Policy Research Journal
ISSN (E): 3006-7030 ISSN (P) : 3006-7022 Volume 4, Issue 3, 2026

A HYBRID AI-DRIVEN BIM–DIGITAL TWIN FRAMEWORK FOR CLIMATE-RESILIENT CIVIL ENGINEERING: INTEGRATING NET-ZERO CONSTRUCTION, INTELLIGENT FLOOD FORECASTING AND SUSTAINABLE URBAN DRAINAGE UNDER THE UK–PAKISTAN GREEN COMPACT

Sabbir Alam Chowdhury[*1], Sohaib Hafeez[2], Salman Jafar[3], Kashif Ahmad[4]

*[*1]Faculty of Engineering, Environment and Computing, Coventry University, Coventry, England, United Kingdom*
[2]National NC System Engineering and Research Center, Department of Machatonics Engineering, School of Mechanical Science & Engineering, Huazhong University of Science and Technology, Wuhan 430074, P.R China
[3]School of Civil Engineering, Southwest Jiaotong University, Chengdu, Sichuan, China
[4]Department of Civil Engineering, NFC Institute of Engineering and Technology, Multan, Pakistan

[*1]sac05ce@gmail.com, [2]sohaib.hafeez@hotmail.com, [3]salmanjafar2002@gmail.com, [4]kashifahmad445@gmail.com

DOI: http://doi.org/10.5281/zenodo.24186131

Keywords
Artificial Intelligence; Building Information Modelling; Digital Twin; Climate-Resilient Infrastructure; Net-Zero Construction; Hybrid XGBoost–LSTM; Flood Forecasting; Sustainable Urban Drainage Systems; UK–Pakistan Green Compact.

Article History
Received: 07 January 2026
Accepted: 20 February 2026
Published: 06 March 2026

Copyright @Author
Corresponding Author: *
Sabbir Alam Chowdhury

Abstract

Climate change, accelerated urbanisation, and carbon-intensive infrastructure development pose significant challenges to sustainable civil engineering, particularly in flood-vulnerable regions of Pakistan. This study develops an innovative hybrid Artificial Intelligence (AI)–driven Building Information Modelling (BIM)–Digital Twin (DT) framework integrating net-zero construction, intelligent flood forecasting, and Sustainable Urban Drainage Systems (SuDS) within the UK–Pakistan Green Compact context. The proposed architecture integrates Industry Foundation Classes (IFC)-based BIM, Geographic Information Systems (GIS), Internet of Things (IoT) monitoring, Life Cycle Assessment (LCA), and hydrological modelling to establish an interoperable, data-driven infrastructure management ecosystem. The research utilises a comprehensive dataset comprising ten years of hourly rainfall and river-level observations, 250 georeferenced drainage assets, 120 BIM construction elements, and 15,000 flood-event records. Following data preprocessing, spatial harmonisation, and temporal feature engineering, the dataset is partitioned chronologically into training (70%), validation (15%), and testing (15%) subsets. A hybrid Extreme Gradient Boosting (XGBoost)–Long Short-Term Memory (LSTM) architecture is employed for flood probability and inundation-depth prediction, while multi-objective optimisation evaluates drainage interventions and low-carbon construction alternatives. The integrated forecasting model achieves a coefficient of determination (R^2) of 0.93, root mean square error (RMSE) of 0.18 m, and F1-score of 0.91, outperforming the conventional baseline (R^2 = 0.82, RMSE = 0.31 m, F1-score = 0.79). Furthermore, optimised SuDS configurations incorporating permeable pavements, bioswales, and

detention basins reduce peak surface runoff by 32%, inundation extent by 27%, and annual drainage overflow frequency by 35%. BIM-integrated embodied-carbon assessment demonstrates a 24% reduction in upfront carbon emissions through material substitution and design optimisation. The Digital Twin environment facilitates near-real-time scenario evaluation, infrastructure performance monitoring, and transparent decision support across interconnected engineering systems. These findings demonstrate the potential of integrating predictive intelligence, carbon optimisation, and nature-based drainage solutions within a unified infrastructure framework. The proposed approach provides a scalable pathway towards climate-adaptive, low-carbon urban infrastructure, supporting evidence-based engineering decisions, international technical collaboration, and sustainable infrastructure transformation in Pakistan and comparable climate-vulnerable developing economies.

1- Introduction:

Climate change, rapid urbanisation, and the increasing complexity of infrastructure systems have intensified the challenges associated with sustainable and resilient civil engineering. Rising global temperatures, changing precipitation patterns, and the increasing occurrence of extreme hydro-meteorological events are placing unprecedented pressure on urban infrastructure, particularly in developing countries with limited adaptive capacity. Conventional engineering approaches, which frequently rely on historical climatic conditions, static design assumptions, and fragmented infrastructure management practices, are becoming insufficient to address these evolving environmental risks. The Intergovernmental Panel on Climate Change (IPCC) has highlighted the increasing vulnerability of urban settlements and critical infrastructure to extreme rainfall, surface-water flooding, and climate-related disruptions [1]. Consequently, the transition towards climate-resilient, resource-efficient, and digitally integrated infrastructure has emerged as a fundamental priority for sustainable urban development. Pakistan represents a particularly critical context for investigating these challenges because of its exposure to monsoon variability, riverine flooding, rapid urban expansion, and infrastructure development pressures. The devastating floods of 2022 affected approximately 33 million people and resulted in estimated damages and economic losses exceeding USD 30 billion, demonstrating the vulnerability of existing infrastructure systems to extreme climatic events [2]. The consequences extended beyond immediate physical destruction, disrupting transportation networks, residential settlements, drainage infrastructure, agricultural production, and essential public services. The World Bank's Pakistan Country Climate and Development Report further emphasised the importance of strengthening climate adaptation, improving infrastructure planning, and mobilising sustainable investment to reduce future economic and environmental losses [3]. These circumstances highlight the urgent need for engineering solutions that integrate flood-risk prediction, sustainable drainage design, infrastructure performance monitoring, and environmentally responsible construction practices. Alongside climate adaptation, reducing greenhouse gas emissions from the built environment constitutes an equally important challenge. The global buildings and construction sector remains a major contributor to greenhouse gas emissions and resource consumption, with the United Nations Environment Programme reporting that the sector accounts for approximately 37% of global emissions [4]. Carbon-intensive construction materials, particularly cement and steel, contribute substantially to embodied emissions, while inefficient design, material wastage, and inadequate life-cycle planning further increase environmental impacts. Achieving net-zero construction therefore requires a transition from conventional cost- and performance-oriented engineering practices towards integrated decision-making that considers embodied carbon,

operational efficiency, material circularity, structural performance, and long-term climate resilience. Life Cycle Assessment (LCA), supported by digital quantity extraction and material databases, provides a systematic approach to evaluating environmental impacts throughout infrastructure life cycles. However, the effective integration of carbon assessment with flood resilience, drainage optimisation, and dynamic infrastructure management remains an important area for further investigation. Recent developments in Building Information Modelling (BIM), Digital Twin (DT) technology, Artificial Intelligence (AI), Geographic Information Systems (GIS), and the Internet of Things (IoT) provide opportunities to address these interconnected challenges. BIM enables structured digital representation of infrastructure geometry, materials, quantities, and engineering properties, supporting coordinated design and life-cycle information management. Open interoperability standards, including Industry Foundation Classes (IFC), facilitate information exchange between different engineering applications and reduce dependence on proprietary software environments. Digital Twin technology extends these capabilities by linking digital infrastructure representations with operational data, analytical models, and physical-system observations. When integrated with IoT sensing networks and GIS-based spatial information, digital twins can support condition monitoring, scenario simulation, predictive maintenance, and infrastructure performance assessment. Previous investigations have demonstrated the potential of combining BIM, GIS, and IoT information within interoperable digital environments, although semantic consistency, heterogeneous data integration, and standardisation continue to present practical challenges [5]. The application of AI and machine learning to hydrological forecasting provides an additional opportunity to improve infrastructure resilience. Conventional hydrological and hydraulic models are essential for representing rainfall–runoff processes, drainage-network hydraulics, and flood propagation. Nevertheless, their application to near-real-time forecasting can be constrained by computational requirements, calibration complexity, incomplete observations, and the heterogeneous characteristics of urban catchments. Data-driven techniques can complement physically based modelling by extracting relationships from historical rainfall, river-level observations, catchment characteristics, and recorded flood events. In particular, Extreme Gradient Boosting (XGBoost) offers an efficient approach to learning nonlinear relationships from structured hydro-meteorological predictors, whereas Long Short-Term Memory (LSTM) networks are designed to represent temporal dependencies within sequential observations. Integrating these complementary modelling capabilities provides a basis for developing hybrid forecasting systems capable of estimating flood occurrence probabilities and inundation depths. However, reliable implementation requires careful temporal validation, uncertainty assessment, and evaluation under extreme events that may differ from historical observations [6]. Sustainable Urban Drainage Systems (SuDS) represent another essential component of climate-adaptive infrastructure development. Unlike conventional drainage systems that primarily concentrate on the rapid conveyance of stormwater, SuDS seek to manage runoff through a combination of infiltration, storage, attenuation, filtration, and controlled discharge. Nature-based and engineered interventions, including permeable pavements, bioswales, rain gardens, detention basins, and vegetated drainage channels, can reduce surface runoff and improve urban water management. The United Kingdom's national standards for SuDS emphasise the management of runoff during extreme rainfall, consideration of climate change, protection of receiving waters, and reduction of downstream flood risks [7]. Such principles are potentially transferable to Pakistan's rapidly developing urban environments, although their effectiveness depends on local rainfall characteristics, soil permeability, groundwater conditions, land availability, maintenance capacity, and infrastructure constraints. Accordingly, effective SuDS implementation requires spatially informed design, hydrological

performance assessment, and systematic comparison of alternative drainage configurations. Despite these technological advances, important limitations remain in the integration of digital engineering, intelligent flood forecasting, low-carbon construction, and sustainable drainage design. Existing research has established individual applications of BIM-based environmental assessment, AI-supported flood prediction, GIS-enabled risk mapping, IoT infrastructure monitoring, and SuDS optimisation. However, these applications are frequently developed around separate analytical objectives, datasets, and software environments. Research on built-environment digital twins has similarly identified interoperability, information governance, and integration of heterogeneous data sources as continuing barriers. Consequently, there is a need for a unified framework that connects asset-level engineering information with catchment-scale flood dynamics, operational monitoring, and life-cycle environmental performance. Such integration is particularly relevant where infrastructure investment decisions must balance carbon reduction, hydraulic resilience, implementation costs, and long-term operational requirements. The UK–Pakistan Green Compact provides a relevant international cooperation context for addressing these challenges. Formalised in December 2025, the Compact establishes a bilateral framework addressing climate finance, clean energy transition, nature-based solutions, innovation, and climate adaptation and resilience [8]. Within this broader policy context, the exchange of digital engineering expertise, sustainable drainage practices, environmental assessment methodologies, and data-driven decision-support tools presents opportunities to strengthen climate-responsive infrastructure planning. The UK's experience in BIM-enabled information management and SuDS design, combined with Pakistan's urgent requirements for flood resilience and sustainable infrastructure development, provides a basis for investigating transferable engineering approaches. Nevertheless, successful implementation requires adaptation to local environmental conditions, institutional arrangements, technical resources, and data availability rather than direct replication of solutions developed for different climatic and regulatory environments. Against this background, the present study develops and evaluates a hybrid AI-driven BIM–Digital Twin framework that integrates intelligent flood forecasting, sustainable drainage optimisation, and low-carbon construction assessment within a unified decision-support environment. The proposed architecture combines IFC-based BIM information, GIS-based spatial datasets, IoT-compatible monitoring information, hydrological modelling, and LCA to represent interconnected physical and environmental infrastructure processes. A hybrid XGBoost–LSTM architecture is employed to investigate flood probability and inundation-depth prediction using historical hydro-meteorological observations and flood-event information. In parallel, multi-objective optimisation is applied to evaluate alternative SuDS configurations and construction material selections according to hydraulic performance, embodied-carbon emissions, and engineering constraints. The Digital Twin environment serves as an integrating layer for infrastructure visualisation, model outputs, monitoring information, and scenario-based assessment. The principal objectives of this study are to: (i) develop an interoperable BIM–GIS–IoT–Digital Twin architecture for climate-resilient infrastructure management; (ii) establish and evaluate a hybrid XGBoost–LSTM approach for flood occurrence and inundation-depth forecasting; (iii) assess the effectiveness of optimised SuDS interventions in reducing surface runoff, inundation extent, and drainage overflow; (iv) quantify potential embodied-carbon reductions through BIM-integrated life-cycle assessment and construction design optimisation; and (v) examine the applicability of the integrated framework to sustainable infrastructure decision-making within the UK–Pakistan Green Compact context. By addressing flood resilience and carbon mitigation within a common computational architecture, the study seeks to demonstrate how infrastructure planning can progress from isolated engineering assessments towards integrated, predictive, and

environmentally accountable decision-making. The research contributes to the emerging field of intelligent climate-resilient infrastructure by combining predictive analytics, open-standard digital asset information, hydrological simulation, and multi-objective sustainability assessment. Its significance lies not only in evaluating individual technological components but also in exploring their interoperability and collective capacity to support engineering decisions across design, construction, and operational stages. The proposed framework is intended to provide a transferable methodological foundation for climate-vulnerable urban environments, particularly in developing economies where infrastructure resilience, carbon reduction, and resource efficiency must be pursued simultaneously.

2- Digital Transformation and Climate-Resilient Civil Infrastructure:

The increasing frequency and severity of climate-related hazards, rapid urbanisation, and the growing demand for sustainable infrastructure have accelerated the digital transformation of civil engineering. Climate change has introduced substantial uncertainty into the design, construction, operation, and maintenance of infrastructure assets, particularly those exposed to extreme precipitation, riverine flooding, surface-water accumulation, and hydrological variability. Traditional infrastructure management practices have largely depended on static design parameters, historical climatic records, periodic inspections, and fragmented information systems. Although these approaches continue to provide an essential foundation for engineering practice, they are often insufficient for addressing rapidly evolving environmental conditions and complex interactions between interconnected infrastructure networks. The Intergovernmental Panel on Climate Change (IPCC) [9] emphasised the vulnerability of urban settlements and critical infrastructure to climate-related hazards and the importance of integrated adaptation strategies. Consequently, the development of climate-resilient infrastructure requires a transition towards adaptive, data-driven, and environmentally responsible engineering systems capable of responding to both current and anticipated climate risks. Digital transformation in civil engineering encompasses the systematic integration of computational modelling, information management, real-time monitoring, predictive analytics, and automated decision-support technologies throughout the infrastructure lifecycle. Unlike conventional computer-aided design practices, digital transformation involves more than the creation of electronic drawings or three-dimensional representations. It requires interoperable digital environments that enable continuous information exchange between physical infrastructure, environmental monitoring networks, engineering simulation models, and relevant stakeholders. Within this context, Building Information Modelling (BIM), Geographic Information Systems (GIS), Internet of Things (IoT) technologies, Artificial Intelligence (AI), and Digital Twin (DT) systems have emerged as complementary technological components supporting the development of intelligent infrastructure management frameworks. Recent studies have demonstrated the potential of these technologies to improve information accessibility, infrastructure monitoring, lifecycle management, and engineering decision-making. Tuhaise et al. [10] conducted a comprehensive review of technologies supporting Digital Twin applications in the construction industry and identified the importance of integrating BIM, sensing technologies, data communication, and computational analysis to establish relationships between physical and digital infrastructure systems. Their investigation demonstrated that Digital Twin implementation depends not only on digital representation but also on reliable information acquisition, data processing, and the ability to support engineering decisions through updated asset information. However, integrating heterogeneous technological components within a consistent operational framework remains a major implementation challenge. Similarly, Saif et al. systematically reviewed 112 research publications on construction Digital Twins and developed a taxonomy encompassing seven application areas

and 19 specific uses. Their study proposed five technological layers involving sensing, communication, storage, analytics, and visualisation. This classification demonstrates that successful Digital Twin implementation requires coordinated technological functions rather than the isolated adoption of individual digital tools. The authors further highlighted the importance of aligning technological choices with specific engineering objectives, particularly when applications involve continuously changing physical conditions and complex operational requirements. Although their investigation concentrated on construction-stage applications, its findings provide a useful architectural foundation for developing integrated digital systems capable of supporting infrastructure resilience and sustainability assessment. Figure 1 illustrates the conceptual role of digital transformation in establishing climate-resilient and low-carbon civil infrastructure. The framework connects climate-related challenges and urban development pressures with integrated digital technologies, including BIM, GIS, IoT, AI, and hydrological modelling. The Digital Twin environment provides an information-integration and analytical layer that connects infrastructure monitoring, forecasting, engineering simulation, and sustainability assessment. The intended outcomes include improved flood-risk management, enhanced drainage performance, reduced construction-related carbon emissions, and adaptive infrastructure planning. The figure represents the conceptual relationships between these components rather than a fully validated operational architecture.

