



Real-time control of retention basins for stormwater management and Rainwater Reuse

Downloaded from: <https://research.chalmers.se>, 2026-10-13 12:28 UTC

Citation for the original published paper (version of record):

Knutsson, J. (2025). Real-time control of retention basins for stormwater management and Rainwater Reuse. Urban Water Journal, 22(6): 706-717. <http://dx.doi.org/10.1080/1573062X.2025.2496958>

N.B. When citing this work, cite the original published paper.



Real-time control of retention basins for stormwater management and Rainwater Reuse

Jesper Knutsson

To cite this article: Jesper Knutsson (2025) Real-time control of retention basins for stormwater management and Rainwater Reuse, Urban Water Journal, 22:6, 706-717, DOI: [10.1080/1573062X.2025.2496958](https://doi.org/10.1080/1573062X.2025.2496958)

To link to this article: <https://doi.org/10.1080/1573062X.2025.2496958>



© 2025 The Author(s). Published by Informa UK Limited, trading as Taylor & Francis Group.



Published online: 30 Apr 2025.



[Submit your article to this journal](#)



Article views: 1842



[View related articles](#)



[View Crossmark data](#)



Citing articles: 2 [View citing articles](#)

RESEARCH ARTICLE



Real-time control of retention basins for stormwater management and Rainwater Reuse

Jesper Knutsson 

Department of Architecture and Civil Engineering, Chalmers University of Technology, Gothenburg, Sweden

ABSTRACT

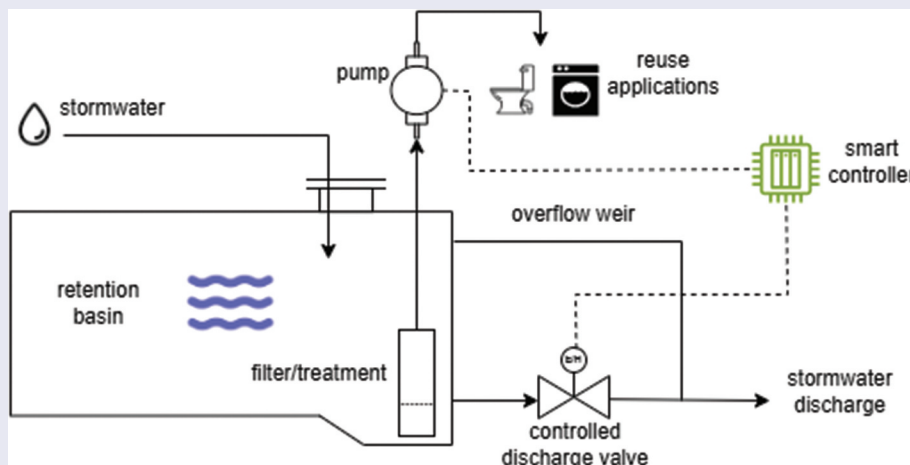
This study examines the potential of transforming stormwater retention basins into multifunctional systems for flood mitigation and rainwater harvesting, addressing urban challenges of flood risk and sustainable water management. By integrating real-time control (RTC) mechanisms, the research explores how traditional basins can serve dual purposes. A Python-based hydrological model tested forecast-based control (FBC) strategies against rule-based and business-as-usual (BAU) systems. In a case study from Gothenburg, Sweden, FBC reduced overflow volumes by up to 50% compared to rule-based control and met up to 95% of water reuse demand. Experimental validation showed strong agreement between simulated and observed data, highlighting the benefits of FBC in optimizing water discharge and reuse. These results demonstrate the feasibility of repurposing existing retention basins into multifunctional infrastructure, offering environmental and economic advantages while enhancing urban water resilience.

ARTICLE HISTORY

Received 20 September 2024
Accepted 17 April 2025

KEYWORDS

Stormwater management;
real-time control (RTC);
rainwater harvesting;
forecast-based control (FBC);
urban water resilience;
hydrological modeling



Introduction

Urban stormwater management presents a growing challenge as cities face increasing pressures from climate change, urbanization, and water scarcity. The intensification of storm events due to climate variability exacerbates the risks of urban flooding, degrading water quality, and stressing conventional stormwater infrastructure (van Duin et al. 2021).

Traditional systems, which prioritize flood control through peak flow reduction, have been largely underutilized in addressing water reuse potential. This gap is critical as urban areas across the globe grapple with escalating demands for freshwater resources, driven by population growth and industrialization (Goonetilleke, Liu, and Gardner 2016), and there is an increasing need to enhance the sustainability of the urban water systems (La Torre Rapp, Knutsson, and Wallin 2024).

Stormwater represents a significant yet underutilized resource. Research shows that, in many cities, the annual volume of stormwater runoff exceeds the demand for imported potable water, highlighting the untapped potential for water reuse (Lazarova et al. 2001). As fresh water supplies become increasingly stressed, particularly in arid and semi-arid regions, the integration of stormwater reuse into urban water management strategies offers a viable solution to enhance water resilience while reducing reliance on conventional water sources (Goonetilleke, Liu, and Gardner 2016).

Recent technological advancements, particularly in real-time control (RTC) systems, provide an opportunity to repurpose existing stormwater infrastructure for multifunctional purposes, combining flood mitigation with rainwater harvesting (Kerkez et al. 2016). By integrating RTC mechanisms with predictive modeling, stormwater retention basins can be dynamically

managed to optimize both water storage and release based on forecasted storm events (Luthy, Sharvelle, and Dillon 2019). This shift from static, rule-based systems to adaptive, real-time strategies ensures that stormwater systems not only mitigate flood risks but also serve as supplementary water resources for urban reuse.

The transformative potential of RTC in stormwater systems is increasingly recognized across the field of urban water management (Wong 2017). outlines how RTC mechanisms enable dynamic adaptation to changing conditions through sensor integration and predictive control strategies to optimize both flood retention and water reuse in legacy basins, demonstrating significant environmental and economic benefits (Wong 2017). Kerkez et al. (2016). highlight the role of real-time data and sensors in stormwater management, showing how RTC can optimize both flood control and pollutant removal (Kerkez et al. 2016).

Similarly, Schmitt, Hodges, and Dymond (2020), explore the retrofitting of stormwater detention basins with RTC, noting the potential to reduce peak flows and improve water quality during small to medium storm events (Schmitt, Hodges, and Dymond 2020). However, their findings also caution that larger storms may exacerbate peak flow rates without predictive control elements, underscoring the need for advanced strategies like forecast-based control (FBC), which is a strategy that uses precipitation forecasts to dynamically manage stormwater discharge. Gelormino and Ricker (1994). provide foundational evidence for using model predictive control (MPC), demonstrating a 26% annual reduction in combined sewer overflows (CSOs) by optimizing flow and storage in large urban drainage systems (Gelormino and Ricker 1994). This supports the use of FBC to similarly optimize the performance of stormwater retention basins for both flood control and water reuse.

Pumo et al. (2023) offer an experimental evaluation of blue-green roofs (BGRs), which serve dual purposes of stormwater retention and water reuse (Pumo et al. 2023). Their study in semi-arid climates shows how BGRs can efficiently manage water resources while mitigating flood risks. Similarly Luthy, Sharvelle, and Dillon (2019), analyze large-scale stormwater capture projects in Los Angeles and Adelaide, emphasizing the growing recognition of stormwater as a valuable resource (Luthy, Sharvelle, and Dillon 2019). Their emphasis on the role of RTC technologies in optimizing water capture and quality directly aligns with the the FBC-based approach for transforming legacy retention basins into multifunctional systems suggested in the present work.

Focusing on predictive control techniques, several workers have reviewed the application of MPC in urban drainage systems, highlighting its capacity to optimize stormwater management through real-time forecasts. This strengthens the case for integrating FBC into a multifunctional solution, as MPC helps dynamically manage retention basins to enhance stormwater storage and reuse (Abou Rjeily et al. 2018; Lund et al. 2018).

