Mapping research trends on tropical cyclone–induced flood susceptibility: a bibliometric and systematic review method

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ABSTRACT

Climate change has intensified tropical cyclones (TC), increasing extreme rainfall and flood hazards in many regions. Flood susceptibility (FS) mapping is therefore essential for understanding flood risk. This study analyzes global research trends on TC-induced FS by integrating bibliometric analysis and a preferred reporting items for systematic reviews and meta-analyses (PRISMA)-based systematic literature review (SLR) using Google Scholar (GS) publications from 2014 to 2024. A total of 993 journal articles were analyzed, yielding an h-index of 101 and a g-index of 168, indicating strong and growing research interest. The results reveal an increasing application of machine learning (ML), deep learning (DL), remote sensing (RS), and geographic information systems (GIS) for FS mapping. Several gaps remain, including limited use of high-resolution data, underrepresentation of data-scarce and equatorial regions, restricted integration of hybrid models, and a lack of long-term assessments considering climate change and socio-economic factors. The model's performance is also highly dependent on data quality and regional characteristics, limiting its generalizability across different conditions. The main contribution of this study is the knowledge mapping and synthesis of TC-induced FS research, providing a structured foundation for future studies and supporting evidence-based flood risk management and climate adaptation.

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1. INTRODUCTION

Climate change has significantly influenced tropical cyclones (TC) characteristics on a global scale. Increasing sea surface temperatures provide additional energy that enhances TC intensification and contributes to more extreme rainfall events [1]. Although the projected frequency of TC may decrease, climate warming is expected to increase their intensity and the occurrence of severe events [2]. Changes in large-scale environmental conditions have also affected TC trajectories and intensification efficiency, particularly in regions such as the Northwest Pacific [1], [3]. Several studies project that areas affected by TC will experience increased flood extent and depth in the future, as reported in regions such as Xiamen Bay, China, and the Philippines [2], [4]. In tropical regions, TC-related rainfall is generally concentrated near the storm core, with rainfall intensity decreasing at greater distances from the center [5]. Indonesia, as a tropical archipelago located near the equator, is highly vulnerable to flooding due to its climatic and geographical conditions, as evidenced by severe events such as TC Seroja [6]–[8].

Flood susceptibility (FS) mapping has become a crucial method of assessing flood risk and supporting flood mitigation and spatial planning. FS indicates the likelihood of flooding influenced by several environmental, topographical, and hydrological factors [9]. Advances in geographic information system (GIS), remote sensing, and data-driven methodologies have significantly enhanced the accuracy of FS mapping. In recent years, machine learning (ML), deep learning (DL), and artificial intelligence (AI) techniques have been progressively utilized in FS modeling to accurately represent intricate nonlinear linkages in flood processes, showcasing enhanced efficacy relative to traditional statistical methods [10]–[12].

Despite the growing number of studies on FS mapping and TC-related hazards, existing research has largely addressed these topics separately. Although many studies have analyzed FS and TC independently, there is a lack of systematic examinations of global research trends that integrate both subjects, especially through quantitative bibliometric analysis and systematic literature review (SLR) methodologies. Therefore, this study aims to identify global research trends on FS in regions affected by TC by integrating bibliometric analysis with a preferred reporting items for systematic reviews and meta-analyses (PRISMA)-based systematic literature review. The main contribution of this study is to provide a comprehensive review of the research trends, methodologies, geographical distribution of research, and research gaps on TC-induced FS, which may provide implications for future research directions and support policy development for flood mitigation and spatial planning.

2. METHOD

This study applies a two-stage methodological framework comprising an initial bibliometric analysis followed by a PRISMA-based SLR. The framework is designed to follow an exploratory-to-confirmatory sequence, in which the bibliometric stage delineates the general research landscape and emerging directions, and the subsequent PRISMA-based SLR systematically examines studies that explicitly integrate FS and TC. The overall methodological approach adheres to established bibliometric review practices to ensure transparency, rigor, and reproducibility [13].

2.1. Stage 1: bibliometric analysis

The first stage aims to describe the global research landscape and to identify dominating topics in FS-related studies. At this stage, the bibliometric analysis was conducted only on journal papers to guarantee the scientific quality and the consistency of citation-based indicators. The primary source of data used was Google Scholar (GS) due to its wide multidisciplinary coverage and its shown appropriateness for large-scale bibliometric studies, especially in interdisciplinary study fields [14], [15]. GS has extensive coverage; however, its use may influence the observed research patterns due to possible data discrepancies and regional bias. Therefore, the results should be considered as indicative of general trends rather than a fully comprehensive representation of the global research field. Bibliographic records were extracted using the Publish or Perish (PoP) software. The software provides access to citation metrics, which are routinely used in bibliometric investigations, such as publication counts and citation-based indices [16], [17].