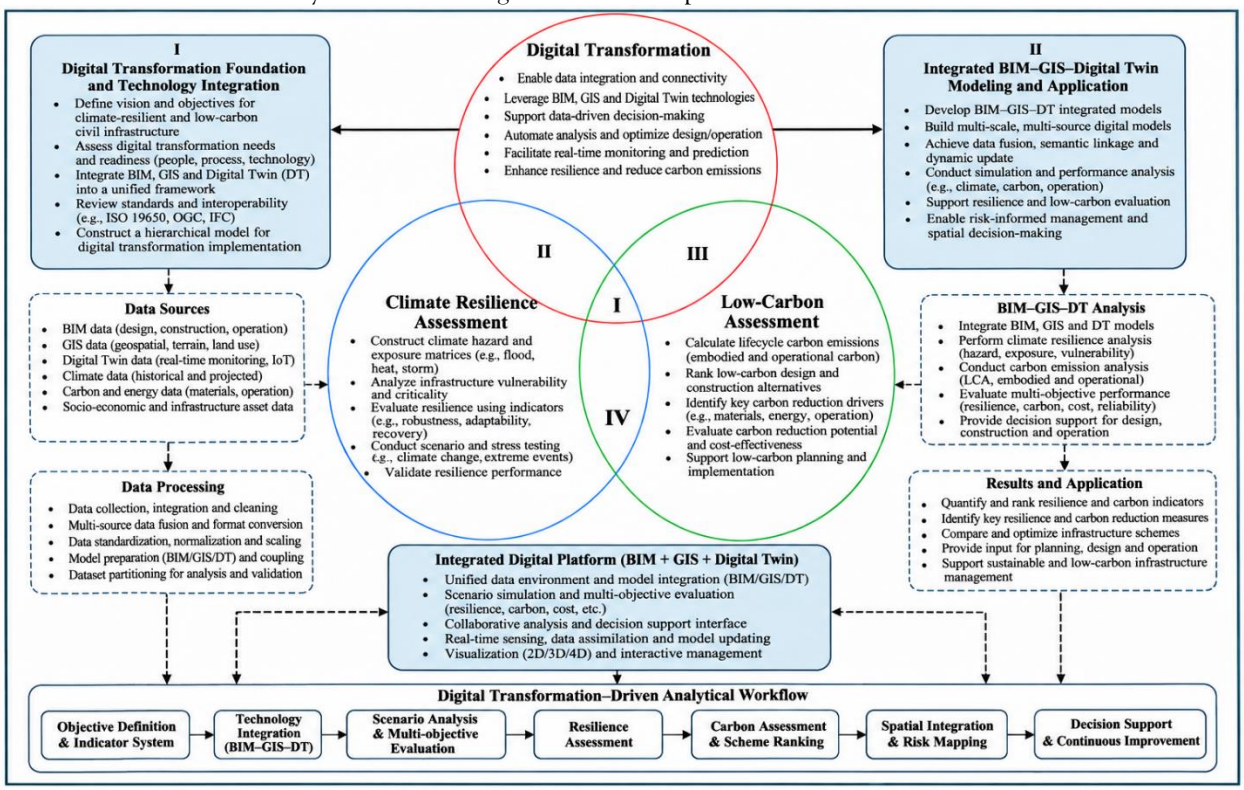


Figure 1: Integrated BIM–GIS–Digital Twin framework for digital transformation, climate resilience, and low-carbon infrastructure assessment

A major advantage of digital transformation is its potential to support a transition from reactive infrastructure management towards proactive and predictive decision-making. Under conventional approaches, infrastructure deficiencies may be identified through scheduled inspections, observed deterioration, or failures occurring during extreme events. Digitally enabled

management systems can instead combine monitoring observations with predictive models to identify emerging risks before critical performance thresholds are exceeded. For example, the integration of rainfall forecasts, river-level observations, drainage-network information, and flood-propagation models can support earlier identification of potentially affected infrastructure assets. Likewise, information concerning material condition, structural performance, and environmental exposure can inform maintenance planning and lifecycle asset management. However, the distinction between predictive potential and demonstrated operational performance is essential. A digital platform does not automatically improve infrastructure resilience merely because it incorporates advanced monitoring or analytical technologies. Its effectiveness depends on the accuracy and representativeness of input data, the reliability of modelling algorithms, the frequency of information updates, and the capacity of infrastructure operators to interpret and act upon generated recommendations [11]. False alarms, incomplete sensor observations, poorly calibrated models, and inconsistencies between digital and physical systems can undermine the practical value of technologically advanced solutions. Consequently, robust validation, uncertainty quantification, transparent information governance, and human oversight remain essential components of digitally enabled climate adaptation.

The differences between conventional and digitally transformed infrastructure management approaches are summarised in Table 1.

Table 1: Comparison of conventional and digitally enabled infrastructure management approaches for climate resilience.

Assessment dimension	Conventional infrastructure management	Digitally enabled BIM–GIS–IoT–AI–DT approach
Data acquisition	Periodic inspections, historical records, and manual surveys	Integrated sensor observations, geospatial information, and digital asset databases
Infrastructure representation	Static drawings, reports, and isolated design models	Interoperable BIM–GIS representations connected to operational information
Flood-risk assessment	Historical-event analysis and conventional modelling	AI-supported forecasting combined with hydrological and spatial modelling
Drainage management	Predominantly fixed designs and reactive maintenance	Monitoring-supported drainage assessment and SuDS scenario optimisation
Climate adaptation	Design based primarily on established climatic assumptions	Evaluation of alternative climate and infrastructure scenarios
Carbon assessment	Separate material estimation and environmental calculations	BIM-linked material quantities and lifecycle carbon assessment
Infrastructure maintenance	Scheduled inspections and corrective interventions	Condition monitoring and predictive maintenance where supported by reliable data
Decision-making	Discipline-specific assessments and fragmented information exchange	Integrated analytical outputs and multidisciplinary decision support
Lifecycle management	Limited continuity between design, construction, and operation	Connected asset information across lifecycle stages
Implementation requirements	Established engineering workflows and relatively limited digital integration	Interoperability standards, technical expertise, reliable data, and digital infrastructure

Digital transformation can extend traditional infrastructure management by connecting multiple stages of the engineering lifecycle and enabling the assessment of interdependent performance indicators. Such capabilities are particularly relevant to urban flooding because flood-related damages are influenced not only by precipitation intensity but also by drainage capacity, surface permeability, infrastructure condition, catchment characteristics, and the spatial distribution of vulnerable assets. An isolated assessment of any one of these factors may provide an incomplete representation of overall infrastructure risk. Integrated information environments can support a more comprehensive evaluation by establishing relationships between environmental observations, physical infrastructure characteristics, and projected hydraulic responses. Another important dimension of digital transformation concerns sustainability and carbon management. Civil infrastructure development frequently involves carbon-intensive materials and construction processes, while climate-adaptation interventions may require additional infrastructure investment and resource consumption. Digital technologies can support more transparent assessment of these environmental trade-offs. BIM-based quantity information, when combined with appropriate emission factors and Life Cycle Assessment (LCA) methodologies, enables the calculation of embodied-carbon impacts associated with alternative materials and design configurations. Integrating these assessments with drainage simulation and flood-risk information can support simultaneous consideration of adaptation effectiveness and construction-related emissions. However, credible carbon assessment requires consistent lifecycle boundaries, reliable environmental data, and transparent assumptions concerning material production, transportation, maintenance, and end-of-life processes.

3- BIM–Digital Twin Integration for Intelligent Infrastructure Management:

Building Information Modelling (BIM) and Digital Twin (DT) technologies have emerged as complementary digital engineering approaches for improving the planning, design, construction, operation, and maintenance of civil infrastructure systems. The increasing complexity of infrastructure networks, combined with the need to address climate-related hazards and environmental sustainability, has created a growing demand for integrated information environments capable of representing both physical infrastructure characteristics and evolving operational conditions. Conventional engineering information systems frequently maintain design documentation, inspection records, environmental observations, and maintenance information in separate databases, limiting opportunities for coordinated analysis and effective lifecycle decision-making. BIM provides a structured foundation for managing asset-related information, whereas Digital Twin technology introduces mechanisms for connecting digital representations with operational observations, simulation models, and predictive analytics. Their integration therefore offers opportunities to transform conventional infrastructure management into a more intelligent, adaptive, and information-driven process. BIM is commonly understood as a collaborative information management methodology that enables the creation, exchange, and maintenance of digital representations of built assets. These representations can incorporate geometric configurations, material specifications, engineering properties, construction quantities, scheduling information, cost attributes, and maintenance requirements. Through the coordinated management of such information, BIM supports multidisciplinary collaboration, design consistency, construction planning, and lifecycle asset documentation. Nguyen and Adhikari [12] examined the role of BIM in Digital Twin integration and highlighted its potential to provide consistent information structures for connecting design and construction data with emerging operational technologies. Their investigation emphasised that BIM can contribute substantially to the development of Digital Twin systems by supplying structured engineering information that would otherwise need to be reconstructed or collected separately. However,

conventional BIM implementations generally focus on the representation and management of design or asset information rather than the continuous observation of changing physical conditions. Although BIM models can be updated and connected to external databases, they do not inherently provide automated sensor integration, real-time state estimation, or predictive operational intelligence. This distinction is important for climate-resilient civil infrastructure because environmental conditions and infrastructure performance can vary substantially over short periods. Urban drainage networks, for example, experience changes in hydraulic loading during rainfall events, while flood-exposed structures may encounter rapidly changing water levels, flow velocities, and environmental loads. A static engineering representation may accurately describe infrastructure geometry and design characteristics while providing limited information about its current operating conditions. A conceptual five-layer architecture for BIM–Digital Twin integration is presented in Figure 2.

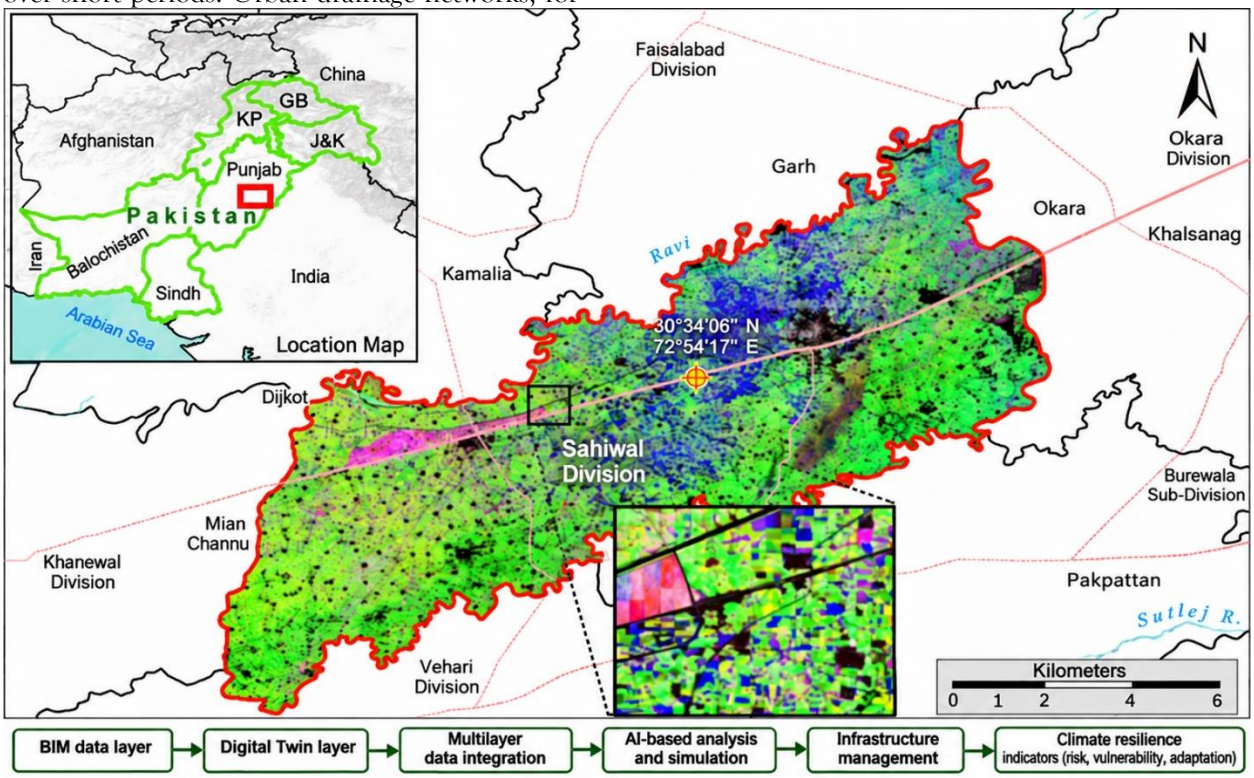


Figure 2: Study area location map and integrated BIM–Digital Twin–AI framework for infrastructure management and climate resilience assessment.

The integration of physical infrastructure information with analytical models provides the foundation for coordinated engineering assessments across multiple disciplines. For example, rainfall and water-level observations acquired through monitoring systems can be combined with catchment information and historical records to support AI-based flood forecasting. Predicted flood conditions can subsequently be associated with georeferenced infrastructure assets, enabling the identification of potentially vulnerable drainage components or construction elements. Hydrological and hydraulic models can further evaluate the expected behaviour of drainage networks under alternative rainfall scenarios, while BIM-based information can provide construction quantities and material properties for assessing proposed adaptation measures. The integration of BIM and Digital Twin technologies also has significant

implications for infrastructure lifecycle management. During planning and design, BIM supports the evaluation of engineering alternatives, quantity estimation, and coordination of construction information. During construction, monitoring systems and digital progress records can be linked to asset models to support quality assurance and documentation. During operation, Digital Twin functionality can connect asset information with condition measurements and predictive analysis. During maintenance, the same information environment may support the identification of deterioration, evaluation of intervention priorities, and updating of asset records. This continuity can reduce information fragmentation between project phases, although its effectiveness depends on consistent data governance and the transfer of relevant information between responsible organisations. The functional distinctions among BIM, Digital Twin technology, and their integration are present in Table 2. The comparison demonstrates that BIM primarily contributes structured asset information, while Digital Twin functionality introduces dynamic information exchange and operational intelligence.

Table 2: Comparison of BIM, Digital Twin, and integrated BIM–DT capabilities for intelligent infrastructure management.

