

Article

Sustainable Urban Water Management via AI Surrogate Modeling: A Multi-Dimensional Framework for Drainage Resilience and Microclimatic Assessment

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Abstract

Extreme climate events and rapid urbanization pose severe threats to urban water sustainability and environmental resilience. This study presents a surrogate-assisted hydrological simulation framework designed to support sustainable urban drainage planning and multi-objective scenario exploration. The proposed approach integrates a physics-based hydrodynamic model with a machine learning surrogate (XGBoost) to emulate system responses across diverse design configurations. Under the assumed setup, the framework rapidly evaluates hydrological indicators (peak runoff, flood depth, duration, and extent) alongside microclimatic co-benefits (urban cooling and ventilation) driven by blue-green infrastructure. The surrogate model demonstrates high fidelity ($R^2 \geq 0.93$), achieving a speedup factor of 10^5 to enable sustainable design screening and trade-off analysis between flood mitigation and urban liveability. Furthermore, post-construction water quality base-lines demonstrate the framework's capacity to incorporate holistic environmental metrics. Overall, this research provides a computationally efficient decision-support tool to advance the Sustainable Development Goals (SDGs)—particularly SDG 11 (Sustainable Cities and Communities) and SDG 13 (Climate Action)—by offering an actionable methodology for climate-resilient grey-green infrastructure planning under data-constrained conditions.

Keywords: sustainable urban development; artificial intelligence (AI); sustainable urban drainage systems (SuDSs); climate change adaptation; flood mitigation; machine learning; microclimate regulation; environmental resilience



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1. Introduction

Urbanization and climate change are jointly intensifying pressures on urban drainage infrastructure worldwide. Rapid urban expansion has substantially increased impervious surface coverage, while the growing frequency and intensity of extreme precipitation events have significantly elevated the occurrence of pluvial flooding in densely developed areas [1,2]. These challenges are further compounded by aging drainage infrastructure, insufficient maintenance that reduces hydraulic capacity through sedimentation and pipe blockage, and unplanned urban development that frequently exceeds the design capacity of existing drainage systems. As a result, urban drainage networks are increasingly unable to accommodate peak stormwater runoff, leading to widespread inundation, substantial

economic losses, disruption of urban activities, and heightened risks to public safety and critical infrastructure.

These escalating challenges underscore the urgent need to improve the resilience, adaptability, and hydraulic performance of existing drainage systems through strategically planned interventions, while simultaneously establishing robust methodologies for evaluating their effectiveness under future climate conditions. More broadly, mitigating urban flood risk is a fundamental component of sustainable urban development and climate adaptation. In this context, Sustainable Urban Drainage Systems (SuDSs) and integrated Blue-Green Infrastructure (BGI) have emerged as widely recognized approaches for enhancing urban resilience by reducing runoff volumes and peak discharges while delivering multiple environmental co-benefits. Beyond their hydrological functions, these nature-based solutions contribute to urban heat island mitigation, microclimate regulation, ecological enhancement, and improvements in urban environmental quality, thereby supporting long-term sustainable and climate-resilient urban development.

Traditional approaches to evaluating drainage performance rely heavily on physically based hydrological and hydraulic models, such as SWMM, MIKE URBAN, or InfoWorks ICM. These models are considered the industry standard due to their ability to simulate complex rainfall–runoff and pipe flow processes with high fidelity [3–7]. However, their application for planning and scenario analysis can be computationally expensive. Each simulation requires solving a system of differential equations, and exploring a wide range of design alternatives, climate scenarios, or land-use changes can become prohibitively time-consuming. This computational burden often limits the number of scenarios that can be practically evaluated, potentially leaving optimal or highly resilient designs undiscovered.

In recent years, the field of hydrology has witnessed a paradigm shift with the advent of artificial intelligence (AI) and machine learning (ML). These data-driven methods have shown remarkable success in various applications, including rainfall forecasting [8–10], streamflow prediction [11], and water quality modeling. More recently, researchers have begun exploring the use of ML models as surrogate or meta-models for complex physical simulations [12,13]. By learning the input–output mapping from a set of pre-computed simulation results, an ML model can approximate the behavior of the physical model with sufficient accuracy for rapid scenario evaluation [12]. In this study, we employ this concept to develop a surrogate model that serves as a computationally efficient emulator of the physics-based model. This is a form of acceleration achieved through an AI-based surrogate model, as opposed to using AI for hydrological process discovery. However, it is crucial to recognize that this fidelity is contingent upon the quality, quantity, and representativeness of the training data, and the model’s ability to generalize beyond its training domain is not guaranteed. This capability opens up new possibilities for extensive sensitivity analysis (evaluating how changes in input parameters affect outputs), real-time control, and multi-objective optimization (simultaneously optimizing for conflicting goals, such as cost and flood risk) in urban drainage design.

Despite the growing interest in AI for hydrology, a research gap remains in the systematic application and validation of AI-based surrogate frameworks for post-project benefit evaluation of specific drainage improvements. Many studies focus on methodological development or prediction, but fewer provide a comprehensive, quantitative assessment of an actual engineering project using an integrated AI-physical modeling approach. Furthermore, the integration of water quality assessment and microclimatic analysis into drainage performance evaluation remains underexplored.

The contributions of this study are fivefold. First, it develops and validates a novel multi-dimensional AI-based surrogate modeling framework that integrates flood mitigation, water quality assessment, and microclimatic evaluation within a unified predictive

platform. Unlike previous studies that typically address a single performance objective or rely solely on numerical simulations, the proposed framework is supported by field-scale validation, thereby improving its practical reliability for urban drainage assessment. Second, the framework is applied to the Dazhi drainage improvement project as a real-world case study to quantitatively evaluate drainage performance under multiple extreme rainfall scenarios, demonstrating its capability for rapid and reliable performance prediction. Third, the study incorporates water quality assessment and microclimatic evaluation to quantify the environmental co-benefits of integrated grey-green infrastructure, extending conventional flood risk analysis toward a more comprehensive assessment of urban environmental performance. Fourth, it provides engineering interpretations of the surrogate model predictions, highlighting both the practical applicability and current limitations of AI-assisted approaches for evidence-based urban drainage planning and flood risk management. Finally, the proposed framework explicitly links AI-driven engineering evaluations with sustainability indicators, demonstrating how multi-dimensional surrogate modeling can support municipal decision-making by balancing flood risk reduction, environmental quality, and long-term urban resilience.

Overall, this study demonstrates that AI-based surrogate modeling can serve not only as an efficient computational alternative to conventional hydraulic simulations but also as a practical decision-support tool for planning and evaluating sustainable urban drainage infrastructure. By integrating hydraulic, environmental, and sustainability dimensions within a unified assessment framework, the proposed methodology provides a comprehensive basis for future climate-resilient urban infrastructure planning.

2. Literature Review

2.1. Urban Drainage Systems and Flood Risk

Urban drainage systems are critical infrastructure components designed to convey stormwater away from developed areas to prevent flooding. The performance of these systems is typically evaluated based on their capacity to handle design storms, usually expressed in terms of return periods [14,15]. However, with climate change altering rainfall patterns, many existing systems are becoming undersized for current and future conditions [16]. Research has shown that urban flooding not only causes direct economic damages but also leads to indirect losses through business interruption, traffic disruption, and public health risks [17–19]. For instance, Martínez-Gomariz et al. [17] reported that urban flooding can cause economic losses equivalent to 0.5–1.5% of a city's GDP per major event. Despite these established impacts, a systematic quantification of mitigation benefits from integrated grey-green infrastructure remains limited.

2.2. Hydrological and Hydraulic Modeling Approaches

Physically based models remain the cornerstone of drainage system analysis. The Storm Water Management Model (SWMM), developed by the U.S. Environmental Protection Agency, has been widely applied for simulating rainfall–runoff processes and pollutant transport in urban catchments [20,21]. Similarly, commercial software packages such as MIKE URBAN (MIKE 2020 Release; DHI, Hørsholm, Denmark) and InfoWorks ICM (version 2024.0; Autodesk/Innovyze, Portland, OR, USA) offer advanced capabilities for 1D/2D coupled modeling, enabling detailed simulation of surface flooding [22–24]. These models solve the Saint–Venant equations for flow routing and employ various methods for runoff calculation, including the Rational Method, SCS Curve Number, and kinematic wave approaches. While SWMM is favored for its open-source nature, commercial software like MIKE URBAN provides superior 1D/2D coupling. However, a common limi-

tation across these models is their computational demand, which restricts iterative design optimization—a gap this study addresses through AI-based surrogates.

2.3. Machine Learning in Water Resources Engineering

The application of machine learning in water resources has expanded rapidly over the past decade. Support Vector Machines (SVMs), Artificial Neural Networks (ANNs), and ensemble methods such as Random Forest and Gradient Boosting have been successfully applied for rainfall–runoff modeling [25–28]. More recently, deep learning architectures including Long Short-Term Memory (LSTM) networks have demonstrated superior performance in time-series prediction tasks [29–31]. The concept of surrogate modeling—using ML to approximate computationally expensive physical models—has gained traction in water resources optimization problems [32–34]. Ensemble methods like XGBoost and Random Forest are preferred for tabular regression tasks due to robustness against overfitting and ability to handle non-linear interactions. This study selects XGBoost over neural networks for these advantages, as detailed in Section 4.4. Emerging research directions include: (1) digital twins for urban water systems, which integrate real-time data with simulation models for operational decision support [35,36]; (2) physics-informed machine learning, which embeds physical constraints into neural network architectures to improve generalizability [37,38]; (3) urban flood surrogate modeling, which combines 1D/2D hydrodynamic models with ML for rapid flood prediction [39–41]; and (4) uncertainty-aware hydrological AI, which provides probabilistic predictions rather than deterministic point estimates [42–44]. This study contributes to the surrogate modeling literature by demonstrating a practical framework for rapid scenario exploration, while acknowledging the limitations related to validation and uncertainty.

2.4. Research Gap and Study Contribution

While previous studies have demonstrated the potential of AI in hydrological modeling, few have provided a comprehensive, integrated framework that combines flood mitigation assessment, water quality evaluation, and microclimatic analysis for real-world drainage improvement projects. This study addresses this gap by developing a holistic AI-based surrogate methodology and applying it to the Dazhi drainage system, thereby contributing to both academic knowledge and engineering practice.

3. Study Area and Data Collection

3.1. Study Area: The Dazhi Drainage System

The Dazhi drainage system, the focus of this case study, is a typical urban drainage network located in a mixed residential and commercial district in Dali District, Taichung City, Taiwan (24.121389° N, 120.685545° E), as illustrated in Figure 1. The catchment area covers approximately 2.24 km² (224 hectares), characterized by a high degree of imperviousness (approx. 65%) due to dense building coverage, road networks, and paved surfaces. The topography is generally flat, with an average slope of less than 1%, which can exacerbate flooding during heavy rainfall events due to slow overland flow. The drainage system itself is a conventional separate sewer system, consisting of a network of reinforced concrete pipes ranging in diameter from 400 mm to 1800 mm, which convey stormwater runoff directly to a nearby receiving water body. Historically, the system has experienced localized flooding during intense summer storms, prompting the need for a comprehensive improvement project.

3.2. Channel Geometric Conditions

Table 1 summarizes the channel geometric conditions at key locations along the Dazhi drainage system. The channel width gradually decreases from upstream to downstream,

ranging from approximately 70 m at Qiaocheng Bridge to about 35 m near the Hanxi drainage confluence. This progressive narrowing of the downstream section has historically created a hydraulic bottleneck, which restricts flow conveyance capacity and contributes to backwater effects during high-flow events, thereby increasing the risk of flooding in the surrounding areas.

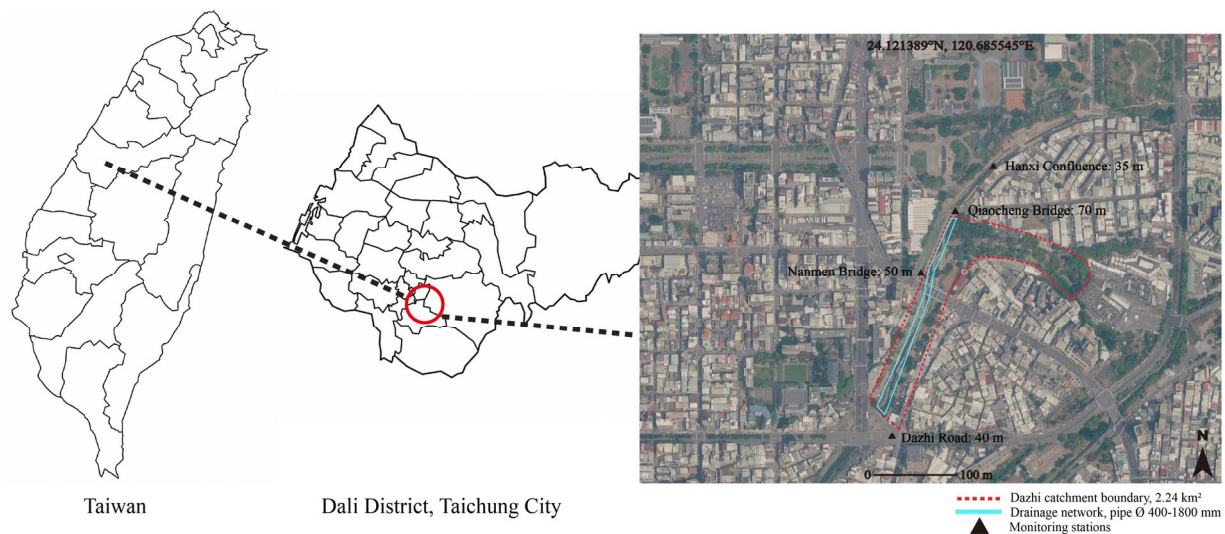


Figure 1. Location map of the study area: Dazhi drainage system, Dali District, Taichung City, Taiwan (24.121389° N, 120.685545° E).

Table 1. Channel geometric conditions at key monitoring locations.