In this stage, the search strategy focused exclusively on the keyword "flood susceptibility" to capture the overall development, publication volume, and thematic structure of FS-related research. The search was restricted to journal publications in the English language published between 2014 and 2024. Research growth and scholarly influence were evaluated based on bibliometric variables such as publication count, citation count, h-index, and g-index. Further, keyword co-occurrence analysis and network visualisation were performed using VOSviewer to identify dominant research clusters and emerging themes in the FS literature [18]–[20]. The bibliometric workflow is shown in Figure 1.

The outcomes of this bibliometric analysis indicate that, while the majority of FS studies remain focused on general hydrometeorological, topographical, and environmental factors, only a limited number of studies explicitly address TC as a driving factor. Nevertheless, the presence and gradual emergence of TC-related keywords suggest a growing research interest and indicate a potential research direction toward FS influenced by TC, thereby justifying a more focused and systematic investigation.

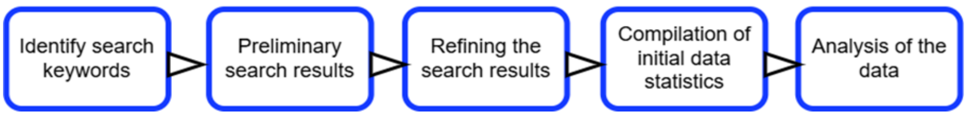

Figure 1. Flow of bibliometrics

2.2. Stage 2: SLR based on PRISMA

The second stage, guided by the results of the bibliometric analysis, was the process of conducting a PRISMA-based SLR to investigate research that explicitly integrates FS and TC. The PRISMA framework was implemented to ensure scientific rigour, transparency, and reproducibility throughout the study selection process [21]. The literature searches applied in this stage were limited exclusively to GS, in order to maintain consistency with the data source applied in the bibliometric analysis. The use of one comprehensive database is regarded as suitable for systematic screening when accompanied by a transparent search strategy and well-defined eligibility criteria, especially under restrictions of limited access to curated subscription-based resources [15], [20]. A refined Boolean search method based on the key concepts in Table 1 was consistently implemented across the database. The inclusion and exclusion criteria for the PRISMA-based SLR were defined a priori as: (i) only journal articles employing quantitative, qualitative, or mixed-method approaches were included; (ii) review articles and book chapters were excluded to maintain a focus on primary research; (iii) only English-language publications with worldwide coverage published between 2014 and 2024 were conside and (iv) studies were required to explicitly address FS in relation to TC.

Table 1. Boolean search keyword

Concept	Keywords
FS	"Flood susceptibility"
TC	"TC", "tropical cyclone", "hurricane", "typhoon", "cyclone", "bagyo", "severe TC"
Modeling approach	"Machine learning", "deep learning", "artificial intelligence", "statistical learning", "predictive analytics", "data-driven modeling", "computational learning", "deep neural networks", "advanced neural networks", "hierarchical learning"
Spatial analysis	"GIS", "geographic information system", "geospatial analysis", "spatial data", "geographic information", "geodata"
Remote sensing	"Remote sensing", "earth observation", "satellite imagery", "radar imaging", "LiDAR", "SAR", "image processing"

The PRISMA screening process followed four sequential stages: identification, screening, eligibility, and inclusion as in Figure 2. During the identification stage, 1,920 records were retrieved through a GS database search using a web browser, restricted to English-language journal publications from 2014 to 2024. In the screening stage, titles and abstracts were assessed for relevance, resulting in 15 records proceeding to full-text evaluation. During the eligibility stage, 2 full-text articles were excluded because they did not address the research focus on FS–TC integration. Consequently, 13 full-text articles met all inclusion criteria and were retained for qualitative synthesis. The detailed screening process and corresponding article counts at each stage are illustrated in the PRISMA flow diagram.

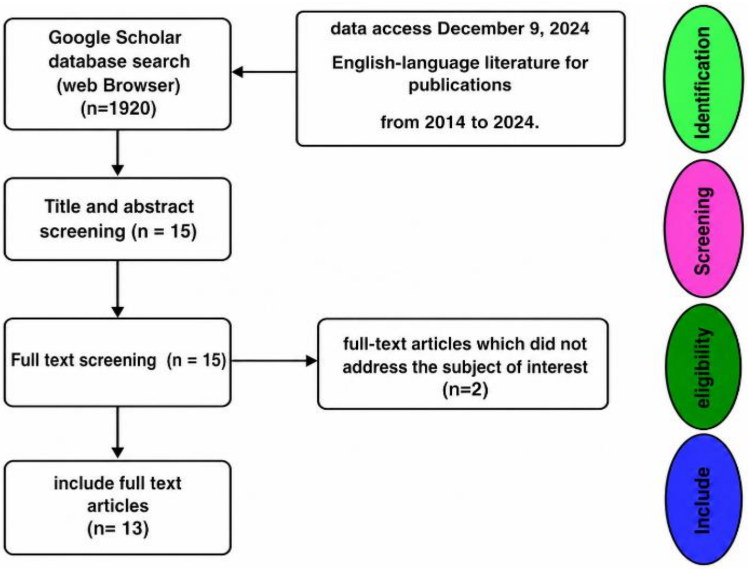

Figure 2. Literature search flow

2.3. Quality assessment

The selected articles were evaluated based on peer-review status, methodological clarity, relevance to FS-TC integration, and data transparency. This study focused on identifying research trends, methodological patterns, and emerging directions, rather than evaluating individual publications' impact. Therefore, no citation weighting or normalization was applied.