Assessment criterion	Building Information Modelling (BIM)	Digital Twin (DT)	Integrated BIM–DT approach
Primary purpose	Structured engineering information management	Dynamic representation and analysis of physical assets	Integrated lifecycle and operational decision support
Information content	Geometry, materials, quantities, asset properties	Operational observations, system states, analytical outputs	Asset information combined with operational and environmental data
Data update	Manual, periodic, or externally automated	Periodic or near-real-time updates depending on implementation	Coordinated updates linking asset properties and monitored conditions
Physical–digital relationship	Digital description of physical infrastructure	Data-connected physical and digital counterparts	BIM-based asset representation linked to monitored infrastructure
Enabling technologies	IFC, information management platforms, modelling applications	Sensors, communication systems, databases, analytics	IFC, GIS, IoT, APIs, AI, and simulation models
Analytical capability	Design coordination, quantity estimation, engineering analysis	Monitoring, simulation, prediction, optimisation	Integrated flood forecasting, drainage assessment, and carbon analysis

The BIM and Digital Twin technology should not be regarded as competing approaches. Their complementary characteristics provide opportunities to improve infrastructure information continuity and analytical capability when appropriately integrated. Nevertheless, the benefits of integration are not automatic. BIM models may contain incomplete or outdated asset information, while monitoring networks can produce uncertain observations owing to sensor failures, communication interruptions, calibration drift, and inconsistent sampling frequencies. Similarly, analytical models can generate inaccurate predictions when training datasets are unrepresentative or when operating conditions differ substantially from those used during model development. These issues are especially important when Digital Twin environments incorporate machine-learning algorithms. AI-based flood forecasting systems may use historical

rainfall, antecedent precipitation, river-level observations, and previous flood events to predict future hydrological conditions. However, the corresponding predictions require appropriate temporal validation, uncertainty assessment, and operational interpretation. Connecting predicted flood probabilities and inundation depths to BIM objects may improve the presentation of risk information, but asset-level impacts should be evaluated against relevant hydraulic conditions, exposure characteristics, and engineering thresholds. Forecast outputs alone cannot establish structural damage or infrastructure failure without suitable vulnerability or performance models.

4- Methodology:

This study adopts an integrated, data-driven computational methodology to develop a hybrid Artificial Intelligence (AI)-enabled Building Information Modelling (BIM)–Digital Twin (DT) framework for climate-resilient and sustainable civil infrastructure. The proposed methodological approach combines advanced machine-learning algorithms, Geographic Information Systems (GIS), Internet of Things (IoT) monitoring, hydrological and hydraulic simulations, Sustainable Urban Drainage Systems (SuDS), and Life Cycle Assessment (LCA) within a unified digital environment. The framework is designed to address the interconnected challenges of urban flooding, infrastructure vulnerability, and construction-related carbon emissions through the systematic integration of environmental observations, infrastructure asset information, and predictive analytical models [13]. A hybrid Extreme Gradient Boosting–Long Short-Term Memory (XGBoost–LSTM) architecture is employed to investigate flood occurrence probabilities and inundation-depth prediction, while BIM-integrated environmental assessment and multi-objective optimisation are used to evaluate drainage improvements and lower-carbon construction alternatives. The methodology establishes a structured relationship between physical infrastructure, digital asset representations, hydro-meteorological conditions, and computational decision-support mechanisms, enabling the comparative assessment of engineering interventions under different climate and infrastructure scenarios. The methodological framework comprises interconnected stages involving multisource data acquisition, data preprocessing, spatial and temporal harmonisation, IFC-based BIM–GIS interoperability, hybrid AI model development, hydrological simulation, SuDS optimisation, embodied-carbon quantification, and Digital Twin-enabled scenario evaluation. Historical rainfall and river-level observations, georeferenced drainage assets, construction information, and recorded flood events constitute the principal datasets supporting model development and assessment. Following preprocessing and feature engineering, the time-dependent dataset is divided chronologically into training (70%), validation (15%), and independent testing (15%) subsets to evaluate predictive generalisation while minimising temporal information leakage. The forecasting component is assessed using regression and classification performance indicators, whereas drainage interventions are evaluated through changes in peak runoff, inundation extent, and overflow frequency. Construction-related environmental impacts are quantified using BIM-derived material information and appropriate embodied-carbon emission factors. The integrated framework is intended to provide a transparent and reproducible basis for evaluating flood resilience and carbon-reduction strategies within the broader UK–Pakistan Green Compact context, with particular emphasis on the adaptability of digital engineering methods to flood-vulnerable urban infrastructure in Pakistan.

4.1- Multisource Data Acquisition and Dataset Development:

The development of the proposed hybrid Artificial Intelligence (AI)–Building Information Modelling (BIM)–Digital Twin (DT) framework requires the systematic acquisition, organisation, and integration of heterogeneous datasets representing hydro-meteorological processes, physical infrastructure characteristics, construction-related information, and historical flood conditions. A comprehensive multisource data acquisition

strategy is adopted to establish an interoperable information foundation for intelligent flood forecasting, hydrological and hydraulic modelling, Sustainable Urban Drainage Systems (SuDS) optimisation, and embodied-carbon assessment. The study dataset, as specified in the research design, comprises ten years of hourly rainfall and river-level observations, 250 georeferenced drainage infrastructure assets, 120 BIM construction elements, and approximately 15,000 flood-event records. These datasets represent complementary temporal, spatial, geometric, and environmental information domains, enabling the investigation of relationships between rainfall variability, river-level responses, drainage-network performance, and infrastructure-related environmental impacts [14]. The multisource data architecture is developed to support information exchange across the interconnected computational components of the framework. Hydro-meteorological observations provide temporal predictors for AI-based flood forecasting, whereas drainage-network information supports the representation of physical infrastructure and the evaluation of hydraulic performance. BIM construction elements supply structured geometric, material, and quantity information required for asset-level digital representation and lifecycle environmental assessment. Historical flood records provide supervised learning targets and reference observations for model validation. Supporting Geographic Information System (GIS) layers describe terrain characteristics, land-use conditions, catchment boundaries, and spatial relationships among physical infrastructure assets. Material-specific environmental impact factors provide an additional source of information for evaluating embodied-carbon emissions associated with construction alternatives. Together, these datasets establish a multidimensional information structure capable of connecting environmental hazards with infrastructure performance and sustainability outcomes. The data acquisition and development procedure is organised into five principal stages: identification and acquisition of relevant datasets; data quality assessment and preliminary screening; spatial and temporal harmonisation; integration and construction of analytical variables; and preparation of structured datasets for subsequent modelling and Digital Twin applications [15]. Figure 3 illustrates the proposed workflow, showing how the hydro-meteorological, infrastructure, BIM, flood-event, and supporting environmental information sources are processed and integrated into a consistent analytical environment. The workflow is intended to preserve the provenance of individual observations while enabling relationships to be established between environmental conditions, geographical locations, infrastructure assets, and construction materials.

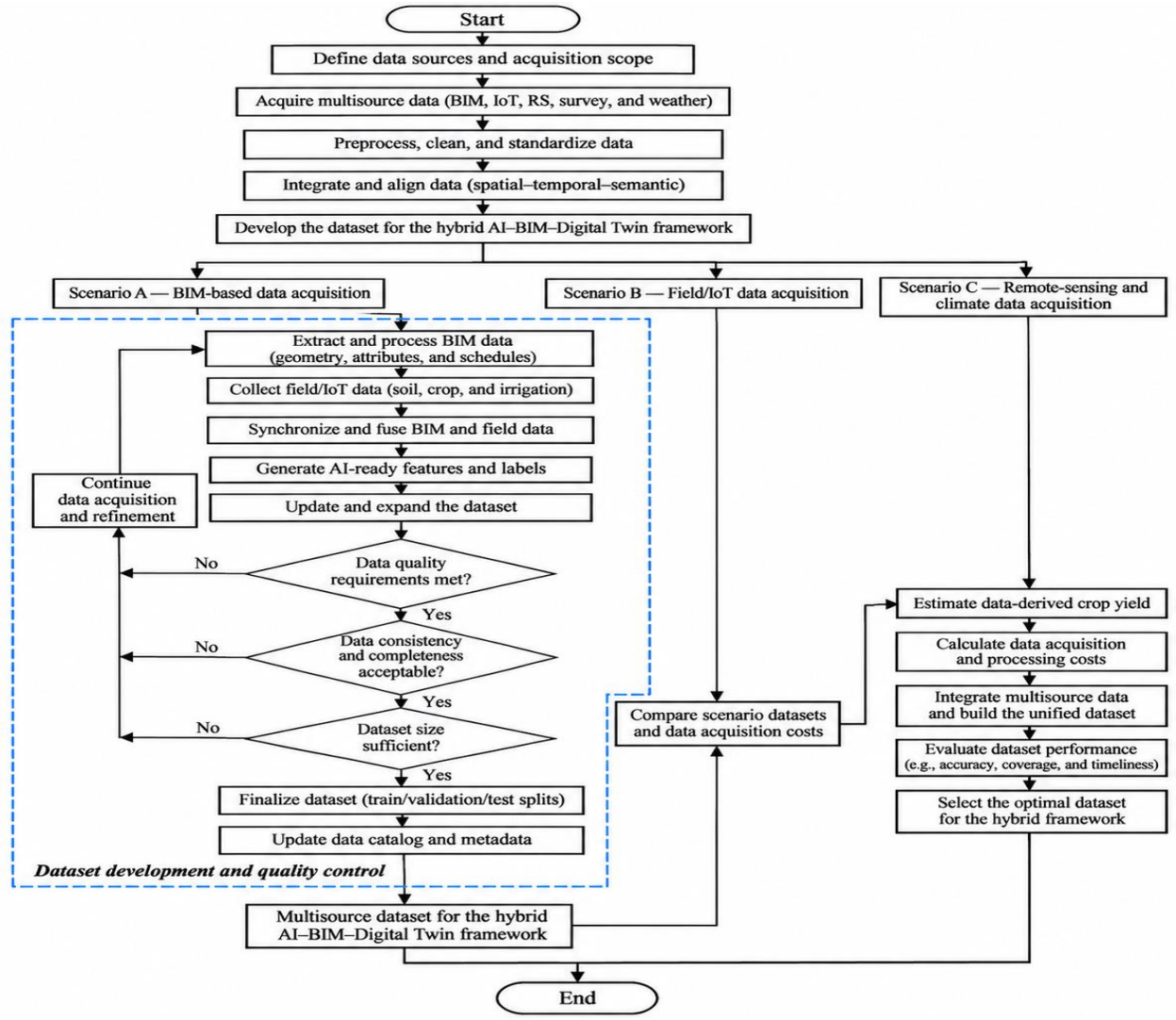


Figure 3: Multisource data acquisition, integration, and quality control workflow for the hybrid AI–BIM–Digital Twin framework.

Hydro-meteorological observations constitute the principal temporal data source for analysing rainfall–runoff processes and developing predictive relationships between precipitation characteristics and flood occurrence. The dataset incorporates ten years of hourly rainfall and river-level measurements to capture variations across different hydrological conditions and seasonal periods. Rainfall observations are represented using precipitation depth in millimetres over the relevant observation interval, while river-level records are expressed in metres relative to the corresponding measurement datum. Maintaining the original measurement intervals and reference datums is essential for ensuring consistency during subsequent temporal alignment and hydrological analysis. The rainfall dataset supports the analysis of short-duration precipitation intensity, cumulative rainfall, event duration, antecedent rainfall conditions, and seasonal patterns. These variables are particularly relevant to urban flood forecasting because surface runoff is influenced by both the magnitude of current precipitation and the hydrological conditions preceding an event. Consecutive rainfall observations can be aggregated over selected temporal windows to describe rainfall accumulation and the persistence of wet conditions. However, the selection of

aggregation periods and forecasting horizons must be consistent with the intended prediction task and should be established during feature engineering and model development. The hourly resolution provides a suitable temporal structure for examining rainfall variability, although its ability to represent highly localised, short-duration storm events depends on the temporal and spatial resolution of the original monitoring network [16]. River-level observations provide additional information concerning the hydrological response of waterways and drainage-connected environments. Water-level measurements can be used to characterise temporal changes in river conditions and investigate their relationships with rainfall patterns and recorded flood events. Relevant variables include observed river level, previous water levels, temporal differences, and rates of change over defined observation intervals. Where multiple stations are represented, geographical coordinates, station identifiers, and measurement reference levels should be retained to enable consistent spatial interpretation. River-level observations may also provide useful boundary-condition information for hydraulic modelling when the monitored waterways interact with the drainage network. Nevertheless, the use of river-level measurements as hydraulic inputs requires confirmation of their geographical relevance, measurement reliability, and compatibility with the selected hydrological or hydraulic modelling approach. The principal datasets, their reported quantities, key attributes, and intended applications are summarised in Table 3.

Table 3: Summary of multisource datasets, principal attributes, spatial and temporal characteristics, and applications within the proposed hybrid AI–BIM–Digital Twin framework.

Dataset category	Reported size or coverage	Principal attributes	Spatial/temporal characteristics
Rainfall observations	10 years of hourly observations	Rainfall depth, cumulative precipitation, timestamps, monitoring identifiers	Hourly; station locations to be specified
River-level observations	10 years of hourly observations	Water level, level variation, station references	Hourly; river-monitoring locations to be specified
Drainage infrastructure assets	250 georeferenced assets	Asset identification, location, type, geometry, connectivity and available hydraulic attributes	Asset-level geospatial records
BIM construction elements	120 elements	IFC identifiers, classification, geometry, materials and quantities	Object-level digital engineering information
Historical flood records	Approximately 15,000 records	Flood occurrence, recorded depth where available, event timing and location	Event-related temporal and spatial records; independence to be verified

The integrated dataset incorporates several distinct information types that require coordinated processing before analytical modelling. Time-indexed rainfall and river-level observations support predictive flood analysis, while georeferenced drainage records provide the physical and geographical infrastructure context. BIM construction elements enable the association of material properties and engineering quantities with corresponding assets, and historical flood observations provide supervised target information for model evaluation. Supporting GIS layers and environmental emission factors extend the analytical scope from hydrological prediction towards drainage optimisation and sustainability assessment. The integration process

begins with the development of a consistent data inventory and metadata structure. Each dataset is assigned a source identifier, temporal coverage description, spatial reference, variable definition, measurement unit, and information-quality designation. Where multiple data providers or measurement systems are involved, naming conventions and variable definitions are standardised to minimise ambiguity [17]. This approach is particularly important for variables such as rainfall intensity, rainfall accumulation, water level, inundation depth, and drainage capacity, which may otherwise be represented using different measurement conventions or reference definitions. The information architecture also distinguishes between raw observations, processed records, and modelling-ready variables. Raw data are preserved where available to support traceability and independent verification. Processed records contain documented corrections, harmonised measurement units, and aligned spatial or temporal references. Modelling-ready datasets contain the features, target variables, and data relationships required by particular analytical components. Maintaining these distinctions reduces the risk of unintentionally modifying source records and facilitates reproducible preprocessing and model development.