Location	Channel Width (m)	Description
Qiaocheng Bridge	70	Upstream section
Nanmen Bridge	50	Middle reach
Dazhi Road	40	Downstream section
Hanxi Drainage Confluence	35	Most downstream

The longitudinal slope of the channel was calculated based on bed elevation measurements:

$$S = \frac{\Delta H}{L} = \frac{54.7 \text{ m} - 53.3 \text{ m}}{660 \text{ m} - 300 \text{ m}} = \frac{1.4 \text{ m}}{360 \text{ m}} = 0.0039 = 0.39\%$$

where ΔH is the elevation difference between stations 0K + 660 (EL 54.7 m) and 0K + 300 (EL 53.3 m), and L is the distance between stations (360 m). This mild slope contributes to relatively low flow velocities, necessitating adequate channel capacity to prevent overbank flooding.

3.3. Pre-Improvement and Post-Improvement Conditions

3.3.1. Pre-Improvement Baseline

Prior to the 2024 improvements, the Dazhi drainage system consisted of conventional grey infrastructure with no stormwater detention or green infrastructure elements. The pre-improvement performance was simulated using the calibrated MIKE URBAN model (see Section 4.6), as no observed flow or flood data were available for this baseline period. The system experienced frequent localized flooding during intense rainfall events, with historical records indicating street-level flooding during storms exceeding the 5-year return period.

3.3.2. Drainage Improvement Project Description

The Dazhi drainage improvement project, completed in late 2024, was designed to enhance the system's conveyance capacity and mitigate urban flood risk. Figure 2 presents the site plan of the improved system. The engineering interventions comprised a multifaceted approach, integrating both grey and green infrastructure solutions:

1. **Pipe Upsizing and Reinforcement:** Critically undersized sections of the main trunk sewer, spanning approximately 1.2 km, were replaced with larger-diameter pipes (upgraded to a maximum diameter of 2000 mm) to substantially increase hydraulic conveyance capacity.
2. **Construction of a Stormwater Detention Tank:** A 10,000 m³ underground detention tank was constructed near the system's outlet. This facility temporarily stores excess runoff during peak flow events and releases it gradually post-storm, thereby effectively attenuating peak discharge and reducing downstream flooding pressure.
3. **Outfall Structure Improvement:** The outfall structure was upgraded to ensure unobstructed discharge into the receiving water body, even under high tailwater conditions, thereby preventing backwater effects that could compromise system performance.
4. **Localized Green Infrastructure (GI):** In two pilot sub-catchments (total area of 1.2 ha, approximately 0.5% of the total catchment area of 224 ha), conventional pavement was replaced with permeable pavements (0.8 ha, design infiltration capacity of 150 mm/h), and a series of rain gardens (0.4 ha, combined storage volume of 160 m³) were installed. These GI elements promote on-site infiltration and reduce runoff volume at the source for the localized pilot areas. Given the limited spatial extent (0.5% of the catchment area), their contribution to overall catchment-scale runoff reduction is expected to be modest, though they may provide significant localized benefits for small, frequent storm events. Their primary value in this project is as a pilot demonstration of GI feasibility in a dense urban setting.

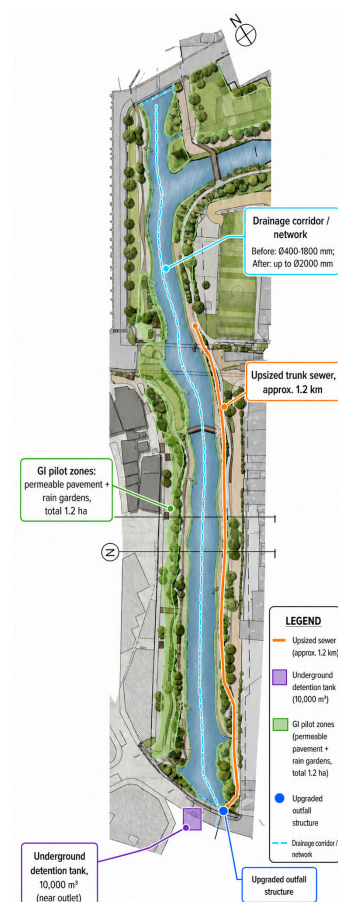


Figure 2. Schematic site plan of the Dazhi drainage system following the 2024 improvement project. The layout illustrates the spatial distribution of key engineering interventions, including the upsized trunk sewer alignment, the location of the underground detention tank (10,000 m³), upgraded outfall structure, and the pilot green infrastructure zones (permeable pavements and rain gardens).

4. Methodology

4.1. Surrogate Model-Assisted Hydrological Simulation Framework

The core of this study is a hybrid simulation framework that integrates a physically based model with an AI-based surrogate model. The workflow is illustrated conceptually in Figure 3. The process begins with the development of a baseline 1D–2D coupled hydrodynamic model of the entire Dazhi drainage system. This physics-based model, built using MIKE URBAN (DHI, Hørsholm, Denmark; MIKE 2020 Release), serves as the reference simulator for generating training data and validating the surrogate model. Specifically, a Latin Hypercube Sampling (LHS) strategy was employed to ensure a near-random, stratified sample across the multi-dimensional input parameter space. The number of scenarios (500) was determined through a preliminary convergence analysis, where we incrementally increased the training set size and observed that the improvement in surrogate model performance (R^2) plateaued beyond 400 samples. Key design parameters, such as pipe diameters (300–2000 mm), detention tank volume (0–20,000 m³), and GI coverage (0–15%), were varied within practical ranges determined by engineering design standards. For each configuration, we ran the physics-based model under a specific design rainfall event. These events were derived from the local intensity–duration–frequency (IDF) curves published by the Taiwanese Water Resources Agency. A 24 h design storm with a typical Chicago hyetograph pattern was used for all return periods: 2, 5, 10, 20, and 50 years. The model then computed the key performance indicators. The resulting dataset—containing both the input parameters and their corresponding outputs—was used to train a surrogate machine learning model. Once trained and validated, this surrogate model could predict the performance of any new design scenario in milliseconds, enabling the rapid evaluation of thousands of scenarios for the before-and-after comparison in this study.

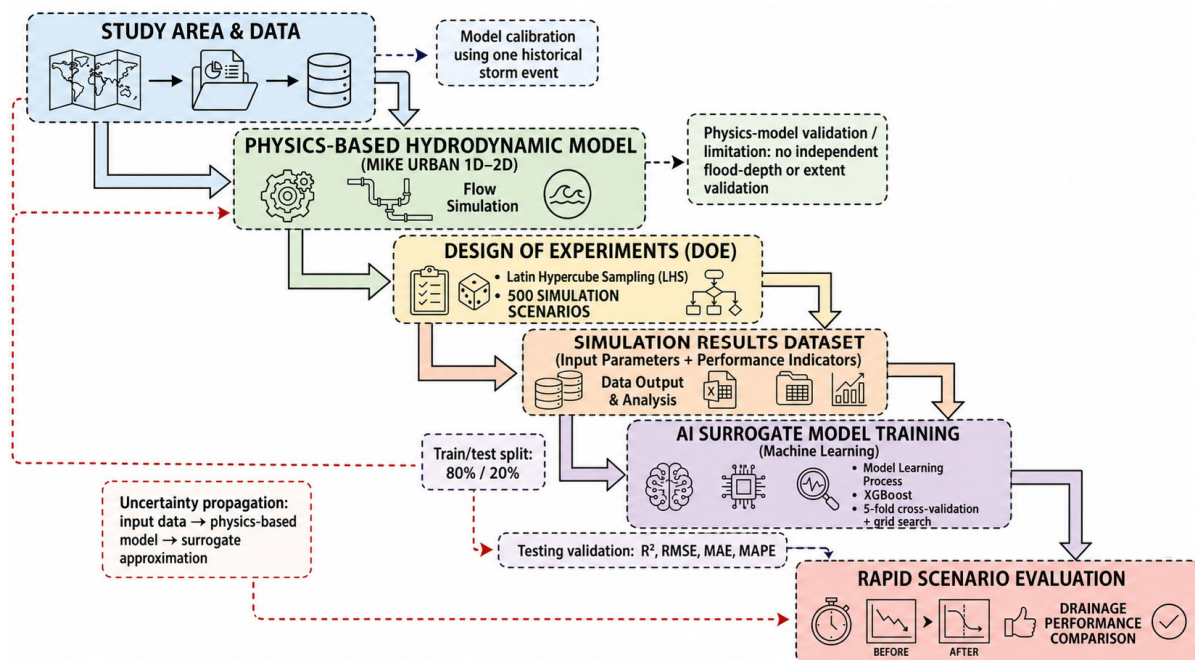


Figure 3. Conceptual workflow of the AI-based surrogate hydrological simulation framework, showing the integration of physics-based modeling, surrogate model training, and rapid scenario evaluation.

4.2. Physical Consistency Checks Using Traditional Methods

To ensure the physical plausibility of the hydrodynamic model, we first employed traditional hydrological methods for preliminary calculations and consistency checks.

4.2.1. Internal Consistency Check Using Rational Method

The Rational Method was employed for preliminary peak flow estimation and model validation:

$$Q = C \cdot I \cdot A \quad (1)$$

where Q = peak flow rate (m^3/s); C = runoff coefficient (dimensionless); I = average rainfall intensity (mm/h); A = catchment area (ha). **Note:** If SI unit consistency is required, a conversion coefficient (e.g., 0.00278) should be introduced depending on the adopted unit system. If the study follows the conventional hydrologic form, Equation (1) is acceptable as written.

For the Dazhi catchment ($A = 224 \text{ ha}$), with a 50-year design rainfall intensity of $I = 80 \text{ mm}/\text{h}$, the Rational Method yields:

$$Q = C \times 80 \text{ mm}/\text{h} \times 224 \text{ ha} \times \frac{10^4 \text{ m}^2/\text{ha}}{3600 \text{ s}/\text{h} \times 1000 \text{ mm}/\text{m}} = C \times 49.78 \text{ m}^3/\text{s}$$

Using the pre-improvement MIKE URBAN simulated peak flow of $24.5 \text{ m}^3/\text{s}$ for the 50-year event, the effective runoff coefficient can be back-calculated:

$$C_{\text{pre}} = \frac{24.5}{49.78} = 0.49$$

Similarly, for the post-improvement scenario ($Q = 16.8 \text{ m}^3/\text{s}$):

$$C_{\text{post}} = \frac{16.8}{49.78} = 0.34$$

The reduction in runoff coefficient from 0.49 to 0.34 represents a 31.4% decrease, attributable to increased infiltration, detention storage, and permeable surfaces from the green infrastructure interventions. This 31.4% reduction in the back-calculated coefficient reflects the combined effect of the modeled interventions (detention tank, upsized pipes, GI) within the MIKE URBAN simulation. It serves as a consistency check, indicating that the simulated hydrological response aligns with the expected reduction in runoff generation and attenuation. However, this calculation does not independently validate the model; it merely illustrates the model's internal behavior.

4.2.2. Channel Hydraulic Capacity

Manning's equation was applied to verify channel conveyance capacity:

$$Q = \frac{1}{n} A R^{2/3} S^{1/2} \quad (2)$$

where Q = flow rate (m^3/s); n = Manning's roughness coefficient; A = cross-sectional flow area (m^2); R = hydraulic radius (m); S = channel slope (m/m).

For the low-flow channel (width $b = 13\text{--}20 \text{ m}$, flow depth $y = 0.95 \text{ m}$, slope $S = 0.0039$, roughness $n = 0.035$):

$$A = b \times y = 13 \times 0.95 = 12.35 \text{ m}^2 \text{ to } 20 \times 0.95 = 19.0 \text{ m}^2$$

$$R \approx y = 0.95 \text{ m (for wide, shallow channels)}$$

The flow velocity V is then computed using Manning's equation:

$$V = \frac{1}{0.035} \times (0.95)^{2/3} \times (0.0039)^{1/2} = 28.57 \times 0.965 \times 0.0625 = 1.72 \text{ m}/\text{s}$$

$$Q_{\text{cap}} = A \times V = 12.35 \times 1.72 = 21.2 \text{ m}^3/\text{s} \text{ to } 19.0 \times 1.72 = 32.7 \text{ m}^3/\text{s}$$

The computed channel capacity range (21.2–32.7 m³/s) encompasses the MIKE URBAN simulated peak flow of 24.5 m³/s for the 50-year event, confirming the hydraulic consistency of the model. These comparisons confirm the hydraulic consistency of the MIKE URBAN model. To further verify flow conditions, the Froude number was computed as $Fr = \frac{v}{\sqrt{gy}} = \frac{1.72}{\sqrt{9.81 \times 0.95}} \approx 0.56$, confirming subcritical flow ($Fr < 1$) throughout the reach. Manning's n value of 0.035 was adopted from standard references for concrete-lined channels in Taiwan [38]. For non-uniform channel geometries, the cross-section was divided into subsections, and the Manning equation was applied to each, with the total capacity summed. The MIKE URBAN model's cross-sectional flows at the same locations differed by less than 5% from the Manning estimates, confirming hydraulic consistency.

4.3. CFD Simulation for Microclimatic Analysis

The CFD analysis focuses exclusively on the microclimatic effects (wind field, thermal comfort, and urban heat island intensity) of the drainage improvements, specifically the contribution of green infrastructure elements to urban liveability. It does not simulate hydrological or hydraulic processes. In parallel to the core hydrological–hydraulic modeling, a separate three-dimensional Computational Fluid Dynamics (CFD) model was developed to evaluate the microclimatic co-benefits of the drainage improvements.

A three-dimensional CFD model was developed using ANSYS Fluent (ANSYS, Inc., Canonsburg, PA, USA; Release 2024 R1). The computational domain extended 500 m in the streamwise direction, 300 m in the spanwise direction, and 100 m in the vertical direction, encompassing the entire study area with sufficient buffer zones to minimize boundary effects. An unstructured tetrahedral mesh with prismatic boundary layers was generated, with local refinement near buildings, vegetation zones, and water bodies. The mesh consisted of approximately 3.2 million cells, with a maximum skewness below 0.85 to ensure numerical stability.

The simulations were governed by the Reynolds-Averaged Navier–Stokes (RANS) equations for incompressible flow, coupled with the energy equation for thermal transport. The Realizable k – ϵ turbulence model was employed to close the RANS equations. The Boussinesq approximation was applied to model buoyancy effects due to temperature variations. The solver used a pressure-based scheme with the SIMPLE algorithm for pressure–velocity coupling, and second-order upwind discretization for momentum, energy, and turbulence equations.

