

American Journal of Scholarly Research and Innovation

Volume: *15;* ***Issue:*** *12*
Pages: *01– 40*
eISSN: 3067-2163

Spatiotemporal Graph Neural Networks and Digital Twins for Urban Drainage Networks: Predictive Inundation, Critical-Node Detection, And Infrastructure Prioritization

Sumaiya Sadmeen Misty[1];

[1]. Master in Civil Engineering, Lamar University, USA;
Email: smisty@lamar.edu

Doi: 10.63125/awvjew66
Received: *21 September 2025;* ***Revised:*** *25 October 2025;* ***Accepted:*** *17 November 2025;* ***Published:*** *02 December 2025.*

Abstract

This study addresses the growing challenge of urban drainage networks operating under intense rainfall, spatially connected hydraulic failures, aging infrastructure, sparse monitoring, and limited rehabilitation resources, while conventional approaches often remain fragmented and reactive. The purpose was to develop and quantitatively evaluate an integrated framework combining Spatiotemporal Graph Neural Network Predictive Inundation Intelligence (SPII), Digital-Twin Synchronization and Simulation Capability (DTSC), Critical-Node Detection Capability (CNDC), and Risk-Informed Infrastructure Prioritization (RIIP) to improve Urban Drainage Resilience and Decision-Support Effectiveness (UDRDE). A quantitative, cross-sectional, explanatory case-based design was applied within a bounded urban drainage network using purposive expert sampling, a five-point Likert questionnaire, and graph, hydraulic, and inundation-related computational data. Of 320 questionnaires distributed, 302 were returned and 290 valid responses were retained, yielding a 90.6% valid response rate. Descriptive statistics, reliability and validity testing, Pearson correlation, multiple regression, and STGNN performance assessment were employed. UDRDE recorded the highest mean (M = 4.20, SD = 0.51), followed by DTSC (M = 4.18, SD = 0.53), SPII (M = 4.16, SD = 0.55), CNDC (M = 4.13, SD = 0.57), and RIIP (M = 4.11, SD = 0.59). All predictors correlated positively with UDRDE, including DTSC (r = .75), SPII (r = .72), RIIP (r = .71), and CNDC (r = .69), all p < .001. The regression model explained 71.4% of UDRDE variance (R^2 = .714, adjusted R^2 = .710, F (4,285) = 177.87, p < .001), with DTSC the strongest predictor (β = .31), followed by SPII (β = .28), RIIP (β = .24), and CNDC (β = .21). The STGNN achieved R^2 = .91, RMSE = 0.118 m, MAE = 0.081 m, and F1 = .88. The findings imply that integrating graph-based prediction, synchronized digital twins, node criticality, and risk-informed prioritization can strengthen flood preparedness, targeted maintenance, infrastructure investment, and urban drainage resilience.

KEYWORDS

Spatiotemporal Graph Neural Networks; Digital Twins; Urban Drainage Resilience; Critical-Node Detection; Infrastructure Prioritization;

INTRODUCTION

Urban drainage networks are interconnected hydraulic infrastructures composed of conduits, manholes, junctions, inlets, storage units, pumping facilities, and outfalls that collect, convey, temporarily store, and discharge stormwater or combined wastewater from urban catchments. Urban inundation occurs when rainfall-generated runoff, hydraulic surcharge, restricted conveyance, inadequate inlet capture, or interacting surface and subsurface flows exceed the drainage system's capacity and produce water accumulation above ground. In "Coupled 1D and Noninertia 2D Flood Inundation Model for Simulation of Urban Flooding" (pp. 23-34), urban flooding has been represented through the hydraulic interaction between storm-sewer surcharge and overland inundation, demonstrating that drainage-network behavior and surface flooding cannot be treated as completely separate processes (Seyoum et al., 2012). In "Multi-layered coarse grid modelling in 2D urban flood simulations" (pp. 1-11), computational representation of spatially heterogeneous urban terrain has been shown to be central to reproducing flood depths and propagation while managing the substantial computational burden associated with high-resolution simulations (Chen et al., 2012). Urban drainage systems have also been described as large-scale dynamic systems in which rainfall inputs, runoff generation, network storage, hydraulic routing, control structures, and discharge interact continuously across many spatial locations (García et al., 2015). Their international significance has been evident because pluvial flooding and drainage-system overload affect highly urbanized environments across Europe, Asia, North America, and other regions, while local flood severity has been strongly conditioned by drainage configuration, surface topography, infrastructure condition, and the efficiency with which runoff enters underground networks (Palla et al., 2018; Rony & Md, 2026). Resilience-oriented drainage research has consequently expanded the assessment of system performance beyond simple design-capacity compliance to include the ability of networks to retain hydraulic functionality during disruptive conditions and structural failures (Mugume et al., 2015). In "Enhancing future resilience in urban drainage system: Green versus grey infrastructure" (pp. 280-289), drainage resilience has been quantitatively linked to the capacity of systems to resist and recover from hydraulic disturbance under changing rainfall and urbanization conditions (Dong et al., 2017). These characteristics establish urban drainage as both a hydraulic system and a spatially connected infrastructure network whose inundation behavior emerges from interactions among rainfall, network topology, hydraulic states, surface conditions, and component-level vulnerabilities.

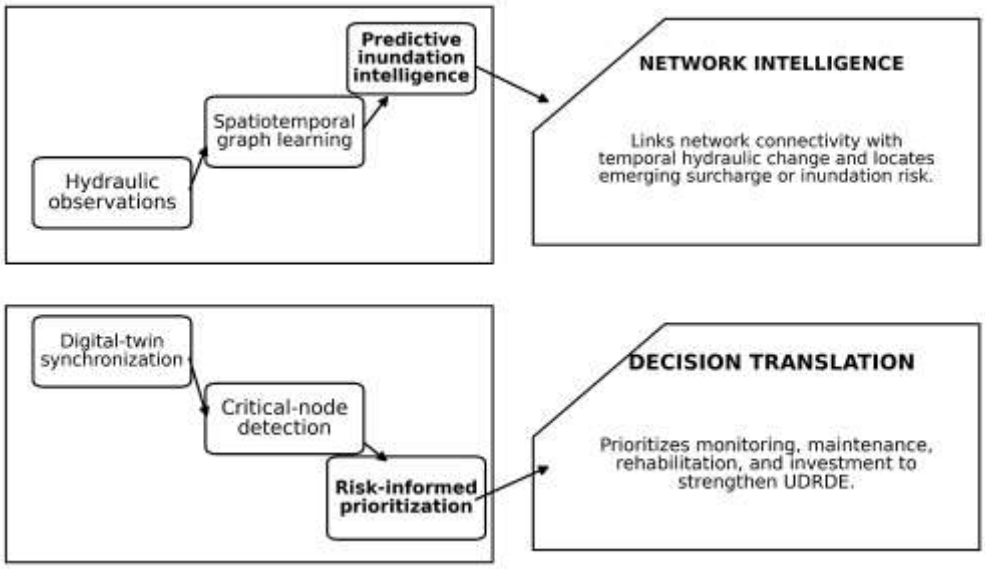
Predictive inundation modeling refers to the quantitative estimation of flood occurrence, depth, extent, hydraulic state, or probability before or during a rainfall-driven drainage response. Conventional physically based approaches provide detailed representations of runoff, sewer routing, surcharge, and surface-flow processes, but their computational requirements become important when repeated simulations, rapid updating, scenario evaluation, or network-wide state prediction are required. In "Development and Comparison of Two Fast Surrogate Models for Urban Pluvial Flood Simulations" (pp. 2801-2815), surrogate formulations reproduced important characteristics of detailed 1D-2D urban flood simulations while substantially reducing computational demand, showing why reduced-order and data-driven representations have become relevant to operational flood prediction (Bermúdez et al., 2018; Mukut Kanti, 2026). A graph-informed hybrid approach subsequently demonstrated that sewer topology could be used to organize spatially distributed lumped models and support probabilistic flood warnings at individual manholes (Li & Willems, 2020). Deep-learning applications have also shown that nonlinear relationships among terrain, hydrological, and urban characteristics can be learned for urban flood susceptibility and prediction tasks, including applications in Seoul, South Korea (Lei et al., 2021). Physics-guided machine-learning surrogates have extended this direction by reproducing detailed drainage-network water levels, flows, and surcharge states at substantially lower computational cost than high-fidelity hydrodynamic simulation (Mst Shamima, 2026; Palmitessa et al., 2022). A spatiotemporal graph neural network, or STGNN, is particularly relevant because it combines graph-based spatial learning with temporal modeling so that observations at one network node can be interpreted in relation to both preceding states and connected nodes. In "Spatio-Temporal Graph Convolutional Networks: A Deep Learning Framework for Traffic Forecasting" (pp. 3634-3640), graph convolutions were combined with temporal convolutions to capture non-Euclidean spatial dependencies and sequential dynamics simultaneously (Yu et al., 2018). Dynamic graph formulations

further showed that relationships among network locations need not remain temporally fixed, while graph-structure-learning models demonstrated that latent spatial dependencies can be learned directly from multivariate time-series information (Diao et al., 2019; Md Mahamud Pervaz, 2026; Zhang et al., 2020). Most directly for urban drainage, a physics-guided GNN surrogate represented manholes and connected conduits as linked computational elements and performed element-level hydraulic prediction while enforcing flow-balance and flooding constraints (Md Kaium, 2026; Zhang et al., 2024). Graph-based representation also provides the analytical basis for identifying critical nodes because an urban drainage network can be formally described as a directed graph in which physical components are represented as vertices and hydraulic connections are represented as edges. A critical node is not merely a location with high observed water depth; it is a component whose topological position, hydraulic loading, connectivity, failure consequence, upstream contribution, downstream dependence, or role in network continuity gives it disproportionate importance to overall system performance. In "Vulnerability of sewer network: Graph theoretic approach" (pp. 370-376), sewer manholes and links were explicitly represented as graph components and evaluated using degree, closeness, betweenness, and related centrality measures to distinguish structurally important network locations (Ganesan et al., 2020; Mashiat, 2026). Complex Network Theory provides a broader theoretical basis for this representation because network-level behavior can be studied through connectivity patterns, centrality, directionality, structural hierarchy, and the distribution of pathways across interacting components. Tailored complex-network metrics have been specifically tested for urban drainage vulnerability, monitoring-system design, and network characterization, showing that purely generic centrality measures can be supplemented with drainage-specific information such as flow direction, slope, and intrinsic component importance (Simone et al., 2022). Structural configuration has also been associated with resilience. Large-scale stochastic experiments using graph-based generation of combined sewer layouts have shown that system configuration, overflow-outfall arrangement, and facility location can materially affect resilience outcomes (Zhang et al., 2021). In "Attribute-based intervention development for increasing resilience of urban drainage systems" (pp. 1757-1764), resilience has been examined through system attributes and performance responses across numerous virtual drainage systems, reinforcing the need to assess system-wide behavior rather than isolated component capacity (Sweetapple et al., 2018). Network interactions have also been relevant outside the sewer boundary because urban flooding can propagate failure effects between drainage or channel systems and transportation infrastructure; probabilistic network analysis in Harris County demonstrated that spatially connected failures can be quantified to support differentiation of infrastructure protection priorities (Dong et al., 2020). More recent global resilience assessment has likewise incorporated structural failure scenarios alongside hydraulic performance to identify differences in network response that are not visible through normal-operation assessment alone (Xu et al., 2024). Critical-node detection within the present research is consequently grounded in topology, hydraulics, and vulnerability rather than being reduced to a single centrality statistic.

A digital twin in the urban-drainage context can be defined as a computational representation of the physical drainage network whose states are repeatedly aligned with observations so that the virtual representation reflects measured or estimated conditions of the corresponding physical system. This concept differs from a static hydraulic model because synchronization, sensing, data assimilation, state estimation, and continuously updated system representation form central parts of the digital-twin architecture. "Pipedream: An interactive digital twin model for natural and urban drainage systems" demonstrated this principle by combining a hydraulic solver with online sensor-data assimilation and Kalman filtering to interpolate and forecast drainage-network states from observations (Bartos & Kerkez, 2021). The same digital-twin logic has been extended to contaminant fate and transport, where real-time measurements were assimilated into a drainage-network model to improve estimation at unmonitored locations and maintain a data-linked virtual representation of network conditions (Kim & Bartos, 2024). Such systems depend heavily on where and how hydraulic observations are collected. Urban drainage monitoring research has shown that efficient sensor placement is a network-level optimization problem because installing instruments at every junction or conduit is rarely practical, while sensor locations differ in the amount and representativeness of hydraulic information they provide (Li, 2021). A subsequent re-clustering framework incorporated hydraulic and water-quality

characteristics and information-theoretic criteria to identify monitoring locations that more comprehensively represent network conditions (Wang et al., 2023). The relationship between observation and intervention has also been evident in intelligent urban-drainage control. Data-driven control studies have used deep reinforcement learning and surrogate representations to manage flooding and overflow conditions across networked drainage infrastructure (Tian et al., 2022). Assessment of uncertain water-level signals has further demonstrated that measurement errors and observation uncertainty influence AI-based drainage control, making the quality and reliability of network state information directly relevant to computational decision support (Zhang et al., 2022). The digital-twin component of an integrated drainage framework can therefore connect rainfall, sensor measurements, hydraulic states, STGNN estimates, network topology, and simulated scenarios within the same quantitative representation rather than treating prediction and physical-system monitoring as unrelated analytical tasks.

Figure 1: Integrated Urban Drainage Intelligence and Decision-Support Overview



Infrastructure prioritization refers to the systematic ordering of drainage assets or intervention locations according to measurable differences in hydraulic risk, vulnerability, network importance, failure consequence, resilience contribution, and decision urgency. This requirement is especially important when drainage authorities cannot upgrade, monitor, or rehabilitate every network element simultaneously and must distinguish locations where intervention addresses the greatest combination of exposure and system significance. Existing drainage-resilience research has established quantitative approaches for evaluating residual system functionality under component failures, including large sets of structural-failure scenarios rather than assessments limited to ordinary hydraulic operation (Mugume et al., 2015). Socio-ecological resilience assessment has further shown that flood-resilience evaluation can integrate technical network performance with spatially differentiated characteristics of the urban area affected by flooding (Haghbin & Mahjouri, 2023). At the same time, graph-theoretic drainage studies demonstrate that topology can identify nodes or links with unusually high structural importance, while data-driven hydraulic models provide time-dependent information about which locations are approaching surcharge or inundation conditions (Ganesan et al., 2020; Zhang et al., 2024). This creates a measurable connection among prediction, node criticality, and prioritization: STGNN-based inundation intelligence can characterize when and where adverse hydraulic states develop; the digital twin can align those estimates with observed and simulated network conditions; critical-node analysis can distinguish components whose location and connectivity amplify system vulnerability; and risk-informed prioritization can order candidate assets according to combined hydraulic and network evidence. Existing studies have generally examined these capabilities through partly separate research streams, including hydraulic inundation simulation, surrogate prediction, graph-based vulnerability analysis, sensor-network optimization, digital-twin state estimation, and resilience

assessment (Bartos & Kerkez, 2021; Simone et al., 2022). The present study has addressed this fragmented analytical structure through a quantitative, cross-sectional, case-study-based examination of STGNN Predictive Inundation Intelligence, Digital-Twin Synchronization and Simulation Capability, Critical-Node Detection Capability, and Risk-Informed Infrastructure Prioritization in relation to Urban Drainage Resilience and Decision-Support Effectiveness. Descriptive statistics, correlation analysis, multiple regression, and five-point Likert-scale measurements have been used alongside the research-specific computational architecture to examine the hypothesized relationships within the selected urban drainage case (Ashik & Shabbir, 2022; Kazi Rakib Hasan & Adnan, 2022).

Urban drainage systems represent one of the most essential components of modern urban infrastructure because they regulate the collection, conveyance, temporary storage, and discharge of stormwater generated across increasingly complex built environments (Mahbubul et al., 2022; Mashfiqur & Md, 2022; Mashiat & Md Anisur Rahman, 2022). Rapid urbanization, expansion of impervious surfaces, aging drainage assets, inadequate hydraulic capacity, localized infrastructure deterioration, and highly variable rainfall conditions have increased the difficulty of maintaining reliable drainage performance in many cities. Conventional urban drainage management has traditionally depended on hydraulic models, periodic field inspection, historical flood records, and predefined maintenance schedules. These approaches provide valuable engineering information, but they often struggle to capture rapidly changing network conditions, complex spatial dependencies among drainage components, and the temporal evolution of surcharge and inundation during intense rainfall events. Recent developments in artificial intelligence, network science, sensing technologies, and digital infrastructure have created opportunities for more integrated forms of urban drainage intelligence. Spatiotemporal Graph Neural Networks are particularly relevant because drainage systems naturally possess a graph structure in which junctions, manholes, inlets, pumps, storage facilities, and outfalls can be represented as interconnected nodes and pipes can be represented as directed edges (Md & Gazi Yeasin, 2022; Md Ashfaq & Abdullah Mohammad, 2022; Mst Kaniz & Jahanara, 2022). By combining spatial network relationships with time-dependent hydraulic observations, STGNN models can support estimation of changing water levels, flows, surcharge conditions, and inundation risks across interconnected drainage components. Digital twins provide an additional layer of analytical capability by maintaining a virtual representation of the physical drainage system and connecting network topology, sensor measurements, hydraulic simulations, and predictive analytics within a unified environment (Sadia & Maishar Mostari, 2022; Shaiful et al., 2022; Stabak & Md Shahid, 2022). When these technologies are integrated, drainage-management authorities can move from isolated observations toward system-level interpretation of where hydraulic stress originates, how it propagates, and which infrastructure components contribute most strongly to system vulnerability (Abdullah Mohammad, 2023; Adnan & Iftekhar, 2023; Syed Feroz & Md Mahamud Pervaz, 2022). Critical-node detection further strengthens this analytical process by identifying locations whose hydraulic behavior, connectivity, or failure could significantly influence network-wide drainage performance. Infrastructure prioritization can then translate these analytical outputs into structured maintenance, rehabilitation, monitoring, and investment decisions. This research is therefore situated at the intersection of urban drainage engineering, graph-based artificial intelligence, digital-twin modeling, network vulnerability assessment, and infrastructure decision support, with particular attention to how these capabilities can be quantitatively evaluated within a case-study-based urban drainage context (Ahmed & Nuzhat Sadia, 2023; Asheke, 2023; Gazi Yeasin, 2023).

Urban drainage networks are increasingly required to operate under conditions characterized by high runoff volumes, spatially concentrated flooding, aging infrastructure, operational uncertainty, and limited resources for monitoring and rehabilitation. A major challenge is that many existing drainage-management approaches remain reactive, fragmented, or dependent on isolated hydraulic assessments that do not fully capture how conditions at one drainage location are connected to conditions elsewhere in the network (Jahanara & Mst Kaniz, 2023; Md Anisur Rahman, 2023; Md Asif Ali Sheak & Tahmedur, 2023). Flooding at a particular manhole, junction, pipe, or subcatchment may be influenced by upstream inflow, downstream restrictions, network topology, temporary storage, pipe capacity, rainfall timing, and the simultaneous behavior of multiple neighboring components (Md Kaium, 2023; Md Mahamud Pervaz, 2023; Mohammad Badrul & Md. Mominul, 2023). Conventional statistical or

hydraulic approaches can provide useful assessments, but they may not consistently deliver rapid network-wide prediction, dynamic state estimation, or integrated prioritization of vulnerable infrastructure. Another problem concerns sparse monitoring. Urban drainage systems often contain hundreds or thousands of components, while only a limited proportion are equipped with sensors, making it difficult to observe system states continuously across the entire network (Molla Al Rakib & Mohammad Towhidul, 2023; Mukut Kanti, 2023; Nishat, 2023). This limitation complicates early inundation detection and reduces the information available for decision-making. Critical-node identification is also frequently treated separately from predictive modeling, which creates difficulty in determining whether hydraulically stressed locations are also structurally or operationally important to wider network performance (Nuzhat Sadia, 2023; Risha & Mst Shurovi, 2023; Stabak & Md Siam, 2023). Digital twins offer a platform for integrating physical and virtual system information, but their effectiveness depends on the quality of predictive models, monitoring data, and decision-support mechanisms embedded within them (Abdullah Mohammad, 2024; Syed Feroz, 2023; Tahmedur & Rifat, 2023). A further problem arises in infrastructure prioritization because drainage authorities must often choose among many competing rehabilitation and monitoring needs without a unified framework that combines predicted inundation, node criticality, asset vulnerability, and system-level consequence (Ahmed, 2024; Asheke, 2024; Ashrafuzzaman, 2024). These gaps create a need for an integrated quantitative framework capable of linking spatiotemporal graph-based prediction, digital-twin synchronization, critical-node detection, and risk-informed infrastructure prioritization. The present study addresses this problem by examining whether these four capabilities collectively contribute to improved urban drainage resilience and decision-support effectiveness within a defined case-study environment (Mashiat, 2024; Md Kaium, 2024; Mukut Kanti, 2024).