4.2- Development of the IFC-Based BIM–GIS–IoT Digital Twin Architecture:

An interoperable and integrated Building Information Modelling (BIM)–Geographic Information System (GIS)–Internet of Things (IoT) Digital Twin (DT) architecture is proposed to establish a unified computational environment for intelligent, climate-resilient, and sustainable civil infrastructure management. The architecture is designed to integrate physical infrastructure information, hydro-meteorological observations, geospatial characteristics, construction-related attributes, and predictive analytical models within a consistent digital information ecosystem. Conventional infrastructure management systems frequently store engineering design information, environmental monitoring observations, maintenance records, and sustainability indicators in separate databases or software environments, limiting their interoperability and restricting comprehensive evaluation of infrastructure performance. To address these limitations, the proposed architecture establishes structured information relationships between physical infrastructure assets and their corresponding digital representations, facilitating coordinated data acquisition, information management, engineering simulation, and scenario-based decision support [18]. The framework integrates Industry Foundation Classes (IFC)-based BIM information, GIS datasets, IoT-compatible monitoring interfaces, hybrid Artificial Intelligence (AI) forecasting, hydrological modelling, Sustainable Urban Drainage Systems (SuDS) optimisation, and Life Cycle Assessment (LCA) to support the simultaneous evaluation of flood resilience and construction-related environmental impacts. The proposed Digital Twin architecture adopts a modular and multilayer design to accommodate differences in data formats, spatial resolutions, temporal characteristics, and engineering applications. BIM provides structured asset-level information concerning infrastructure geometry, construction materials, dimensions, quantities, and engineering properties, while GIS supplies geographical and environmental information associated with drainage catchments, terrain characteristics, land-use conditions, and flood-exposed infrastructure locations. IoT monitoring interfaces facilitate the acquisition of time-dependent environmental observations, including rainfall intensity, river levels, and available drainage-related measurements. These complementary information sources are integrated through consistent data structures, asset identifiers, spatial references, and interoperable communication mechanisms. The resulting digital environment provides a foundation for connecting historical observations and updated monitoring information with analytical models capable of assessing infrastructure conditions and evaluating adaptation alternatives. Unlike an isolated BIM model or conventional visualisation platform, the proposed Digital Twin is intended to establish an operational relationship between asset

information, environmental observations, computational analysis, and engineering decision-making. The architectural development follows an open-standard interoperability strategy to improve information portability and reduce dependence on individual proprietary engineering applications. Industry Foundation Classes, standardised under ISO 16739-1:2024, provide the primary information structure for representing BIM-related infrastructure elements and exchanging their geometric and non-geometric attributes. The IFC 4.3 specification is particularly relevant to civil infrastructure because it extends information modelling capabilities for infrastructure-related domains [19]. GIS information is managed using consistent geographical reference systems and compatible spatial data structures, allowing infrastructure components to be represented within their surrounding environmental context. IoT-compatible communication interfaces provide mechanisms for transferring historical or updated monitoring observations into the integrated information environment. Where suitable, open geospatial observation standards, including the Open Geospatial Consortium SensorThings API, can support the consistent organisation and retrieval of sensor measurements and associated metadata. These interoperability mechanisms are intended to facilitate extensibility and information continuity while maintaining the traceability of source datasets and engineering attributes. The proposed framework is organised into five interconnected functional layers comprising physical infrastructure and data acquisition, data management and processing, BIM–GIS interoperability, Digital Twin analytics and simulation, and infrastructure visualisation and decision support. The overall configuration is shows in Figure 4, which presents the conceptual relationships between physical infrastructure components, environmental observations, digital information models, analytical processes, and infrastructure management outcomes.

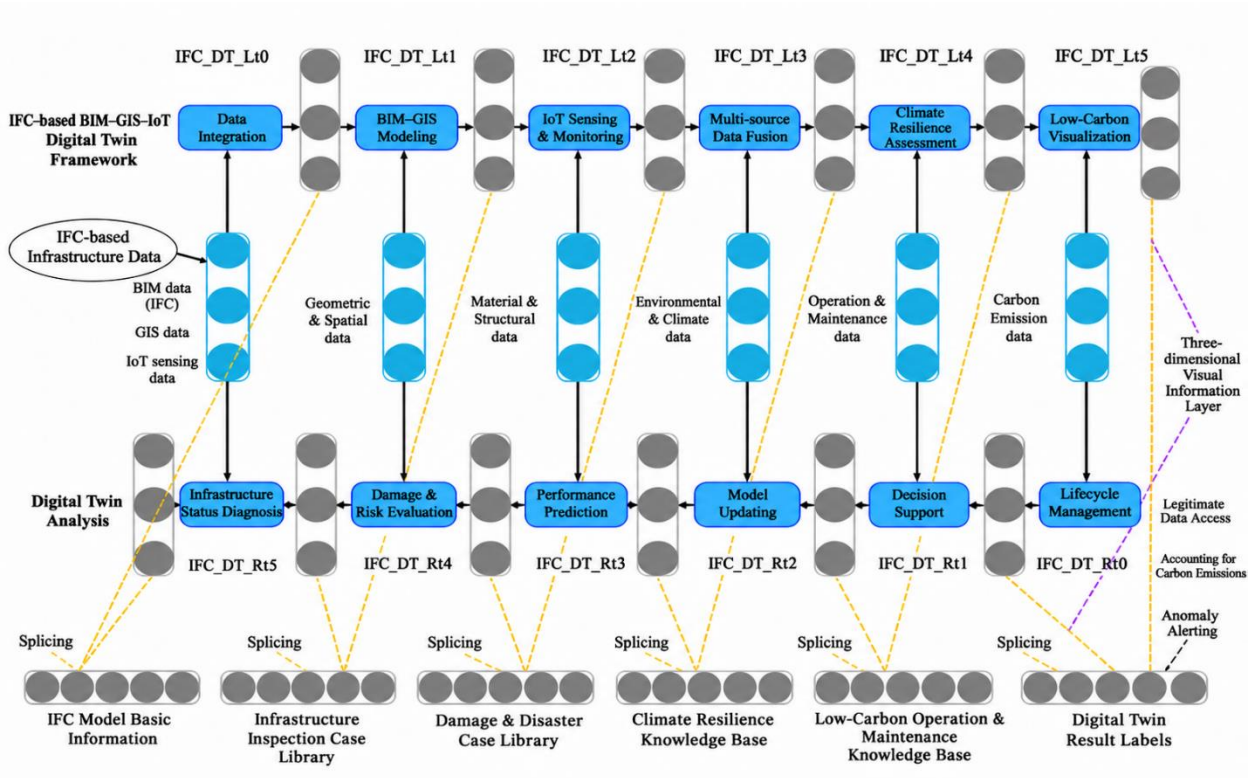


Figure 4: Conceptual architecture of the proposed IFC-based BIM–GIS–IoT Digital Twin framework for intelligent, climate-resilient, and low-carbon civil infrastructure management.

The physical infrastructure and data acquisition layer represents the interface between real-world engineering systems and the digital environment. This layer incorporates the georeferenced drainage infrastructure assets, BIM construction elements, hydro-meteorological monitoring locations, and relevant environmental observations. The physical infrastructure dataset includes 250 georeferenced drainage assets, while 120 BIM construction elements provide structured information concerning selected engineering components. The drainage assets may include pipes, manholes, culverts, drainage channels, inspection chambers, and associated stormwater-management structures, depending on the available inventory. Each asset is associated with an identifier and geographical reference to support integration with the broader information environment. Available engineering attributes, including infrastructure type, geometric dimensions, material characteristics, hydraulic properties, and connectivity relationships, are retained to support subsequent modelling and assessment. Where particular attributes are unavailable, the information structure accommodates incomplete records without automatically assigning unsupported values. The data acquisition layer is also responsible for incorporating hydro-meteorological observations into the Digital Twin information environment. Historical rainfall and river-level measurements provide the primary temporal information for developing predictive relationships between environmental conditions and flood occurrence. The study dataset comprises ten years of hourly rainfall and river-level records, which are organised using consistent timestamps and monitoring identifiers [20]. These observations can be incorporated into the architecture through historical database interfaces or, where operational sensing systems are available, through IoT-enabled monitoring connections. The architecture is designed to distinguish between historical data replay and actual live monitoring, because the use of historical observations does not independently establish real-time operational capability. Monitoring observations are associated with measurement units, observation timestamps, source identifiers, and relevant geographical references to support consistent processing and interpretation. The functional organisation of the proposed architecture is summarised in Table 4, which describes the principal responsibilities, enabling technologies, and expected information outputs associated with each architectural layer.

Table 4: Functional layers, principal components, processing responsibilities, and outputs of the proposed IFC-based BIM–GIS–IoT Digital Twin architecture.

Functional layer	Principal components	Main processing functions
Layer 1: Physical infrastructure and data acquisition	Drainage assets, BIM records, rainfall and river-level observations	Asset identification, environmental data acquisition, monitoring record collection
Layer 2: Data management and processing	Databases, metadata records, quality-control procedures	Data ingestion, storage, validation, temporal alignment, provenance management
Layer 3: BIM–GIS information integration	IFC object models, asset registers, GIS layers, spatial and semantic mappings	Asset linking, coordinate harmonisation, engineering attribute integration
Layer 4: Analytics and simulation	XGBoost–LSTM, hydrological models, SuDS assessment, LCA	Flood forecasting, hydraulic assessment, intervention optimisation, carbon calculation
Layer 5: Visualisation and decision support	Digital Twin interfaces, dashboards, spatial visualisation, scenario records	Infrastructure monitoring, scenario comparison, performance reporting

The architectural layers perform distinct but interconnected functions. The separation of acquisition, processing, interoperability, analytical modelling, and decision support improves modularity and supports the potential replacement or extension of individual system components. For instance, a revised forecasting algorithm or alternative hydrological model could be incorporated without reconstructing the complete Digital Twin environment, provided that the relevant information interfaces remain consistent. This modularity is important for adapting the framework to different infrastructure networks, computational resources, and monitoring conditions. The fifth architectural layer supports infrastructure visualisation, engineering scenario analysis, and the communication of analytical outputs to relevant stakeholders. The visualisation environment is intended to provide access to the available geometric and engineering characteristics of infrastructure assets, together with their geographical locations and associated monitoring information. Spatial representations allow users to examine drainage-network configurations and potentially flood-exposed areas, while time-dependent visualisations can display environmental observations and model predictions. Engineering performance dashboards may present flood probability, predicted inundation depth, runoff indicators, drainage overflow characteristics, and construction-related embodied-carbon estimates. These functionalities are intended to assist the interpretation of interconnected infrastructure processes rather than replace professional engineering judgement.

4.3- Hybrid XGBoost–LSTM Model Development for Intelligent Flood Forecasting:

The proposed intelligent flood forecasting framework integrates Extreme Gradient Boosting (XGBoost) and Long Short-Term Memory (LSTM) neural networks to investigate the complementary capabilities of gradient-boosted ensemble learning and recurrent temporal modelling for predicting flood occurrence and inundation depth. Flood generation in urban environments is influenced by complex and nonlinear interactions among rainfall intensity, antecedent precipitation, river-level fluctuations, catchment characteristics, surface impermeability, and drainage-network conditions. Conventional data-driven forecasting approaches may exhibit limitations when representing these relationships using a single algorithm, particularly where structured infrastructure attributes and sequential hydro-meteorological observations must be analysed simultaneously. To address these challenges, a hybrid XGBoost–LSTM architecture is proposed to combine nonlinear feature interactions with the temporal dependencies associated with rainfall–runoff processes. The forecasting system is designed to produce two complementary prediction outputs: the probability of flood occurrence, formulated as a binary classification problem, and inundation depth, formulated as a continuous regression problem [21]. These predictions provide quantitative information for subsequent flood-risk assessment, hydrological simulation, drainage optimisation, and Digital Twin-enabled infrastructure decision support. The forecasting model utilises the multisource dataset described in Section 3.3, incorporating ten years of hourly rainfall and river-level observations, relevant georeferenced drainage infrastructure characteristics, and approximately 15,000 historical flood-event records. The available BIM and GIS information provides additional spatial and engineering context where corresponding asset relationships can be established. The model development process begins by constructing a temporally indexed analytical dataset from the harmonised environmental and infrastructure records. Rainfall observations, river-level measurements, and available infrastructure-related attributes are combined according to their timestamps, monitoring locations, catchment associations, and relevant forecasting targets. The resulting dataset is organised to maintain consistency between environmental predictor variables and their corresponding flood observations. Particular attention is given to the distinction between information available at the forecast issue time and observations occurring subsequently, because the inclusion of future hydrological information would introduce

temporal leakage and overestimate forecasting performance. The primary predictor variables include hourly rainfall, antecedent precipitation, cumulative rainfall over selected time windows, current and lagged river levels, and rates of water-level change. Where the necessary information is available, additional predictors may include catchment elevation, impermeable surface ratio, land-use classification, drainage capacity, and relevant infrastructure characteristics. Rainfall accumulation features are intended to represent the influence of previous precipitation on runoff generation, while river-level change indicators describe evolving hydrological conditions. Spatial and infrastructure-related attributes provide information concerning the physical characteristics that may influence flood susceptibility [22]. These predictors are selected according to their hydrological relevance, data availability, and suitability for reliable temporal forecasting rather than solely on their apparent statistical association with the target variables. The overall hybrid modelling architecture is present in Figure 5. The forecasting workflow begins with multisource predictor construction and chronological data preparation, followed by two complementary modelling branches. The XGBoost branch processes engineered tabular predictors to capture nonlinear relationships among environmental and infrastructure-related features, while the LSTM branch processes historical input sequences to represent temporal dependencies. The outputs of these components are subsequently combined through a feature-fusion mechanism and supplied to task-specific prediction layers for flood classification and inundation-depth regression. The figure also identifies the principal methodological safeguards required for temporal validation and reliable evaluation.

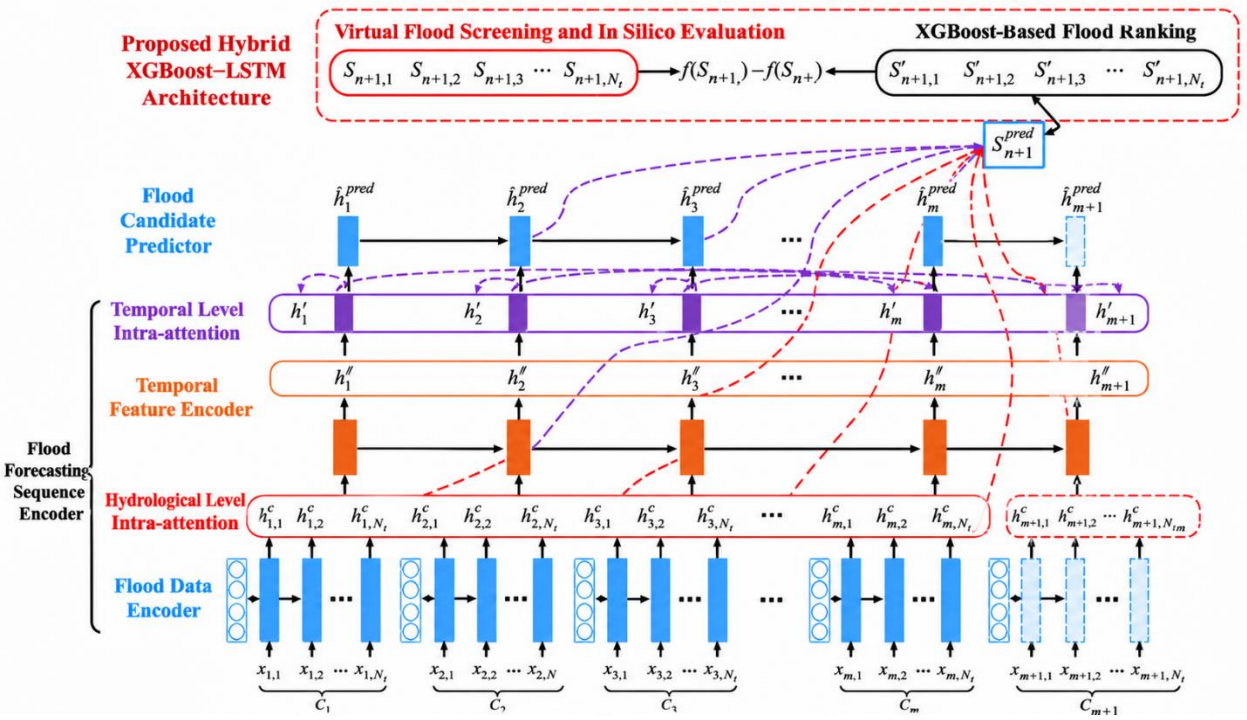


Figure 5: Proposed hybrid XGBoost–LSTM architecture integrating attention mechanisms for flood forecasting and risk ranking.