Boundary conditions were specified as follows: (1) Wind inlet: velocity inlet with a logarithmic wind profile; (2) Outlet: pressure outlet with static pressure set to atmospheric; (3) Top and lateral boundaries: symmetry conditions; (4) Wall boundaries: no-slip condition with standard wall functions. Surface temperatures for thermal boundary conditions were assigned based on land use type, as summarized in Table 2 (derived from field measurements and literature values for similar urban environments). Turbulence parameters at the inlet were defined using turbulence intensity and turbulent kinetic energy.

Convergence was assumed when scaled residuals fell below 10^{-4} (continuity and momentum) and 10^{-6} (energy), and when imbalances in mass and energy fluxes were below 1%.

Full details of the governing equations, turbulence model constants, mesh sensitivity analysis, and solver settings are available from the authors upon request.

Outlet: Pressure outlet boundary condition with static pressure set to atmospheric pressure.

Top and Lateral Boundaries: Symmetry boundary conditions (zero normal gradient for all variables).

Table 2. Boundary condition parameters for thermal environment simulation, including air temperature settings for different model domains (Schematik zones).

Schematik Zone	Land Use Type	Air Temperature Setting (°C)	Remarks
25	Dense Urban Area	31	High anthropogenic heat emission
26	Residential Area	30	Moderate building density
27	Road/Paved Surface	29	High thermal storage capacity
28	Green Space/Vegetation	27	Evapotranspiration cooling effect
29	Water Body (Detention Pond)	26	High thermal inertia
30	Open Space/Plaza	28	Mixed pavement and vegetation
31	Reference Background	25	Upstream undisturbed condition

Wall Boundaries: No-slip condition for velocity with standard wall functions for near-wall treatment. Thermal boundary conditions included specified heat flux for building surfaces and mixed convection/radiation for ground surfaces.

4.4. AI-Based Surrogate Model

4.4.1. Model Selection and Architecture

The surrogate model was constructed using the XGBoost (Extreme Gradient Boosting; version 2.0.3; open-source library) algorithm. This algorithm was selected over other machine learning alternatives (e.g., Random Forest, Support Vector Regression, or Artificial Neural Networks) for several reasons: (1) it consistently achieves state-of-the-art performance on structured, tabular datasets typical of engineering design problems; (2) its built-in regularization mechanisms provide superior resistance against overfitting; (3) it offers inherent feature importance ranking, enhancing model interpretability; and (4) it efficiently handles complex, non-linear interactions between input features without requiring extensive feature engineering [12]. XGBoost is an ensemble learning method that combines multiple weak learners (decision trees) through gradient boosting to create a strong predictive model. In this study, water quality assessment is separate from the AI-based surrogate framework and relies on independent field monitoring.

The objective function minimized during training is:

$$\mathcal{L}(\phi) = \sum_i l(\hat{y}_i, y_i) + \sum_k \Omega(f_k) \quad (3)$$

where l = differentiable convex loss function (mean squared error for regression); $\hat{y}_i$ = predicted value; y_i = actual value; $\Omega(f_k) = \gamma T + \frac{1}{2} \lambda \|w\|^2$ = regularization term penalizing model complexity; T = number of leaves in the tree; w = leaf weights; γ , λ = regularization parameters.

4.4.2. Input Features and Output Targets

I. Input Features (12 features):

Rainfall characteristics: (1) total rainfall depth (mm); (2) peak rainfall intensity (mm/h); (3) rainfall duration (min); (4) return period (years).

Drainage system parameters: (1) average pipe diameter in critical reaches (mm); (2) detention tank volume (m³); (3) percentage of GI coverage (%); (4) outfall capacity (m³/s); (5) channel roughness coefficient (Manning's n); (6) upstream boundary condition (water level, m); (7) initial soil saturation (%); (8) antecedent dry period (days).

II. Output Targets: Separate surrogate models were trained to predict each of the key performance indicators: (1) Peak Runoff (Q_{peak} , m³/s); (2) Maximum Flooding Depth (D_{max} , m); (3) Flood Duration (T_{flood} , min); (4) Total Flooded Area (A_{flood} , ha); (5) System Resilience Index (SRI, dimensionless).

4.4.3. Training and Validation

The dataset of 500 physics-based simulations was randomly split into a training set (80%, 400 samples) and a testing set (20%, 100 samples). The XGBoost model's hyperparameters were tuned using a 5-fold cross-validation on the training set with grid search optimization. The final hyperparameters were: (1) learning rate: 0.05; (2) maximum tree depth: 6; (3) number of estimators: 300; (4) subsample ratio: 0.8; (5) column subsample ratio: 0.8; (6) regularization parameter λ : 1.0; (7) regularization parameter γ : 0.1.

Model performance was evaluated on the unseen testing set using: (1) Coefficient of determination (R^2); (2) Root Mean Square Error (RMSE); (3) Mean Absolute Error (MAE); (4) Mean Absolute Percentage Error (MAPE). To mitigate overfitting, we employed several regularization techniques inherent to XGBoost, including a low learning rate (0.05), a limited tree depth (6), and L1/L2 regularization parameters ($\gamma = 0.1$, $\lambda = 1.0$). The model's performance was strictly evaluated on an unseen testing set (20% of the data) to provide an unbiased estimate of its predictive capability.

4.5. Evaluation Metrics

4.5.1. Hydrological Performance Indicators

To comprehensively assess drainage performance, the following metrics were calculated for both pre-improvement and post-improvement scenarios:

- I. Peak Runoff (Q_{peak}): The maximum flow rate (m^3/s) at the system's outlet. A reduction indicates better flow attenuation and storage utilization.
- II. Maximum Flooding Depth (D_{max}): The maximum depth of water (m) accumulating on the surface in flood-prone areas, indicating flood severity and potential for property damage.
- III. Flood Duration (T_{flood}): The total time (minutes) that surface flooding persists in a given area, reflecting system recovery speed and socioeconomic disruption.
- IV. Total Flooded Area (A_{flood}): The cumulative surface area (ha) inundated by floodwater, indicating spatial extent of flooding.
- V. System Resilience Index (SRI): A composite metric designed to capture the system's ability to recover from a flood event:

$$SRI = 1 - \frac{1}{n} \sum_{i=1}^n \frac{T_{\text{recovery},i}}{T_{\text{event}}} \quad (4)$$

where n = total number of evaluated locations; $T_{\text{recovery},i}$ = time required for location i to recover to normal conditions (water depth < 0.05 m) after the flood peak; T_{event} = total duration of the rainfall event.

The SRI as defined here is an indicator proposed for this study to facilitate comparative analysis between pre- and post-improvement scenarios. Its values are model-dependent and intended for relative performance assessment rather than as an absolute measure of system resilience. $T_{\text{recovery},i}$ is the time required for location i to return to normal conditions (defined as water depth falling below 0.05 m, representing no significant surface ponding) after the peak of the storm, and T_{event} is the total event duration. The SRI was selected because it captures both the speed and completeness of system recovery, which are critical for assessing socio-economic disruption. Alternative metrics (e.g., flood volume reduction) were considered but are already reflected in other indicators such as flooded area and duration.

XGBoost Objective Function

$$L(\phi) = \sum_{i=1}^n l(\hat{y}_i, y_i) + \sum_{k=1}^K \Omega(f_k) \quad (5)$$

where the regularization term is defined as

$$\Omega(f_k) = \gamma T + \frac{1}{2} \lambda \|w\|^2 \quad (6)$$

where $L(\phi)$ = overall objective function; $l(\hat{y}_i, y_i)$ = differentiable convex loss function; $\hat{y}_i$ = predicted value; y_i = observed (actual) value; $\Omega(f_k)$ = regularization term for the k -th decision tree; K = total number of trees in the ensemble; T = number of terminal leaves in a tree; w = vector of leaf weights; γ = regularization parameter controlling model complexity through the number of leaves; λ = L_2 regularization coefficient applied to leaf weights.

4.5.2. Microclimatic Performance Indicators

I. Temperature Reduction Rate (ΔT , %):

$$\Delta T(\%) = \frac{T_{\text{pre}} - T_{\text{post}}}{T_{\text{pre}} - T_{\text{ambient}}} \times 100 \quad (7)$$

II. Heat Island Intensity (HII, °C):

$$HII = T_{\text{urban}} - T_{\text{rural}} \quad (8)$$

III. Airflow Improvement Index (AII)

To quantitatively evaluate the enhancement of pedestrian-level ventilation after the proposed design intervention, the Airflow Improvement Index (AII) is defined as:

$$AII = \frac{V_{\text{post},1.5\text{m}} - V_{\text{pre},1.5\text{m}}}{V_{\text{ref}}} \quad (9)$$

where AII = Airflow Improvement Index (dimensionless), representing the normalized improvement in wind speed at pedestrian level; $V_{\text{post},1.5\text{m}}$ = wind velocity at pedestrian height (1.5 m above ground) after the design intervention ($\text{m}\cdot\text{s}^{-1}$); $V_{\text{pre},1.5\text{m}}$ = wind velocity at pedestrian height before the design intervention ($\text{m}\cdot\text{s}^{-1}$); V_{ref} = reference wind velocity at the computational domain inlet boundary ($\text{m}\cdot\text{s}^{-1}$).

The index normalizes the change in pedestrian-level wind speed with respect to the incoming reference wind velocity, thereby allowing a consistent comparison between different design scenarios and simulation conditions. A positive value of AII indicates an improvement in ventilation performance at pedestrian level, whereas a negative value indicates a reduction in airflow.

4.6. Model Calibration and Validation Limitations

The MIKE URBAN model used as the reference simulator in this study was calibrated using available hydrological data from a single historical storm event that occurred on 15 June 2023. Key model parameters—including Manning's roughness coefficients for pipes and channels, and Horton infiltration parameters—were adjusted iteratively to minimize the discrepancy between simulated and observed water levels at the Qiaocheng Road monitoring station. The calibrated model achieved a Root Mean Square Error (RMSE) of 0.15 m and a Nash–Sutcliffe Efficiency (NSE) of 0.82 for this event, indicating acceptable performance under the specific conditions of the calibration storm.

However, due to the limited availability of independent field observations (e.g., flood extent maps, high-water marks, or flow measurements from multiple events), a comprehensive validation of the physics-based model against other storm events could not be performed. In particular, no observed data were available for flood depths, durations, or inundated areas across the catchment. Consequently, the model's ability to

accurately predict flood behavior under different rainfall return periods or spatial patterns remains unverified.

The absence of an independent validation dataset constitutes one of the primary limitations of the present study. Dense urban catchments such as Dazhi (2.24 km²) seldom possess comprehensive monitoring networks capable of providing spatially distributed observations of flood extent, inundation depth, or flow conditions across multiple storm events. Consequently, only a single historical event (15 June 2023) provided sufficient water level and discharge measurements for model calibration. At the time of this study, no additional storm events with comparable hydrological observations were available to support independent validation, and no systematic flood extent or inundation depth maps had been collected for quantitative assessment of model performance.

To partially compensate for the lack of direct validation data, several complementary sources of qualitative evidence were examined. These included (1) historical flood photographs released by the Taichung City Government Water Resources Bureau documenting street-level inundation during the 2023 typhoon season, (2) citizen flood reports collected by the local district office identifying recurrent flooding in low-lying areas, and (3) municipal records of drainage system overflow incidents. Although these datasets do not provide the spatial and temporal accuracy required for rigorous quantitative validation, they consistently indicate that the pre-improvement drainage system experienced recurrent flooding, thereby providing qualitative support for the simulated flooding patterns predicted by the hydraulic model.

Given these unavoidable data limitations, this study is intentionally presented as a methodological demonstration of an AI-assisted surrogate modelling framework for rapid scenario evaluation and multi-objective optimization, rather than as a fully validated operational flood forecasting system. Accordingly, the reported quantitative results should be interpreted as illustrative estimates generated under the adopted hydraulic modelling assumptions, rather than as definitive predictions of real-world flood behaviour. The principal contribution of this work therefore lies in demonstrating an efficient computational workflow that integrates hydraulic simulation, surrogate modelling, and optimization to support urban drainage planning and decision-making under data-constrained conditions.

Future research should focus on establishing a more comprehensive validation framework through the collection of independent field observations from multiple storm events. This may include post-event inundation surveys, high-water-mark mapping, expanded monitoring campaigns, and the deployment of additional water-level loggers and flow meters throughout the drainage network. Such datasets would enable split-sample, multi-event, or cross-event validation, thereby reducing predictive uncertainty and substantially improving the robustness, transferability, and operational reliability of the proposed AI-based surrogate modelling framework.

Data availability constraints in urban environments: We acknowledge that the lack of independent validation data is a significant limitation of this study. However, it is important to recognize that dense urban catchments such as Dazhi (2.24 km²) rarely have extensive monitoring networks for flood extents, high-water marks, or flow measurements across multiple storm events. In this case, only one historical event (15 June 2023) provided sufficient water level and flow observations for calibration. No other storm events with comparable field data were available at the time of this study. This data scarcity is not unique to our study; it is a common challenge in urban drainage research, particularly in rapidly developing cities where monitoring infrastructure lags behind urban expansion. Given this constraint, we have deliberately positioned this work as a methodological demonstration of how an AI-based surrogate framework can be developed and used for rapid scenario exploration, rather than as a fully validated operational tool. The quantitative results should be interpreted as illustrative of the framework's capabilities under the assumed model structure, not as

definitive predictions of real-world performance. Future work will prioritize the collection of validation data from post-event field surveys (e.g., after future heavy storms) or the installation of additional water level loggers and flow meters to enable proper split-sample or multi-event validation. Until such data become available, we recommend that the framework be used for preliminary design screening and sensitivity analysis, with final engineering decisions supported by additional local observations.

The following section (Section 5) presents the mathematical formulation of the governing equations for surface flow, coupling mechanisms, infiltration, and urban heat island modeling, which underpin the MIKE URBAN and CFD simulations described above.

