Sustainable Cities and Society 118 (2025) 105982

Contents lists available at ScienceDirect

Sustainable Cities and Society

journal homepage: www.elsevier.com/locate/scs

Stormwater digital twin with online quality control detects urban flood hazards under uncertainty☆

Yeji Kim *, Jeil Oh, Matthew Bartos

Department of Civil, Architectural, and Environmental Engineering, University of Texas at Austin, Austin, 78712, TX, USA

ARTICLE INFO

Dataset link: https://github.com/future-water/waller-creek-model

Keywords:
Digital twin
Online stormwater model
Wireless sensor networks
Online quality control
Threshold extended Kalman filter

ABSTRACT

Urban drainage systems face increased floods and combined sewer overflows due to climate change and population growth. To manage these hazards, cities are seeking stormwater *digital twins* that integrate sensor data with hydraulic models for real-time response. However, these efforts are complicated by unreliable sensor data, imperfect hydrologic models, and inaccurate rainfall forecasts. To address these issues, we introduce a stormwater digital twin system that uses online data assimilation to estimate stormwater depths and discharges under sensor and model uncertainty. We first derive a novel state estimation scheme based on Extended Kalman Filtering that fuses sensor data into a hydraulic model while simultaneously detecting and removing faulty measurements. The system's accuracy is evaluated through a long-term deployment in Austin's flood-prone Waller Creek watershed. The digital twin model demonstrates enhanced accuracy in estimating stormwater depths at ungauged locations and delivers more accurate near-term forecasts. Moreover, it effectively identifies and removes sensor faults from streaming data, achieving a Receiver Operating Characteristic Area Under the Curve (ROC AUC) of over 0.99 and significantly reducing the potential for false flood alarms. This study provides a complete software implementation, offering water managers a reliable framework for real-time monitoring, rapid flood response, predictive maintenance, and active control of sewer systems.

1. Introduction

Cities face increasing stormwater challenges due to rapid urbanization, climate change, and aging infrastructure (Kerkez et al., 2016). As impermeable surfaces grow, less water is absorbed, leading to greater stormwater runoff. When drainage systems are overwhelmed by heavy rainfall, urban flooding occurs, causing water to accumulate in streets and low-lying areas (Committee on Urban Flooding in the United States, Program on Risk, Events, Policy and Global Affairs, Water Science and Technology Board, Division on Earth and Life Studies, & National Academies of Sciences, Engineering, and Medicine, 2019). Aging infrastructure further worsens the issue, as outdated systems struggle to handle rising demands and extreme weather events. At the same time, pollutants from stormwater runoff, such as nutrients and sediments, degrade aquatic habitats (Booth & Jackson, 1997; Walsh et al., 2005). Combined sewer overflows (CSOs) release pathogens into natural water bodies when storm runoff overwhelms sewer pipes that carry human waste (U.S. Environmental Protection Agency, 2004). These issues are expected to worsen with more severe storms and increasing impervious land cover due to urbanization (Vörösmarty, McIntyre, Gessner, Dudgeon, Prusevich, Green, Glidden, Bunn, Sullivan, Liermann, & Davies, 2010). Effective stormwater management is critical, but current static design practices struggle to keep up with these stressors (Kerkez et al., 2016).

To address these problems, water managers are seeking *digital twins* of stormwater systems that provide timely and accurate information on hazards like flooding and enable more effective real-time response (Pedersen, Borup, Brink-Kjær, Christiansen, & Mikkelsen, 2021a; Sarni, White, Webb, Cross, & Glotzbach, 2019; Valverde-Pérez, Johnson, Wärff, Lumley, Torfs, Nopens, & Townley, 2021). A digital twin refers to a dynamic virtual representation of an actual physical system for real-time monitoring, decision support, and control (Rasheed, San, & Kvamsdal, 2020; VanDerHorn & Mahadevan, 2021). Enabled by advances in low-power sensing and wireless communications, digital twins combine online sensor data with hydraulic models to provide a real-time picture of stormwater dynamics (Pedersen et al., 2021a). These systems promise real-time flood warnings at the street scale (Edmondson et al., 2018; Ford & Wolf, 2020; Kazuhiko & Atsushi, 2018), pre-emptive detection of sewer blockages (Edmondson et al., 2018; Owen, 2023), and active control of valves and gates to prevent CSOs (Montestruque & Lemmon, 2015; Tabuchi, Blanchet,

☆ Funding sources: This work was supported in part by the National Science Foundation, United States under Grant 2220516.

* Corresponding author.
E-mail address: yejikim@utexas.edu (Y. Kim).

https://doi.org/10.1016/j.scs.2024.105982
Received 11 July 2024; Received in revised form 9 November 2024; Accepted 10 November 2024
Available online 24 November 2024
2210-6707/© 2024 Elsevier Ltd. All rights are reserved, including those for text and data mining, AI training, and similar technologies.

& Rocher, 2020; Tao et al., 2020; Valverde-Pérez et al., 2021). By enabling targeted and adaptive stormwater management, these systems address flooding and pollution while reducing the need for expensive infrastructure expansions (Sarni et al., 2019).

However, despite the promotion of digital twins in the stormwater sector, their real-world capabilities remain under-researched. Little published information exists on their design and construction, and few studies have examined the hardware, software, or mathematical techniques needed to build a robust and reliable digital twin system (Pedersen et al., 2021a). Moreover, few studies have assessed their performance under real-world uncertainty. Poor sensor data quality is a persistent concern (Owen, 2023; Pedersen et al., 2021a), and it is unclear if existing digital twin models can detect hazards with the certainty needed for real-time response. Therefore, research is needed to understand how digital twin systems can provide actionable information under real-world conditions where model and sensor uncertainty are significant. This study aims to build and evaluate a complete digital twin for an urban watershed, integrating a physically-based hydrologic–hydraulic model, continuous rainfall forecasts, real-time stream gauge data, and online data assimilation. This study is the first to apply online data assimilation using a Threshold Extended Kalman Filter, which integrates sensor data into a hydraulic model to improve accuracy while concurrently performing anomaly detection to identify and reject sensor faults.

2. Background and previous work

2.1. Offline stormwater modeling

Stormwater models have historically been used for infrastructure planning, such as sizing pipes and reservoirs to mitigate floods and reduce pollutant loads (Butler, Digman, Makropoulos, & Davies, 2018). Water managers use a combination of (i) *hydrologic models* to predict infiltration and runoff, (ii) *hydraulic models* to route runoff through the drainage network, and (iii) *water quality models* to track contaminants (Bedient, Huber, Vieux, et al., 2008; Zoppou, 2001). Engineers use computer models such as the EPA's Storm Water Management Model (SWMM), the Hydrologic Engineering Center's Hydrologic Modeling System and River Analysis System (HEC-HMS/RAS), and MIKE URBAN to simulate design storms and plan facilities that prevent flooding and meet water quality goals. However, after these models are implemented continuous monitoring is rare, and model validation is generally limited to sparse and infrequent manual measurements (Blecken, Hunt, Al-Rubaei, Viklander, & Lord, 2017). Changing site conditions due to land use, climate patterns, or poor maintenance cause stormwater facilities to underperform (Rosenberg et al., 2010). In certain cases, interventions aimed at improving flood control and water quality may worsen these problems (Criss & Shock, 2001; Emerson, Welty, & Traver, 2005). Without continuous monitoring, these issues often go undetected until negative impacts occur (Blecken et al., 2017; Wright & Marchese, 2017).

2.2. Continuous monitoring

Recognizing the need for more continuous data, many cities are now seeking real-time monitoring systems to characterize the internal dynamics of their urban drainage systems (Kerkez et al., 2016; Webber, Fletcher, Farmani, Butler, & Melville-Shreeve, 2022). These developments are enabled by recent advances in wireless technologies, low-power sensing, and embedded systems that have accompanied the *Internet of Things (IoT)* (Kerkez et al., 2016). While stream gage networks have long been used to assess flood risks and promote restoration of aquatic ecosystems (Eberts, Woodside, Landers, & Wagner, 2019), these new advances are enabling monitoring at finer spatial and temporal scales than have been achievable in the past. Low-cost sensors such as submersible pressure transducers, ultrasonic depth sensors, and radar-based velocimeters are enabling cost-effective monitoring of stormwater conditions not only in major waterways, but also in smaller tributaries and storm sewers (Khan et al., 2021; Panagopoulos, Papadopoulos, Poulis, Nikiforakis, & Dimitriou, 2021). These dense networks provide new capabilities, such as monitoring of floods at individual roadways (Silverman, Brain, Branco, sai venkat Challagonda, Choi, Fischman, Graziano, Hénaff, Mydlarz, Rothman, & Toledo-Crow, 2022) and detecting sewer blockages (See, Horoshenkov, abd alhmeed, Hu, & Tait, 2011).

2.3. Online modeling

Alongside continuous monitoring, recent years have seen the development of *online models* that simulate urban drainage dynamics. These models are updated with continuous input data, ensuring that the simulations reflect current conditions. This ongoing update process supports rapid response to storm events and enhances decision-making during hazards such as floods and combined sewer overflows. Efforts have focused on large river basins using software like HEC-HMS, HEC-RAS, the Hydrologic Engineering Center's Real Time Simulation (HEC-RTS), and EPA SWMM. Che and Mays (2015) integrate HEC-RAS/HEC-HMS for optimizing river-reservoir releases during floods; (Teal & Allan, 2017) develop a flood warning system for the San Diego River using HEC-RTS; Zeng, Yuan, Liang, and Li (2021) implement WEB-SWMM in China for real-time urban stormwater management. Other studies offer custom frameworks for early warning systems (Ming, Liang, Xia, Li, & Fowler, 2020; Wang et al., 2022; Xu et al., 2017). While many implementations exist, online models typically include hydraulic and hydrologic models with real-time rainfall inputs and web platforms to estimate discharges and water depths. However, existing efforts often focus on 'open-loop' models that do not incorporate field-deployed sensors, making it difficult to verify model accuracy and complicating decision-making for emergency managers.

