

1 **Flood Impacts on Transportation Infrastructure: Current Trends and** 2 **Future Perspectives**

3 **Abstract**

4 Flooding poses a growing threat to transportation networks worldwide, disrupting critical
5 infrastructure, mobility, and economic activities. As the backbone of societal functioning, resilient
6 transportation systems are vital for disaster response, economic stability, and equitable access. This
7 review synthesises recent advancements and methodologies in assessing flood impacts on
8 transportation infrastructure, focusing on data integration, modeling approaches, and impact
9 assessments. The study maps the landscape of current research, highlights emerging trends, and
10 identifies key gaps, including underrepresentation of advanced AI techniques, limited focus on
11 diverse flood types, and insufficient integration of climate change projections. The review
12 underscores the potential of interdisciplinary collaboration, real-time data application, and
13 standardised frameworks to enhance resilience. By addressing these gaps, this work offers a roadmap
14 for future research to safeguard transportation networks against escalating flood risks and align them
15 with sustainable urban development goals.

16 **Keywords:** Accessibility; Flood risk assessment; Flood Impacts; Mobility; Modelling;
17 Transportation infrastructure; Resilience

18 **1. Introduction**

19 Transportation networks are the lifelines of modern society, serving as the backbone of economic
20 activity by enabling the efficient movement of goods, services, and people (Chen *et al.*, 2024). These
21 networks facilitate global trade, support local economies, and connect communities, ensuring that
22 essential resources such as food, medicine, and fuel are delivered where they are needed most (Assaad
23 *et al.*, 2024). They also play a critical role in fostering social interaction, enabling access to education,
24 healthcare, and employment opportunities (Tessier *et al.*, 2024). In addition, transportation networks
25 are integral to the functioning of emergency services, allowing for rapid response to crises and
26 disasters. By linking urban and rural areas, they promote regional development and help to bridge the
27 gap between different socioeconomic groups, contributing to overall societal well-being and cohesion
28 (Munshi, 2023).

29 Among the various causes of network failures and disruptions, flooding is particularly critical due to
30 its unpredictability and the increasing difficulty of management (Bakhtiari *et al.*, 2023; Piadeh *et al.*,
31 2023). This challenge is further compounded by the rising frequency and intensity of flood events
32 worldwide, driven largely by climate change (Ferdowsi *et al.*, 2024; Girotooa *et al.*, 2024). Even local
33 flooding may have cascading effects, disrupting not only the catchment area but also regional and
34 national transportation routes (Wenzel *et al.*, 2023). Flooding also can severely damage infrastructure
35 such as roads, bridges, railways, and tunnels, leading to long-term closures and costly repairs
36 (Urlainis *et al.*, 2022). In the context of emergency response, flooding can impede the delivery of
37 critical services and hinder evacuation efforts, putting lives at risk (Thapa *et al.*, 2022). Additionally,
38 Industries reliant on just-in-time delivery models, such as manufacturing and retail, are particularly
39 vulnerable, as delays can result in production halts and financial losses (Smorodinskaya *et al.*, 2021).
40 Furthermore, the broader economy can suffer from reduced access to markets, labour, and resources,
41 further compounding the effects of a flood event (Kumar *et al.*, 2021). In urban areas, where
42 transportation networks are dense and populations are high, the disruption of public transit systems,

43 for instance, can leave millions of commuters stranded and unable to reach their workplaces,
44 exacerbating economic losses and social inequalities (Bakhtiari *et al.*, 2024).

45 Understanding and mitigating the impacts of flooding on transportation networks is not only essential
46 for infrastructure resilience but also crucial for maintaining economic stability, public safety, and
47 social equity (Pregnoiato *et al.*, 2016; Piadeh *et al.*, 2022). In this regard, numerous studies have
48 developed models to assess the impacts of flooding on transportation networks. These models -
49 ranging from statistical and physical to artificial intelligence (AI) based approaches - generally follow
50 a structured process. They begin with the collection and integration of relevant data, followed by the
51 training and testing of the models to evaluate their efficiency and predictive capabilities. They then
52 are used to simulate and demonstrate the potential impacts of flooding on infrastructure, such as
53 disruptions, damage, and long-term closures, providing valuable insights for risk management and
54 mitigation strategies (He *et al.* 2023; Shahdani *et al.* 2023).

55 Despite the growing body of research in this field, a few review papers have comprehensively mapped
56 the intricate relationships between data, methodologies, and the specific impacts of different types of
57 flooding on transportation systems, as listed in Table 1. Some reviews limited their scope to bibliometric
58 or scientometric analyses, concentrating on the effects of sea-level rise on roadways and railways
59 (Nazarnia *et al.*, 2020), flood modelling and spatial analysis related to road connectivity (Kadaverugu
60 *et al.*, 2021), the impact of extreme events on road transportation infrastructure (Abreu *et al.*, 2023), or
61 vulnerability assessments of transportation networks in the context of natural hazards (Amlan *et al.*,
62 2023). Some studies, however, provide more in-depth and critical analyses. For example,
63 Tachaudomdach *et al.* (2018) outlined two dimensions and ten principles for assessing the resilience of
64 transportation infrastructure in the face of natural disasters. Johnston *et al.* (2021) investigated the
65 effects of flooding on the stability of transportation embankments, particularly for roads and railways.
66 Watson and Ahn (2022) also proposed a three-stage framework for assessing the effects of flooding on
67 transportation resilience, but no furthered classification was provided. Analysis on these works shows
68 while they heavily focus to map the impacts, model applications have not been highlighted well.

Table 1. Recent review papers on the intersection of flooding and transportation

Theme	Focused area			Reference
	Data collection	Model application	Impact demonstration	
Resilience of transportation infrastructures	NF	NF	Technical or organisational criteria for resilience of transportation	Tachaudomdach <i>et al.</i> (2018)
Adaptation of civil and environmental infrastructures	NF	NF	Impacts and adaptations on railroads and roads	Nazarnia <i>et al.</i> (2020)
Impact assessment approaches for underground infrastructures in urban areas	NF	Risk assessment methods used for the impact of flooding on metro transportation systems	Direct and indirect impacts on metro transportation systems	Forero-Ortiz <i>et al.</i> (2020)
Resilience modelling concepts in transportation systems	NF	Optimisation, simulation, and qualitative methods	Impacts on travel time and accessibility	Ahmed and Dey (2020)
Stability of transportation embankments	NF	NF	Physical impacts on road and railroad embankments	Johnston <i>et al.</i> (2021)
Transportation networks	NF	Probabilistic approach, Analytical approach and fuzzy inference methods, graph theory, and hybrid models	Short-term, medium, and long-term impacts in both direct and indirect aspects	Rebally <i>et al.</i> (2021)
Road connectivity	NF	Bibliometric analysis on the applied methods	Impacts on road connectivity	Kadaverugu <i>et al.</i> (2021)
Transportation infrastructure resilience	NF	NF	Transportation vulnerability analysis	Watson & Ahn (2022)
Climate change impacts on the road transport infrastructure	NF	NF	Biophysical impacts	Abreu <i>et al.</i> (2023)
Vulnerability assessment of transportation network	NF	Classifying methods based on transportation metrics	Impacts on travel time and accessibility	Amlan <i>et al.</i> (2023)
Impact analysis and risk assessment of road traffic	NF	Classification of methods, based on the related impacts	Direct and indirect non-physical impacts	He <i>et al.</i> (2023)
Hybrid methodologies in assessing indirect impacts on transportation	Classification for data type but not the source	Macroscopic, microscopic, and mesoscopic methods	Static and dynamic “indirect impacts” of flooding on transportation	Shahdani <i>et al.</i> (2023)

NF: Not focused

71 To address this gap, Ahmed and Dey (2020) categorised the literature based on transportation modes
72 and the analytical techniques employed. Forero-Ortiz *et al.* (2020) focused specifically on the risk
73 aspects of pluvial flooding in underground transportation systems and examined relevant adaptation
74 measures. Rebally *et al.* (2021) explored the use of statistical optimisation and simulation techniques
75 to analyse the impacts of flooding on transportation networks. He *et al.* (2023) distinguished between
76 two types of road inundation -focusing solely on pluvial flooding- and examined both the direct and
77 indirect non-physical impacts on road transportation. Finally, Shahdani *et al.* (2023) conducted a
78 review of flood risks and their impacts on transportation networks, with a focus on indirect impacts
79 through static and dynamic network analysis methods. Hence, while these studies provide valuable
80 insights into various aspects of flooding impacts, modelling techniques, impact analysis and flood
81 types, more in-depth investigation is still required. Furthermore, the critical role of data collection
82 and its use as the foundation for modelling - central to understanding how these models have
83 functioned - has not been sufficiently addressed and therefore warrants further exploration.