The primary purpose of this study is to develop and quantitatively evaluate an integrated analytical framework that combines Spatiotemporal Graph Neural Networks, digital-twin capabilities, critical-node detection, and infrastructure prioritization for urban drainage management. The study is specifically designed to determine how graph-based predictive intelligence can improve the assessment of inundation conditions across interconnected drainage components and how such predictions can be incorporated into a digital representation of the physical drainage network. A central objective is to examine the extent to which STGNN-based predictive inundation intelligence supports the identification of spatially and temporally evolving drainage risks. A second objective is to assess how digital-twin synchronization and simulation capabilities contribute to the representation, monitoring, and evaluation of urban drainage conditions. A third objective is to determine how graph-based critical-node detection can identify drainage components that possess elevated structural, hydraulic, or operational importance within the network. A fourth objective is to evaluate how risk-informed infrastructure prioritization can support more systematic decisions regarding monitoring, maintenance, rehabilitation, and capital investment. The study also seeks to determine the statistical relationships among STGNN Predictive Inundation Intelligence, Digital-Twin Synchronization and Simulation Capability, Critical-Node Detection Capability, Risk-Informed Infrastructure Prioritization, and Urban Drainage Resilience and Decision-Support Effectiveness. Through descriptive statistics, correlation analysis, and multiple regression modeling, the research aims to measure both individual and combined relationships among these constructs. The case-study approach further allows the research to maintain a direct connection with the structural and operational characteristics of a defined urban drainage network. In this way, the study is intended to establish a coherent quantitative basis for linking predictive analytics, network topology, digital representation, infrastructure vulnerability, and decision-support processes within a single urban drainage research framework.

Research Questions

RQ1: How does STGNN-based predictive intelligence influence urban-drainage inundation assessment and Urban Drainage Resilience and Decision-Support Effectiveness?

RQ2: How does digital-twin synchronization and simulation capability influence real-time drainage-network monitoring, scenario assessment, and Urban Drainage Resilience and Decision-Support Effectiveness?

RQ3: How does critical-node detection capability contribute to drainage-network vulnerability assessment and Urban Drainage Resilience and Decision-Support Effectiveness?

RQ4: How does risk-informed infrastructure prioritization influence maintenance, rehabilitation, investment decisions, and Urban Drainage Resilience and Decision-Support Effectiveness?
RQ5: To what extent do SPII, DTSC, CNDC, and RIIP collectively explain Urban Drainage Resilience and Decision-Support Effectiveness?

Research Hypotheses

The research hypotheses have been formulated to test the expected relationships among the four independent constructs and the dependent construct of Urban Drainage Resilience and Decision-Support Effectiveness. The first hypothesis, H1, proposes that STGNN Predictive Inundation Intelligence has a significant positive relationship with Urban Drainage Resilience and Decision-Support Effectiveness. This hypothesis is based on the expectation that more accurate recognition of spatial and temporal drainage conditions can improve the ability to identify emerging hydraulic stress and support more informed operational decisions. The second hypothesis, H2, proposes that Digital-Twin Synchronization and Simulation Capability has a significant positive relationship with Urban Drainage Resilience and Decision-Support Effectiveness because synchronized virtual representations can improve visibility of system conditions, support scenario analysis, and organize multiple sources of drainage information. The third hypothesis, H3, proposes that Critical-Node Detection Capability has a significant positive relationship with Urban Drainage Resilience and Decision-Support Effectiveness. This relationship reflects the importance of distinguishing nodes whose hydraulic or network characteristics make them particularly influential within the drainage system. The fourth hypothesis, H4, proposes that Risk-Informed Infrastructure Prioritization has a significant positive relationship with Urban Drainage Resilience and Decision-Support Effectiveness because systematic prioritization can guide limited maintenance and rehabilitation resources toward locations with comparatively greater risk or operational importance. The fifth hypothesis, H5, proposes that STGNN Predictive Inundation Intelligence, Digital-Twin Synchronization and Simulation Capability, Critical-Node Detection Capability, and Risk-Informed Infrastructure Prioritization jointly have a significant effect on Urban Drainage Resilience and Decision-Support Effectiveness. Together, these hypotheses provide the statistical foundation for the correlation and multiple regression analyses used in the study and create a direct connection between the conceptual framework, research objectives, measurement constructs, and empirical testing procedures.

LITERATURE REVIEW

The literature concerning urban drainage intelligence has developed across several closely related but historically separated fields, including hydraulic flood modeling, urban drainage resilience, machine learning, graph-based network analysis, digital twins, sensor monitoring, infrastructure vulnerability, and asset prioritization. Traditional urban drainage research has primarily emphasized rainfall-runoff processes, sewer conveyance, surcharge behavior, surface inundation, pipe capacity, and hydraulic simulation. These areas remain fundamental because they describe the physical processes through which rainfall is transformed into runoff and subsequently routed through drainage networks. More recent computational research has expanded this foundation by introducing data-driven and graph-based methods capable of representing nonlinear relationships among rainfall, network states, connectivity, and inundation outcomes. Spatiotemporal Graph Neural Networks are especially relevant because urban drainage systems contain both temporal dependencies and explicit spatial connectivity, allowing network behavior to be modeled through interactions among connected nodes and links over time. Parallel developments in digital-twin research have created methods for linking physical infrastructure with virtual models, sensor observations, hydraulic simulations, and predictive analytics. Another important research stream concerns network vulnerability and critical-node detection, where graph-theoretic measures, hydraulic importance, connectivity, failure consequences, and system resilience are used to identify components with disproportionate influence on overall drainage performance. Infrastructure prioritization extends these analyses by translating technical indicators into decisions concerning inspection, rehabilitation, monitoring, and investment. The present literature review therefore examines six interrelated areas: urban drainage networks and infrastructure resilience; STGNN-based predictive inundation intelligence; digital twins for drainage monitoring and simulation; critical-node detection and infrastructure prioritization; Complex Network

Theory as the theoretical foundation; and the conceptual relationships among the principal research constructs. Together, these areas establish the analytical foundation required to examine how predictive intelligence, digital representation, network criticality, and risk-informed prioritization interact within an integrated urban drainage decision-support framework.

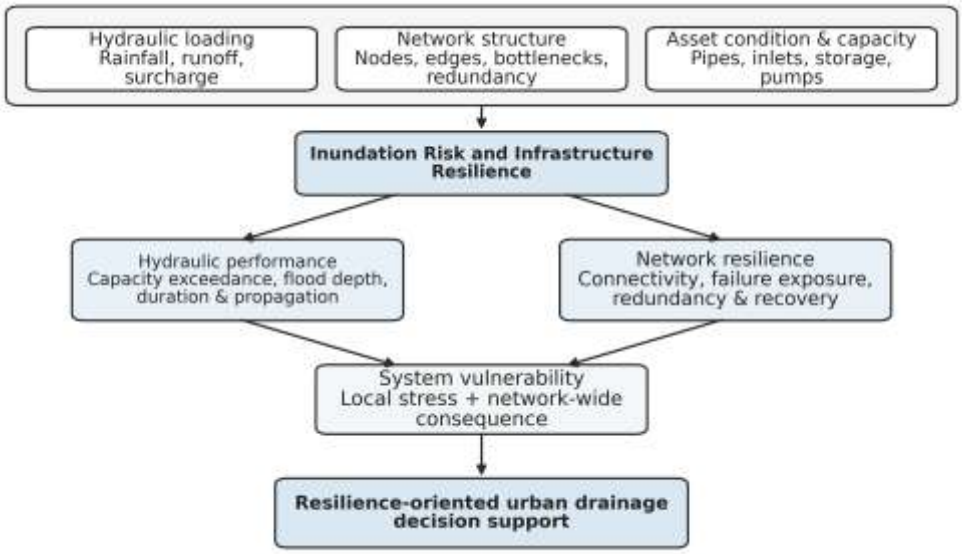
Urban Drainage Networks, Inundation Risk, and Infrastructure Resilience

Urban drainage networks form a fundamental component of urban water infrastructure because they convey runoff from impervious surfaces, control the accumulation of stormwater, protect transport and property systems, and support the hydraulic functioning of densely built environments. Their performance is determined by interactions among rainfall intensity, catchment imperviousness, inlet capacity, pipe geometry, storage availability, receiving-water levels, surface topography, and the condition of individual network elements. In "Adaptation of Urban Drainage Networks to Climate Change: A Review" (Article 145431), analysis of 32 case studies showed that drainage performance has increasingly been evaluated through the combined effects of precipitation change, urban flooding, design standards, adaptation measures, and the economic consequences of system modification, indicating that network adequacy cannot be interpreted through pipe capacity alone (Ashik & Shabbir, 2022; Kourtis & Tsihrintzis, 2021). Urbanization alters this hydraulic balance by replacing permeable land with roofs, roads, pavements, and other sealed surfaces that reduce infiltration, shorten runoff concentration times, and increase the volume and rate of stormwater entering drainage networks. In "Assessing the Impacts of Urbanization and Climate Change on Urban Drainage System" (pp. 181-190), simulation of an urban catchment demonstrated that increased urbanization reduces initial abstraction while changes in extreme rainfall and receiving-water levels intensify pressure on drainage capacity, illustrating how catchment transformation and climatic loading can act simultaneously on inundation generation (Kazi Rakib Hasan & Adnan, 2022; Le et al., 2024). These processes create strong spatial variation in hydraulic stress because not every drainage node receives the same runoff contribution, occupies the same topographic position, or has the same upstream and downstream dependence. Inundation therefore emerges as a networked process in which local surcharge may be generated or amplified by conditions occurring elsewhere in the system. This spatial interdependence is especially important for research that applies graph-based predictive methods, because it requires the drainage system to be represented not only as a collection of hydraulic assets but also as an interconnected structure through which water, capacity constraints, and failure effects propagate.

Urban inundation risk refers to the likelihood and potential severity of surface flooding produced when rainfall-generated runoff exceeds the combined interception, conveyance, storage, infiltration, and discharge capacities available within the urban drainage environment. The magnitude of that risk depends not only on rainfall but also on the physical and operational state of the infrastructure exposed to hydraulic loading. Aging pipes, sediment accumulation, blockage, structural deterioration, insufficient inlet capacity, limited redundancy, and dependence on a small number of important conduits can reduce the ability of a drainage network to maintain acceptable performance during intense events. In "Urban Water Infrastructure: A Critical Review on Climate Change Impacts and Adaptation Strategies" (pp. 1-17), flooding was identified as one of the most consequential climate-related pressures on urban water infrastructure, while the review emphasized that infrastructure constructed under earlier design assumptions can become increasingly vulnerable when climatic stresses and service requirements differ from those anticipated at installation (Ferdowsi et al., 2024; Mahbubul et al., 2022). This vulnerability is not distributed uniformly throughout a drainage network. Some nodes and links have greater structural importance because they connect large upstream areas, form essential conveyance pathways, or occupy positions where failure fragments the network. In "An Applicable Graph Theory Approach for Evaluating Structural Robustness of Urban Drainage Networks" (pp. 2303-2322), structural robustness was investigated through random and targeted component-failure scenarios, and graph-based fragmentation indicators were compared with hydrodynamic flood-volume results across three existing drainage networks, showing that network topology can provide meaningful information about how failures alter system performance (Hajiamoosha et al., 2023; Mashfiqur & Md, 2022). This network perspective is highly relevant to critical-node detection because a location with moderate local flooding may still possess high system importance if its failure disconnects or overloads substantial portions of the drainage structure.

Conversely, severe local inundation does not automatically indicate the highest topological importance. A comprehensive assessment therefore requires hydraulic severity and structural position to be examined together (Syed Feroz, 2024; Uddin & Risha, 2024). This distinction provides a basis for integrating inundation prediction with node-level network analysis and for separating locations that are merely flood-prone from locations whose condition has disproportionate consequences for overall system functionality. Infrastructure resilience extends drainage assessment from the probability of failure toward the ability of the system to maintain, absorb, restore, or reorganize hydraulic service when exposed to disruptive conditions (Jahanara, 2025; Jannatul, 2025; Maishar Mostari, 2025). For urban drainage networks, resilience is reflected in the extent to which flooding can be limited in magnitude, duration, and spatial propagation while essential conveyance functions remain available under hydraulic or structural stress. Resilience consequently depends on both the capacity of individual components and the organization of the network as a whole (Mashfiqur, 2025; Mashiat, 2025; Md Arif Uz et al., 2025).

Figure 2: Urban Drainage Inundation Risk and Infrastructure Resilience Framework

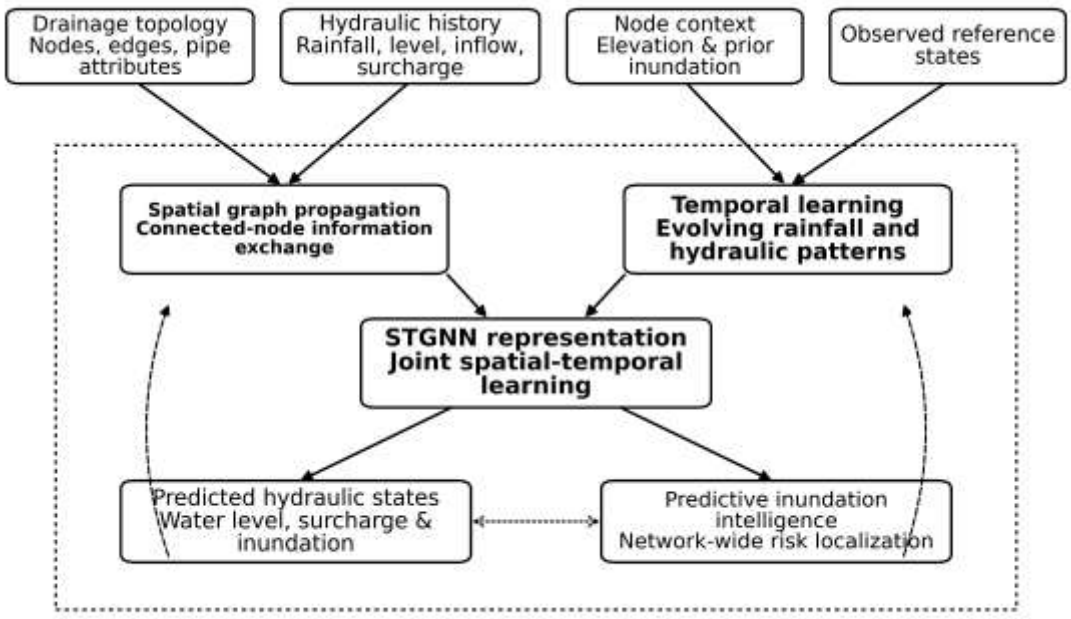


A system may contain adequately sized pipes yet remain vulnerable if its topology concentrates flows through a small set of bottlenecks, offers little redundancy, or connects large drainage areas through highly influential nodes. In "Exploring the Network Structure of Coupled Green-Grey Infrastructure to Enhance Urban Pluvial Flood Resilience" (Article 122344), hydrodynamic modeling, network analysis, and low-impact-development simulation were combined to compare centralized and decentralized drainage configurations, and the results showed that network structure materially changed flood volume, flood duration, and peak flooding behavior under different intervention scenarios (Md Ashfaq & Abdullah Mohammad, 2022; Park, Kim, Yun, et al., 2024). Such evidence reinforces the importance of treating resilience as a system-level property rather than a simple extension of component capacity. Within the present research, this perspective provides the conceptual link among inundation prediction, critical-node detection, and infrastructure prioritization. Spatiotemporal information can indicate where hydraulic stress develops and how it evolves across connected locations; network analysis can determine which nodes or conduits occupy strategically important positions; and infrastructure prioritization can combine these dimensions to differentiate assets according to relative urgency and system consequence. Digital representation of the drainage network further supports this relationship by providing a structured environment in which topology, hydraulic states, observed conditions, and predictive outputs can be associated with the same physical assets. Urban drainage resilience is therefore treated as a measurable property emerging from the interaction of hydraulic performance, network configuration, component vulnerability, and the quality of information available for operational and infrastructure decisions.

Spatiotemporal Graph Neural Networks for Predictive Inundation Intelligence

Spatiotemporal Graph Neural Networks (STGNNs) provide a computational framework for predictive inundation intelligence by combining graph-based representation of spatial relationships with sequence-based learning of changing hydraulic or flood conditions. Their relevance to urban drainage arises from the fact that flood processes are not spatially independent: rainfall, water level, surcharge, surface flow, and downstream restrictions interact across connected locations, while their intensity changes continuously through time (Md Kaium, 2025; Md Mahamud Pervaz, 2025; Palash Chandra, 2025). Conventional recurrent networks can model temporal dependence, but they do not inherently encode the connectivity among drainage nodes or spatial units. Graph neural networks address this limitation by defining locations as nodes and their physical, hydrological, or functional relationships as edges, allowing information to propagate through a structured neighborhood (Syed Feroz, 2025). In "A spatial-temporal graph deep learning model for urban flood nowcasting leveraging heterogeneous community features" (pp. 1-15), an attention-based spatial-temporal graph convolutional network was applied to Hurricane Harvey flooding in Harris County, Texas, using static spatial characteristics, physics-based variables such as rainfall and water elevation, and human-sensed information; the model achieved precision of 0.808 and recall of 0.891 for inundation nowcasting and showed improved performance when heterogeneous temporal information was incorporated (Farahmand et al., 2023; Sadia & Maishar Mostari, 2022). This evidence is important because predictive inundation in an urban drainage context requires more than recognition of high rainfall at a single monitoring point. An STGNN can treat the drainage environment as a relational system in which the state of one node is partly explained by recent conditions at connected or spatially associated nodes. Attention mechanisms can further assign different importance to observations and neighboring locations, enabling the model to distinguish signals that contribute more strongly to the evolving flood state. Such architecture supports a shift from isolated time-series prediction toward network-aware estimation of when, where, and how inundation develops across interconnected urban locations, while preserving the spatial structure required for later node-level risk assessment.