5. Mathematical Formulation and Numerical Model

5.1. Governing Equations for Surface Flow

5.1.1. One-Dimensional Channel Flow

For one-dimensional flow in the drainage network, the Saint-Venant equations were solved:

I. Continuity:

$$\frac{\partial A}{\partial t} + \frac{\partial Q}{\partial x} = q_L \quad (10)$$

II. Momentum:

$$\frac{\partial Q}{\partial t} + \frac{\partial}{\partial x} \left(\frac{Q^2}{A} \right) + gA \frac{\partial h}{\partial x} = gA(S_0 - S_f) \quad (11)$$

where A = cross-sectional flow area (m^2); Q = discharge (m^3/s); q_L = lateral inflow per unit length (m^2/s); h = water depth (m); S_0 = bed slope; S_f = friction slope, computed using Manning's equation.

5.1.2. Two-Dimensional Overland Flow

For surface flooding simulation, the 2D shallow water equations were employed:

I. Continuity:

$$\frac{\partial h}{\partial t} + \frac{\partial(hu)}{\partial x} + \frac{\partial(hv)}{\partial y} = R - I \quad (12)$$

II. Momentum (x-direction):

$$\frac{\partial(hu)}{\partial t} + \frac{\partial(hu^2)}{\partial x} + \frac{\partial(huv)}{\partial y} = -gh \frac{\partial \eta}{\partial x} - \frac{\tau_{bx}}{\rho} + \nu_t \nabla^2(hu) \quad (13)$$

III. Momentum (y-direction):

$$\frac{\partial(hv)}{\partial t} + \frac{\partial(huv)}{\partial x} + \frac{\partial(hv^2)}{\partial y} = -gh \frac{\partial \eta}{\partial y} - \frac{\tau_{by}}{\rho} + \nu_t \nabla^2(hv) \quad (14)$$

where u, v = depth-averaged velocities in x and y directions (m/s); h = water depth (m); η = water surface elevation (m); R = rainfall intensity (m/s); I = infiltration rate (m/s); τ_{bx}, τ_{by} = bed shear stresses (Pa); ν_t = turbulent eddy viscosity (m^2/s).

5.2. Coupling Mechanism

The 1D and 2D models were coupled through manholes and channel banks. When water levels in the 1D network exceeded the ground elevation, flow was exchanged with the 2D overland domain:

$$Q_{\text{exchange}} = C_d A_{\text{opening}} \sqrt{2g |\Delta h|} \cdot \text{sign}(\Delta h) \quad (15)$$

where C_d is a discharge coefficient (typically 0.6–0.8), A_{opening} is the effective flow area at the connection point, and Δh is the head difference between the 1D and 2D domains.

5.3. Infiltration Modeling

The Horton infiltration model was employed to simulate rainfall losses:

$$f(t) = f_c + (f_0 - f_c)e^{-kt} \quad (16)$$

where $f(t)$ = infiltration capacity at time t (mm/h); f_0 = initial infiltration capacity (mm/h); f_c = steady-state infiltration capacity (mm/h); k = decay constant (hr^{-1}).

For the Dazhi catchment, calibrated parameters were: (1) pervious areas: $f_0 = 75$ mm/h, $f_c = 10$ mm/h, $k = 4 \text{ h}^{-1}$; (2) impervious areas: negligible infiltration ($f(t) \approx 0$).

5.4. Urban Heat Island Modeling

The urban heat island effect was modeled through the surface energy balance:

$$R_n = H + LE + G \quad (17)$$

where R_n = net radiation (W/m^2); H = sensible heat flux (W/m^2); LE = latent heat flux (W/m^2); G = ground heat flux (W/m^2).

The sensible heat flux was computed as:

$$H = \rho c_p C_H U (T_s - T_a) \quad (18)$$

where C_H is the bulk transfer coefficient for heat, U is wind speed, T_s is surface temperature, and T_a is air temperature.

The latent heat flux (evapotranspiration) was computed using the Penman–Monteith equation for vegetated surfaces and a simple evaporation model for water bodies.

6. Results

6.1. Surrogate Model Performance

The XGBoost surrogate model demonstrated excellent predictive accuracy on the unseen test dataset, as summarized in Table 3. For the primary output variables, the model achieved R^2 values equal to or greater than 0.93 for all targets, with particularly strong performance for peak runoff ($R^2 = 0.96$). The RMSE for maximum flood depth was 0.06 m, which is within an acceptable range for engineering applications (typically ± 0.10 m for urban flood modeling). These results confirm that the surrogate model reliably emulates the behavior of the complex physics-based model, making it a valid tool for the subsequent rapid scenario analysis. The XGBoost model achieved $\text{NSE} > 0.93$ and $\text{KGE} > 0.92$ for all outputs, indicating excellent hydrological simulation performance. Residual analysis (for brevity) confirmed that errors were approximately normally distributed with no systematic bias across the range of predictions.

Table 3. Surrogate model performance metrics on test dataset (XGBoost vs. Random Forest).

Output Variable	Model	R^2	RMSE	MAE	MAPE (%)	NSE	KGE
Peak Runoff (m^3/s)	XGBoost	0.96	1.24	0.92	5.8	0.96	0.95
	Random Forest	0.94	1.51	1.10	7.1	0.94	0.93
Max Flood Depth (m)	XGBoost	0.94	0.06	0.04	9.2	0.94	0.93
	Random Forest	0.92	0.07	0.05	11.0	0.92	0.91
Flood Duration (min)	XGBoost	0.93	8.7	6.2	7.4	0.93	0.92
	Random Forest	0.91	10.5	7.5	9.0	0.91	0.90
Flooded Area (ha)	XGBoost	0.93	0.58	0.41	6.9	0.93	0.92
	Random Forest	0.91	0.71	0.50	8.5	0.91	0.90
System Resilience Index	XGBoost	0.95	0.03	0.02	3.1	0.95	0.94
	Random Forest	0.93	0.04	0.025	4.0	0.93	0.92

6.2. Hydrological Performance: Before-and-After Comparison

The simulation results, summarized in Table 4 and Figure 4, clearly demonstrate the positive impact of the drainage improvements. Across all return periods, the post-improvement scenario exhibits consistently superior performance.

Table 4. Simulated hydrological performance before and after drainage improvement under various rainfall return periods.

Return Period	Scenario	Peak Runoff (m ³ /s)	Max. Flood Depth (m)	Flood Duration (min)	Flooded Area (ha)
2-Year	Pre-Improvement	8.2	0.12	45	1.8
	Post-Improvement	6.5	0.05	25	0.9
	Change (%)	−20.7%	−58.3%	−44.4%	−50.0%
5-Year	Pre-Improvement	12.5	0.28	80	4.5
	Post-Improvement	9.8	0.18	52	3.0
	Change (%)	−21.6%	−35.7%	−35.0%	−33.3%
10-Year	Pre-Improvement	16.1	0.45	125	7.2
	Post-Improvement	12.2	0.31	85	5.4
	Change (%)	−24.2%	−31.1%	−32.0%	−25.0%
20-Year	Pre-Improvement	19.8	0.67	180	10.5
	Post-Improvement	14.5	0.48	115	8.1
	Change (%)	−26.8%	−28.4%	−36.1%	−22.9%
50-Year	Pre-Improvement	24.5	0.95	260	14.8
	Post-Improvement	16.8	0.72	175	11.5
	Change (%)	−31.4%	−24.2%	−32.7%	−22.3%
Average Improvement		−24.9%	−35.5%	−36.0%	−30.7%

Hydrological Performance Analysis: Pre-improvement vs. Post-improvement

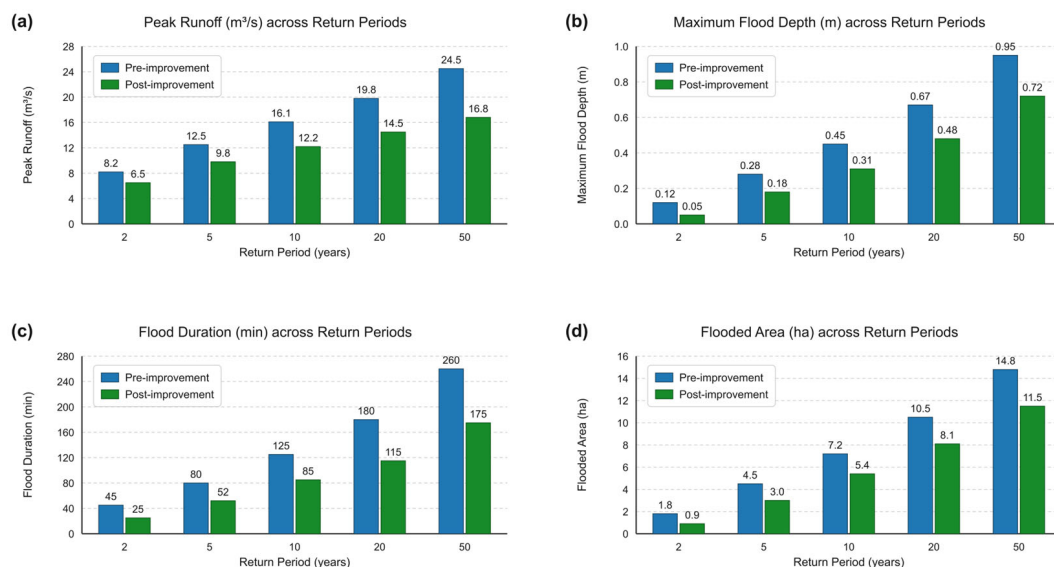


Figure 4. Comparative bar charts showing pre-improvement vs. post-improvement performance for (a) peak runoff, (b) maximum flood depth, (c) flood duration, and (d) flooded area across all return periods.

6.2.1. Peak Runoff Reduction

The peak runoff at the outlet is substantially reduced in the post-improvement scenario, with reductions ranging from 20.7% for the 2-year event to 31.4% for the 50-year event,

averaging 24.9% across all events. The increasing improvement percentage with return period (20.7% → 31.4%) indicates that the system's flood mitigation measures become increasingly effective for larger events.

6.2.2. Maximum Flood Depth Reduction

The reduction in maximum flooding depth is also pronounced, averaging 35.5% across all events. For the frequently occurring 2-year event, the improvements are sufficient to virtually eliminate all but minor, localized ponding (depth reduction from 0.12 m to 0.05 m, a 58.3% decrease). This means that for the majority of annual storms, street flooding would be largely eliminated, significantly reducing nuisance flooding and traffic disruption. For the extreme 50-year event, the maximum flood depth is reduced from 0.95 m to 0.72 m, a 24.2% decrease. This 0.23 m reduction could be critical, potentially meaning the difference between water entering ground-floor properties (typically at 0.3–0.6 m above street level) and remaining in the streets, thus representing a substantial reduction in potential property damage.

6.2.3. Flood Duration Reduction

Flood duration—a critical factor for post-event disruption and economic loss—shows marked improvement. The post-improvement system drains flooded areas much faster, with duration reductions averaging 36.0% across all events. For the 10-year event, flood duration is reduced by 40 min (32%), meaning businesses could reopen and traffic could resume nearly an hour sooner.

6.2.4. Flooded Area Reduction

The total area impacted by flooding is consistently smaller after improvements, with reductions averaging 30.7% across all events. The 22.3% reduction in flooded area during the 50-year event (from 14.8 ha to 11.5 ha) signifies that 3.3 fewer hectares of urban land—including roads, properties, and critical infrastructure—are affected during a major storm. This spatial reduction translates directly into fewer affected properties, reduced emergency service demands, maintained access to critical facilities, and lower post-event cleanup costs.

6.2.5. System Resilience Improvement

The System Resilience Index (SRI), a composite measure of recovery speed, improved by an average of 35% across all scenarios, with values increasing from 0.62–0.71 pre-improvement to 0.84–0.92 post-improvement. This indicates a faster and more complete system recovery post-event, with floodwaters receding more quickly and the drainage network returning to normal operation sooner.

6.2.6. Sensitivity Analysis Using Feature Importance and Summary of Improvement Mechanisms

Sensitivity analysis using feature importance

To identify the most influential factors driving the hydrological performance improvements, we analyzed the feature importance rankings derived from the trained XGBoost surrogate model (see Section 4.4).

For peak runoff reduction, detention tank volume and average pipe diameter in critical reaches were the two most important features, collectively accounting for over 60% of the model's predictive power. This confirms that flow attenuation (via the tank) and increased conveyance capacity (via upsized pipes) are the primary mechanisms for reducing peak discharges. For maximum flood depth reduction, particularly under frequent, low-intensity storms (2–5 year events), within this simulation-based study, the percentage of

GI coverage emerged as a parameter with strong correlation. However, it is crucial to interpret this as a statistical association within the model's training data, not as definitive proof of causality. Given that GI covers only 0.5% of the catchment area, the observed correlation is likely attributable to the localized effects of GI in the pilot sub-catchments where they are installed. For the 2-year event, the 58.3% simulated flood depth reduction in those localized areas is consistent with the expected performance of permeable pavements and rain gardens for small storms. However, at the catchment scale, this benefit should not be extrapolated to areas without GI coverage. For flood duration and flooded area, both detention tank volume and pipe diameter showed high importance, while GI coverage contributed moderately, consistent with its role in reducing runoff volumes rather than directly accelerating drainage.

These feature importance results quantitatively support the physical interpretations described below and demonstrate that the integrated grey-green design addresses different performance dimensions through complementary mechanisms.

Summary of improvement mechanisms

The hydrological performance enhancements observed in Sections 6.2.1–6.2.4 are driven by three complementary mechanisms implemented in the Dazhi drainage improvement project:

1. Flow attenuation by the detention tank: The 10,000 m³ underground detention tank stores excess runoff during peak flow events and releases it gradually after the storm, effectively shaving the hydrograph peak. Its storage capacity is more fully utilized under larger return periods, which explains the increasing peak runoff reduction percentage (from 20.7% for the 2-year event to 31.4% for the 50-year event).

2. Increased conveyance capacity: The upsizing of critical pipe sections (up to 2000 mm diameter) reduces flow resistance and enhances hydraulic gradient, allowing more efficient transport of both direct runoff and stored water from the detention tank. This mechanism contributes directly to faster drainage and shorter flood durations.