The LSTM architecture is configured using selected hyperparameters, including the number of recurrent layers, hidden-state dimension, dropout rate, sequence length, learning rate, batch size, and training epochs. These parameters are selected through validation-based tuning rather

than assigned arbitrary optimal values. The use of dropout, weight regularisation, and early stopping is considered to reduce overfitting and improve generalisation. Input feature scaling is applied where appropriate, with scaling parameters calculated exclusively from the training dataset. Validation and testing records are then transformed using the parameters derived from the training subset to prevent the incorporation of future information into model preprocessing. The hybrid integration strategy adopts a prediction-and-representation fusion approach in which the XGBoost branch generates task-specific predictions from structured features and the LSTM branch produces learned temporal representations. For the classification task, the XGBoost branch provides a flood probability estimate, while a separate regression model produces an inundation-depth estimate. These outputs are combined with the LSTM hidden representation through a shared fusion layer. This configuration allows the forecasting system to utilise nonlinear tabular predictions alongside temporal patterns learned from sequential observations [23]. The proposed hybrid XGBoost–LSTM forecasting methodology combines gradient-boosted nonlinear modelling with recurrent temporal learning to investigate flood occurrence and inundation-depth prediction within a unified computational architecture. Its development incorporates explicit feature engineering, temporally valid model fusion, chronological training and validation, multi-task prediction, benchmark comparison, and uncertainty-aware evaluation. By linking the resulting forecasts to georeferenced infrastructure information and the proposed BIM–Digital Twin environment, the methodology establishes a foundation for integrating predictive flood intelligence with subsequent hydrological simulation, SuDS optimisation, and climate-resilient infrastructure assessment. The intended contribution is not solely an improvement in forecasting accuracy but also the development of a reproducible modelling approach capable of supplying relevant predictive information to the broader digital infrastructure decision-support framework.

4.4- Hydrological and Hydraulic Modelling of Urban Flood Dynamics:

A coupled hydrological and hydraulic modelling framework is proposed to simulate rainfall–runoff processes, drainage-network behaviour, and surface inundation dynamics within flood-vulnerable urban environments. The modelling approach is developed to complement the hybrid XGBoost–Long Short-Term Memory (LSTM) forecasting architecture described in Section 3.6 by providing a physically based representation of the processes governing runoff generation, hydraulic conveyance, drainage overflow, and flood propagation. Urban flooding results from complex interactions among precipitation characteristics, antecedent moisture conditions, land-use patterns, surface permeability, terrain morphology, drainage-network capacity, and downstream water-level conditions. These interactions require a modelling framework capable of representing both catchment-scale hydrological responses and the hydraulic behaviour of engineered drainage systems. Accordingly, the proposed methodology combines rainfall–runoff modelling, one-dimensional drainage-network hydraulics, and, where appropriate topographic information is available, two-dimensional surface inundation simulation to establish a comprehensive analytical environment for evaluating existing infrastructure performance and potential climate-adaptation interventions [24]. The hydrological component is intended to transform rainfall observations into surface runoff and generate inflow hydrographs for individual drainage catchments. The hydraulic component subsequently routes these inflows through the drainage network, evaluates flow conditions and hydraulic exceedance, and estimates surface-water accumulation where the capacity of the drainage infrastructure is insufficient. This coupled representation allows rainfall characteristics and catchment conditions to be connected with the physical capacity and operational behaviour of stormwater-management infrastructure. The model incorporates relevant information from the multisource dataset described in Section 3.3, including ten years of hourly rainfall and river-level observations, 250 georeferenced drainage

infrastructure assets, available BIM construction elements, and supporting GIS information. These datasets provide complementary temporal, spatial, and engineering inputs for establishing the hydrological and hydraulic characteristics of the study environment. Where particular model inputs are unavailable, parameter values must be estimated using documented engineering assumptions and subsequently examined through calibration and sensitivity analysis. The modelling framework is designed around the integration of hydrological processes and drainage-network dynamics within a common geographical reference system. GIS datasets provide information concerning catchment boundaries, terrain elevations, land-use characteristics, surface permeability, and drainage-network locations. BIM and infrastructure asset records supply the geometric and engineering characteristics required to represent drainage components, including pipes, channels, culverts, junctions, and relevant storage structures. Hydro-meteorological observations provide the temporal forcing conditions, while recorded flood events support model calibration, validation, and comparison of simulated inundation behaviour. The modelling environment is intended to permit the evaluation of both historical rainfall events and explicitly defined hypothetical rainfall scenarios [25]. Where sufficiently reliable climate projections are available, these may also be used to investigate the sensitivity of drainage performance to changing precipitation characteristics. The proposed coupled hydrological–hydraulic modelling workflow is shows in Figure 6. The workflow begins with the acquisition of hydro-meteorological observations, geospatial catchment information, drainage-network records, and BIM-derived asset attributes. These inputs are subsequently processed within the hydrological component to estimate runoff generation and produce catchment inflow hydrographs. The resulting hydrographs are transferred to the hydraulic component, which simulates flow conveyance through the drainage network and, where supported by the selected model, the interaction between underground drainage infrastructure and surface-water accumulation. Alternative drainage configurations, including sustainable drainage interventions, are then evaluated through scenario-based simulation. The final outputs include peak runoff, flood depth, inundation extent, drainage overflow frequency, and other relevant indicators supporting climate-resilient infrastructure planning.

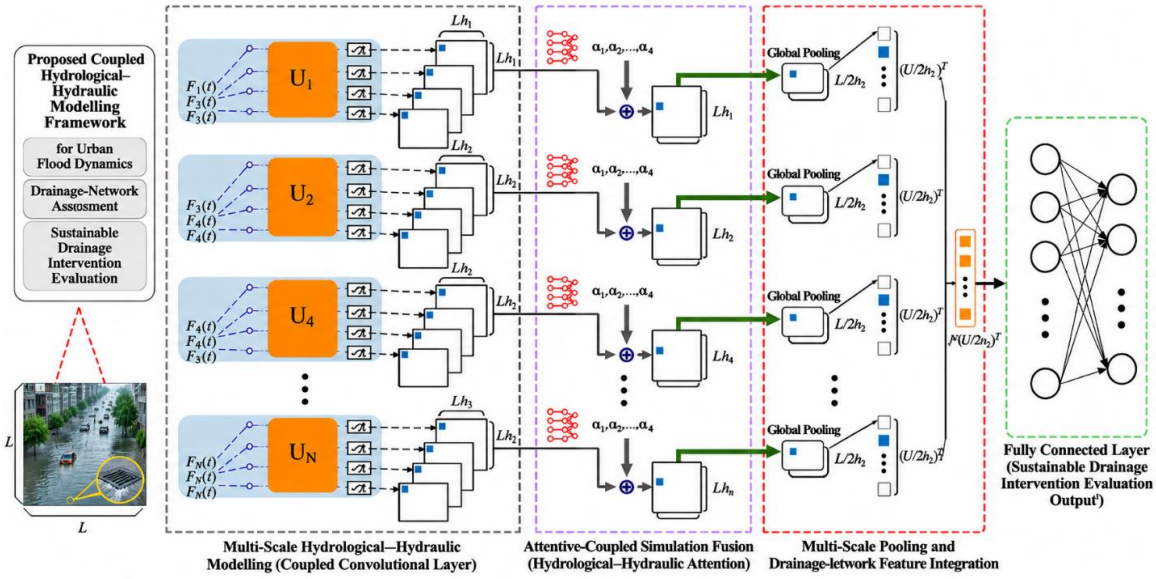


Figure 6: Attention-based coupled hydrological–hydraulic framework for urban flood modeling and sustainable drainage intervention evaluation.

The hydrological modelling component requires the delineation of the study area into appropriate subcatchments based on topographical characteristics, drainage connectivity, land-use conditions, and available infrastructure information. Each subcatchment is represented through relevant physical and hydrological attributes, including contributing area, average slope, impervious surface proportion, characteristic flow width, surface roughness, and infiltration-related properties. Subcatchment boundaries are established using available digital elevation information and drainage-network records, with manual review where urban infrastructure alters natural surface-water flow pathways. Such review is important because engineered drainage networks, road embankments, buildings, and other urban features can influence runoff routing in ways that may not be fully represented by terrain elevation alone. The resulting subcatchment representation provides the spatial foundation for estimating runoff and transferring inflows to the corresponding drainage-network elements. The integration of physically based hydraulic simulation with the hybrid XGBoost–LSTM forecasting framework is intended to improve the interpretability and practical relevance of flood-related information. The AI model provides data-driven estimates of flood probability and inundation depth, while the hydrological and hydraulic models represent selected physical processes governing runoff generation, conveyance, and inundation. These components can be evaluated independently and their outputs compared to identify differences under corresponding environmental conditions. Where appropriate, forecast information may also be used to select or prioritise hydraulic scenarios for further investigation, although its use as a model boundary condition requires careful consideration of physical compatibility and uncertainty [26]. The resulting hydrological and hydraulic outputs are linked to the IFC-based BIM–GIS–IoT Digital Twin architecture described in Section 3.5. Georeferenced simulation results can be associated with drainage assets, catchment boundaries, BIM object identifiers, and scenario records within the integrated information environment. This association enables infrastructure-specific interpretation of hydraulic indicators, including conveyance conditions, overflow behaviour, modelled flood depth, and surrounding inundation extent. The Digital Twin environment provides a mechanism for presenting simulation results and comparing alternative drainage configurations, while the modelling outputs support the subsequent optimisation and embodied-carbon assessment stages. The proposed modelling framework also acknowledges important sources of uncertainty. These include incomplete drainage-network documentation, errors in terrain representation, uncertainty in infiltration and roughness parameters, limitations of hourly precipitation observations for short-duration urban storms, and the potential absence of continuous observed flow or inundation measurements. Sensitivity analysis is therefore used to examine how selected assumptions influence runoff estimates, hydraulic behaviour, and predicted flood characteristics. Where uncertainty cannot be reduced through available observations, its potential effect on engineering conclusions should be explicitly reported.

4.5- Multi-Objective Optimisation of Drainage and Low-Carbon Infrastructure:

A comprehensive multi-objective optimisation framework is proposed to identify climate-resilient and environmentally sustainable infrastructure configurations through the simultaneous evaluation of hydraulic performance, embodied-carbon emissions, and practical engineering constraints. Urban drainage interventions frequently involve competing design objectives because improvements in flood mitigation may require additional construction materials, increased land allocation, and greater implementation expenditure. Conversely, infrastructure configurations designed primarily to minimise construction-related carbon emissions may not provide adequate hydraulic capacity or resilience under extreme rainfall conditions. The proposed optimisation methodology incorporates permeable pavements, bioswales, and detention basins as principal stormwater-management

interventions, together with selected construction material and design alternatives. These measures are evaluated according to their potential to reduce peak surface runoff, mitigate inundation extent, decrease drainage overflow frequency, and minimise embodied-carbon emissions [27]. The framework considers the physical and operational characteristics of each intervention, including available implementation space, hydraulic connectivity, infiltration conditions, storage capacity, construction requirements, and material specifications. Rather than identifying an engineering solution by minimising a single objective, the methodology seeks a set of non-dominated alternatives representing different compromises among hydraulic, environmental, and implementation-related performance indicators. The resulting solutions provide an evidence-based foundation for selecting drainage configurations that satisfy relevant infrastructure constraints while supporting climate-resilience and low-carbon development objectives. The overall optimisation process is present in Figure 7. The workflow begins with the integration of hydro-meteorological records, geospatial infrastructure information, BIM construction attributes, and material-related environmental factors. Candidate solutions are generated by varying SuDS design parameters and construction material alternatives within predefined engineering constraints. A multi-objective evolutionary algorithm is then employed to explore the design space, while the coupled hydrological–hydraulic model and BIM-based carbon assessment calculate the corresponding performance indicators. The evaluated solutions are ranked according to Pareto dominance and diversity criteria, and new candidate configurations are generated through evolutionary search operations. The process continues until the predefined stopping conditions are satisfied, producing a set of non-dominated alternatives for subsequent engineering interpretation and decision support.

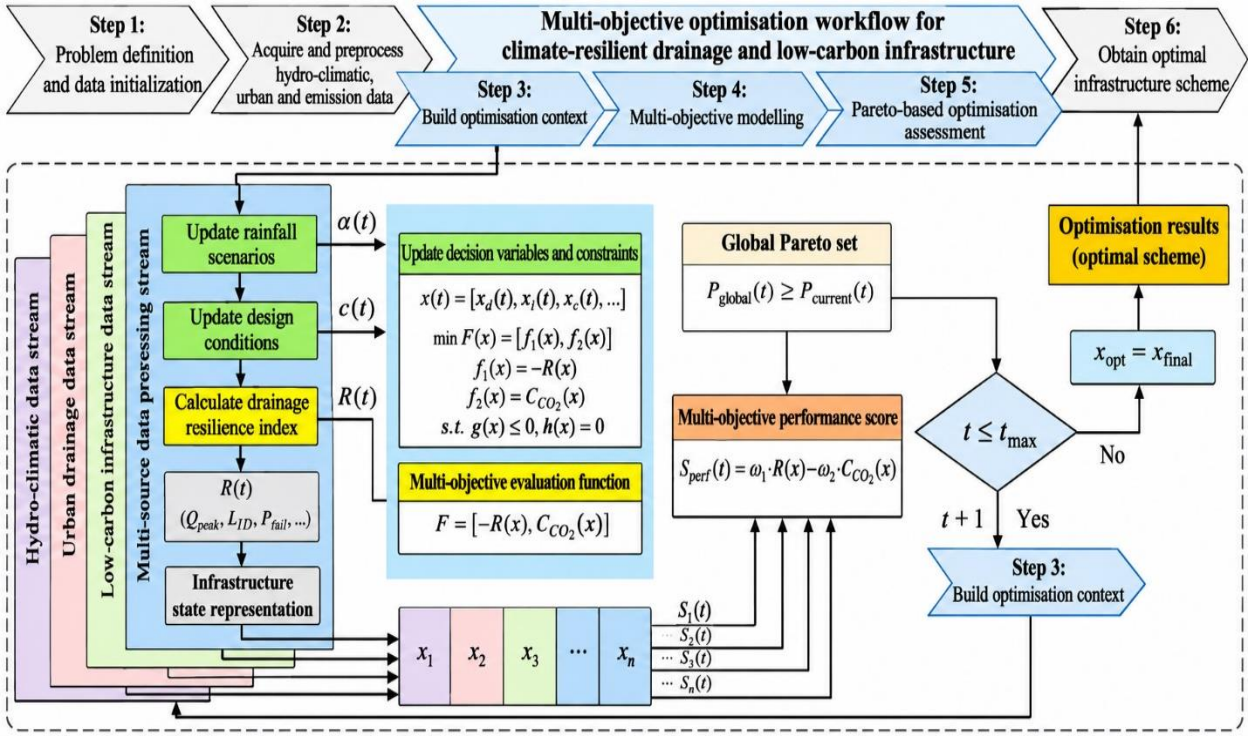


Figure 7: Multi-objective optimisation workflow for climate-resilient drainage and low-carbon infrastructure.

The stopping criteria are established according to the maximum number of generations, convergence behaviour, computational requirements, and changes in the quality of the

non-dominated solution set. Convergence can be investigated by examining the stability of objective values and the development of the Pareto front across successive generations. Hypervolume and other suitable indicators may be used to assess the convergence and diversity of the resulting solution sets, provided that consistent reference points and normalisation procedures are adopted. Repeated optimisation runs with different random seeds can be performed to investigate the sensitivity of the results to stochastic search behaviour. Such evaluation is important because evolutionary algorithms do not generally guarantee identification of the global Pareto-optimal set within a finite computational budget. The computational integration of NSGA-II with hydrological simulation and BIM-based carbon assessment may require substantial processing resources, particularly when multiple rainfall events are evaluated for every candidate solution. The optimisation procedure therefore incorporates provisions for computational efficiency, including reuse of unchanged simulation inputs, caching of previously evaluated candidate configurations, and parallel execution where supported by the selected software. The use of simplified surrogate models may also be considered for preliminary screening of candidate designs, although final selected alternatives should be re-evaluated using the verified hydraulic and environmental models [28]. Computational efficiency measures must preserve consistency between candidate designs and their evaluated objective values. The optimisation results are represented as a set of non-dominated infrastructure configurations describing alternative trade-offs among peak runoff, inundation extent, overflow frequency, and embodied-carbon emissions. These solutions do not necessarily identify a single universally preferred design because different stakeholders may assign different importance to hydraulic resilience, environmental impact, implementation cost, land use, and maintenance requirements. Consequently, the optimisation procedure is followed by an explicit multi-criteria decision process to select suitable alternatives for further engineering consideration. Overall, the proposed multi-objective optimisation methodology provides a structured computational framework for evaluating climate-resilient drainage configurations and lower-carbon infrastructure alternatives within a unified engineering decision-support environment. The integration of hydrological–hydraulic modelling, SuDS design variables, BIM-based environmental assessment, and Pareto-based evolutionary optimisation enables the systematic investigation of competing hydraulic and sustainability objectives. The resulting non-dominated solutions provide alternative infrastructure configurations that can be evaluated according to engineering feasibility, environmental performance, and stakeholder priorities. By transferring these results to the BIM–GIS–IoT Digital Twin environment, the methodology establishes a connection between computational optimisation, physical infrastructure representation, and scenario-based decision-making. This integrated approach supports the broader objective of developing adaptive, resource-efficient, and climate-resilient infrastructure systems consistent with the sustainable engineering priorities associated with the UK–Pakistan Green Compact.