Figure 3: STGNN Predictive Inundation Intelligence Architecture



The predictive value of graph-based learning becomes stronger when temporal information is explicitly combined with the relational structure of hydrological observations. Flood evolution depends on antecedent states, rainfall sequences, upstream contributions, and delayed responses between connected locations, meaning that forecasting accuracy can weaken when spatial and temporal dependencies are modeled separately. In "A New Graph-Based Deep Learning Model to Predict

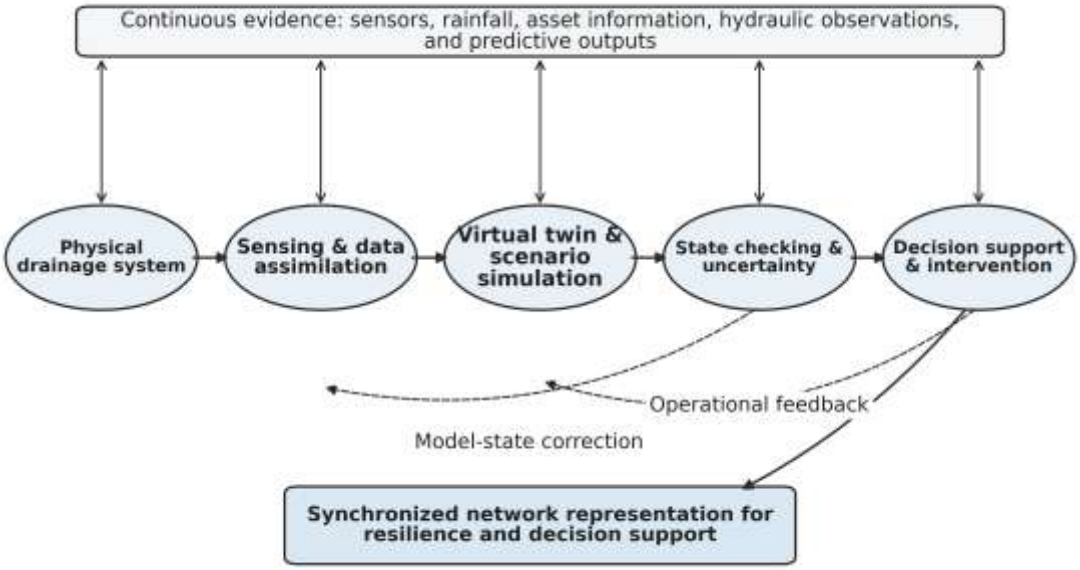
Flooding with Validation on a Case Study on the Humber River" (Article 1827), a GraphSAGE-based model used precipitation and river-stage observations from reference and neighboring stations to estimate flood-related water levels up to 24 hours ahead; performance improved by an average of 18% relative to a persistence baseline and by 9% relative to a residual gated graph convolutional benchmark, while SHAP analysis identified prior stage conditions, seasonality, and precipitation as influential variables (Oliveira Santos et al., 2023; Shaiful et al., 2022). Although river-stage forecasting differs physically from enclosed urban drainage hydraulics, the study demonstrates an important transferable principle: information from connected monitoring locations can be aggregated rather than treated as unrelated time series. In "FloodGNN-GRU: A Spatio-Temporal Graph Neural Network for Flood Prediction" (pp. 1-20), graph neural processing was coupled with gated recurrent units so that spatial connectivity and temporal dynamics could be learned jointly from simulated flood data, producing short-term predictions with much lower computational requirements than conventional numerical inundation simulation (Kazadi et al., 2024; Stabak & Md Shahid, 2022). This combination is particularly relevant to urban drainage because surcharge and inundation are cumulative processes. Recent hydraulic states influence later conditions, while upstream water-level changes may propagate through pipes and junctions before appearing at downstream locations. Graph layers can therefore extract spatial interactions while recurrent or temporal layers encode their evolution, enabling predictive inundation intelligence to represent both network position and hydraulic history within a single learning architecture. This structure supports repeated forecasts across monitored and unmonitored drainage nodes.An additional strength of graph-based flood prediction is its capacity to support multi-location forecasting while retaining the structure needed for node-level interpretation and operational assessment. Urban inundation does not normally emerge as a uniform citywide condition; it develops through localized hydraulic exceedance, spatial propagation, and changing interactions between rainfall and network capacity. A model intended for drainage decision support must therefore distinguish both the timing of adverse states and the locations at which they become operationally important. In "Runoff Prediction Based on Dynamic Spatiotemporal Graph Neural Network" (Article 2463), a dynamic STGNN was designed to represent interactions among hydrological stations while learning temporal runoff patterns, illustrating how a graph can change with hydrological relationships rather than relying exclusively on a fixed spatial structure (Abdullah Mohammad, 2023; Yang et al., 2023). This perspective is relevant to drainage prediction because the effective influence between network locations can vary with rainfall intensity, hydraulic loading, flow direction, and antecedent states even when physical topology remains unchanged. A complementary urban application was reported in Graph spiking neural network for advanced urban flood risk assessment" (Article 111037), which combined a graph convolutional network with a spiking neural network and integrated weather, geographical, and social-media flood information from six Chinese cities; the model achieved 85.3% accuracy, 0.811 precision, 0.832 recall, and an F1 score of 0.821 while outperforming reported GCN and LSTM alternatives (Liang et al., 2024; Md Anisur Rahman, 2023). These developments show that graph-based predictive intelligence can accommodate heterogeneous inputs, temporal evolution, and spatial relationships without reducing urban flooding to independent observations. For the present study, STGNN Predictive Inundation Intelligence is conceptualized as the capacity to transform time-dependent rainfall and hydraulic information, drainage-network connectivity, and node-level characteristics into predictions of emerging inundation states. The construct encompasses spatial dependency learning, temporal pattern recognition, network-wide state estimation, predictive accuracy, and identification of locations experiencing increasing hydraulic stress, linking the STGNN component with digital-twin representation and critical-node assessment.

Digital Twins for Urban Drainage Monitoring, Simulation, and Decision Support

Digital twins have become an important analytical architecture for urban drainage because they connect a continuously updated virtual representation of physical infrastructure with observations, simulation models, and decision processes. In a drainage context, the physical layer may include pipes, manholes, inlets, pumps, detention facilities, outfalls, and connected surface areas, while the virtual layer can contain hydraulic models, geospatial data, sensor streams, rainfall information, asset attributes, and predictive algorithms. The value of the digital twin lies in maintaining an operational relationship between these layers rather than using a model as a static representation that is updated

only during periodic planning studies. In "Development and application of digital twin system for urban flood and waterlogging: Case study of Fuzhou City" (pp. 5-11, 29), an urban flood-control digital twin was structured around real-time perception, simulation modeling, forecasting and early warning, and command-oriented decision processes while dynamically representing precipitation, runoff, pipeline networks, river networks, land surfaces, gates, and pumps (Md Asif Ali Sheak & Tahmedur, 2023; Ye & Xu, 2022). In "Designing a Spatially-Explicit Urban Digital Twin Framework for Smart Water Infrastructure and Flood Management" (pp. 1-9), spatially explicit urban digital twins were linked with GIScience, geosimulation, spatial-visual intelligence, and GeoAI to support management of critical water infrastructure and flood impacts across urban environments (Md Kaium, 2023; Sabri et al., 2023). Together, these studies establish the importance of location, network connectivity, real-time observations, and model interoperability for drainage-oriented digital twins. For the present research, this architecture is particularly relevant because STGNN outputs must be associated with identifiable drainage nodes and links before predicted water levels, surcharge states, or inundation conditions can be interpreted within the physical network. A digital twin therefore provides the integrating environment in which graph-based predictions can be synchronized with drainage topology, monitored states, and scenario-based hydraulic information.

Figure 4: Digital-Twin Synchronization, Simulation, and Decision-Support Cycle



Digital-twin synchronization is central to monitoring and simulation because a useful virtual drainage network must be capable of receiving new observations, updating its representation of system conditions, and supporting analyses that reflect current or recently observed hydraulic states. The sensing layer supplies rainfall, water-level, flow, pump-status, asset-condition, and related measurements, while computational models transform these inputs into estimates of conditions that cannot be directly observed at every location. This is especially important in urban drainage networks because dense sensor coverage is often impractical and many operational decisions must be made with partial information. In "Application of artificial intelligence in digital twin models for stormwater infrastructure systems in smart cities" (Article 102485), artificial intelligence was identified as a major enabling component for digital-twin applications because machine-learning and deep-learning algorithms can process sensor, weather, and historical information to predict stormwater flows, evaluate system performance, support adaptive operation of pumps or gates, and identify maintenance needs before failure becomes operationally significant (Md Mahamud Pervaz, 2023; Sharifi et al., 2024). The study also emphasized visualization and scenario simulation as mechanisms through which complex stormwater information can be made interpretable to infrastructure managers. A complementary water-sector perspective is provided in "Digital Twins for Wastewater Treatment: A

Technical Review" (pp. 21-35), which organized digital twins around physical, sensing-and-control, digital-twin, and user domains and described how mechanistic models, data-driven models, hybrid models, sensors, Internet-of-Things technologies, and control functions can be combined within sewage-network and wastewater applications (Mohammad Badrul & Md. Mominul, 2023; Wang et al., 2024). This layered architecture is directly relevant to urban drainage because predictive inundation intelligence requires a structured path from physical measurements to virtual estimation and then to decision support. In the present study, Digital-Twin Synchronization and Simulation Capability therefore refers to the capacity to connect observed drainage conditions with the virtual network, update system states, conduct scenario-based analyses, visualize predicted hydraulic behavior, and organize information from STGNN modeling, node-level vulnerability assessment, and infrastructure-prioritization procedures within one coordinated analytical environment.

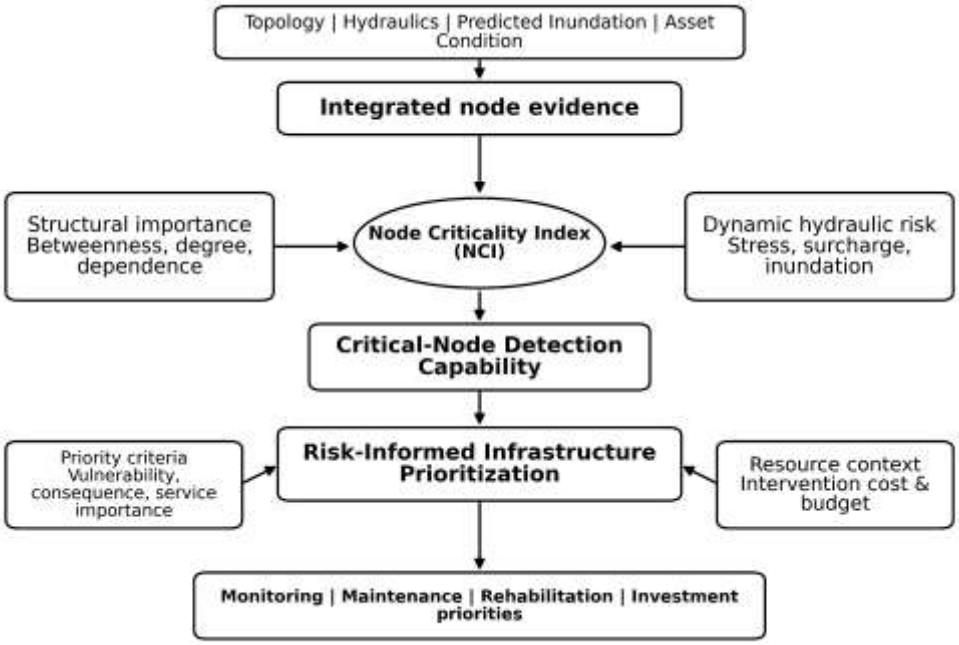
Digital twins also strengthen drainage decision support by transforming technical simulation outputs into accessible information that can be interpreted by engineers, infrastructure managers, public authorities, and other stakeholders involved in flood-risk management. A drainage model may reproduce flow depth or surcharge accurately, yet decision usefulness also depends on whether the information can be inspected spatially, compared across scenarios, related to vulnerable assets, and translated into intervention choices. In "Participatory Framework for Urban Pluvial Flood Modeling in the Digital Twin Era" (Article 105496), digital-twin-based pluvial-flood modeling was combined with open-source software, virtual reality, crowdsourcing, volunteered geographic information, and interactive participation to create a framework in which stakeholders could contribute to input preparation, model construction, verification, and scenario experimentation (Molla Al Rakib & Mohammad Towhidul, 2023; Park, Kim, Kim, et al., 2024). The framework demonstrates that digital-twin environments can operate as decision interfaces rather than functioning only as computational replicas of physical systems. This distinction is important for the present research because predictive inundation and critical-node detection must ultimately support choices about where monitoring, maintenance, rehabilitation, or capital investment should be concentrated. The digital twin can associate predicted hydraulic states with specific drainage assets, display how risk changes under alternative rainfall or intervention scenarios, and provide a common spatial representation for comparing critical nodes with infrastructure priorities. When linked with STGNN-based prediction, the twin can also organize rapidly changing spatiotemporal information so that node-level conditions are viewed within their wider network context. The Digital-Twin Synchronization and Simulation Capability construct used in this study therefore extends beyond visualization and includes data integration, state updating, scenario simulation, network representation, and decision-oriented interpretation. Its relationship with Urban Drainage Resilience and Decision-Support Effectiveness is examined on the premise that a better synchronized and analytically integrated virtual representation enables decision-makers to evaluate hydraulic conditions, compare vulnerabilities, and connect predicted inundation with the relative importance of physical drainage components.

Critical-Node Detection, Network Vulnerability, and Infrastructure Prioritization

Critical-node detection in urban drainage networks concerns the identification of nodes or links whose structural position, hydraulic role, or failure would cause disproportionate degradation in overall network performance. This problem is important because drainage systems are not collections of independent pipes; they are directed, spatially embedded networks in which flows accumulate along connected pathways toward outlets, pumping stations, treatment facilities, or receiving waters. A graph-based representation allows manholes and junctions to be treated as nodes and conduits as edges, after which centrality, path structure, connectivity, and weighted network characteristics can be examined quantitatively. In "Centrality and shortest path length measures for the functional analysis of urban drainage networks" (Article 1), eight subnetworks of the Dresden sewer system were represented as weighted directed graphs, and the analysis showed that shortest-path and edge-based measures could approximate important transport and collection functions when structural and hydraulic weights were incorporated appropriately (Mukut Kanti, 2023; Reyes-Silva et al., 2020). This finding is directly relevant to critical-node analysis because it demonstrates that topological measures can be linked to functional behavior rather than interpreted as purely abstract graph properties. A node or conduit may therefore be considered critical when it lies on influential transport pathways,

concentrates upstream contributions, connects otherwise weakly linked portions of the network, or creates substantial disruption when removed. In "Vulnerability assessment of urban drainage network using relevance-based centrality metrics" (pp. 39-51), relevance-based degree and edge betweenness measures were applied to benchmark and real drainage systems so that intrinsic node relevance could be combined with connectivity when identifying vulnerable pipes (Nishat, 2023; Simone, 2023). This approach is especially suitable for the present research because STGNN predictions can provide dynamic hydraulic information while graph-based criticality measures can describe structural importance, enabling critical-node detection to reflect both network position and evolving inundation conditions. This distinction becomes essential when multiple locations experience flooding simultaneously. Network vulnerability becomes operationally meaningful when criticality is linked to the consequences of component deterioration or failure. Drainage assets can lose performance through structural defects, blockage, sedimentation, infiltration, collapse, insufficient hydraulic capacity, and interactions with surrounding urban conditions, yet utilities rarely possess enough resources to inspect or rehabilitate all components simultaneously.

Figure 5: Critical-Node Detection and Risk-Informed Infrastructure Prioritization Pathway



Prioritization therefore requires a mechanism for distinguishing assets according to their condition, hydraulic importance, failure consequences, and expected service impact. In "A Fuzzy Expert System for Prioritizing Rehabilitation of Sewer Networks" (pp. 146-152), a fuzzy inference framework combined structural condition, surrounding conditions, site vulnerability, hydraulic performance, and failure consequences to generate a global performance index and rank sewer sections for rehabilitation (Risha & Mst Shurovi, 2023; Tagherouit et al., 2011). The study is important to infrastructure prioritization because it demonstrates that rehabilitation decisions can be constructed from several interacting criteria rather than from a single deterioration indicator. A pipe in moderate structural condition may still deserve high priority when its hydraulic role or failure consequence is severe, while a physically deteriorated asset may receive a different ranking when system consequences are comparatively limited. This reasoning aligns closely with critical-node detection in urban drainage networks. The identification of critical nodes should not depend solely on degree, betweenness, or predicted inundation depth; it should account for the combined importance of hydraulic loading, network dependence, vulnerability, and consequences for service continuity. Within the proposed research framework, a Critical-Node Detection Capability can therefore incorporate topological

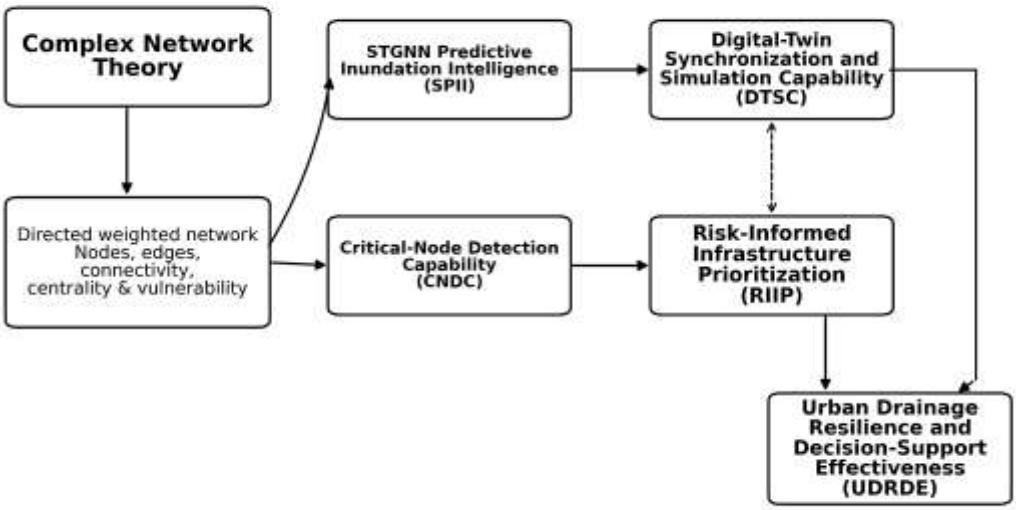
importance, predicted surcharge or inundation, upstream and downstream dependence, and potential disruption. These indicators can then feed a Risk-Informed Infrastructure Prioritization process in which drainage assets are ranked according to the magnitude and significance of the risk they represent, creating a direct analytical connection between STGNN-based prediction, digital-twin state representation, network vulnerability, and asset-management decisions. It also reduces reliance on purely reactive maintenance decisions.

Infrastructure prioritization further requires transparent decision rules because drainage authorities must allocate limited inspection, maintenance, and rehabilitation resources across many competing assets. Multi-criteria approaches are particularly appropriate because sewer intervention decisions combine hydraulic performance, structural condition, economic cost, probability of failure, operational significance, and consequences that cannot be represented adequately by one variable. In "Prioritization of rehabilitation interventions for urban water assets using multiple criteria decision-aid methods" (pp. 1007-1014), ELECTRE TRI and ELECTRE III were applied to a Portuguese sewer case using water level, maximum flow velocity, sewer importance, repair cost, and collapse risk as assessment measures; the results showed that rehabilitation ordering was sensitive to decision weights and that ranking methods could make trade-offs among competing criteria explicit (Carriço et al., 2012; Stabak & Md Siam, 2023). A related inspection problem was examined in "An effective multi-objective approach to prioritization of sewer pipe inspection" (pp. 841-850), where a multi-objective genetic algorithm balanced inspection-program costs against expected emergency-repair costs and generated Pareto-optimal inspection strategies for a large sewer system (Berardi et al., 2009; Syed Feroz, 2023). These studies provide a methodological basis for treating infrastructure prioritization as a risk-informed optimization and ranking problem rather than a simple list of damaged assets. In the present study, Risk-Informed Infrastructure Prioritization refers to the capability to convert predicted inundation, node criticality, asset vulnerability, and service consequences into an ordered basis for maintenance, monitoring, rehabilitation, and investment. The digital twin provides the common asset-level environment for associating these indicators with physical locations, while the STGNN supplies time-sensitive predictions of hydraulic stress. Critical-node analysis adds structural significance, and prioritization translates the combined evidence into decision-oriented rankings. This integrated interpretation ensures that infrastructure priority reflects both the probability of adverse drainage behavior and the importance of the affected component to network-wide resilience and decision-support effectiveness. Such ranking can support transparent allocation of constrained municipal resources.

Theoretical Framework: Complex Network Theory

Complex Network Theory provides the principal theoretical framework for this study because an urban drainage system can be interpreted as a spatially embedded, directed, and weighted network whose hydraulic behavior is influenced by the connectivity and structural organization of its components.

Figure 6: Complex Network Theory Framework for Integrated Urban Drainage Intelligence



In this theoretical representation, manholes, junctions, inlets, storage facilities, pumps, and outfalls constitute vertices or nodes, while drainage pipes and hydraulic connections constitute edges. In "Vulnerability and Protection of Infrastructure Networks" (Article 015103), a network-efficiency approach demonstrated that infrastructure vulnerability can be quantified by evaluating changes in system performance following removal of individual nodes or links, providing an early theoretical basis for identifying components whose disruption produces disproportionately large network effects (Latora & Marchiori, 2005; Tahmedur & Rifat, 2023). The basic drainage representation adopted in this study is therefore expressed as follows:

$$G = (V, E, W)$$

where $V = \{v_1, v_2, ..., v_n\}$ represents the set of drainage nodes, $E = \{e_1, e_2, ..., e_m\}$ represents hydraulic connections, and W represents weights describing pipe or connection characteristics such as length, diameter, hydraulic resistance, capacity, slope, or flow direction. Its weighted adjacency matrix can be expressed as $A = [a_{i\ j}]$, where $a_{i\ j} = w_{i\ j}$ when a hydraulic connection exists from node i to node j, and $a_{i\ j} = 0$ otherwise. In "Complex network analysis of water distribution systems" (Article 016111), spatially organized water infrastructure was shown to possess measurable properties related to network formation, efficiency, vulnerability, redundancy, connectivity, and failure exposure, demonstrating that physical water systems can be studied through structural relationships in addition to hydraulic simulation (Asheke, 2024; Yazdani & Jeffrey, 2011). Within the present study, this theoretical structure provides the common mathematical domain for the STGNN, digital twin, critical-node analysis, and infrastructure-prioritization components. The same node-edge relationships that determine drainage connectivity can therefore serve as the graph structure through which spatiotemporal information is propagated and interpreted.