Gomes et al. (2024) present a novel MPC strategy that dynamically balances flood mitigation with water quality objectives in detention ponds, a key aspect of the present work. Their approach optimizes stormwater retention and discharge based on forecasted inflows, achieving significant reductions in peak

flows and extended detention times. This supports the multi-functional use of retention basins for both flood control and water reuse (Gomes et al. 2024).

Eggimann et al. (2017) provide a broad review of data-driven urban water management (UWM), emphasizing the importance of real-time control and predictive models for optimizing stormwater and wastewater systems. Their findings underscore the value of real-time data to improve flood management and enhance water reuse in urban drainage systems (Eggimann et al. 2017).

While the transformative potential of RTC and model predictive control (MPC) has been well-documented in the existing literature, several knowledge gaps remain. Most notably, there is a lack of comprehensive studies that integrate FBC into the retrofitting of legacy stormwater retention basins for multi-functional purposes, particularly those that simultaneously address flood mitigation and water reuse. The research reviewed so far has primarily focused on either flood control (Gelormino and Ricker 1994; Schmitt, Hodges, and Dymond 2020) or water reuse strategies (Luthy, Sharvelle, and Dillon 2019; Pumo et al. 2023), but few have demonstrated how these objectives can be achieved concurrently in real-world urban settings.

Additionally, while model-based control strategies like MPC have been shown to be effective (Abou Rjeily et al. 2018; Lund et al. 2018), there remains a significant opportunity to optimize their application for systems where water reuse must be prioritized without sacrificing flood control. Many studies (e.g. Schmitt, Hodges, and Dymond (2020)) caution that without predictive elements like FBC, retrofitted systems may exacerbate peak flow rates during extreme weather events, suggesting that predictive strategies could mitigate these risks. However, a cohesive framework that combines FBC, real-time data inputs, and scalable control strategies has not yet been fully realized in urban water management (Eggimann et al. 2017).

Moreover, the integration of advanced data-driven approaches, such as reinforcement learning (Mullapudi et al. 2020; Mullapudi, Wong, and Kerkez 2017), remains largely experimental, with limited practical demonstrations of their scalability and adaptability in complex, multi-basin urban settings. This gap in the literature emphasizes the need for further research into how such advanced control strategies can complement FBC, enhancing computational efficiency and allowing for more flexible and adaptive stormwater management systems.

The present paper makes a significant contribution by presenting a novel approach that integrates FBC to repurpose existing retention basins into multifunctional infrastructure capable of both flood mitigation and rainwater harvesting. By using real-time hydrological modeling and predictive controls, it is demonstrated how FBC can proactively manage inflows to ensure optimal stormwater retention and reuse without compromising on flood control.

Materials and methods

The modeling approach employed in this study utilizes a Python-based hydrological simulation to model the dynamics of stormwater runoff, retention, and the reuse of rainwater in

a domestic setting. This model uses precipitation time series data as the primary input to calculate runoff volumes and incorporates a snow reservoir and melt model to capture water availability for reuse. The primary aim is to evaluate the effectiveness of retention basins equipped with RTC capabilities in managing stormwater for dual purposes: flood mitigation and non-potable water reuse.

The model assesses basin performance in optimizing water levels, ensuring a reliable supply of treated rainwater for non-potable household uses such as toilet flushing and washing machines, while also preventing overflow and managing controlled discharges during extreme weather events. The flexibility of the Python-based model enables real-time adjustments based on both stormwater inflow and water demand, allowing for more comprehensive sensitivity analyses and operational optimizations, ultimately contributing to enhanced urban water resilience.

The hydrological model developed in this study relies on several key input parameters to simulate the dynamics of a real-time controlled retention basin designed for stormwater management and rainwater reuse. The model inputs include hourly precipitation and air temperature data provided by the Swedish Meteorological and Hydrological Institute (SMHI) (Swedish Meteorological and Hydrological Institute 2024), as well as water use and demand patterns derived from empirical data collected at the HSB Living Lab (described in detail elsewhere (Knutsson and Knutsson 2021; Knutsson and Marx 2016)). The hourly precipitation data is used to calculate the inflow to the basin, while the air temperature data is critical for determining snow accumulation and melt processes, which significantly impact runoff dynamics in colder climates.

The key hydrological equations used in the model were

The runoff volume Q (dm^3) was calculated using the rational method:

$$Q = I \times A_r \times t_r \quad (1)$$

Where I is the rainfall intensity (mm/hr) and A_r is the catchment area (m^2) and t is the duration (hr).

The snowmelt M (mm) is determined using a degree-day factor approach

$$M = k \times (T - T_m) \quad (2)$$

Where k is the degree-day factor ($\text{mm}/^\circ\text{C}/\text{hour}$), T is the air temperature ($^\circ\text{C}$) and T_f is the freezing temperature (0°C).

Inflow to the Basin: The inflow $I_{\text{tl_lt}}$ at time ttt is given by:

$$I_t = Q_t + M_t \quad (3)$$

Where Q_t is the runoff volume and M_t is the snowmelt volume.

The water demand data used in the model refer specifically to non-potable uses such as toilet flushing and washing machine operation. These data were collected from the HSB Living Lab over three years. Water demand data, particularly for non-potable uses such as toilet flushing and washing machine operation, was derived from a three-year average of normalized consumption patterns, measured using water meters installed on each individual micro consumer at the HSB Living Lab (see Table 1). These patterns reflect the temporal variability in water use, ensuring the simulation accurately represents daily, weekly, and seasonal changes in demand (see Figure 1).

The simulation model implemented in Python uses an advanced approach to manage stormwater runoff in a retention basin equipped with RTC. This method allows for the dynamic regulation of water discharge and enhances rainwater reuse potential by integrating hydrological processes with both simple and forecast-based control strategies.

The model's structure revolves around a simulation loop that processes hourly time steps across the input data. The choice to use hourly timestep was made to balance computational efficiency with the accuracy needed for hydrological processes in urban stormwater management. While sub-hourly resolution may capture rapid flow dynamics during intense rainfall events, the hourly timestep is appropriate for the scale of the study, given the available precipitation data and the typical response times of the retention basin. This choice ensures that the model can effectively simulate stormwater runoff, storage, and reuse without excessive computational complexity.

Precipitation and temperature data are loaded at the initialization phase, along with essential parameters such as basin characteristics (area, maximum storage, and discharge rate), snow accumulation and melt rate (based on a degree-day factor), and water demand for household uses like toilet flushing and washing machines. This hourly loop calculates demand, run-off (using the rational method), inflow to the basin, reuse, and adjusts for snow accumulation or melt.

Figure 1 shows the operational logic of the Python-based simulation model developed for the dynamic management of stormwater retention basins. A core feature of the model is the discharge control logic, which differentiates between simple

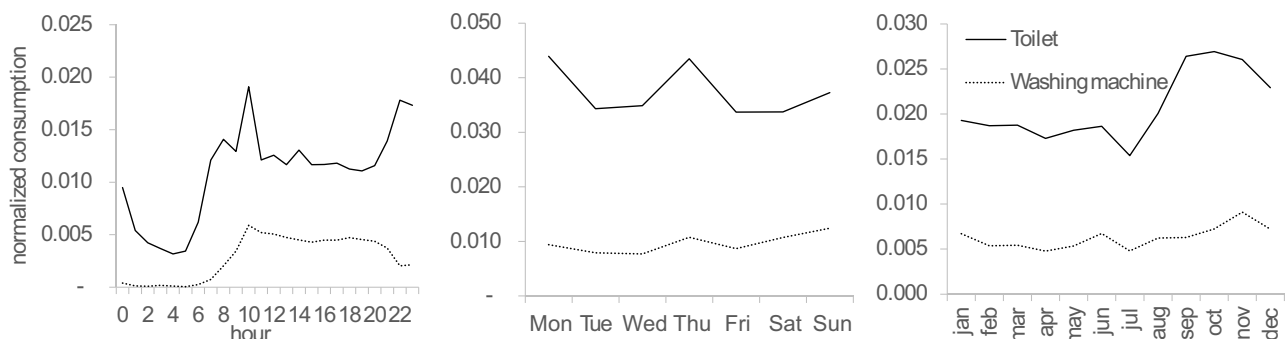


Figure 1. Graphs showing the temporal pattern of toilet and washing machine use normalized per hour, week day and month respectively, left to right.