3. RESULTS AND DISCUSSION

The bibliometric and PRISMA-based systematic review aimed to identify research trends, thematic development, and knowledge gaps related to TC-induced FS. This part focuses on the quantitative mapping of publications and the qualitative synthesis of selected papers to show new trends and future research plans in this area.

3.1. Bibliometrics

The metric comparison in Table 2 identified 1000 articles concerning "FS" from 2014 to 2024, with over 36,300 citations. After filtering and refining the data, 993 articles were identified as relevant and valuable. This indicates that data refinement improves dataset relevance and consistency. The h-index (101) and g-index (168) show that FS research is a popular subject in academia and has a significant impact on scientific publications. The clustering analysis shown in Figure 3 implies that FS, FS mapping, and risk assessment are the key components of the research landscape. These current themes are closely associated with methodological techniques such as GIS, ML, and statistical models. This pattern indicates that most of the recent studies are increasingly based on advanced modeling approaches and predictive modeling. The increasing utilization of ML techniques indicates a shift towards data-centric modeling, recognized for its capability to identify nonlinear interactions in hydrological systems [9], [22].

However, keywords exclusively related to TC are rare and weakly connected to the main FS clusters. This indicates that although FS research has advanced significantly, the actual implementation of meteorological drivers like TC still shows limited progress. In several cases, extreme weather factors are included implicitly rather than explicitly modelling them as primary drivers, which may reduce the physical interpretability of FS models. As indicated by previous research, a significant part of TC exacerbates precipitation and flood hazards, which shows the importance of explicitly integrating such features into flood modelling frameworks [1], [4].

Table 2. Metrics comparison

Data metrics	Initial search	Refinement search
Query	from 2014 to 2024	from 2014 to 2024
Source	GS	GS
Papers	1000	993
Citations	36300	36291
Years	10	10
Cites_Year	3630	3629.1
Cites_Paper	36.30	36.55
Cites_Author	10424.43	10421.43
Papers_Author	353.27	349.24
Authors_Paper	3.58	3.59
h_index	101	101
g_index	168	168
hc_index	112	112
hl_index	24.06	24.06
hl_norm	51	51
Cites_Author_Year	1042.44	1042.14

The network system shown in Figure 4 indicates that FS research predominantly focuses on modeling approaches. The primary clusters consist of keywords such as "FS," "model," "mapping," and "GIS." The principal features are closely linked to sophisticated techniques, including random forest (RF), decision tree (DT), and frequency ratio models. Furthermore, TC-related variables are outside factors that identify a conceptual gap in the integrated application of atmospheric dynamics into FS models. This gap is particularly important because TC-induced rainfall is a major trigger of extreme flooding in tropical and subtropical regions.