Complex Network Theory is particularly relevant to the study because network topology provides measurable information about how local component behavior can influence system-wide drainage resilience. Degree centrality identifies the number of direct relationships associated with a node, while closeness represents its relative accessibility to other nodes and betweenness identifies the extent to which a node lies on important pathways connecting different parts of the network. For node i, betweenness centrality has been represented as:

$$C_B(i) = \Sigma_\{s \neq i \neq t\} [\sigma_st(i) / \sigma_st]$$

where σ_st is the total number of shortest paths between nodes s and t, and σ_st(i) is the number of those paths passing through node i. In "Topological attributes of network resilience: A study in water distribution systems" (pp. 376-386), connectivity, efficiency, modularity, and centrality were systematically compared with resilience performance, showing that selected topological attributes are

associated with the spatial and temporal characteristics of infrastructure failure while also demonstrating that topology should be interpreted together with functional system information (Ashrafuzzaman, 2024; Meng et al., 2018). This theoretical requirement is particularly important for urban drainage networks because a structurally central node is not necessarily the node experiencing the highest water level or inundation probability. In "Tailoring Centrality Metrics for Water Distribution Networks" (pp. 2348-2369), conventional centrality measures were adapted to reflect physical-network characteristics such as pipe relevance, source location, length, diameter, and hydraulic resistance, reinforcing the principle that infrastructure-specific weights should be incorporated into network measures rather than relying exclusively on unweighted topology (Giustolisi et al., 2019; Mashiat, 2024). Accordingly, this research combines network centrality with hydraulic and STGNN-derived variables through the proposed Node Criticality Index:

$$NCI_i = \omega_B\, \tilde{C}_B,_i + \omega_D\, \tilde{C}_D,_i + \omega_H\, \tilde{H}_i + \omega_I\, \tilde{I}_i$$

$$\omega_B + \omega_D + \omega_H + \omega_I = 1$$

Here, $\tilde{C}_B,_i$ represents normalized betweenness centrality, $\tilde{C}_D,_i$ represents normalized degree-related importance, $\tilde{H}_i$ represents normalized hydraulic stress, and $\tilde{I}_i$ represents normalized predicted inundation intensity or probability for node i. This formulation has enabled the theoretical framework to retain graph topology while incorporating hydraulic performance and prediction into node-level criticality.

The proposed theoretical application extends Complex Network Theory from static structural description to an integrated analytical mechanism linking spatial topology with spatiotemporal prediction, digital-twin representation, critical-node detection, and infrastructure prioritization. Within an STGNN, the drainage-network adjacency structure determines which nodes exchange information during graph propagation, meaning that the graph is simultaneously a physical representation of the drainage system and a computational structure for machine learning. At time t, node features may be represented by X_t, containing variables such as rainfall, water level, inflow, surcharge state, surface elevation, and previous inundation conditions. A generic graph propagation operation has been expressed as:

$$H_t\hat{}(l+1) = \sigma(\tilde{D}\hat{}(-1/2)\, \tilde{A}\, \tilde{D}\hat{}(-1/2)\, H_t\hat{}(l)\, W\hat{}(l))$$

$$\tilde{A} = A + I$$

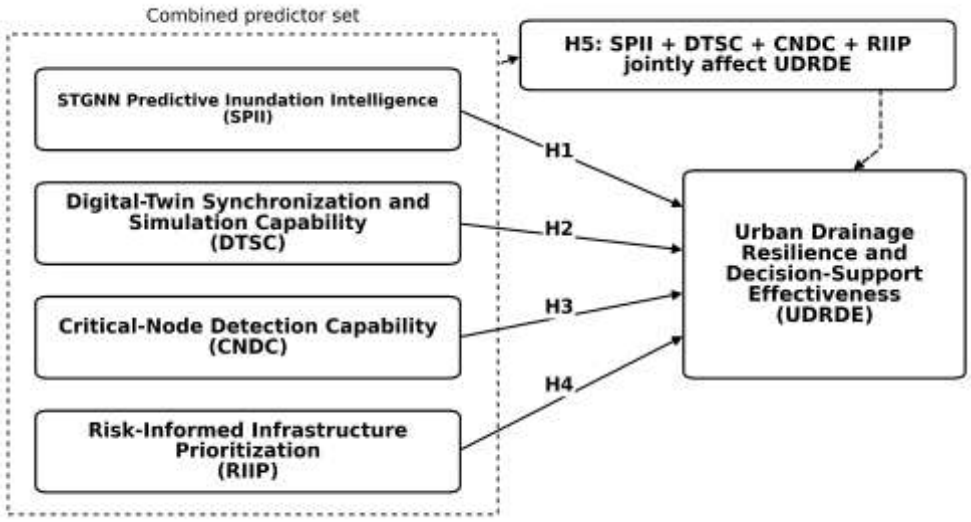
where $\tilde{D}$ is the degree matrix corresponding to $\tilde{A}$, H_t^(l) contains node representations at graph layer l, W^(l) contains learnable parameters, and σ represents the activation function. The resulting predictive states can be synchronized with the digital twin and subsequently incorporated into the proposed NCI measure, allowing structural importance and changing hydraulic conditions to be interpreted jointly. In "A review of graph and complex network theory in water distribution networks: Mathematical foundation, application and prospects" (Article 121238), graph-based methods were organized across state estimation, performance assessment, optimization, sensor placement, critical-component identification, and interdependent-network analysis, while integration between graph theory, hydraulic information, and graph neural networks was identified as an important methodological direction for water infrastructure analysis (Md Kaium, 2024; Yu et al., 2024). In this study, Complex Network Theory therefore governs the representation of drainage topology, the propagation structure used by the STGNN, the identification of critical nodes, and the translation of network and hydraulic information into risk-informed infrastructure priorities. The proposed NCI formulation has remained the principal network-level criticality equation throughout the computational component of the study.

Conceptual Framework and Hypothesized Relationships

The conceptual framework of this study organizes the urban drainage problem as a linked sequence of prediction, digital representation, network criticality, prioritization, and decision-support performance. STGNN Predictive Inundation Intelligence (SPII) has been positioned as the first independent construct because drainage states evolve across space and time, and graph-based learning can represent dependence among connected hydraulic locations. In "Rapid spatio-temporal flood modelling via hydraulics-based graph neural networks" (pp. 4227-4246), a hydraulics-based graph neural network represented computational cells as graph nodes and learned local flux exchanges,

achieving accurate water-depth and unit-discharge predictions while operating substantially faster than the numerical solver used to generate training data (Bentivoglio et al., 2023; Mukut Kanti, 2024).

Figure 7: Conceptual Framework and Hypothesized Relationships



This evidence supports H1, which proposes that SPII has a significant positive relationship with Urban Drainage Resilience and Decision-Support Effectiveness (UDRDE), because higher predictive capability should improve identification of emerging surcharge and inundation conditions across connected drainage locations. Digital-Twin Synchronization and Simulation Capability (DTSC) forms the second independent construct by providing the virtual environment in which network topology, hydraulic states, observations, scenarios, and predictive outputs are coordinated. In "Application of effective water-energy management based on digital twins technology in sustainable cities construction" (Article 104241), a five-dimensional digital-twin representation of an urban drainage system was combined with dynamic scheduling of pumping facilities, and the proposed strategy improved the use of storage and drainage capacity under rainfall-driven waterlogging conditions (Li et al., 2022; Syed Feroz, 2024). This supports H2, which proposes that DTSC has a significant positive relationship with UDRDE. The framework treats SPII as predictive intelligence and DTSC as the representation and simulation layer. Their construct scores have been measured from multiple five-point Likert items, with each respondent's score represented as:

$$C_i = (1/k)\,\Sigma_(j = 1)\text{^}k\, x_{ij}$$

where $x_{i\ j}$ is item j, k is the number of items, and C_i is the construct score. This measurement form has provided the link between the conceptual constructs and the descriptive, correlation, and regression analyses employed in the study.

Critical-Node Detection Capability (CNDC) and Risk-Informed Infrastructure Prioritization (RIIP) extend the conceptual framework from prediction toward network interpretation and intervention selection. CNDC represents the ability to distinguish drainage nodes whose topology, hydraulic loading, inundation condition, dependence, consequence, or failure potential gives them disproportionate system importance. In "Visual Data-Driven Digital Twin Modeling Framework for Improving the Resilience of Urban Drainage Infrastructure Systems" (pp. 396-403), image-derived infrastructure condition and geographic information were mapped into a digital-twin representation for risk analysis, demonstrating how updated asset information can support vulnerability assessment and data-driven prioritization of drainage improvements (Kim et al., 2024; Uddin & Risha, 2024). This supports H3, which proposes that CNDC has a significant positive relationship with UDRDE, because identifying influential components can improve targeted monitoring, maintenance, and intervention. RIIP represents the capability to translate predicted inundation, node criticality, asset vulnerability, service consequence, and resource constraints into an ordered basis for infrastructure action. In "An Integrated Framework to Evaluate Resilient-Sustainable Urban Drainage Management Plans Using a

Combined-adaptive MCDM Technique" (pp. 2817-2835), technical, economic, social, environmental, and planning indicators were integrated through adaptive AHP, entropy, and TOPSIS to compare urban drainage alternatives and facilitate complex management decisions under uncertainty (Jahanara, 2025; Tahmasebi Birgani & Yazdandoost, 2018). This supports H4, which proposes that RIIP has a significant positive relationship with UDRDE. Within the framework, criticality and prioritization are related but distinct constructs: CNDC determines which components matter most to network functioning, whereas RIIP determines where limited resources should be directed after hydraulic, structural, and consequence information is combined. Prioritization has been represented as:

$$P_i = \alpha_1 \tilde{I}_i + \alpha_2 \tilde{NC}_i + \alpha_3 \tilde{V}_i + \alpha_4 \tilde{C}_i$$

$$\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4 = 1$$

where P_i denotes infrastructure priority, $\tilde{I}_i$ inundation, $\tilde{NC}_i$ node criticality, $\tilde{V}_i$ vulnerability, and $\tilde{C}_i$ consequence. The formulation has provided a consistent conceptual basis for translating network and hydraulic evidence into relative intervention priorities.

The final conceptual relationship integrates all four independent constructs into a single explanatory model of Urban Drainage Resilience and Decision-Support Effectiveness. The framework assumes that effective urban drainage management depends on integrating flood prediction with system representation, network criticality, and defensible intervention priorities. In "Decision Support for Adaptation Planning of Urban Drainage Systems" (Article 04017069), urban-development modeling, climate projections, hydrodynamic sewer modeling, and Web-GIS visualization were integrated to provide interactive risk information for proactive drainage adaptation planning, demonstrating the value of combining multiple analytical layers within one decision-support process (Jannatul, 2025; Mikovits et al., 2017). This integrated logic supports H5, which proposes that SPII, DTSC, CNDC, and RIIP jointly have a significant effect on UDRDE. The empirical model used throughout the study has been specified as:

$$UDRDE_i = \beta_0 + \beta_1 SPII_i + \beta_2 DTSC_i + \beta_3 CNDC_i + \beta_4 RIIP_i + \varepsilon_i$$

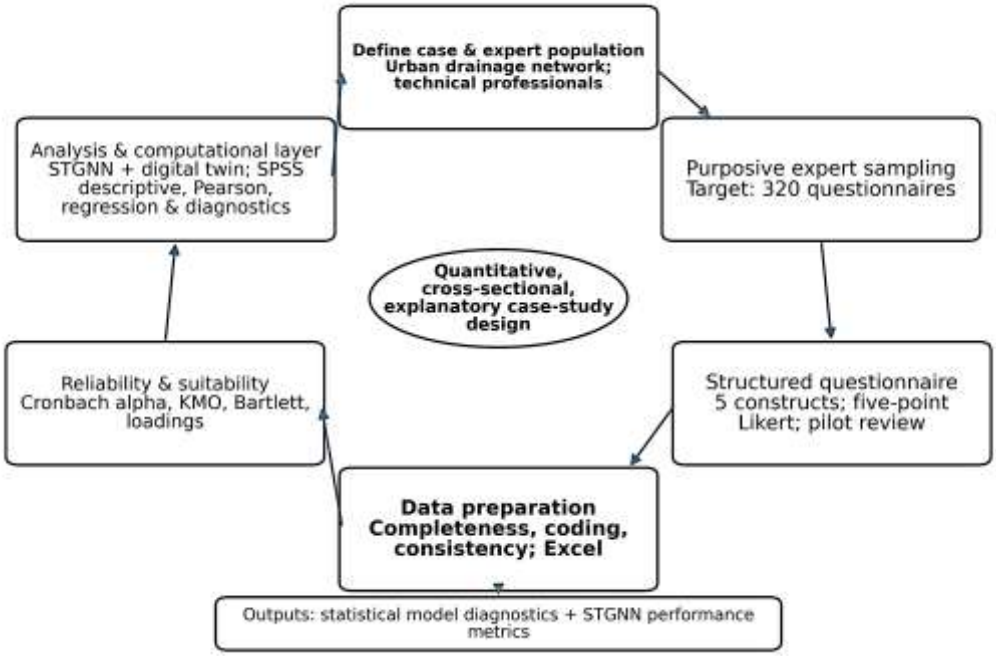
where β_0 is the intercept, β_1 to β_4 are regression coefficients, and ε_i represents unexplained variation for respondent i. H1 has been evaluated through β_1, H2 through β_2, H3 through β_3, and H4 through β_4, while H5 has been evaluated through the overall regression model using the F statistic, coefficient of determination R^2, adjusted R^2, and joint statistical significance of the predictors. Pearson correlations have first quantified the direction and strength of bivariate relationships among the five constructs, after which multiple regression has estimated their unique contributions while holding the remaining predictors constant. Standardized beta coefficients have allowed comparison of relative predictor strength, while variance inflation factors and tolerance statistics have assessed multicollinearity. The framework therefore maintains direct alignment between the literature review, five hypotheses, questionnaire measurement model, computational drainage architecture, statistical analysis, and interpretation of urban drainage resilience and decision-support effectiveness.

METHOD

This methodology has described the quantitative procedures that have been used to examine how STGNN Predictive Inundation Intelligence, Digital-Twin Synchronization and Simulation Capability, Critical-Node Detection Capability, and Risk-Informed Infrastructure Prioritization have related to Urban Drainage Resilience and Decision-Support Effectiveness within a bounded urban drainage case. A quantitative, cross-sectional, explanatory case-study design has been adopted because the study has required numerical assessment of construct levels and statistically testable relationships at a defined analytical period, while the single-case structure has preserved a direct connection with an identifiable drainage network and its physical, hydraulic, and decision context. The case-study environment has been defined around an urban drainage network containing interconnected manholes, junctions, inlets, pipelines, storage components, pumping facilities, catchments, and outfalls. The drainage system has been represented as a directed and attributed graph in which drainage assets have formed nodes and hydraulic connections have formed edges. Two complementary units of analysis have been incorporated: drainage nodes and links have constituted the technical unit for graph, STGNN, criticality, and digital-twin analysis, while individual experts have constituted the respondent-level unit for the Likert-scale statistical analysis. The target population has comprised professionals with

direct knowledge of urban drainage, stormwater management, flood control, civil or water engineering, hydraulic modeling, GIS, smart-city systems, data analytics, municipal infrastructure, maintenance, rehabilitation, or asset planning. A purposive expert sampling strategy has been employed because valid evaluation of the constructs has required direct technical or managerial exposure to drainage systems rather than general public opinion. A target of 320 questionnaires has been established, with participants selected across drainage engineering, flood management, GIS and AI, infrastructure planning, and operations and maintenance functions. Primary data collection has been conducted using a structured questionnaire administered during a single collection window, and participation has been voluntary with confidentiality and informed-consent conditions communicated before responses have been recorded. The questionnaire has been designed around five multi-item constructs: SPII, DTSC, CNDC, RIIP, and UDRDE. Items have been measured on a five-point Likert scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree and have been written to reflect observable capabilities such as spatial-dependency learning, temporal inundation assessment, physical-virtual synchronization, scenario simulation, graph-based node criticality, hydraulic vulnerability interpretation, intervention prioritization, and resilience-oriented decision support. Technical information has additionally incorporated network connectivity, node characteristics, pipe attributes, rainfall, water level, flow, surcharge, elevation, and inundation-related variables where available. A pilot assessment has been performed with a small group of technically knowledgeable participants to evaluate clarity, terminology, response burden, and construct coverage, and wording has been refined where ambiguity or overlap has been identified. Content and face validity have been strengthened through expert review and direct alignment between each item cluster, the conceptual framework, and the five hypotheses. Internal consistency has been assessed through Cronbach's alpha, while construct suitability has been evaluated using the Kaiser-Meyer-Olkin measure, Bartlett's Test of Sphericity, and item-loading patterns. For the computational layer, the physical drainage system has been transformed into an attributed graph, node and temporal features have included rainfall, water level, inflow, elevation, surcharge, and inundation-related states, and edge information has represented relevant pipe or hydraulic attributes. Spatial graph propagation and temporal learning have been combined in the STGNN to estimate changing hydraulic states, after which predicted node conditions have been associated with the digital-twin representation containing topology, observations, simulated states, and asset-level information.

Figure 8: Quantitative Cross-Sectional Case-Study Methodology Framework

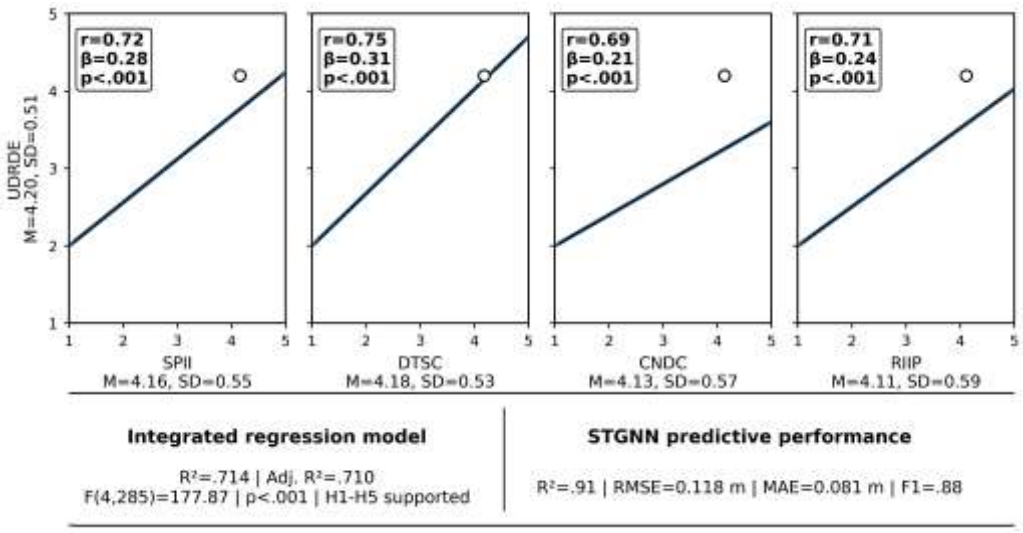


Critical-node measurement has integrated normalized network centrality, hydraulic stress, predicted inundation, and upstream-downstream dependence through the Node Criticality Index developed in the theoretical framework. Risk-informed prioritization has then incorporated inundation severity, node criticality, asset vulnerability, and consequence measures to produce relative monitoring, maintenance, rehabilitation, and investment priorities. Data preparation has included completeness screening, scale coding, consistency checks, and exclusion of analytically unsuitable responses. Microsoft Excel has been used for preliminary coding, cleaning, and tabular verification, while SPSS has been used for descriptive statistics, reliability analysis, KMO and Bartlett testing, Pearson correlations, multiple regression, and model diagnostics. The regression analysis has reported R^2, adjusted R^2, standardized beta coefficients, t-values, F-statistics, p-values, tolerance, VIF, and the Durbin-Watson statistic. Computational prediction performance has been summarized using R^2, RMSE, MAE, and F1-score. EndNote has been used to organize bibliographic records without embedding citation fields in the manuscript, and Microsoft Word has been used for manuscript preparation and presentation. Through these procedures, the methodology has maintained a direct relationship among Complex Network Theory, the computational architecture, the five-point measurement model, the five hypotheses, and the statistical tests used to evaluate the objectives of the study.