2.4. Digital twins

Combining advances in wireless sensing and online modeling, water managers are increasingly seeking *digital twins* to track stormwater dynamics by integrating process models with sensor data. A digital twin is a real-time virtual representation of a physical system applied in various fields like manufacturing, healthcare, and urban planning (Rasheed et al., 2020; VanDerHorn & Mahadevan, 2021). While a universal definition is elusive, digital twins typically combine online modeling, real-time measurements, and 2D/3D visualizations to provide operators with up-to-date status information on critical systems (Park & You, 2023). Moreover, these models continuously evolve and learn from new data and experiences, enhancing their predictive accuracy over time.

For stormwater management, most of the literature on digital twins have focused on combining online hydraulic models with real-time sensor data to deliver actionable information to water managers. These stormwater digital twins have been used as a basis for real-time control operations—for instance, controlling water levels in inland waterways to prevent flooding and ensure channel navigability (Ranjbar et al., 2024), or controlling stormwater inflows to water resource recovery facilities (Lumley, Polesel et al., 2024; Lumley, Wanninger et al., 2024). Many existing implementations use proprietary software (Lumley, Wanninger et al., 2024) or simplified hydraulic models (Ranjbar et al., 2024). Bartos and Kerkez (Bartos & Kerkez, 2021) introduced PipeDream, a stormwater digital twin model that combines a physically-based hydraulic solver with a data assimilation approach to track depths and flows in urban drainage systems. By combining models and measured data, water infrastructure digital twins help detect and localize anomaly events (Wu et al., 2023), and estimate system states at unmonitored locations (Bartos & Kerkez, 2021). Thus, digital twins support informed decision-making, enabling timely alerts and control systems to reduce the risk of flooding (Sadler, Goodall, Behl, Bowes, & Morsy, 2020), pollution loads (Oh & Bartos, 2023; Zhang, Cai, & Wang, 2018), and sewage overflows (Botturi et al., 2020).

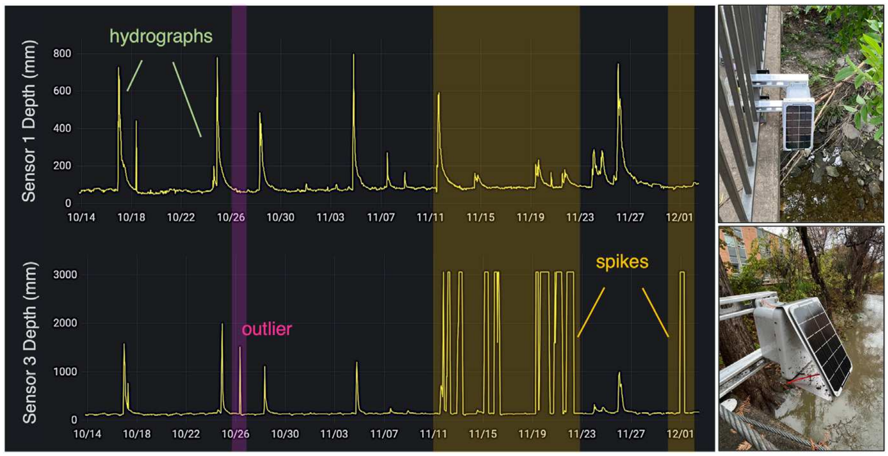

Fig. 1. Types of sensor faults collected from low-cost ultrasonic depth sensors.

2.5. Uncertainties in simulation and monitoring

While sensor networks and online models enhance real-time observability of urban drainage systems, they are subject to inherent uncertainties that impact decision support and emergency response, including poor data quality and uncertain process models (Oberascher, Rauch, & Sitzenfrei, 2022; Weil, Bibri, Longchamp, Golay, & Alahi, 2023). This section explores these uncertainties and outlines strategies to improve accuracy and reliability in modeling and monitoring.

Model uncertainty. Stormwater models are subject to uncertainties in input data (e.g., precipitation forecasts), model parameters (e.g., soil characteristics), and imperfect mathematical descriptions of physical reality (Butts, Payne, Kristensen, & Madsen, 2004; Freni, Mannina, & Viviani, 2009). These factors can lead to inaccurate forecasts of discharges and water depths that negatively impact decision-making. Urban flood forecasting with stormwater models is particularly challenging due to the need for accurate rainfall forecasts at fine spatio-temporal resolutions and the complex interactions between runoff and infrastructure (Hapuarachchi, Wang, & Pagano, 2011). There is a notable lack of models capable of reliably forecasting flash floods in urban areas (Hapuarachchi et al., 2011).

Measurement uncertainty. Despite advances in low-cost sensing devices, measurement errors remain a challenge. Low-cost sensors often report faulty measurements due to factors such as installation location, wind conditions, and obstructions like vegetation and water surface turbulence (Pereira, de Carvalho, Mendes, & Formiga, 2022; Schmidt & Kerkez, 2023). Fig. 1 demonstrates sensor faults from two ultrasonic water depth sensors examined in this study, exhibiting multiple types of faults, including outliers and spikes (Ni et al., 2009). These faults pose a significant challenge for urban flood monitoring because the rising limb of a flood wave often resembles a sensor spike, making it difficult to distinguish between faults and true flood events in real time. Without proper quality control, sensor-based flood warning systems may disseminate false alarms, complicating real-time response.

2.5.1. Strategies for mitigating simulation uncertainties

To address uncertainties in stormwater models, researchers have refined strategies focusing on global model calibration, validation, and data assimilation (Moradkhani & Sorooshian, 2008). Data assimilation methods like Particle Filtering (Xu et al., 2017), Extended Kalman Filtering (EKF) (Bartos & Kerkez, 2021), Ensemble Kalman Filtering (EnKF) (Baumann, egh Ravn, & Schaum, 2022), and mixed variational-Monte Carlo data assimilation (Ercolani & Castelli, 2017) integrate real-time observational data to improve prediction accuracy. These strategies improve the accuracy of estimated water depths and discharges but depend on accurate observational data. Existing data assimilation studies utilize mainly synthetic or pre-processed data, with only a few studies applying these techniques in real-world scenarios where significant sensor data uncertainty is present (Liu, Weerts, Clark, Franssen, Kumar, Moradkhani, Seo, Schwanenberg, Smith, van Dijk, van Velzen, He, Lee, Noh, Rakovec, & Restrepo, 2012). However, real-world sensor data is subject to faults and biases that compromise direct application of data assimilation. As a result, the ability of digital twin models to accurately estimate stormwater depths and discharges under real-world conditions remains largely unknown.

2.5.2. Data quality control for reducing measurement uncertainty

Automated quality assurance and quality control (QAQC) is essential for the application of real-time environmental sensor data (Campbell et al., 2013). Anomaly detection methods for sensor data fall into three categories: (i) *data-driven approaches* that rely on patterns in data, including supervised and unsupervised methods; (ii) *knowledge-based approaches* that use domain knowledge and predefined rules to identify anomalies; and (iii) *model-based approaches* that flag anomalies when observed data deviate from models, and offer the advantage of improved interpretability (Chandola, Banerjee, & Kumar, 2009; Huang, Yang, Wang, Xu, & Lu, 2021; Khalastchi, Kalech, Kaminka, & Lin, 2015).

Recent stormwater monitoring studies have focused on data-driven approaches, like modified Z-scores (Bae & Ji, 2019) and Support Vector Machines (SVMs) (Schmidt & Kerkez, 2023) for outlier detection. However, few have examined model-based approaches due to the lack of software models that are capable of real-time state estimation. Our study addresses this gap by using EKF to dynamically remove anomalies in real-time and update modeling results.

2.6. Study objectives

This study focuses on developing and evaluating a functioning real-world digital twin for an urban watershed. The study is divided into two key phases:

Development. In this phase, we propose and implement a stormwater digital twin architecture by integrating (i) a wireless sensor network, (ii) a physically-based hydrologic–hydraulic model, and (iii) online data assimilation. The data assimilation process employs model-based anomaly detection using a threshold EKF to remove real-time anomalies, ensuring that only valid sensor data is assimilated into the model.

Evaluation. In this phase, we assess the system's performance in (i) detecting and rejecting sensor faults, (ii) improving water level estimates at ungauged locations, and (iii) enhancing water level forecasts.