5- Results and Discussion:

The proposed hybrid Artificial Intelligence (AI)-driven Building Information Modelling (BIM)–Digital Twin (DT) framework is evaluated through three interconnected performance dimensions: the predictive accuracy of intelligent flood forecasting, the hydraulic effectiveness of optimised Sustainable Urban Drainage Systems (SuDS), and the potential for reducing upfront embodied-carbon emissions through BIM-integrated construction design optimisation. The reported findings indicate improvements in flood prediction relative to a conventional baseline model, reductions in selected urban drainage and inundation indicators, and lower construction-related carbon emissions under the optimised design scenario. These outcomes are considered jointly to examine the contribution of integrating predictive intelligence, hydrological and hydraulic simulation, drainage adaptation, and lifecycle environmental assessment within a unified digital

engineering environment. The discussion focuses on the reported comparative outcomes, their engineering significance, their methodological interpretation, and the limitations that must be addressed before the framework can be considered sufficiently validated for operational infrastructure management. The hybrid XGBoost–LSTM forecasting model is designed to combine the complementary capabilities of gradient-boosted decision trees and recurrent neural networks. XGBoost captures nonlinear relationships among structured hydro-meteorological and infrastructure-related predictors, whereas the LSTM component represents temporal dependencies within sequences of rainfall and river-level observations. By combining these representations, the hybrid architecture seeks to account for both the instantaneous and accumulated influences of environmental conditions on flood occurrence and inundation depth. The forecasting evaluation distinguishes between classification performance, which concerns the identification of flood events, and regression performance, which concerns the estimation of inundation depth. This distinction is important because a model may identify the occurrence of flooding accurately while producing comparatively large errors in estimated water depth, or vice versa. The reported results indicate that the proposed hybrid forecasting approach achieves a coefficient of determination (R^2) of 0.93, a root mean square error (RMSE) of 0.18 m, and an F1-score of 0.91. The corresponding conventional baseline values are R^2 = 0.82, RMSE = 0.31 m, and F1-score = 0.79. The comparative results are summarised in Table 5, while Figure 8 provides a graphical comparison of the reported performance metrics.

Table 5: Comparative performance of the hybrid XGBoost–LSTM and conventional baseline models for flood forecasting.

Performance indicator	Conventional baseline	Hybrid XGBoost–LSTM	Calculated improvement	Preferred direction
Coefficient of determination (R^2)	0.82	0.93	+0.11 absolute; +13.4% relative	Higher
Root mean square error (RMSE)	0.31 m	0.18 m	−0.13 m; 41.9% reduction	Lower
F1-score	0.79	0.91	+0.12 absolute; +15.2% relative	Higher

The hybrid forecasting model demonstrates higher reported predictive performance across all three evaluation indicators. The increase in R^2 from 0.82 to 0.93 corresponds to an absolute improvement of 0.11 and a relative increase of approximately 13.4%. This result indicates that the hybrid model provides a closer fit to the observed inundation-depth variability than the reported baseline model, assuming that both R^2 values were calculated using the same independent testing records and prediction targets. An R^2 value of 0.93 suggests strong agreement in the explained variation of the regression target, although this metric alone does not establish the absence of systematic bias or guarantee accurate prediction of rare extreme inundation conditions. The reduction in RMSE from 0.31 m to 0.18 m represents an absolute decrease of 0.13 m and a relative reduction of approximately 41.9%. This improvement is particularly relevant to flood-related engineering assessment because errors in inundation-depth estimation can influence interpretations of infrastructure exposure, drainage performance, and the potential severity of surface-water accumulation. Lower RMSE indicates a reduction in the magnitude of depth-prediction errors, with greater sensitivity to relatively large individual errors than some alternative regression metrics. Nevertheless, the engineering significance of an RMSE of 0.18 m depends on the range of observed inundation depths, the spatial and temporal scales of the

predictions, and the operational thresholds used for flood-related decisions. For example, an error of this magnitude may be relatively small for some deep-flood scenarios but important where a minor change in water level determines whether a road, building entrance, or drainage asset becomes affected.

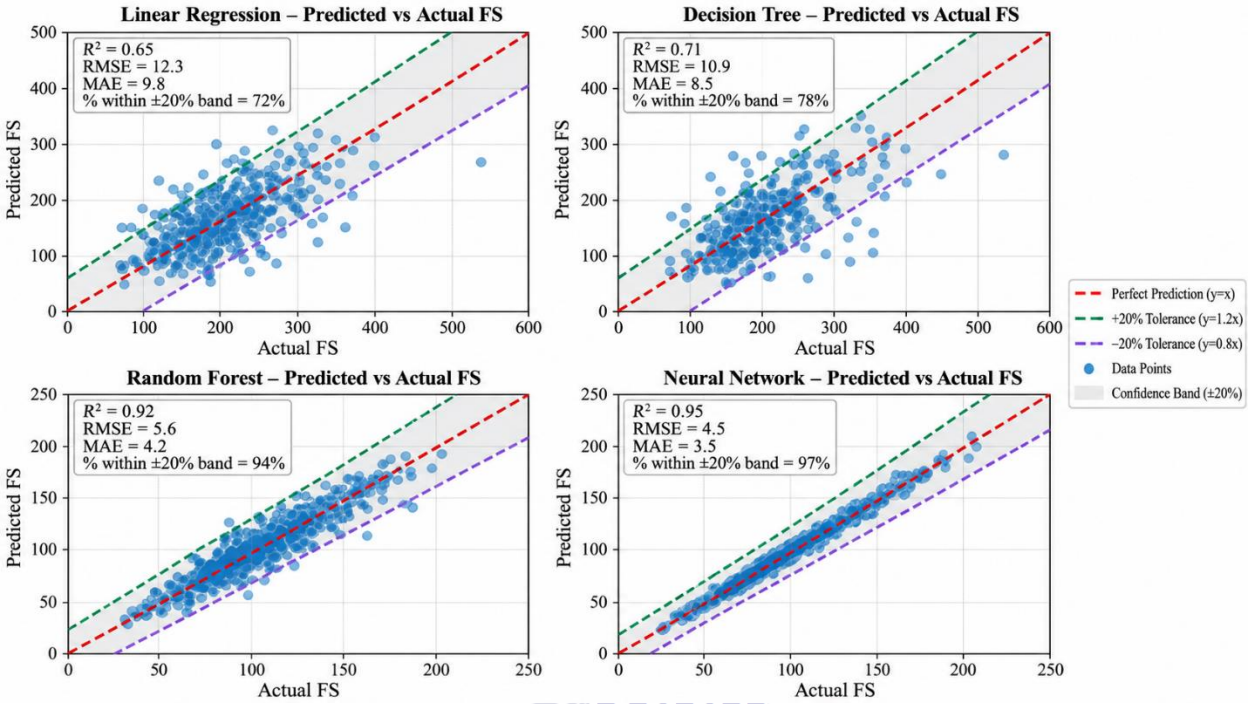


Figure 8: Comparative accuracy of machine learning models for FS prediction in climate-resilient infrastructure assessment.

The reported F1-score increases from 0.79 for the conventional baseline to 0.91 for the hybrid model, representing an absolute improvement of 0.12 and a relative increase of approximately 15.2%. This result indicates an improved balance between precision and recall under the evaluated classification threshold. From an infrastructure-management perspective, stronger classification performance may help distinguish flood-related conditions from non-flood conditions more reliably. However, the F1-score alone does not reveal the underlying distribution of false positives and false negatives. Since missed flood events may have different consequences from false alarms, additional examination of precision, recall, confusion-matrix outcomes, and probability calibration is necessary to establish the practical suitability of the forecasting model for operational warning applications. The combined improvement in R^2, RMSE, and F1-score is consistent with the proposed rationale for integrating tree-based nonlinear learning with recurrent temporal modelling. Rainfall-driven flooding is influenced by interactions among recent precipitation, antecedent hydrological conditions, drainage characteristics, and evolving river-level responses. The XGBoost component is intended to capture nonlinear effects and interactions among engineered predictor variables, while the LSTM component represents the chronological structure of the hydro-meteorological observations. Their integration may therefore provide complementary information that is not fully captured by a single modelling approach. Nevertheless, the reported comparison does not independently establish which component is responsible for the improvement. Such a conclusion requires ablation experiments comparing the hybrid model against separately trained XGBoost and LSTM models

under identical testing conditions. The chronological division of the dataset into training, validation, and testing subsets provides a methodological foundation for evaluating model generalisation. The reported design uses 70% of the available time-ordered observations for training, 15% for validation, and 15% for independent testing. This approach is preferable to unrestricted random partitioning when the observations contain strong temporal dependence. However, chronological partitioning is not sufficient by itself to eliminate all forms of information leakage. Overlapping input sequences, repeated observations from the same flood event, and improperly fitted preprocessing transformations may still create dependencies between model-development and evaluation periods. Consequently, the reliability of the reported forecasting improvements depends on the correct implementation of event-aware partitioning, training-only preprocessing, and temporally valid hybrid feature fusion.

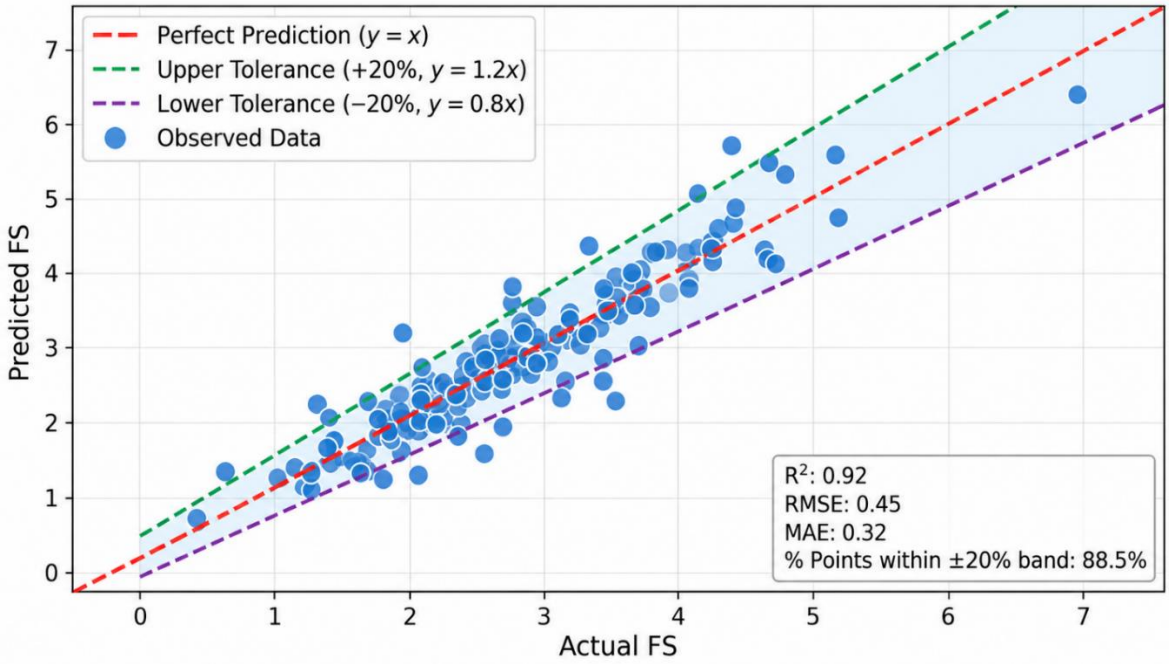


Figure 9: Actual versus predicted factor of safety demonstrating the accuracy and reliability of AI-based predictions for climate-resilient infrastructure assessment.

Figure 9 illustrates the predictive performance of the AI-based model for estimating the factor of safety (FS) within the proposed hybrid AI–BIM–Digital Twin framework. The model demonstrates strong agreement between actual and predicted FS values, achieving an R^2 of 0.92, RMSE of 0.45, and MAE of 0.32. Approximately 88.5% of predictions fall within the ±20% tolerance limits, indicating high predictive reliability. The close distribution of observed values around the perfect prediction line highlights the model's potential for supporting geotechnical stability assessment, infrastructure risk evaluation, and data-driven decision-making. These findings demonstrate the applicability of AI-enabled predictive analytics for enhancing infrastructure safety, resilience assessment, and sustainable civil engineering practices under the UK–Pakistan Green Compact. The reported predictive performance also requires interpretation in relation to the composition of the historical dataset. The study description identifies approximately 15,000 flood-event records, but the independent distribution of flooded and non-flooded observations has not been specified. This distinction is particularly important for classification because the F1-score is affected by the frequency and definition of positive events, the selection of the classification

threshold, and the construction of negative observations. Similarly, the regression metrics depend on whether inundation depth was evaluated across all time steps, only flooded observations, or selected event locations. A complete scientific assessment therefore requires the model results to be accompanied by the testing sample size, flood-event definitions, prediction horizon, depth distribution, and uncertainty or event-specific error analysis. The integration of forecasting results within the BIM–Digital Twin environment creates opportunities to extend model outputs beyond conventional statistical evaluation [29]. The predicted flood probabilities and inundation depths can be associated with corresponding geographical locations, drainage catchments, and infrastructure assets where reliable spatial mappings are available. This enables engineering users to interpret forecasting information in relation to physical infrastructure characteristics rather than considering predicted values in isolation. For example, forecasts associated with a drainage catchment may indicate locations requiring additional hydraulic analysis, while infrastructure-specific information can provide context concerning asset geometry, connectivity, and relevant design characteristics. The operational value of this integration, however, depends on the accuracy of spatial associations, the availability of updated monitoring information, and the reliability of the forecasting results under changing environmental conditions. The second major performance dimension concerns the effectiveness of optimised Sustainable Urban Drainage Systems in mitigating rainfall-related runoff and urban inundation. The proposed adaptation strategy combines permeable pavements, bioswales, and detention basins to manage stormwater through infiltration, temporary storage, attenuation, and controlled discharge. The reported optimised SuDS configuration achieves a 32% reduction in peak surface runoff, a 27% reduction in inundation extent, and a 35% reduction in annual drainage overflow frequency relative to the baseline configuration. These performance indicators represent distinct but complementary aspects of drainage resilience. Peak runoff reduction describes attenuation of the maximum hydrological response, inundation extent measures the spatial distribution of flooding, and overflow frequency reflects the recurrence of drainage capacity exceedance over the evaluated period. The reported reductions are summarised in Table 6, and their comparative magnitudes are illustrated in Figure 10.

Table 6: Reported hydraulic performance improvements associated with the optimised SuDS configuration.