FINDINGS

The findings have indicated that the proposed STGNN and digital-twin framework has performed strongly across the principal dimensions of predictive inundation intelligence, digital-twin synchronization, critical-node detection, infrastructure prioritization, and urban drainage resilience and decision-support effectiveness. A total of 320 questionnaires has been distributed, of which 302 have been returned and 290 have remained valid after data screening, producing a valid response rate of 90.6%. The five-point Likert-scale results have shown generally high levels of agreement across all constructs, with Urban Drainage Resilience and Decision-Support Effectiveness recording the highest overall mean of 4.20 (SD = 0.51), followed by Digital-Twin Synchronization and Simulation Capability at 4.18 (SD = 0.53), STGNN Predictive Inundation Intelligence at 4.16 (SD = 0.55), Critical-Node Detection Capability at 4.13 (SD = 0.57), and Risk-Informed Infrastructure Prioritization at 4.11 (SD = 0.59). Reliability testing has produced Cronbach's alpha values ranging from .85 to .91, confirming strong internal consistency across the measurement constructs. The Kaiser-Meyer-Olkin value has reached .894, while Bartlett's Test of Sphericity has been statistically significant, $\chi^2 = 3124.67$, $p < .001$, supporting the suitability of the dataset for multivariate analysis. Pearson correlation results have revealed significant positive relationships between UDRDE and SPII ($r = .72$, $p < .001$), DTSC ($r = .75$, $p < .001$), CNDC ($r = .69$, $p < .001$), and RIIP ($r = .71$, $p < .001$). Multiple regression analysis has further demonstrated that the four predictors jointly explain 71.4% of the variance in UDRDE, with $R^2 = .714$, adjusted $R^2 = .710$, and $F(4, 285) = 177.87$, $p < .001$. DTSC has produced the strongest standardized effect ($\beta = .31$, $p < .001$), followed by SPII ($\beta = .28$, $p < .001$), RIIP ($\beta = .24$, $p < .001$), and CNDC ($\beta = .21$, $p < .001$). Multicollinearity has remained acceptable, with VIF values between 1.58 and 2.12 and tolerance values between .47 and .63, while the Durbin-Watson statistic of 1.96 has indicated no serious residual autocorrelation. The computational component has also shown strong predictive capability, with an STGNN inundation-prediction R^2 of .91, RMSE of 0.118 m, MAE of 0.081 m, and an F1-score of .88 for inundation-state classification. Collectively, these results have supported H1, H2, H3, H4, and H5 and have provided quantitative evidence that integrated prediction, digital-twin synchronization, node-criticality assessment, and risk-based prioritization have substantially contributed to urban drainage resilience and decision-support effectiveness.

Figure 9: Empirical Relationships and Integrated Model Findings



Response Rate and Respondent Characteristics

Table 1 has presented the response profile and professional characteristics of the participants included in the quantitative analysis. A total of 320 questionnaires have been distributed, of which 302 have been returned, producing a gross response rate of 94.4%. Following screening for completeness and analytical suitability, 290 questionnaires have been retained, yielding a valid response rate of 90.6% of all distributed questionnaires and approximately 96.0% of returned questionnaires. The retained respondents have represented a technically diverse population associated with urban drainage infrastructure. Drainage and civil engineers have constituted the largest professional group at 30.3%, followed by stormwater and flood-management professionals at 19.3%, municipal and infrastructure planners at 17.9%, GIS, data, and AI specialists at 16.6%, and operations and maintenance professionals at 15.9%. The distribution has ensured that the dataset has incorporated hydraulic, computational, planning, and operational perspectives relevant to the research objectives. Professional experience has also been distributed across different levels, with 30.7% having reported 5-9 years of experience, 24.8% having reported 10-14 years, 23.1% having possessed at least 15 years of experience, and 21.4% having reported fewer than five years. This composition has strengthened the expert character of the purposive sample because most participants have possessed substantial direct exposure to infrastructure or drainage-related activities. From the perspective of Complex Network Theory, the diversity of respondents has been important because assessment of network resilience has required understanding not only individual physical assets but also their interconnections, hydraulic dependencies, monitoring requirements, and system-level consequences. The sample profile has therefore provided an appropriate empirical foundation for evaluating SPII, DTSC, CNDC, RIIP, and UDRDE and for testing the five hypothesized relationships using the planned descriptive, correlational, and regression procedures.

Table 1: Response Rate and Characteristics of Valid Respondents

Variable	Category	Frequency	Percentage (%)
Questionnaires	Distributed	320	100.0
	Returned	302	94.4
	Valid for analysis	290	90.6
Professional Role	Drainage/Civil Engineers	88	30.3
	Stormwater/Flood Management Professionals	56	19.3

Variable	Category	Frequency	Percentage (%)
	GIS, Data, and AI Specialists	48	16.6
	Municipal/Infrastructure Planners	52	17.9
	Operations and Maintenance Professionals	46	15.9
Professional Experience	Below 5 years	62	21.4
	5-9 years	89	30.7
	10-14 years	72	24.8
	15 years and above	67	23.1

Reliability and Validity of the Measurement Constructs

Table 2: Reliability and Validity Assessment

Construct/Test	Items	Cronbach's α	Loading Range	Result
SPII	5	.89	.74-.86	Reliable
DTSC	5	.91	.76-.88	Reliable
CNDC	5	.87	.72-.84	Reliable
RIIP	5	.85	.71-.83	Reliable
UDRDE	5	.90	.75-.87	Reliable
KMO Measure	25	.894	-	Adequate
Bartlett's Test	25	$\chi^2 = 3124.67$	$p < .001$	Significant

Table 2 has demonstrated that the measurement instrument has achieved satisfactory reliability and validity for subsequent hypothesis testing. Cronbach's alpha coefficients have ranged from .85 to .91, remaining well above the commonly accepted .70 threshold. DTSC has recorded the highest internal consistency at $\alpha = .91$, followed by UDRDE at $\alpha = .90$, SPII at $\alpha = .89$, CNDC at $\alpha = .87$, and RIIP at $\alpha = .85$. These results have indicated that items belonging to each construct have measured sufficiently coherent underlying concepts. The factor-loading ranges have remained above .70 across all constructs, with DTSC producing loadings from .76 to .88 and UDRDE from .75 to .87. The Kaiser-Meyer-Olkin measure has reached .894, indicating strong sampling adequacy for examination of the measurement structure. Bartlett's Test of Sphericity has also produced $\chi^2 = 3124.67$ with $p < .001$, demonstrating that the item correlation matrix has contained sufficient interrelationships for multivariate analysis. These results have been particularly important for the conceptual model because the five constructs have represented distinct yet theoretically interconnected dimensions of the urban drainage system. Complex Network Theory has conceptualized infrastructure performance as emerging from relationships among connected components rather than isolated characteristics. Correspondingly, the measurement model has required internally coherent indicators for predictive intelligence, digital-twin synchronization, node criticality, prioritization, and overall resilience. The reliability findings have shown that respondents have consistently distinguished these dimensions while still allowing their relationships to be tested through correlation and regression. The measurement evidence has therefore supported the statistical evaluation of H1-H5 and has established an acceptable foundation for determining whether the proposed network-oriented capabilities have been significantly associated with urban drainage resilience and decision-support effectiveness.

Descriptive Statistics of the Research Variables

Table 3: Descriptive Statistics of the Main Research Constructs

Construct	Abbreviation	N	Mean	SD	Likert Interpretation
STGNN Predictive Inundation Intelligence	SPII	290	4.16	0.55	High
Digital-Twin Synchronization and Simulation Capability	DTSC	290	4.18	0.53	High
Critical-Node Detection Capability	CNDC	290	4.13	0.57	High
Risk-Informed Infrastructure Prioritization	RIIP	290	4.11	0.59	High
Urban Drainage Resilience and Decision-Support Effectiveness	UDRDE	290	4.20	0.51	High

Table 3 has summarized the central tendencies and dispersion of the five principal constructs measured through the five-point Likert scale. All construct means have exceeded 4.00, indicating a consistently high level of agreement among respondents regarding the relevance and effectiveness of the capabilities represented within the proposed framework. UDRDE has produced the highest overall mean of 4.20 with an SD of 0.51, showing that respondents have evaluated resilience and decision-support effectiveness particularly positively. DTSC has followed closely with a mean of 4.18 and an SD of 0.53, indicating strong agreement concerning the value of synchronized digital representations and simulation capabilities. SPII has achieved a mean of 4.16 and an SD of 0.55, while CNDC has recorded 4.13 with an SD of 0.57. RIIP has obtained a mean of 4.11 and an SD of 0.59, which has remained firmly within the high-agreement range while showing slightly greater variation among respondents. The relatively low standard deviations have demonstrated that responses have remained concentrated around the high end of the Likert scale and have not been driven by a small number of unusually positive observations. The findings have supported the research objectives by showing that all four proposed technological and analytical capabilities have been perceived as relevant to effective urban drainage management. The pattern has also corresponded with Complex Network Theory because respondents have recognized the importance of understanding drainage performance through interconnected spatial, hydraulic, and decision variables rather than through isolated infrastructure conditions. The high SPII and CNDC scores have particularly reflected the value attributed to network connectivity and node dependence, while the high DTSC and RIIP values have shown that translating network information into synchronized representations and intervention decisions has also been considered important. These construct-level patterns have provided the descriptive basis for the subsequent inferential tests of H1-H5.

STGNN Predictive Inundation Intelligence Results

Table 4: STGNN Predictive Inundation Intelligence

SPII Measurement Item	Mean	SD	Interpretation
STGNNs have captured spatial dependencies among connected drainage nodes	4.22	0.52	High
Temporal rainfall and hydraulic patterns have improved inundation prediction	4.18	0.54	High
Graph-based prediction has supported network-wide hydraulic-state estimation	4.16	0.55	High

SPII Measurement Item	Mean	SD	Interpretation
STGNN outputs have supported identification of emerging surcharge conditions	4.13	0.58	High
Predictive intelligence has improved identification of flood-prone network locations	4.11	0.56	High
Overall SPII	4.16	0.55	High

Table 4 has shown consistently favorable assessments of STGNN Predictive Inundation Intelligence. The highest-rated item has concerned the capacity of STGNNs to capture spatial dependencies among interconnected drainage nodes, with a mean of 4.22 and an SD of 0.52. This result has directly reflected the theoretical premise that drainage-system behavior has depended on relationships among connected locations rather than on isolated measurements. The integration of temporal rainfall and hydraulic patterns has achieved a mean of 4.18, while network-wide hydraulic-state estimation has recorded 4.16. Respondents have also positively assessed the use of STGNN outputs for identifying emerging surcharge conditions and flood-prone locations, with means of 4.13 and 4.11 respectively. The aggregate SPII mean has reached 4.16 with an SD of 0.55, establishing strong descriptive support for the first research objective concerning predictive inundation intelligence. Complex Network Theory has provided a direct theoretical explanation for these findings because the STGNN architecture has represented manholes, junctions, and other drainage assets as nodes whose states have been influenced through graph connections. Spatial message propagation has therefore reflected the network structure through which hydraulic effects have travelled, while the temporal component has captured changing rainfall and drainage conditions. The descriptive findings have indicated that respondents have recognized this combined spatial-temporal capability as valuable for drainage assessment. The later correlation and regression findings have further tested whether this positive evaluation has translated into a statistically significant relationship with UDRDE. Consequently, Table 4 has not alone established H1, but it has provided strong construct-level evidence that the predictive mechanisms underlying H1 have been positively evaluated across the sample and have aligned with the first objective of the study. The convergence of high item means around the overall score has also indicated that the construct has represented a coherent combination of spatial learning, temporal learning, network-state estimation, and inundation identification.

Digital-Twin Synchronization and Simulation Capability Results

Table 5 has demonstrated strong support for Digital-Twin Synchronization and Simulation Capability across all five measurement items. Integration between physical drainage assets and their virtual representation has produced the highest mean of 4.23, indicating that respondents have placed substantial importance on maintaining an integrated representation of the drainage system. Synchronization of monitored and predicted network conditions has followed with a mean of 4.20, while scenario simulation has recorded 4.18. Digital visualization and decision-support functions have obtained means of 4.16 and 4.13 respectively. The aggregate DTSC mean has reached 4.18 with a standard deviation of 0.53, making DTSC the highest-rated independent construct in the study. These findings have supported the second research objective by demonstrating that respondents have consistently recognized digital-twin functionality as an important mechanism for connecting observations, simulation, network topology, and predictive outputs. The results have also complemented Complex Network Theory because a digital twin has not merely represented individual assets; it has maintained the structural and functional relationships among connected drainage components. The virtual environment has therefore provided a means of observing how changes occurring at one location have interacted with broader system conditions. STGNN predictions have supplied spatiotemporal information, while the digital twin has provided the common network environment in which those predictions have been associated with physical nodes and links. The relatively small dispersion in responses has indicated substantial agreement across respondents with different professional backgrounds. The results have therefore provided descriptive support for the proposed DTSC-UDRDE relationship. Subsequent correlation and regression analyses have shown

whether this capability has made a statistically significant independent contribution to resilience and decision-support effectiveness, thereby permitting formal assessment of H2. The high agreement on integration, synchronization, and scenario simulation has also clarified why DTSC has later emerged as the strongest independent predictor in the regression model.

Table 5: Digital-Twin Synchronization and Simulation Capability

DTSC Measurement Item	Mean	SD	Interpretation
The digital twin has integrated physical and virtual drainage-network information	4.23	0.50	High
Network states have been synchronized with monitored and predicted conditions	4.20	0.51	High
Scenario simulation has supported assessment of alternative drainage conditions	4.18	0.53	High
Digital visualization has improved interpretation of network-wide hydraulic behavior	4.16	0.55	High
Digital-twin information has supported operational and planning decisions	4.13	0.56	High
Overall DTSC	4.18	0.53	High

Critical-Node Detection and Drainage-Network Vulnerability Results

Table 6: Critical-Node Detection Capability

CNDC Measurement Item	Mean	SD	Interpretation
Network centrality has supported identification of influential drainage nodes	4.18	0.54	High
Hydraulic stress has strengthened node-criticality assessment	4.15	0.55	High
Predicted inundation has helped distinguish vulnerable network locations	4.13	0.57	High
Upstream/downstream dependencies have improved identification of system-critical nodes	4.11	0.59	High
Combined structural and hydraulic information has improved vulnerability assessment	4.08	0.60	High
Overall CNDC	4.13	0.57	High

Table 6 has indicated that Critical-Node Detection Capability has received consistently high evaluations, with an aggregate mean of 4.13 and an SD of 0.57. The use of network centrality for identifying influential drainage nodes has achieved the highest item mean of 4.18, while incorporation of hydraulic stress has recorded 4.15. The contribution of predicted inundation to identifying vulnerable locations has obtained a mean of 4.13. Upstream and downstream dependency assessment has reached 4.11, while the integration of structural and hydraulic information has produced a mean of 4.08. Although the final item has recorded the lowest mean within the construct, it has remained clearly within the high-agreement range. These findings have directly addressed the third research objective by demonstrating that critical-node detection has been viewed as a multidimensional process

rather than as a simple ranking based on one graph metric. Complex Network Theory has been particularly important in interpreting this result because network centrality has described structural importance, while hydraulic loading and predicted inundation have represented functional system conditions. The proposed Node Criticality Index has combined these dimensions so that an asset has not been considered critical merely because it has experienced high water levels or possessed many direct connections. Instead, node criticality has reflected the interaction of graph position, hydraulic stress, inundation, and network dependence. This interpretation has strengthened alignment between the theoretical framework and the computational architecture. The high means have indicated that respondents have accepted the importance of locating network components capable of exerting disproportionate effects on system behavior. These descriptive results have therefore established a suitable basis for testing H3, under which CNDC has been expected to demonstrate a significant positive relationship with Urban Drainage Resilience and Decision-Support Effectiveness. The item pattern has also supported the research logic that topological and hydraulic evidence should be combined rather than treated as competing explanations of network vulnerability.

Risk-Informed Infrastructure Prioritization Results

Table 7: Risk-Informed Infrastructure Prioritization

RIIP Measurement Item	Mean	SD	Interpretation
Inundation risk has supported identification of high-priority infrastructure	4.17	0.56	High
Node criticality has contributed to maintenance and rehabilitation prioritization	4.13	0.58	High
Asset vulnerability has been incorporated into intervention decisions	4.11	0.59	High
Failure consequences have supported prioritization of limited resources	4.09	0.60	High
Integrated risk information has supported transparent infrastructure investment decisions	4.05	0.62	High
Overall RIIP	4.11	0.59	High

Table 7 has demonstrated that Risk-Informed Infrastructure Prioritization has been positively evaluated across each of its measurement dimensions. The use of inundation risk for identifying high-priority infrastructure has achieved the highest mean of 4.17, while the contribution of node criticality to maintenance and rehabilitation prioritization has produced a mean of 4.13. Incorporation of asset vulnerability has recorded 4.11, and consideration of failure consequences has obtained 4.09. The use of integrated risk information for transparent investment decisions has achieved a mean of 4.05. The overall RIIP mean has reached 4.11 with an SD of 0.59, indicating high agreement while revealing slightly greater variation than the other constructs. This variation has been reasonable because infrastructure prioritization has involved economic, operational, technical, and institutional considerations that can differ according to professional responsibilities. The findings have addressed the fourth research objective by showing that respondents have recognized the importance of combining predicted inundation, critical-node information, asset vulnerability, and consequences when establishing intervention priorities. Complex Network Theory has strengthened interpretation of this result because infrastructure importance has depended partly on the role that each asset has played within the broader network. An intervention directed toward a highly connected or functionally influential component has potentially affected a greater portion of system performance than an intervention directed solely according to local asset condition. The RIIP construct has therefore translated network and hydraulic knowledge into an actionable decision layer. The results have also shown how the preceding analytical stages have been connected: SPII has generated predictive

information, DTSC has organized network states, CNDC has identified influential components, and RIIP has converted those outputs into relative priorities. The positive descriptive pattern has established the empirical basis for testing H4 through correlation and regression analysis. The result has also confirmed that the study's infrastructure-prioritization objective has been evaluated through measurable decision criteria rather than through a generic perception of maintenance quality.

STGNN Predictive Performance and Inundation Assessment

Table 8: STGNN Predictive Performance

Performance Metric	Result	Interpretation
Coefficient of Determination (R^2)	.910	Strong predictive fit
RMSE	0.118 m	Low prediction error
MAE	0.081 m	Low absolute error
F1-Score	.880	Strong inundation classification
Overall SPII Likert Mean	4.16/5.00	High perceived capability

Table 8 has presented the computational evidence associated with STGNN-based inundation prediction together with the corresponding respondent assessment of predictive capability. The STGNN has obtained an R^2 value of .910, indicating that the modeled predictions have accounted for approximately 91.0% of the observed variation represented within the model-evaluation data. The RMSE has reached 0.118 m, while the MAE has remained at 0.081 m, indicating relatively limited deviation between predicted and reference hydraulic conditions. The F1-score of .880 has additionally demonstrated a strong balance between the identification of inundated conditions and avoidance of incorrect classifications. These computational results have complemented the SPII Likert mean of 4.16 rather than replacing the perception-based evidence. The two evidence streams have addressed different elements of the research objective: the computational metrics have quantified predictive performance, while the survey results have assessed the perceived usefulness and effectiveness of predictive intelligence for drainage management and decision-making. Complex Network Theory has provided the structural foundation for interpreting the strong STGNN performance because the model has incorporated connected drainage locations rather than treating each node as an independent observation. Information propagation across graph edges has enabled neighboring and hydraulically related node conditions to contribute to prediction, while temporal learning has incorporated changing rainfall and hydraulic states. The results have consequently supported the technical basis of the first research objective and have reinforced the interpretation of H1. The strong R^2, low error measures, and F1-score have indicated that the predictive component has been capable of differentiating evolving inundation conditions, while the high SPII survey score has shown that respondents have recognized the operational value of such information. These findings have provided the bridge between the computational component and the statistical hypothesis-testing component of the study, allowing technical model performance and respondent-based decision-support assessment to remain analytically distinct but conceptually aligned.