84 Hence, this study aims to address the identified gaps by exploring data sources, applied models, and
85 flood impact objectives to bridge the gap between flood impact modelling and transportation
86 infrastructure. This approach seeks to deliver a comprehensive and holistic perspective on the
87 interplay between these critical areas. By employing both scientometric and critical analyses, this
88 research maps the existing knowledge domain, categorises well-explored areas, and identifies
89 emerging trends. Furthermore, it sheds light on overlooked yet promising avenues, paving the way
90 for future research and innovation in this critical field.

91 **2. Research design and methodology**

92 To conduct this review, seven search and screening strategies (S₁-S₈) were implemented, as illustrated
93 in Figure 1. These strategies were guided by the PRISMA (Preferred Reporting Items for Systematic
94 Reviews and Meta-Analyses) guidelines and checklist to refine the selection process (Moher *et al.*,
95 2010). PRISMA's four-phase flow, meaning identification, screening, eligibility, and inclusion,
96 helped trace each paper's progression through the selection process and ensured consistency across

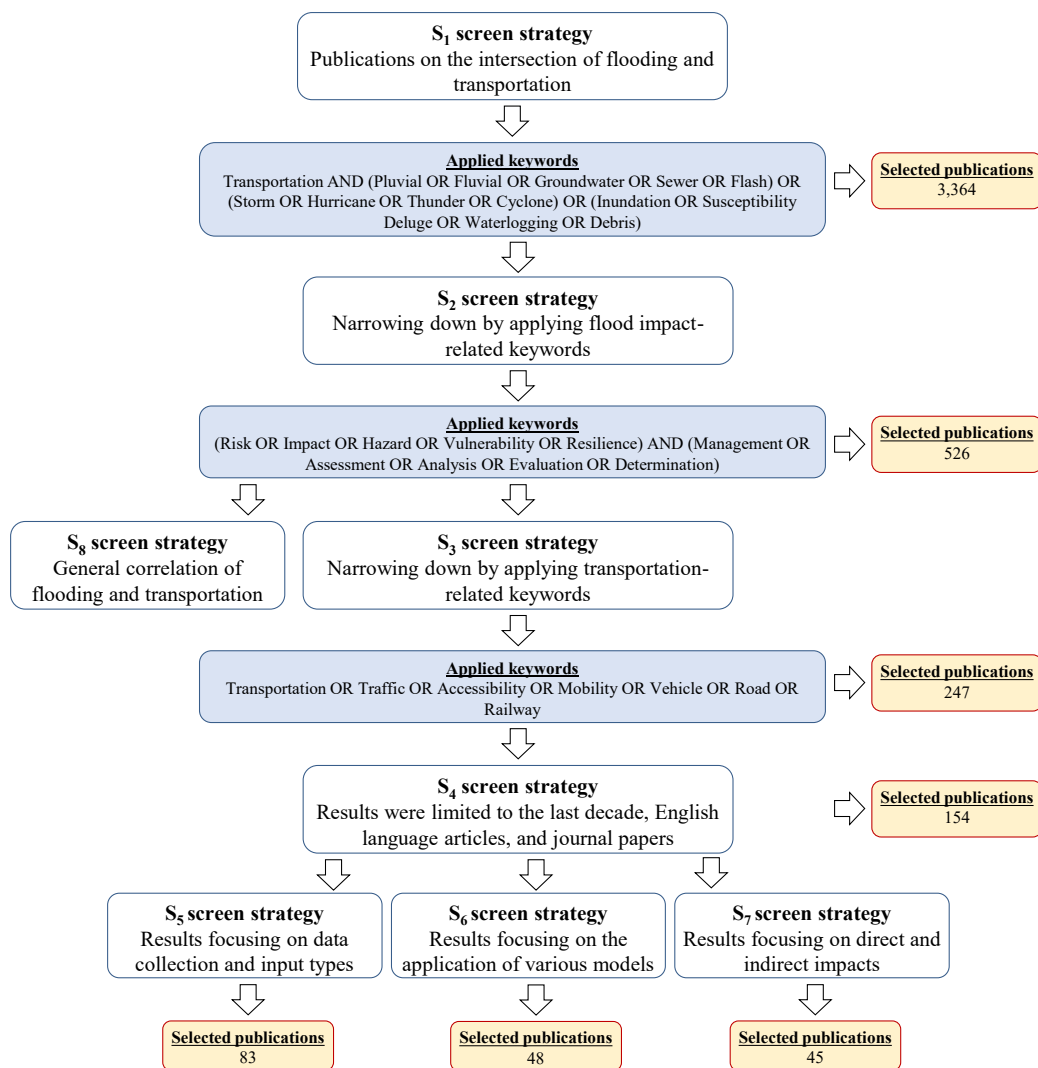
97 the seven search strategies (S1–S7). Its checklist facilitated transparent documentation of inclusion
98 and exclusion criteria, minimizing bias and enhancing the reproducibility of the review.

99 The initial search strategy (S₁) aimed to identify studies focusing on a specific type of flooding and
100 its connection to one component of transportation networks (see Figure 1 for applied keywords).
101 Keywords for flooding types were derived from Hamill’s (2010) recommendations, including terms
102 such as “pluvial,” “fluvial,” “groundwater,” “sewer,” and “flash”. Additionally, extreme weather-
103 related terms, including “storm,” “hurricane,” “thunder,” and “cyclone,” were incorporated following
104 suggestions from Ferdowsi *et al.* (2024). These keywords were used to search bibliographic
105 information (title, keywords, and abstract), covering study characteristics such as research design,
106 key findings, conclusions, and methodological quality (Higgins *et al.*, 2023). Boolean operators
107 (AND, OR, NOT) were employed to effectively combine these keywords (Kumar and Thilagam,
108 2019). For further investigation, additional flood impact-related terms such as “inundation,”
109 “susceptibility,” “deluge,” “waterlogging,” and “debris” were added based on further
110 recommendations (Piadeh *et al.*, 2022). The initial search yielded approximately 3,364 papers.

111 To refine the correlation between flooding and transportation, the impacts of flooding were limited
112 to the themes of "Risk," "Vulnerability," and "Resilience" inspired by Asghari *et al.*, (2024). This
113 approach aimed to more specifically identify how transportation systems are affected by flooding,
114 resulting in the S₂ strategy, as shown in Figure 1, which yielded 526 relevant papers. This reduction
115 to 16% of the initially found research indicates that a larger proportion of studies have focused
116 primarily on flooding, rather than specifically on transportation and its vulnerability to flooding
117 impacts.

118 At the next stage (S₃), the search was narrowed to include studies that addressed specific
119 transportation modes and their terminology. This revealed that while many papers recognised the
120 significance of flooding on transportation, most did not focus specifically on its impacts. To extract
121 these papers, the classifications of Rebally *et al.*, (2021) and Shahdani *et al.*, (2023) are followed.

122 The search was further refined to include studies from the last 10 years, aligned with contemporary
 123 research trends (S₄ in Figure 1). Older studies were excluded when more recent, comprehensive
 124 research was available. Additionally, only English-language, peer-reviewed journal articles focusing
 125 on titles, keywords, and abstracts were included. After a full screening, the methodological quality of
 126 each paper was assessed using the PRISMA checklist, which resulted in a final selection of 154 papers
 127 in S₄.



128
129

Figure 1. Flowchart of screen strategies for selecting research works used in this study

130 The selected papers were categorised using grounded theory (Hirschfeld & Hill, 2022), with key
 131 concepts identified through open coding, broader themes through axial coding, and integration into a
 132 cohesive narrative using selective coding. These papers were grouped according to flood modelling
 133 principles recommended by Piadeh *et al.* (2022): 83 papers focused on data collection and input types

134 (S₅), 48 papers on the application of various models (S₆), and 45 papers on direct and indirect impacts
135 of flooding on transportation (S₇). Each selected paper was then synthesised using both a narrative
136 approach to contextualise the findings and a quantitative approach for meta-analysis (Higgins *et al.*,
137 2023).

138 Four types of analysis were conducted in this review: (1) Geographical analysis explored the global
139 distribution of case studies, with a bibliometric analysis using VOSviewer software to analyse co-
140 occurrences of key terms based on the full counting method; (2) Critical analysis provided a
141 comprehensive evaluation of identified themes, particularly in the context of data collection,
142 modelling and impact assessment; (3) Scientometric analysis quantified research output and assessed
143 the impact of key studies in well-explored areas; and (4) Gap analysis identified future research
144 directions and development areas based on existing literature but not specifically in the scope of these
145 paper (refer to S₈ in Figure 1).

146 **3. Brief bibliometric analysis**

147 **3.1. Temporal and spatial distribution**

148 Figure 2a illustrates the cumulative growth of published papers over time, showing a significant
149 increase in publication rates, particularly after 2018. When comparing this trend with advancements
150 in AI, it becomes evident that despite the growth in access to big data and the use of weak learner
151 machine learning (ML) models between 2014 and 2018, this development had little direct impact on
152 the intersection of transportation and flooding research. Instead during this period, the focus was
153 primarily on statistical or physical modeling, using big data databases. However, a notable increase
154 in research occurred when more advanced AI techniques, such as deep learning (DL) and recurrent
155 neural networks (RNN), were adopted alongside satellite data. This suggests that the integration of
156 AI technologies and large datasets has aligned with the rising trend in research within this field,
157 emphasising the importance of both data collection methods and modelling in advancing studies on
158 transportation and flooding.

