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OVERVIEW

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Smart management of combined sewer overflows: From an ancient technology to artificial intelligence

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Abstract

Sewer systems are an essential part of sanitation infrastructure for protecting human and ecosystem health. Initially, they were used to solely convey stormwater, but over time municipal sewage was discharged to these conduits and transformed them into combined sewer systems (CSS). Due to climate change and rapid urbanization, these systems are no longer sufficient and overflow in wet weather conditions. Mechanistic and data-driven models have been frequently used in research on combined sewer overflow (CSO) management integrating low-impact development and gray-green infrastructures. Recent advances in measurement, communication, and computation technologies have simplified data collection methods. As a result, technologies such as artificial intelligence (AI), geographic information system, and remote sensing can be integrated into CSO and stormwater management as a part of the smart city and digital twin concepts to build climate-resilient infrastructures and services. Therefore, smart management of CSS is now both technically and economically feasible to tackle the challenges ahead. This review article explores CSO characteristics and associated impact on receiving waterbodies, evaluates suitable models for CSO management, and presents studies including above-mentioned technologies in the context of smart CSO and stormwater management. Although integration of all these technologies has a big potential, further research is required to achieve AI-controlled CSS for robust and agile CSO mitigation.

This article is categorized under:

Abbreviations: ANFIS, adaptive neuro-fuzzy inference system; AI, artificial intelligence; ANN, artificial neural network; ArcGIS, aeronautical reconnaissance coverage geographic information system; CANOE, Logiciel Intégré de Conception et de Diagnostic des Réseaux d'Assainissement; CCTV, closed circuit television; COD, chemical oxygen demand; CSO, combined sewer overflow; CSS, combined sewer systems; DL, deep learning; GA, genetic algorithm; GIS, geographic information system; InfoWorks CS, InfoWorks combined sewer; InfoWorks ICM, InfoWorks integrated catchment modeling; LID, low-impact development; LULC, land use land cover; ML, machine learning; MLP, multilayer perceptron; MPC, model predictive control; NSGA-II, nondominated sorting genetic algorithm II; PSO, particle swarm optimization; RF, random forests; RTC, real-time control; SCP, sponge city program; SIMDEUM, simulation of water demand, and end-use model; SVMs, support vector machines; SWMM, storm water management model; TREX, two-dimensional runoff, erosion, and export model; TRENOE, TREX-CANOE; TSS, total suspended solids; WWTP, wastewater treatment plant.

Engineering Water > Sustainable Engineering of Water
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KEYWORDS
artificial intelligence, combined sewer overflow, geographic information system, remote sensing, sewer system modeling, smart management

1 | INTRODUCTION

The history of urban water supply and sanitation can be traced back to the Bronze Age (ca. 3200–1100 BC) in Crete, Aegean islands, and Indus valley civilizations (Angelakis & Zheng, 2015; De Feo et al., 2014). For example, the planned city of Mohenjo-Daro (Sindh, Pakistan), established around 2450 BC, contained at least 700 wells, bathrooms in the houses, sewers in the streets, and thermal baths. Furthermore, sewerage and drainage systems were used in Prehistoric Greece since in the early Bronze Age (Ahmed et al., 2020). The palace of Minos at Knossos (Greece) included sewage and rainwater drains that flowed beneath the majority of the palace. In addition, rainwater gathered from the rooftops was directed to the bathrooms on the top floor. Drainage systems were typically constructed with dressed stones that were large enough to be cleaned and maintained and airshafts were used to ventilate sewers. The sanitary and stormwater sewers constructed 4000 years ago in the Vila of Hagia Triada (Greece) appears to be the most advanced ancient Minoan drainage and sewerage system (Gikas & Angelakis, 2009).