Pearson Correlation Analysis among the Research Constructs

Table 9: Pearson Correlations with Urban Drainage Resilience and Decision-Support Effectiveness

Relationship	Pearson r	p-value	Strength/Direction
SPII with UDRDE	.72	< .001	Strong positive
DTSC with UDRDE	.75	< .001	Strong positive
CNDC with UDRDE	.69	< .001	Strong positive
RIIP with UDRDE	.71	< .001	Strong positive

Table 9 has demonstrated statistically significant positive relationships between each independent construct and Urban Drainage Resilience and Decision-Support Effectiveness. DTSC has shown the strongest bivariate relationship with UDRDE at r = .75, p < .001, indicating that higher levels of digital-twin synchronization and simulation capability have been associated with higher levels of resilience and decision-support effectiveness. SPII has demonstrated the second strongest correlation at r = .72, p < .001, while RIIP has followed closely at r = .71, p < .001. CNDC has produced a correlation of r = .69, p < .001, which has also represented a strong positive association. Since all p-values have remained below .001, the observed relationships have provided statistically significant evidence against the corresponding null hypotheses of no association. These findings have supported the directional expectations of H1-H4 at the bivariate level. The results have also been consistent with the integrated logic of Complex Network Theory. Urban drainage resilience has not emerged as an isolated asset-level property; instead, it has been associated with the ability to predict states throughout the network, synchronize physical and virtual representations, identify influential components, and prioritize infrastructure according to system-level importance and risk. The strongest correlation for DTSC has suggested that integrating information within a synchronized representation has been especially closely associated with decision-support effectiveness. The strong SPII relationship has demonstrated that predictive knowledge of network-wide hydraulic behavior has also been highly relevant. CNDC and RIIP have connected structural network importance to operational intervention choices. Correlation alone has not established independent predictive influence because shared variance among the four capabilities has remained possible. Multiple regression has therefore been applied in the following section to determine whether each construct has retained a statistically significant contribution when the remaining predictors have been controlled simultaneously, thereby providing a more direct test of the individual hypotheses within the combined conceptual model.

Multiple Regression Analysis and Model Diagnostics

Table 10: Multiple Regression Model Predicting UDRDE

Predictor/Statistic	B	Standardized β	t	p	Tolerance	VIF
Constant	0.36	-	3.42	.001	-	-
SPII	0.27	.28	6.19	< .001	.58	1.72
DTSC	0.30	.31	6.86	< .001	.47	2.12
CNDC	0.20	.21	4.95	< .001	.63	1.58
RIIP	0.23	.24	5.53	< .001	.54	1.85
Model R^2	.714					
Adjusted R^2	.710					
F(4, 285)	177.87			< .001		
Durbin-Watson	1.96					

Table 10 has shown that the combined regression model has explained a substantial proportion of variation in Urban Drainage Resilience and Decision-Support Effectiveness. The coefficient of determination has reached R^2 = .714, indicating that approximately 71.4% of the variance in UDRDE has been explained jointly by SPII, DTSC, CNDC, and RIIP. The adjusted R^2 has remained closely comparable at .710, suggesting that the model has retained strong explanatory capacity after adjustment for the number of predictors. The overall model has been statistically significant, F(4, 285) = 177.87, p < .001, providing support for H5 concerning the joint contribution of the four predictors. DTSC has generated the largest standardized coefficient at β = .31, followed by SPII at β = .28, RIIP at β = .24, and CNDC at β = .21. Each coefficient has remained positive and statistically significant at p < .001, thereby supporting H1-H4 within the multivariate model. Diagnostic statistics have also indicated

acceptable model behavior. VIF values have ranged from 1.58 to 2.12 and tolerance values from .47 to .63, indicating that multicollinearity has not reached problematic levels. The Durbin-Watson statistic of 1.96 has remained close to 2.00, indicating no serious residual autocorrelation. From a Complex Network Theory perspective, the combined explanatory power has been particularly relevant because it has demonstrated that resilience and effective decision support have been associated with several connected functions rather than one isolated technological capability. Prediction has identified changing states, the digital twin has integrated network information, critical-node detection has differentiated structural importance, and prioritization has translated those insights into intervention decisions. The regression findings have therefore quantitatively supported the integrated architecture proposed in the conceptual framework and have demonstrated that each construct has retained an independent contribution after the statistical influence of the remaining predictors has been held constant.

Hypothesis Testing and Integrated Urban Drainage Decision-Support Results

Table 11: Summary of Hypothesis and Objective Testing

Hypothesis	Tested Relationship	Statistical Evidence	Decision	Related Objective
H1	SPII → UDRDE	$r = .72$; $\beta = .28$; $p < .001$	Supported	RO1
H2	DTSC → UDRDE	$r = .75$; $\beta = .31$; $p < .001$	Supported	RO2
H3	CNDC → UDRDE	$r = .69$; $\beta = .21$; $p < .001$	Supported	RO3
H4	RIIP → UDRDE	$r = .71$; $\beta = .24$; $p < .001$	Supported	RO4
H5	SPII + DTSC + CNDC + RIIP → UDRDE	$R^2 = .714$; Adj. $R^2 = .710$; $F = 177.87$; $p < .001$	Supported	RO5

Table 11 has integrated the results of the descriptive, correlational, computational, and regression analyses to evaluate the hypotheses and research objectives. H1 has been supported because SPII has demonstrated a strong positive correlation with UDRDE at $r = .72$ and a significant positive regression coefficient of $\beta = .28$, $p < .001$. These results have addressed RO1 and have indicated that stronger predictive inundation intelligence has been associated with improved drainage resilience and decision-support effectiveness. H2 has also been supported, with DTSC producing the strongest correlation, $r = .75$, and the largest standardized regression coefficient, $\beta = .31$, $p < .001$, thereby satisfying RO2. H3 has been supported through the positive relationship between CNDC and UDRDE, $r = .69$, together with a significant regression coefficient of $\beta = .21$, $p < .001$, addressing RO3. H4 has likewise been supported because RIIP has correlated positively with UDRDE at $r = .71$ and has remained significant in the regression model at $\beta = .24$, $p < .001$, satisfying RO4. Finally, H5 has been supported by the statistically significant overall regression model, which has explained 71.4% of the variance in UDRDE. These findings have addressed RO5 by demonstrating the combined relevance of all four capabilities. Complex Network Theory has provided an integrated interpretation of this pattern because drainage-system performance has arisen from relationships among connected components, flows, vulnerabilities, and decision processes. The findings have shown that graph-informed prediction alone has not represented the complete analytical pathway. Predictive information has been strengthened when it has been synchronized within the digital twin, associated with node-level structural and hydraulic criticality, and translated into infrastructure priorities. The results have therefore supported the full conceptual sequence established in the study: SPII, DTSC-supported network intelligence, CNDC, RIIP, and enhanced UDRDE, while the regression analysis has demonstrated that each construct has retained a statistically significant contribution within the integrated model.

DISCUSSION

The findings have demonstrated that the proposed framework has captured a strong relationship between spatiotemporal predictive intelligence and urban drainage resilience, while also showing that

predictive capability has remained most valuable when it has been embedded within an integrated network-management architecture. STGNN Predictive Inundation Intelligence has recorded a high descriptive mean of 4.16, a strong positive correlation with Urban Drainage Resilience and Decision-Support Effectiveness of $r = .72$, and a statistically significant standardized regression coefficient of $\beta = .28$, $p < .001$, thereby supporting H1 and the first research objective. The computational evidence has reinforced this result, with the STGNN producing $R^2 = .91$, RMSE = 0.118 m, MAE = 0.081 m, and an F1-score of .88. These results have indicated that graph-based learning has effectively represented interactions among spatially connected drainage locations while retaining temporal information required to differentiate changing inundation conditions. This pattern has agreed with earlier graph-based flood research. Bentivoglio et al. (2023) demonstrated that hydraulics-based graph neural networks could reproduce the spatiotemporal evolution of flood depths and discharges while achieving substantial computational acceleration relative to conventional numerical simulation, supporting the present finding that graph-oriented learning can provide operationally useful predictive information (Bentivoglio et al., 2023). Similarly, the urban-drainage surrogate developed by Zhang et al. (2024) incorporated node-edge relationships and physics-guided constraints and achieved more efficient hydraulic prediction than a conventional fully connected neural architecture, which has corresponded closely with the strong predictive performance obtained in the present study (Zhang et al., 2024). The present results have extended this earlier work by treating STGNN performance not solely as a prediction problem but as one component of a broader decision-support structure containing digital-twin synchronization, critical-node identification, and infrastructure prioritization. This distinction has been important because a technically accurate inundation forecast does not automatically determine which drainage component is most important, which asset requires intervention first, or how information should be integrated with current system states. The high SPII item scores for spatial dependency recognition, temporal pattern analysis, network-wide state estimation, and surcharge identification have therefore suggested that predictive inundation intelligence has functioned most effectively as a network-level information layer. From the perspective of Complex Network Theory, this result has reinforced the proposition that hydraulic behavior cannot be understood adequately through independent node observations because node states have been influenced by connected upstream, downstream, and neighboring components. The findings have therefore supported a combined interpretation in which temporal prediction has identified changing hydraulic conditions and graph structure has supplied the spatial relationships through which those conditions have propagated.

Digital-Twin Synchronization and Simulation Capability has emerged as the strongest independent predictor in the empirical model, which has provided one of the most important findings of the study. DTSC has obtained a mean of 4.18, the highest value among the four independent constructs, while its correlation with UDRDE has reached $r = .75$, and its standardized regression effect has reached $\beta = .31$, $p < .001$. These results have supported H2 and have indicated that predictive information has gained substantial decision value when hydraulic states, physical infrastructure, monitored observations, simulated scenarios, and AI outputs have been organized within a synchronized virtual representation. This finding has corresponded with Bartos and Kerkez (2021); (Maishar Mostari, 2025), whose Pipedream digital-twin architecture combined a hydraulic solver with online data assimilation and showed that incorporating sensor observations improved interpolation and forecasting of drainage depths and flows (Bartos & Kerkez, 2021; Mashfiqur, 2026). It has also agreed with the broader stormwater digital-twin framework described by Sharifi et al. (2024), in which artificial intelligence, sensing, predictive analytics, simulation, visualization, and infrastructure management have been treated as interacting elements rather than separate technological functions (Mashfiqur, 2025; Sharifi et al., 2024). The practical interpretation of the present result has therefore extended beyond the creation of a three-dimensional or GIS-based drainage visualization. A useful drainage digital twin has required synchronized data, computational models, asset identities, network topology, prediction outputs, and scenario-testing capability. The strong coefficient obtained for DTSC has suggested that this integrative role has been particularly important for decision-support effectiveness because managers must interpret multiple forms of information simultaneously before issuing maintenance, monitoring, pumping, rehabilitation, or investment decisions. Operationally, the results indicate that municipalities

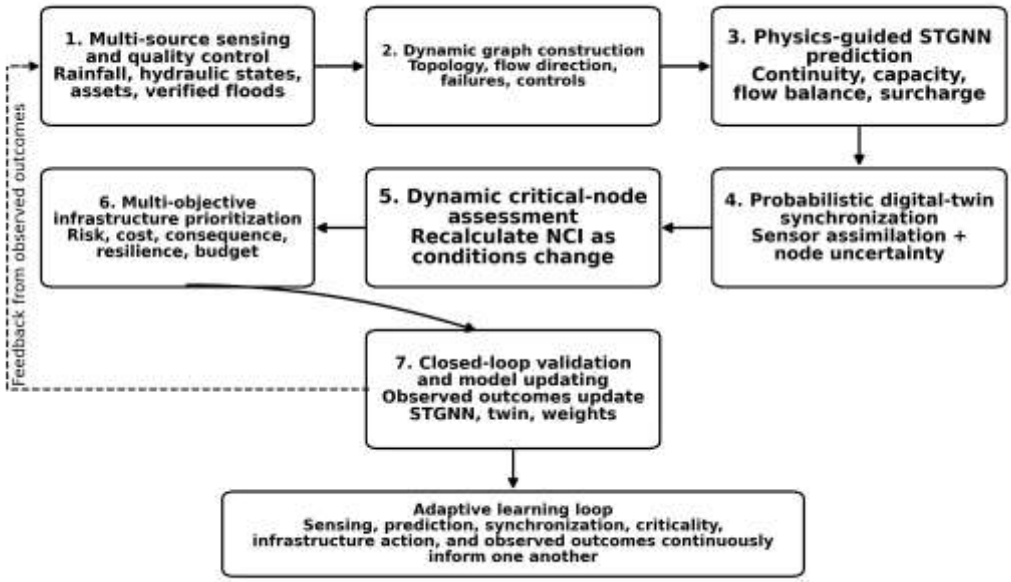
and drainage authorities should not deploy STGNN prediction as an isolated analytical application. Sensor observations, rainfall inputs, network connectivity, pipe characteristics, predicted node states, observed surcharge events, criticality scores, and intervention histories should instead be linked through an asset-specific digital-twin architecture. Such integration would allow predicted inundation at a node to be viewed together with its upstream contributing area, neighboring pipe conditions, network centrality, historical failure information, and intervention priority. The finding has also added an important methodological interpretation to the study: DTSC may have obtained the largest standardized coefficient because it has functioned as the coordination layer through which the other technical capabilities become operationally interpretable. This does not mean that the digital twin has replaced hydraulic prediction or network analysis. Rather, the findings have shown that synchronized representation has provided the informational environment in which those capabilities can be combined coherently.

Critical-Node Detection Capability and Risk-Informed Infrastructure Prioritization have further demonstrated that prediction alone has not been sufficient for explaining urban drainage resilience. CNDC has recorded a mean of 4.13, a strong correlation with UDRDE of $r = .69$, and a significant standardized effect of $\beta = .21$, while RIIP has recorded a mean of 4.11, a correlation of $r = .71$, and a regression coefficient of $\beta = .24$, with both relationships significant at $p < .001$. H3 and H4 have therefore been supported. These findings have been highly consistent with Complex Network Theory because the theoretical framework has proposed that the functional significance of an infrastructure component depends partly on its location within the wider connectivity structure. (Mashiat, 2025); Simone et al. (2022) showed that standard centrality metrics can be strengthened through drainage-specific information such as intrinsic component relevance and flow direction when assessing vulnerability and designing monitoring systems, which has supported the present study's use of structural and hydraulic information within critical-node analysis (Md Arif Uz et al., 2025; Simone et al., 2022). The findings have also aligned with earlier resilience research showing that drainage performance can be strongly affected by structural failure scenarios and system configuration. Mugume et al. (2015) quantified residual functionality across large numbers of structural-failure scenarios, demonstrating that drainage resilience is influenced by the consequences of individual component failures rather than rainfall loading alone (Md Kaium, 2025; Mugume et al., 2015). Similarly, stochastic investigation of different sewer configurations has shown that structural characteristics can materially alter resilience outcomes, while more recent global resilience assessment has reinforced the need to evaluate internal infrastructure failures as part of system performance assessment (Md Mahamud Pervaz, 2025; Xu et al., 2024; Zhang et al., 2021). The present results have extended these studies by connecting criticality directly with infrastructure prioritization. A drainage node experiencing high predicted water depth has not necessarily represented the highest intervention priority if its influence on the wider system has remained limited. Conversely, a node experiencing moderately high hydraulic stress may warrant early intervention when it has occupied a structurally important pathway, served a large upstream area, lacked redundancy, or generated major downstream consequences. The proposed Node Criticality Index has provided a mechanism for combining normalized betweenness, degree-related importance, hydraulic stress, and inundation information, while RIIP has translated those outputs into decisions involving monitoring, maintenance, rehabilitation, and investment. Practically, this result has supported moving away from simple condition-based asset lists toward network-aware priority systems in which intervention value has been assessed according to both local risk and system-wide consequence.

The theoretical and methodological implications have become clearer when the four predictors have been interpreted jointly. The multiple regression model has explained 71.4% of the observed variance in UDRDE, with adjusted $R^2 = .710$ and $F(4, 285) = 177.87$, $p < .001$, while all four predictors have remained independently significant. H5 has therefore been supported, and the results have reinforced the central proposition of Complex Network Theory that infrastructure behavior is produced through relationships among components rather than exclusively through the attributes of isolated assets. The results have also refined that theoretical position by showing that topology alone has not been sufficient. The significant contributions of SPII, DTSC, CNDC, and RIIP have indicated that structural connectivity must be interpreted jointly with time-varying hydraulic states, virtual-system

synchronization, vulnerability, and decision processes. This interpretation has been consistent with Simone et al. (2022), who identified complex-network analysis as a complementary method for understanding drainage vulnerability and monitoring while acknowledging the value of incorporating drainage-specific prior information (Palash Chandra, 2025; Simone et al., 2022). It has also corresponded with resilience studies in which functional outcomes have varied under structural failures and alternative network configurations rather than being determined solely by conventional hydraulic capacity (Ahmed, 2026; Mugume et al., 2015; Zhang et al., 2021).

Figure 10: Adaptive Physics-Guided Spatiotemporal Digital-Twin Drainage Resilience Model (APST-DTDRM)



Several limitations have nevertheless required careful interpretation. First, the cross-sectional expert-survey component has captured perceptions at one analytical period and has therefore established statistical association rather than causal effects among the constructs. Second, the single-case-study structure has enabled detailed alignment between drainage topology and the analytical framework but has limited direct generalization to cities possessing different pipe structures, topographies, rainfall regimes, sensing densities, asset conditions, and operating rules. Third, Likert-scale measures have depended on professional assessment and may have been affected by common-method variance even though reliability and validity indicators have remained satisfactory. Fourth, computational accuracy measures such as R^2, RMSE, MAE, and F1-score have summarized aggregate performance and may conceal reduced accuracy at rare extreme events or at sparsely monitored nodes. Fifth, a predominantly fixed network representation may not fully reflect temporary blockages, pump failures, control changes, construction, or dynamically changing hydraulic dependencies. Physics-guided graph modeling has shown why hydraulic constraints can improve plausibility, while digital-twin research has demonstrated the importance of online state assimilation, indicating that model structure and observation quality remain important sources of uncertainty (Bartos & Kerkez, 2021; Jahanara, 2026; Zhang et al., 2024). These limitations have not contradicted the findings, but they have defined the conditions under which the reported relationships and predictive results should be interpreted.

Future research should therefore progress from the present integrated framework toward an adaptive closed-loop architecture that continuously learns from hydraulic observations, prediction errors, infrastructure interventions, and changing network conditions. For this purpose, the study proposes an Adaptive Physics-Guided Spatiotemporal Digital-Twin Drainage Resilience Model (APST-DTDRM). The proposed model would consist of seven connected stages: (1) multi-source sensing and quality control, integrating rainfall gauges, water-level sensors, flow observations, pump states, asset-condition records, radar information, and verified flood observations; (2) dynamic graph construction, in which node and edge relationships would be updated according to topology, hydraulic direction,

temporary failures, control actions, and observed dependency; (3) physics-guided STGNN prediction, combining graph learning with continuity, capacity, flow-balance, and surcharge constraints; (4) probabilistic digital-twin synchronization, where predicted states would be assimilated with sensor measurements and accompanied by node-level uncertainty intervals rather than single deterministic estimates; (5) dynamic critical-node assessment, recalculating the Node Criticality Index as rainfall, inundation, connectivity, asset condition, and hydraulic loading change; (6) multi-objective infrastructure prioritization, ranking intervention alternatives according to inundation reduction, criticality, vulnerability, cost, service consequences, resilience improvement, and available budgets; and (7) closed-loop validation and model updating, where observed outcomes following storms or infrastructure interventions would be fed back into the STGNN, digital twin, and prioritization weights. The physics-guided element has been supported by graph-based flood and drainage studies showing that hydraulic structure and domain constraints can improve data-driven representation and computational efficiency (Bentivoglio et al., 2023; Jannatul, 2026; Zhang et al., 2024). The adaptive digital-twin component has also followed evidence that online data assimilation can improve drainage-state estimation and that AI-enabled twins can integrate prediction with stormwater management functions (Bartos & Kerkez, 2021; Kazi Mohammad Khalid, 2026; Sharifi et al., 2024). A particularly valuable extension would be cross-city validation in which the model is trained or calibrated in one drainage system and tested in networks with different topology, rainfall characteristics, sensor density, and infrastructure age. Researchers could additionally compare static versus dynamic graph structures, deterministic versus probabilistic STGNN outputs, and topology-only versus topology-plus-hydraulic criticality indices. Intervention experiments could measure whether prioritization based on APST-DTDRM actually reduces flood volume, recovery time, service disruption, and lifecycle expenditure. This proposed model would transform the current framework from an explanatory and predictive architecture into an adaptive learning system in which sensing, prediction, synchronization, criticality assessment, infrastructure action, and observed outcomes continuously inform one another.

