.2021.0120162.
[39.] L. Luo *et al.*, "Exploration of the spatiotemporal characteristics and triggering factors of flash flood in China," *Ecological Indicators*, vol. 176, p. 113698, Jun. 2025, doi: https://doi.org/10.1016/j.ecolind.2025.113698.
[40.] Akram Elghouat *et al.*, "Integrated approaches for flash flood susceptibility mapping: spatial modeling and comparative analysis of statistical and machine learning models. A case study of the Rheraya watershed, Morocco," *Journal of Water and Climate Change*, Jul. 2024, doi: https://doi.org/10.2166/wcc.2024.726.
[41.] Chiranjit Singha, Vikas Kumar Rana, Quoc Bao Pham, D. C. Nguyen, and E. Łupikasza, "Integrating machine learning and geospatial data analysis for comprehensive flood hazard assessment," *Environmental Science and Pollution Research*, vol. 31, no. 35, pp. 48497–48522, Jul. 2024, doi: https://doi.org/10.1007/s11356-024-34286-7.
[42.] Y. Qiu, X. Shi, and X. He, "Enhancing flood prediction in the Lower Mekong River Basin by a scale-independent interpretable deep learning model," *Environmental Impact Assessment Review*, vol. 116, p. 108130, Aug. 2025, doi: https://doi.org/10.1016/j.eiar.2025.108130.
[43.] F. Y. Dtissibe, A. A. A. Ari, H. Abboubakar, A. N. Njoya, A. Mohamadou, and O. Thiare, "A comparative study of Machine Learning and Deep Learning methods for flood forecasting in the Far-North region, Cameroon," *Scientific African*, vol. 23, p. e02053, Mar. 2024, doi: https://doi.org/10.1016/j.sciaf.2023.e02053.
[44.] Alireza Arabameri *et al.*, "Modeling Spatial Flood using Novel Ensemble Artificial Intelligence Approaches in Northern Iran," *Remote Sensing*, vol. 12, no. 20, pp. 3423–3423, Oct. 2020, doi: https://doi.org/10.3390/rs12203423.
[45.] C. Gonzales-Inca *et al.*, "Geospatial Artificial Intelligence (GeoAI) in the Integrated Hydrological and Fluvial Systems Modeling: Review of Current Applications and Trends," *Water*, vol. 14, no. 14, pp. 2211–2211, Jul. 2022, doi: https://doi.org/10.3390/w14142211.
[46.] A. R. M. Towfiqul Islam *et al.*, "Flood susceptibility modelling using advanced ensemble machine learning models," *Geoscience Frontiers*, vol. 12, no. 3, p. 101075, May 2021, doi: https://doi.org/10.1016/j.gsf.2020.09.006.
[47.] B. T. Pham *et al.*, "GIS Based Hybrid Computational Approaches for Flash Flood Susceptibility Assessment," *Water*, vol. 12, no. 3, p. 683, Mar. 2020, doi: https://doi.org/10.3390/w12030683.
[48.] R. Costache *et al.*, "Flash-Flood Susceptibility Assessment Using Multi-Criteria Decision Making and Machine Learning Supported by Remote Sensing and GIS Techniques," *Remote Sensing*, vol. 12, no. 1, p. 106, Dec. 2019, doi: https://doi.org/10.3390/rs12010106.
[49.] M. Reichstein *et al.*, "Deep learning and process understanding for data-driven Earth system science," *Nature*, vol. 566, no. 7743, pp. 195–204, Feb. 2019, doi: https://doi.org/10.1038/s41586-019-0912-1.
[50.] R. Costache *et al.*, "Flash-Flood Potential Mapping Using Deep Learning, Alternating Decision Trees and Data Provided by Remote Sensing Sensors," *Sensors*, vol. 21, no. 1, p. 280, Jan. 2021, doi: https://doi.org/10.3390/s21010280.