Historically, conduits were constructed for stormwater management. They were used for the collection and conveyance of stormwater to the nearest waterbody. Over time, domestic wastewater was discharged into these drains transforming them into combined sewers. These systems were extensively used since they required a lower investment in their construction than that of separate storm and sanitary sewers (Bohannon & Lin, 2005; Field & Struzeski, 1972; Li et al., 2014). Combined sewer systems (CSS; Bohannon & Lin, 2005; Butler et al., 2018; Field & Struzeski, 1972; Sartor & Boyd, 1972) are collection and drainage facilities that transport domestic, industrial, and commercial wastewater and stormwater through a single pipeline. However, population growth, intense urbanization, and increased frequency of extreme precipitations due to climate change made CSS insufficient. In wet weather, the collected urban wastewater and runoff lead to an increase in flow that can exceed the end-of-pipe wastewater treatment plant (WWTP) capacity. The excess water, called combined sewer overflow (CSO), significantly contributes to water pollution, and adversely affects human health and receiving water bodies (Bohannon & Lin, 2005; Burm et al., 1968; Field & Struzeski, 1972; Goore Bi et al., 2015; He & Marsalek, 2009; Li et al., 2010). Consequently, during heavy rains, once CSSs overflow, untreated effluent is discharged into surrounding receiving waters using bypass line within the WWTP. The sewer system would surcharge if there is no way of releasing the pressure, and sewage would back up into buildings, block storm drains, and flood streets. In this context, extending WWTP capacities and redesigning sewer systems by separating storm water conduits and domestic wastewater pipes can be considered as options to deal with the overflows (Figure 1). However, enlarging WWTP capacities and sewer system renewal might to not be feasible due to changes in land use over the pipe lines, land restrictions in heavily urbanized regions, and simply economic reasons (Field & Struzeski, 1972). After recognition of sanitation problems associated with CSOs, the modern urban drainage systems were mainly designed according to the separation of the wet and dry weather flows principle. In separated sewer systems, as illustrated in Figure 1, wastewater is conveyed with separated sewers from stormwater. During dry weather conditions where there is no precipitation, the separated sewer system will only carry wastewater. However, in wet weather conditions where precipitation happens in terms of heavy rains and snow, the separated sewer system conveys wastewater to the WWTP, and the separated stormwater system carries the runoff to the nearest waterbody.

Reaching a worldwide data regarding the type and length of the sewer systems is impossible due to several factors including the unwillingness of some organizations to make this data public in some countries. However, within this article, the intent was to collect as much data as possible to relate the sewer network type with the development status of the countries. In Europe, an average sewer network length of 6.7 m is connected per capita (EurEau, 2021). This value substantially differs from country to country. For instance, this value is greater than 11 m in Finland and less than 3 m in Bulgaria. Combined sewers comprise 70% of the length of sewer systems in France, Germany, and the UK and 45% of the total length of sewers in Denmark (Butler et al., 2018). In Italy, the sewer network is 100% combined sewers (EurEau, 2021). China's sewer network consists of 192,100 km of sanitary sewer, 211,200 km of storm sewer,

