

Article

Integrating Policy Instruments for Enhanced Urban Resilience: A Machine Learning and IoT-Based Approach to Flood Mitigation

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Abstract: In the context of global urbanization, the interconnected architecture of economic, social, and administrative activities in modern cities cultivates a complex web of interdependencies. This intricacy amplifies the impacts of natural disasters such as urban flooding, presenting unprecedented challenges in risk management and disaster responsiveness. To address these challenges, this study defines the concept of urban flood resilience and outlines its practical applications in flood risk management, proposing an integrated resilience governance framework. The framework systematically enhances urban flood management by combining structural flood mitigation methods with advanced technologies, including the Internet of Things (IoT) and non-structural decision-support tools powered by Machine Learning Algorithms (MLAs). This integrated approach aims to improve early flood warning systems, optimize urban infrastructure planning, and reduce flood-related risks. The case study of the Cypress Creek watershed validates the framework's effectiveness under specific scenarios, achieving reductions of 25% in inundation area, 30% in peak flow, and 20% in total flood volume. These results not only demonstrate the framework's efficacy in mitigating flood impacts but also provide empirical support for developing resilient urban governance models, highlighting the essential role of adaptive policy instruments in urban flood management.

Keywords: urban resilience; flood risk management; policy instruments; Internet of Things; machine learning; genetic algorithm; resilience governance



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1. Introduction

Floods are considered one of the world's greatest catastrophes [1]. In the 20th century, the estimated global average economic loss caused by flooding was about USD 30 billion per year, about one-third of the total economic damage compared to other types of natural disasters. Between 1980 and 2009, floods worldwide are believed to have affected the lives of an estimated 2.8 billion individuals, leading to 4.56 million people being displaced, 540,000 fatalities, and 360,000 injuries [2]. It cannot be denied that floods cause significant loss of life and infrastructure damage. The causes of flooding in uninhabited and urban areas are fundamentally different and cannot be considered in the same way [3]. Thereinto, the major factor that makes flooding a serious issue in the urban area during the late 20th century is the rapid process of urbanization. Urbanization is typically viewed as a key aspect of society's social, political, and economic evolution. However, it also significantly alters the environment, resulting in many challenges such as housing shortages, waste management issues, and sewage problems, including floodings.

To be specific, natural land cover is replaced by urban development areas due to the city expansion, and these development areas are normally considered to have impervious surfaces. Although the engineered drainage system is used to take over from the original natural stream system, such significant changes alter the natural rainfall–runoff process

such as decreasing the concentration time of runoff and increasing its peak discharges, meaning that the designed conveyance capacity of these engineered drainage systems cannot meet the requirement of some specific rainfall event that is higher than the rainfall intensity that was used to design the drainage system. Moreover, due to city expansion, some of the assets face no choice but to expose the flood zone, which increases the risk of damage and other impacts during flooding disasters. Therefore, not only is flooding a factor that impacts cities' assets, but also urbanization leads to excessive vulnerability, known as 'an anthropic vulnerability' [4], which is another significant driving-force that aggravates the complexity of urban risk management.

In such a case, catastrophe risk cannot be completely avoided, so the goal of risk management is not to eliminate risk but to provide appropriate and reasonable control over the level of residual risk. To establish an acceptable flood risk management model, cities must take adaptive measures to design their urban infrastructure settings with full consideration of the changing likelihood of flood damages [5]. The essence of building cities based on risk change is to improve future urban resilience. Given this context, it becomes imperative to adopt a more integrated strategy for urban flood management that combines advanced policy tools with technological innovations. This paper proposes leveraging policy instruments in conjunction with emerging technologies such as the Internet of Things (IoT) and machine learning to optimize flood management strategies and enhance urban resilience. To validate the effectiveness of the proposed strategies, a case study is employed, providing measurable insights into their ability to mitigate flood impacts. By doing so, we aim to explore synergistic effects within various administrative contexts and determine how technological advancements can refine risk predictions and management responses, ultimately supporting robust policy development to mitigate economic impacts and improve civic preparedness.

2. Solutions for Enhancing Urban Resilience in Flood Management

Our approach challenges the conventional reliance on 'rigid' flood management methods, advocating instead for a resilient governance model that adapts to changing urban environments and risk profiles. This research seeks to answer critical questions regarding the optimal integration of policy tools and technology in urban flood management and to delineate the characteristics of effective, forward-thinking flood resilience strategies. Through this exploration, we aim to contribute substantively to the discourse on improving urban flood resilience by demonstrating the indispensable role of integrated policy and technology in contemporary risk management practices.

2.1. Traditional Flood Mitigation Approaches

Conventionally, there are two flood mitigation strategies used to mitigate flood hazards, namely structural and non-structural approaches [6]. The structural approach aims to reduce floods using hard structures like levees, detention and retention ponds, dam or reservoirs, and other control hydraulic structures as part of the peak flow can be detained by these hydraulic structures during a flood event [7], while the non-structural approach uses, for instance, flood forecasting technologies to provide flood risk mapping as well as insurance programs and warnings for the community in advance to minimize economic losses. Therefore, non-structural flood mitigation strategies refer to measures that do not involve physical construction but focus on designing policies, practices, and technologies aimed at minimizing flood risks and impacts without altering the physical environment. These strategies enhance societal resilience and proactive risk management.

However, although a structural approach has been practiced in many engineering cases, it is known that urban flooding issues have not been eliminated from our lives. And applying a non-structural approach, for example, the flood insurance program, simply transfers the financial losses of the insurance-covered individuals to the whole society. The financial damage caused by the floods still exists. Thus, addressing urban flooding requires

a holistic and collaborative approach that enhances understanding and perception of complex risk changes, thereby increasing societal resilience and proactive risk responses [8].

2.2. Understanding Resilience

This paper presents a tentative study to improve the urban area's ability to resist natural risks by incorporating the concept of resilience with the structural and non-structural approaches at the very beginning of urban construction. In the first part, we will define the concept of resilience and its practical implications in flood management. In the second part, from the perspective of urban resilience, we will integrate the concept with a proposed structure approach based on IoT and a non-structural approach that is a decision support tool for flood mitigation based on a machine learning genetic algorithm. The findings of this study will help cities to issue early flood warnings and to provide the rational planning of urban infrastructure to reduce the risks associated with floods.

2.2.1. Conception of Resilience

Globalization has created an interdependent networked world, and rapid urbanization has linked economic, political, and social activities into an interactive framework, and this change and impact has given rise to a new set of uncertain risks [9] for traditional natural hazards [10]. These uncertainties and the inherent complexity of the system [11] have prompted urban risk management to evolve from a focus on risk prevention and control to enhancing urban resilience [12]. UNESCO defines resilience as “the ability of an individual, community, city or country to withstand, absorb or recover from shocks (e.g., extreme floods) and/or to successfully adapt to adversity or changes in conditions (e.g., climate change or economic downturns) in a timely and effective manner” [13]. The definition is shown in Figure 1.