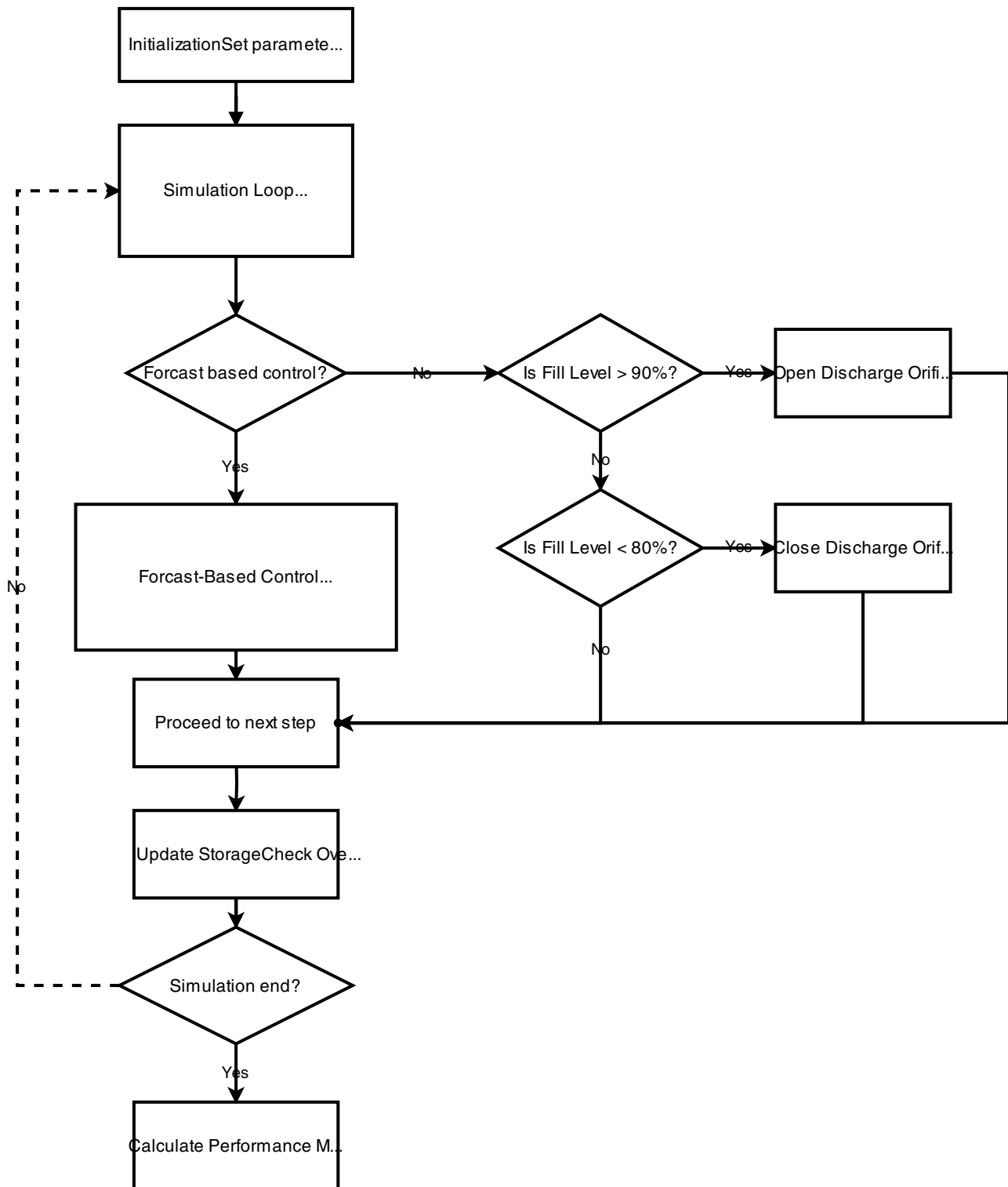


Figure 2. Flowchart depicting the logic of the Python-based simulation model for RTC detention basin management.

threshold-based control and forecast-based control. The simple control logic opens the discharge orifice when the basin fill level exceeds 90% and closes it when it drops below 80%. In contrast, the forecast-based control utilizes precipitation forecasts and storage availability to optimize discharge decisions, aiming to mitigate overflow risks while maximizing water reuse.

This model iterates through hourly time steps, executing a series of processes to calculate water demand, inflow, and reuse. In the model, the forecasted inflow is calculated by simulating probable precipitation using observed precipitation data, with adjustments for uncertainty through a noise factor. By factoring in future inflows and demands, the forecast-based control method

Table 1. Overview of input data used for the RTC model simulation. Precipitation and temperature data were obtained from the Swedish Meteorological and Hydrological Institute (SMHI) to model runoff, snow accumulation, and melt processes. Water use and demand data were sourced from the HSB living lab, representing normalized average non-potable water consumption over a three-year period.

Data set	Source/provider	Comment
Hourly precipitation (mm)	SMHI	Input for runoff and snow processes
Hourly air temperature (°C)	SMHI	Used to calculate snowmelt and accumulation
Water use/demand data	HSB Living Lab	Calculated from a three-year normalized average consumption data for non-potable uses such as toilet flushing and washing machines.

seeks to optimize stormwater management beyond the capabilities of static systems, making it more adaptive and resilient under varying hydrological conditions. This approach is especially relevant for multifunctional stormwater infrastructure where the balance between flood prevention and water reuse is a key concern.

Both control methods are integrated within the broader simulation loop, where each timestep involves updating storage levels, calculating overflows, and handling snowpack accumulation or melting based on the temperature data (see Figure 2). Once the simulation reaches the end of the time series, the model calculates performance metrics, including reuse efficiency and overflow volume, allowing for an evaluation of the system's effectiveness under different control strategies. The simulation code can be accessed through a public repository on Github (Knutsson 2024).

The performance assessment parameters and scoring methodology were meticulously designed to evaluate the effectiveness of the control strategies employed in the detention basin management. These parameters provided a comprehensive understanding of how well the system met its objectives of minimizing overflow and maximizing water reuse.

In order to evaluate the effectiveness of different basin control strategies, a multi-objective performance score. This score accounts for the dual goals of RTC detention basins: (1) minimizing overflow to prevent overloading downstream stormwater systems, and (2) maximizing water reuse by retaining water during non-storm events. The scoring system compares the RTC basin's performance against a baseline system, which is a detention basin discharging water continuously at a fixed rate. This baseline is assumed to minimize overflow at the expense of water reuse.

The performance score is composed of two normalized metrics: overflow management and water reuse. Each metric is weighted based on its relative importance to the system design. The overall score is designed to reward the basin control strategy that best balances reuse optimization without significantly compromising overflow management.

The overflow score is calculated by comparing the total overflow volume of the RTC basin to the baseline overflow volume. The closer the RTC basin's overflow is to the baseline, the higher the overflow score, with an ideal score of 1.0 indicating that the RTC basin matches or outperforms the baseline. The equation for normalized overflow score (O_n) is

$$O_n = \min\left(\frac{\text{Baseline overflow} + \epsilon}{\text{RTC overflow} + \epsilon}, 1\right) \quad (4)$$

where *Baseline Overflow* is the overflow volume from the business-as-usual (BAU) retention basin, *RTC Overflow* is the

overflow volume from the real-time controlled basin and ϵ is a small value, typically 0.1–1% of the maximum storage capacity of the simulated basin.