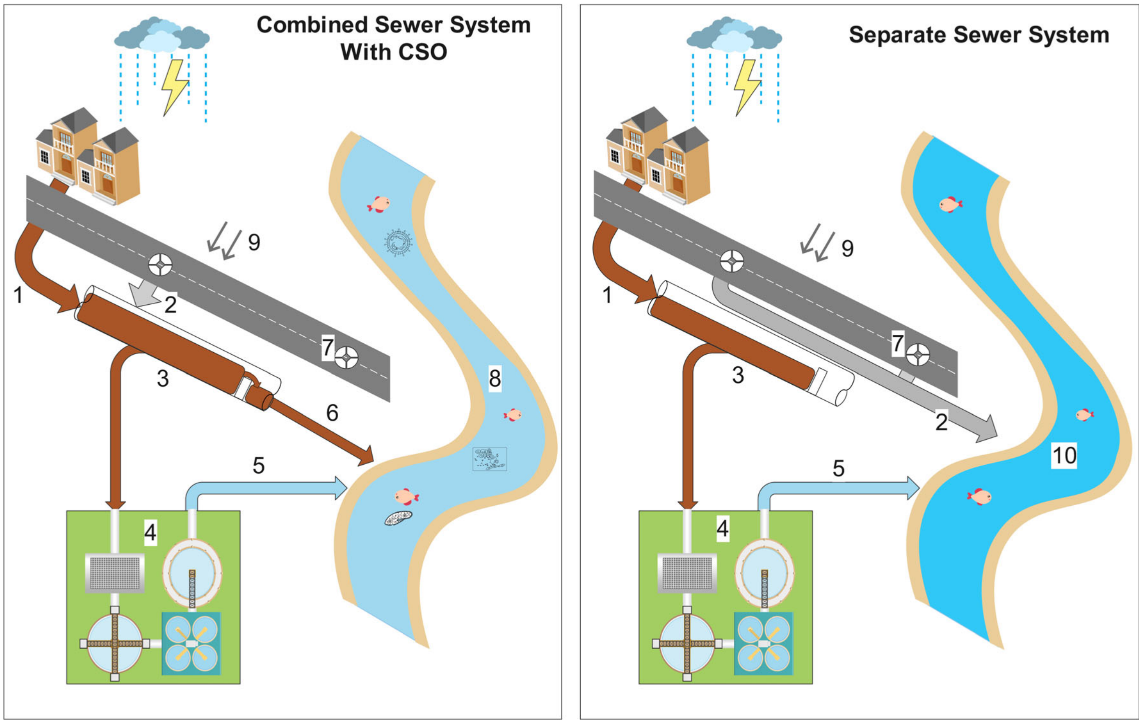

FIGURE 1 Combined and separate sewer system. 1—Wastewater; 2—stormwater; 3—CSS; 4—WWTP; 5—WWTP discharge; 6—WW bypass; 7—manhole; 8—polluted receiving waterbody; 9—urban runoff; 10—receiving waterbody

and 107,900 km of combined sewer. Thus, combined sewers account for 21% of the total system (Huang et al., 2018). In Ireland, the estimated length of the sewer system is 25,000 km, with the majority of combined pipes being built in metropolitan areas where stormwater comes into the sewers (IrishWater & Ervia, 2015). This can result in flooding incidents during heavy rains, overflows into rivers and streams, and an increased load and capacity conveyed to wastewater treatment plants and infrastructure.

In Chicago, 100% of the 8000 km sewer network is reported to be combined sewer (Lossouarn et al., 2016). The CSS ratio in New York is reported to be 60% (in a city with 12,070 km of sewerage infrastructure) and in Paris, this ratio is 66% (of 3200 km of sewerage infrastructure; Lossouarn et al., 2016). The length of the sewer network in Beijing, Buenos Aires, London, Los Angeles, and Tokyo are 14,290, 11,000, 21,720, 10,780, and 16,000 km, respectively (Lossouarn et al., 2016). In Istanbul, both combined and separate systems are being used (Samsunlu, 2020). Currently, a total of 30,609 km of sewer network and 4621 km of stormwater system are being used in Istanbul for urban water management and an additional 4649 km of stormwater pipes is required. The data available in the literature of some countries and megacities supports the fact that combined sewers represent a significant proportion of the network in developed countries.

CSO increases the concentration of pathogens, toxic substances, bacteria, solids, and debris in the receiving water bodies (McGinnis et al., 2022; Miller Alyssa et al., 2022; Whelan et al., 2022). Moreover, as a result of the decrease in the oxygen level due to the degradable organic matter, it creates important public health, aquatic organism stress, and water quality concerns (Bohannon & Lin, 2005; Field, 1985; House et al., 1993; Mailhot et al., 2015). The water quality concern brought the requirement of legislations such as the urban wastewater treatment directive (UWWTD; EC, 1991) and WFD (EC, 2000) to control CSO pollution in Europe. CSO characteristics were discussed in several studies (Botturi et al., 2020; García et al., 2017; Li et al., 2010). CSO characteristics are primarily reported as total suspended solid, organic matter, total nitrogen and phosphorous, heavy metals, and microbial pollution in literature (Table 1). Sandoval et al. (2013) indicated that CSO quantity is mostly determined by the maximum rainfall intensity, whereas CSO pollutant concentrations are primarily influenced by the rainfall duration. Additionally, CSO pollutant loads are mainly affected by the dry weather duration preceding the rainfall (Sandoval et al., 2013).