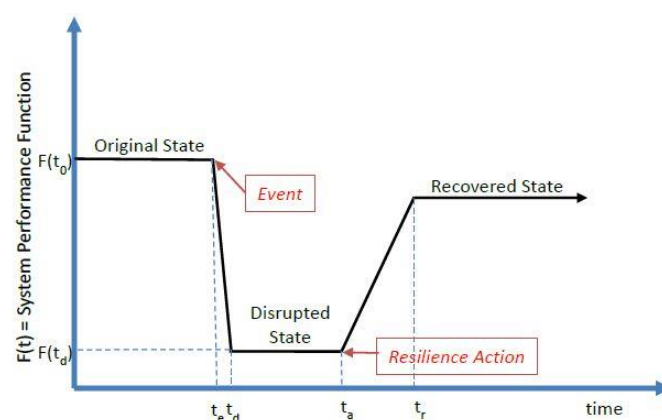


Figure 1. Graphical representation of resilience.

This concept has different interpretations in different disciplinary applications. For instance, engineering considers resilience as how to resist disturbances and recover at a rate of predetermined standards to achieve static equilibrium [14]; ecology considers persistence, change, and unpredictability as influences on dynamic equilibrium. Unlike engineering, which focuses on ‘survival and recovery’, ecology considers resilience as an adaptive system that can absorb certain disturbances and ‘evolve’ to a new state before changing and adapting to its structure [15].

2.2.2. Resilience Implications in Flood Management

Scholars often discuss how to define the concept of flood resilience in the literature on urban water management [16–19]. Given the diversity of cities and the interplay of economic and social factors, along with the complexity of river processes and natural environments, the ecological concept of resilience is particularly applicable to flood risk management [20]. This concept considers that disturbances are not necessarily negative

and, based on the idea of innovation, learning and adaptation to change, can fully engage city managers in creating a new model of risk management [21], forming a model that can evolve, adapt [22,23], recover, absorb change [24,25], and persist in innovation as a system. This requires cities to develop learning capacity [26–28] and predictive capacity [29] in the face of flood hazards to increase the resilience of risk management.

A resilient system of flood risk management implies combining engineering and ecological resilience approaches to achieve a process of continuous learning and feedback, i.e., learning from past flood management experiences to shift risk management from a goal of restoring the original state to improving and creating a new state of urban management. For instance, research conducted by Leon et al. highlights the effectiveness of constructing water storage ponds to detain part of the flood peak, potentially mitigating flood severity [30]. However, their later studies indicate that such structural approaches might have limited operational effectiveness as these ponds could become fully inundated during sequential flood events, lacking the capacity to manage additional water, and they emphasize that the lack of coordinated management of these storage structures can limit their effectiveness in flood mitigation [31]. Furthermore, Tang et al. suggest an integrated approach where all individual storage systems within a watershed are managed in a coordinated manner to effectively mitigate floods, known as the “watershed approach” [32]. This method is gaining traction as it aligns with the broader ecological principles of resilience by treating the watershed as an interconnected system rather than isolated components [33,34].

In fact, when urban modifications to a watershed intensify flow generation and exacerbate flooding, it is crucial to implement measures aimed at controlling floods and restoring hydrological functions to mitigate these adverse effects, rather than merely coping with them. These studies of flood reduction measures from ‘rigid’ to ‘resilient’ imply that urban planning policies should reflect the idea of ‘building the city’ together with water dynamics.

2.3. Public Policy’s Role in Enhancing Urban Flood Resilience

The policy system is pivotal in shaping effective disaster management strategies [35]. It directly influences the provision of public goods and services, setting the foundation for effective flood prevention and mitigation efforts. Extensive research has explored the dynamics between flood disaster management policy tools and their evolution. Glaus et al. explored how flood exposure, risk perception, and policy preferences interact within Swiss municipalities. Their findings revealed that while flood exposure itself was not directly linked to policy preferences, flood risk perception significantly influenced governmental choices in implementing diverse policy combinations, emphasizing the need for heightened public awareness of flood risks [36]. In a similar vein, Nordbeck et al. examined the creation of knowledge and the institutionalization of the science–policy interface amidst climate change, underscoring the significant role of scientific expertise in shaping policies that effectively manage flood risks [37]. Additionally, Haque et al. studied the evolution of policies in Bangladesh from 1947 to 2019, highlighting a shift towards human-centered approaches in flood risk management and emphasizing the critical role of community involvement in policymaking and implementation processes [38]. Consequently, in response to the ever-evolving risk environment caused by globalization and rapid urbanization, city managers need to develop a flexible and forward-thinking policy toolkit that integrates traditional risk management methods with modern technological innovations. This paper defines urban resilience governance as a comprehensive management strategy involving multiple stakeholders, aimed at enhancing a city’s capacity to respond, recover, and adapt to risks. This strategy emphasizes the creation of adaptive and forward-looking policy frameworks that foster sustainable and inclusive urban infrastructure development to address contemporary environmental and societal challenges. Accordingly, the study focuses on exploring how the interaction between policy instruments can improve the city’s flood management capabilities.

3. Methodology

This paper attempts to design a specific combination of policy instruments and employs empirical analysis to practice the theoretical vision described above. This comprehensive resilient framework aims to increase urban resilience and reduce the negative impacts of flooding hazards by optimizing the city's infrastructure and applying the 'watershed approach'. The research conducted by Leon et al. and Yun et al. [7,30] proposed a flow control model that integrates the machine learning genetic algorithm function with a hydrologic and hydraulic modeling system to determine the optimal flow releasing from hypothetical inland wetlands. Additionally, Qin et al. [39] and Verma et al. [40] developed an architecture of remotely operated gates based on Internet of Technology, which can be installed on a sloping pipe to release water automatically from water ponds either ahead of or in the middle of heavy rainfall events or both. In this way, the storage capacity of these water ponds can be further increased.

3.1. Structural Approach: IoT-Based Remotely Automatic Water Gate

The architecture of the remotely automatically operated water gate is presented in Figure 2. The architecture consists of four functional layers, which are the control center, virtual private network (VPN) router, Programmable Logic Controller (PLC), and hardware deployed in the field.

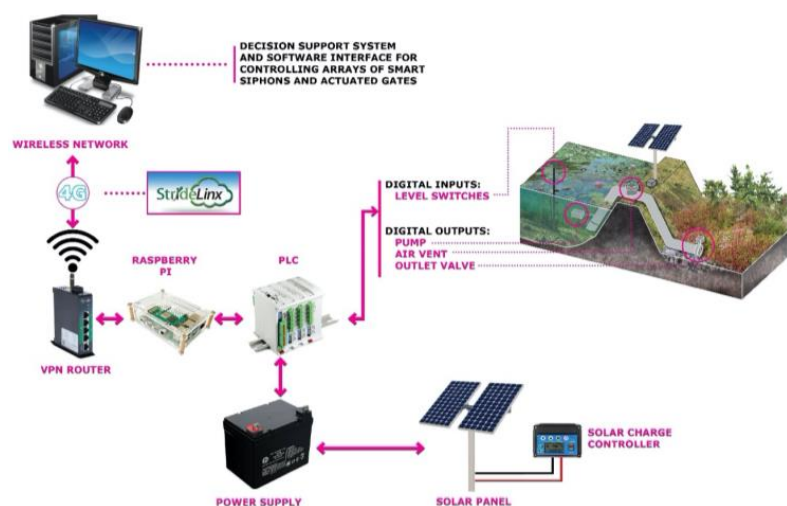


Figure 2. Structural approach for the IoT of the resilience framework.