This adjustment ensures that when both the RTC and baseline overflow volumes are very small, the score calculation remains stable and prevents extreme penalties for minor differences.

The reuse score is calculated as the percentage of the total water demand that is met by the RTC basin. A higher reuse score reflects better utilization of stored water for non-potable purposes (e.g. toilet flushing). The score is normalized to range from 0 to 1, where 1 indicates that the RTC basin meets 100% of the reuse demand. The Equation for normalized reuse score (R_n) then is

$$R_n = \frac{\text{Total Actual Reuse}}{\text{Total Reuse Demand}} \quad (5)$$

where *Total Actual Reuse* is the volume of water reused from the basin and *Total Reuse Demand* is the theoretical water demand for reuse applications.

This approach allows us to prioritize overflow management or water reuse depending on the context. For instance, in flood-prone areas, overflow management may be assigned a higher weight, while in water-scarce regions, reuse may be more critical. The equation for total performance score (S_p) were:

$$S_p = w_o \cdot O_n + w_r \cdot R_n \quad (6)$$

where S_p is the total performance score and w_o and w_r are the weights assigned to overflow management and reuse, respectively. O_n is the normalized overflow score and R_n is the normalized reuse score. In this study, weights $w_o = 0.7$ and $w_r = 0.3$ were chosen to reflect the priority of flood mitigation in urban environments. This balance ensures that overflow prevention remains the primary objective while maximizing water reuse. However, in other management contexts other weights can be assigned to reflect local priorities.

This dual-objective evaluation framework helps stakeholders choose a strategy that optimally balances flood risk reduction and water resource management, depending on specific environmental or infrastructural priorities.

The case study used to test and demonstrate the RTC model is based on a residential property, Studio 1, located in Gothenburg, Sweden. The property was selected due to its urban setting, the current existence of a retention basin and the potential for integrating stormwater management with rainwater reuse for domestic purposes.

The basin volume was predetermined in accordance with local regulations, which mandate that properties must retain

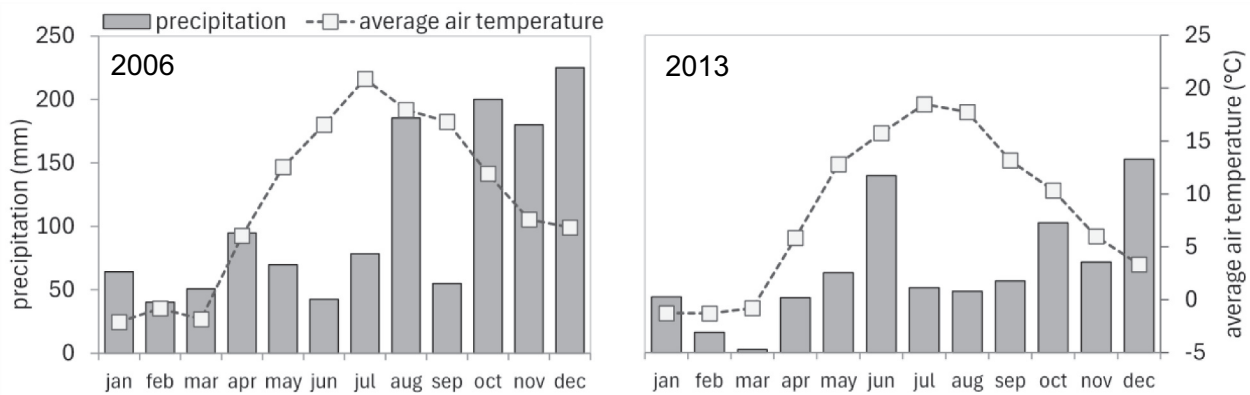


Figure 3. Monthly precipitation and average air temperature data used in the modeling simulations. The left panel represents the precipitation data (bars) alongside the average air temperature (line with square markers) for hydraulic year 1 (2006), while the right panel shows the corresponding data for hydraulic year 2 (2013). Precipitation is shown in millimeters (mm) and average air temperature in degrees Celsius (°C).

the first 10 mm of precipitation from any event. The maximum discharge rate was set to reflect the site's pre-development hydrological conditions, ensuring that the post-development stormwater discharge did not exceed the pre-development runoff rate.

The base daily water use was derived using demographic data for the property, which consists of 59 households. Based on statistical averages, the property is estimated to house 123 people, and the average total daily water use per person in Sweden is 140 liters.

A validation experiment was conducted to evaluate the performance of a rainwater harvesting system under controlled conditions. The experimental setup consisted of a scaled down roof area, water storage container, and automated measurement and control system, designed to simulate and monitor the collection, usage, and overflow of rainwater. The setup was scaled as to emulate the properties of the case study in the simulation. Location of the experimental setup was rural, south-west Sweden (latitude 57.508, longitude 13.408).

The experiment utilized a roof section clad with sheet metal, covering an area of approximately 5.6 m². This roofing material was selected to ensure consistent runoff characteristics. Rainwater runoff from the roof was directed into a High-Density Polyethylene (HDPE) container with a nominal storage capacity of > 100 liters.

An Arduino Uno R3 microcontroller was employed as the central processing unit for the system. The water level within the HDPE container was continuously monitored using an ultrasound sensor (JSN-SR04T/AJ-SR04M). This sensor provided real-time measurements of water depth (accuracy of ± 3 mm), allowing for monitoring of storage levels. A single 12V submersible pump, with a measured flow rate of 7.9 liters per minute (± 0.4 liters per minute, determined by 20 pumping cycles under different water depths and pump heights), was integrated into the system to emulate two key processes: (a) the reuse of stored water, specifically for toilet flushing purposes, and (b) the discharge of excess water based on forecasted precipitation and current water level in the container.

For the reuse emulation, the Arduino was programmed to start the pump once per hour, simulating the water demand for toilet flushing. The pump would operate for

a duration sufficient to mimic the typical volume of water used per flush, ensuring that the system accurately replicated the timing and volume of real-world toilet water use (a).

In addition to reuse, the system also managed overflow prevention by discharging excess water when necessary. The discharge pumping (b) was dynamically controlled based on both the current water level in the container and forecasted precipitation. Forecast precipitation data was obtained from the open-meteo.com API which was called from within the model script to return hourly forecast data of precipitation. The response returned (in json format) was processed in the script and used in the control logic.

The Arduino continuously monitored the water level and, using the forecast data, determined whether additional capacity was needed in the container to accommodate incoming precipitation.

To manage overflows, an overflow orifice was installed at a predetermined height within the container. Any excess water beyond the container's capacity was directed through this orifice and collected in a secondary container. The secondary container was regularly controlled and weighted to quantify the total volume of overflow, providing data on the system's efficiency in managing excess rainfall. The Arduino system logged data hourly to an SD card for subsequent analysis.

This experimental setup provided a controlled environment to assess the effectiveness of rainwater harvesting system components and control strategies, offering insights into the potential for scaling such systems in real-world applications.

Results

The performance of the RTC retention basin was evaluated using a simulation model applied to two distinct hydrological years: 2006 and 2013. These years represent contrasting precipitation patterns, allowing for a robust assessment of the system's performance under both wet and dry conditions (Figure 3). The results are presented in terms of overflow management, water reuse potential, and overall system performance, with comparisons made between FBC and rule-based control (RBC strategies).