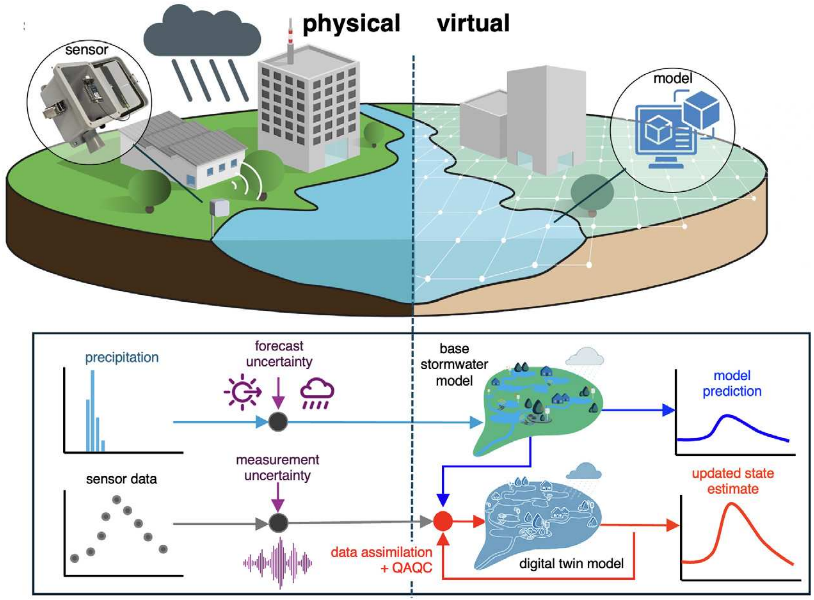

Fig. 2. Conceptual diagram of digital twin model for stormwater.

3. Methodology

The proposed stormwater digital twin system integrates a wireless sensor network, an online hydrologic–hydraulic model, and a data assimilation framework to monitor hydraulic states (depths and flows) in urban drainage networks (see Fig. 2). The following sections detail: (i) deployment of the sensor network in an urban watershed, (ii) design and implementation of the real-time hydrologic–hydraulic model, (iii) development of a data assimilation scheme using threshold-based Extended Kalman Filtering, and (iv) the comprehensive software architecture of the digital twin model.

3.1. Wireless sensor network

3.1.1. Waller creek watershed

This study focuses on the Waller Creek watershed in Austin, TX. The Waller Creek watershed is a heavily urbanized catchment approximately 14.5 km^2 in area that drains from north Austin into the Lower Colorado River (City of Austin Watershed Protection, 2016). Due to a lack of cohesive land development planning, Waller Creek suffers from severe water quality, erosion, and flooding problems (City of Austin Watershed Protection, 2016), ranking among the worst areas in the city for both localized (pluvial) flooding and riverine (fluvial) flooding. To characterize the potential for real-time flood detection, we focus on four sites located near bridges and low-lying roadways near the mainstem of Waller Creek that are prone to flash floods.

3.1.2. Wireless sensor network architecture

A wireless sensor network is deployed in the Waller Creek watershed to collect real-time depth measurements along the channel mainstem. Each sensor node features a Maxbotix MB7384 ultrasonic sensor and a Particle Boron microcontroller with a cell module for 3G/4G LTE communication. The system is powered by a Tenergy Li-ion 3.7 V battery supplemented by a solar panel and managed by a SparkFun Sunny Buddy charger to ensure continuous operation. Sensor nodes transmit data via HTTPS POST requests to an Amazon EC2 cloud server, where data is stored using the InfluxDB time-series database. Water level measurements are calculated by subtracting the distance between the sensor and the channel bottom from the ultrasonic readings and are then visualized as continuously updated time-series using the Grafana platform (see Fig. 1).

3.1.3. Wireless sensor network deployment

This study focuses on the Waller Creek watershed in Austin, TX (City of Austin Watershed Protection, 2016). Four wireless sensor nodes (N1, N2, N3, and N4) are deployed near a flood-prone confluence. The sensor nodes in Fig. 3 uses ultrasonic depth sensors to collect water level data every 15 min.

3.2. Stormwater digital twin model

A digital twin model of the urban watershed and stormwater system is constructed to simulate stormwater dynamics in real-time and track the current state of the stormwater system. The digital twin model consists of (i) a hydrologic model that uses precipitation data to compute runoff into the channel network, (ii) a hydraulic model based on the Saint-Venant equations that routes surface runoff through the channel and pipe network to estimate flood depths, and (iii) a sensor data assimilation scheme based on Extended Kalman Filtering.

3.2.1. Input data

Inputs to the hydrologic model include precipitation data from rain gauges near 23rd Street in the Waller Creek watershed (Fig. 3), reported every 15 min by the City of Austin, and minute-by-minute forecasts from the `tomorrow.io` API for the upcoming hour. Rain gauge data simulate current and past runoff, while forecasts predict future runoff (Tomorrow.io Weather API, 2023).

3.2.2. Hydrology model

A parsimonious hydrologic model is developed to compute runoff into the channel and pipe network using the Soil Conservation Service (SCS) Curve Number (CN) method (NRCS, 2004), with calibrated curve numbers provided by the City of Austin. The SCS-CN method estimates precipitation excess (runoff) for storms with durations under 24 h using a conceptual relationship between runoff and moisture storage in the soil:

$$P_e = \frac{(P - I_a)^2}{(P - I_a) + S} \text{ , for } P > I_a \tag{1}$$

$$S = \frac{1000}{CN_c} - 10 \tag{2}$$

$$CN_c = CN_p + \left(\frac{P_{imp}}{100}\right)(98 - CN_p) \tag{3}$$

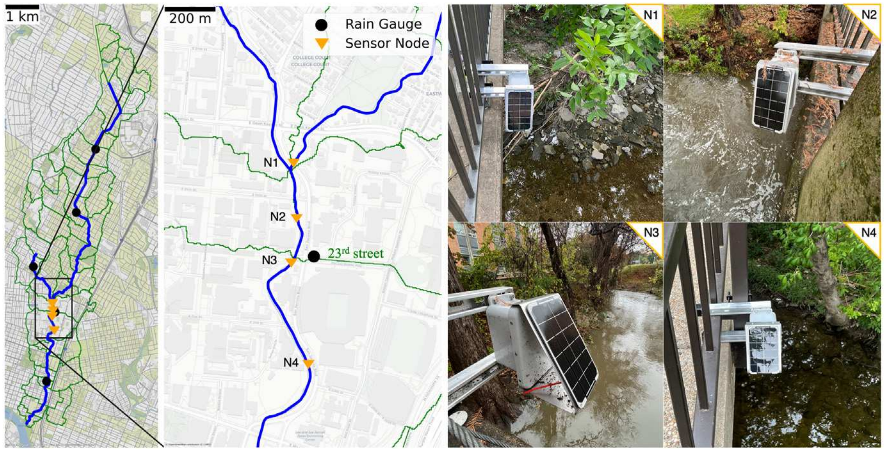

Fig. 3. Map and photos of wireless sensor network in Waller Creek watershed.

where P_e is accumulated precipitation excess at time t, P is accumulated rainfall depth at time t, S is the potential maximum soil moisture retention, I_a is the initial abstractions, CN_c is composite runoff curve number, CN_p is previous runoff curve number, P_{imp} is the percent of connected impervious areas.

The conventional SCS-CN method is designed for event-based simulations only, and has no mechanism to allow drying of soil after infiltration occurs. To enable continuous simulation, we modify the SCS-CN method to allow moisture to leave the soil over time via evaporation or baseflow using a decay parameter (Algorithm 1). Within this scheme, P_t is rainfall at time t, D is decay rate, L is loss, P_{pre} is accumulated precipitation excess at time t-1, and P_{inc} is the accumulated precipitation excess at time t.

After computing infiltration and excess precipitation using the SCS-CN method, the direct runoff hydrograph for overland flow is obtained through discrete convolution of the precipitation excess with a unit hydrograph, representing the travel time distribution of the watershed (Feldman, 2000).

Algorithm 1: Continuous SCS-CN algorithm

Input: P, P_t, CN, D
Output: P_{inc}
$t \leftarrow 1$
$S \leftarrow 1000/CN - 10$
$I_a \leftarrow 0.2S$
while $t < n$ **do**
  $P \leftarrow P + P_t$
  $L \leftarrow P \times (1 - D)$
  if $P - L \leq 0$ **then**
    $L \leftarrow 0$
  end
  $P \leftarrow P - L$
  if $P \leq I_a$ **then**
    $P_e \leftarrow 0$
  else
    $P_e \leftarrow (P - 0.2S)^2/(P + 0.8S)$
  end
  $P_{inc} \leftarrow P_e - P_{pre} + L$
  $P_{pre} \leftarrow P_e$
end

3.2.3. Hydraulic model

Overland flow generated by the hydrologic model is routed into a physically-based hydraulic model, which computes the discharges and water depths in the pipe and channel network. The hydraulic model of the urban drainage system is implemented using the *PipeDream* solver (Bartos & Kerkez, 2021), which solves the Saint-Venant equations for unsteady flow in conduits and open channels using a staggered-grid implicit discretization scheme (Ji, 1998).

$$\frac{\partial A}{\partial t} + \frac{\partial Q}{\partial x} = q_{in} \tag{4}$$

$$\frac{\partial Q}{\partial t} + \frac{\partial}{\partial x}(Qu) + gA\left(\frac{\partial h}{\partial x} - S_0 + S_f + S_L\right) = 0 \tag{5}$$

Where Q is the flow rate, A is the cross-sectional area of flow, u is the average velocity, h is the pressure hydraulic head above the bottom of the conduit, x is distance, t is time, q_{in} is the exogenous flow input per unit length, and S_o, S_f and S_L represent the conduit bottom slope, friction head loss slope, and local head loss slope (due to contractions and expansions), respectively. The Saint-Venant equations represent the full physical dynamics of 1D unsteady flow, with Eq. (4) incorporating conservation of mass and Eq. (5) incorporating conservation of momentum. The solver thus models the complex hydrodynamics of urban drainage systems, including backwater effects and surcharged flow. For the hydraulic solver, parameters such as channel connectivity, geometry, and roughness are specified based on data from a HEC-RAS model previously developed and calibrated by the City of Austin for flood modeling.