The control center layer has an optimal flood control decision support system, which is a user-interface-oriented software developed based on C# programming language. The VPN layer is used to achieve IOT communication function, which remotely controls the water gate via a fourth-generation (4G) connection between the control software and the PLCs. The PLC layer establishes a link between the field-deployed hardware and the VPN router. The final layer encompasses all field equipment, such as water level switches and actuated valves. The user sends commands remotely to each PCL for opening/closing the actuated water gates in the field through the user-interface-oriented software. This framework has been well documented in previous studies [39,40].

3.2. Non-Structural Approach: Decision Support System

Figure 3 below presents an optimal flow control model that integrates hydrologic and hydraulic modeling with a machine learning genetic algorithm optimization solver which is developed by Dr. Leon [41]. As the framework shows, HEC-HMS will be used to simulate the runoff for a watershed for several random scenarios as the initial population. The genetic algorithms will pick the best scenario as the parents' generation to populate the children's generation and send the simulated runoff data to HEC-RAS to perform hydraulic

simulation. This process will be iterated until the desired flood control elevation in the river is obtained. Subsequently, the best individual will be used to generate the flood inundation map, which can be used for early flood warning and government decision makers. This framework can perfectly serve as a decision support system for the non-structural approach. The optimization solver is well-documented in the study conducted by Dr. Leon and Dr. Bian [41], and the model is available for public use for research purposes at the following website: https://web.eng.fiu.edu/arleon/Code_Flood_Control_DSS.html (20 November 2024).

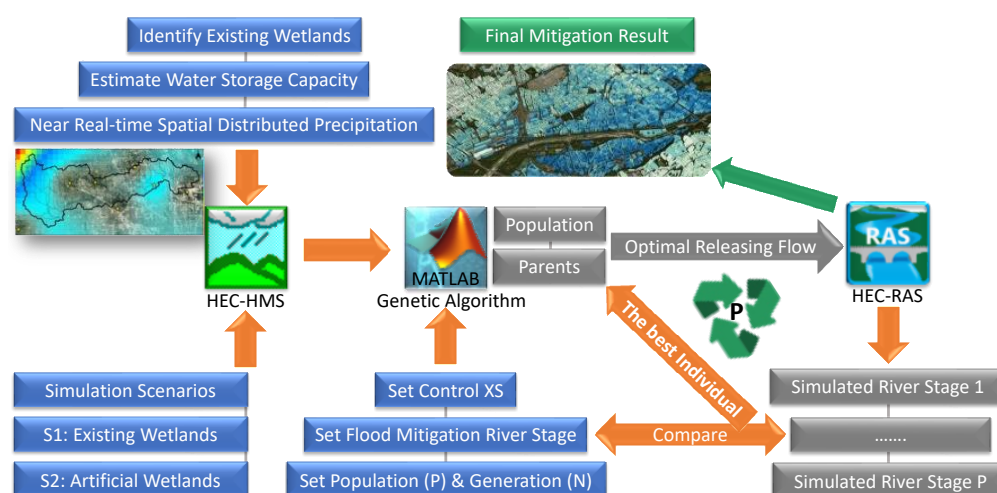


Figure 3. Non-structural approach for the decision support system of the resilience framework.

Their research provides a practical engineering solution to increase the resilience ability of a watershed towards flood hazards. By integrating policy tools with technological innovations such as IoT and machine learning and emphasizing the central role of public policy in establishing effective flood prevention and mitigation measures, a comprehensive governance framework is constructed. This framework will significantly enhance the city's capability for accurate flood monitoring and prediction, enable effective urban infrastructure planning, and thereby foster safer, more resilient urban spaces.

3.3. Proposing a Comprehensive Resilient Framework for Flood Management

Figure 4 below shows the framework used to improve urban resilience. As the figure shows, in general, non-structural and structural approaches were incorporated with the concept of urban resilience, and the simulated results would be useful for early flood warnings and government decision makers, subsequently impacting on the societal response towards the flooding hazards and mitigating the economic loss and speeding up its recovery.

This framework presents an optimal flow control model that integrates hydrologic and hydraulic modeling with a machine learning optimization solver which is developed by Dr. Leon [41]. As the framework shows, in this framework, an ML genetic algorithm interacts with hydrological and hydraulic simulation software (HEC-HMS 4.9 and HEC-RAS 5.0.7) to determine the optimal releasing flow for alleviating the flooding in the regulation area. A remotely controlled water-releasing structure developed based on the IOT is used to release the optimal flow from the storage area ahead of the rainfall event to increase the storage capacity in the whole watershed. In such a way, the watershed will be more resilient for a rainfall event, which forecasts to generate the flood. To demonstrate the effectiveness of this approach, a study area is chosen, and this framework is applied to it.

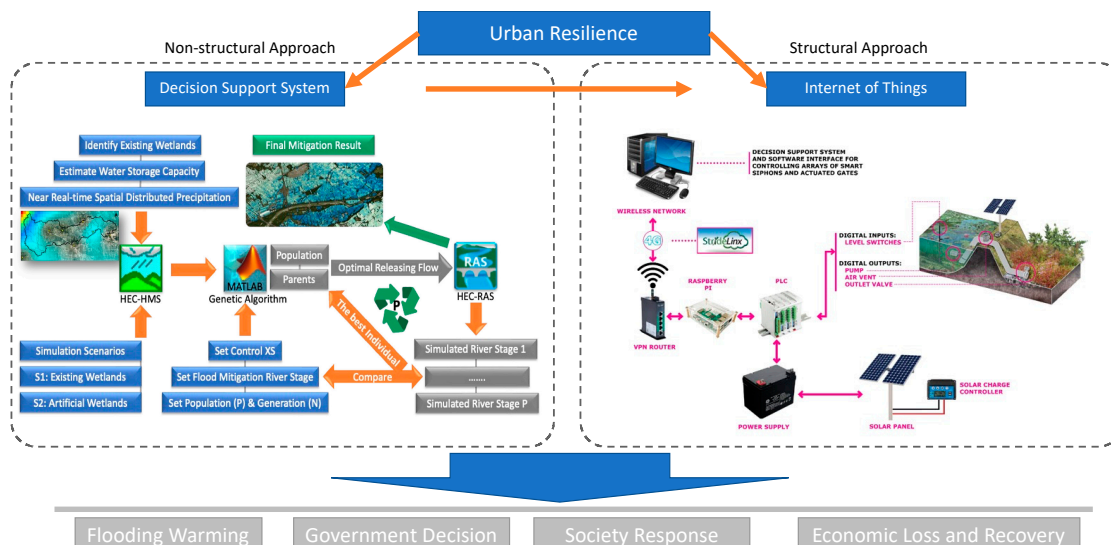


Figure 4. The framework for urban resilience improvement.