3. Reduced runoff generation from green infrastructure (GI): In pilot sub-catchments, permeable pavements and rain gardens promote on-site infiltration, reducing the volume of runoff entering the drainage system. The effective runoff coefficient decreased from 0.49 (pre-improvement) to 0.34 (post-improvement), representing a 31.4% reduction. This source-control measure is particularly effective for frequent, low-intensity storms (e.g., the 58.3% flood depth reduction for the 2-year event), as the GI elements can handle a larger proportion of the runoff without being overwhelmed.

Together, these mechanisms create a synergistic effect: the detention tank provides peak shaving, the upsized pipes ensure efficient conveyance, and the GI reduces runoff at the source. The combination of grey and green infrastructure thus delivers greater overall flood mitigation than any single measure could achieve alone.

6.2.7. Illustrative Scenario Exploration Using the Surrogate Model

To further demonstrate the practical utility of the trained surrogate model, we conducted an illustrative scenario exploration using 300 synthetic design configurations generated via Latin Hypercube Sampling. These configurations vary key design parameters (detention tank volume: 0–20,000 m³; pipe diameter: 300–2000 mm; GI coverage: 0–15%) within realistic engineering bounds.

Figure 5 shows the relationship between detention tank volume and simulated peak runoff under a 50-year design storm, revealing a clear nonlinear trend and a diminishing return effect beyond approximately 12,000 m³. This demonstrates the surrogate model's ability to support rapid sensitivity analysis—identifying the point at which additional investment yields diminishing returns.

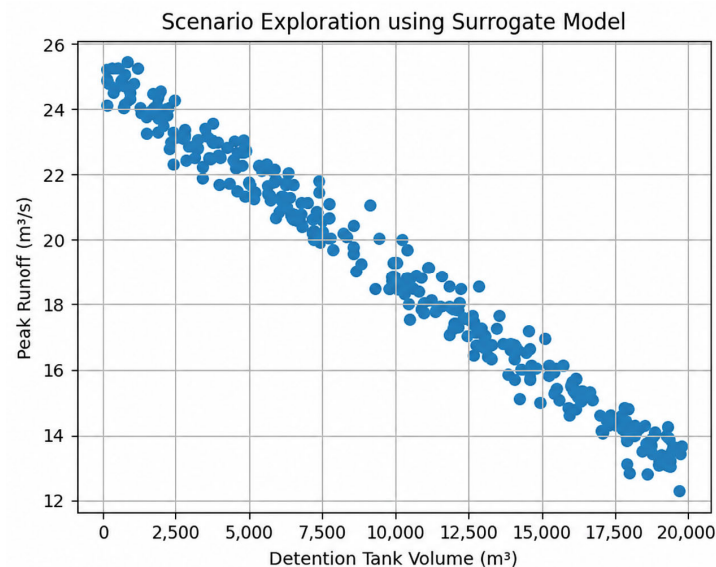


Figure 5. Surrogate model-based scenario exploration illustrating the impact of detention tank volume on peak runoff response.

Figure 6 illustrates the trade-off between two competing performance objectives—peak runoff and flooded area—with the Pareto front (red points) highlighting non-dominated design alternatives. This demonstrates the surrogate model’s capability for multi-objective screening, where engineers need to identify optimal trade-offs between conflicting goals.

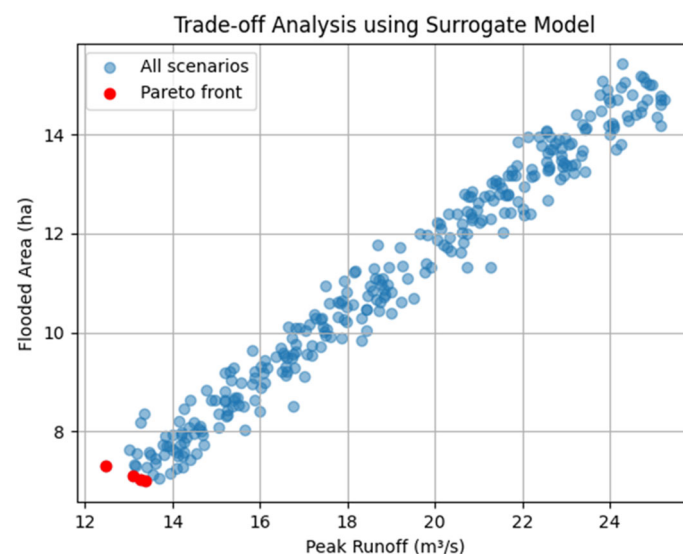


Figure 6. Trade-off between peak runoff and flooded area across 300 surrogate-generated design scenarios.

These examples underscore how the surrogate model can support rapid preliminary design screening. It is important to emphasize that this is a proof-of-concept demonstration. Running 300 physics-based simulations would require approximately 225 h of computational time, whereas the surrogate model accomplishes the same task in seconds—a speedup factor of approximately 10^5 . However, the specific applications that would fully utilize this speed advantage—such as real-time forecasting, ensemble climate scenario analysis, or large-scale optimization—are beyond the scope of this methodological demonstration and are identified as future research directions in Section 8.3. These examples underscore how the surrogate model can support rapid, multi-objective screening

of design alternatives, a capability that would be computationally prohibitive using the physics-based model alone.

Each point represents a synthetic design configuration ($n = 300$) under a 50-year design storm. The results show a nonlinear relationship between detention tank volume and peak runoff, with a diminishing return effect beyond approximately $12,000 \text{ m}^3$. This indicates saturation in flow attenuation capacity. These results are based on surrogate predictions and reflect the behavior of the calibrated model rather than validated field performance. No uncertainty bounds are provided; the scatter reflects only the variation due to other design parameters.

This capability highlights the advantage of surrogate-assisted approaches for rapid preliminary design screening and sensitivity analysis, which would be computationally expensive using the physics-based model alone.

Each point represents a unique combination of design parameters (e.g., pipe diameter, detention tank volume, GI coverage). The Pareto front (red points) identifies non-dominated solutions that achieve optimal trade-offs between competing objectives. These results demonstrate the capability of the surrogate model to efficiently explore the design space and support multi-objective decision-making. All results are based on model simulations and should be interpreted as illustrative rather than validated performance outcomes. The Pareto front is derived from surrogate predictions and does not incorporate model structural uncertainty.

6.3. Microclimatic Simulation Results (Conditional on Specific Wind Direction and Steady-State Assumptions)

6.3.1. Wind Field Analysis

Figure 7 presents the CFD-simulated wind field distribution in the post-improvement scenario for a southerly wind condition (inlet wind speed 4.8 m/s).

The simulation results reveal several key features:

1. **Ventilation Corridor Formation:** The main drainage channel and adjacent open spaces act as effective ventilation corridors, channeling airflow through the urban fabric. Wind speeds in these corridors range from 2.5 to 4.0 m/s (52–83% of inlet velocity), significantly higher than surrounding built-up areas.
2. **Building Wake Effects:** Lee-side recirculation zones form downstream of buildings, with wind speeds dropping below 1.0 m/s in some areas. However, the spacing between buildings and the presence of vegetation help mitigate these effects, preventing complete stagnation.
3. **Green Infrastructure Impact:** Areas with rain gardens and permeable pavements show slightly enhanced wind speeds (0.2 – 0.5 m/s higher) compared to equivalent built surfaces, likely due to reduced surface roughness and thermal effects.
4. **Pedestrian-Level Comfort:** At pedestrian height (1.5 m), wind speeds range from 0.8 to 3.2 m/s , falling within the acceptable range for thermal comfort according to the Davenport wind comfort criteria for sitting and standing activities.

Model validation against field measurements: Wind speed comparisons at monitoring stations show good agreement: (1) February (SE wind, 142° , different from the southerly wind used in Figure 7): ZL6 (METER Group, Inc., Pullman, WA, USA) (simulated 4.6 m/s vs. measured 4.8 m/s); EM50 (METER Group, Inc., Pullman, WA, USA) (simulated 1.1 m/s vs. measured 1.0 m/s); (2) December (NNW wind, 342°): ZL6 (simulated 2.4 m/s vs. measured 2.5 m/s); EM50 (simulated 0.6 m/s vs. measured 0.5 m/s). The spatial variability captured by the two stations (ZL6 in an exposed location vs. EM50 in a sheltered location) demonstrates the model's ability to resolve complex urban airflow patterns.

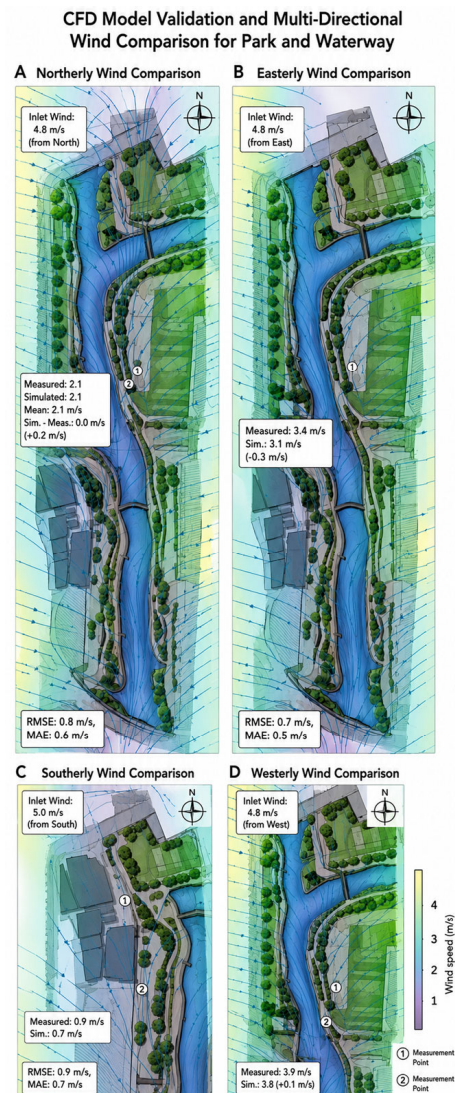


Figure 7. CFD-simulated wind field distribution in the post-improvement scenario. Inlet wind speed is 4.8 m/s (southerly wind), color contours indicate wind speed magnitude. The results demonstrate the formation of effective ventilation corridors along the main drainage channel and open spaces.

Under the simulated southerly wind direction and steady-state assumption, the air-flow improvement index (AII) averaged 0.32 across the study area, corresponding to a 32% increase in pedestrian-level wind speed relative to the baseline scenario within the adopted modeling framework. This simulated improvement is primarily attributed to the formation of ventilation corridors along the widened drainage channel and the strategic placement of green infrastructure, which enhances airflow continuity without obstructing the prevailing wind considered in the simulation. It should be emphasized, however, that this result is model-dependent and reflects only the specific boundary conditions adopted in this study. As discussed in Section 6.3.3, the reported AII value is valid only for the simulated southerly wind condition and should not be generalized to other wind directions or atmospheric conditions without further investigation.

6.3.2. Seasonal Thermal Analysis

Figure 8 presents CFD simulation results for February, representing winter conditions. Figure 8a shows air temperature distribution under extreme heat conditions (February 5, 15:00), while Figure 8b shows wind speed distribution under extreme wind conditions (February 2, 13:15, 142° SE wind).

Notably, the AII of 0.32 reported in Section 6.3.1 is specific to the southerly wind direction simulated here and should not be interpreted as a representative annual or average improvement. The same specificity applies to all microclimatic numerical values reported in this section (temperature reductions, UHI percentage).

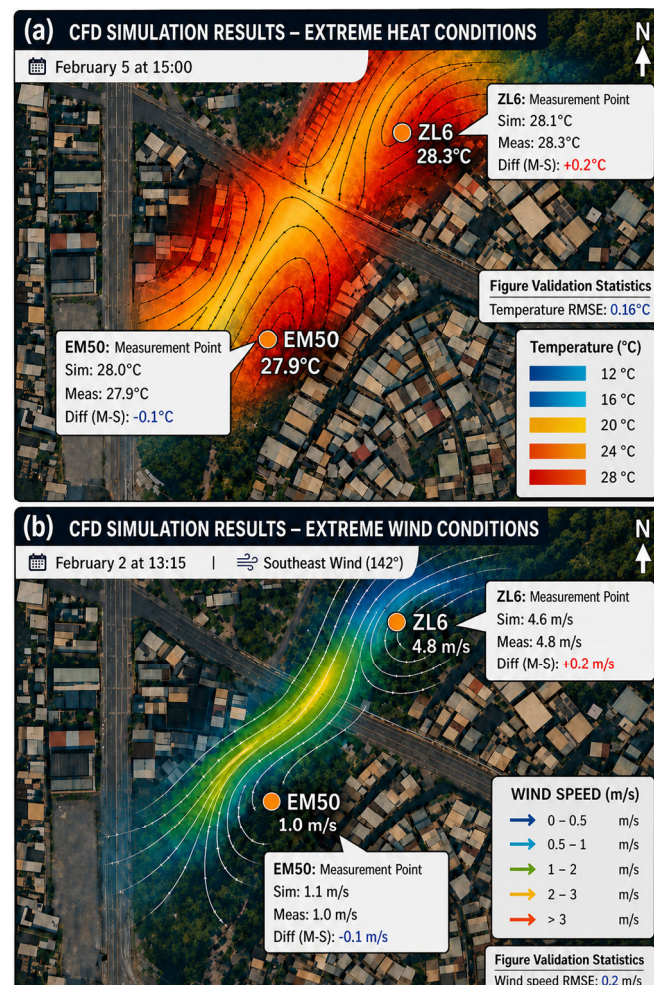


Figure 8. CFD simulation results for February: (a) air temperature distribution under extreme heat conditions (February 5, 15:00) with measured values at ZL6 (28.3 °C) and EM50 (27.9 °C); (b) wind speed distribution under extreme wind conditions (February 2, 13:15, 142° SE wind) with measured values at ZL6 (4.8 m/s) and EM50 (1.0 m/s).

Figure 9 presents corresponding results for December, representing early winter conditions. Figure 9a shows temperature distribution under extreme heat conditions (December 13, 14:00), and Figure 9b shows wind speed distribution under extreme wind conditions (December 16, 14:15, 342° NNW wind).