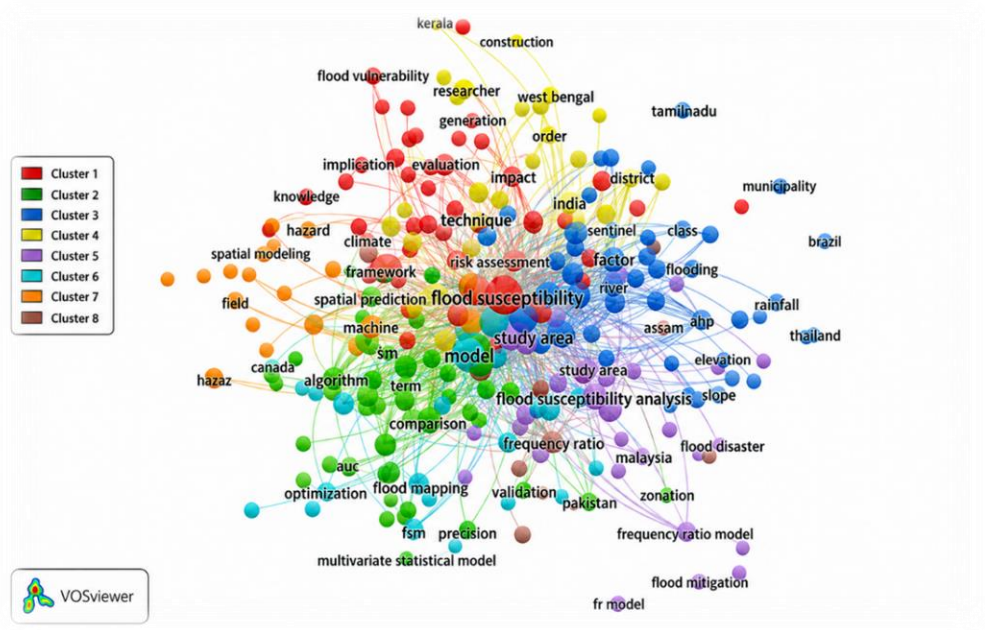

Figure 3. Network visualization of keyword clustering

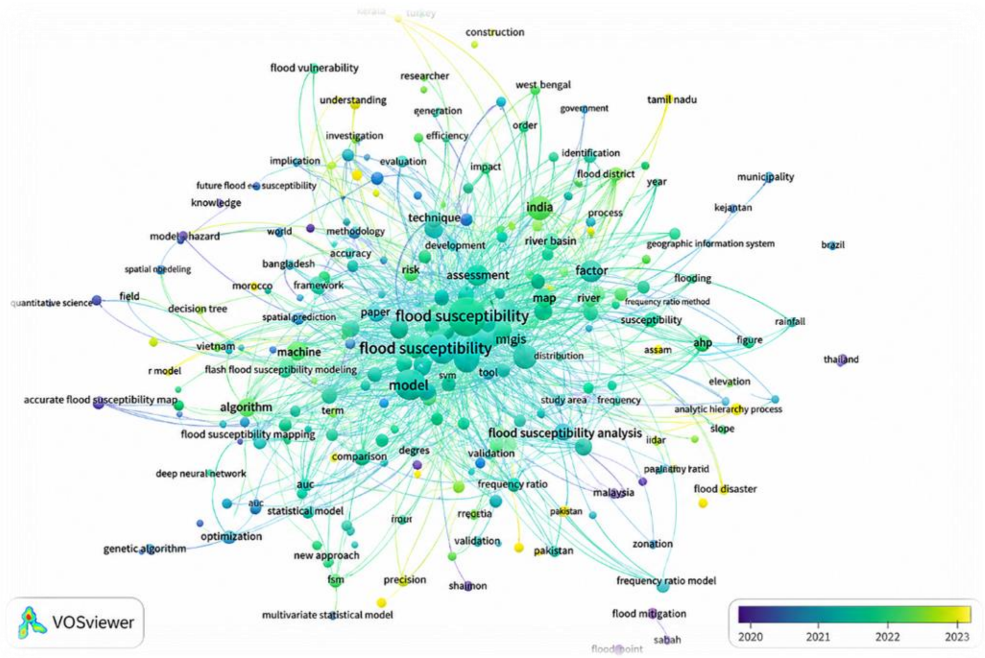

Figure 4. Visualization of publication years with the topic of FS

The intensity-of-occurrence visualization in Figure 5 shows the current trends in research that focus on FS mapping, modeling, and advanced methods that use ML and algorithms. This indicates a significant shift from traditional statistical approaches to data-driven and DL-oriented models. The increasing adoption of ML and DL approaches reflects both methodological advancement and improved availability of high-resolution geospatial and remote sensing data. These methods are particularly suitable for capturing complex nonlinear relationships in flood processes. In terms of methodological advancement, there remains a gap in topics focusing on TC-induced FS. This means that current models are not fully employed to examine TC-related flood mechanisms.