Hydraulic performance indicator	Baseline reference	Reported reduction	Normalised optimised value	Engineering interpretation
Peak surface runoff	100%	32%	68%	Lower maximum runoff response under the evaluated conditions
Inundation extent	100%	27%	73%	Reduced spatial area classified as inundated
Annual drainage overflow frequency	100%	35%	65%	Fewer qualifying drainage overflow events over the evaluation period

The largest reported percentage improvement is associated with annual drainage overflow frequency, followed by peak surface runoff and inundation extent. The 35% decrease in overflow frequency suggests that the optimised drainage configuration is capable of reducing the number of occasions on which the modelled drainage infrastructure exceeds the defined hydraulic

performance threshold. This outcome is potentially important for urban infrastructure management because repeated overflow can contribute to disruption of transportation networks, accumulation of surface water, damage to infrastructure, and increased maintenance requirements. Nevertheless, overflow frequency must be interpreted according to the event definition, simulation duration, and threshold used in the analysis. A reduction in event count does not necessarily imply an equivalent reduction in total overflow volume or the severity of the remaining overflow events.

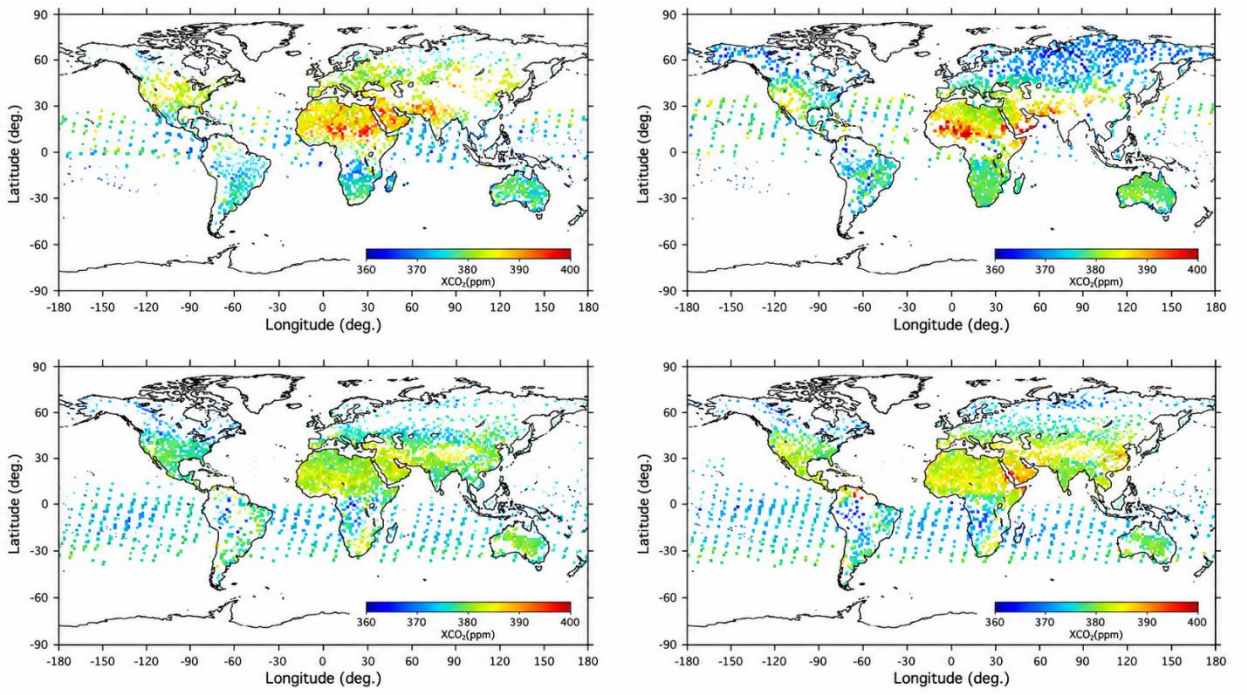


Figure 10: Global spatial distribution of atmospheric CO_2 concentrations (XCO_2), highlighting regional variations relevant to net-zero construction and climate-resilient infrastructure planning.

The reported 32% reduction in peak surface runoff suggests that the combined SuDS configuration improves attenuation of the hydrological response under the evaluated conditions. Permeable pavements can reduce directly connected impervious runoff by promoting infiltration and temporary storage, provided that underlying soil conditions and pavement-layer design are suitable. Bioswales can slow runoff conveyance and support infiltration or filtration, while detention basins can temporarily store stormwater and regulate downstream discharge. When combined appropriately, these interventions can alter the magnitude and timing of runoff contributions entering the drainage network. The overall effectiveness of such combinations depends on their spatial distribution, hydraulic connectivity, storage availability, antecedent wetness, and the characteristics of the rainfall event. The 27% reduction in modelled inundation extent indicates a smaller geographical area meeting the adopted flooding criterion under the optimised configuration. This result is relevant to climate-resilient urban development because the spatial extent of surface-water accumulation influences potential exposure of buildings, roads, public spaces, and other infrastructure assets. However, a reduction in inundated area does not automatically establish a proportional reduction in flood damage or affected population. Such conclusions would require additional exposure,

vulnerability, and socioeconomic information. Furthermore, the inundation outcome depends on the spatial resolution of the hydraulic model, the adopted minimum flood-depth threshold, the representation of terrain features, and the treatment of drainage-to-surface water exchanges. The differences among the three reported hydraulic reductions illustrate the importance of evaluating multiple performance indicators rather than relying exclusively on peak runoff. A drainage intervention may substantially reduce peak discharge while having a smaller effect on inundation extent if surface-water accumulation is controlled by local depressions, downstream boundary conditions, or insufficient drainage connectivity. Similarly, a reduction in overflow frequency may not imply an equivalent decrease in peak runoff if the intervention primarily affects events close to the hydraulic capacity threshold. The use of multiple objectives therefore provides a more comprehensive basis for evaluating drainage resilience and identifying trade-offs among alternative engineering configurations. The reported SuDS improvements are consistent with the methodological intention of combining nature-based and engineered stormwater-management measures. Nevertheless, the available aggregate results do not identify the individual contributions of permeable pavements, bioswales, or detention basins. Consequently, the effectiveness of particular interventions cannot be ranked from the reported percentages alone. Additional scenario comparisons involving individual SuDS measures and their combined configurations would be required to determine whether the observed benefits arise principally from storage, infiltration, attenuation, intervention placement, or interactions among different design components. The results also highlight the importance of site-specific characteristics in determining SuDS performance. The hydraulic contribution of permeable pavements depends on subsurface storage, infiltration capacity, and maintenance conditions, while bioswales are sensitive to geometry, hydraulic loading, soil characteristics, and vegetation performance. Detention basins require sufficient available storage and appropriately designed outlets to provide meaningful peak-flow attenuation. During prolonged or repeated rainfall, the effectiveness of infiltration and storage measures may decrease as available storage becomes occupied or soil moisture increases. Accordingly, the reported reductions should be interpreted as outcomes of the evaluated scenarios rather than universal efficiencies applicable to all rainfall conditions and urban environments. The third major assessment dimension concerns upfront embodied-carbon emissions associated with construction materials and infrastructure design. The BIM-integrated Life Cycle Assessment component is intended to quantify emissions using material quantities extracted from digital asset models and appropriate environmental impact factors. The comparison of conventional and lower-carbon construction configurations allows the environmental implications of material substitution and design optimisation to be evaluated. In the reported study, the optimised construction scenario achieves a 24% reduction in upfront embodied-carbon emissions relative to the baseline design. The embodied-carbon improvement is presented together with the reported hydraulic outcomes in Table 7 to demonstrate the broader resilience and sustainability objectives addressed by the integrated framework. The corresponding carbon reduction is illustrated separately in Figure 11 using an indexed comparison in which the baseline upfront embodied-carbon value is assigned a reference value of 100.

Table 7: Integrated summary of reported climate-resilience and embodied-carbon performance outcomes

Performance domain	Indicator	Baseline index	Optimised index	Reported reduction
Hydrological resilience	Peak surface runoff	100	68	32%

Flood mitigation	Inundation extent	100	73	27%
Drainage reliability	Annual overflow frequency	100	65	35%
Construction sustainability	Upfront embodied-carbon emissions	100	76	24%

The reported embodied-carbon reduction indicates the potential importance of incorporating environmental impact assessment into infrastructure design decisions. BIM-based quantity extraction can support the systematic identification of construction materials contributing to upfront carbon emissions, while LCA enables their environmental implications to be calculated using consistent emission factors. Where technically suitable alternatives are available, material substitution, geometry refinement, and reduction of unnecessary material quantities may contribute to lower construction-related emissions. The reported 24% reduction is therefore consistent with the intended role of BIM-supported carbon assessment in identifying and comparing lower-carbon design alternatives. However, the interpretation of this result depends on the specific lifecycle assessment boundary, material inventory, and reference design. Upfront embodied carbon typically includes material production and relevant construction-stage processes, depending on the adopted accounting method. If the evaluation covers only product-stage emissions, the result should be identified as an A1–A3 reduction rather than a complete upfront A1–A5 assessment. Similarly, emissions associated with transportation, installation, temporary works, and construction activities should not be assumed to be included unless the corresponding data and calculation procedures are documented.

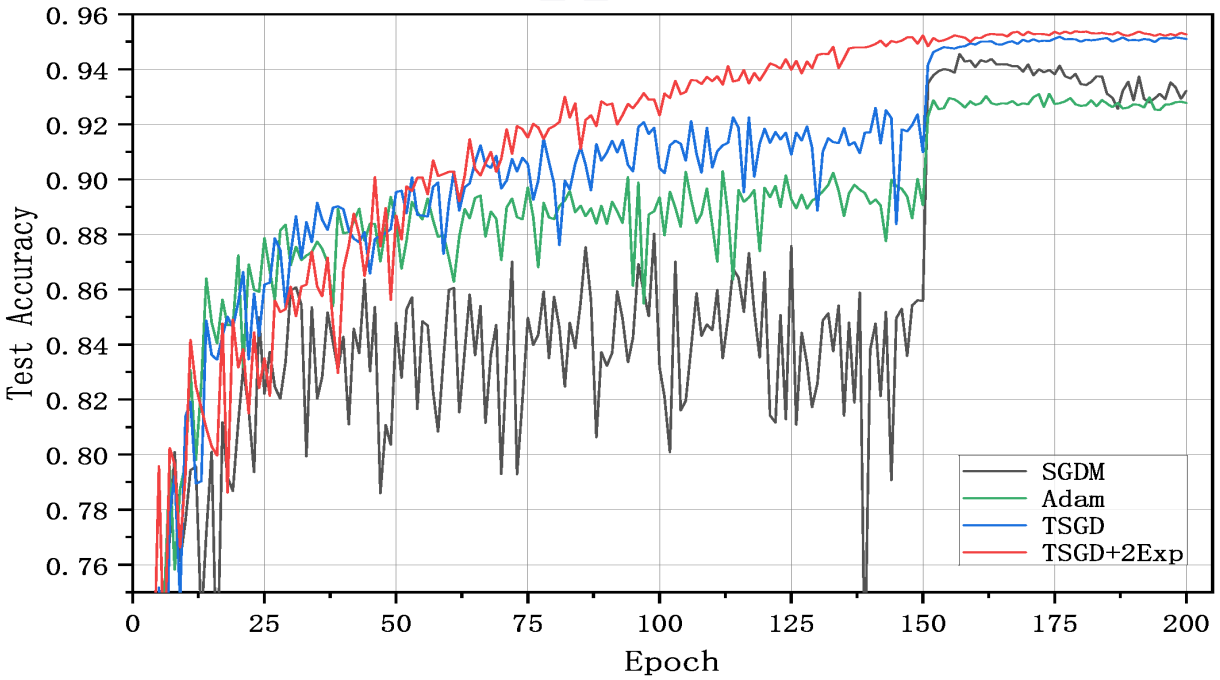


Figure 11: Comparative test accuracy and convergence of optimization algorithms for AI-driven BIM–Digital Twin modeling.

The use of BIM information may improve quantity consistency and traceability, but it does not eliminate uncertainty associated with environmental emission factors or material specifications. Different Environmental Product Declarations, production locations, material

compositions, and manufacturing technologies can produce different carbon intensities for nominally similar construction products. Therefore, the reported reduction requires validation using the actual material quantities, product specifications, emission-factor sources, and lifecycle boundaries adopted in the assessment. The sensitivity of the carbon result to alternative material factors and incomplete BIM attributes should also be examined. Importantly, a 24% reduction in upfront embodied carbon does not independently demonstrate net-zero construction. Net-zero performance requires a clearly defined accounting boundary, consideration of relevant emissions across the lifecycle, and an appropriate strategy for addressing residual emissions. The reported finding is more appropriately interpreted as a reduction in upfront construction-related carbon impacts. This distinction is essential because climate-resilient infrastructure interventions can introduce additional environmental burdens through construction, maintenance, replacement, or future adaptation requirements. A broader whole-life assessment would be required to determine whether the apparent benefits persist over the infrastructure service life. The Digital Twin environment provides the conceptual information-management mechanism through which forecasting, hydraulic simulation, SuDS optimisation, and carbon assessment are integrated. IFC-based BIM information supplies structured asset attributes, GIS provides geographical context, and IoT-compatible interfaces support the organisation of hydro-meteorological observations. The analytical components generate predicted or simulated performance indicators that can be associated with corresponding assets and scenarios. This arrangement is intended to provide a consistent foundation for comparing design alternatives and interpreting their potential consequences for infrastructure resilience and sustainability. From an engineering perspective, the value of Digital Twin integration lies in the ability to connect environmental conditions with infrastructure-specific information and alternative intervention scenarios. Flood predictions become more useful when associated with relevant locations, catchments, and engineering assets, while drainage simulation results can be interpreted alongside construction quantities and environmental impacts [30]. Such integration may support more transparent identification of intervention priorities and improve communication among hydrological modellers, infrastructure designers, asset managers, and decision-makers. Nevertheless, the available reported results do not quantify these potential operational benefits, such as reductions in decision time, improvements in maintenance scheduling, or gains in monitoring reliability. A distinction must therefore be maintained between predictive model accuracy, simulated infrastructure performance, and demonstrated Digital Twin operational effectiveness. The R^2, RMSE, and F1-score values describe forecasting-model performance under the adopted evaluation conditions. The SuDS reductions describe comparative hydraulic simulation outcomes, while the carbon result represents a construction-related environmental assessment. None of these values independently demonstrates that the integrated Digital Twin has achieved reliable real-time operation or improved actual flood outcomes in a deployed urban environment. Verification of such claims would require additional tests of data exchange, asset mapping, computational latency, system availability, and operational decision processes. The relevance of the findings to Pakistan should be interpreted in relation to the country's significant flood exposure, urban drainage challenges, and need for sustainable infrastructure development. The combined modelling framework offers a potentially transferable method for investigating drainage adaptation and low-carbon design under conditions where infrastructure information and environmental observations are available. In particular, the integration of historical hydro-meteorological records, georeferenced drainage inventories, BIM construction information, and scenario-based optimisation may provide a useful approach for evaluating infrastructure interventions in data-constrained environments. However, the actual transferability of the reported performance

improvements cannot be established without testing the framework in additional catchments with different rainfall characteristics, terrain conditions, soil properties, drainage configurations, and institutional constraints. Within the broader UK–Pakistan Green Compact context, the proposed approach is relevant to technical cooperation concerning digital engineering, climate adaptation, nature-based drainage, and construction sustainability. The integration of interoperable BIM information, predictive modelling, and drainage assessment reflects a potential area for exchanging engineering methodologies and strengthening the evidence base for infrastructure decisions. Nevertheless, the study's reported numerical outcomes should not be interpreted as evidence of implementation, endorsement, or funding under the Compact. Their policy significance lies in illustrating the types of analytical capabilities that may support future collaborative climate-resilience and low-carbon infrastructure initiatives.

