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Urban Flooding Monitoring and Management in Geospatial Perspective

Data, Techniques, and Platforms

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URBAN SUSTAINABILITY SCIENCE

As one of the most prevalent natural disasters worldwide, floods have been posing severe threats to human life, infrastructure, and ecosystems, and also leading to hindrances to socially sustainable development (Jongman et al., 2015; Francesch-Huidobro et al., 2017; Wagenaar et al., 2020). With the influences of ongoing global climate change, floods caused by extreme precipitation have become more frequent and intensive, which in turn increases flood risks, particularly for densely populated urban areas (Hallegatte et al., 2013; UNDRR, 2015; Alfieri et al., 2017; IPCC, 2021). Recent studies reveal that 23% of the world's population is directly exposed to 1-in-100-year floods, and estimates suggest that the proportion of people affected by floods has increased by 24% globally since the turn of the century (Tellman et al., 2021; Rentschler et al., 2022). Urban regions with dense populations and infrastructure are especially susceptible to flood disasters. In many urban areas worldwide, the concurrent issue of rapid urbanization exacerbating flood risks makes this problem more serious. The reduced water permeability due to increased impervious surfaces and often poorly planned urban drainage systems leads to enhanced vulnerability of urban areas to flooding (Douglas et al., 2008; Sampson et al., 2015).

Floods in urban environments can result in significant physical damage to human lives, properties, and infrastructure, as well as economic losses, social disruption, and health problems (Ashley et al., 2005; Hallegatte et al., 2013; Foudi et al., 2017). The current situation of increasingly frequent and intensive floods reveals an urgent need for effective monitoring and management strategies to mitigate the adverse effects of urban flooding and ensure life and property

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security. Effective urban flood monitoring and management have become critical in disaster response, facilitating a better understanding of the risks and helping people prepare and adapt more effectively.

In the field of flood monitoring and management, advancements in geospatial techniques have revolutionized the approach. Specifically, flood monitoring provides vital information that can assist in disaster response, as real-time data acquisition capabilities enable a timely response to flood events (Schumann et al., 2007). Real-time flood information, offered by remote sensing technologies, can facilitate timely evacuations, emergency response planning, and post-disaster relief actions (Fakhruddin et al., 2015). Similarly, comprehensive flood management plans can enhance urban resilience, reduce the vulnerability of populations, and ensure a more efficient allocation of resources for disaster risk reduction (Di Baldassarre et al., 2014). These geospatial techniques leverage data from various sources to offer a holistic view of urban flood situations, providing invaluable tools for predicting, monitoring, and managing flooding events in urban areas. Furthermore, geospatial technologies enable the development of powerful flood systems and platforms, which have been designed to integrate data from multiple sources to support urban flood monitoring and management.

Nevertheless, flood monitoring and management are still challenging tasks due to their dynamic processes and the variety of complex environments, especially in urban areas. For example, the effectiveness of geospatial techniques in flood monitoring and management is significantly influenced by data quality and availability. Additionally, gaps exist in the technical capabilities of geospatial techniques and their practical applications (Paprotny et al., 2018). These challenges necessitate continued research and development of geospatial techniques in the field, particularly in the incorporation of multi-source and multi-sensor data, as well as the integration of geospatial techniques with emerging technologies such as artificial intelligence and digital twin. The subsequent content of this chapter aims to provide a brief review of recent achievements in urban flood monitoring and management from a geospatial perspective, focusing primarily on three aspects as shown in Figure 3.1, i.e., data, techniques, and platforms. The goal is to identify the current problems and future prospects in the field.

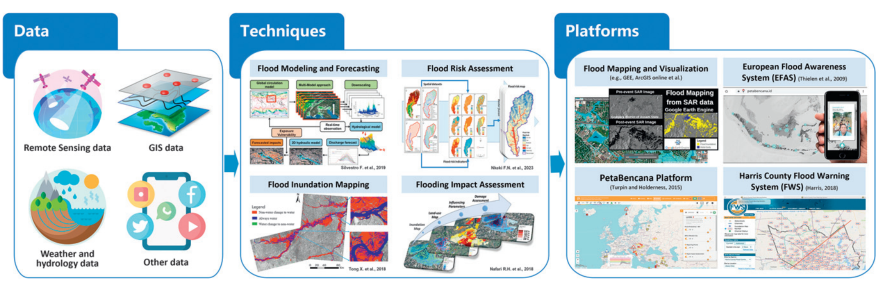

FIGURE 3.1 Framework of flood monitoring and management: data, techniques, and platforms.