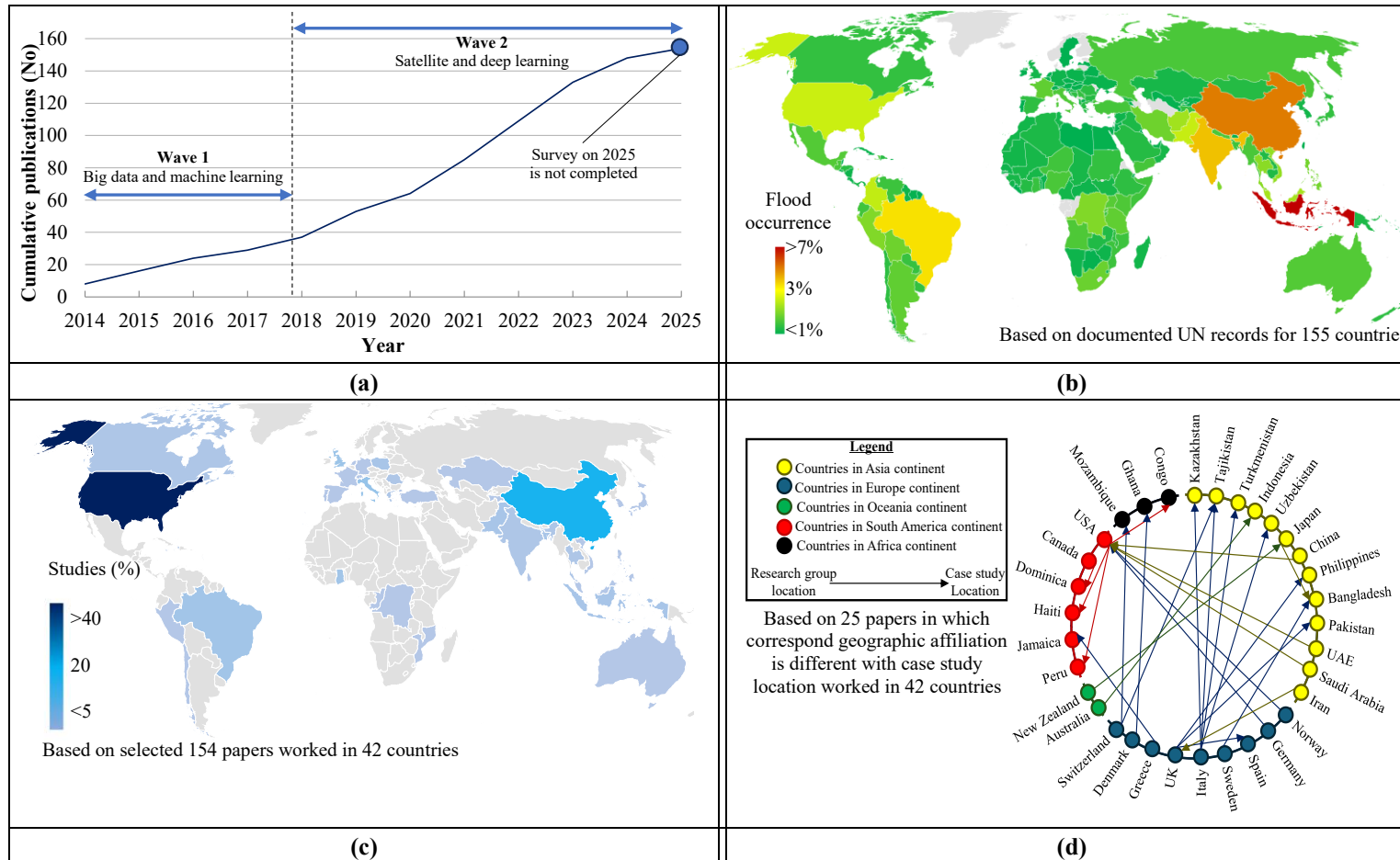


Figure 2. Dashboard of temporal and spatial analysis: (a) timeline of research trends, (b) flood occurrence for the past 10 years, (c) share of geographical distribution, (d) international contribution of those case study with international authors

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161 Figure 2b presents the magnitude of flood occurrences over the past decade. A comparison with
162 Figure 2c reveals that, while 155 countries have experienced flooding, research on its impact on
163 transportation infrastructure has primarily focused on just 42 countries. This can be attributed to the
164 fact that, in developing regions such as Africa and the Middle East, the priority is often placed on
165 affected populations rather than infrastructure (Quintana *et al.*, 2022; Ikram *et al.*, 2024). However,
166 it is important to recognise that transportation infrastructure plays a critical role in emergency
167 response and early action, which can significantly influence the rate of human casualties. The
168 distribution also highlights an imbalance between economically strong countries, particularly USA
169 and China, and some regions such as India, Europe, and Brazil, where dense but vulnerable
170 transportation infrastructures are prevalent, particularly in India and Southeast Asia. On the other
171 hand, limited research has been conducted in developing countries in Africa and Central Asia that
172 show promising potential for further exploration in these and similar regions.

173 In other words, although the frequency and severity of flood events are notably higher in countries
174 such as India, Brazil, and other regions of South Asia, the volume of scholarly publications addressing
175 the impacts of these floods on transportation systems remains disproportionately low. This imbalance
176 underscores a critical research gap and highlights the need for greater empirical investigation within
177 these high-risk regions. Expanding case study research in these contexts would not only enhance the
178 regional understanding of flood-induced transportation disruptions but also contribute to the global
179 knowledge base on the infrastructure resilience and adaptation strategies. In contrast, as illustrated in
180 Figure 2c, countries such as the United States and China exhibit a more proportionate relationship
181 between national flood risk exposure and the extent of academic research focusing on transportation-
182 related flood impacts. This alignment reflects more mature research engagement and institutional
183 capacity in integrating flood risk assessment with transportation system resilience studies.

184 Finally, 75% of the selected studies were found to be local in nature, with the corresponding author
185 sharing the same nationality as the case study location (129 out of 154). While the impact of flooding

186 on transportation is heavily dependent on the local characteristics of each case study, this suggests
187 that local knowledge and resource mobilisation have been effectively utilised. However, for other
188 works (25 papers shows in Figure 2d where correspond and case study countries are different), the
189 importance of knowledge transfer becomes apparent. As illustrated in Figure 2d, European
190 researchers predominantly lead international studies, often focusing on Asian regions, while USA-
191 based researchers tend to concentrate on North American case studies. This finding underscores the
192 potential for expanding international collaboration and strengthening the exchange and flow of
193 knowledge between countries.

194 **3.2. Keyword analysis**

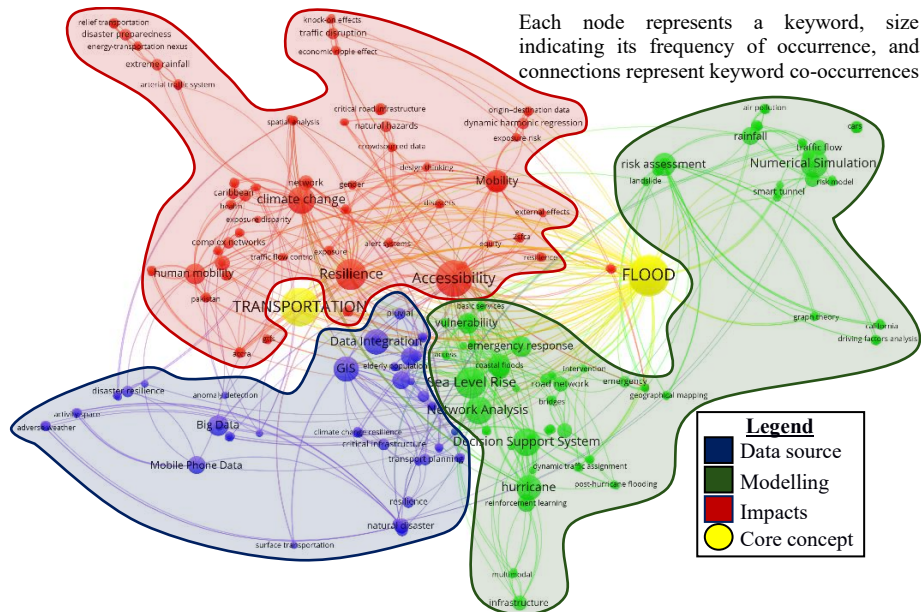
195 Figure 3 presents a keyword analysis of the selected papers. While Figure 3 focuses on bibliometric
196 characteristics of the reviewed literature, this analysis serves as a foundation for identifying the
197 prevailing research themes that guide the critical evaluation in the following sections. The analysis
198 examines other keywords in relation to core concepts ("transportation" and "flood" as primary
199 keywords across nearly all studies).