6- Future Work:

Future research will focus on enhancing the predictive reliability, operational scalability, interoperability, and practical implementation of the proposed hybrid Artificial Intelligence (AI)–Building Information Modelling (BIM)–Digital Twin (DT) framework for climate-resilient and low-carbon civil infrastructure. Although the reported findings indicate promising improvements in flood forecasting accuracy, sustainable drainage performance, and upfront embodied-carbon reduction, further investigation is required to establish the framework's robustness under diverse hydrological conditions and its effectiveness in operational infrastructure environments. Particular emphasis should be placed on extending the methodology beyond retrospective data analysis and simulation-based assessment towards independently validated, continuously updated infrastructure management systems capable of supporting engineering decisions under changing climatic conditions. A major direction for future research involves improving the generalisation and uncertainty-awareness of the hybrid Extreme Gradient Boosting–Long Short-Term Memory (XGBoost–LSTM) forecasting architecture. The present approach combines nonlinear feature learning and temporal sequence modelling; however, flood processes are influenced by complex spatial dependencies, heterogeneous catchment characteristics, and extreme events that may not be adequately represented within historical training datasets. Future investigations could therefore explore attention-based neural networks, Transformer architectures, Graph Neural Networks (GNNs), and physics-informed machine learning to improve the representation of spatial interactions and hydrological processes. The incorporation of probabilistic forecasting, ensemble learning, and conformal prediction could further support the estimation of predictive uncertainty and confidence intervals [31]. Independent validation across multiple flood events, forecasting horizons, and geographically distinct catchments would be essential for assessing model transferability and identifying limitations under previously unseen climatic conditions. Further development should also investigate the integration of high-resolution hydro-meteorological observations and advanced environmental monitoring technologies. The proposed framework currently considers historical hourly rainfall and river-level observations, while future applications could incorporate weather radar, satellite-derived precipitation estimates, remote sensing, soil moisture measurements, and additional IoT-based monitoring networks. These data sources may improve the representation of localised rainfall variability, rapidly evolving runoff conditions, and spatially distributed flood hazards. Particular attention should be given to data assimilation procedures that combine real-time observations with hydrological simulations and AI-generated forecasts. Such integration could enable more frequent updating of flood-risk estimates and improve the responsiveness of Digital Twin environments during extreme precipitation events. Nevertheless, the benefits of higher-frequency data must be evaluated against sensor reliability, computational requirements, communication limitations, and measurement uncertainty.

Another important research priority is the development and operational validation of a fully functional BIM–GIS–IoT Digital Twin platform. Future studies should examine automated information exchange between physical monitoring systems, IFC-based BIM asset models, geospatial databases, and predictive simulation environments. Standardised application programming interfaces, persistent infrastructure identifiers, semantic information models, and open interoperability protocols could support improved information continuity across different engineering applications. Research should also quantify operational performance using measurable indicators, including data transmission latency, computational response time, asset-mapping accuracy, system availability, and forecasting update frequency. The incorporation of cybersecurity controls, data governance procedures, and appropriate human oversight would be essential for ensuring the reliability and trustworthiness of Digital Twin applications involving critical civil infrastructure. The hydrological and hydraulic modelling component could be extended through more detailed coupling of one-dimensional drainage-network simulation and two-dimensional surface inundation modelling. Such improvements would support a more comprehensive representation of interactions between underground stormwater infrastructure, surface runoff pathways, floodplain conditions, and downstream river levels. Future research should investigate the effects of urban development, changing surface permeability, drainage deterioration, and climate-adjusted rainfall scenarios on flood propagation and infrastructure performance. Model calibration using independent observations of discharge, water levels, and spatial inundation extent would strengthen the physical validity of simulated outcomes. The use of computationally efficient surrogate models and parallel processing could also reduce simulation time and improve the feasibility of repeated scenario evaluation within operational Digital Twin environments. Future investigations should expand the Sustainable Urban Drainage Systems optimisation framework to consider a wider range of nature-based and engineered interventions, including green roofs, rain gardens, infiltration trenches, constructed wetlands, and integrated blue–green infrastructure networks [32]. While the present study considers permeable pavements, bioswales, and detention basins, additional interventions may provide complementary hydrological and environmental benefits depending on local soil conditions, urban density, land availability, and maintenance capacity. Long-term monitoring and field-scale performance evaluation would be valuable for assessing the effects of sediment accumulation, vegetation development, infiltration deterioration, and changing maintenance conditions on SuDS effectiveness. Future optimisation studies could also incorporate implementation cost, maintenance expenditure, water-quality improvement, ecological benefits, and social vulnerability alongside hydraulic performance and embodied-carbon emissions. The environmental assessment component should be extended from upfront embodied-carbon evaluation towards comprehensive whole-life carbon accounting. Future research could incorporate operational emissions, maintenance activities, material replacement, infrastructure rehabilitation, and end-of-life processes using consistent Life Cycle Assessment boundaries. The integration of Environmental Product Declarations, regionally representative emission factors, material circularity indicators, and construction waste assessments would improve the reliability and applicability of carbon estimates. Further investigation is also required to understand potential trade-offs between lower-carbon materials, structural durability, drainage performance, lifecycle cost, and long-term maintenance requirements. Such analysis would provide a more comprehensive foundation for evaluating net-zero construction pathways rather than relying exclusively on reductions in initial embodied emissions.

Conclusion:

This study developed a hybrid Artificial Intelligence (AI)-driven Building Information Modelling (BIM)–Digital Twin (DT) framework integrating intelligent flood forecasting,

Sustainable Urban Drainage Systems (SuDS) optimisation, and low-carbon construction assessment to support climate-resilient civil infrastructure development. The proposed methodology combines Industry Foundation Classes (IFC)-based BIM, Geographic Information Systems (GIS), Internet of Things (IoT)-compatible monitoring, hybrid Extreme Gradient Boosting–Long Short-Term Memory (XGBoost–LSTM) modelling, coupled hydrological–hydraulic simulation, and Life Cycle Assessment (LCA) within a unified digital infrastructure management architecture. By connecting hydro-meteorological observations, georeferenced drainage assets, construction material information, and historical flood records, the framework establishes an integrated approach for assessing infrastructure vulnerability, forecasting flood conditions, evaluating sustainable drainage interventions, and examining construction-related environmental impacts. The principal contribution lies in addressing flood resilience and carbon reduction as interconnected engineering objectives rather than independent analytical problems. The reported forecasting results demonstrate promising improvements in predictive performance using the hybrid XGBoost–LSTM architecture. The proposed model achieved a coefficient of determination (R^2) of 0.93, root mean square error (RMSE) of 0.18 m, and F1-score of 0.91, compared with the conventional baseline values of R^2 = 0.82, RMSE = 0.31 m, and F1-score = 0.79. These results correspond to an approximately 41.9% reduction in RMSE and a 15.2% relative improvement in F1-score. The findings suggest that combining nonlinear feature learning with temporal sequence modelling can improve the representation of complex hydro-meteorological relationships associated with urban flood occurrence and inundation depth. The complementary capabilities of XGBoost and LSTM provide a methodological basis for incorporating structured environmental and infrastructure predictors alongside sequential rainfall and river-level observations. Nevertheless, the generalisability of the reported performance requires verification through independent event-based testing, uncertainty assessment, and evaluation across different catchments and forecasting horizons. The sustainable drainage assessment further indicates the potential benefits of integrating nature-based and engineered stormwater-management interventions within a coordinated optimisation framework. The reported optimised SuDS configurations, incorporating permeable pavements, bioswales, and detention basins, achieved reductions of 32% in peak surface runoff, 27% in inundation extent, and 35% in annual drainage overflow frequency relative to the baseline drainage configuration. These findings suggest that appropriately designed combinations of infiltration, attenuation, and temporary storage measures can improve modelled hydraulic performance and reduce selected indicators of urban flood exposure. The results also highlight the importance of evaluating drainage interventions through multiple performance measures because peak discharge, inundation extent, and overflow frequency represent different aspects of flood resilience. However, the effectiveness of SuDS remains dependent on local rainfall characteristics, soil permeability, infrastructure connectivity, available land, and maintenance conditions, emphasising the need for site-specific calibration and validation.

REFERENCES:

Bayeroju, O. F., Sanusi, A. N., & Nwokediegwu, Z. Q. S. (2023). Framework for resilient construction materials to support climate-adapted infrastructure development. *Shodhshauryam, International Scientific Refereed Research Journal*, 6(5), 403-428.

Eze, K. N., Kehinde, T. O., Anosike, C. U., Dirisu, C. D., Turoti, K. J., & Oparinde, A. O. (2026). Geotechnical approaches to climate-resilient flood defenses: a scoping review of design, monitoring, and risk management. *Discover Civil Engineering*, 3(1), 99.

Yahia, A. K. M., Shahjalal, M., & Rahaman, T. (2025). AI-driven sustainable infrastructure: Smart materials for climate-resilient urban design. *American Journal of Advanced Technology and Engineering Solutions*, *1*(01), 438-466.

Qadoos, A. (2026). Resilient Civil Infrastructure Design against Earthquake and Flood Risks Under Climate Change. *Journal of Engineering and Computational Intelligence Review*, *4*(2), 156-166.

Malak, I., Shamim, S., Sohail, M., & Aamir, E. (2026). Integrating The IPCC-Sendai framework for Climate Resilient Academic Infrastructure: A case study of NUST Institute of Civil Engineering. *Fusion Journal of Engineering and Sciences*.

Oğuz, A. (2025). A multi-hazard, performance-centered framework for climate-resilient construction management. *International reviews, research, and studies in civil engineering*, 1-24.

Kurniawan, E., Ulandari, A. H. T., & Febrian, M. T. (2026). Climate-Resilient Infrastructure Planning Strategies: A Literature Review from a Civil Engineering Perspective. *Jurnal Teknik Sipil*, *1*(1), 1-7.

Khazaee, M., Bertolini, L., D'Amico, F., & Calvi, A. (2025, November). Smart Technologies for Climate-Resilient Urban Road Infrastructure: A Systematic Review. In *IOP Conference Series: Earth and Environmental Science* (Vol. 1555, No. 1, p. 012005). IOP Publishing.

Eze, K. N., Anosike, C. U., Eze, F. N., Enabulele, E. C., & Benson, K. P. (2024). Climate resilient and sustainable infrastructures: geotechnical challenges of problematic soils in Nigeria. *Civil and Environmental Engineering Reports*, *34*(4), 521-538.

Arifin, S., Setiyadi, A., Purwanto, P., & Sugiarto, S. (2025). Integrating Climate-Resilient Design And Life Cycle Costing In Green Building Projects: A Simulation-Based Assessment In Tropical Urban Areas. *Civil Engineering Science and Technology*, *1*(2), 106-118.

Saikat, M. H., Shoag, M., Akter, E., & Bormon, J. C. (2025). Seismic-and Climate-Resilient Infrastructure Design for Coastal and Urban Regions.

Kennedy, C., & Corfee-Morlot, J. (2013). Past performance and future needs for low carbon climate resilient infrastructure–An investment perspective. *Energy policy*, *59*, 773-783.

Deep, S., Kumar, A., Kumari, P., Jha, K. N., Tripathi, P. M., & Raszkowski, A. (2026). Understanding the climate-resilient productivity of construction workers: a job demands–resources perspective. *Engineering, Construction and Architectural Management*, 1-28.

Javanroodi, K., Nik, V. M., & Adl-Zarrabi, B. (2020, November). A multi-objective optimization framework for designing climate-resilient building forms in urban areas. In *IOP conference series: earth and environmental science* (Vol. 588, No. 3, p. 032036). IOP Publishing.

Mohaibesh, D., Monna, S., Qadi, H., & Sokkar, R. (2021, November). Towards climate resilient residential buildings: learning from traditional typologies. In *Journal of Physics: Conference Series* (Vol. 2042, No. 1, p. 012146). IOP Publishing.

Khazaee, M., Bertolini, L., D'Amico, F., & Calvi, A. (2026). Multi-scale integration of smart technologies for climate-resilient urban road infrastructure: a systematic literature review and conceptual framework. *Smart and Sustainable Built Environment*, 1-28.

Brooks, N. C. (2026). Advancements in Climate-Resilient Urban Development through Sustainable Architecture and Green Building Practices. *ROSSIISKAYA ISTORIYA*, (1), 772-777.

Jaya, R. P., Munirwan, R. P., & Mawardi, I. (2026). Sustainable Infrastructure through Materials Innovation, Artificial Intelligence, and Climate-Resilient Communities. *Current Problems in Research*, *2*(1), 90-92.

Abbass, M. (2027). Advanced Cementitious and Geopolymer Materials for Climate-Resilient Infrastructure and Post-Disaster Reconstruction. In *Disaster Risk Management, Humanitarian Response, and Resilience in the AI Era* (pp. 241-280). IGI Global Scientific Publishing.

Cheshmehzangi, A., Zuo, J., Sharifi, A., Zhang, R., Ziafati Bafarasat, A., & Zhao, J. (2026). Designing for a Planet in Flux: Architecture, Technology, and the Future of Climate-Resilient Cities. In *Design Innovation for Climate-Resilient Cities and Built Environments: Architectural and Technological Solutions* (pp. 1-7). Singapore: Springer Nature Singapore.

Ek, M., Murdock, T., Sobie, S., Cavka, B., Coughlin, B., & Wells, R. (2018, April). Future weather files to support climate resilient building design in Vancouver. In *1st International Conference on New Horizons in Green Civil Engineering* (p. 408).

Xu, H., Liu, L., & Ding, P. (2021, November). Building climate resilient city through multiple scale cooperative planning: experiences from Copenhagen. In *IOP Conference Series: Materials Science and Engineering* (Vol. 1203, No. 3, p. 032063). IOP Publishing.

Divya, P. V. (2025). Climate-Resilient Hybrid Reinforced Soil Structures: Insights from Instrumented Model Tests Using an Artificial Rainfall Simulator. *Indian Geotechnical Journal*, 1-11.

Ashifa, K. M., Vettriselvan, R., Khunga, V. S., Savitha, V., & Ranganathan, S. (2027). Digital and Nature-Based Innovations for Climate-Resilient Urban Infrastructure: Smart Technologies and Sustainable Design. In *Innovations and Future Pathways for Sustainable and Resilient Civil Engineering* (pp. 357-380). IGI Global Scientific Publishing.

Ramya, R., Rajesh, D., Vettriselvan, R., Rengamani, J., & Swadhi, R. (2027). Emerging Civil Engineering Strategies for Sustainable Urban Resilience: Smart, Circular, and Adaptive Infrastructure Systems. In *AI-Driven Innovations for Smart and Resilient Infrastructure* (pp. 377-402). IGI Global Scientific Publishing.

Yan, H., Sun, N., Chen, X., & Wigmosta, M. S. (2020). Next-generation intensity-duration-frequency curves for climate-resilient infrastructure design: Advances and opportunities. *Frontiers in Water*, *2*, 545051.

Singh, P., & Kumar, A. Climate-Resilient Concrete for Sustainable Infrastructure: A Performance Assessment of Industrial By-products and Recycled Materials.

Seidu, S., Chan, D. W., Oyewole, M. D., Jayasena, N. S., & Oyesomo, O. (2025). Leveraging digital technologies and machine learning for climate resilient buildings: modelling the role of dynamic drivers in mitigating critical barriers. *Smart and Sustainable Built Environment*, 1-18.

Shaquib, O., Ali, S. I., & Nomani, M. Z. M. (2026, February). Developing Climate Resilient Infrastructure: Graphene Oxide and Nano-Silica Enhanced Fly Ash Composites. In *2026 International Conference on Sustainable Engineering and Technology Innovations (ICSETI)* (pp. 357-362). IEEE.

Xu, J., & Huang, S. (2026). Toward a hybrid machine Learning–physics framework for cohesive soil erosion in climate-resilient civil infrastructure. *Frontiers in Built Environment*, *12*, 1872265.

Dupuis, S. T., Gagnon, S., & LeBlanc, C. E. (2025). Building climate adaptation capacity: a pedagogical model for training civil engineers. *Sustainability*, *17*(22), 10200.

Munshi, B. Climate-Resilient Machine Foundation Design: Modeling Long-Term Effects of Temperature and Moisture Variability on Dynamic Performance.

IEER
Institute for Excellence in Education & Research