4. Case Analysis

Prior to applying the framework in the study area detailed below, some of the construction prototype (see Figure 5) and small-scale applications were successfully implemented in real-time scenarios. As depicted in Figure 5, the water is released from an electric butterfly valve integrated into an IoT-based, remotely controlled water release structure, all operated using Wi-Fi or 3/4G networks. And some of the most notable small applications for the IoT structure won the first place of U.S. Environmental Protection Agency Campus RainWork Competition for the Master Plan Category in 2019 and the second place of US EPA Campus RainWork Competition for the Demonstrate Project Category in 2020. Details on the project narratives and an introduction video are available on the official website: <https://www.epa.gov/green-infrastructure/2019-campus-rainworks-challenge-results#FIU> (20 November 2024) and <https://www.epa.gov/green-infrastructure/2020-campus-rainworks-challenge-results#Second-Place-DP> (20 November 2024). Readers interested in the implementation details can refer to these EPA links and the research presented in the reference paper [42]. After exploring these small-scale applications, the following part provides a more detailed case analysis of the Cypress Creek watershed to validate the effectiveness of the proposed resilience governance framework.



Figure 5. The prototype of the automatic remotely water releasing structure.

4.1. Study Area

Cypress Creek watershed in Houston, TX, U.S., is chosen to be the study area as it experiences severe flooding issues every year. The characteristics of this area—such as urbanization-driven impervious surfaces, recurring flood impacts, and high residential density—make it an ideal study case. As is shown in Figure 6, the watershed is separated into three subbasins, hydrologically. The landcover type of the upstream sub-watershed is

mainly nature and agriculture; a mixing type of agriculture and residence can be observed throughout the middle sub-watershed; and the downstream sub-watershed is predominantly covered by residence areas [43]. The estimated population within the Cypress Watershed is approximately 216,000. Urban expansion has increasingly replaced natural areas with impervious surfaces, making this watershed a major source of substantial urban runoff. Annually, the area experiences about two to three floods. The catastrophic flooding caused by Hurricane Harvey in August 2017 resulted in 82 fatalities and estimated economic damages totaling USD 180 billion. Consequently, with such frequent flooding and high residential density within the Cypress Creek watershed, it is vital to comprehend the flood mitigation effects after practicing the resilience strategy presented in this paper.

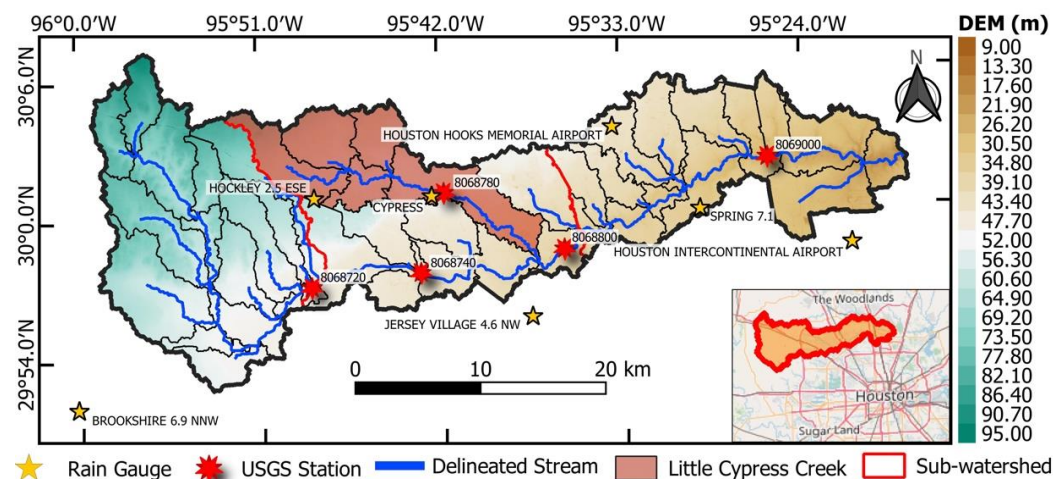


Figure 6. The hydrological information condition in the Cypress Creek Watershed.

4.2. Data Collection and Model Performance

4.2.1. Terrain Data

The terrain data used in this study for flood simulation are Light Detection and Ranging high-resolution digital elevation model (LiDAR-DEM), obtained and downloaded from the Texas Natural Resources Information System (TNRIS) under the Texas Water Development Board as part of the Texas Strategic Mapping Program (Strat Map).

The Nominal Pulse Spacing (NPS) in LiDAR is smaller than 0.5 m (or point density is greater than 4 points per square meter) during data collection in the study area. After a third-party quality assurance check and an internal quality control process, the datasets are assured to minimize errors and meet or exceed the accuracy requirements for this study.

4.2.2. Rainfall Data and River Flow Data

Within or near the study area, there are seven meteorological stations with 99% data coverage of the historically observed rainfall records. Based on data from these meteorological stations, the Cypress Creek watershed has undergone multiple severe rainfall events that have resulted in widespread flood inundation disasters. Figure 7 shows the accumulated precipitation for recent flood events.

Figure 7 illustrates that during the 2017 rainfall event, the observed maximum accumulated precipitation amount exceeded 1000 mm at the Jersey Village 4.6 NW meteorological station, situated near the downstream urban and residential sub-watershed. Similarly, during the 2016 rainfall event, the observed accumulated precipitation amount during the rainfall period is estimated to have exceeded 1200 mm at the Hockley 2.5 ESE meteorological station, located near the upstream sub-watershed. The accumulated rainfall volumes for the 2014 and 2015 events were approximately half of those recorded during the 2016 and the 2017 events. Therefore, the 2014 and 2015 events can be classified as medium storm events, and the 2016 and the 2017 events can be classified as extreme rainfall events in this study. These four rainfall events were chosen for HEC-HMS model calibration and

validation, and subsequently used for flood simulation in HEC-RAS as indicated in the framework in Table 1.

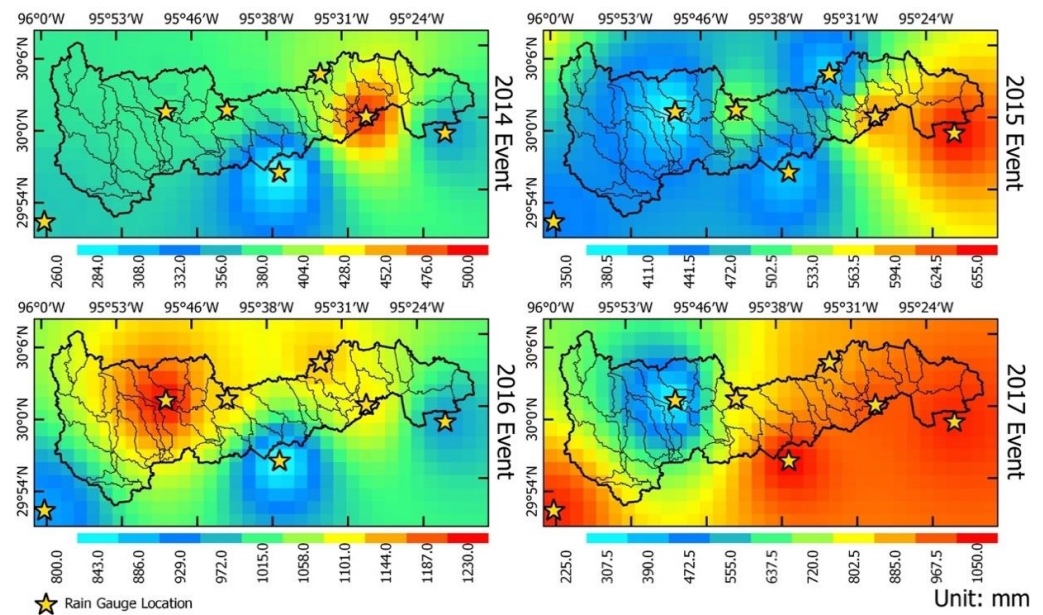


Figure 7. The precipitation distribution of the interpolated observed accumulated rainfall records for the seven meteorological stations in the Cypress Creek watershed.