200 Cluster analysis reveals three main keyword clusters based on co-occurrence patterns: (1) Data source
201 cluster (see blue area in Figure 3a which includes keywords related to data sources and preprocessing
202 techniques, such as data collection, infilling, and integration methods. Findings indicate a strong
203 emphasis on data integration and anomaly detection, with a preference for large datasets based on
204 GIS data capturing demographics (e.g., elderly populations), surface transportation networks, and
205 critical infrastructure. Additionally, mobile phone data emerges as a prominent source for resilience
206 analysis in natural disaster scenarios. (2) Modeling cluster (green area) which represents analytical
207 methods applied in the selected papers, particularly for modeling the vulnerability of infrastructure
208 impacted by factors such as sea level rise and hurricanes. Common methods within this cluster include
209 decision support systems (DSS) and numerical simulations. (3) Impact cluster (red area) which
210 focuses on the impacts of flooding on transportation, with keywords such as mobility, accessibility,

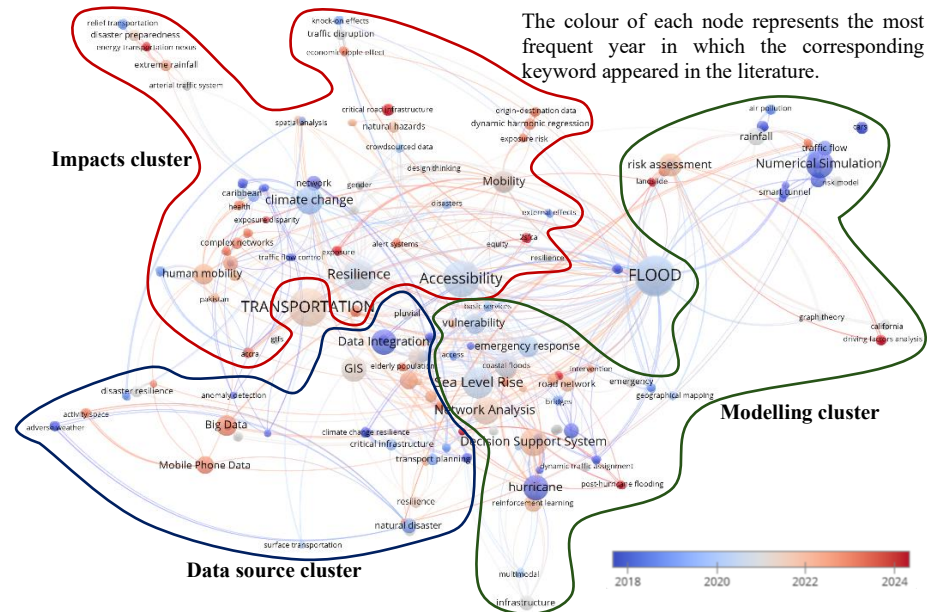
211 and resilience. Notably, "climate change" appears prominently in this cluster, highlighting its strong
212 association with the effects of flooding on transportation networks.

213 An additional analysis conducted here is a timeline analysis of keyword occurrences, as shown in
214 Figure 3b, revealing trends in popular topics and identifying keywords that may evolve into core
215 concepts in the future. Between the two primary concepts - flooding and transportation - there has
216 been a recent shift from viewing issues predominantly through the lens of flooding to a more
217 transportation-centred perspective. This shift is particularly significant because it reflects an
218 increasing recognition of the transportation's critical role in disaster resilience and urban mobility.
219 The data source cluster reveals a growing focus on the application of big data and mobile phone data,
220 with particular attention given to the elderly population as a key user group. In the modelling cluster,
221 well-established numerical simulations have shifted in prominence, making way for network analysis
222 and DSS. Within the impact analysis cluster, human mobility and exposure risk are emerging as key
223 topics of interest.

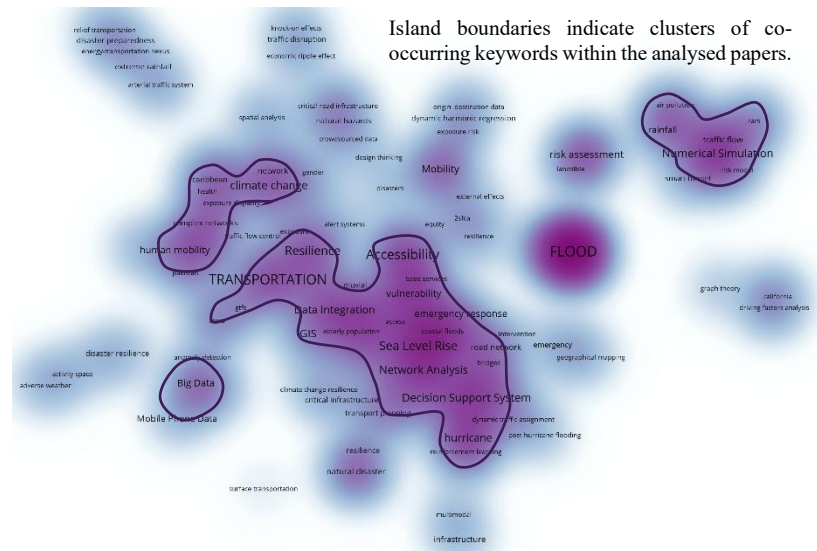
224 A density analysis, shown in Figure 3c, illustrates keyword groupings and interdependencies.
225 Keywords are organised into "islands," representing clusters that share strong correlations. While
226 "flood" stands independently as a distinct island, "transportation" is positioned alongside GIS data
227 sources within the data cluster, DSS and network analysis within the modelling cluster, and resilience
228 and accessibility within the impacts cluster (Compare Figure 3a with 3c). Conversely, the relationship
229 between "climate change" and both "flooding" and "transportation" appears less integrated,
230 suggesting that the direct impacts of climate change are not yet a focal point in this context. Similar
231 observations can be made for big data applications, indicating potential areas for further integration.



(a)



(b)



(c)

232 Figure 3. Bibliometric analysis of the selected research studies: (a) cluster analysis of keywords, (b) timeline analysis of hot keywords, (c) Density analysis of keywords correlation

233 **4. Critical analysis of flood impacts on transportation infrastructure**

234 Three main themes are considered here, according to outputs of cluster analysis (refer to Figure
235 3a): (1) Data types and their contribution of flood impact assessment which offers insights into
236 flood-related disruptions and analysing the impacts of flooding on transportation systems.
237 These varied data categories enable the identification of vulnerable components within
238 transportation infrastructure and provide a deeper understanding of how flooding affects
239 movement, accessibility, and overall system resilience; (2) Data sources and their contribution
240 of flood impact assessment which provides valuable information for supporting a multi-layered
241 analysis of transportation resilience; (3) Applied models on flood impact assessment, which
242 demonstrates advantages for understanding and mitigating flood-related risks.

243 **4.1. Data types used for transportation-based flood impact assessment**

244 Table 1 presents a range of data types used as an essential for understanding and mitigating the
245 impacts of flooding on transportation systems, with a focus on early warning systems and
246 resilience improvement. Here six types of data input are recognised: (1) traffic data, (2)
247 infrastructure, (3) point of interest (PoI), (4) location characteristics, (5) mobile based data, and
248 (6) text/video content. Traffic data, including traffic volume, traffic flow, and travel behavior,
249 is fundamental for understanding how flood events disrupt routine mobility patterns. By
250 analyzing traffic volume, congestion levels and identify areas are quantified likely to
251 experience severe bottlenecks during floods - critical insights for emergency routing and
252 evacuation planning. Traffic flow data, in turn, highlights fluctuations in vehicle speeds and
253 overall network reliability, helping pinpoint specific routes that become impediments under
254 flood conditions. Additionally, understanding travel behavior can reveal how commuters adapt
255 their routes and transportation modes in response to flooding, offering a predictive foundation
256 for future transportation planning in flood-prone areas.

257 Data on road and transportation networks provides critical information into the connectivity
258 and robustness of infrastructure. These datasets help identify segments of the network most
259 vulnerable to flooding, such as low-lying bridges or key intersections, which may require
260 mitigation efforts to withstand flood impacts. Combined with vulnerability assessments, this
261 information enables targeted interventions to strengthen the segments most critical for
262 maintaining regional connectivity and access during adverse events, thus enhancing overall
263 system resilience.

264 Equally important are datasets related to points of interest, demographics, buildings, and land
265 use/cover. PoI data identifies essential services such as hospitals, fire stations, and shelters that
266 must remain accessible during floods to ensure effective emergency responses. Demographic
267 data provides context on populations impacted by transportation disruptions, highlighting at-
268 risk groups such as the elderly or economically disadvantaged individuals who may rely
269 heavily on public transit. Building data informs flood resilience planning in urban areas, where
270 damage to structures near major routes could exacerbate transportation issues. Land use data
271 helps understand flood pathways, revealing how different surfaces - urban, agricultural, or
272 forested - affect water flow and identifying zones at higher flood risk.