3.3. Data assimilation

We select the *PipeDream* solver for the hydraulic model due to its state–space representation of system dynamics, which facilitates data assimilation via Extended Kalman Filtering (EKF). EKF combines a physically-based process model with measured data to generate updated posterior estimates of system states (Kalman, 1960). The Saint-Venant equations are linearized at each timestep and transformed into a state–space representation, enabling direct application of the EKF for sensor data assimilation (Bartos & Kerkez, 2021). Here, $\mathbf{x}_k$ is the state vector of junction heads at time k, A_k is the state transition matrix, B_k is the input transition matrix, $\mathbf{u}_k$ is the input vector, $\mathbf{w}_{k-1}$ is system noise at time $k-1$, $\mathbf{z}_k$ is the observation data from sensor, H is the observation matrix, and $\mathbf{v}_k$ is measurement noise.

$$\mathbf{x}_k = A_k \mathbf{x}_{k-1} + B_k \mathbf{u}_k + \mathbf{w}_{k-1} \tag{6}$$

$$\mathbf{z}_k = H \mathbf{x}_k + \mathbf{v}_k \tag{7}$$

By fusing the real-time sensor data, the minimum mean-squared error estimator of the state, $\hat{\mathbf{x}}_{k|k}$, can be estimated recursively in two steps. First, the predict step projects the state vector (Eq. (8)) and error covariance matrix (Eq. (9)) forward in time using the state-space model.

$$\hat{\mathbf{x}}_{k|k-1} = A_k \hat{\mathbf{x}}_{k-1|k-1} + B_k \mathbf{u}_k \tag{8}$$

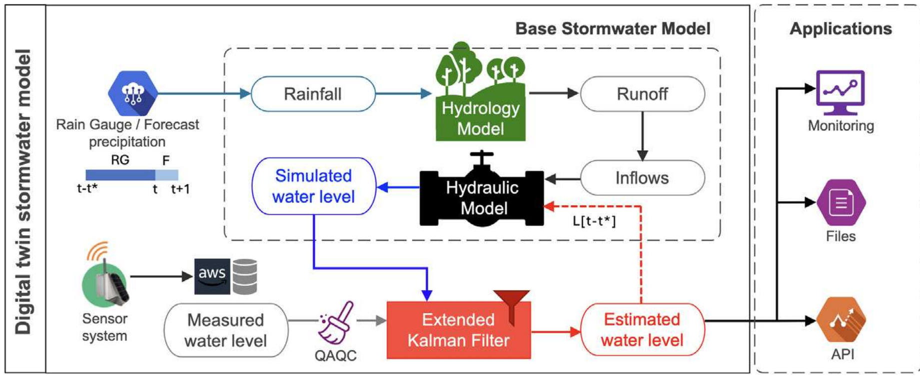

Fig. 4. Software architecture diagram of stormwater digital twin.

$$P_{k|k-1} = A_k P_{k-1|k-1} A_k^T + W \tag{9}$$

where W is the covariance matrix of the process noise $\mathbf{w}_{k-1}$ and $P_{k-1|k-1} = E[(x_{k-1} - \hat{x}_{k-1|k-1})(x_{k-1} - \hat{x}_{k-1|k-1})^T]$ is the error covariance matrix at time $k-1$. Next, the update step corrects the estimated state by combining the current prediction with a measurement from the sensors.

$$\tilde{\mathbf{y}}_k = \mathbf{z}_k - H\hat{\mathbf{x}}_{k|k-1} \tag{10}$$

$$L_k = P_{k|k-1} H^T (H P_{k|k-1} H^T + V)^{-1} \tag{11}$$

where $\tilde{\mathbf{y}}_k$ is Kalman innovation or measurement pre-fit residual, L_k is the Kalman gain, $P_{k|k-1}$ is the prior covariance matrix. V is the covariance matrix of the measurement noise $\mathbf{v}_k$. The posterior state and covariance matrix at the next time step are given by (Eq. (12)) and (Eq. (13)), respectively:

$$\hat{\mathbf{x}}_{k|k} = \hat{\mathbf{x}}_{k|k-1} + L_k \tilde{\mathbf{y}}_k \tag{12}$$

$$P_{k|k} = (I - L_k H) P_{k|k-1} \tag{13}$$

3.4. Anomaly detection

To handle non-Gaussian sensor errors, we discard measurements with residuals ($\tilde{\mathbf{y}}_k$) exceeding a user-specified threshold (η):

$$\tilde{\mathbf{y}}_k^T \tilde{\mathbf{y}}_k > \eta \tag{14}$$

During the Kalman filter's update phase, if the innovation is within the threshold, it refines the state estimate using the Kalman gain, resulting in the posterior state estimate ($\hat{\mathbf{x}}_{k|k}$) (Mu & Yuen, 2015). If the innovation exceeds the threshold, the update step is skipped, and the hydraulic state at the next time step is determined based on the prediction step, utilizing the hydraulic model (Eq. (8)).

3.5. Software architecture for real-time implementation

Fig. 4 shows the software architecture of the digital twin model, detailing the integration between the sensor network and the stormwater model:

- **Rainfall Input**: Simulates every 15 min using current rain gauge data ($RG[t - t^*]$) and forecasted rainfall data ($F[t + 1]$).
- **Hydrologic Model**: Calculates runoff for each sub-basin based on the rainfall input using the continuous SCS-CN method and then routes overland flow into channels via discrete convolution with sub-basin specific unit hydrographs.
- **Hydraulic Model**: Simulates water levels and flows in the channel and pipe network using the *PipeDream* hydraulic solver.
- **Sensor System**: Collects and stores real-time water levels and then passes these data to the digital twin model.
- **Data Assimilation**: Excludes sensor measurements outside the innovation threshold and merges valid data with model predictions using EKF.
- **Applications**: Provides updated water levels for monitoring, storage, or API access.

3.6. Evaluation methods

The stormwater digital twin model is evaluated on its ability to (i) reject outliers in raw sensor data and (ii) accurately estimate depths and flows at ungauged locations. These two tests represent important use cases for water managers, who desire real-time observability of depths and flows for flood management but are frequently limited by uncertain models and sparse and poor quality sensor data.

3.6.1. Anomaly rejection performance

The evaluation of anomaly rejection performance is conducted by analyzing the Area Under the Curve (AUC) of the Receiver Operating Characteristic (ROC). The ROC curve visually represents the performance of the binary classifier model across various threshold values by plotting the true positive rate (TPR) against the false positive rate (FPR) at each threshold.

$$TPR = \frac{TP}{TP + FN}, \quad FPR = \frac{FP}{FP + TN} \tag{15}$$

Where TP is the number of true positives, TN is the number of true negatives, FP is the number of false positives, and FN is the number of false negatives. AUC offers a comprehensive measure of performance across all conceivable classification thresholds (Bradley, 1997). In this paper, we utilize AUC metric to assess the classifier's performance in distinguishing sensor faults from true high-water events. The assessment involves a comparison between Extended Kalman Filtering (EKF) and other common anomaly detection algorithms. These anomaly detection approaches include conventional statistical techniques like Z-scores, as well as unsupervised machine learning approaches like Robust Random Cut Forest (RRCF), K-Nearest Neighbors (KNN), One-class SVM, and Spectral Residual Detector (SRD).

3.6.2. Model performance

A holdout assessment is performed to evaluate the digital twin model's performance at predicting water levels at ungauged locations. Taking Sensors 3 and 4 as the two holdout sites, we use EKF to fuse data from Sensors 1 and 2 into the model and then quantify the extent to which the performance at sensor sites 3 and 4 is improved. We assess the digital twin model's performance using the Kling–Gupta Efficiency (KGE), a widely adopted metric in hydrologic research for model evaluation (Knoben, Freer, & Woods, 2019). The KGE quantifies

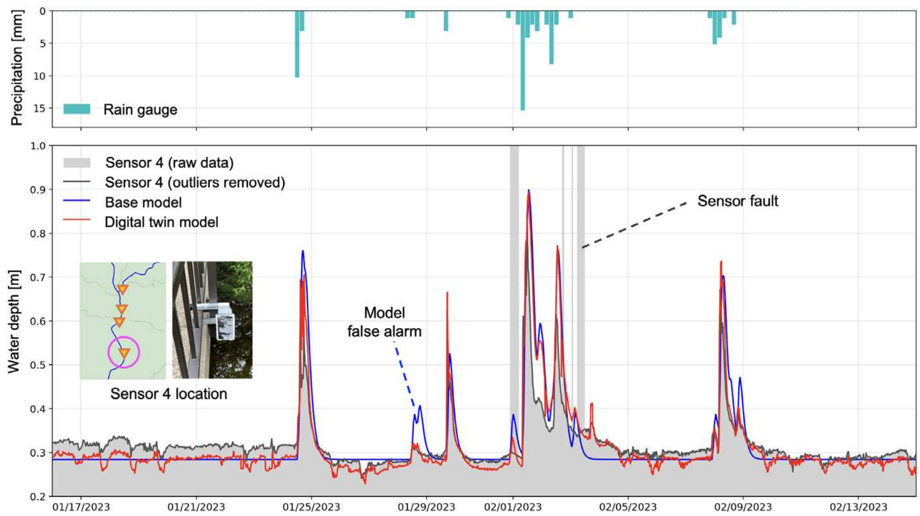

Fig. 5. Visualization of simulated and observed depth for Sensor 4 location.

model performance by calculating the Euclidean distance based on bias, standard deviation, and correlation coordinates, as outlined below:

$$KGE = 1 - \sqrt{(r-1)^2 + (\alpha-1)^2 + (\beta-1)^2} \quad (16)$$

where, r is the Pearson correlation coefficient, measuring the relationship between the simulated and observed data, $\alpha = \sigma_s/\sigma_o$ and $\beta = \mu_s/\mu_o$. σ_s and σ_o as the standard deviations of the simulated and observed data, respectively, μ_s and μ_o as the means of and the corresponding data sets. While the Pearson correlation gauges the linear relationship between observed and simulated values, the KGE provides a comprehensive evaluation by capturing patterns, variability, and averages.