Table 1. The rainfall events used for the hydrological and hydraulic simulation.

Rainfall Event	Simulation Period		Category	Hydrologic Simulation
Hydrological Simulation				
2014 Event	1 May	30 June	Medium Event	Calibration Event
2015 Event	1 May	30 June		
2016 Event	1 March	30 April	Extreme Event	Validation Event
2017 Event	1 August	30 September		
Hydraulic Simulation				
2014 Event	22 May	31 May	Medium Event	Calibration Event
2015 Event	20 May	31 May		
2016 Event	14 April	27 April	Extreme Event	Validation Event
2017 Event	21 August	31 August		

The Cypress Creek watershed is also equipped with multiple United States Geological Survey (USGS) stream gauges to record long-term historical observed streamflow from 1989 to 2021, with time increments ranging from half an hour to one day. Five stream gauges, as presented in Table 2, were used in this study to evaluate and compare the simulated streamflow.

Table 2. The USGS hydrological stations and their information.

USGS ID	08068720	08068740	08068800	08068780	08069000
Latitude	29°57'00"	29°57'32"	29°58'24"	30°00'57"	30°02'08"
Longitude	95°48'29"	95°43'03"	95°35'54"	95°41'50"	95°25'43"
Location	Upstream	Midstream	Midstream	Midstream	Downstream
Drainage Area	284.8 km ²	339.2 km ²	554.2 km ²	106.2 km ²	738.1 km ²
Stream	Cypress	Cypress	Cypress	Little Cypress	Cypress

4.2.3. HEC-HMS Model Calibration and Model Performance Assessment

The HEC-HMS model was the first calibration by using the selected rainfall event. During this process, slight modifications were made to the hydrological parameter, such as the curve number and routing lag time in the river. After the calibrated simulated streamflow shows a good alignment with the observed river flow, validation rainfall events were used to test the HEC-HMS model performance. Since the accuracy of the hydraulic simulation is largely determined by the hydrological model, after the HEC-HMS model is validated, the simulated streamflow will be used as the boundary condition for the HEC-RAS model.

To validate the model's ability to accurately simulate the rainfall–runoff dynamics within the specified watershed, a set of widely recognized statistical indices were employed for cross-validation between the recorded streamflow and the predicted streamflow generated by varying precipitation data across both calibration and validation phases. The indices selected to evaluate the HEC-HMS model performance for the different precipitation data are Nash–Sutcliffe Efficiency (NSE), the root mean square error ratio (RSR), the percentage bias (PBIAS), and coefficient of determination (R^2). These indices effectively quantify the agreement on peak discharge, peak time, and volume between the observed and the predicted streamflow.

NSE is calculated by Equation (1).

$$NSE = 1 - \frac{\sum_{i=1}^N (P_i - O_i)^2}{\sum_{i=1}^N (O_i - \bar{O})^2} \quad (1)$$

PBIAS is calculated by Equation (2).

$$PBIAS = 100 \cdot \frac{\sum_{i=1}^N (P_i - O_i)^2}{\sum_{i=1}^N O_i} \quad (2)$$

RSR is calculated by Equation (3).

$$RSR = \frac{RSME}{STDEV_{obs}} = \frac{\sqrt{\sum_{i=1}^N (P_i - O_i)^2}}{\sqrt{\sum_{i=1}^N (O_i - \bar{O})^2}} \quad (3)$$

The coefficient of determination is calculated by Equation (4).

$$R^2 = \left[\frac{\sum_{i=1}^n (O_i - \bar{O})(P_i - \bar{P})}{\sqrt{\sum_{i=1}^n (O_i - \bar{O})^2} \sqrt{\sum_{i=1}^n (P_i - \bar{P})^2}} \right]^2 \quad (4)$$

Among the above equations, O_i is observed runoff on day i ; $\bar{O}$ is average observed runoff; P_i is the simulated value on day i ; and N is the total simulated period.

Proposed by the U.S. Army Corps of Engineers, the criteria to evaluate the performance of the hydrologic model for the different precipitation data are shown in Table 3 below.

Table 3. Performance ratings of the evaluation metrics for a daily time step simulation.

Performance Rating	R ²		NSE		RSR		PBIAS	
	Min	Max	Min	Max	Min	Max	Min	Max
Very Good	0.65	1.00	0.65	1.00	0.00	0.60	−15	+15
Good	0.55	0.65	0.55	0.65	0.60	0.70	[−20, −15)	(+15, +20]
Satisfactory	0.40	0.55	0.40	0.55	0.70	0.80	[−30, −20)	(+20, +30]
Unsatisfactory	0.00	0.40	-	0.40	0.80	-	(−∞, −30)	(+30, +∞)

4.3. Results

4.3.1. HEC-HMS Simulated Streamflow Validation

The statistical results of the model performance metrics for the HEC-HMS model, based on rain-gauge-derived interpolated precipitation data from storm events spanning 2014 to 2017, show a close agreement between the model-predicted hydrographs and the observed USGS streamflow data. According to Table 3, the RSR values for the calibration and validation periods ranged from the minimum value of 0.27 to the maximum value of 0.57, while the minimum value of the NSE observed during these events was 0.68, suggesting robust model performance as per the U.S. Army Corps of Engineers' standards. Additionally, the coefficient of determination (R²) varied from 0.78 to 0.94, affirming the model's accuracy in mirroring the actual streamflow patterns. Despite the PBIAS values occasionally suggesting an overestimation of streamflow, they remain within acceptable limits. Figure 8 illustrates the comparison between the simulated stream flowrate and observed one for the validation event of 2017 rainfall event. Additionally, while the simulation results show a good performance from the statistic matrix perspective, the streamflow rate also shows a good alignment along the time perspective. And the summary of the statistic indices for the hydrologic model for the rain-gauge-based interpolated precipitation is shown in Table 4 below.

Table 4. The summary of the statistic indices for the hydrologic model for the rain-gauge-based interpolated precipitation.