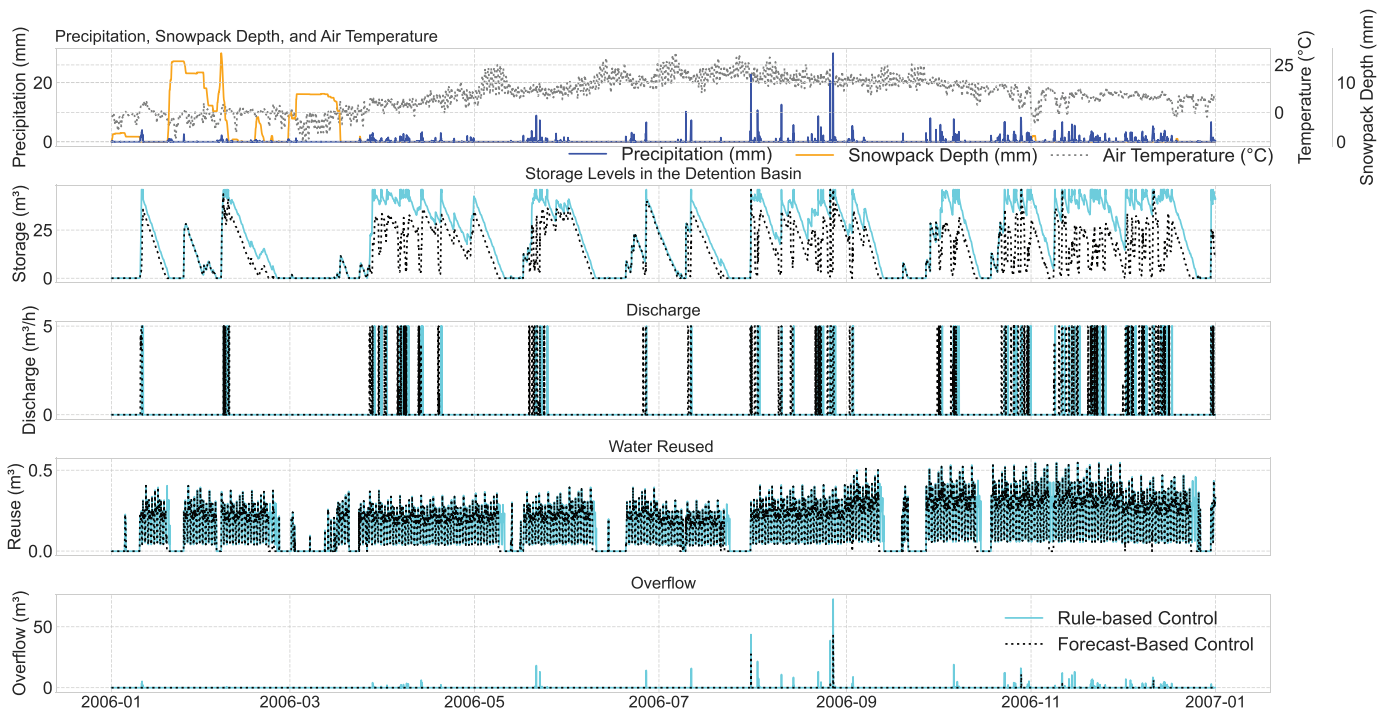


Figure 4. Comparison of rule-based (90/80% thresholds) and forecast-based control strategies for a retention basin in 2006. The top panel shows the precipitation (blue) and air temperature (grey), along with snowpack depth (orange), highlighting the snow accumulation and melt periods. Subsequent panels illustrate the detention basin's storage levels, discharge rates, water reuse volumes, and overflow occurrences under both control strategies.

Table 2. Comparison of control types (rule-based and forecast-based) for retention basins during the years 2006 and 2013. Key performance metrics are shown, including overflow volume, reuse volume, normalized overflow and reuse values, and the overall performance score. The performance score reflects a weighted balance between minimized overflow and maximized reuse.

Year	Control type	Overflow volume (m ³)	Reuse volume (m ³)	Normal-ized overflow	Normal-ized reuse	Perform-ance score	Open/close threshold
2006	Rule based	392.9	1331.4	0.88	0.96	0.895	0.9/0.8
2006	Rule based	343.1	1201.2	0.90	0.86	0.891	0.9/0.4
2006	Rule based	275.0	1089.3	0.92	0.78	0.895	0.8/0.2
2006	Rule based	279.3	1085.0	0.92	0.78	0.893	0.7/0.3
2006	Forecast based	151.5	1292.9	0.95	0.93	0.950	–
2013	Rule based	97.1	1154.6	0.95	0.83	0.932	0.9/0.8
2013	Rule based	61.8	1059.9	0.97	0.76	0.934	0.9/0.4
2013	Rule based	50.9	978.1	0.98	0.70	0.929	0.8/0.2
2013	Rule based	48.3	1008.4	0.98	0.72	0.934	0.7/0.3
2013	Forecast based	32.8	1151.6	0.98	0.83	0.957	–

Wet year performance

In 2006, which recorded 1286 mm of precipitation, FBC consistently outperformed RBC in key performance metrics, particularly in reducing overflow and stabilizing water reuse. The total overflow volume under FBC was reduced to 151.5 m³, significantly lower than the lowest overflow volume observed under RBC, which was 275.0 m³ (Figure 4). This reduction demonstrates FBC's ability to anticipate storm events and optimize discharges in response to forecasted inflows, ensuring effective flood mitigation.

In terms of water reuse, the total reused volume for FBC was 1292.9 m³, slightly lower than the 1331.4 m³ under RBC. However, FBC achieved a more stable and consistent reuse rate, particularly during peak storm events, optimizing reuse without compromising flood prevention. The overall performance score for FBC was 0.950, higher than RBC's best score of 0.895, reflecting FBC's

capacity to balance reuse and overflow prevention under wet conditions (Table 2).

Dry year performance

In the dry year of 2013, with only 790 mm of precipitation, FBC again demonstrated superior performance, particularly in managing water reuse under limited rainfall. The total overflow volume for FBC was 32.8 m³, compared to 48.3 m³ under RBC, with FBC outperforming RBC by dynamically managing storage and discharge in response to forecasted storm events (see Figure 5 and Table 2).

The reuse volume for FBC was 1151.6 m³, which exceeded RBC's best reuse volume of 1008.4 m³. The stable and consistent water reuse rate under FBC highlights its effectiveness in maximizing rainwater harvesting