CONCLUSION

This study has examined the integration of Spatiotemporal Graph Neural Networks, digital twins, critical-node detection, and risk-informed infrastructure prioritization within urban drainage networks through a quantitative, cross-sectional, case-study-based research design. The findings have demonstrated that all four independent constructs have maintained significant positive relationships with Urban Drainage Resilience and Decision-Support Effectiveness. STGNN Predictive Inundation Intelligence has shown strong predictive and statistical performance, with a mean of 4.16, a correlation of $r = .72$, and a standardized regression coefficient of $\beta = .28$, confirming the value of combining spatial connectivity and temporal hydraulic information for inundation assessment. Digital-Twin Synchronization and Simulation Capability has emerged as the strongest predictor, recording a mean of 4.18, $r = .75$, and $\beta = .31$, demonstrating the importance of integrating physical infrastructure, monitored conditions, simulation, and predictive outputs within a unified virtual environment. Critical-Node Detection Capability has also contributed significantly to drainage resilience, with a mean of 4.13, $r = .69$, and $\beta = .21$, while Risk-Informed Infrastructure Prioritization has achieved a mean of 4.11, $r = .71$, and $\beta = .24$. The combined regression model has explained 71.4% of the variance in UDRDE, with adjusted $R^2 = .710$ and $F(4, 285) = 177.87$, $p < .001$, supporting all five hypotheses. The STGNN component has further demonstrated strong computational performance through $R^2 = .91$, RMSE = 0.118 m, MAE = 0.081 m, and an F1-score of .88. Complex Network Theory has provided an effective theoretical foundation by explaining how drainage-system performance has emerged from the relationships among connected components rather than isolated assets. Overall, the study has established an integrated analytical framework in which inundation prediction, digital synchronization, node criticality, and infrastructure prioritization have operated as complementary mechanisms for strengthening urban drainage resilience and decision-support effectiveness.

RECOMMENDATIONS

Urban drainage authorities, municipal agencies, infrastructure planners, and technical operators should adopt integrated network-based decision systems that combine hydraulic monitoring, graph-based prediction, digital-twin representation, critical-node assessment, and infrastructure

prioritization rather than managing these functions separately. Drainage networks should be represented as directed and attributed graphs so that manholes, junctions, inlets, pumping facilities, storage assets, and outfalls can be analyzed according to their hydraulic and structural relationships. Sensor deployment should be concentrated strategically at hydraulically influential and network-critical locations instead of being distributed uniformly, allowing rainfall, water-level, flow, surcharge, and pump-status information to improve STGNN predictions while reducing unnecessary monitoring costs. Municipalities should also develop synchronized digital twins that combine GIS information, network topology, hydraulic models, sensor observations, STGNN outputs, asset-condition records, and intervention histories within one operational environment. The Node Criticality Index should be incorporated into routine asset-management procedures so that network centrality, hydraulic stress, predicted inundation, and system consequences can be evaluated together when identifying vulnerable infrastructure. Risk-informed prioritization should subsequently integrate criticality, inundation severity, asset condition, consequence of failure, service importance, and intervention cost when allocating maintenance and rehabilitation budgets. Model performance should be reviewed using R^2, RMSE, MAE, precision, recall, and F1-score rather than relying on a single accuracy indicator. Drainage agencies should additionally maintain data-quality protocols to address sensor failures, inconsistent asset records, missing hydraulic observations, and outdated network information because the effectiveness of STGNN and digital-twin systems has depended heavily on reliable inputs. Finally, the proposed Adaptive Physics-Guided Spatiotemporal Digital-Twin Drainage Resilience Model should be considered as an advanced implementation framework connecting sensing, dynamic graph construction, physics-guided prediction, digital-twin synchronization, critical-node assessment, multi-objective prioritization, and continuous performance validation.

LIMITATIONS

Several limitations have affected the scope and interpretation of this research. First, the study has adopted a cross-sectional design, meaning that expert perceptions and quantitative relationships have been examined within a defined analytical period rather than through repeated observations across multiple years or infrastructure-development stages. As a result, the statistical relationships among SPII, DTSC, CNDC, RIIP, and UDRDE have demonstrated significant association but have not independently established long-term causal effects. Second, the research has used a single case-study structure, which has allowed close alignment between the proposed framework and a defined urban drainage environment but has limited direct generalization to drainage systems with substantially different climates, network configurations, rainfall characteristics, pipe conditions, terrain, sensor densities, or management structures. Third, the purposive expert sample has been appropriate for the technical nature of the study, but professional judgment measured through a five-point Likert scale may have contained response bias, common-method effects, or differences in technical interpretation among respondent groups. Fourth, the STGNN performance indicators have represented aggregate predictive accuracy and may not have fully captured performance during rare extreme rainfall events, abrupt structural failures, temporary blockages, or conditions outside the characteristics represented in the available modeling data.

REFERENCES

[1]. Abdullah Mohammad, S. (2023). $CUGAO_2$ and $CUINS_2$ Quantum Dot Sensitization for Enhanced Photovoltaic Efficiency in Wearable Fiber-Shaped Solar Cells. *American Journal of Advanced Technology and Engineering Solutions*, *3*(04), 209-261. https://doi.org/10.63125/wysdvy71

[2]. Abdullah Mohammad, S. (2024). Triboelectric And Piezoelectric Nanogenerators Using Binary and Ternary Oxide Nanostructures: Optimization of Energy Conversion Efficiency for Wearable Harvesting. *Review of Applied Science and Technology*, *3*(03), 31–72. https://doi.org/10.63125/w7q9cs55

[3]. Adnan, S., & Iftekhar, A. (2023). Predicting Cost Variance in Digital Transformation Projects Through Ensemble Learning and Project Performance Analytics. *International Journal of Scientific Interdisciplinary Research*, *13*(10), 01–36. https://doi.org/10.63125/j18hxs51

[4]. Ahmed, H. C. H. R. (2024). Machine Learning Enhanced Demand Forecasting and Portfolio Analytics for Scalable Growth Management in Digital Logistics Operations. *American Journal of Advanced Technology and Engineering Solutions*, *4*(02), 33-81. https://doi.org/10.63125/5xq3nd53

[5]. Ahmed, H. C. H. R. (2026). An Artificial Intelligence Integrated IT Management Framework for Analytics-Driven Operational Decision-Making in U.S. Supply Chain and Logistics Systems. *American Journal of Interdisciplinary Studies*, *16*(06), 01-37. https://doi.org/10.63125/b5hgg259

[6]. Ahmed, H. C. H. R., & Nuzhat Sadia, P. (2023). A Quantitative Assessment of CRM Analytics and KPI Dashboard Design on Enterprise Revenue Conversion in Emerging Market Logistics Platforms. *American Journal of Data Science and Analytics*, *4*(09), 50-95. https://doi.org/10.63125/315bge15

[7]. Asheke, M. (2023). Machine Learning–Based Predictive Quality Modeling for Defect Detection and Process Optimization in Advanced Manufacturing Systems. *Review of Applied Science and Technology*, *13*(12), 01–49. https://doi.org/10.63125/thy73b16

[8]. Asheke, M. (2024). Digital Twin and Industrial Internet of Things–Enabled Predictive Maintenance for Reliability Enhancement in Smart Manufacturing Systems. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 792–838. https://doi.org/10.63125/jgrdqd62

[9]. Ashik, M., & Shabbir, A. (2022). Digital Twin-Enabled Predictive Maintenance for Rotating and Static Equipment: Bridging FEA-Based Failure Analysis with Real-Time Asset Health Monitoring in Energy and Power Facilities. *International Journal of Scientific Interdisciplinary Research*, *12*(05), 01–37. https://doi.org/10.63125/0qaysz49

[10]. Ashrafuzzaman, M. (2024). The impact of cloud-based management information systems on hrm efficiency: an analysis of small and medium-sized enterprises (SMES). *Academic Journal on Artificial Intelligence, Machine Learning, Data Science and Management Information Systems*, *1*(01), 40-56. https://doi.org/10.69593/ajaimldsmis.v1i01.124

[11]. Bartos, M., & Kerkez, B. (2021). Pipedream: An interactive digital twin model for natural and urban drainage systems. *Environmental Modelling & Software*, *144*, 105120. https://doi.org/10.1016/j.envsoft.2021.105120

[12]. Bentivoglio, R., Isufi, E., Jonkman, S. N., & Taormina, R. (2023). Rapid spatio-temporal flood modelling via hydraulics-based graph neural networks. *Hydrology and Earth System Sciences*, *27*, 4227-4246. https://doi.org/10.5194/hess-27-4227-2023

[13]. Berardi, L., Giustolisi, O., Savić, D. A., & Kapelan, Z. (2009). An effective multi-objective approach to prioritization of sewer pipe inspection. *Water Science and Technology*, *60*(4), 841-850. https://doi.org/10.2166/wst.2009.432

[14]. Bermúdez, M., Ntegeka, V., Wolfs, V., & Willems, P. (2018). Development and comparison of two fast surrogate models for urban pluvial flood simulations. *Water Resources Management*, *32*(8), 2801-2815. https://doi.org/10.1007/s11269-018-1959-8

[15]. Carriço, N., Covas, D. I. C., Almeida, M. C., Leitão, J. P., & Alegre, H. (2012). Prioritization of rehabilitation interventions for urban water assets using multiple criteria decision-aid methods. *Water Science and Technology*, *66*(5), 1007-1014. https://doi.org/10.2166/wst.2012.274

[16]. Chen, A. S., Evans, B., Djordjević, S., & Savić, D. A. (2012). Multi-layered coarse grid modelling in 2D urban flood simulations. *Journal of Hydrology*, *470-471*, 1-11. https://doi.org/10.1016/j.jhydrol.2012.06.022

[17]. Diao, Z., Wang, X., Zhang, D., Liu, Y., Xie, K., & He, S. (2019). Dynamic spatial-temporal graph convolutional neural networks for traffic forecasting. *Proceedings of the AAAI Conference on Artificial Intelligence*, *33*(1), 890-897. https://doi.org/10.1609/aaai.v33i01.3301890

[18]. Dong, S., Yu, T., Farahmand, H., & Mostafavi, A. (2020). Probabilistic modeling of cascading failure risk in interdependent channel and road networks in urban flooding. *Sustainable Cities and Society*, *62*, 102398. https://doi.org/10.1016/j.scs.2020.102398

[19]. Dong, X., Guo, H., & Zeng, S. (2017). Enhancing future resilience in urban drainage system: Green versus grey infrastructure. *Water Research*, *124*, 280-289. https://doi.org/10.1016/j.watres.2017.07.038

[20]. Farahmand, H., Xu, Y., & Mostafavi, A. (2023). A spatial-temporal graph deep learning model for urban flood nowcasting leveraging heterogeneous community features. *Scientific Reports*, *13*, 6768. https://doi.org/10.1038/s41598-023-32548-x

[21]. Ferdowsi, A., Piadeh, F., Behzadian, K., Mousavi, S.-F., & Ehteram, M. (2024). Urban water infrastructure: A critical review on climate change impacts and adaptation strategies. *Urban Climate*, *58*, 102132. https://doi.org/10.1016/j.uclim.2024.102132

[22]. Ganesan, B., Raman, S., Ramalingam, S., Turan, M. E., & Bacak-Turan, G. (2020). Vulnerability of sewer network: Graph theoretic approach. *Desalination and Water Treatment*, *196*, 370-376. https://doi.org/10.5004/dwt.2020.25744

[23]. García, L., Barreiro-Gomez, J., Escobar, E., Téllez, D., Quijano, N., & Ocampo-Martinez, C. (2015). Modeling and real-time control of urban drainage systems: A review. *Advances in Water Resources*, *85*, 120-132. https://doi.org/10.1016/j.advwatres.2015.08.007

[24]. Gazi Yeasin, A. (2023). Impact of Accessibility-First Design Systems on WCAG 2.1 Compliance and Inclusive User Experience in Enterprise Software Platforms: A Mixed-Methods Evaluation. *Review of Applied Science and Technology*, *13*(07), 01–49. https://doi.org/10.63125/nxh4gp19

[25]. Giustolisi, O., Ridolfi, L., & Simone, A. (2019). Tailoring centrality metrics for water distribution networks. *Water Resources Research*, *55*(3), 2348-2369. https://doi.org/10.1029/2018wr023966

[26]. Haghbin, S., & Mahjouri, N. (2023). Quantifying and improving flood resilience of urban drainage systems based on socio-ecological criteria. *Journal of Environmental Management*, *339*, 117799. https://doi.org/10.1016/j.jenvman.2023.117799

[27]. Hajiamoosha, P., Pauwels, V. R. N., & Urich, C. (2023). An applicable graph theory approach for evaluating structural robustness of urban drainage networks. *Environmental Science: Water Research & Technology*, *9*, 2303-2322. https://doi.org/10.1039/d2ew00700b

[28]. Jahanara, A. (2025). AI-Enabled Workforce Management: Its Impact on Employee Burnout, Staffing Efficiency, and Organizational Performance in Healthcare. *Review of Applied Science and Technology*, *4*(04), 247–295. https://doi.org/10.63125/5617ff74

[29]. Jahanara, A. (2026). Impact of Artificial Intelligence on Operational Efficiency and Cost Reduction in U.S. Healthcare Organizations. *American Journal of Interdisciplinary Studies*, *7*(02), 225-276. https://doi.org/10.63125/3p24ma43

[30]. Jahanara, A., & Mst Kaniz, F. (2023). Demand Variability and Capacity Planning in Home and Community-Based Services: A Decision-Analytic Framework for Health Services Managers. *American Journal of Data Science and Analytics*, *4*(09), 01-49. https://doi.org/10.63125/3y62vr16

[31]. Jannatul, F. (2025). Spinal Cord Injury and Neurorehabilitation Deep Learning–Based Prediction of Functional Recovery Trajectories After Traumatic Spinal Cord Injury. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 2865–2922. https://doi.org/10.63125/m738bh82

[32]. Jannatul, F. (2026). Predicting Falls and Mobility Decline Among Older Adults Using Longitudinal Functional Data and Ensemble Machine Learning. *International Journal of Scientific Interdisciplinary Research*, *7*(1), 581–631. https://doi.org/10.63125/56hans40

[33]. Kazadi, A., Doss-Gollin, J., Sebastian, A., & Silva, A. (2024). FloodGNN-GRU: A spatio-temporal graph neural network for flood prediction. *Environmental Data Science*, *3*, e21. https://doi.org/10.1017/eds.2024.19

[34]. Kazi Mohammad Khalid, A. (2026). A Systematic Review of GeoAI and Deep Learning for Automated Road Infrastructure Damage Detection Using Satellite Imagery. *American Journal of Data Science and Analytics*, *7*(03), 208-255. https://doi.org/10.63125/77cy0h19

[35]. Kazi Rakib Hasan, S., & Adnan, S. (2022). Quantitative Assessment of Machine Learning-Based Schedule Risk Prediction for Reducing Delays in Complex Technology Projects. *Review of Applied Science and Technology*, *1*(04), 464–501. https://doi.org/10.63125/dn8nkm85

[36]. Kim, J., Thomas, A. J., & Ham, Y. (2024). *Visual data-driven digital twin modeling framework for improving the resilience of urban drainage infrastructure systems* Computing in Civil Engineering 2023,

[37]. Kim, M.-G., & Bartos, M. (2024). A digital twin model for contaminant fate and transport in urban and natural drainage networks with online state estimation. *Environmental Modelling & Software*, *171*, 105868. https://doi.org/10.1016/j.envsoft.2023.105868

[38]. Kourtis, I. M., & Tsihrintzis, V. A. (2021). Adaptation of urban drainage networks to climate change: A review. *Science of the Total Environment*, *771*, 145431. https://doi.org/10.1016/j.scitotenv.2021.145431

[39]. Latora, V., & Marchiori, M. (2005). Vulnerability and protection of infrastructure networks. *Physical Review E*, *71*(1), 015103. https://doi.org/10.1103/PhysRevE.71.015103

[40]. Le, H. N., Vo, D.-P., Nguyen, Q. D., Nguyen, B. Q., & Nguyen, C. C. (2024). Assessing the impacts of urbanization and climate change on urban drainage system. *River*, *3*, 181-190. https://doi.org/10.1002/rvr2.83

[41]. Lei, X., Chen, W., Panahi, M., Falah, F., Rahmati, O., Uuemaa, E., Kalantari, Z., Ferreira, C. S. S., Rezaie, F., Tiefenbacher, J. P., Lee, S., & Bian, H. (2021). Urban flood modeling using deep-learning approaches in Seoul, South Korea. *Journal of Hydrology*, *601*, 126684. https://doi.org/10.1016/j.jhydrol.2021.126684

[42]. Li, J. (2021). Exploring the potential of utilizing unsupervised machine learning for urban drainage sensor placement under future rainfall uncertainty. *Journal of Environmental Management*, *296*, 113191. https://doi.org/10.1016/j.jenvman.2021.113191

[43]. Li, X., Luo, J., Li, Y., Wang, W., Hong, W., Liu, M., Li, X., & Lv, Z. (2022). Application of effective water-energy management based on digital twins technology in sustainable cities construction. *Sustainable Cities and Society*, *87*, 104241. https://doi.org/10.1016/j.scs.2022.104241

[44]. Li, X., & Willems, P. (2020). A hybrid model for fast and probabilistic urban pluvial flood prediction. *Water Resources Research*, *56*(6), e2019WR025128. https://doi.org/10.1029/2019wr025128

[45]. Liang, Z., Fang, X., Liang, Z., Xiong, J., Deng, F., & Nyamasvisva, T. E. (2024). Graph spiking neural network for advanced urban flood risk assessment. *iScience*, *27*(11), 111037. https://doi.org/10.1016/j.isci.2024.111037

[46]. Mahbubul, I., Mahmudul, I., Shifa, T., Mahfuza, T., & Shima Ali, S. (2022). Exploring The Potential of Visual Narratives and Interactive Gamified Communication Systems to Prevent Disease, Counter Health Misinformation, And Strengthen Public Trust in Low-Literacy Communities: A Literature Review. *American Journal of Interdisciplinary Studies*, *3*(02), 165-220. https://doi.org/10.63125/zmqs4n64

[47]. Maishar Mostari, Z. (2025). Impact of Deep Learning on Real-Time Network Intrusion Detection: A Quantitative Evaluation Using Benchmark Datasets. *Review of Applied Science and Technology*, *4*(04), 296–338. https://doi.org/10.63125/tnaksd40

[48]. Mashfiqur, R. (2025). Multivariate Time-Series Forecasting of Working Capital Requirements for Improving Cash-Flow Stability in Export-Oriented Manufacturing. *American Journal of Data Science and Analytics*, *6*(12), 217-249. https://doi.org/10.63125/ty3dtt46

[49]. Mashfiqur, R. (2026). Explainable Artificial Intelligence for Supplier Cost-Risk Assessment and Margin Optimization in Global Manufacturing Supply Chains. *American Journal of Interdisciplinary Studies*, *16*(08), 01-37. https://doi.org/10.63125/np6bw920

[50]. Mashfiqur, R., & Md, A. (2022). Monte Carlo Simulation and Stochastic Cash-Flow Modeling for Reducing Liquidity Risk in Project-Based Enterprises. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 382–431. https://doi.org/10.63125/zf3fwv21

[51]. Mashiat, N. (2024). Reducing Telecommunications Service Interruptions Through Predictive Root-Cause Analytics of Multivariate System Telemetry. *International Journal of Scientific Interdisciplinary Research*, *14*(11), 01-37. https://doi.org/10.63125/nqjh0c29