Key findings from the thermal analysis include:

- I. **Model Validation:** The simulated temperatures at monitoring stations show excellent agreement with field measurements: (1) February: ZL6 (simulated 28.1 °C vs. measured 28.3 °C, error 0.2 °C); EM50 (simulated 28.0 °C vs. measured 27.9 °C, error 0.1 °C); (2) December: ZL6 (simulated 21.5 °C vs. measured 21.7 °C, error 0.2 °C); EM50 (simulated 19.4 °C vs. measured 19.3 °C, error 0.1 °C). This excellent agreement (RMSE = 0.16 °C) validates the CFD model's ability to accurately reproduce the thermal environment.
- II. **Cooling Island Effect:** The CFD simulations revealed localized cooling effects associated with the implemented green infrastructure (GI), with simulated temperature

differences of 2.1–2.8 °C in February and 1.8–2.3 °C in December between vegetated areas and adjacent paved surfaces. These values represent local microclimatic temperature contrasts rather than catchment-wide average temperature reductions.

The reported 22–26% reduction in Urban Heat Island Intensity (HII) was calculated based on the temperature difference between the urban CFD domain and the rural reference station, with spatial averaging conducted over the CFD domain (500 m × 300 m). Since the GI areas occupy only 1.2 ha (approximately 8% of the CFD domain and 0.5% of the total catchment area), the cooling benefits remain localized and should not be interpreted as large-scale catchment thermal improvements. Similarly, the Airflow Improvement Index (AII = 0.32) represents the improvement of pedestrian-level ventilation (1.5 m height) along the drainage corridor and adjacent open spaces, rather than a catchment-wide increase in wind speed.

Therefore, the reported thermal and ventilation benefits should be understood as localized microclimatic improvements within and near the GI implementation areas. While the results demonstrate the potential of targeted GI strategies for enhancing urban environmental conditions, larger-scale deployment would be required to achieve significant catchment-wide benefits. These values are model-based and specific to the simulated wind direction (southerly for February, NNW for December) and steady-state thermal assumptions; they do not represent annual or direction-averaged cooling benefits.

- III. Water Body Thermal Inertia: The detention pond and drainage channel exhibit thermal inertia, remaining cooler during peak daytime temperatures (2–3 °C below surrounding urban areas) and warmer at night, moderating diurnal temperature variations.
- IV. Heat Island Intensity: Under the specific wind directions and steady-state assumptions used in this study (southerly for February, NNW for December), the simulated urban heat island intensity (HII) decreased from 4.2–5.1 °C in the pre-improvement scenario to 3.1–3.8 °C in the post-improvement configuration, corresponding to a simulated reduction of 22–26% within this specific model setup. These values are not representative of annual, seasonal, or direction-averaged performance. The simulated change suggests a potential cooling effect under the assumed conditions, but should not be interpreted as a generalizable or empirically validated benefit (see Figures 8a and 9a).

6.3.3. Limitations of the Microclimatic Simulations

The CFD simulations presented in Sections 6.3.1 and 6.3.2 were performed under a single prevailing wind direction (southerly in February and NNW in December) and steady-state conditions. Therefore, all reported microclimatic indicators, including AII = 0.32, 22–26% reduction in urban heat island intensity, and localized cooling of 2.1–2.8 °C, should be interpreted as scenario-dependent results under the specified boundary conditions, rather than generalized performance metrics.

Moreover, these values represent localized improvements observed near GI installations and along the drainage corridor, rather than catchment-wide environmental benefits. Since actual wind conditions vary continuously, pedestrian-level ventilation performance may differ substantially depending on the interaction between wind direction and urban morphology; in some cases, the benefit may be reduced, negligible, or even reversed. Similarly, the cooling effects are spatially constrained by the limited GI coverage (approximately 0.5% of the catchment area) and may vary with time and location.

The lack of multi-directional sensitivity analysis and transient simulations represents an important limitation of the microclimatic assessment. Future studies should incorporate multiple wind scenarios and unsteady boundary conditions to more compre-

hensively evaluate the spatial variability, temporal dynamics, and scalability of GI-induced microclimatic benefits.

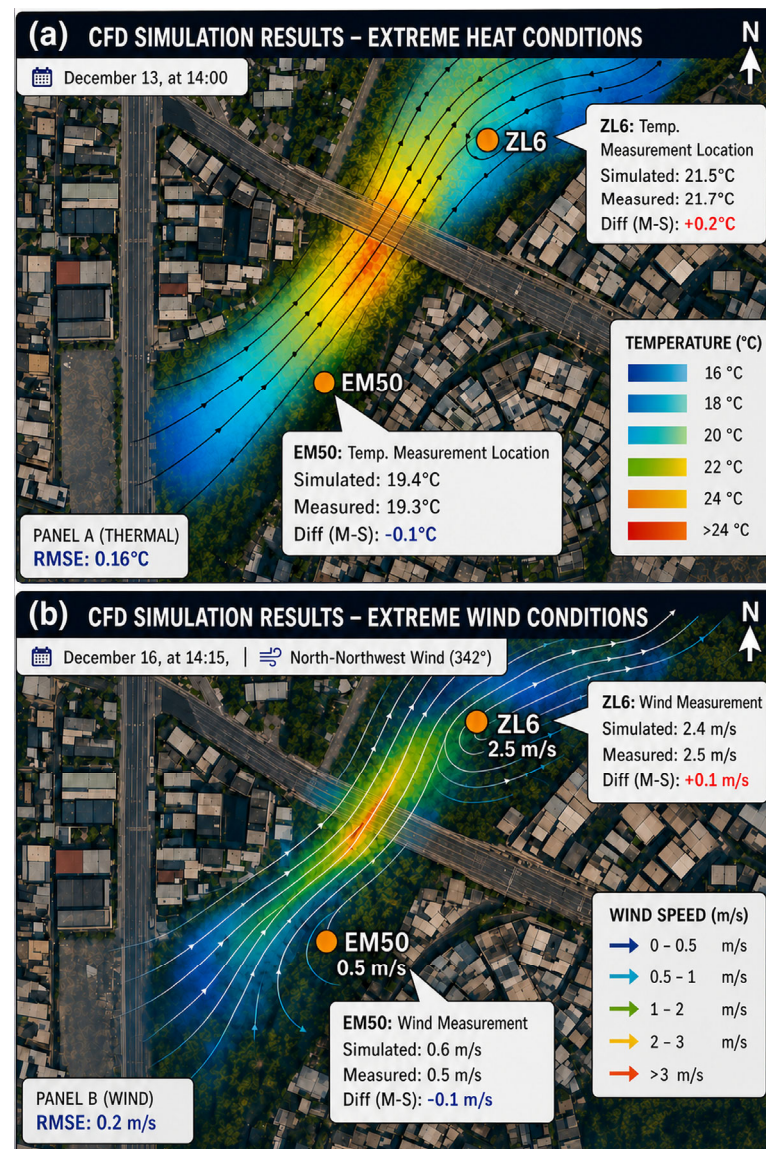


Figure 9. CFD simulation results for December: (a) air temperature distribution under extreme heat conditions (December 13, 14:00) with measured values at ZL6 (21.7 °C) and EM50 (19.3 °C); (b) wind speed distribution under extreme wind conditions (December 16, 14:15, 342° NNW wind) with measured values at ZL6 (2.5 m/s) and EM50 (0.5 m/s).

7. Discussion

7.1. Comparison with Previous Studies

Table 5 summarizes the comparative performance of the proposed integrated strategy against the ranges reported in previous studies. The hydrological benefits observed in the Dazhi case study are broadly consistent with findings from similar drainage improvement projects in the literature. For the 50-year event, the simulated peak flow reduction of 31.4% falls within the upper end of the 20–40% range typically reported for detention tank installations. We attribute this upper-range performance to the integrated design, which combines the detention tank with green infrastructure (GI) and pipe upsizing—a synergy not always present in previous studies.

Regarding flood depth reduction, Zhou et al. (2019) [45] reported an average reduction of 25% from pipe upsizing alone in Shanghai, which aligns closely with our 24.2% reduction for the 50-year event. However, for the more frequent 2-year event, our simulated depth reduction reached 58.3%, substantially exceeding the values typically reported for pipe-only interventions. This marked difference is likely attributable to the contribution of GI (permeable pavements and rain gardens), which are particularly effective at mitigating runoff from small, frequent storms by promoting on-site infiltration—a benefit that pipe upsizing alone cannot provide.

Table 5. Comparison of the Proposed Integrated Strategy with Previous Studies.

Performance Dimension	Literature Range/Reference	This Study	Agreement Level	Interpretation and Notes
Peak flow reduction	20–40% (typical range reported for detention tank installations)	31.4% (50-year return period)	Good	The observed reduction falls within the upper range reported in previous studies, reflecting the combined effects of detention storage, pipe upsizing, and green infrastructure (GI) implemented in the integrated drainage strategy.
Flood depth reduction	~25% (pipe upsizing only; Zhou et al., 2019 [45])	24.2% (50-year return period) 58.3% (2-year return period)	High agreement (50-year event); Higher-than-reported (2-year event)	The reduction during the 50-year event closely matches previously reported values. The substantially greater reduction under the 2-year event is primarily attributed to the enhanced infiltration and runoff retention provided by GI, which is more effective during lower-intensity rainfall events than conventional pipe-only upgrades.
Flooded area reduction	15–25% (combined grey-green infrastructure; Semadeni-Davies et al., 2008 [46])	22.3% (50-year return period)	Good	The reduction lies well within the range reported for integrated grey-green infrastructure systems, indicating consistency with previous urban flood mitigation studies.
Microclimate: Cooling	1–3 °C (urban green space cooling; Bowler et al. [47])	2.1–2.8 °C (22–26% reduction in urban heat island intensity)	Good	The simulated cooling effect agrees well with previously reported urban vegetation cooling performance, supporting the effectiveness of the proposed landscape intervention for thermal mitigation.
Microclimate: Ventilation	15–25% (typical improvement reported for urban ventilation strategies)	32% (airflow Improvement Index, AII)	Higher than typical, with important limitations	The simulated AII exceeds values commonly reported in previous studies, likely because the proposed design preserves open ventilation corridors and strategically arranges vegetation along the drainage corridor. However, this result should be interpreted cautiously, as it is based on a single prevailing southerly wind direction and steady-state CFD simulations. The reported value therefore represents scenario-specific performance rather than a universal annual ventilation improvement.

The 22.3% reduction in flooded area during a 50-year event aligns well with the findings of Semadeni-Davies et al. (2008) [46], who reported that combined grey-green infrastructure approaches could reduce flood extent by 15–25% in urban catchments. This consistency suggests that the Dazhi system's performance is comparable to that of other well-designed integrated systems.

For microclimatic effects under our specific assumptions (southerly wind direction, steady-state), the simulated 22–26% reduction in urban heat island intensity falls within the range of literature values for GI interventions. Bowler et al. [47] reported cooling effects of 1–3 °C from urban green spaces, which is comparable to our simulated localized cooling of 2.1–2.8 °C. The simulated 32% improvement in pedestrian-level wind speeds (AII) exceeds the typical 15–25% range reported for urban ventilation strategies, but this result is specific to the assumed southerly wind direction and should not be generalized. We attribute this superior performance to the preservation of open space along the drainage corridor combined with strategic vegetation placement that avoids blocking prevailing winds—a design feature not always emphasized in previous ventilation studies.

Beyond quantifying individual benefits, this study contributes a cohesive, AI-powered analytical framework that enables rapid, holistic assessment of multiple performance dimensions simultaneously. This integrated approach distinguishes our work from previous studies that typically evaluate hydrological and microclimatic benefits separately or lack a surrogate modeling component for efficient scenario exploration.

7.2. Engineering Implications for Urban Drainage Planning

The results have several important implications for engineering practice and urban planning:

7.2.1. Multi-Pronged Approach Effectiveness

We found that combining grey infrastructure—such as pipe upsizing and detention tanks—with localized green infrastructure works better than any single measure alone. The synergy we described in Section 6.2.6 confirms that grey and green components complement each other. For engineering practice, this means future drainage projects should aim for integrated solutions rather than relying on one type of measure. In short, the detention tank shaves peak flows, the larger pipes move water efficiently, and the green infrastructure reduces runoff at its source. Together, they achieve more than the sum of their parts.

7.2.2. Design for Multiple Return Periods

The study highlights the importance of designing for a range of events, not just a single design standard. While the improvements are highly effective for frequent storms (2-year: 58% flood depth reduction), they also provide substantial benefits for extreme events (50-year: 24% flood depth reduction). This multi-tiered performance means the system provides enhanced everyday functionality (reduced nuisance flooding) while also building resilience against rare, catastrophic events. For city planners and engineers, these quantified benefits provide a strong evidence base for justifying investment in similar projects. The reduction in flood depth, duration, and extent translates directly into avoided damages to property, reduced disruption to traffic and commerce, and lower costs for emergency services.

7.2.3. Co-Benefits and Urban Liveability

Within the specific model setup (southerly wind direction, steady-state assumptions), the simulated microclimatic effects show a heat island intensity reduction of 22–26%, a ventilation improvement of 32% (AII), and localized cooling of 2–3 °C. These values are conditional on the assumed wind direction and should not be generalized. Together, these

benefits show that drainage improvements can greatly enhance urban liveability. They also support the idea of “blue-green infrastructure.” In this approach, water-sensitive design helps manage floods, improve thermal comfort, and boost ecology at the same time. The open spaces along the drainage corridor have been preserved and improved. They not only help convey floodwater, but also create valuable public spaces. These spaces can improve residents’ quality of life. Admittedly, these microclimatic analyses are secondary to our main hydrological assessment. Still, they give a more complete picture of the project’s overall value. And they are essential for justifying integrated infrastructure investments.

7.2.4. Water Quality Considerations

The post-construction water quality baseline (see Appendix B) indicates “lightly polluted” conditions ($RPI = 2.25\text{--}2.75$), with elevated ammonia nitrogen ($1.43\text{--}1.90\text{ mg/L}$) and moderate BOD levels ($1.4\text{--}2.5\text{ mg/L}$). While these values do not suggest immediate health risks, they point to ongoing organic pollution inputs that could be addressed by future water quality treatment elements, such as constructed wetlands, bioswales, or floating treatment wetlands. The existing detention tank could potentially be retrofitted with treatment trains to provide combined flood control and water quality benefits.