4. Results

The digital twin model excels in both rejecting sensor faults and improving stormwater model accuracy. Fig. 5 compares the digital twin model (bottom panel, red) with raw sensor data (light gray) and the base model without data assimilation (blue) for storms occurring in January and February 2023. Here, the digital twin model refers to the hydraulic-hydrologic model with data assimilation, while the base model refers to the same model without data assimilation. First, while the raw sensor data exhibits multiple faults that would otherwise register as false alarms, the digital twin model filters these outliers, producing continuous estimates of the water depth in the creek. Moreover, while the base model tends to overpredict peak depths, the digital twin model rejects these overestimates by incorporating the depth sensor data into the final estimate. In general, the digital twin output mediates between the model estimates and sensor measurements, producing an output that is consistent with both data sources. To complete an hourly simulation, the base model requires roughly 0.26 s, while the digital twin model requires 1.14 s (on an AWS t3.small EC2 instance), meaning that the system is capable of comfortably running in real-time for our watershed test case. The following sections discuss sensor fault rejection (Section 4.1), model accuracy improvement (Section 4.2), and model forecast improvement (Section 4.3) in greater detail.

4.1. Real-time sensor anomaly rejection

The performance of model-based anomaly detection is assessed using sensor measurements from June 27, 2022, to May 20, 2023. Over several storm events, the ultrasonic sensors reported multiple sensor faults: 38 for Sensor 1; 1097 for Sensor 2; 0 for Sensor 3; and 87 for Sensor 4 (see Fig. 6a). Anomalies in the collected data arise from reflected or attenuated ultrasonic signals caused by obstacles such as tree branches and surface water turbulence. These sensor faults appear as anomalously high water levels at depth positions ranging between 2 and 4 [m].

The proposed anomaly detection method based on EKF successfully distinguishes sensor faults from true high-water events in all cases considered. Fig. 6a illustrates the output of the digital twin model (red) in comparison with raw sensor measurements (gray). Here, it can be seen that EKF successfully rejects nearly all sensor faults while also correctly admitting true hydrograph peaks. The digital twin model with EKF exhibits markedly better detection of sensor faults than competing anomaly detection algorithms. Fig. 6b shows ROC curves for the EKF-based anomaly detection (red) compared to other unsupervised anomaly detection algorithms across the three sites with sensor faults. Here, it can be seen that EKF-based anomaly detection obtains nearly perfect fault classification performance, achieving a True Positive Rate of 100% while simultaneously obtaining a False Positive Rate close to 0%. By contrast, competing unsupervised methods often struggle to perform better than random chance (as indicated by the diagonal dashed line on the ROC curves). Table 1 reports AUC values, which quantify binary classification performance for all anomaly detection methods at all sensor sites. The proposed EKF-based anomaly detection method achieves an AUC of 0.99 on average (with 1.0 representing perfect classification performance), while competing methods range from a high of 0.748 (Z-Score) to a low of 0.565 (KNN). These results hold when using either gage precipitation or forecasted precipitation as inputs to the digital twin model (see SI Section S2.1). Overall, EKF demonstrates remarkable efficacy in detecting anomalies, especially when these anomalies resemble hydrograph peaks, substantially outperforming other unsupervised methods.

4.2. Improving real-time simulation accuracy

Model performance is evaluated using KGE for both the base and digital twin models, using both forecasted and gauge-recorded precipitation data. For the digital twin model, sensor data is assimilated at sites 1 and 2, and performance is assessed at sites 3 and 4. Overall, data assimilation via EKF significantly improves model performance, even at ungauged locations.

In Fig. 7, the base model without data assimilation yields KGE values of 0.683 and 0.633 (relative to a perfect KGE of 1.0) when utilizing gauged (left) and forecasted (right) rainfall inputs, respectively. Especially during simulations involving forecasted precipitation, the basic model consistently predicts higher water depth values compared

Table 1
AUC values for different anomaly detection methods.

Sensor	Rainfall	EKF	Zscore	SRD	One-class SVM	KNN	RRCF
1	Gauge	0.99	0.61	0.56	0.53	0.39	0.32
2	Gauge	1.00	0.60	0.44	0.55	0.35	0.39
4	Gauge	0.99	0.92	0.62	0.84	0.77	0.88
2	Forecast	0.99	0.86	0.65	0.62	0.75	0.72

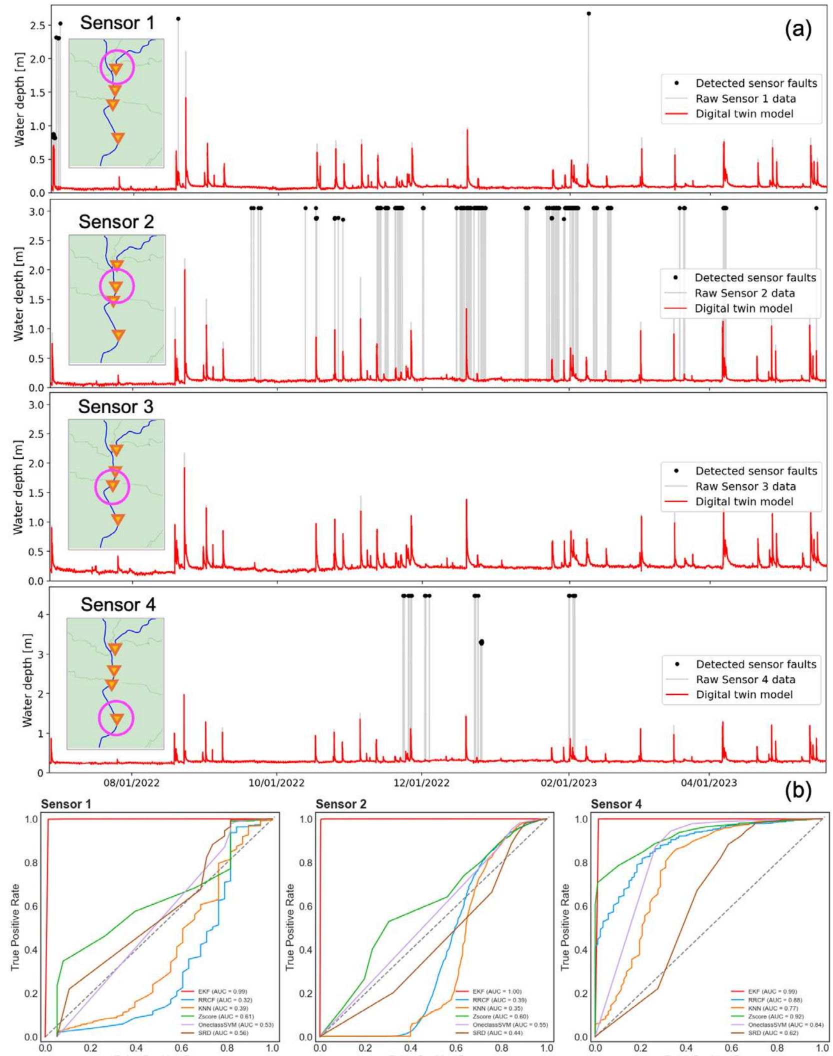

Fig. 6. (a) Sensor fault detection and (b) ROC comparison under gage precipitation.

to sensor measurements. This divergence is attributed to the model's tendency to overestimate rainfall. For instance, for observed depth values of 0.25 [m], the model simulation results under forecasted rainfall span from roughly 0.25 to 0.7 [m] (Fig. 7, right). In contrast, the digital twin model outperforms in prediction, achieving a KGE of 0.784 and (c) 0.786 for gauged rainfall and forecast rainfall, respectively. Figure S6 offers additional perspective on the KGE evaluation, presenting simulation outcomes and observational data at Sensor 3, which is closer to the data assimilation point. Here, the digital twin model also shows improved accuracy over the base model—especially under the forecasted rainfall input where the KGE improves from 0.817 (base model) to 0.886 (digital twin model). Overall, the digital twin model enhances the accuracy of monitoring water depth in the watershed, both at gauged and ungauged locations.