GEOSPATIAL DATA FOR URBAN FLOODING MONITORING

Geospatial data sources for flood monitoring can be broadly divided into four categories, namely, remote sensing data, Geographic Information Systems (GIS) data, weather and hydrological data, and other data. Each data source plays an important role in urban flooding monitoring and management. 1) Remote sensing data acquired through satellite and aerial platforms, such as MODIS, Landsat, Sentinel-1/2, and unmanned aerial vehicles (UAVs), plays a vital role in flood monitoring and is commonly used to acquire essential information such as surface water extent, topography, and land cover and use. They offer images over a wide range of areas, facilitating the detection of flooded regions and tracking their changes over time. 2) GIS data provides necessary spatial and attribute information for flood monitoring, such as population, urban infrastructure, road networks, and digital elevation models (DEMs). Particularly, DEMs are essential for the modeling of flood dynamics and flood risk assessment (Li et al., 2022). 3) Weather and hydrology data, including rainfall, river discharge, groundwater levels, and soil moisture content, provide essential information for understanding the hydrological processes leading to flooding and are vital for forecasting future flood events. Weather and hydrological data are usually available as real-time data feeds or historical archives. 4) The other data, including social media data, can also serve as auxiliary information sources that promote the monitoring of floods (Li et al., 2021; Sadiq et al., 2022). For example, through the analysis of real-time social media data, relevant information about flood events, including time, location, and affected areas, can be obtained, which is important for flood monitoring, impact assessment, and emergency response.

Integrating multi-source geospatial data is necessary for comprehensive flood monitoring and assessment, in which data from different sources is combined to provide more complete and diverse information on the flood situation. Techniques such as image fusion, data assimilation, and machine learning algorithms are frequently used for integrating remote sensing, GIS, weather and hydrology, and other data. The integration of these various data sources and the subsequent analysis have created a new paradigm in flood monitoring, enriching the understanding of flood dynamics and enhancing flood prediction and response capabilities.

GEOSPATIAL TECHNIQUES FOR URBAN FLOODING MANAGEMENT

Geospatial techniques have revolutionized the way we monitor and manage flooding scenarios. In this chapter, we mainly focus on the techniques for urban flooding management in three aspects. Through the utilization of these techniques, urban flooding can be more effectively managed.

Flood Modeling and Forecasting

The use of hydrological models in predicting flood occurrences has gained prominence over the years (Silvestro et al., 2019). These models use geospatial data to estimate how rainfall, evapotranspiration, and land use can impact flood dynamics. As one of the commonly used hydrological models, the physically based model involves the numerical representation of hydrological processes and needs high-resolution geospatial data (Bates et al., 2010). While computationally intensive, the physically based model provides a more accurate prediction of the spatial and temporal distribution of floodwaters. Besides, rainfall-runoff models can also be utilized for predicting urban flooding. They function by simulating the transformation of rainfall into runoff and its conveyance to the outlet of a watershed. The integration of rainfall-runoff models with geospatial data enhances the accuracy of flood forecasting. For example, the model has been integrated into the Soil and Water Assessment Tool (SWAT) (Arnold et al., 1998), which uses geospatial data like land use, soil characteristics, and topography to simulate the hydrological cycle.

Flood Mapping and Risk Assessment

Satellite remote sensing provides timely and up-to-date data for flood mapping over large areas. As the two main types of remote sensing data sources applied in flood mapping, optical and synthetic aperture radar (SAR) images are applied in different aspects for their respective characteristics (Tong et al., 2018). On the one hand, in general, SAR data have been widely used in flood mapping because they are independent of weather conditions and imaging periods. However, flood monitoring with SAR data in urban areas is relatively constrained due to the limitations of the SAR imaging mechanism (Notti et al., 2018; Liang & Liu, 2020; McCormack et al., 2022). On the other hand, optical satellite images can provide rich spectral information for surface information extraction and flood detection; however, they are easily affected by clouds, leading to the missing information of the ground surface in images and reducing the frequency of valid observations (Notti et al., 2018; Goffi et al., 2020; Zeng et al., 2020). Considering the revisit cycles of satellites and the duration of floods with their respective intervals, the frequency of satellite observation is crucial for flood monitoring (Tulbure et al., 2022), which therefore necessitates improvements in flood monitoring frequency by combining optical satellite data and SAR data obtained from multiple sensors.