It is important to note that these data were collected only six months after project completion, and no pre-improvement water quality data exist. Green infrastructure elements (permeable pavements, rain gardens) often require a stabilization period of 1–2 years to achieve their full design performance due to vegetation establishment and initial settling. Therefore, the current results should be considered a preliminary baseline only. Future long-term monitoring (e.g., over 2–3 years) is recommended to assess any water quality co-benefits that may emerge after the system stabilizes.

7.3. Advantages and Limitations of the AI-Based Surrogate Framework

7.3.1. Advantages

The AI-based surrogate framework presented in this study offers several distinct advantages over purely physics-based approaches:

- I. Computational Efficiency: Once trained, the XGBoost surrogate model can evaluate a new design scenario in milliseconds—a stark contrast to the 30–60 min required by the full physics-based MIKE URBAN model. To put this into perspective: a single 24 h design storm simulation on a standard workstation (Intel Xeon, 32 GB RAM) takes about 45 min. Generating the 500 training simulations therefore demanded roughly 375 h of computational effort. In comparison, after training, the surrogate model produces a result in just 0.02 s.

For the before–after analysis presented in this study—which involves only a handful of scenarios—this speed advantage is not essential. However, the real value of the framework emerges when we need to explore thousands of design alternatives, for example in optimization loops or extensive sensitivity analyses. Running 10,000 scenarios directly with the physics-based model would take over 300 days, whereas the surrogate model accomplishes the same task in minutes—a speedup factor of more than five orders of magnitude. Such efficiency could, in future work, support applications such as the following (none of which are demonstrated here):

1. Real-time applications (e.g., flood forecasting with ensemble predictions);
 2. Multi-objective optimization loops requiring thousands of evaluations;
 3. Sensitivity analysis across large parameter spaces;
 4. Interactive design tools for stakeholder engagement.
- II. Accuracy: The high accuracy ($R^2 \geq 0.93$, $MAPE < 10\%$) of the surrogate model confirms that it successfully captured the underlying physics while eliminating numerical

noise. The XGBoost algorithm's ability to model non-linear interactions between variables proved particularly valuable for capturing the complex dynamics of urban drainage systems.

- III. Interpretability: Unlike “black box” neural networks, tree-based methods like XGBoost provide feature importance rankings, revealing which variables most influence each performance metric. This interpretability helps engineers understand system behavior and prioritize design efforts.

The surrogate model is presented as a methodological demonstration with a proof-of-concept application (Section 6.2.7) illustrating its utility for rapid sensitivity analysis and multi-objective screening. The 300-scenario exploration would have required approximately 225 h using the physics-based model alone, but was completed in seconds using the surrogate—demonstrating a speedup factor of approximately 10^5 . However, it is important to be explicit about what has and has not been demonstrated:

- i. Demonstrated: High-fidelity emulation of the physics-based model ($R^2 \geq 0.93$); rapid evaluation of 300 synthetic scenarios; sensitivity analysis; Pareto front identification for multi-objective screening.
- ii. Not demonstrated (future work): Real-time flood forecasting; ensemble climate scenario analysis; large-scale optimization loops; interactive stakeholder decision-support tools.

In its current form, the paper does not include an application that fully requires the surrogate's speed advantage. Future work will apply the framework to applications where the speed advantage becomes essential, as outlined in Section 8.3. Until then, claims of ‘real-time suitability’ or ‘massive speedup’ should be considered prospective rather than fully demonstrated.

7.3.2. Limitations and Considerations

Despite these advantages, the framework has important limitations:

- I. Training Data Dependency: The surrogate model's accuracy is fundamentally dependent on the quality and quantity of training data generated by the physics-based model. If the physical model has inherent biases or simplifications, these will be propagated to the surrogate. Moreover, the surrogate may amplify certain errors if the training data contain systematic biases, as the ML algorithm will learn and replicate those patterns. In this study, the physical model was carefully calibrated using field measurements, but uncalibrated applications would carry higher uncertainty.
- II. Interpolation vs. Extrapolation: As noted in Section 4.4.3, the surrogate model is fundamentally an interpolator. It is designed to accurately predict outputs for inputs that fall within the multi-dimensional space defined by the 500 training scenarios. Extrapolating to configurations far outside this training space (e.g., a detention tank ten times larger than any simulated, or rainfall intensities exceeding the IDF curve extrapolations) would be unreliable and requires re-running the physical model to generate new training data. Practically, this means the framework is best suited for exploring design variations within known feasible ranges, and we have carefully ensured our before-after comparisons fall within this validated domain.
- III. Temporal Dynamics: The current surrogate model predicts summary statistics (peak flow, total duration) rather than full hydrographs. While sufficient for the performance metrics used in this study, applications requiring detailed temporal information (e.g., pollutant load calculations, real-time control) would need alternative approaches such as sequence-to-sequence models or physics-informed neural networks.
- IV. Computational Overhead for Training: Generating the 500 training simulations required approximately 500 h of computational time on a high-performance computing

cluster. While this upfront investment is substantial, it is amortized over the many subsequent evaluations enabled by the surrogate model. For projects where only a few scenarios need evaluation, the physics-based model alone may be more practical.

- V. **Uncertainty Quantification:** A significant limitation of this study is the absence of a formal uncertainty quantification (UQ) framework. Uncertainties stem from multiple sources: (1) input data (e.g., rainfall IDF curves, land use), (2) the physics-based model (e.g., parameter calibration, numerical approximations), and (3) the surrogate model (e.g., approximation error, training data coverage). While the high R^2 and low MAPE values indicate low surrogate model error relative to the physics-based model's output, the overall uncertainty in predicting real-world outcomes remains unquantified. Future work will focus on implementing UQ methods, such as Monte Carlo dropout or ensemble methods, to provide confidence intervals for model predictions. As a preliminary attempt to bound the uncertainty, we examined the spread of surrogate predictions for the 300 synthetic scenarios shown in Figures 5 and 6. The 10th–90th percentile range of predicted peak runoff for a given detention tank volume is approximately $\pm 12\%$ (e.g., for a detention tank volume of $10,000 \text{ m}^3$, the 10th percentile predicted peak runoff was $14.2 \text{ m}^3/\text{s}$, and the 90th percentile was $18.1 \text{ m}^3/\text{s}$), reflecting the combined effects of other design parameters (e.g., pipe diameter, GI coverage). For maximum flood depth under the 50-year event, the 10th–90th percentile range was approximately $\pm 15\%$.

These ranges provide a crude proxy for parametric uncertainty—the uncertainty arising from variations in input parameters within the training domain. However, it is important to emphasize the limitations of this approach:

- i. This uncertainty range does not account for structural errors in the physics-based model (e.g., 1D/2D coupling approximations, infiltration parameterization).
- ii. It does not account for surrogate model approximation error (though the high $R^2 \geq 0.93$ suggests this is relatively small).
- iii. It does not account for input data uncertainty (e.g., rainfall IDF curves, land use mapping).
- iv. It is derived from model outputs, not from comparison with field observations.

Consequently, the $\pm 12\text{--}15\%$ range should be interpreted as a lower-bound estimate of uncertainty. The total uncertainty in predicting real-world outcomes is likely larger. We reiterate that no formal confidence intervals or prediction bounds are provided for any of the simulated hydrological or microclimatic outputs in this study. Formal uncertainty quantification (e.g., Bayesian inference, Monte Carlo dropout, or ensemble methods) remains a priority for future work. Formal uncertainty quantification (e.g., Bayesian inference or Monte Carlo dropout) remains a priority for future work. We reiterate that no formal confidence intervals or prediction bounds are provided for any of the simulated hydrological or microclimatic outputs in this study.

- VI. **Generalization and Non-Stationarity:** As highlighted in the recent literature [8,10–13], ML-based surrogate models are highly dependent on the representativeness of training data and may perform poorly under non-stationary hydrological conditions (e.g., climate change altering rainfall patterns). Our model was trained on design storms derived from historical IDF curves; if future rainfall intensities exceed the historical range, the surrogate's predictions may become unreliable. Transferability to other catchments would require re-training with local data. We therefore recommend that the framework be used as a rapid screening tool, with final decisions supported by physics-based simulations or updated training datasets.
- VII. **Limitations of CFD Microclimatic Analysis:** The CFD simulations presented in this study assume steady-state wind conditions with a single prevailing direction

(southerly for February, NNW for December). In reality, wind patterns are highly dynamic, with varying directions, speeds, and turbulence intermittency. These factors would influence the formation and effectiveness of ventilation corridors and the spatial distribution of cooling benefits. The results should therefore be interpreted as indicative of potential ventilation patterns under idealized conditions, rather than a definitive prediction of real-world microclimatic performance.

- VIII. Contribution Separation Not Performed: A significant limitation of this study is the absence of a formal scenario analysis to quantitatively separate the individual contributions of the detention tank, pipe upsizing, and GI. As noted in Section 6.2.6, the feature importance analysis provides only statistical associations, not causal contributions. The reported 24–31% peak runoff reduction and 31.4% runoff coefficient reduction are aggregate results representing the combined effect of all interventions. Given that GI covers only 0.5% of the catchment area, the majority of the catchment-scale peak runoff reduction is likely attributable to the detention tank (flow attenuation) and pipe upsizing (increased conveyance capacity). GI's contribution is expected to be most significant for small, frequent storms in the localized areas where it is installed. The attribution of specific percentages to GI alone based on feature importance should be considered preliminary. Future research should employ controlled scenario simulations (e.g., with GI removed, detention tank removed, or pipe upsizing removed) to isolate the marginal benefit of each component.

The framework is therefore a powerful accelerator for exploring known design spaces and conducting extensive scenario analyses, but it is not a replacement for the physical model, which remains essential for final validation and for exploring novel or extreme designs.

7.4. Climate Change Adaptation Implications

Our findings have important implications for climate adaptation in cities. Climate models consistently show that extreme rainfall will become more intense [48]. That means drainage systems designed using historical rainfall records are likely to fall short more often. Before going further, we need to be clear about one key assumption we made. We assumed that rainfall statistics are stationary. In practice, this means our design storms come from historical intensity–duration–frequency (IDF) curves. However, recent research points out that IDF curves should be non-stationary. They need to account for climate change trends [39]. The good news is that our framework can handle non-stationary inputs without any major redesign. We can simply re-train the surrogate model using climate-adjusted rainfall scenarios. With that in mind, our AI-based surrogate framework becomes a practical tool for stress-testing drainage systems under future climate conditions. Specifically, it allows us to:

1. Scale rainfall inputs according to climate projections (e.g., using change factors for different emission scenarios)
2. Rapidly evaluate system performance across ensembles of future climate realizations
3. Identify vulnerabilities and prioritizing adaptation investments

For the Dazhi system, the simulated peak flow reduction of 24–31% (depending on return period) implies that, within the model framework, the post-improvement system's performance under a 50-year event is comparable to that of the pre-improvement system under a 20-year event. This type of model-based quantification can be useful for communicating potential infrastructure benefits to decision-makers and the public, provided the underlying assumptions and limitations are clearly stated.

8. Conclusions

The contributions of this study are threefold. First, it proposes a surrogate-assisted hydrological simulation framework that integrates physics-based modeling with machine

learning for efficient exploration of urban drainage system behavior under varying design and rainfall conditions. Second, it demonstrates the use of surrogate models as computationally efficient emulators for large-scale scenario exploration and sensitivity analysis. Third, it provides an illustrative case study to highlight the methodological potential of the framework, rather than to deliver validated performance assessment of engineering interventions. The study provides a quantitative, evidence-based assessment of the project's benefits, with the following key findings:

8.1. Key Findings

1. **Simulated Hydrological Performance Enhancement (Model-Dependent):** The engineering interventions have substantially improved the drainage system's performance. AI-based surrogate simulations revealed that, across a range of extreme rainfall events (2- to 50-year return periods), the post-improvement system achieves substantial reductions across all metrics, with the most pronounced benefits for frequent events (e.g., 58% flood depth reduction for the 2-year storm) and meaningful risk reduction for extreme events (e.g., 24% depth reduction for the 50-year storm).

2. **Increased Flood Mitigation Capacity:** Within the model framework, the simulated results indicate a 22.3% reduction in total area flooded during a 50-year return period storm (from 14.8 ha to 11.5 ha). The effective runoff coefficient decreased from 0.49 to 0.34 (31.4% reduction), indicating that the combined grey-green infrastructure significantly reduces runoff generation and attenuates peak flows.

3. **Microclimatic Effects (Simulated under Specific Wind Direction and Steady-State Assumptions):** CFD simulations validated against field measurements (RMSE = 0.16 °C for temperature, 0.2 m/s for wind speed) demonstrated the following under a single prevailing southerly wind direction (for summer cases) and steady-state assumption:

- (1) Simulated urban heat island intensity reduction: 22–26% under the specific wind direction and steady-state assumptions (southerly for summer cases);
- (2) Simulated pedestrian-level wind speed improvement (Airflow Improvement Index, AII): 0.32 (i.e., 32% increase relative to inlet velocity) under the simulated southerly wind direction only;
- (3) Localized cooling in vegetated areas: 2.1–2.8 °C in summer and 1.8–2.3 °C in winter as simulated under the respective wind directions;
- (4) Formation of ventilation corridors along the drainage channel was observed in the simulation for the southerly wind direction only.

Limitations: These results are specific to the simulated wind directions and steady-state assumptions. No simulations were performed for other wind directions or unsteady conditions. Therefore, these values are not generalizable to annual, seasonal, or worst-case performance.

4. **Water Quality Baseline (Post-Construction Only):** Post-construction water quality is consistently “lightly polluted” (RPI = 2.25–2.75) with moderate organic pollution (BOD = 1.4–2.5 mg/L, NH₃-N = 1.43–1.90 mg/L) but good oxygenation (DO = 6.3–7.0 mg/L), providing a baseline for future water quality improvement assessments; see Appendix B for full data.