USGS Station	RSR	NSE	PBIAS	R ²
2014 Calibration Event				
08068720	0.38	0.86	24.90	0.91
08068740	0.30	0.91	18.72	0.94
08068800	0.27	0.93	23.20	0.94
08068780	0.32	0.90	19.72	0.91
08069000	0.46	0.79	−7.98	0.79
2015 Calibration Event				
08068720	0.47	0.78	−16.16	0.79
08068740	0.40	0.84	−1.96	0.84
08068800	0.38	0.85	5.47	0.86
08068780	0.47	0.78	−16.58	0.79
08069000	0.46	0.79	−3.81	0.79

Table 4. Cont.

USGS Station	RSR	NSE	PBIAS	R ²
2016 Calibration Event				
08068720	0.52	0.73	8.69	0.78
08068740	0.48	0.77	17.99	0.81
08068800	0.30	0.91	19.03	0.82
08068780	0.54	0.71	23.94	0.72
08069000	0.28	0.92	−3.80	0.93
2017 Validation Event				
08068720	0.57	0.68	24.83	0.81
08068740	0.34	0.88	6.03	0.87
08068800	0.27	0.93	12.08	0.92
08068780	0.33	0.89	−2.73	0.91
08069000	0.37	0.86	12.06	0.89

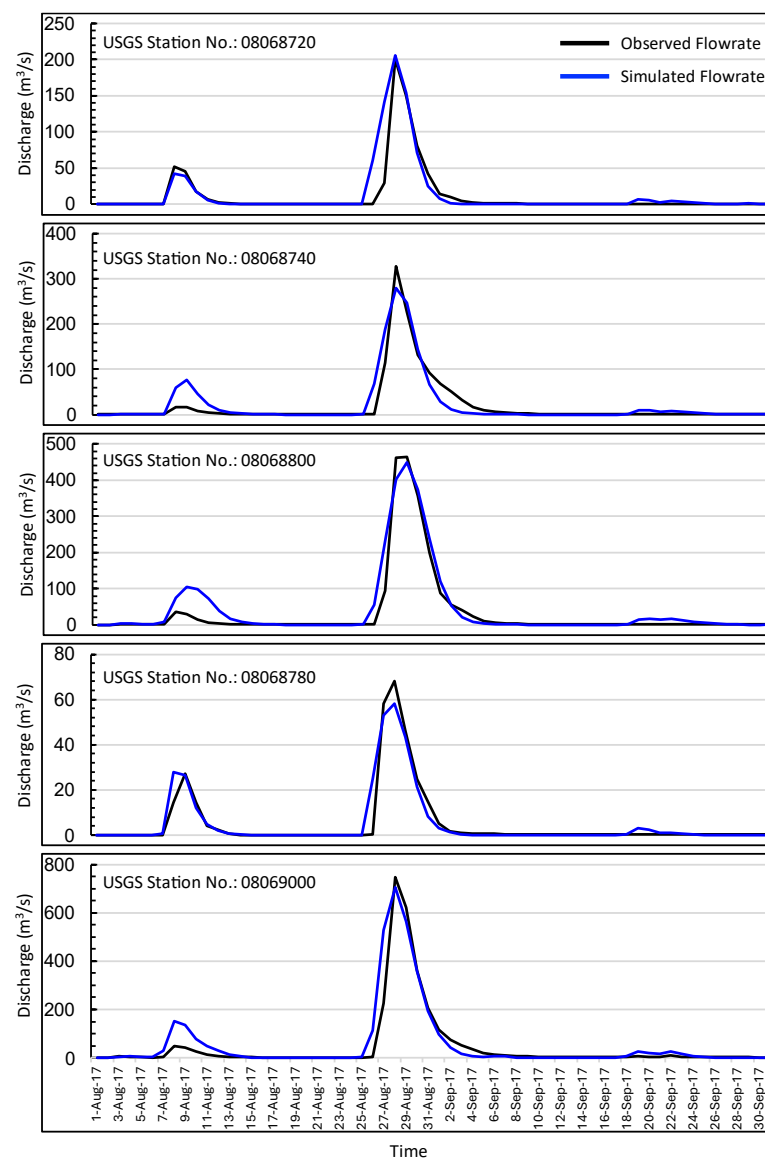


Figure 8. The comparison of the hydrographs between the simulated and the observed streamflow.

4.3.2. HEC-RAS Simulated Flood Inundation

Figure 9 below shows the flooding inundation area for the 2014 and 2015 events with 5%, 10%, and 15% of the wetland area that implements the resilience strategy proposed in this study. The diagram demonstrates that only 5% of the wetland implementation area in the recommended sub-basins can markedly reduce both the peak river stage and the flood inundation areas for the downstream sub-watershed during the 2014 and 2015 events.

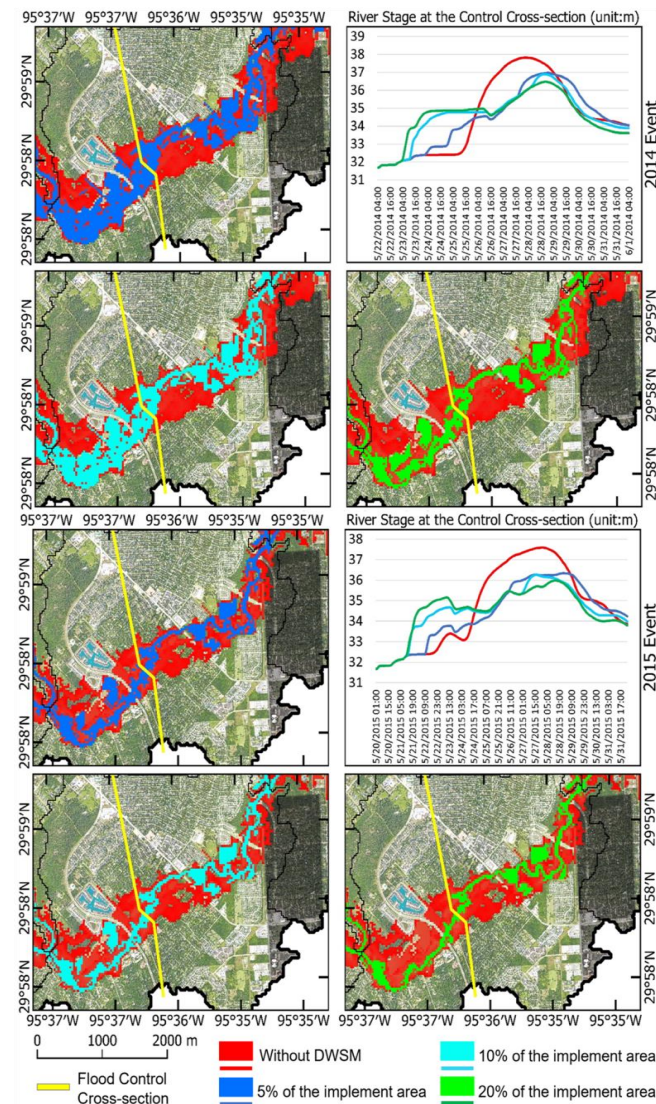


Figure 9. Flood mitigation effect for medium rainfall events.