Besides, flood risk assessments under the framework of Crichton's Risk Triangle, which is defined as a function of three key components: hazard, exposure, and vulnerability (Crichton, 1999), have been studied at global and regional scales (Merz et al., 2004; Haynes et al., 2008; Darabi et al., 2019). The generated flood risk maps can be integrated into spatial decision support systems that guide urban planning. These systems can provide insights into the suitability of areas for infrastructure development, the best locations for flood defenses, and areas that require evacuation plans (Zhang et al., 2019; He et al., 2021). Particularly as one of the indicators of flood risk, flood vulnerability can be mapped by considering factors such as population density, infrastructure, and land use. Vulnerability maps can show areas with higher exposure to flood hazards and populations that may be more impacted by floods. Such vulnerability information can guide response and evacuation efforts and assist in infrastructure development and land-use planning. In this aspect, multi-criteria decision analysis (MCDA) is a common technique used to evaluate flood risk by integrating various flood-related factors (Chowdhury et al., 2009; Pham et al., 2021; Nkeki et al., 2023).

Flooding Impact Assessment, Recovery, and Adaptation

After a flood event, geospatial techniques can be employed to evaluate its impact and monitor the recovery process. A better understanding of the impacts of severe floods is essential for policymaking and site-specific adaptation and response plans, especially in urban areas. Flood damage to infrastructure, such as buildings, can be effectively monitored from remote sensing images (Chen & Yu, 2019; Nex et al., 2019; Adriano et al., 2021). High-resolution satellite images can be used to identify flood-damaged areas, quantify the extent of the flood, and assess the recovery process. For example, a study by Adriano et al. (2021) suggested the building damage mapping method can use the fusion of high-resolution optical imagery and high-to-moderate-resolution SAR data obtained before and after a disaster. Based on a deep convolutional neural network, the damaged buildings can be identified and compared with the pre-disaster situation. The assessment of flood impact can inform future flood risk management and mitigation strategies (Joyce et al., 2009; Nafari, 2018). These techniques could be applied not only for flood disaster damage monitoring but also for analyzing the flood recovery progress by continuously monitoring with time-series satellite images. In addition, geospatial techniques can also aid in flood response, such as evacuation and rescue. Flood extent maps can be used to identify safe routes for evacuation and to locate stranded individuals. Besides, evacuation routes can be optimized with geospatial techniques, which can also be used to help distribute resources effectively during the rescue process. Furthermore, geospatial techniques can support adaptation strategies for urban flooding, which can be applied to long-term planning, such as the development of flood defense infrastructure (e.g., levees, dams, and flood walls), land use planning, and the design of efficient drainage systems.

GEOSPATIAL PLATFORMS FOR URBAN FLOODING MANAGEMENT

Geospatial platforms play an increasingly crucial role in urban flood monitoring and management by providing a sophisticated interface for data collection, analysis, visualization, and dissemination. In this chapter, these platforms are broadly introduced, including web-based mapping and visualization platforms, decision support platforms for flood risk assessment and management, and real-time flood monitoring and warning platforms.

Web-based mapping and visualization platforms are designed to process large amounts of geospatial data, providing visual representations of complex and dynamic flood situations. These platforms allow the tracking of flooding events and serve as a valuable tool for both disaster response teams and the public. They can provide flooding information, including water levels, flood hazard predictions, vulnerable areas, and evacuation routes, improving the overall efficiency of disaster response and adaptation (Sheffield et al., 2018). Google Earth Engine (GEE) is an example of a web-based platform that has been widely used for flood monitoring

(DeVries et al., 2020). It provides access to a comprehensive catalog of satellite imagery and geospatial datasets, allowing users to perform online image processing and spatial data analysis and create dynamic visualizations of flood events (Gorelick et al., 2017). Similar platforms include Esri ArcGIS Online, QGIS Cloud, and Mapbox, each with its own unique features and advantages, also showing their potential for flood monitoring.

In addition, geospatial platforms play an integral role in decision support systems designed for flood risk assessment and management. These systems are designed to provide relevant and timely information to facilitate informed decision-making by integrating geospatial data with hydrological models and risk assessment methodologies (Tingsanchali, 2012). For example, the Hydrologic Engineering Center's River Analysis System (HEC-RAS), developed by the U.S. Army Corps of Engineers, is an integrated system for floodplain management that includes a GIS component for geospatial data handling and analysis (USACE, 2010). The DSS-Flood, developed by the National Institute of Water and Atmospheric Research (NIWA) in New Zealand, combines hydrodynamic modeling, geospatial data, and a user-friendly interface to support decision-making during flood events (Fewtrell et al., 2011).