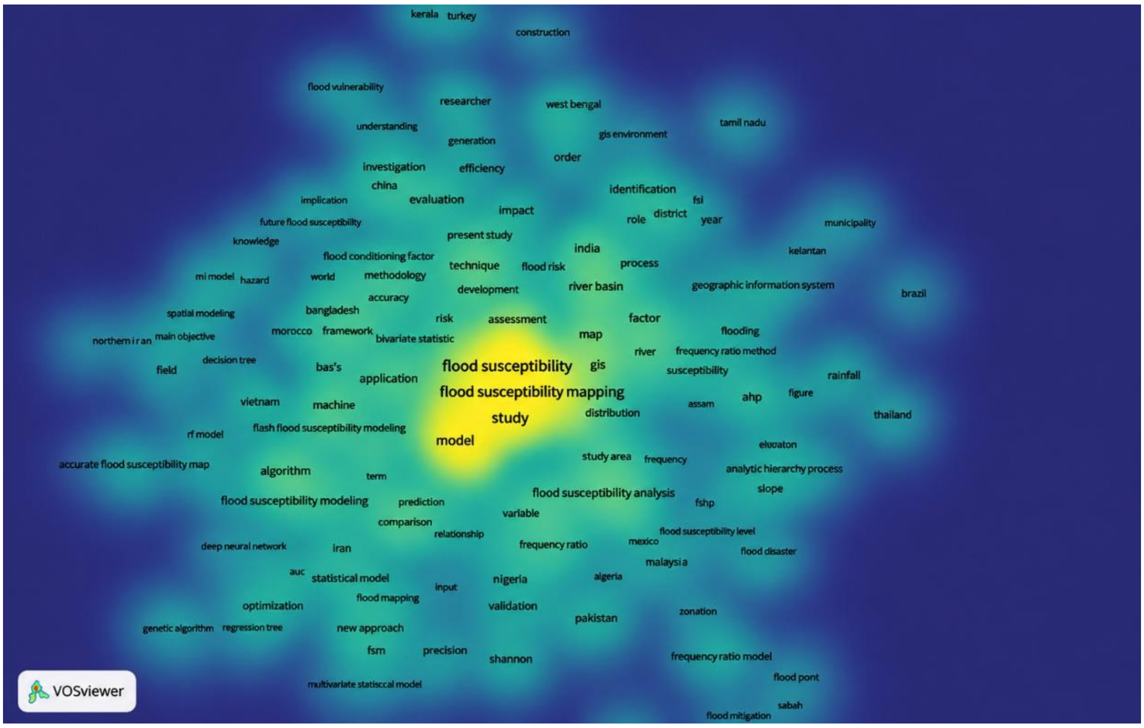

Figure 5. Visualization of the intensity of occurrence of FS-related topics

Figure 6 shows that a few highly recognized authors are in the lead of FS research through strong networks of collaboration around the world. The linkages are most evident in Asia and the Middle East, which suggests that research and knowledge sharing are focused on specific areas. Figure 7 shows the global distribution of research studies. It shows that FS research is widely used in Asia, Europe, and North America, with an increasing emphasis on Southeast Asia, as it is highly vulnerable to flooding. The dominance of Asia in FS research can be explained by the region's high exposure to TC and associated flood hazards. Countries such as China, India, and those in Southeast Asia frequently experience severe TC impacts, which drive research prioritization, funding allocation, and data availability.

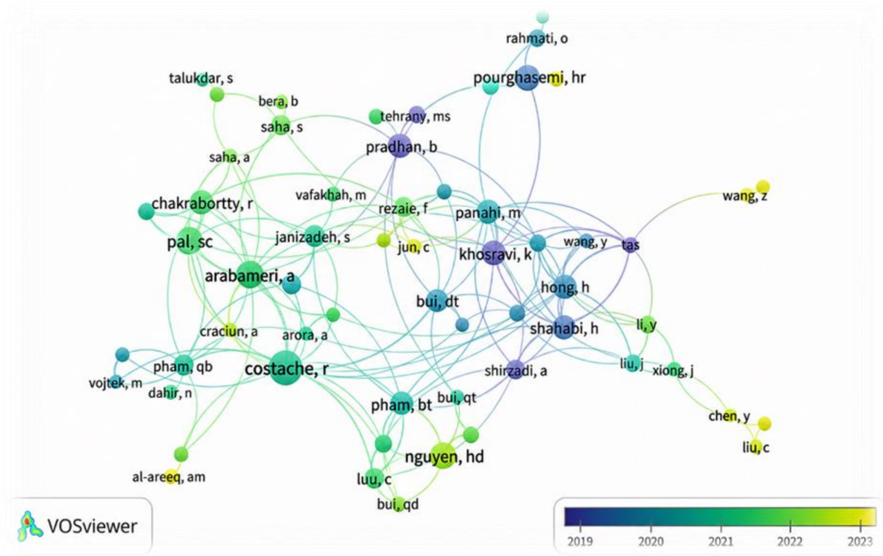

Figure 6. Visualization of collaboration networks between researchers in FS research

Figure 7. Locations where research has been conducted in the world

3.2. PRISMA systematic literature review

Figure 8 shows that FS research related to TC is spread across several regions in South and Southeast Asia, including countries such as Vietnam, Thailand, and Pakistan, as well as African regions such as Madagascar and Nigeria. In addition, research was also conducted in coastal Australia, which is vulnerable to TC impacts. This indicates that research is focused on tropical and subtropical regions that are often exposed to large storms.

Figure 8. Locations where research has been conducted

Figure 9 shows that the number of published articles is increasing every year. This indicates an increasing research interest in this field, especially from 2019 to 2021, when the number of articles published was at its highest. This trend shows that advanced computational techniques are becoming more important for reducing the damage caused by TC flooding, and that more research is being conducted on this in recent years.

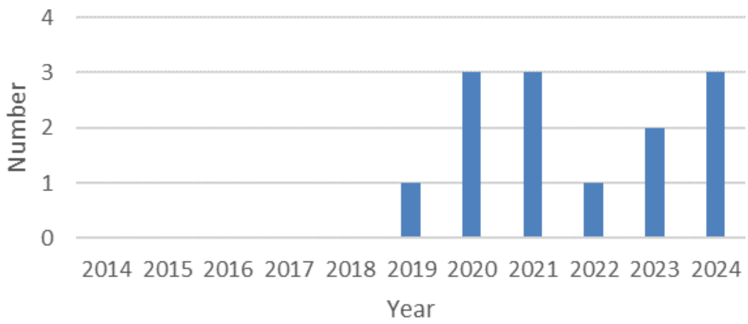

Figure 9. Graph of the number of articles per year

The analysis of modeling approaches in Table 3 shows an evident frequency of ML, DL, and hybrid models in current studies. Combining optimization algorithms with ML techniques in hybrid approaches consistently results in improved predictive performance. This is primarily because these methods can identify and optimize model parameters for complex nonlinear relationships quickly. These results align with recent studies finding that hybrid and DL-based models perform better than conventional statistical methods in flood forecasting [22]–[24].