Table 1 Data types utilised in transportation-based flood impact assessment*

Type of data	Definition	Flood impact	Reference
Traffic data			
Traffic volume	The number of vehicles per hour approaching a traffic signal from all directions at different times	Enabling estimation of congestion levels and accessibility constraints during and after floods, critical for emergency routing	Sun <i>et al.</i> (2021)
Traffic flow	A traffic flow carries data that is exchanged between the terminals during a communication service	Helping in assess of speed and reliability of network segments affected by flooding, indicating vulnerable routes	Bucar & Hayeri (2020)
Travel behaviour	The allocation of resources, such as time and money, to activities and movements from one place to another	Revealing behavioural adjustments due to flood impacts, helping to forecast demand for alternative routes	Abenayake <i>et al.</i> (2022)
Infrastructure			
Road network	Inter-city roads connecting settlements, and all road data designed for vehicle or pedestrian use in the city	Supporting analysis of flood-related disruptions, identifying high-risk segments and potential traffic rerouting options	Panakkal <i>et al.</i> (2023)
Transportation network	A set of links, nodes, and lines that represent the infrastructure or supply side of the transportation	Assisting in resilience assessments, highlighting crucial network links that require mitigation efforts against flood risks	Alabbad <i>et al.</i> (2021)
Infrastructure vulnerability	Information and metrics that assess the susceptibility of the systems such as roads, bridges, railways, airports, and ports	Identifying areas of high susceptibility, guiding the prioritisation of flood protection efforts	Alam <i>et al.</i> (2021)
Transportation specification	Details on the design, layout, and condition of transportation structures and how they function to support the movement of people and goods	Assessing damage to infrastructure and planning recovery efforts	Kim <i>et al.</i> (2021)
Point of interest	Information about specific, significant locations or landmarks, such as businesses, public facilities, tourist attractions, hubs, and natural features	Emergency planning by identifying critical services, such as hospitals and shelters, that must remain accessible during floods	Rajput <i>et al.</i> (2023)
Location characteristics			
Demographic	Characteristics of different stakeholder and social groups, including age, gender, ethnicity, education, and marital status	Evaluating the social impacts of flood-related transportation disruptions, focusing on vulnerable communities	Papilloud & Keiler (2021)
Building	Structures, including residential, commercial, industrial, and public buildings, detailing their location, dimensions, use, construction materials, age, condition, and occupancy	Assessing potential shelter sites and predicting flood-induced accessibility issues in urban areas	Helderop & Grubescic (2019)
Land use/cover	Data on coverage ratio of both natural and man-made land types including forests, wetlands, impervious surfaces, and agriculture	Helping understands natural water flow paths and flood-prone areas, aiding in transportation planning around affected zones	Hierink <i>et al.</i> (2020)
Mobile based			
Mobile signals	Information collected from mobile devices and cell towers, capturing the location, movement, and connectivity of mobile users. It includes signal strength, call records, location coordinates, and usage patterns	Providing real-time traffic flow and user density, enabling the identification of high-demand evacuation routes and areas requiring immediate access	Tang <i>et al.</i> (2023)
Smartphone apps	Location specifications generated and collected from applications on smartphones	Tracking user movement and alternative routing choices during floods, aiding in understanding behavior under disrupted transportation conditions	Ghorbanzadeh <i>et al.</i> (2021)
Text/video content	Information derived from text or video content related to mobility, such as social media posts, travel blogs, surveillance footage, or traffic camera	Validating real-time flood impacts on transportation, such as road blockages, and assists in tracking emergency needs	Florath <i>et al.</i> (2024)

*: Data was extracted from all the selected research papers, with references included selectively for brevity.

275 **4.2. Data sources used for transportation-based flood impact assessment**

276 Table 2 classifies the main data sources and their contribution to assessing flood impacts on
277 transportation networks. Here three main data sources are identified: (1) qualitative data sources, (2)
278 Official and documented database, and (3) data collected locally or regionally by remote sensing.
279 Qualitative data from interviews and field surveys provides critical on-the-ground perspectives,
280 capturing local knowledge and real-time observations of how flooding impacts transportation
281 infrastructure. For instance, interviews with residents, local officials, and emergency responders
282 reveal how effectively routes remain accessible and how infrastructure withstands increased stress
283 during flood events. Field surveys further complement these insights by documenting visible impacts,
284 such as road closures and water levels, aiding in the mapping of physical damages and assessing the
285 usability of affected infrastructure.

286 Structured government data is another vital component in flood impact studies. National, state, and
287 municipal databases offer extensive information on infrastructure locations, historical flooding events,
288 and maintenance records. These datasets enable large-scale risk mapping and support resource
289 allocation to enhance resilience. Official data, often spanning extensive timelines, helps researchers
290 identify trends, forecast future vulnerabilities, and strengthen long-term flood preparedness strategies.
291 Data from private entities, such as ride-sharing companies and logistics providers, provides real-time
292 insights into traffic patterns and user responses to flooding. This private data is invaluable for
293 understanding mobility shifts during flood events and informing emergency transportation planning.
294 For example, ride-sharing data can highlight areas with rising or falling demand for transportation,
295 guiding the allocation of resources to support evacuation efforts or maintain access to essential services.

Table 2. Data sources supporting flood impact assessment in transportation*

Source of data	Definition	Flood impact	Reference
Qualitative			
Self-conducted interviews	Direct conversations with individuals or groups to collect opinions on mobility-related experiences and behaviours	Including residents, transportation officials, or emergency personnel and their opinions about the effects of flooding on transportation accessibility and evacuation routes.	Husain <i>et al.</i> (2024)
Filed survey	On-site data observations and questionnaires to assess mobility patterns, infrastructure, and user preferences	Direct observation and documentation of flood-affected transportation infrastructures, such as road blockages and damages	Farahmand <i>et al.</i> (2024)
Database			
Government	Mobility-related data provided by national authorities, such as transportation statistics, policies, and infrastructure details.	Analysing infrastructure vulnerabilities and planning improvements	Stefanska & Wiśniewski (2019)
State level	Data collected and maintained by regional governments, focusing on state-wide transportation networks and mobility trends	Added value in regional transportation resilience, supporting targeted mitigation and resource allocation efforts	Shen <i>et al.</i> (2022)
City council	Local data on urban transportation, including public transit schedules, road maintenance, and city planning initiatives	Helping to track localised flood impacts and infrastructure maintenance requirements, supporting response coordination	Mitsakis <i>et al.</i> (2014)
Private authorities	Mobility information collected by private entities, such as ride-sharing companies, logistics firms, and infrastructure operators	Providing real-time mobility patterns, indicating impacted areas and optimising emergency transportation options.	Fan <i>et al.</i> (2021)
Remote sensing			
Lidar and IoT sensors	Data collected from sensors and IoT devices to monitor traffic flow, vehicle speed, and pedestrian movement in real time	Useful for real-time detection of flooded areas, allowing immediate rerouting and efficient evacuation planning.	Pyatkova <i>et al.</i> (2019)
Geotagged images	Photos tagged with location data, providing visual information into mobility conditions, infrastructure, and surroundings	Enabling visual verification of flood impacts on transportation networks, especially useful for inaccessible or high-risk zones.	Lu <i>et al.</i> (2024)
Street view images	Panoramic images capturing street-level views used for analysing road conditions, signage, and urban design.	Providing visual context for assessing road conditions, signage visibility, and infrastructure damage post-flood	Qiang & Xu (2019)
Satellite	High-altitude imagery providing large-scale views of transportation networks, land use, and environmental factors affecting mobility	Facilitating broad flood impact analysis by mapping affected areas and transportation network disruptions across large regions	Preisser <i>et al.</i> (2023)

*: Data was extracted from all the selected research papers, with references included selectively for brevity.

298 Remote sensing data sources, including lidar, satellite imagery, and geotagged street views,
299 offer detailed and scalable insights into flood impacts on transportation networks. Lidar and
300 sensor data enable precise, real-time monitoring of traffic flow, vehicle speeds, and water
301 levels, while satellite imagery provides comprehensive, large-scale views of affected regions.
302 Geotagged photos further enrich this data by offering localised perspectives, facilitating
303 thorough mapping of impacted areas and aiding in disaster response and infrastructure
304 assessment.

305 **4.3. Modelling approaches used for transportation-based flood impact assessment**

306 Table 3 lists the modelling methodologies used for evaluating and mitigating flood-related
307 disruptions in transportation infrastructure. Generally, four types of modelling approaches are
308 extracted based on reviewing of all the selected research works: (1) spatial analysis, (2)
309 decision support system (DSS), (3) Artificial intelligence (AI) models, and (4) statistical
310 analysis. Spatial analysis, including static and dynamic network analysis, plays a crucial role
311 in evaluating the connectivity and functionality of transportation networks. Static network
312 analysis focuses on the structural aspects of transportation systems, identifying critical nodes
313 and links whose disruption due to flooding could significantly impair connectivity. In contrast,
314 dynamic network analysis examines network performance over time, offering a real-time
315 understanding of how flood events affect mobility and usability. GIS-based modeling further
316 enhances spatial analysis by mapping flood-prone areas, visualising potential accessibility
317 constraints, and enabling rapid assessments of transportation network connectivity during flood
318 events.