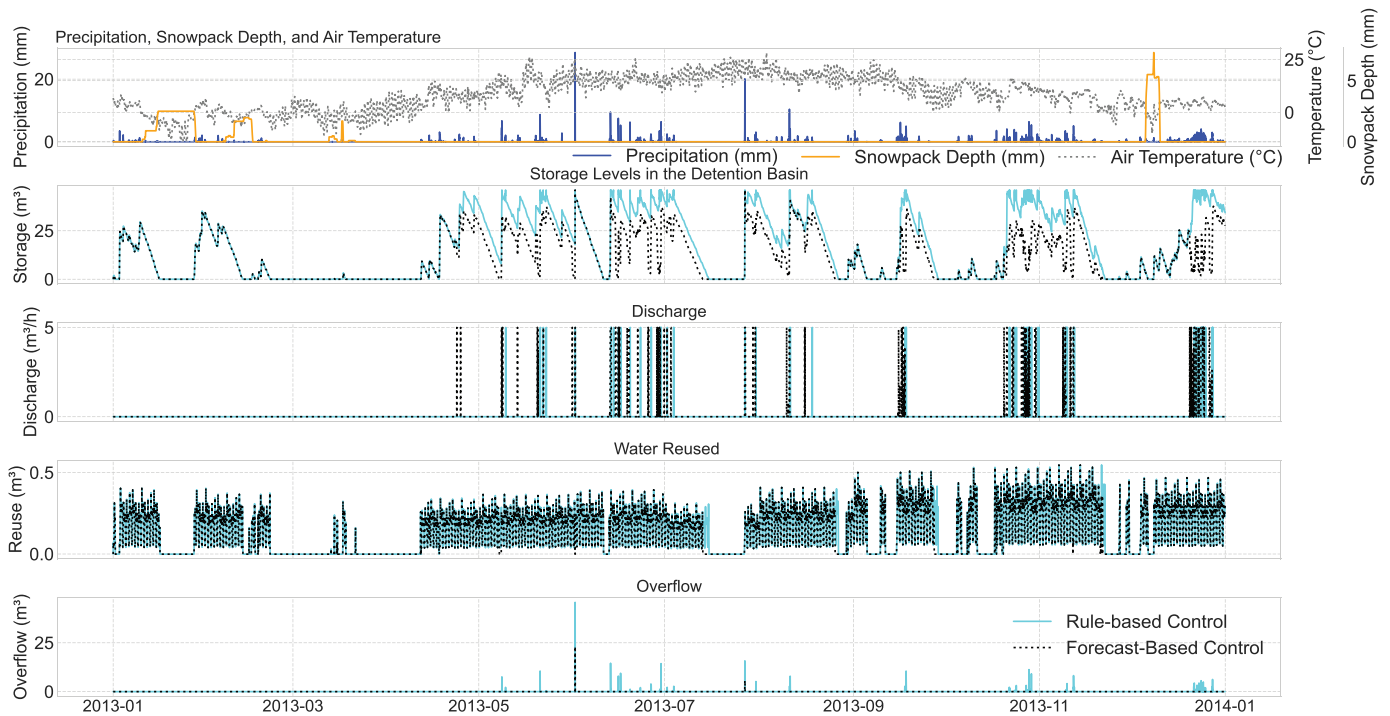


Figure 5. Long-term performance comparison of rule-based control and forecast-based control in a stormwater detention basin. The figure shows the system's response to precipitation, snowpack depth, and air temperature, with storage levels, discharge, water reuse, and overflow over the course of a year.

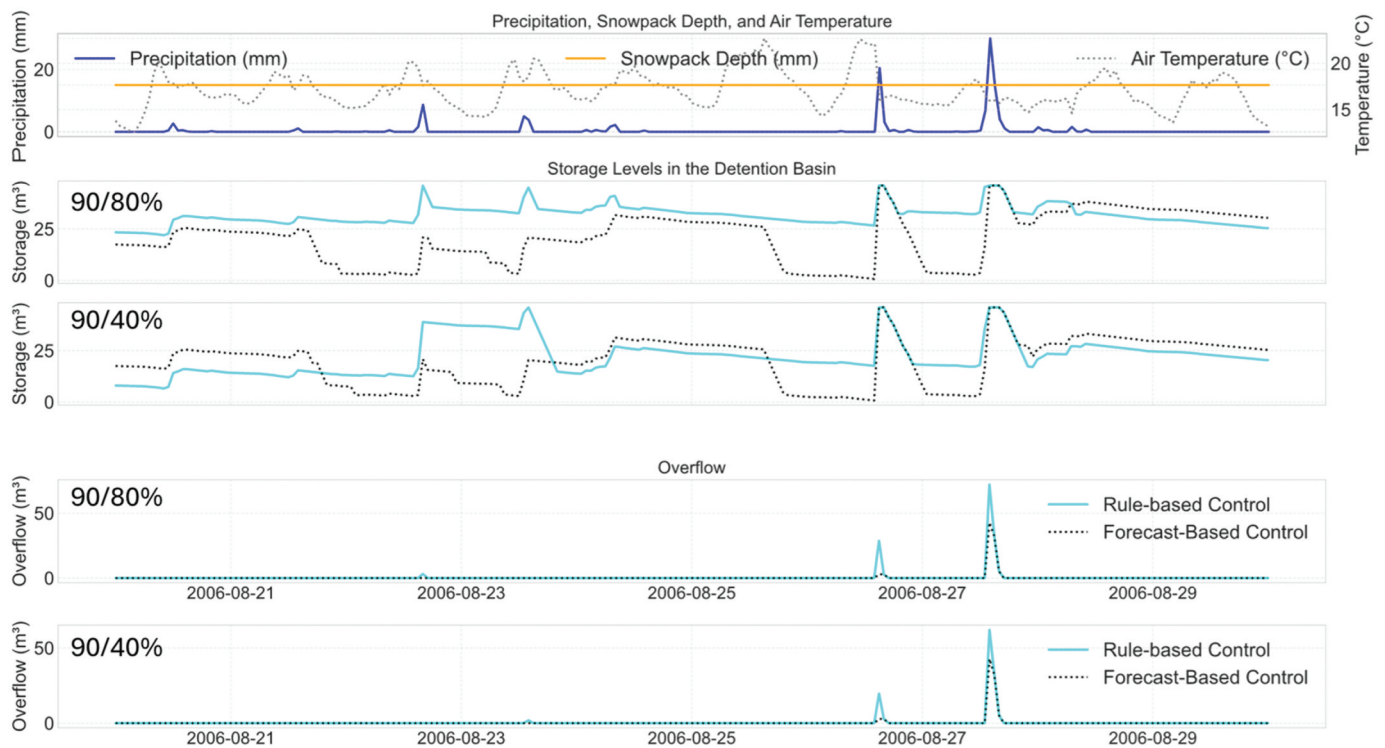


Figure 6. Comparison of rule-based and forecast-based control strategies for a retention basin during a two-week period in August 2006. The top panel shows precipitation, air temperature, and snowpack depth. The middle panels compare storage levels for two rule-based control thresholds (90/80% and 90/40%) with forecast-based control (dotted lines).

during dry periods. The performance score for FBC was 0.957, higher than RBC's score of 0.934, demonstrating FBC's ability to optimize both flood control and water reuse under drier conditions.

System performance across control strategies

Across both years, FBC consistently achieved higher performance scores compared to RBC, with FBC reducing overflow by up to 50% while maintaining high reuse volumes. This was especially evident during peak precipitation events in 2006 and dry spells in 2013, where FBC demonstrated superior adaptability in managing both stormwater and water reuse (Figure 6). By leveraging forecast data, FBC optimized system performance, balancing flood prevention with water harvesting for non-potable uses.

The results show that FBC is a more flexible and resilient strategy than RBC, making it a viable option for multifunctional retention basins in urban environments.

Validation experiment

A validation experiment was conducted to assess the accuracy of the simulation model in predicting basin levels, reuse volumes, and discharge events. The validation was performed using a scaled-down version of the system in a controlled environment, where observed and modeled results were compared.

Figure 7 illustrates the validation results for storage water levels and forecasted and observed precipitation. It's apparent from this that the actual precipitation over

the whole period exceeded the forecast data significantly (454.2 and 331.6 mm respectively). However, the top panel shows a strong correlation between observed and modeled water levels, indicating that the model effectively captures the dynamics of stormwater storage in the basin. Both time series show similar peaks and troughs, with minor discrepancies mainly caused by variations in forecasted and observed precipitation, as shown in the bottom panel.

The key results from the validation are shown in Table 3. The experimental setup demonstrated that the model was able to accurately capture the general dynamics of the basin, with some minor discrepancies. The reused volume was 0.678 m^3 in the experiment compared to 0.691 m^3 in the model, and the normalized reuse values were 0.92 and 0.90, respectively. The lower modeled reuse volume may be attributed to the simplified representation of pump operation in the model, which calculated reuse based on nominal pump flow rate and running time, potentially leading to an overestimation in the experimental setting.

This demonstrates that the forecast-based control system effectively mitigated flood risks in the experiment, corroborating the simulation results.

These validation results provide confidence in the model's capacity to simulate the real-world dynamics of retention basins and their control systems. The high correlation between observed and modeled basin levels further confirms the model's accuracy, making it a reliable tool for evaluating RTC strategies.