Despite these improvements, several limitations remain that need to be addressed. Most studies use datasets with a moderate level of detail, like shuttle radar topography mission (SRTM) digital elevation model (DEM) (30 m), which could fail to demonstrate the local variation in landforms in areas that are likely to flood properly. Also, most studies are conducted in data-rich regions, which may limit the applicability of these models in data-scarce regions. This indicates how important it is to have modelling methods that are more adaptable and operate effectively with a smaller dataset.

Table 3. Algorithmic methods used

Ref.	Algorithm method
[22]	The hybrid technique combines quantum-behaved particle swarm optimization (QPSO) as an optimization model with committee decision tree (CDT) ensemble approaches in ML.
[23]	Model optimization: the equilibrium optimizer (EO) algorithm is applied to optimize the parameters of the hybrid model: HEsSysfor.
[24]	ML Model: deep 1D-convolutional neural networks (1D-CNN); optimization model: ADAM algorithm.
[25]	ML model: extreme learning machine (ELM); optimization model: PSO.
[26]	ML model: multivariate adaptive regression splines (MARS); optimization model: PSO.
[27]	ML model: support vector machine (SVM); optimization model: frequency ratio models.
[28]	ML model: CDT; optimization model: QPSO algorithm.
[29]	Optimization model: group method of data handling (GMDH); ML model: CNN.
[30]	Optimization model: ADAM algorithm; ML model: 1DCNN.
[31]	ML model: RF; optimization model: SHapley Additive exPlanations (SHAP).
[32]	ML: deep neural networks (DNNs); model optimization: genetic algorithms (GAs).
[33]	ML model: Extreme gradient boosting (XGB); optimization model: CatBoost (CB).
[34]	Artificial neural network multi layer perceptron (ANNMLP), support vector regression (SVR), gradient boosting regressor (GBR), and lasso regression are all examples of ML models. There are two optimization models: the grasshopper optimization algorithm (GOA) and the PSO.

Figure 10 illustrates the primary processes for creating an FS map through a flowchart. The process requires collecting data and preparation, sample distribution, and the identification of variables correlated with flooding, such as precipitation, elevation, and land use. Subsequently, ML techniques are employed to assess the data. These methods require validation to ensure reliability before producing accurate FS maps.

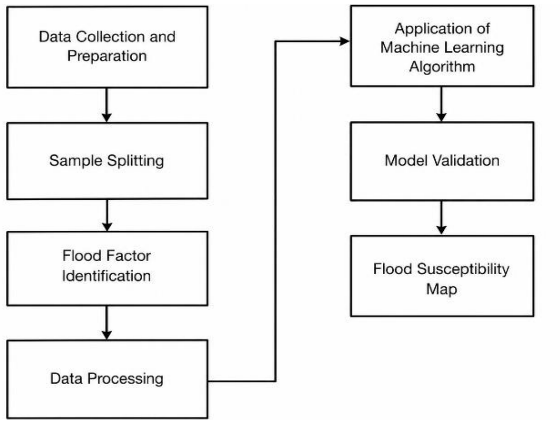

Figure 10. Flowchart of the FS map in general

The analysis of conditioning factors in Figure 11 shows that slope, rainfall, elevation, and topographic indices are the most commonly used variables in FS modeling. These parameters play a critical role in determining hydrological responses and flood dynamics. However, the limited inclusion of TC-specific variables suggests that current models may not fully represent the physical processes associated with TC-induced flooding.