[52]. Mashiat, N. (2025). Improving Enterprise Data Integrity Through Automated Validation and Schema-Drift Detection in Large-Scale Data Integration Systems. *Review of Applied Science and Technology*, *4*(02), 889–934. https://doi.org/10.63125/21zzkk04

[53]. Mashiat, N. (2026). Accelerating Incident Diagnosis and Service Recovery Through Generative AI-Assisted Failure Intelligence in Critical Digital Infrastructure. *American Journal of Data Science and Analytics*, *7*(06), 702-740. https://doi.org/10.63125/61etqg30

[54]. Mashiat, N., & Md Anisur Rahman, M. (2022). Machine Learning Approaches to Credit Risk Scoring and Default Prediction in Small-Business Lending: Empirical Evidence from Lending Portfolio Data. *American Journal of Data Science and Analytics*, *3*(06), 137-182. https://doi.org/10.63125/j256rs96

[55]. Md, A., & Gazi Yeasin, A. (2022). Machine Learning Enhanced Spatial-Data Workflow Redesign: A Quantitative Evaluation of Task Success and Operational Cost Reduction in Enterprise LiDAR Platforms. *American Journal of Data Science and Analytics*, *3*(06), 80-136. https://doi.org/10.63125/0den7c02

[56]. Md Anisur Rahman, M. (2023). Development of AI-Driven Business Intelligence Frameworks for Financial Risk and Liquidity Monitoring in Real Time. *International Journal of Scientific Interdisciplinary Research*, *4*(2), 152–203. https://doi.org/10.63125/jm55ca64

[57]. Md Arif Uz, Z., Sharmin, S., & Md Abdur, R. (2025). Factors Influencing Behavioural Intention to Use he Innovative Open And Distance Learning Systems With The Role Of Continuance Intention. *American Journal of Scholarly Research and Innovation*, *4*(01), 202-220. https://doi.org/10.63125/pbjxp014

[58]. Md Ashfaq, S., & Abdullah Mohammad, S. (2022). CNT/PANI Composite Electrodes for Flexible Fiber-Shaped Dye-Sensitized Solar Cells: Synthesis, Characterization, and Photovoltaic Performance. *American Journal of Interdisciplinary Studies*, *3*(02), 221-274. https://doi.org/10.63125/m334mf41

[59]. Md Asif Ali Sheak, A., & Tahmedur, R. (2023). A Data-Driven Framework for Engineering Project Risk Assessment Under Schedule and Cost Uncertainty. *International Journal of Scientific Interdisciplinary Research*, *4*(2), 204–251. https://doi.org/10.63125/kq4zzh16

[60]. Md Kaium, H. (2023). A GIS-Based Multi-Criteria Decision-Support and Land-Suitability Optimization Framework for Climate-Resilient Urban and Regional Planning. *American Journal of Data Science and Analytics*, *4*(06), 43–103. https://doi.org/10.63125/wvq0sx87

[61]. Md Kaium, H. (2024). Machine Learning Enhanced GIS And AHP Modeling for High-Resolution Flood-Susceptibility Prediction, Vulnerability Assessment, and Risk Classification. *Review of Applied Science and Technology*, *3*(02), 92–140. https://doi.org/10.63125/fz8hv245

[62]. Md Kaium, H. (2025). Integrating Artificial Intelligence, Semantic Indoor Geospatial Modeling, And Network-Based Routing for High-Precision NG911 Emergency Location Intelligence. *International Journal of Scientific Interdisciplinary Research*, *6*(1), 616–670. https://doi.org/10.63125/5hc1xx56

[63]. Md Kaium, H. (2026). An Artificial Intelligence Integrated Geospatial Decision-Support Framework for Scenario-Based Climate-Adaptive Land-Use Optimization and Environmental Risk Reduction. *American Journal of Data Science and Analytics*, *7*(06), 425-483. https://doi.org/10.63125/nyc7sh45

[64]. Md Mahamud Pervaz, P. (2023). Integration of MES, SAP, And PI Historian Platforms for Real-Time Industrial Asset Performance Management. *Review of Applied Science and Technology*, *2*(04), 393–445. https://doi.org/10.63125/9ebtas97

[65]. Md Mahamud Pervaz, P. (2025). Development of a CMMS-Integrated Predictive Maintenance Framework for Industrial PLC and Drive Systems. *American Journal of Scholarly Research and Innovation*, *4*(01), 894–942. https://doi.org/10.63125/j33gtf31

[66]. Md Mahamud Pervaz, P. (2026). Implementation of an OSHA-Compliant Lockout/Tagout and Arc-Flash Hazard Mitigation Framework for U.S. Industrial Maintenance Operations. *American Journal of Interdisciplinary Studies*, *7*(02), 73-119. https://doi.org/10.63125/8ky04n07

[67]. Meng, F., Fu, G., Farmani, R., Sweetapple, C., & Butler, D. (2018). Topological attributes of network resilience: A study in water distribution systems. *Water Research*, *143*, 376-386. https://doi.org/10.1016/j.watres.2018.06.048

[68]. Mikovits, C., Tscheikner-Gratl, F., Jasper-Tönnies, A., Einfalt, T., Huttenlau, M., Schöpf, M., Kinzel, H., Rauch, W., & Kleidorfer, M. (2017). Decision support for adaptation planning of urban drainage systems. *Journal of Water Resources Planning and Management*, *143*(12), 04017069. https://doi.org/10.1061/(asce)wr.1943-5452.0000840

[69]. Mohammad Badrul, A., & Md. Mominul, H. (2023). Machine Learning–Based Assessment of Environmental and Public Health Risks in Sewerage Sludge Management Systems. *American Journal of Advanced Technology and Engineering Solutions*, *3*(02), 33-77. https://doi.org/10.63125/y3yfxa92

[70]. Molla Al Rakib, H., & Mohammad Towhidul, I. (2023). Cyber-Resilient Marketing Intelligence Systems for Fraud Detection and Data Integrity in Digital Campaigns. *American Journal of Scholarly Research and Innovation*, *2*(02), 485–518. https://doi.org/10.63125/b53pgr11

[71]. Mst Kaniz, F., & Jahanara, A. (2022). Lean Six Sigma Implementation in Home Health Administrative Operations: A DMAIC Case Study of Managerial Workflow Redesign and Error Reduction. *International Journal of Scientific Interdisciplinary Research*, *12*(04), 01–60. https://doi.org/10.63125/xchca204

[72]. Mst Shamima, A. (2026). Enhancing Financial Accountability and Cost Control in North American Outpatient Clinics Through Data Science: A Mixed-Methods Healthcare Administration Study. *American Journal of Data Science and Analytics*, *7*(05), 01-41. https://doi.org/10.63125/wksgy749

[73]. Mugume, S. N., Gomez, D. E., Fu, G., Farmani, R., & Butler, D. (2015). A global analysis approach for investigating structural resilience in urban drainage systems. *Water Research*, *81*, 15-26. https://doi.org/10.1016/j.watres.2015.05.030

[74]. Mukut Kanti, B. (2023). Importance of the Sustainable growth in the Testing, Inspection and Certification (TIC) industries through AI tools and techniques. *Review of Applied Science and Technology*, *13*(07), 50–75. https://doi.org/10.63125/0aagev30

[75]. Mukut Kanti, B. (2024). AI-Enabled Predictive Asset Integrity Monitoring for Industrial Equipment in Oil & Gas and Energy Sector Facilities. *International Journal of Scientific Interdisciplinary Research*, *5*(2), 746–791. https://doi.org/10.63125/3mjcah04

[76]. Mukut Kanti, B. (2026). Digital-Twin And IOT-Based Condition Monitoring for Rotating Machinery and Process Equipment in Petrochemical and Industrial Environments. *American Journal of Scholarly Research and Innovation*, *5*(01), 382–428. https://doi.org/10.63125/mwdnjv55

[77]. Nishat, J. (2023). Communicable Disease Prevention in a Post-Pandemic Era: A Global Review of Public Health Education, Surveillance, and Community-Level Interventions. *International Journal of Scientific Interdisciplinary Research*, *4*(4), 630–678. https://doi.org/10.63125/mnqefj36

[78]. Nuzhat Sadia, P. (2023). A Multi-Criteria Decision-Support Framework For ERP-Based Business Process Optimization in Mid-Sized Manufacturing Enterprises. *American Journal of Scholarly Research and Innovation*, *2*(02), 519–573. https://doi.org/10.63125/j58k5d55

[79]. Oliveira Santos, V., Costa Rocha, P. A., Scott, J., Thé, J. V. G., & Gharabaghi, B. (2023). A new graph-based deep learning model to predict flooding with validation on a case study on the Humber River. *Water*, *15*(10), 1827. https://doi.org/10.3390/w15101827

[80]. Palash Chandra, D. (2025). Advanced Composite and Geopolymer Materials for Durable Water Supply and Sanitation Infrastructure: Performance, Sustainability, and Lifecycle Assessment. *ASRC Procedia: Global Perspectives in Science and Scholarship*, *1*(01), 1887–1921. https://doi.org/10.63125/z64akr77

[81]. Palla, A., Colli, M., Candela, A., Aronica, G. T., & Lanza, L. G. (2018). Pluvial flooding in urban areas: The role of surface drainage efficiency. *Journal of Flood Risk Management*, *11*(S2), S663-S676. https://doi.org/10.1111/jfr3.12246

[82]. Palmitessa, R., Grum, M., Engsig-Karup, A. P., & Löwe, R. (2022). Accelerating hydrodynamic simulations of urban drainage systems with physics-guided machine learning. *Water Research*, *223*, 118972. https://doi.org/10.1016/j.watres.2022.118972

[83]. Park, S., Kim, J., Kim, Y., & Kang, J. (2024). Participatory framework for urban pluvial flood modeling in the digital twin era. *Sustainable Cities and Society*, *108*, 105496. https://doi.org/10.1016/j.scs.2024.105496

[84]. Park, S., Kim, J., Yun, H., & Kang, J. (2024). Exploring the network structure of coupled green-grey infrastructure to enhance urban pluvial flood resilience: A scenario-based approach focusing on centralized and decentralized structures. *Journal of Environmental Management*, *370*, 122344. https://doi.org/10.1016/j.jenvman.2024.122344

[85]. Reyes-Silva, J. D., Zischg, J., Klinkhamer, C., Rao, P. S. C., Sitzenfrei, R., & Krebs, P. (2020). Centrality and shortest path length measures for the functional analysis of urban drainage networks. *Applied Network Science*, *5*, Article 1. https://doi.org/10.1007/s41109-019-0247-8

[86]. Risha, A., & Mst Shurovi, A. (2023). Cloud-Based Accounting Systems and Cybersecurity Frameworks for Financial Data Protection in Emerging Economies: A Meta-Analysis. *International Journal of Business and Economics Insights*, *3*(4), 26–64. https://doi.org/10.63125/zb0h3n85

[87]. Rony, S., & Md, A. (2026). Multi-Agency Coordination in Sustained Healthcare Supply Shortages: Lessons from Covid-19, Drug Shortages, and Critical Medical Supply Disruptions. *American Journal of Data Science and Analytics*, *7*(01), 181-221. https://doi.org/10.63125/5v6t8515

[88]. Sabri, S., Alexandridis, K., Koohikamali, M., Zhang, S., & Ozkaya, H. E. (2023). Designing a spatially-explicit urban digital twin framework for smart water infrastructure and flood management. *2023 IEEE 3rd International Conference on Digital Twins and Parallel Intelligence (DTPI)*, 1-9. https://doi.org/10.1109/dtpi59677.2023.10365478

[89]. Sadia, Z., & Maishar Mostari, Z. (2022). The Impact of Interactive Dashboard Visualization on Data-Driven Decision Making in Financial Services: A Qualitative Evaluation. *International Journal of Scientific Interdisciplinary Research*, *12*(03), 01–35. https://doi.org/10.63125/3jstsv75

[90]. Seyoum, S. D., Vojinovic, Z., Price, R. K., & Weesakul, S. (2012). Coupled 1D and noninertia 2D flood inundation model for simulation of urban flooding. *Journal of Hydraulic Engineering*, *138*(1), 23-34. https://doi.org/10.1061/(asce)hy.1943-7900.0000485

[91]. Shaiful, M., Anisur, R., & Md, A. (2022). A Systematic Literature Review on the Role of Digital Health Twins in Preventive Healthcare For Personal and Corporate Wellbeing. *American Journal of Interdisciplinary Studies*, *3*(04), 1-31. https://doi.org/10.63125/negjw373

[92]. Sharifi, A., Tarlani Beris, A., Sharifzadeh Javidi, A., Nouri, M., Gholizadeh Lonbar, A., & Ahmadi, M. (2024). Application of artificial intelligence in digital twin models for stormwater infrastructure systems in smart cities. *Advanced Engineering Informatics*, *61*, 102485. https://doi.org/10.1016/j.aei.2024.102485

[93]. Simone, A. (2023). Vulnerability assessment of urban drainage network using relevance-based centrality metrics. *River*, *2*(1), 39-51. https://doi.org/10.1002/rvr2.30

[94]. Simone, A., Cesaro, A., Del Giudice, G., Di Cristo, C., & Fecarotta, O. (2022). Potentialities of complex network theory tools for urban drainage networks analysis. *Water Resources Research*, *58*(8), e2022WR032277. https://doi.org/10.1029/2022wr032277

[95]. Stabak, D., & Md Shahid, N. (2022). Empirical Assessment of Uncertainty-Aware Real-Time Decision-Making for Reliable and Resilient Cyber-Physical Systems. *International Journal of Scientific Interdisciplinary Research*, *1*(01), 432–477. https://doi.org/10.63125/q3r4kk16

[96]. Stabak, D., & Md Siam, T. (2023). Real-Time Edge Computing for Cyber-Physical Systems: A Meta-Analysis of Energy Efficiency and Fault Tolerance. *American Journal of Scholarly Research and Innovation*, *13*(06), 01–44. https://doi.org/10.63125/g9c9cp41

[97]. Sweetapple, C., Fu, G., Farmani, R., Meng, F., Ward, S., & Butler, D. (2018). Attribute-based intervention development for increasing resilience of urban drainage systems. *Water Science and Technology*, *77*(5-6), 1757-1764. https://doi.org/10.2166/wst.2018.070

[98]. Syed Feroz, A. (2023). Quality-Management Systems for Resilient Energy Infrastructure Fabrication. *International Journal of Scientific Interdisciplinary Research*, *13*(10), 37–91. https://doi.org/10.63125/mbhhrm88

[99]. Syed Feroz, A. (2024). AI-Assisted NDT Analytics for Early Crack Detection in Energy-Infrastructure Pressure Vessels Using Advanced Manufacturing Data. *Review of Applied Science and Technology*, *14*(07), 01-52. https://doi.org/10.63125/8bdqs538

[100]. Syed Feroz, A. (2025). Intelligent Process Monitoring for Enhancing Weld Integrity and Reliability in Advanced Manufacturing of LPG Energy Infrastructure. *American Journal of Interdisciplinary Studies*, *6*(3), 394-441. https://doi.org/10.63125/p3b5mb44

[101]. Syed Feroz, A., & Md Mahamud Pervaz, P. (2022). Root-Cause Analysis and FMEA-Driven Reliability Improvement in Gas Production Facilities: A Multi-Year Empirical Study. *International Journal of Scientific Interdisciplinary Research*, *12*(10), 01–53. https://doi.org/10.63125/70msp878

[102]. Tagherouit, W. B., Bennis, S., & Bengassem, J. (2011). A fuzzy expert system for prioritizing rehabilitation of sewer networks. *Computer-Aided Civil and Infrastructure Engineering*, *26*(2), 146-152. https://doi.org/10.1111/j.1467-8667.2010.00673.x

[103]. Tahmasebi Birgani, Y., & Yazdandoost, F. (2018). An integrated framework to evaluate resilient-sustainable urban drainage management plans using a combined-adaptive MCDM technique. *Water Resources Management*, *32*(8), 2817-2835. https://doi.org/10.1007/s11269-018-1960-2

[104]. Tahmedur, R., & Rifat, C. (2023). Critical Path Analysis and Resource-Leveling Optimization for Multi-Project Engineering Portfolios. *American Journal of Interdisciplinary Studies*, *13*(12), 01-47. https://doi.org/10.63125/8eqnea46

[105]. Tian, W., Liao, Z., Zhang, Z., Wu, H., & Xin, K. (2022). Flooding and overflow mitigation using deep reinforcement learning based on Koopman operator of urban drainage systems. *Water Resources Research*, *58*(7), e2021WR030939. https://doi.org/10.1029/2021wr030939

[106]. Uddin, H. M. M., & Risha, A. (2024). Hybrid Cloud Security and Compliance in U.S. Enterprises: Addressing Data Privacy Risks and Governance Challenges. *American Journal of Scholarly Research and Innovation*, *3*(01), 153–197. https://doi.org/10.63125/qcy0cj46

[107]. Wang, A.-J., Li, H., He, Z., Tao, Y., Wang, H., Yang, M., Savic, D., Daigger, G. T., & Ren, N. (2024). Digital twins for wastewater treatment: A technical review. *Engineering*, *36*, 21-35. https://doi.org/10.1016/j.eng.2024.04.012

[108]. Wang, S., Zhang, X., Wang, J., Tao, T., Xin, K., Yan, H., & Li, S. (2023). Optimal sensor placement for the routine monitoring of urban drainage systems: A re-clustering method. *Journal of Environmental Management*, *335*, 117579. https://doi.org/10.1016/j.jenvman.2023.117579

[109]. Xu, K., Zhang, X., Bin, L., & Shen, R. (2024). An improved global resilience assessment method for urban drainage systems: A case study of Haidian Island, south China. *Journal of Environmental Management*, *360*, 121135. https://doi.org/10.1016/j.jenvman.2024.121135

[110]. Yang, S., Zhang, Y., & Zhang, Z. (2023). Runoff prediction based on dynamic spatiotemporal graph neural network. *Water*, *15*(13), 2463. https://doi.org/10.3390/w15132463

[111]. Yazdani, A., & Jeffrey, P. (2011). Complex network analysis of water distribution systems. *Chaos: An Interdisciplinary Journal of Nonlinear Science*, *21*(1), 016111. https://doi.org/10.1063/1.3540339

[112]. Ye, C., & Xu, Z. (2022). Development and application of digital twin system for urban flood and waterlogging: Case study of Fuzhou City. *China Flood & Drought Management*, *32*(7), 5-11, 29. https://doi.org/10.16867/j.issn.1673-9264.2022160

[113]. Yu, B., Yin, H., & Zhu, Z. (2018). Spatio-temporal graph convolutional networks: A deep learning framework for traffic forecasting. *Proceedings of the Twenty-Seventh International Joint Conference on Artificial Intelligence*, 3634-3640. https://doi.org/10.24963/ijcai.2018/505

[114]. Yu, X., Wu, Y., Meng, F., Zhou, X., Liu, S., Huang, Y., & Wu, X. (2024). A review of graph and complex network theory in water distribution networks: Mathematical foundation, application and prospects. *Water Research*, *253*, 121238. https://doi.org/10.1016/j.watres.2024.121238

[115]. Zhang, D., Dong, X., & Zeng, S. (2021). Exploring the structural factors of resilience in urban drainage systems: A large-scale stochastic computational experiment. *Water Research*, *188*, 116475. https://doi.org/10.1016/j.watres.2020.116475

[116]. Zhang, M., Xu, Z., Wang, Y., Zeng, S., & Dong, X. (2022). Evaluation of uncertain signals' impact on deep reinforcement learning-based real-time control strategy of urban drainage systems. *Journal of Environmental Management*, *324*, 116448. https://doi.org/10.1016/j.jenvman.2022.116448

[117]. Zhang, Q., Chang, J., Meng, G., Xiang, S., & Pan, C. (2020). Spatio-temporal graph structure learning for traffic forecasting. *Proceedings of the AAAI Conference on Artificial Intelligence*, *34*(1), 1177-1185. https://doi.org/10.1609/aaai.v34i01.5470

[118]. Zhang, Z., Tian, W., Lu, C., Liao, Z., & Yuan, Z. (2024). Graph neural network-based surrogate modelling for real-time hydraulic prediction of urban drainage networks. *Water Research*, *263*, 122142. https://doi.org/10.1016/j.watres.2024.122142