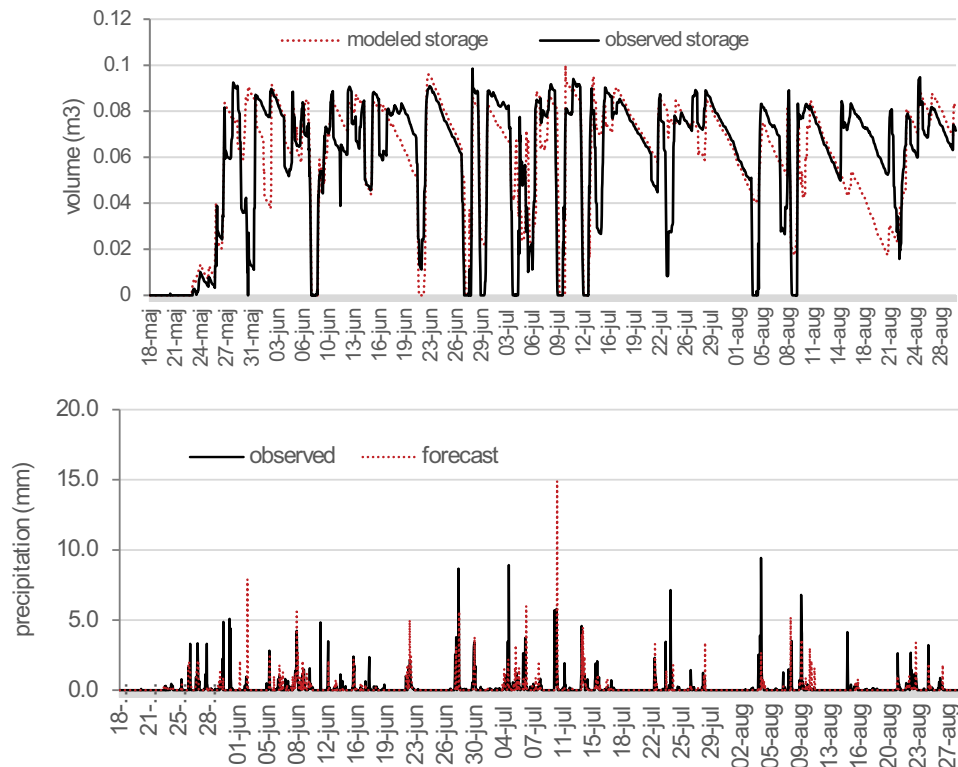


Figure 7. Comparison between observed and modelled storage level data for the real-time controlled retention basin over the period from May 18th to August 29th. The top panel shows the water level within the basin, with the modelled levels indicated by the red dashed line and the observed levels by the solid black line. The bottom panel shows the forecasted and observed precipitation during the experiment.

Table 3. Validation and model comparison of stormwater management performance. The table presents discharge volume, reused volume, normalized reuse, and overflow for both validation and model scenarios.

	Validation experiment	Model output
Discharge volume (m ³)	1.067	1.800
Reused volume (m ³)	0.691	0.678
Normalized reuse	0.92	0.90
Overflow (m ³)	0.016	0.000
Calculated inflow (m ³)	1.857	2.547
Performance score	0.317	0.971

Discussion

The results of this study highlight the significant potential of retrofitting existing stormwater retention basins with RTC mechanisms, transforming them into multifunctional infrastructure capable of both flood mitigation and rainwater reuse. By comparing FBC strategies with RBC and legacy BAU systems, we have demonstrated the effectiveness of RTC systems in optimizing the management of stormwater for dual purposes. The forecast-based approach, in particular, showed superior performance in balancing overflow prevention with water reuse, providing valuable insights into the future direction of urban water management practices.

Our findings align with earlier studies that underscore the advantages of real-time control in stormwater management. Kerkez et al. (2016) emphasized the role of smart stormwater systems in enhancing urban water resilience, and our results corroborate their observations by showing that FBC systems can significantly reduce overflow volumes while maximizing rainwater reuse. The 50% reduction in overflow volumes, as demonstrated in the Gothenburg case study, echoes similar results from urban drainage system research that explore RTC strategies (Wong 2017). However, this study advances the field by not only focusing on flood control but also integrating rainwater harvesting for non-potable reuse, which is an emerging topic in stormwater management literature (Luthy, Sharvelle, and Dillon 2019).

The clear reduction in overflow volumes in the FBC scenarios compared to BAU and RBC highlights the capacity of forecast-based methods to anticipate storm events and manage inflows preemptively. Previous research by Pumo et al. (2023) explored the importance of hydrological forecasting for drainage systems, and our results affirm that the integration of forecast data into control strategies can substantially improve both flood mitigation and resource conservation. By addressing reuse demand and preventing overflows simultaneously, this study contributes to the growing recognition of multifunctional infrastructure as a key component of sustainable urban water systems (Fletcher et al. 2015).

The study highlights an important trade-off in stormwater management between retaining water for reuse and ensuring sufficient storage capacity to mitigate flood risks. The FBC approach excelled in maintaining this balance by optimizing discharges in anticipation of forecasted precipitation. Compared to rule-based control, FBC consistently maintained lower overflow volumes without sacrificing reuse potential, meeting up to 95% of water demand in the validation case. In contrast, RBC systems, though effective in preventing overflow

during extreme events, often resulted in reduced reuse efficiency, reflecting the limitations of simpler control strategies that do not incorporate real-time forecasts.

The validation experiment demonstrated a high level of agreement between observed and simulated results. The model's ability in predicting overflow events, as evidenced by the normalized overflow values (0.92 for observed vs. 1.00 for the model), underscores the reliability of the RTC approach in practical applications. The minor discrepancies in reused volume (92% observed vs. 90% modeled) could be attributed to mainly to difference between forecast and actual precipitation.

The sensitivity analysis revealed that increasing forecast uncertainty led to noticeable declines in reuse efficiency, overflow prevention, and overall system performance, which is to be expected when applying a deterministic approach to model a probabilistic phenomenon. When forecast accuracy decreased, reuse demand met dropped from 95% to approximately 92%, while overflow volumes spiked in scenarios with greater uncertainty (e.g. an increase from 152 m³ to 156 m³ at a 0.4 uncertainty scale). This finding is consistent with other studies that have shown how the accuracy of hydrological forecasts directly influences the efficacy of real-time control strategies (Lund et al. 2018). Despite the performance degradation under higher uncertainty, the FBC system still maintained better overall performance compared to rule-based control, demonstrating its robustness in less-than-ideal forecasting conditions.

However, incorporating predictive uncertainty would improve the robustness and applicability of water management systems. As Bertoli, Balzarolo, and Todini (2022) demonstrated, probabilistic forecasts integrated with stochastic dynamic programming (SDP) effectively account for future uncertainties, enabling optimized decision-making under complex scenarios (Bertoli, Balzarolo, and Todini 2022). Similarly Coccia and Todini (2011), emphasized Bayesian updating and ensemble forecasting as pivotal tools for managing reservoir systems under uncertain inflow predictions (Coccia and Todini 2011). By leveraging Bayesian model calibration, as outlined in Draper and Krnjajic (2010), we can refine predictive accuracy and further mitigate uncertainty effects (Draper and Krnjajic 2010). These techniques align with the objectives of this study, enhancing the decision-making capabilities of the proposed model. Future work will include implementing ensemble-based forecasts and Bayesian updating to quantify uncertainty at various stages, ensuring more reliable system performance under changing climatic and operational conditions.

The broader implications of this study lie in the feasibility of repurposing existing stormwater retention basins into multifunctional systems that can serve both flood control and water reuse needs. As cities worldwide face increasing pressures from climate change, including more frequent and intense rainfall events, the need for adaptable, resilient urban water infrastructure has never been greater. Retrofitting existing infrastructure, rather than building new systems from scratch, offers a resource-efficient and cost-effective solution for municipalities. By integrating RTC systems, these basins can be

transformed into dual-purpose assets that reduce reliance on potable water sources, particularly for non-potable uses such as toilet flushing and irrigation, while maintaining their original flood prevention function.