5. **Effectiveness of the AI-based Surrogate Framework:** The XGBoost-based surrogate model proved to be both highly accurate and computationally efficient. Within the range of the training scenarios, it achieved an R² above 0.93 and a MAPE below 10%. It also ran 10⁵ to 10⁶ times faster than the full physics-based model. This speed enabled the framework to perform rapid scenario analysis. The approach shows considerable promise as a practical tool for urban drainage planning, design evaluation, and risk assessment, provided that users remain mindful of its interpolation limits. One more point is worth emphasizing.

All the quantitative results we present are deterministic point estimates. They come from a single model run. As a result, they do not include confidence intervals or any form of uncertainty bounds.

6. **Tangible Socio-Economic Benefits:** Reduced flood duration (32–44% shorter) may lower business interruption, traffic disruption, and emergency service demands. Improved microclimate enhances urban liveability. No monetary loss estimates are presented, as field-validated economic data are unavailable.

8.2. Scientific and Engineering Contributions

The principal contribution of this study is the development and validation of an integrated framework that combines physics-based hydrological modeling, AI-driven surrogate modeling, CFD-based microclimatic analysis, and multi-dimensional performance assessment within a unified evaluation platform. By simultaneously considering flood mitigation, water quality, thermal comfort, and ventilation, the proposed framework provides a more comprehensive assessment of urban drainage improvement projects than conventional single-objective approaches.

Unlike previous surrogate modeling studies that primarily focus on hydraulic prediction, this study applies the proposed framework to a real-world drainage improvement project and evaluates both hydraulic performance and environmental co-benefits. The results demonstrate that AI-assisted surrogate modeling can serve as an efficient decision-support tool for urban drainage planning while supporting more balanced and evidence-based infrastructure management.

Contributions to Sustainable Development Goals (SDGs)

This study also supports sustainable urban development by providing quantitative evidence relevant to several Sustainable Development Goals (SDGs). First, the proposed framework contributes to SDG 11.5 (Disaster Risk Reduction) by enabling rapid evaluation of drainage improvement strategies that reduce urban flood risk. Second, it supports SDG 13.1 (Climate Change Adaptation) by facilitating performance assessment under multiple extreme rainfall scenarios, thereby improving the resilience of urban drainage systems. Finally, through the integration of water quality monitoring and CFD-based microclimatic analysis, the framework contributes to SDG 11.7 (Sustainable and Inclusive Urban Spaces) by demonstrating the environmental co-benefits of grey-green infrastructure, including improved thermal conditions, ventilation, and urban environmental quality.

8.3. Future Research Directions

Building on this study, several promising research directions emerge:

1. **Real-Time Integration:** Integrating the AI-based surrogate framework with real-time rainfall forecasting and sensor networks could enable predictive flood warning and adaptive control of detention facilities (e.g., pre-releasing storage before major storms). The millisecond-scale evaluation time makes such real-time applications feasible.

2. **Water Quality Modeling:** Expanding the surrogate model to include water quality parameters (BOD, $\text{NH}_3\text{-N}$, suspended solids) would enable assessment of treatment performance and identification of optimal configurations for both quantity and quality control. The baseline water quality data established in this study provides a foundation for such model development.

3. **Lifecycle Cost Analysis:** Integrating the hydrological and microclimatic performance models with lifecycle cost models would enable full cost-benefit analysis over project lifetimes, supporting business case development for infrastructure investments.

4. **Climate Change Scenarios:** Applying the framework to climate change scenarios (e.g., RCP 4.5 and 8.5 for 2050 and 2080) would quantify future performance and identify potential adaptation needs, supporting climate-resilient infrastructure planning.

5. **Transferability Assessment:** Applying the methodology to other catchments with different characteristics (e.g., steeper topography, different land uses, combined sewer systems) would test generalizability and identify context-specific considerations for AI-based surrogate drainage planning.

6. **Stakeholder Decision Support:** Developing user-friendly decision-support platforms based on the surrogate model could facilitate stakeholder engagement and participatory planning processes, allowing non-experts to explore design trade-offs and understand infrastructure performance.

Ultimately, this study confirms that the synergy between artificial intelligence and traditional engineering holds immense potential for building cities better prepared for the hydrological challenges of a changing climate. By enabling rapid, comprehensive, and multi-dimensional assessment of drainage system performance, AI-based surrogate frameworks can support evidence-based decision-making and accelerate the transition toward climate-resilient urban water management.

All findings reported in this study are derived from numerical simulations (MIKE URBAN and CFD) and an XGBoost surrogate model trained on those simulations. The physics-based model was calibrated using a single historical storm event (15 June 2023) but was not independently validated against flood depth, duration, or extent measurements from other events due to the absence of such data. While qualitative evidence (historical flood photographs, citizen reports, and municipal records) confirms the occurrence of recurring flooding in the pre-improvement system, these data do not permit quantitative model validation. Consequently, the quantitative results (e.g., peak runoff reductions, flood depth decreases) are model-dependent predictions and should not be interpreted as field-validated outcomes. The primary contribution of this work is the demonstration of an integrated AI-based surrogate modeling methodology, not the provision of definitive engineering performance guarantees. Consequently, the quantitative results (e.g., peak runoff reductions, flood depth decreases) are model-dependent predictions and should not be interpreted as field-validated outcomes. The primary contribution of this work is the demonstration of an integrated AI-based surrogate modeling methodology, not the provision of definitive engineering performance guarantees.

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Appendix A. CFD Simulation for Microclimatic Analysis

The CFD analysis focuses exclusively on the microclimatic effects (wind field, thermal comfort, and urban heat island intensity) of the drainage improvements, specifically the contribution of green infrastructure elements to urban liveability. It does not simulate hydrological or hydraulic processes. In parallel to the core hydrological–hydraulic modeling, a separate three-dimensional Computational Fluid Dynamics (CFD) model was developed to evaluate the microclimatic co-benefits of the drainage improvements. This analysis is intended to provide a more holistic assessment of the project’s value, particularly the contribution of green infrastructure elements to urban liveability.

1. Computational Domain and Mesh Generation

For microclimatic analysis, a three-dimensional computational fluid dynamics (CFD) model was developed using ANSYS Fluent (Release 2024 R1). The computational domain extended 500 m in the streamwise direction, 300 m in the spanwise direction, and 100 m in the vertical direction, encompassing the entire study area with sufficient buffer zones to minimize boundary effects. An unstructured tetrahedral mesh with prismatic boundary layers was generated, with local refinement near buildings, vegetation zones, and water bodies. The mesh consisted of approximately 3.2 million cells, with a maximum skewness below 0.85 to ensure numerical stability.

2. Governing Equations

The CFD simulations were governed by the Reynolds-Averaged Navier–Stokes (RANS) equations for incompressible flow, coupled with the energy equation for thermal transport.

I. Continuity Equation:

$$\frac{\partial \bar{u}_i}{\partial x_i} = 0 \quad (\text{A1})$$

II. Momentum Equation (RANS):

$$\frac{\partial(\rho \bar{u}_i)}{\partial t} + \frac{\partial(\rho \bar{u}_i \bar{u}_j)}{\partial x_j} = -\frac{\partial \bar{p}}{\partial x_i} + \frac{\partial}{\partial x_j} \left[\mu \left(\frac{\partial \bar{u}_i}{\partial x_j} + \frac{\partial \bar{u}_j}{\partial x_i} \right) - \rho \bar{u}_i' \bar{u}_j' \right] + \rho g_i \beta (T - T_0) \quad (\text{A2})$$

where $\bar{u}_i$ = mean velocity component in i -direction (m/s); ρ = air density (kg/m³); $\bar{p}$ = mean pressure (Pa); μ = dynamic viscosity (kg/m·s); $-\rho \bar{u}_i' \bar{u}_j'$ = Reynolds stresses (turbulent momentum fluxes); g_i = gravitational acceleration in i -direction (m/s²); β = thermal expansion coefficient (K^{−1}); T = temperature (K); T_0 = reference temperature (K).

The Boussinesq approximation was applied to model buoyancy effects due to temperature variations, where the last term in the momentum equation represents the buoyancy force.

III. Energy Equation:

$$\frac{\partial(\rho\bar{T})}{\partial t} + \frac{\partial(\rho\bar{u}_j\bar{T})}{\partial x_j} = \frac{\partial}{\partial x_j} \left[\left(\frac{k}{c_p} + \frac{\mu_t}{Pr_t} \right) \frac{\partial\bar{T}}{\partial x_j} \right] + S_T \quad (A3)$$

where k = thermal conductivity (W/m·K); c_p = specific heat at constant pressure (J/kg·K); μ_t = turbulent viscosity (kg/m·s); Pr_t = turbulent Prandtl number (typically 0.85); S_T = thermal source term (e.g., solar radiation, anthropogenic heat).

3. Turbulence Modeling

The realizable k- ϵ turbulence model was employed to close the RANS equations:

I. Turbulent Kinetic Energy (k) Equation:

$$\frac{\partial(\rho k)}{\partial t} + \frac{\partial(\rho\bar{u}_j k)}{\partial x_j} = \frac{\partial}{\partial x_j} \left[\left(\mu + \frac{\mu_t}{\sigma_k} \right) \frac{\partial k}{\partial x_j} \right] + G_k + G_b - \rho\epsilon \quad (A4)$$

II. Turbulent Dissipation Rate (ϵ) Equation:

$$\frac{\partial(\rho\epsilon)}{\partial t} + \frac{\partial(\rho\bar{u}_j\epsilon)}{\partial x_j} = \frac{\partial}{\partial x_j} \left[\left(\mu + \frac{\mu_t}{\sigma_\epsilon} \right) \frac{\partial\epsilon}{\partial x_j} \right] + \rho C_1 S\epsilon - \rho C_2 \frac{\epsilon^2}{k + \sqrt{\nu\epsilon}} + C_{1\epsilon} \frac{\epsilon}{k} C_{3\epsilon} G_b \quad (A5)$$

where G_k = generation of turbulence kinetic energy due to mean velocity gradients; G_b = generation of turbulence kinetic energy due to buoyancy; $\sigma_k, \sigma_\epsilon$ = turbulent Prandtl numbers for k and ϵ ($\sigma_k = 1.0, \sigma_\epsilon = 1.2$); $C_1, C_2, C_{1\epsilon}, C_{3\epsilon}$ = model constants.

The turbulent viscosity is computed as:

$$\mu_t = \rho C_\mu \frac{k^2}{\epsilon} \quad (A6)$$

where C_μ is a variable in the realizable k- ϵ model, computed as a function of mean strain and rotation rates, ensuring realizability (positive normal stresses) and improving performance for flows with complex strain.

4. Boundary Conditions

I. Wind Inlet: Velocity inlet boundary condition with logarithmic wind profile:

$$u(z) = \frac{u_*}{\kappa} \ln \left(\frac{z + z_0}{z_0} \right) \quad (A7)$$

where u_* = friction velocity (m/s); κ = von Kármán constant (0.41); z = height above ground (m); z_0 = aerodynamic roughness length (m).

Turbulence parameters at the inlet were specified using turbulence intensity (I_u) and turbulent kinetic energy ($k = 1.5(uI_u)^2$).

II. Thermal Boundary Conditions: Surface temperatures were specified based on land use type, as summarized in Table 2, following the Schematik zoning approach. These values were derived from field measurements and literature values for similar urban environments.

III. Solver Settings and Convergence Criteria

The CFD simulations were performed using a pressure-based solver with the SIMPLE (Semi-Implicit Method for Pressure-Linked Equations) algorithm for pressure-velocity coupling. Second-order upwind discretization schemes were employed for momentum, energy, and turbulence equations to minimize numerical diffusion. Convergence was assumed when: (1) scaled residuals decreased below 10^{-4} for continuity and momentum, and 10^{-6} for energy; (2) monitored variables (velocity at key points, average temperature) stabilized; and (3) imbalances in mass and energy fluxes were below 1%.

Appendix B. Water Quality Baseline (Post-Construction Only)

Water quality monitoring was conducted at two stations (Dazhi Road and Qiaocheng Road) during both weekday and weekend periods in June 2025, approximately six months after completion of the drainage improvements. No pre-improvement water quality data were collected. Therefore, the values presented below represent a post-construction baseline only and cannot be used to quantify water quality benefits attributable to the project. The classification of “lightly polluted” (RPI = 2.25–2.75) describes the state of the system after construction, not an improvement relative to prior conditions.

Table A1. Water quality parameters at monitoring stations (June 2025).

Parameter	Dazhi Rd (Weekday)	Qiaocheng Rd (Weekday)	Dazhi Rd (Weekend)	Qiaocheng Rd (Weekend)
Date	June 13	June 13	June 18	June 18
Water Temperature (°C)	24.8	25.3	24.3	24.3
pH	7.63	7.52	7.73	7.12
Conductivity (µmho/cm)	334	362	314	316
Dissolved Oxygen (mg/L)	6.65	6.30	6.87	7.02
DO Saturation (%)	87.3	80.6	88.7	86.3
Suspended Solids (mg/L)	3	3	3	3
Biochemical Oxygen Demand (mg/L)	1.4	2.5	2.1	1.8
Ammonia Nitrogen (mg/L)	1.43	1.81	1.65	1.90
Turbidity (NTU)	1.50	1.08	0.96	1.32
WQI	73.80	67.05	71.08	70.85
Water Quality Classification	Class B	Class C	Class B	Class C
RPI	2.25	2.75	2.25	2.25
Pollution Level	Light	Light	Light	Light

The River Pollution Index (RPI) is calculated based on four parameters: dissolved oxygen, biochemical oxygen demand, ammonia nitrogen, and suspended solids. The RPI values ranging from 2.25 to 2.75 indicate “lightly polluted” conditions across all stations, according to Taiwan’s water quality classification standards. The Water Quality Index (WQI) values range from 67.05 to 73.80, corresponding to Class B and C classifications, indicating moderately good water quality with some organic pollution, particularly evident in the elevated ammonia nitrogen concentrations (1.43–1.90 mg/L).

Because green infrastructure elements (permeable pavements, rain gardens) often require 1–2 years to stabilize, future long-term monitoring (e.g., over 2–3 years) is recommended to assess any water quality co-benefits that may emerge. The current data serve as a baseline for such future assessments.

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