Releasing water from wetlands prior to rainfall events enhances the available storage for managing peak runoff, which leads to a reduction in the peak river stage during flood occurrences. Consequently, the flood inundation areas are significantly decreased. For instance, in the absence of dynamic water storage management, the peak river stage reached 37.82 m at 3:00 on 28 May 2014 and 37.59 m at 01:00 on 28 May 2015. However, with the application of dynamic water storage management in just 5% of the wetland areas within the recommended sub-basins, the peak river stages were reduced to 36.96 m at 00:00 on 29 May 2014 and 36.33 m at 01:00 on 29 May 2015, showing reductions of 0.86 m and 1.26 m, respectively. Additionally, this management strategy postponed the peak river stage by about one day, providing a critical buffer period for flood mitigation. In terms of flood inundation, the areas affected in the 2014 and 2015 events without dynamic management were approximately 9.82 square kilometers and 7.35 square kilometers, respectively. By

implementing dynamic water storage management across only 5% of the wetland areas, the flood inundation was substantially reduced by 43.25% for the 2014 event and 53.37% for the 2015 event. These results demonstrate that dynamic water storage management significantly impacts medium-scale flood events by reducing flood inundation areas, lowering peak river stages, and delaying peak times. The efficacy of this strategy is likely to increase further with the expansion of the wetland areas used for this purpose.

Nevertheless, this resilience strategy proves less effective during extreme rainfall events. As Figure 10 illustrates, the impact of dynamic water storage management on flood mitigation during severe extreme rainfall events, such as those in 2016 and 2017, is minimal. As depicted in Figure 7, the areas of flood inundation remain virtually unchanged, regardless of whether dynamic water storage management is applied. Except for 20% of the wetland implementation areas, in scenarios where only 5% and 10% of the wetland areas are utilized, the reductions in flood inundation are insignificant. Specifically, in the downstream sub-watershed with 5% of the wetland areas applying dynamic water storage management, the reduction in flood inundation is merely 4.58% for the 2016 event, and an almost negligible 2.39% for the 2017 event. It is only when the implementation of wetland areas is increased to 20% in the recommended sub-basins that the effectiveness of dynamic water storage management becomes considerable, with reductions in flood inundation reaching 14.13% and 10.57% for the 2016 and 2017 events, respectively.

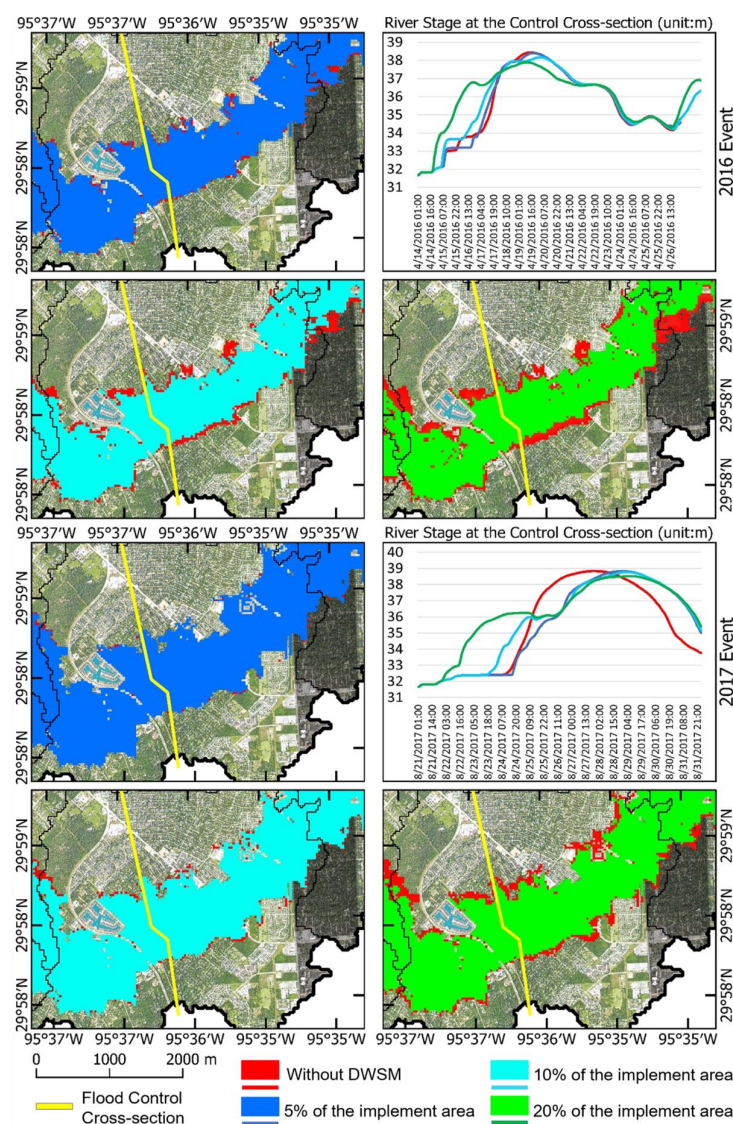


Figure 10. Flood mitigation for extreme rainfall events.

However, it is worth noting that although the implementation of the resilience strategy has minor effects on the flood mitigation for extreme rainfall events, this strategy shows considerable effectiveness in delaying the river stage peak time. In particular, taking the example of the 2017 event, the peak river stage is around 38.80 m for the simulated scenarios of 5%, 10%, and 20% of the wetland implementation areas with dynamic water storage management and the existing wetlands without the dynamic water storage management, while the river stage peak time is delayed from 23:00 27th to 10:00 29th August 2017, which is approximately 2.5 days. The postponement of flood peaks in cases of extreme rainfall events provides a crucial time window for property relocation, resident evacuation, and the initiation of early flood warnings and disaster management.

5. Discussion and Implications

5.1. Discussion

Indeed, currently there are no technologies that can prevent floods caused by extreme rainfall events, but based on the study of this paper, the damage can be alleviated to an extensive level by applying IoT-based dynamic flood mitigation strategies. The case study findings provide empirical validation for the resilience governance framework. In such conditions, evacuating as many lives as possible also protects the properties that may be damaged by floods [43]. Therefore, this study introduces the integration of Internet of Things (IoT) and machine learning technologies, demonstrating how these advancements can enhance the efficiency of policy instruments, especially in data collection, risk prediction, and infrastructure monitoring. The application of these technologies not only refines the precision of policy instruments but also shifts policymaking towards a data-driven approach, enabling real-time responses to urban flood management challenges.

Furthermore, flood management is just one aspect of urban crisis management, and as society evolves, the demand for Smart Government Services (SGSs) becomes increasingly diverse. Government departments should regularly survey citizen needs and employ interactive technologies such as Virtual Reality (VR) and Augmented Reality (AR) to increase public participation throughout the policymaking and daily supervision processes [44]. Additionally, the application of information encryption technologies like blockchain ensures the security and diversity of services, thus meeting the needs of citizens in developing societies. Through such an integrated and intelligent design, not only is the utility and foresight of policy tools enhanced, but continuous updates and optimizations of policies are also ensured, effectively improving the city's resilience to disasters like floods. The construction of policy toolkits supported by data and technology is a key strategy for enhancing urban governance resilience and ensuring sustainable urban development.