4.3. Improving streamflow forecast accuracy

The digital twin stormwater model enhances the accuracy of near-future stream stage forecasts by improving estimates of current hydraulic states with data assimilation and improving the prediction of subsequent stormwater depths by routing forecasted precipitation. Fig. 8 demonstrates forecasted depth estimates produced by the digital twin model (red) compared to the base stormwater model without data assimilation (blue). Initially, the digital twin model calculates runoff using aggregated precipitation data that includes rain gauge measurements up to the present (6 pm, May 13th, 2023), along with future forecasts (from 6 pm, May 13th, 2023 to 12 am, May 20, 2023). Next, it assimilates measurements from Sensor 1 up to the present time (6 pm, May 13th, 2023), thereby pushing the simulated state of the system closer to the ground truth. As a result, the digital twin model demonstrates improved alignment with Sensor 1 observations over the

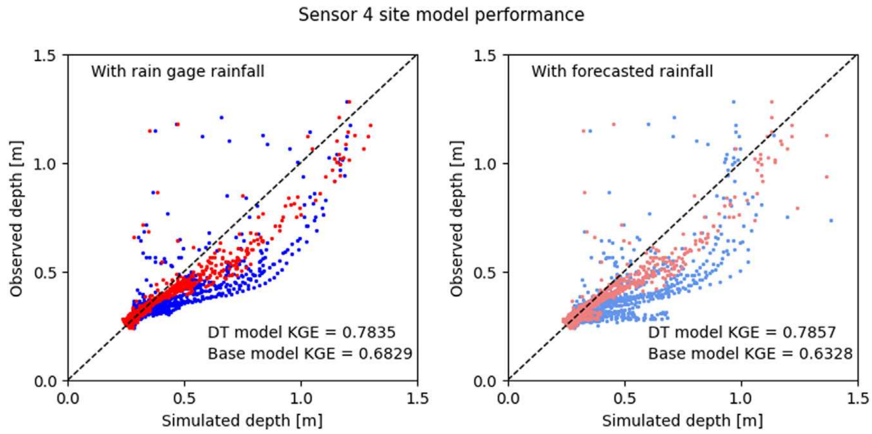

Fig. 7. Comparative Analysis of Kling–Gupta Efficiency for base model vs. digital twin model at sensor site 4 under (left) gauge and (right) forecasted rainfall.

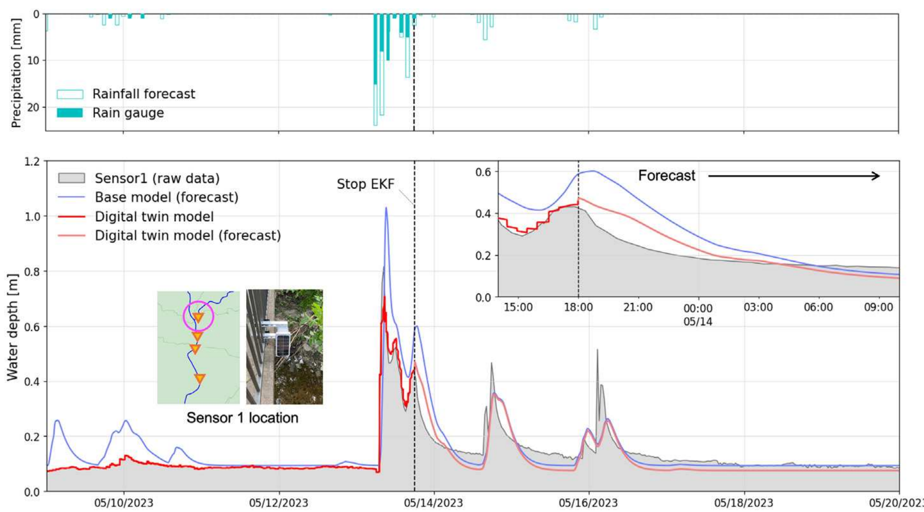

Fig. 8. Forecasted water depth under base model and digital twin model.

forecast horizon (approximately 12 h ahead) compared to the base model using forecasted precipitation alone.

5. Discussion

This study evaluates the practical application of stormwater digital twin models for data quality control, monitoring, and prediction of stormwater depths and discharges within urban drainage systems. With respect to data quality control, the digital twin model reinforced by the Extended Kalman Filter demonstrates exceptional performance, outperforming alternative unsupervised methods. This superiority is evident in ROC curve analysis, where EKF consistently achieves an AUC exceeding 0.99. The remarkable AUC persists when using both rain gauge and forecasted precipitation data to force the hydrologic model, underscoring the model's robustness across diverse inputs. Model-based state estimation outperforms competing unsupervised anomaly detection methods because it incorporates information about the underlying physical system, including expected rainfall inputs. By contrast, statistical and machine learning-based methods must detect anomalies using sensor measurements alone, making it difficult to distinguish hydrograph peaks from sensor faults, especially in a real-time context. The model-based state estimation approach also requires no training aside from basic model calibration, which is standard practice in hydrologic and hydraulic engineering. As such, this approach can readily be applied to any watershed for which a hydrologic–hydraulic model is available.

Regarding monitoring accuracy, the digital twin model significantly enhances estimation of stormwater depths and flows, evidenced by improved KGE values under both gauge and forecasted precipitation. Integrating state estimates into the model also significantly improves forecasting accuracy in the near future by improving estimates of the initial system state at the start of the forecast horizon. The 3D visualization in Fig. 9 illustrates the proposed digital twin model integrated into a real-time user interface, providing water managers with improved estimates of stormwater depths by incorporating sensor measurements and rejecting sensor faults. When combined with real-time data visualization capabilities, the proposed digital twin model promises to enable real-time monitoring and forecasting of stormwater depths, facilitating more effective watershed management.

Unlike earlier studies on digital twins, which have primarily focused on conceptual reviews (Pedersen, Borup, Brink-Kjær, Christiansen, & Mikkelsen, 2021b), the development of real-time 3D visualization platforms (Park & You, 2023), and the creation of software or frameworks for implementation (Bartos & Kerkez, 2021; Ranjbar et al., 2024), this study offers a novel approach for addressing both the modeling and measurement uncertainties that complicate real-time management of stormwater systems. By constructing a fully-operational stormwater digital twin and evaluating our system against real-world storm events, we find that our proposed approach is effective at delivering reliable estimates of stream depth and reducing the potential for false flood alarms. With respect to sensor fault detection, previous research has typically used data-driven methods like modified Z-scores (Bae & Ji,

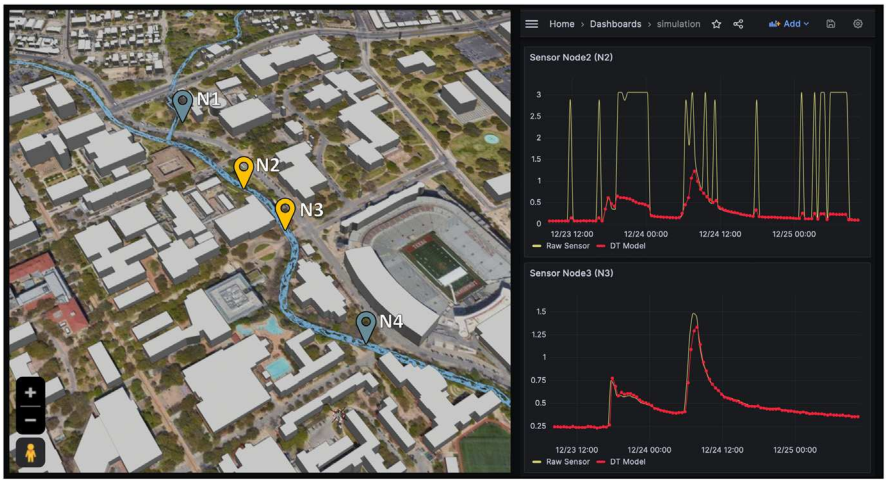

Fig. 9. 3D visualization of water level monitoring in Waller Creek.

2019) and Support Vector Machines (SVMs) (Schmidt & Kerkez, 2023) for online data quality control. In contrast, this study employs a model-based approach that first filters out sensor faults through online quality control and then refines estimates of depth and discharge using data assimilation. This strategy not only improves system interpretability but also enhances accuracy, providing a more dependable solution for real-time stormwater management.

While this study focuses on real-time flood monitoring, future research should expand our digital twin model to enable improved water quality management, given that water quality challenges in urban drainage systems are on par with flooding concerns for many cities. By coupling the proposed digital twin model with a contaminant transport solver like PipeDream-WQ (Kim & Bartos, 2023), future research may explore the potential for real-time tracking of contaminants like sediments or nutrients that impair downstream water quality. Using the method described in our paper, this coupled model has the potential to automatically detect anomalies in water quality data that may indicate algal blooms, fish kills, or unauthorized washoff of sediments. Moreover, the real-time and forecasted simulation capabilities of the stormwater digital twin model may be further extended to encompass active control strategies (Oh & Bartos, 2023), thus enabling the implementation of smart stormwater systems that use dynamic actuation of valves, gates, and pumps to halt combined sewer overflows and improve water quality.

Although this study provides guidelines for implementation of a complete stormwater digital twin system, several social challenges remain. Designing, installing, and maintaining stormwater digital twin models requires a diverse set of technical skills, necessitating teams with expertise in construction, software development, and embedded electronics. Consequently, cross-disciplinary misunderstandings can hinder effective collaboration (Broo, Bravo-Haro, & Schooling, 2022). Moreover, stormwater digital twin systems involve high initial investment costs, including wireless sensor networks and advanced computing systems for real-time modeling, with substantial ongoing operational and maintenance expenses (Ferré-Bigorra, Casals, & Gangolells, 2022). These factors make it challenging to promote and adopt such systems, especially within local government agencies. Finally, addressing cybersecurity concerns is crucial for effective stormwater management and active control (Lee, Kim, & Seo, 2019). Navigating these challenges is key to realizing the benefits of stormwater digital twin models and their integration into public infrastructure.