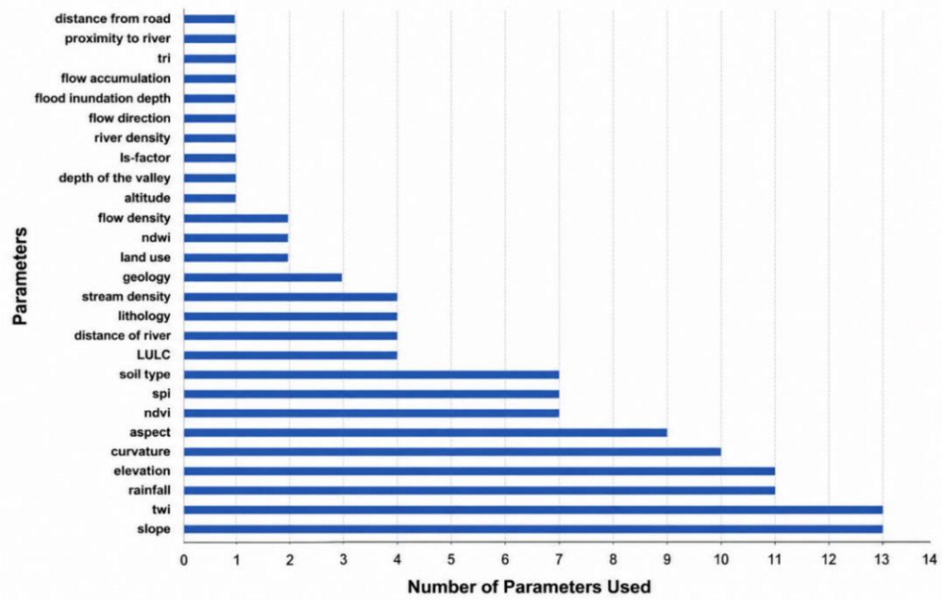

Figure 11. Parameters used in FS modeling

The model performance analysis in Figure 12 (number description: [22] 1, [23] 5, [24] 13, [25] 2, [26] 3, [27] 4, [28] 6, [29] 7, [30] 8, [31] 9,[32] 10, [33] 11, [34] 12) indicates that DL-based models, in particular deep 1D-CNN, and hybrid models, such as HE-SysFor, achieve the highest prediction accuracy (area under the curve or AUC=0.97). This shows that contemporary models are highly capable of capturing complex interactions among flood conditioning elements. These conclusions are strongly dependent on data quality, in particular, the accuracy of flood inventory data sets. Moreover, such performance cannot be directly generalized across different geographic regions or spatial scales. However, improved model performance does not necessarily ensure physical interpretability, especially in DL models, which may be considered black-box methodologies. This constraint underlines the necessity of using explainable AI methodologies in future FS modelling.

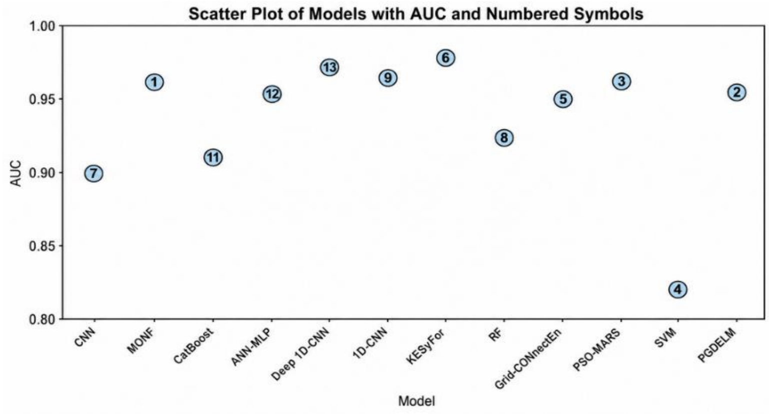

Figure 12. Comparison of AUC values for each model

The analysis of data sources in Tables 4 to 6 shows that most studies rely on widely available datasets, such as SRTM for topography, Sentinel-1 SAR for flood inventory mapping, and rainfall data from meteorological stations or global datasets. While these data sources enable large-scale analysis, their resolution and quality may limit the accuracy of local-scale predictions.

Table 4. DEM data used

Journal	DEM
[22]	Scale of 1:50,000 with an accuracy of 20 meters, and a contour interval of 10 m
[23]	Scale of 1:50,000 with an accuracy of 20 meters
[24]	ALOS - JAXA with 30 m resolution
[25]	Scale of 1:50,000 with an accuracy of 20 meters
[26]	Scale of 1:50,000 with an accuracy of 10 meters
[27]	SRTM with 30 m resolution
[28]	Scale of 1:50,000 with an accuracy of 30 meters
[29]	SRTM with 90 m resolution
[30]	ALOS - JAXA with 30 m resolution
[31]	SRTM with 30 m resolution
[32]	SRTM with 30 m resolution
[33]	LiDAR data with an accuracy of 5 meters
[34]	The Ibaraki lab, corrected to 30 m resolution

Table 5. Data sources for flood inventory map generation

Journal	Flood inventory map
[22]	Landsat 8, flood report and field works
[23]	SAR Sentinel -1 C and field survey
[24]	SAR Sentinel-1 C and field survey
[25]	SAR Sentinel -1A and field survey
[26]	SAR Sentinel-1 C and field survey
[27]	Landsat 5 TM and SRTM data
[28]	SAR Sentinel -1 C and field survey
[29]	SAR Sentinel-1 C
[30]	SAR Sentinel and field survey
[31]	RADARSAT-2 and COSMO-SkyMed-SAR
[32]	SRTM-DEM and IFSAR-Derived DTM and flood report
[33]	Field survey with 5-meter resolution lidar data source
[34]	Field survey

Overall, the synthesis of the selected articles shows that there are several important research gaps as in Table 7. These consist of the constrained use of high-resolution data, lack of implementation in data-scarce regions, limited integration of hybrid models, an absence of long-term climate change considerations, and negligible incorporation of socio-economic aspects. Also, research in equatorial regions is still not well represented, even though they are highly vulnerable to flooding due to TC activity. To make FS modelling stronger, more useful, and more relevant in the context of climate change, it is necessary to fill these gaps.