However, the proposed methodology has several limitations. First, the accuracy of flood simulation heavily relies on the quality of input data, including precipitation, streamflow, and DEM data, which may vary regionally. Inconsistent or missing data from meteorological and hydrological stations can affect the reliability of the model. In addition, remotely sensed data for DEM analysis may be limited by spatial and temporal resolution, which can affect the accuracy of flood inundation predictions. Second, while the integration of IoT and machine learning improves decision-making, the high computational cost of real-time flood simulations, especially during extreme rainfall events, poses scalability challenges for larger or more complex watersheds. Furthermore, although machine learning was employed for optimization and decision support, its potential was not fully realized; incorporating advanced algorithms like neural networks or ensemble methods could enhance prediction accuracy and management outcomes. Finally, implementing the proposed strategies within existing governance frameworks requires addressing institutional and financial barriers. Future research should focus on overcoming these challenges to improve the framework's scalability, efficiency, and applicability. Based on the analysis above, three policy implications are proposed to improve the performance of city resilience governance.

5.2. Implications

5.2.1. Enhancing Smart City Services

To enhance the resilience of urban infrastructure against flood risks, it is essential to not only upgrade physical structures like drainage systems, implement green infrastructure like rain gardens and permeable pavements, and reinforce levees and flood barriers but also to ensure these improvements are supported by well-regulated Smart City Services (SCSs). The disorderly supply of SCS undermines the effectiveness of these infrastructure enhancements and the resilience of the city; governments must enact and enforce a series of laws and policies that define the roles of supervisory departments and establish clear regulatory authority for the SCS supply [45]. This regulatory framework will ensure that the infrastructure development is consistently informed by the latest climate data and flood risk assessments, fostering a resilient urban environment that is both physically robust and efficiently managed.

Additionally, the introduction of economic output indicators and labor productivity analysis has provided new dimensions for evaluating urban flood management [46]. This method of integrating economic indicators not only aids in assessing the return on investment for flood defense infrastructure but also facilitates data-driven policymaking, ensuring the economic efficiency and sustainability of urban flood management strategies. Through this approach, policy instruments and technological innovations, such as the Internet of Things (IoT) and machine learning, can be more effectively integrated and applied to optimize flood management strategies and enhance urban resilience. This not only improves the city's ability to respond to natural disasters but also strengthens the intelligent management of urban infrastructure, making it more adaptable to rapidly changing environmental and social demands.

5.2.2. Promoting Technological Innovation

To innovate integrated policy toolkits for urban flood management, incorporating technological advances is crucial. The integration of Smart City Technologies such as the Internet of Things (IoT), Artificial Intelligence (AI), and machine learning can significantly enhance the efficiency and effectiveness of real-time data collection, flood prediction, and infrastructure monitoring. As the results of the Cypress Creek case study underscore, the practical implications of integrating adaptive policy tools with advanced technologies. For instance, leveraging IoT for real-time flood monitoring facilitates immediate policy responses, while machine learning algorithms enable predictive planning and risk mitigation.

Moreover, the enhancement of Geographical Information Systems (GISs) and remote sensing technologies plays a pivotal role in advancing urban flood management strategies. By improving these technologies, cities can gain a more detailed and accurate understanding of flood risks and urban vulnerabilities. GIS platforms can integrate data from various sources, including satellite imagery and sensors, to create comprehensive risk maps and models. These tools help in identifying critical infrastructural vulnerabilities and planning effective flood mitigation strategies. Remote sensing, on the other hand, offers the capability to monitor changes in land use, track flood events in real-time, and assess the aftermath of flooding, which is essential for both immediate response and long-term recovery planning. Together, these technological advancements form a backbone for an integrated policy toolkit that not only responds to emergencies but also prepares urban environments for future challenges by enhancing resilience and reducing potential damages from flooding events.

5.2.3. Innovating Integrated Policy Tool Kits

Public policy is an essential means for achieving flood disaster management objectives, encompassing specific methods and means designed to solve social issues or achieve governmental objectives. Scholars have systematically categorized these policy tools from various dimensions based on different classification standards. For instance, Rogge categorizes three primary instrument types into economic instruments, regulation, and information [47]. Taylor categorizes regulatory instruments for environmental risks into

direct ‘command and control’ regulation, economic instruments, co-regulation, information-based instruments, civic and self-regulation, and support and capacity building [48]. This article focuses on developing integrated informational policy instruments based on the Internet of Things (IoT) and machine learning to enhance urban resilience. To formulate more effective flood management strategies, policymakers should also consider a broader combination of policy tools and interactions among them and devise a dynamic and comprehensive policy toolkit aimed at strengthening the long-term strategic policies for governance resilience in smart cities. Meanwhile, the impact of smart city development on citizens’ perceived safety is a double-edged sword. Therefore, in formulating policies to enhance urban resilience, it is crucial to consider both the positive and negative effects of these policies and to conduct a thorough analysis of their impacts on different social groups [49].

6. Conclusions

According to Charlotte Heinzle et al. [50], resilience encompasses the ability to resist, recover from, and adapt to adverse conditions. There is a growing consensus that enhancing Urban Flood Risk Management Strategies—encompassing proactive spatial planning for flood prevention, establishing flood defenses, mitigating flood risks, and strategies for both flood preparedness and recovery—significantly bolsters the resilience of urban conglomerates against flood-related challenges [20]. This study provides empirical evidence for these concepts through a case study of the Cypress Creek watershed. The quantified results validate the effectiveness of the integrated management strategy in mitigating flood risks and enhancing urban resilience, offering a general reference framework for designing integrated policy instruments to strengthen urban resilience.

This framework highlights that the integration of adaptive policy instruments and advanced technologies is central to achieving sustainable urban governance. By strategically combining structural measures (e.g., flood barriers and retention basins) with non-structural approaches (e.g., real-time decision-support systems and predictive flood modeling), cities can develop innovative integrated policy toolkits that not only mitigate the immediate impacts of floods but also build long-term resilience. This comprehensive approach ensures that flood risk management is dynamic, data-driven, and inclusive, addressing both the symptoms and root causes of flood-related challenges.

However, this study has certain limitations. First, empirical research may be constrained by the availability and quality of data. This is particularly pertinent in the case of remote sensing data, where challenges in data acquisition and spatiotemporal resolution may be insufficient to meet the demands of detailed urban resilience governance analysis. Additionally, despite rapid advancements in digital technology, urban governance and flood risk conditions can vary significantly across different regions, which might affect the universality of the research findings, necessitating a communication infrastructure that can unify heterogeneous technologies suitable for developing smart cities. Lastly, future research should aim to validate the framework through multi-region and multi-scenario modeling to enhance its applicability and predictive capacity. This will also enable the development and optimization of policy toolkits to improve the practical effectiveness of urban resilience governance. Thus, the future of urban flood management lies in the seamless integration of policy, technology, and community engagement, ensuring that cities not only survive but adapt and thrive in an ever-changing environmental landscape [51]. This holistic approach will empower cities to face the challenges of urban flooding with innovative solutions that are both effective and sustainable, ultimately leading to safer, more resilient urban spaces.

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