6. Conclusions

This study evaluates an end-to-end digital twin system for managing urban drainage hazards. By integrating a wireless sensor network, an online hydrologic–hydraulic model, and data assimilation, the system demonstrates excellent performance in data quality control, prediction of stormwater depths at ungauged locations, and improved near-term forecasts. The digital twin model effectively identifies and removes outliers, surpassing unsupervised methods in sensor fault detection. It also improves stream depth estimates and forecast accuracy by continuously correcting stormwater depth states. This framework enables effective flood alerts, timely emergency response, and real-time control of urban drainage infrastructure, mitigating hazards like sewer overflows. To pave the way for these future developments, this study contributes practical tools—including a full software implementation—to bridge the gap between digital twin concepts and on-the-ground implementation for resilient and sustainable urban watersheds.

CRediT authorship contribution statement

Yeji Kim: Writing – original draft, Visualization, Software, Investigation, Formal analysis, Data curation, Conceptualization. **Jeil Oh:** Writing – review & editing, Software, Conceptualization. **Matthew Bartos:** Writing – review & editing, Validation, Supervision, Software, Project administration, Funding acquisition.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Yeji Kim reports financial support was provided by The University of Texas at Austin. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Funding sources

This work was supported in part by the National Science Foundation, United States under Grant 2220516.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.scs.2024.105982.

Data availability

Data and software for this study are available at https://github.com/future-water/waller-creek-model.

References

Bae, I., & Ji, U. (2019). Outlier detection and smoothing process for water level data measured by ultrasonic sensor in stream flows. *Water*, *11*(5), 951.

Bartos, M., & Kerkez, B. (2021). Pipedream: An interactive digital twin model for natural and urban drainage systems. *Environmental Modelling & Software*, *144*, Article 105120.

Baumann, H., egh Ravn, N. H., & Schaum, A. (2022). Efficient hydrodynamic modelling of urban stormwater systems for real-time applications. *Modelling*, *3*(4), 464–480.

Bedient, P. B., Huber, W. C., Vieux, B. E., et al. (2008). *Hydrology and floodplain analysis, vol. 816*. Prentice Hall Upper Saddle River, NJ.

Blecken, G.-T., Hunt, W. F., Al-Rubaei, A. M., Viklander, M., & Lord, W. G. (2017). Stormwater control measure (SCM) maintenance considerations to ensure designed functionality. *Urban Water Journal*, *14*(3), 278–290. http://dx.doi.org/10.1080/1573062X.2015.1111913.

Booth, D. B., & Jackson, C. R. (1997). Urbanization of aquatic systems: Degradation thresholds, stormwater detection, and the limits of mitigation. *Journal of the American Water Resources Association*, *33*(5), 1077–1090. http://dx.doi.org/10.1111/j.1752-1688.1997.tb04126.x.

Botturi, A., Ozbayram, E. G., Tondera, K., Gilbert, N. I., Rouault, P., Caradot, N., et al. (2020). Combined sewer overflows: A critical review on best practice and innovative solutions to mitigate impacts on environment and human health. *Critical Reviews in Environmental Science and Technology*, *51*(15), 1585–1618.

Bradley, A. P. (1997). The use of the area under the ROC curve in the evaluation of machine learning algorithms. *Pattern Recognition*, *30*(7), 1145–1159.

Broo, D. G., Bravo-Haro, M., & Schooling, J. (2022). Design and implementation of a smart infrastructure digital twin. *Automation in construction*, *136*, Article 104171.

Butler, D., Digman, C., Makropoulos, C., & Davies, J. W. (2018). *Urban drainage*. Crc Press.

Butts, M. B., Payne, J. T., Kristensen, M., & Madsen, H. (2004). An evaluation of the impact of model structure on hydrological modelling uncertainty for streamflow simulation. *Journal of Hydrology*, *298*(1–4), 242–266.

Campbell, J. L., Rustad, L. E., Porter, J. H., Taylor, J. R., Dereszynski, E. W., Shanley, J. B., et al. (2013). Quantity is nothing without quality: Automated QA/QC for streaming environmental sensor data. *BioScience*, *63*(7), 574–585.

Chandola, V., Banerjee, A., & Kumar, V. (2009). Anomaly detection: A survey. *ACM computing surveys (CSUR)*, *41*(3), 1–58.

Che, D., & Mays, L. W. (2015). Development of an optimization/simulation model for real-time flood-control operation of river-reservoirs systems. *Water Resources Management*, *29*(11), 3987–4005.

City of Austin Watershed Protection (2016). *Watershed Profile: North Urban Watersheds - Shoal Creek | Waller Creek | Johnson Creek | Lady Bird Lake*.

Criss, R. E., & Shock, E. L. (2001). Flood enhancement through flood control. *Geology*, *29*(10), 875. http://dx.doi.org/10.1130/0091-7613(2001)029<0875:FETFC>2.0.CO;2.

Eberts, S. M., Woodside, M. D., Landers, M. N., & Wagner, C. R. (2019). *Monitoring the pulse of our Nation's rivers and streams—the US Geological Survey streamgaging network: Technical report*, US Geological Survey.

Edmondson, V., Cerny, M., Lim, M., Gledson, B., Lockley, S., & Woodward, J. (2018). A smart sewer asset information model to enable an 'Internet of Things' for operational wastewater management. *Automation in Construction*, *91*, 193–205. http://dx.doi.org/10.1016/j.autcon.2018.03.003.

Emerson, C. H., Welty, C., & Traver, R. G. (2005). Watershed-scale evaluation of a system of storm water detention basins. *Journal of Hydrologic Engineering*, *10*(3), 237–242. http://dx.doi.org/10.1061/(asce)1084-0699(2005)10:3(237).

Ercolani, G., & Castelli, F. (2017). Variational assimilation of streamflow data in distributed flood forecasting. *Water Resources Research*, *53*(1), 158–183.

Feldman, A. D. (2000). *Hydrologic modeling system HEC-HMS: technical reference manual*. US Army Corps of Engineers, Hydrologic Engineering Center.

Ferré-Bigorra, J., Casals, M., & Gangolells, M. (2022). The adoption of urban digital twins. *Cities*, *131*, Article 103905.

Ford, D. N., & Wolf, C. M. (2020). Smart cities with digital twin systems for disaster management. *Journal of Management in Engineering*, *36*(4), Article 04020027. http://dx.doi.org/10.1061/(ASCE)ME.1943-5479.0000779.

Freni, G., Mannina, G., & Viviani, G. (2009). Uncertainty assessment of an integrated urban drainage model. *Journal of Hydrology*, *373*(3–4), 392–404.

Hapuarachchi, H. A. P., Wang, Q. J., & Pagano, T. C. (2011). A review of advances in flash flood forecasting. *Hydrological Processes*, *25*(18), 2771–2784. http://dx.doi.org/10.1002/hyp.8040.

Huang, H., Yang, L., Wang, Y., Xu, X., & Lu, Y. (2021). Digital twin-driven online anomaly detection for an automation system based on edge intelligence. *Journal of Manufacturing Systems*, *59*, 138–150.

Ji, Z. (1998). General hydrodynamic model for sewer/channel network systems. *Journal of hydraulic engineering*, *124*(3), 307–315.

Kalman, R. E. (1960). A new approach to linear filtering and prediction problems. *Journal of Basic Engineering*.

Kazuhiko, I., & Atsushi, Y. (2018). Building a common smart city platform utilizing FIWARE (case study of Takamatsu city). *NEC Technical Journal*, *13*(1), 28–31.

Kerkez, B., Gruden, C., Lewis, M., Montestruque, L., Quigley, M., Wong, B., et al. (2016). Smarter stormwater systems. *Environmental Science and Technology*, *50*(14), 7267–7273.

Khalastchi, E., Kalech, M., Kaminka, G. A., & Lin, R. (2015). Online data-driven anomaly detection in autonomous robots. *Knowledge and Information Systems*, *43*, 657–688.

Khan, M. R., Gourley, J. J., Duarte, J. A., Vergara, H., Wasielewski, D., Ayral, P.-A., et al. (2021). Uncertainty in remote sensing of streams using noncontact radars. *Journal of Hydrology*, *603*, Article 126809.

Kim, M.-G., & Bartos, M. (2023). A digital twin model for contaminant fate and transport in urban and natural drainage networks with online state estimation. *Environmental Modelling & Software*, Article 105868.

Knoben, W. J., Freer, J. E., & Woods, R. A. (2019). Inherent benchmark or not? Comparing Nash–Sutcliffe and Kling–Gupta efficiency scores. *Hydrology and Earth System Sciences*, *23*(10), 4323–4331.

Lee, J., Kim, J., & Seo, J. (2019). Cyber attack scenarios on smart city and their ripple effects. In *2019 international conference on platform technology and service* (pp. 1–5). IEEE.

Liu, Y., Weerts, A. H., Clark, M., Franssen, H.-J. H., Kumar, S., Moradkhani, H., et al. (2012). Advancing data assimilation in operational hydrologic forecasting: Progresses, challenges, and emerging opportunities. *Hydrology and Earth System Sciences*, *16*(10), 3863–3887. http://dx.doi.org/10.5194/hess-16-3863-2012.

Lumley, D. J., Polesel, F., Refstrup Sø rensen, H., & Gustafsson, L.-G. (2024). Connecting digital twins to control collections systems and water resource recovery facilities: From siloed to integrated urban (waste)water management. *Water Practice & Technology*, http://dx.doi.org/10.2166/wpt.2024.128, wpt2024128.

Lumley, D. J., Wanninger, D., Magnusson, A. s., I'Ons, D., & Gustafsson, L.-G. (2024). Implementing a digital twin for optimized real-time control of Gothenburg's regional sewage system. *Water Practice & Technology*, wpt2024060. http://dx.doi.org/10.2166/wpt.2024.060.