319 DSS strategic planning by balancing multiple objectives, such as minimizing flood damage
320 while ensuring accessibility. Single-objective DSS approaches address specific challenges,
321 such as preserving pavement quality, while multi-criteria decision-making methods evaluate
322 various factors, including economic, social, and accessibility impacts. By integrating spatial

323 analysis, DSS provides a robust framework for transportation planning in flood-prone regions,
324 making it indispensable for resilience planning.

325 AI-based models, including data mining, machine learning, and deep learning techniques,
326 leverage large datasets to enhance predictive capabilities. Data mining uncovers patterns in
327 historical data, pinpointing areas of high flood risk, while machine learning algorithms identify
328 anomalies in traffic data to detect vulnerable network segments. Deep learning applications,
329 such as text and image analysis, integrate real-time social media and video data, offering a
330 dynamic and comprehensive understanding of flood impacts on transportation systems. Finally,
331 statistical analysis forms the foundation of flood impact studies by identifying trends and
332 correlations within data related to mobility, network resilience, and infrastructure damage.
333 Statistical methods quantify disruptions, predict accessibility reductions, and support modeling
334 recovery timelines.

Table 3. Modelling approaches for transportation-based flood impact assessment*

Methodology	Definition	Flood impact	Reference
Spatial analysis			
Static network analysis	Analysing the structure and connectivity of a transportation network based on fixed, unchanging elements	Finding the critical networks links, mapping the flooded area, and modelling the emergency response	Coles <i>et al.</i> (2017)
Dynamic network analysis	Analysing network performance over time, incorporating variations like traffic flow and temporal changes	Applying for infrastructure usability evaluation and user behavior analysis with the advantage of real-time traffic monitoring	Hussain <i>et al.</i> (2018)
GIS	Interpreting spatial data for mobility patterns and infrastructure planning	Simple and fast analysis applied for accessibility analysis, network connectivity analysis, and flood risk mapping.	Shan <i>et al.</i> , (2023)
Decision support system			
Single-objective analysis	Optimising one criterion or objective, such as minimising flood damage	Simply assessing or optimising impact of flooding on the quality of the pavements	Strauch <i>et al.</i> (2015)
MCDM/ MADM	Assessing multiple conflicting criteria to aid in making informed and balanced decisions	Facilitates the assessment of trade-offs between multiple flood-related factors, such as flood damage, traffic disruption, and infrastructure vulnerability, to support decision-making.	Shilling <i>et al.</i> (2016)
Decision tree	A flowchart-like structure used for decision-making by mapping out different outcomes and paths based on specific criteria	Assessing current conditions and planning for future scenarios	Green <i>et al.</i> (2017)
AI-based models			
Data mining	Extracting useful patterns and information from large datasets, used for predicting mobility trends	Discovering trends, for example, analysing historical data to find the vulnerable routs and infrastructure.	Ahmadi <i>et al.</i> (2024)
Machine learning	Employing algorithms to learn from data and make predictions or classifications, improving over time with more data	Anomaly detection purposes, for example finding unusual patterns in the traffic data. Machin learning also have vast application in DSS methods.	Yuan <i>et al.</i> (2023)
Deep learning	Extracting numerical data or quantified pattern from images	Image, video and text analysis, specifically for the social network data	Gazzea <i>et al.</i> (2023)
Statistical analysis	Collection, examination, interpretation, and presentation of data to identify trends, relationships, and patterns within mobility data	Impact assessment and predictive modelling	Suwanno <i>et al.</i> (2021)

*: Data was extracted from all the selected research papers, with references included selectively for brevity.

GIS: Geographical information system

MADM: Multi-Attribute Decision Making

MCDM: Multi-Criteria Decision Making

337 **4.4. Types of flood impacts on transportation**

338 Flood events influence transportation systems through multiple, often interrelated impact
339 pathways. Based on the reviewed literature, four primary categories of flood-inflicted impacts
340 on transportation infrastructure are identified: (1) Accessibility, (2) Disruption, (3)
341 Infrastructure damage, and (4) Indirect/Sequential impacts. Together, these categories highlight
342 both the immediate physical challenges and the broader socio-economic consequences of
343 flooding, underscoring the need for integrated resilience strategies.

344 Accessibility impacts occur when road segments, bridges, or transit routes become inundated,
345 restricting mobility and impeding access to essential services such as hospitals, emergency
346 shelters, or workplaces. These effects are particularly acute for vulnerable populations, who
347 may rely heavily on public transit. Disruption encompasses interruptions to traffic flow,
348 congestion, and delays across networks. Even when infrastructure remains structurally intact,
349 reduced travel speeds and rerouting requirements impose significant time and resource costs.
350 Such disruptions can cascade through regional and national supply chains, reducing the
351 efficiency of emergency response and economic activity.

352 Infrastructure damage reflects direct physical losses, such as erosion of road surfaces, collapse
353 of embankments, scouring of bridges, or failures of drainage systems. These damages often
354 require substantial repair or reconstruction costs, leading to prolonged service interruptions and
355 resource-intensive recovery phases. Indirect/Sequential impacts extend beyond immediate
356 disruptions, capturing broader socio-economic consequences. These include economic costs
357 and productivity losses from business interruptions, reduced workforce mobility, and impacts
358 on logistics and trade. They also involve longer-term resilience challenges, such as decreased
359 property values, inequitable recovery trajectories, and the exacerbation of existing social
360 vulnerabilities. Incorporating these indirect and economic effects is essential to provide a
361 holistic perspective of flood risks to transportation infrastructure.

Table 4: Types of flood impacts on transportation

Type of impact	Definition	Flood impact examples	Reference
Accessibility			
Road accessibility	Extent to which road networks remain usable under flood conditions	Reduced access to critical services and neighbourhoods due to inundated routes	Perazzini <i>et al.</i> (2023); Rajput <i>et al.</i> (2023)
Emergency response access	Ability of emergency vehicles to reach affected areas; accessibility of the emergency centers	Delayed rescue and evacuation operations; restricted ambulance/fire-service mobility	Kutela <i>et al.</i> (2023); Sun <i>et al.</i> (2021)
Disruption			
Traffic flow	Continuity of vehicular movement and speed across the network	Congestion, rerouting, and increased travel times during flood events	Bucar & Hayeri (2020); Ghorbanzadeh <i>et al.</i> (2022)
Public transit	Operation of public transportation, including buses, metro, rail services, and etc.	Suspension or delay of services, causing mobility inequities for transit-dependent users	He <i>et al.</i> (2021); Tariverdi <i>et al.</i> (2023)
Infrastructure damage			
Pavement and roadbed deterioration	Structural degradation of surface layers or subgrade	Cracking, rutting, and material loss leading to road closures	He <i>et al.</i> (2022); Panakkal <i>et al.</i> (2023)
Bridge and embankment failure	Instability or collapse caused by hydraulic pressure and scouring	Loss of connectivity and costly reconstruction requirements	Burghardt <i>et al.</i> (2025); Fan <i>et al.</i> (2025)
Drainage system failure	Blockage or overload of urban drainage networks	Prolonged waterlogging and subsequent road weakening	Kurki-Fox <i>et al.</i> (2025); Obara <i>et al.</i> (2025)
Indirect / Sequential			
Impact on vulnerable populations	Unequal exposure and recovery capacities among social groups	Disproportionate mobility losses for elderly or low-income populations	Yao <i>et al.</i> (2024); Alabbad and Demir (2025)
Long-term resilience and adaptation	Capacity of transport systems to recover and adapt post-event	Policy and infrastructural challenges in sustaining functionality after floods	Bi <i>et al.</i> (2025); Borowska-Stefańska <i>et al.</i> (2025)
Economic costs and productivity losses	Financial and macro-economic consequences of disrupted transportation services	Lost productivity, reduced freight efficiency, reconstruction expenses, and indirect GDP losses	Fant <i>et al.</i> (2021); Shahdani <i>et al.</i> (2022)

*: Data was extracted from all the selected research papers, with references included selectively for brevity.