Real-time flood monitoring platforms are crucial for timely and effective disaster responses. Real-time systems incorporate data from remote sensing, GIS, and hydrometeorological networks to provide up-to-date information on the flood situation. Sensor networks, the Internet of Things (IoT), telemetry systems, and crowd-sourced data platforms also contribute to real-time monitoring. The information gathered can be disseminated to the public and relevant agencies as early warnings to prepare for incoming floods. The European Flood Awareness System (EFAS) is an example of a system that uses real-time data for flood monitoring and early warning (Thielen et al., 2009). Besides, several cities worldwide have successfully leveraged geospatial platforms for urban flood management. In Jakarta, Indonesia, the PetaBencana platform, which means "disaster map" in Indonesian, collects real-time reports from social media and combines them with remote sensing data to create dynamic, crowd-sourced flood maps (Turpin and Holderness, 2015). These maps are accessible to both the public and decision-makers, enhancing the city's resilience to flooding. Another application example is in the city of Houston, Texas, USA, where a real-time flood alert system has been developed using the Harris County Flood Warning System (FWS) (Harris, 2018). The FWS employs geospatial platforms to collect, analyze, and disseminate flood data, thus providing timely flood warnings to residents and enabling proactive measures.

Generally, geospatial platforms are invaluable tools and offer numerous benefits for urban flood management. They facilitate real-time monitoring, foster informed decision-making, and promote public participation. However, their effective implementation requires overcoming challenges such as data accuracy, system complexity, and issues related to privacy and data security. Furthermore, the utility and effectiveness of these platforms often depend on the availability of reliable, high-quality geospatial data and the technical capacity of their users. Thus, addressing these issues would harness the full potential of geospatial platforms for urban flood management.

PROBLEMS AND PROSPECTS

Despite the advancements in geospatial techniques and platforms for urban flooding monitoring and management, challenges in this field remain. Meanwhile, ongoing technological breakthroughs suggest promising prospects for the future. This section presents an overview of these challenges, emerging trends, and future prospects. The goal is to explore the potential for continued progress in this field.

Data Availability and Quality Issues

Data is the foundation of geospatial techniques. However, challenges related to its availability and quality persist. Accessibility to high-resolution, up-to-date data, especially in less-developed regions, remains limited. Similarly, spatial and temporal variations in data quality and the integration of multiple heterogeneous data sources can pose significant challenges (Feng et al., 2016; Zeng et al., 2020). Furthermore, the trade-offs between spatial and temporal resolutions of multi-source satellite images necessitate the incorporation of multi-sensor images and multi-source data fusion for more detailed and timely monitoring of flood situations (DeVries et al., 2020; Huang and Jin, 2020; Tulbure et al., 2022). Another issue pertains to the large volume of data produced by massive remote sensing satellites. Despite the abundance of data, managing, processing, and extracting valuable information in real time remains a challenge due to computational constraints. In this aspect, the ongoing advancement in remote sensing and GIS technologies presents a promising future for urban flood management. Besides, more powerful satellites, such as those part of the Copernicus Program, Sentinel-1/2 provide higher resolution imagery, and rapid data acquisition capabilities, thereby improving the accuracy and timeliness of flood monitoring (Giuliani et al., 2017). Similarly, advances in LiDAR (Light Detection and Ranging) technology are providing unprecedented levels of detail in topographic data, significantly enhancing the precision of flood modeling and risk assessment (Glenn et al., 2016).

Technical Limitations and Gaps

Limitations and gaps exist in geospatial techniques and their practical applications (Paprotny et al., 2018). On the one hand, current modeling techniques for flood prediction and risk assessment are inherently complex, necessitating a high degree of technical expertise. Furthermore, these models often rely on a multitude of assumptions and approximations, resulting in inevitable uncertainties (Beven and Hall, 2014). For example, hydrological models have difficulty accurately representing urban areas due to complex urban morphology and the effects of infrastructural developments on water flow. Also, these models face challenges in integrating dynamic urban landscapes, such as changing land use patterns, population densities, and infrastructure development. This limits their prediction accuracy and their ability to adapt to the evolving nature of urban environments. On the other hand, most critically, most of the previous research results on flooding have not been turned into practical systems and tools for users. The gap exists between flood monitoring technologies and their applications, and the development of intelligent real-time flood monitoring platforms is crucial for governments and individuals to benefit urban flood management, especially in flood-prone areas worldwide.

Geospatial Artificial Intelligence-Enabled Flood Monitoring and Management

The integration of geospatial techniques with artificial intelligence is an emerging trend with considerable potential for flood monitoring. As a subset of artificial intelligence, deep learning algorithms can help manage large volumes of remote sensing data, improve the accuracy of data interpretation, and enhance real-time monitoring capabilities (Zhang et al., 2016; Yuan et al., 2020). Furthermore, machine learning algorithms can help refine hydrological models, reducing their uncertainty and improving their predictive performance. These technologies can also aid in identifying vulnerable areas and populations, thereby informing targeted disaster response and risk reduction strategies. In addition, the combination of physical models (e.g., hydrological models) and machine learning has shown its potential in the fields, which will enhance the advantages of both kinds of methods and thus promote their efficiency in urban flooding monitoring and management.