Ming, X., Liang, Q., Xia, X., Li, D., & Fowler, H. J. (2020). Real-time flood forecasting based on a high-performance 2-D hydrodynamic model and numerical weather predictions. *Water Resources Research*, *56*(7).

Montestruque, L., & Lemmon, M. D. (2015). Globally coordinated distributed storm water management system. In *Proceedings of the 1st ACM international workshop on cyber-physical systems for smart water networks*. ACM Press, http://dx.doi.org/10.1145/2738935.2738948.

Moradkhani, H., & Sorooshian, S. (2008). *General review of rainfall-runoff modeling: model calibration, data assimilation, and uncertainty analysis*. Springer.

Mu, H.-Q., & Yuen, K.-V. (2015). Novel outlier-resistant extended Kalman filter for robust online structural identification. *Journal of Engineering Mechanics*, *141*(1), Article 04014100.

Ni, K., Ramanathan, N., Chehade, M. N. H., Balzano, L., Nair, S., Zahedi, S., et al. (2009). Sensor network data fault types. *ACM Transactions on Sensor Networks*, *5*(3), 1–29.

NRCS, U. (2004). *National engineering handbook: Part 630—hydrology* (pp. 11–15). USDA Soil Conservation Service: Washington, DC, USA.

Oberascher, M., Rauch, W., & Sitzenfrei, R. (2022). Towards a smart water city: A comprehensive review of applications, data requirements, and communication technologies for integrated management. *Sustainable Cities and Society*, *76*, Article 103442.

Oh, J., & Bartos, M. (2023). Model predictive control of stormwater basins coupled with real-time data assimilation enhances flood and pollution control under uncertainty. *Water Research*, *235*, Article 119825.

Owen, D. L. (2023). Smart water management. *River*, *2*(1), 21–29. http://dx.doi.org/10.1002/rvr2.29.

Panagopoulos, Y., Papadopoulos, A., Poulis, G., Nikiforakis, E., & Dimitriou, E. (2021). Assessment of an ultrasonic water stage monitoring sensor operating in an urban stream. *Sensors*, *21*(14), 4689.

Park, D., & You, H. (2023). A digital twin dam and watershed management platform. *Water*, *15*(11), 2106.

Pedersen, A. N., Borup, M., Brink-Kjær, A., Christiansen, L. E., & Mikkelsen, P. S. (2021a). Living and prototyping digital twins for Urban Water Systems: Towards multi-purpose value creation using models and sensors. *Water*, *13*(5), 592. http://dx.doi.org/10.3390/w13050592.

Pedersen, A. N., Borup, M., Brink-Kjær, A., Christiansen, L. E., & Mikkelsen, P. S. (2021b). Living and prototyping digital twins for urban water systems: Towards multi-purpose value creation using models and sensors. *Water*, *13*(5), 592.

Pereira, T. S. R., de Carvalho, T. P., Mendes, T. A., & Formiga, K. T. M. (2022). Evaluation of water level in flowing channels using ultrasonic sensors. *Sustainability*, *14*(9), 5512.

Ranjbar, R., Segovia, P., Duviella, E., Etienne, L., Maestre, J. M., & Camacho, E. F. (2024). Digital twin of calais canal with model predictive controller: A simulation on a real database. *Journal of Water Resources Planning and Management*, *150*(5), Article 05024002. http://dx.doi.org/10.1061/JWRMD5.WRENG-6266.

Rasheed, A., San, O., & Kvamsdal, T. (2020). Digital twin: Values, challenges and enablers from a modeling perspective. *IEEE Access*, *8*, 21980–22012.

Rosenberg, E. A., Keys, P. W., Booth, D. B., Hartley, D., Burkey, J., Steinemann, A. C., et al. (2010). Precipitation extremes and the impacts of climate change on stormwater infrastructure in Washington State. *Climatic Change*, *102*(1–2), 319–349. http://dx.doi.org/10.1007/s10584-010-9847-0.

Sadler, J. M., Goodall, J. L., Behl, M., Bowes, B. D., & Morsy, M. M. (2020). Exploring real-time control of stormwater systems for mitigating flood risk due to sea level rise. *Journal of Hydrology*, *583*, Article 124571.

Sarni, W., White, C., Webb, R., Cross, K., & Glotzbach, R. (2019). *Digital water: Industry leaders chart the transformation journey*: *Technical report*, International Water Association.

Schmidt, J. Q., & Kerkez, B. (2023). Machine learning-assisted, process-based quality control for detecting compromised environmental sensors. *Environmental Science and Technology*.

See, C., Horoshenkov, K., abd alhmeed, R., Hu, Y., & Tait, S. (2011). A low power wireless sensor network for gully pot monitoring in Urban Catchments. *IEEE Sensors Journal*, Article 6081896. http://dx.doi.org/10.1109/JSEN.2011.2174354.

Silverman, A. I., Brain, T., Branco, B., sai venkat Challagonda, P., Choi, P., Fischman, R., et al. (2022). Making waves: Uses of real-time, hyperlocal flood sensor data for emergency management, resiliency planning, and flood impact mitigation. *Water Research*, *220*, Article 118648. http://dx.doi.org/10.1016/j.watres.2022.118648.

Tabuchi, J.-P., Blanchet, B., & Rocher, V. (2020). Integrated smart water management of the sanitation system of the greater Paris region. *Water International*, *45*(6), 574–603. http://dx.doi.org/10.1080/02508060.2020.1830584.

Tao, D. Q., Pleau, M., Akridge, A., Fradet, O., Grondin, F., Laughlin, S., et al. (2020). Analytics and optimization reduce sewage overflows to protect community waterways in Kentucky. *INFORMS Journal on Applied Analytics*, *50*(1), 7–20. http://dx.doi.org/10.1287/inte.2019.1022.

Teal, M. J., & Allan, R. (2017). Creating a flood warning system for the San Diego River using HEC-RTS software. In *World environmental and water resources congress 2017*. American Society of Civil Engineers.

Tomorrow. io Weather API (2023). https://www.tomorrow.io.

Committee on Urban Flooding in the United States, Program on Risk, R., Events, E., Policy and Global Affairs, Water Science and Technology Board, Division on Earth and Life Studies, et al. (2019). *Framing the Challenge of Urban Flooding in the United States* (p. 25381). Washington, D.C.: National Academies Press, http://dx.doi.org/10.17226/25381.

U. S. Environmental Protection Agency (2004). *Report to congress on impacts and control of combined sewer overflows and sanitary sewer overflows*: *Technical report EPA 833-R-04-001*.

Valverde-Pérez, B., Johnson, B., Wärff, C., Lumley, D., Torfs, E., Nopens, I., et al. (2021). Digital water–operational digital twins in the urban water sector: Case studies.

VanDerHorn, E., & Mahadevan, S. (2021). Digital twin: Generalization, characterization and implementation. *Decision Support Systems*, *145*, Article 113524.

Vörösmarty, C. J., McIntyre, P. B., Gessner, M. O., Dudgeon, D., Prusevich, A., Green, P., et al. (2010). Global threats to human water security and river biodiversity. *Nature*, *467*(7315), 555–561. http://dx.doi.org/10.1038/nature09440.

Walsh, C. J., Roy, A. H., Feminella, J. W., Cottingham, P. D., Groffman, P. M., & Morgan, R. P. (2005). The urban stream syndrome: Current knowledge and the search for a cure. *Journal of the North American Benthological Society*, *24*(3), 706–723. http://dx.doi.org/10.1899/04-028.1.

Wang, L., Jiang, R., Chen, X., Xie, J., Liu, X., Tian, L., et al. (2022). Design and application of digital twin platform based smart Weihe River Basin. In M. Mikusova (Ed.), *International conference on smart transportation and city engineering*. SPIE.

Webber, J. L., Fletcher, T., Farmani, R., Butler, D., & Melville-Shreeve, P. (2022). Moving to a future of smart stormwater management: A review and framework for terminology, research, and future perspectives. *Water Research*, *218*, Article 118409.

Weil, C., Bibri, S. E., Longchamp, R., Golay, F., & Alahi, A. (2023). Urban digital twin challenges: A systematic review and perspectives for sustainable smart cities. *Sustainable Cities and Society*, *99*, Article 104862.

Wright, J., & Marchese, D. (2017). Briefing: continuous monitoring and adaptive control: The 'smart' storm water management solution. *Proceedings of the Institution of Civil Engineers - Smart Infrastructure and Construction*, *170*(4), 86–89. http://dx.doi.org/10.1680/jsmic.17.00017.

Wu, Z. Y., Chew, A., Meng, X., Cai, J., Pok, J., Kalfarisi, R., et al. (2023). High fidelity digital twin-based anomaly detection and localization for smart water grid operation management. *Sustainable Cities and Society*, *91*, Article 104446.

Xu, X., Zhang, X., Fang, H., Lai, R., Zhang, Y., Huang, L., et al. (2017). A real-time probabilistic channel flood-forecasting model based on the Bayesian particle filter approach. *Environmental Modelling & Software*, *88*, 151–167.

Zeng, Z., Yuan, X., Liang, J., & Li, Y. (2021). Designing and implementing an SWMM-based web service framework to provide decision support for real-time urban stormwater management. *Environmental Modelling & Software*, *135*, Article 104887.

Zhang, P., Cai, Y., & Wang, J. (2018). A simulation-based real-time control system for reducing urban runoff pollution through a stormwater storage tank. *Journal of Cleaner Production*, *183*, 641–652.

Zoppou, C. (2001). Review of urban storm water models. *Environmental Modelling & Software*, *16*(3), 195–231.