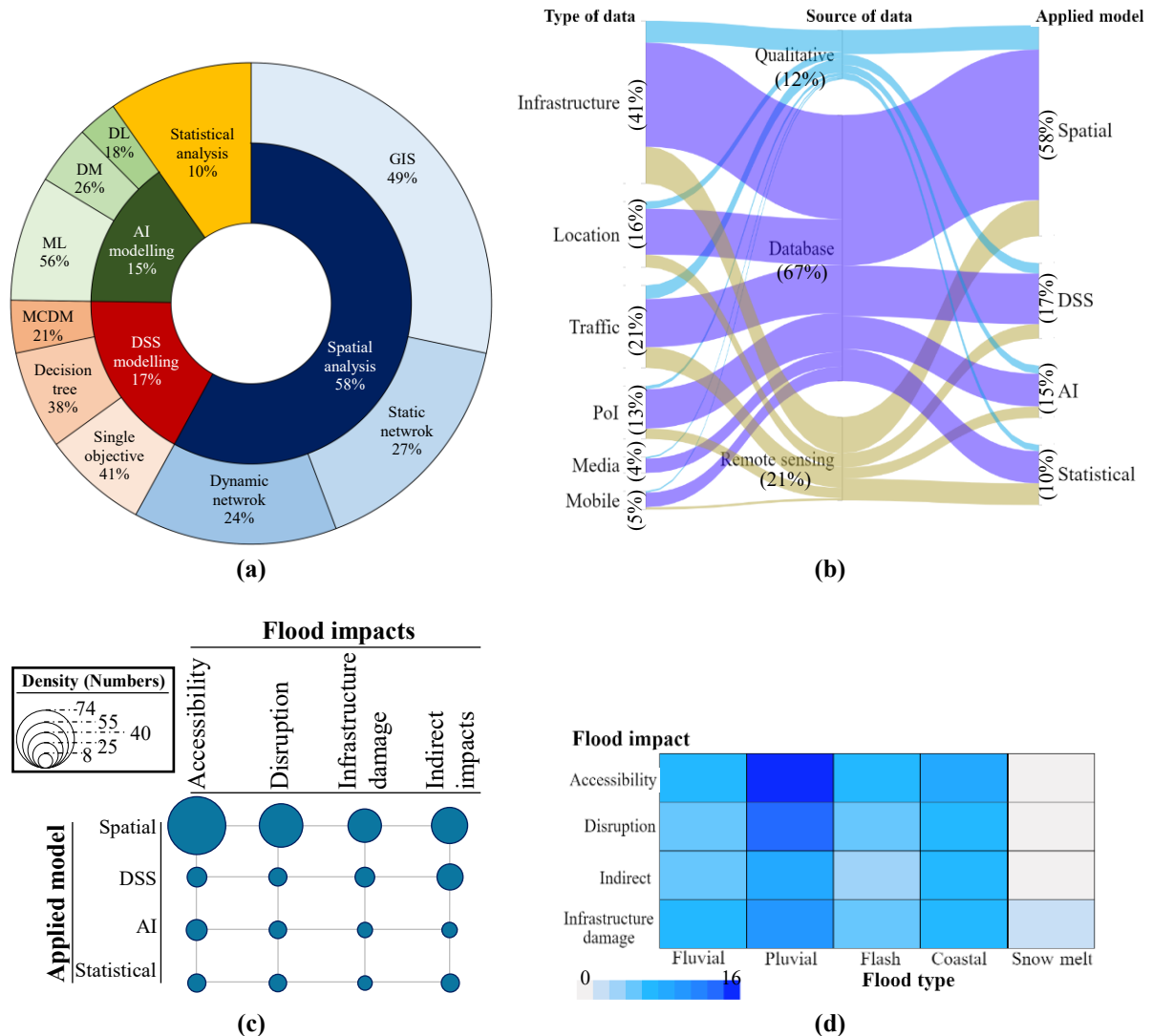
364 **5. Brief scientometric analysis**

365 Figure 4 provides a statistical overview of the types of models, data sources, and impact
366 categories used across the reviewed studies. This analysis was conducted to identify the most
367 frequently applied techniques and to highlight underexplored areas that present opportunities
368 for further research. By examining the distribution of modelling approaches and data
369 applications, the figure helps to contextualise current research trends and emphasise where
370 methodological or thematic gaps remain.

371 Figure 4a presents the distribution of methodologies employed across the reviewed studies.
372 Spatial analysis is the dominant approach, accounting for near 58% of the studies, underscoring
373 the critical role of spatial data in understanding and modelling environmental and
374 transportation systems. Spatial analysis is particularly favoured for its ability to visualise and
375 quantify spatial relationships and patterns, which are essential in transportation research. The
376 relatively lower percentages of AI (15%) and statistical modelling (10%) suggest these
377 techniques are still emerging and have not yet achieved the prominence of spatial analysis in
378 this field.

379 Within the spatial analysis category, GIS analysis is the most frequently used method,
380 comprising near 49% of spatial analysis studies (34% of the total). The popularity of GIS can
381 likely be attributed to its simplicity in calculating distances while offering sufficient accuracy
382 for most research applications. Static and dynamic network analyses have similar shares, at
383 27% and 24%, respectively, reflecting their complementary roles in modelling transportation
384 and environmental networks. In the DSS category, single-objective methods are the most
385 prevalent (41%), followed by decision trees (38%) and MCDM approaches (21%). Notably,
386 single-objective methods and decision trees are often integrated with other methodologies, such
387 as spatial analysis or AI modelling, to enhance their effectiveness. In the AI modelling category,
388 machine learning dominates with a 56% share, aligning with the first wave of data-driven

389 methodologies observed in Figure 2a. While the second wave in Figure 2a indicates a growing
 390 interest in deep learning in recent years, Figure 4a reveals that deep learning still occupies a
 391 smaller portion of AI modelling research (18%), highlighting an area that warrants further
 392 exploration.



393 **Figure 4. Dashboard of Scientometric analysis: (a) burst graph of detailed model applied, (b) alluvial**
 394 **graph of used data and applied model, (c) bubble graph of model applied and flood impacts, (d) heat map**
 395 **of flood impact and flood type**

396 Figure 4b illustrates the relationship between applied methodologies and the types and sources
 397 of data used, with each data source. It is evident that governmental and private repositories
 398 (database) are the most frequently used sources of data (67% of total source of data), with
 399 transportation infrastructure data being particularly prevalent (41% of total data type). Most
 400 research employing spatial analysis (53% of total applied model) relies on infrastructure and

401 location data from databases, with fewer studies utilising remote sensing or qualitative data for
402 this purpose. Remote sensing (only 20% of data source), while frequently used for spatial and
403 statistical analyses, is less commonly applied in DSS and AI modelling. Common remote
404 sensing data types include transportation infrastructure and traffic flow information. An
405 interesting trend noted, is the divergent use of traffic flow data. When sourced from databases,
406 it is primarily employed in DSS, whereas data obtained via remote sensing is more commonly
407 applied in AI modelling or statistical methods. PoI data (only 13% of total data type), typically
408 extracted from databases or remote sensing, is often utilised in AI and statistical models.

409 Figure 4c highlights the correlation between flood impacts and applied methodologies. Spatial
410 analysis and accessibility exhibit the strongest correlation, making them the most commonly
411 paired method and impact. Disruptions and indirect impacts also show a strong association.
412 DSS methods demonstrate the strongest correlation with indirect impacts, while accessibility
413 has the weakest correlation. Conversely, AI modelling exhibits the opposite trend, with
414 accessibility showing the highest correlation and indirect impacts the lowest. Among all
415 methods and impacts, the weakest correlation exists between statistical methods and
416 infrastructure damage.

417 Finally, Figure 4d explores the relationship between different flood types and their associated
418 impacts. Pluvial flooding is the most frequently studied flood type, with its intersection with
419 accessibility being the most common focus (14 studies). Coastal flooding ranks second, with
420 accessibility receiving greater attention than other impacts. In contrast, snowmelt flooding is
421 the least studied flood type in the literature.

422 **6. Identified gaps and overlook area**

423 Despite the advancements in understanding the impacts of flooding on transportation
424 infrastructure, several critical gaps and overlooked areas persist in the current body of research.

425 Addressing these gaps is essential for developing comprehensive strategies to enhance the
426 resilience and functionality of transportation networks in the face of increasing flood risks.

427 **6.1. Geographical gaps in research**

428 One of the most prominent gaps identified is the uneven geographical distribution of research
429 efforts. As illustrated in Figure 2c, the majority of studies are concentrated in developed regions
430 such as North America, Europe, and parts of Asia, particularly China. In contrast, there is a
431 significant lack of research focusing on developing countries in Africa, Central Asia, and parts
432 of Southeast Asia, despite these regions experiencing frequent and severe flooding events. This
433 disparity suggests that vulnerable regions with potentially the most to gain from improved flood
434 impact assessments on transportation are underrepresented in the literature. The lack of
435 research in these areas may be due to limited resources, insufficient data availability, or lesser
436 emphasis on infrastructure compared to immediate humanitarian concerns. Future research
437 should prioritize these regions to develop context-specific solutions that address local
438 challenges, enhance emergency response capabilities, and improve overall transportation
439 resilience.

440 **6.2. Methodological gaps and underutilisation of advanced AI techniques**

441 The scientometric analysis (Figure 4a) reveals a heavy reliance on spatial analysis methods,
442 particularly GIS, which accounts for nearly 58% of the methodologies applied. In contrast,
443 advanced artificial intelligence (AI) techniques, such as deep learning (DL) and recurrent
444 neural networks (RNN), are underrepresented, constituting only about 18% of AI modelling
445 research. While spatial analysis provides valuable insights into the structural aspects of
446 transportation networks, it may not capture the dynamic and complex nature of flood impacts.
447 Advanced AI techniques have the potential to model non-linear relationships, process large
448 datasets, and improve predictive capabilities. The underutilization of these methods represents

449 a significant gap. Integrating AI and machine learning approaches can enhance the accuracy of
450 flood impact predictions, optimise emergency response strategies, and contribute to the
451 development of intelligent transportation systems capable of adapting to flood events in real-
452 time.