Specifically, as for flood hazard prediction, studies on the application of machine learning to flood prediction are at an early stage of development (Mosavi et al., 2018), and improving the quantity and quality of data as well as the hybridization or integration of algorithmic models are deemed to be promising directions to enhance the effectiveness of machine learning methods for flood prediction. In terms of flood mapping, studies using machine learning methods have been proposed in the literature, including supervised learning (Moya et al., 2020), semi-supervised learning (Li et al., 2019a), and unsupervised learning (Li et al., 2019b). Due to the limitations of urban flood datasets, these studies are often trained and tested using the data acquired during the same flood events, hampering testing robustness and the generalization of the developed methods with respect to different urban typologies and severities of flood events. Besides, as urban flood risk is a dynamic process that is mainly affected by climate change and urban land use changes, access to real-time meteorological data and high-frequency land use data is essential for the dynamic assessment and monitoring of flood risks (Zhang et al., 2019). However, the difficulty of accessing real-time hydro-meteorological data and the efficiency of flood forecasting limit the wider applications of most previous flood research results. Therefore, there is an inevitable trend to fuse real-time social media data with machine learning methods in flood risk assessment (Wagenaar et al., 2020). Generally, the leverage of geospatial artificial intelligence will foster improvements in the accuracy and efficiency of geospatial techniques applied for flood monitoring and management.

Integration of Geospatial Platforms with Other Urban Management Systems

To create a more robust and comprehensive approach to urban flood management, it is essential to integrate geospatial platforms with other urban management systems, such as urban planning and infrastructure management systems. This integration can help to align flood management efforts with broader urban development goals, improve the use of resources, and foster a more resilient urban environment (Dottori et al., 2018). For example, in the Netherlands, the 3Di Water Management System integrates geospatial platforms with urban water management and spatial planning systems, enabling more holistic and sustainable flood management solutions. Besides, the digital twin has gained popularity recently due to its strong abilities in 3D visualization and scenario simulation. With the combination of GIS and remote sensing techniques, urban areas can be simulated as a digital twin in which terrain, buildings, infrastructure, and mobility information are integrated (White et al., 2021). Based on the integrated platform with this state-of-the-art flow, tools can be created to assess the impacts of floods by building a digital twin for areas with high flood risk and by realizing flood situations.

Generally, while challenges persist in the implementation of geospatial techniques for urban flood management, advances in remote sensing and GIS technologies, and artificial intelligence, coupled with urban management system integration, are reshaping urban flood management and paving the way for more resilient and flood-adaptive urban environments.

CONCLUSIONS

Due to climate change, recurring urban flooding worldwide increases concerns for urban areas, severely threatening the lives, property, and sustainability of urban environments. Sufficient data, advanced techniques, and effective platforms for urban flood monitoring and management are critical for mitigating the impacts of flood disasters. The importance of geospatial data for urban flooding monitoring is explicit. Various data sources, such as remote sensing imagery, GIS data, weather and hydrological data, and other data, contribute to a comprehensive understanding of flooding dynamics. However, it should be noted that not only data collection but also the integration and analysis of multi-source geospatial data provide detailed and real-time monitoring of flood situations. These techniques, which range from multi-source data fusion to spatial analysis methods, are geared toward reducing the impacts of flooding. Moreover, geospatial techniques are core to urban flooding monitoring and management, which further assist in flood modeling and forecasting, mapping of flooding areas, and identification of high-risk populations, thereby aiding in strategic infrastructure planning and flood mitigation efforts. Furthermore, geospatial techniques also provide a route for post-flood impact assessment, aiding recovery operations, and shaping future adaptation strategies. Geospatial platforms are the integration point for geospatial techniques, which range from web-based mapping and visualization tools and decision support systems to real-time monitoring and warning platforms, all of which contribute to dealing with urban flooding. The successful implementation of geospatial platforms in various cities shows the potential and value they add to flood monitoring and management.

However, there are still challenges in urban flooding monitoring and management. Issues related to data availability and quality, and technical limitations in modeling and analysis often impede the application of geospatial techniques in urban flooding monitoring and management. Encouragingly, the field is advancing with novel remote sensing and GIS technologies, and the integration of geospatial techniques with artificial intelligence and other urban management systems. There is an ongoing need for continued research and development in this field to overcome the current limitations and explore new opportunities. The refinement and advancement of geospatial data, techniques, and platforms would further enhance our ability to deal with future urban floods.

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