Table 6. Rainfall data used in the study

Journal	Research focus
[22]	Rainfall data from 1979 to 2010 were extracted from the climate forecast system reanalysis (CFSR).
[23]	3-day rainfall data from the last 5 years (2016-2019) derived from local and regional monitoring systems.
[24]	Rainfall data was sourced from NASA from July 7, 2021, to August 31, 2021.
[25]	Rainfall data derived from 16 rainfall stations on October 1-12, 2017.
[26]	Rainfall data from meteorological stations from 10-12 October 2017.
[27]	Not explained.
[28]	The maximum rainfall that accumulated in three days over the past twenty years. The data was collected from 24 weather stations in and around Yen Bai Province.
[29]	Using average monthly rainfall data from the World Meteorological Organization (WMO).
[30]	Rainfall data from 2017 to 2021, with a maximum of 15 days recorded. Using the inverse distance weighting method for interpolation.
[31]	Heavy rain was recorded between March 26 and 29, 2017, in the region by the Australian Bureau of Meteorology.
[32]	Rainfall data from 2018 and 2019 were averaged monthly and interpolated.
[33]	The rainfall data from 1975 to 2021 were gathered by interpolation between two meteorological stations.
[34]	Not explained.

Table 7. Research gap

GAP identification	Current research focus	Future research potential
Limited use of high-resolution data	Most studies use 30m resolution DEMs (SRTM), rarely using higher resolution LiDAR.	Examine the application of high-resolution data, such as LiDAR, in improving prediction accuracy.
Lack of implementation in areas with limited data	Research has focused on areas with sufficient data, with little exploration of areas with limited data.	Develop a model that performs effectively in regions with scarce meteorological and geospatial data.
Limited combination of ML models	Most studies implement individual models such as RF, SVM, and ANN.	Increase ensemble and hybrid methods, such as stacking or blending.
Lack of long-term research on climate change	Research focuses on short-term predictions without considering long-term climate change.	Incorporate long-term climate change projections in flood vulnerability predictions.
Limitations of model interpretation	DL models are generally black-box, with only a few studies using SHAP for interpretation.	Emphasizes the use of interpretive methods such as SHAP on more complex models.
Lack of use of socio-economic data	Studies have mainly focused on geospatial factors without taking into account socio-economic factors.	Integrate socio-economic factors to produce a more comprehensive flood risk model.
Operational implementation at scale	Research is mainly conducted on a local or regional scale.	Implement large-scale models for early warning and disaster mitigation nationally or internationally.
Research gaps in the equatorial region	Studies have mainly focused on subtropical regions, with little research on flood risk in equatorial regions vulnerable to TC.	Further research is required in the equatorial regions where the anticipated occurrence of TCs may increase in frequency and intensity as a result of climate change. More research is necessary on ML-based flood research and development in Indonesia, central Africa, and Brazil.

4. CONCLUSION

This study employed a two-stage framework combining bibliometric analysis and a PRISMA-based SLR to examine research on FS in the context of TC. The bibliometric analysis of 993 journal articles published between 2014 and 2024 shows rapid academic growth, as reflected by an h-index of 101 and a g-index of 168. While FS research has increasingly adopted ML, DL, GIS, and remote sensing–based approaches, the bibliometric results reveal that explicit discussion of TC as a driving factor in FS studies remains limited.

This thematic gap identified through bibliometric mapping provided the basis for conducting the PRISMA-based SLR, which enabled a focused synthesis of studies explicitly integrating FS and TC and demonstrated that advanced data-driven models can effectively represent TC-induced flood processes, although their application remains geographically uneven and largely concentrated in data-rich regions. However, this study is subject to limitations, as it relies exclusively on GS and includes only English-language publications, which may affect coverage consistency and the global representativeness of the findings.

Overall, the combined bibliometric and PRISMA-based approach provides a structured pathway from research trend identification to in-depth synthesis, highlighting the need to explicitly incorporate TC dynamics into FS modeling to support more robust flood risk assessment, climate adaptation, and disaster risk reduction strategies. Future research should expand FS–TC modeling by incorporating socio-economic factors, focusing on equatorial and data-scarce regions, and moving toward operational applications such as early warning systems. This study provides an evidence-based foundation to support disaster mitigation and climate adaptation in TC-prone regions.

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AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Giarno	✓	✓		✓	✓	✓			✓	✓		✓		

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that this study was conducted without any conflicts of interest.

DATA AVAILABILITY

The data supporting the findings of this study are accessible from the corresponding author upon a reasonable request.

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