From an environmental perspective, the shift towards multifunctional stormwater management infrastructure aligns with the principles of water-sensitive urban design (WSUD) and low-impact development (LID), both of which advocate for sustainable, decentralized water management solutions (Fletcher et al. 2015). Economically, the potential savings from reduced infrastructure costs, combined with the benefits of lower potable water consumption, make the case for retrofitting existing retention basins compelling. This study provides a foundation for further research into the optimization of RTC systems, particularly in terms of improving forecast accuracy and integrating advanced demand prediction models.

While the results of this study are promising, several areas of future research are warranted. First, improving the precision of hydrological forecasts, possibly through the integration of machine learning techniques, could further enhance the performance of RTC systems. Additionally, expanding the model to account for varying urban conditions, such as differing runoff coefficients and basin geometries, would increase its applicability to a wider range of urban environments. Finally, a cost-benefit analysis of retrofitting retention basins with RTC systems versus traditional stormwater management approaches would provide valuable insights into the long-term economic feasibility of this approach.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Jesper Knutsson  <http://orcid.org/0000-0002-1622-2009>

Data availability statement

The data that support the findings of this study are available from the corresponding author, JK, upon reasonable request.

References

- Abou Rjeily, Y., O. Abbas, M. Sadek, I. Shahrou, and F. Hage Chehade. 2018. "Model Predictive Control for Optimising the Operation of Urban Drainage Systems." *Journal of Hydrology* 566:558–565. <https://doi.org/10.1016/j.jhydrol.2018.09.044>.
- Bertoli, L., D. Balzarolo, and E. Todini. 2022. "On the Benefits of Collaboration Between Decision Makers and Scientists: The Case of Lake Como." *Hydrology* 9 (11): 187. <https://doi.org/10.3390/hydrology9110187>.
- Coccia, G., and E. Todini. 2011. "Recent Developments in Predictive Uncertainty Assessment Based on the Model Conditional Processor Approach." *Hydrology and Earth System Sciences* 15 (10): 3253–3274. <https://doi.org/10.5194/hess-15-3253-2011>.
- Draper, D., and M. Krnjajic. 2010. "Calibration Results for Bayesian Model Specification." *Bayesian Analysis* 1 (1): 1–43.
- Eggimann, S., L. Mutzner, O. Wani, M. Y. Schneider, D. Spuhler, M. Moy de Vitry, P. Beutler, and M. Maurer. 2017. "The Potential of Knowing More: A Review of Data-Driven Urban Water Management." *Environmental Science & Technology* 51 (5): 2538–2553. <https://doi.org/10.1021/acs.est.6b04267>.
- Fletcher, T. D., W. Shuster, W. F. Hunt, R. Ashley, D. Butler, S. Arthur, S. Trowsdale, et al. 2015. "SUDS, LID, BMPs, WSUD and More—The Evolution and Application of Terminology Surrounding Urban Drainage." *Urban Water Journal* 12 (7): 525–542. <https://doi.org/10.1080/1573062X.2014.916314>.
- Gelormino, M. S., and N. L. Ricker. 1994. "Model-Predictive Control of a Combined Sewer System." *International Journal of Control* 59 (3): 793–816. <https://doi.org/10.1080/00207179408923105>.
- Gomes, M. N., A. F. Taha, Luis Miguel Castillo. Rápalo, E. M. Mendiando, and M. H. Giacomoni. 2024. "Real-Time Regulation of Detention Ponds via Feedback Control: Balancing Flood Mitigation and Water Quality." *Journal of Hydrology* 643:131866. <https://doi.org/10.1016/j.jhydrol.2024.131866>.
- Goonetilleke, A., A. Liu, and T. Gardner. 2016. Briefs for GSDDR - Urban Stormwater Reuse: An Agenda for Sustainable Development. *UN Global Sustainable Development Report*.
- Kerkez, B., C. Gruden, M. Lewis, L. Montestruque, M. Quigley, B. Wong, A. Bedig et al. 2016. Smarter Stormwater Systems. *Environmental Science & Technology*, 50 (14): 7267–7273.
- Knutsson, J. 17 september 2024. *RTC-Stormwater-Retention-Basin GitHub Repository*. (GitHub). <https://github.com/jespknut/RTC-stormwater-retention-basin>.
- Knutsson, J., and P. Knutsson. 2021. "Water and Energy Savings from Greywater Reuse: A Modelling Scheme Using Disaggregated Consumption Data." *International Journal of Energy and Water Resources* 5 (1): 13–24. <https://doi.org/10.1007/s42108-020-00096-z>.
- Knutsson, J., and C. Marx. 2016. "The Habitation Lab as a Platform for Sustainable Innovations in the Built Environment: A Case Study." In *16th International Multidisciplinary Scientific GeoConference*, June 28 - July 6. 317–324. Albena, Bulgaria: SGEM2016 Conference Proceedings.
- La Torre Rapp, V., J. Knutsson, and J. Wallin. 2024. "Stakeholder-Driven Development of a Decision Support Framework Targeting Sustainable Water Supply Systems." *Energy Reports* 12:2306–2320. <https://doi.org/10.1016/j.egy.2024.08.030>.
- Lazarova, V., B. Levine, J. Sack, G. Cirelli, P. Jeffrey, H. Muntau, M. Salgot, et al. 2001. "Role of Water Reuse for Enhancing Integrated Water Management in Europe and Mediterranean Countries." *Water Science and Technology* 43 (10): 25–33. <https://doi.org/10.2166/wst.2001.0571>.
- Lund, N. S. V., Anne Katrine Vinther, Falk, M. Borup, H. Madsen, and P. Steen Mikkelsen. 2018. "Model Predictive Control of Urban Drainage Systems: A Review and Perspective Towards Smart Real-Time Water Management." *Critical Reviews in Environmental Science and Technology* 48 (3): 279–339. <https://doi.org/10.1080/10643389.2018.1455484>.
- Luthy, R. G., S. Sharvelle, and P. Dillon. 2019. "Urban Stormwater to Enhance Water Supply." *Environmental Science & Technology* 53 (10): 5534–5542. <https://doi.org/10.1021/acs.est.8b05913>.
- Mullapudi, A., M. J. Lewis, C. L. Gruden, and B. Kerkez. 2020. "Deep Reinforcement Learning for the Real Time Control of Stormwater Systems." *Advances in Water Resources* 140:103600. <https://doi.org/10.1016/j.advwatres.2020.103600>.
- Mullapudi, A., B. P. Wong, and B. Kerkez. 2017. "Emerging Investigators Series: Building a Theory for Smart Stormwater Systems." *Environmental Science: Water Research & Technology* 3 (1): 66–77. <https://doi.org/10.1039/C6EW00211K>.
- Pumo, D., A. Francipane, F. Alongi, and L. V. Noto. 2023. "The Potential of Multilayer Green Roofs for Stormwater Management in Urban Area Under Semi-Arid Mediterranean Climate Conditions." *Journal of Environmental Management* 326:116643. <https://doi.org/10.1016/j.jenvman.2022.116643>.

- Schmitt, Z. K., C. C. Hodges, and R. L. Dymond. 2020. "Simulation and Assessment of Long-Term Stormwater Basin Performance Under Real-Time Control Retrofits." *Urban Water Journal* 17 (5): 467–480. <https://doi.org/10.1080/1573062X.2020.1764062>.
- Swedish Meteorological, and Hydrological Institute. 2024. SMHI Meteorological Observations Data Download. <https://www.smhi.se/data/meteorologi/ladda-ner-meteorologiska-observationer>.
- van Duin, B., D. Z. Zhu, W. Zhang, R. J. Muir, C. Johnston, C. Kipkie, G. Rivard, et al. 2021. "Toward More Resilient Urban Stormwater Management Systems—Bridging the Gap from Theory to Implementation." *Frontiers in Water* 3. <https://doi.org/10.3389/frwa.2021.671059>.
- Wong, B. P. 2017. *Real-Time Measurement and Control of Urban Stormwater Systems*. Ann Arbor, MI: University of Michigan.