453 **6.3. Data gaps and limitations**

454 Quantitative examination of data sources reveals a data source imbalances. Satellite based
455 remote sensing is applied to the majority of studies, as it is used in 104 papers (67 %), while
456 LiDAR and IoT sensors feature in 29 papers (19 %). From the data source point of view,
457 governmental and private databases each appear in 44 papers (28 %), and council or municipal
458 datasets in 38 papers (25 %). In contrast, self-conducted interviews and field surveys are used
459 in only 22 papers (14 %) and 11 papers (7 %), respectively. When considering data types, most
460 analyses rely on infrastructure characteristics (present in 115 papers, 75 %), whereas dynamic
461 traffic flow appears in only 25 papers (16 %), travel behaviour data in 23 papers (15 %), and
462 mobile phone/GPS data in 12 papers (8 %). This heavy dependence on remote sensing and
463 official databases limits the granularity and adaptability of flood analyses; particularly in
464 developing regions where such datasets are sparse. Diversifying data sources to include
465 crowdsourced information, IoT sensors and qualitative inputs from local stakeholders can fill
466 these gaps and provide real-time insights crucial for comprehensive flood impact assessments.

467 **6.4. Limited focus on diverse flood types**

468 Pluvial flooding dominates the literature, appearing in 66 papers (43 %). In comparison, coastal
469 flooding is examined in 36 papers (23 %), fluvial flooding in 27 papers (17 %), and flash or
470 storm-induced flooding in 23 papers (15 %). Only two studies address snow melt related
471 flooding, and just one study considers sea level rise driven flooding. Each of these flood types
472 presents unique mechanisms and impacts on transportation infrastructure; however, the

473 disproportionate focus on pluvial events leaves other hazards underexplored. For instance,
474 coastal flooding influenced by sea-level rise poses significant risks to coastal transportation
475 networks. Similarly, snowmelt flooding can have severe implications in colder regions.
476 Broadening the scope of research to include diverse flood types will lead to more
477 comprehensive risk assessments and the development of targeted mitigation strategies for
478 different environmental contexts.

479 **6.5. Narrow scope of impact assessments**

480 Current research tends to focus predominantly on direct impacts, particularly accessibility and
481 immediate disruptions (Figure 4c), with less emphasis on indirect and long-term effects such
482 as economic losses, social inequalities, and environmental consequences.

483 In this review, 112 studies (72 %) examine direct accessibility impacts, 70 studies (45 %)
484 analyse network disruptions, and 56 studies (36 %) assess physical infrastructure damage. By
485 comparison, only 75 studies (48 %) address indirect or sequential impacts, and within this
486 category the coverage is uneven: only 22 papers (14 %) quantify economic losses and
487 productivity reductions, 34 papers (22 %) explore impacts on vulnerable populations, and 19
488 papers (12 %) investigate long-term resilience and adaptation. Other sub-themes such as public
489 transit disruptions (7 papers, 5 %), road safety (9 papers, 6 %), traffic flow (63 papers, 41 %),
490 road accessibility (55 papers, 36 %) and infrastructure accessibility (30 papers, 19 %) receive
491 sporadic attention. This preoccupation with immediate disruptions and physical damage
492 neglects broader socio-economic consequences, including supply chain interruptions, lost
493 productivity, social inequities and long-term infrastructure degradation that can exceed direct
494 damages. Future studies should incorporate multi-dimensional impact assessments to inform
495 policies and investments that enhance long-term resilience and socio-economic stability.

496 **6.6. Insufficient integration of climate change projections**

497 The keyword analysis (Figure 3c) indicates that "climate change" is not strongly integrated into
498 the analysis of flood impacts on transportation infrastructure. Within the reviewed papers, only
499 one study explicitly considers sea-level rise and just two studies address snow melt-driven
500 flooding, meaning that fewer than 2 % of the reviewed works incorporate climate change
501 induced flood mechanisms or future projections. This gap is critical given the increasing
502 frequency and intensity of extreme weather events due to climate change. Incorporating climate
503 change projections into flood impact models is essential for anticipating future risks and
504 developing adaptive strategies. Neglecting this aspect may lead to underestimating the severity
505 and frequency of future flood events, resulting in inadequate preparedness and resilience
506 planning. Researchers should integrate climate models with transportation infrastructure
507 assessments to provide forward-looking insights that inform long-term planning and
508 policymaking.

509 **6.7. Lack of interdisciplinary approaches**

510 The current literature shows limited integration of social, economic, and environmental
511 perspectives, often focusing on technical aspects of transportation and flood modelling.
512 Demographic and socio-economic datasets are incorporated in only 37 studies (24 %),
513 building-level data in 8 studies (5 %), and qualitative inputs such as self-conducted interviews
514 and field surveys in 22 studies (14 %) and 11 studies (7 %), respectively. In contrast, technical
515 datasets (e.g. infrastructure attributes and remote sensing outputs) dominate the literature.

516 Transportation infrastructure operates within a complex socio-economic and environmental
517 system. An interdisciplinary approach that includes urban planning, sociology, economics,
518 environmental science, and public health can provide a more comprehensive understanding of
519 flood impacts. Engaging with stakeholders, including community members, policymakers, and

520 industry professionals, can enhance the relevance and applicability of research findings,
521 leading to more effective and inclusive resilience strategies.

522 **6.8. Underexploited potential of real-time data and early warning systems**

523 Advancements in technology offer opportunities for real-time monitoring and early warning
524 systems using IoT devices, mobile data, and social media analytics. However, the application
525 of these technologies in flood impact assessments on transportation is limited. Across the 154
526 papers reviewed, only 12 studies (8 %) incorporate mobile phone or GPS data, and 29 studies
527 (19 %) employ IoT sensors for real-time monitoring. Real-time data can significantly improve
528 the responsiveness and effectiveness of emergency management during flood events.
529 Leveraging technologies such as IoT sensors, mobile applications, and social media platforms
530 can provide immediate insights into evolving situations, enabling dynamic rerouting, timely
531 evacuations, and efficient resource allocation. Future research should explore the integration
532 of real-time data analytics into transportation models to enhance adaptive capacity and
533 resilience.

534 **6.9. Need for standardisation in methodologies and metrics**

535 The review identifies a lack of standardized methodologies and metrics for assessing flood
536 impacts on transportation infrastructure, leading to challenges in comparing results across
537 studies and regions. Establishing standardized assessment frameworks and performance
538 metrics is crucial for consistency, comparability, and scalability of research findings.
539 Standardization can facilitate the sharing of best practices, enable benchmarking, and support
540 collaborative efforts across different regions and disciplines. Developing universally accepted
541 guidelines and protocols will enhance the quality and impact of future research.

542 **5. Conclusion**

543 Flooding presents escalating challenges to transportation infrastructure, undermining urban
544 resilience, mobility, and accessibility. This review identifies critical gaps in current research
545 and offers strategies to enhance the adaptability and sustainability of transportation systems in
546 the face of increasing flood risks. Key findings reveal notable gaps, including an uneven
547 geographical focus, limited adoption of advanced modelling techniques such as AI,
548 underutilisation of diverse data sources, and insufficient integration of climate change
549 projections. Moreover, the emphasis on direct impact assessments over indirect and long-term
550 consequences highlights the need for a more holistic evaluation of flood impacts.

551 To address these gaps, this review underscores the necessity of expanding research efforts to
552 underrepresented regions, particularly in developing countries where vulnerability to flooding
553 is high, and data availability is often limited. Leveraging advanced technologies such as deep
554 learning and IoT sensors, combined with qualitative insights from local stakeholders, can
555 facilitate comprehensive and real-time assessments of flood impacts. Additionally, broadening
556 the scope to encompass diverse flood types and aligning research with climate change
557 projections are critical steps toward future-proofing urban transportation systems.

558 Interdisciplinary collaboration is paramount to bridging the technical, socio-economic, and
559 environmental dimensions of flood impact research. Engaging urban planners, policymakers,
560 community stakeholders, and industry professionals ensures that resilience strategies are
561 inclusive, context-specific, and actionable. Standardising methodologies and performance
562 metrics across studies is imperative to foster comparability, scalability, and the effective
563 dissemination of best practices.

564 By addressing these gaps and adopting a holistic framework, future research can contribute to
565 the development of transportation networks that are not only resilient to flooding but also
566 aligned with the broader goals of sustainable urban development. This review serves as a

567 valuable foundation for guiding researchers, policymakers, and practitioners in their efforts to
568 enhance transportation resilience and ensure equitable access to mobility amid intensifying
569 climate challenges.

570

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