In terms of impact on the water quality of a receiving stream, untreated overflows from combined sewers were proven to be a significant pollution source, particularly during wet weather as runoff collects several pollutants

TABLE 1 Combined sewer system overflow characteristics

Study location	TSS (mg/L)	BOD_5 (mg/L)	COD (mg/L)	TN (mg/L)	TP (mg/L)	Cd (μg/L)	Cu (μg/L)	Pb (μg/L)	Zn (μg/L)	*E. coli* (100 ml)	References
Europe	105–721	39.9–200	148–530	2.1–14.4	2.4–4.0	1.1–9.6	37–170	42–450	357–1070	10^7–10^8	(Ferrier & Jenkins, 2009)
United States	237–635	43–95	120–560	2.9–4.8	–	–	–	150–290	–	–	(Ferrier & Jenkins, 2009)
United Kingdom	425	90	260–507	8.3	10	–	–	250	870	10^6–10^8	(Ferrier & Jenkins, 2009)
Canada	190	–	–	8.3	1.4	–	–	–	–	–	(Ferrier & Jenkins, 2009)
Santiago de Compostela, Spain	160–411	70.5–171	134–540	–	0.5–4.6	–	–	0.4–14	44–123	–	(Diaz-Fierros etal., 2002)
Slovakia	430	175	445	16.8	2.63	<0.02	<0.50	<0.20	0.57	1.3×10^5	(Sztruhár et al., 2002)
Paris, France	135–353	36–180	136–446	–	1.2–5.4	–	–	–	–	–	(Gasperi et al., 2012)
Germany	174.5	60	141	12.6	1.25	1.4	97.5	70	280	–	(Brombach et al., 2005)
Korea	73.5–1021.3	77–129.7	163–368.7	–	5–10.2	–	–	10–490	–	–	(Lee & Bang, 2000)
Shanghai, China (Combined)	91–529	111–178	243–484	–	–	–	–	–	–	–	(Li et al., 2010)

Abbreviations: BOD_5, 5-day biochemical oxygen demand; Cd, cadmium; COD, chemical oxygen demand; Cu, copper; *E. coli*, *Escherichia coli*; Pb, lead; TN, total nitrogen; TP, total phosphorous; TSS, total suspended solid; Zn, zinc.

generated via different urban pollution sources (Bohannon & Lin, 2005; Burm et al., 1968; Field & Struzeski, 1972; Li et al., 2010). Mean concentrations of micropollutants such as heavy metals, polycyclic aromatic hydrocarbons (PAH), pesticides, pharmaceuticals, benzotriazoles, sweeteners, and phthalates were measured for more than 110 overflow events at 10 CSO facilities across Bavaria, Germany (Nickel & Fuchs, 2019). The results indicated that CSOs must be incorporated in discussions on micropollutant emissions, and that knowledge of their concentrations at a regional level must be strengthened. CSOs, in comparison to wastewater treatment plants, are a significant source of pollution and cause failure to achieve good chemical status of surface waters.

CSO management has become a challenge. Many researchers have sought to address this through proactive actions comprising problem prevention at its source, problem quantification and risk analysis, and reactive actions including solving the problem prior to further deterioration. Much of the literature on CSO and stormwater (Ahammed, 2017; Botturi et al., 2020; Imran et al., 2013; Shishegar et al., 2018) concentrates on a single point of view, for example, stormwater models or real-time control (RTC) applications in sewer system management (Creaco et al., 2019; Lund et al., 2018; van Daal et al., 2017; van der Werf et al., 2022; Wang & Xie, 2018). Amidst such studies, Garzón et al. (2022) reviewed recent articles on machine learning-based surrogate modeling for urban water networks (Garzón et al., 2022). Rizzo et al. (2020) surveyed constructed wetlands (CWs) for CSO treatment. Their survey described the current treatment schemes through a literature analysis, discussed the treatment performance of standard pollutants, micropollutants, and microbial contamination, presented a summary of modeling studies, and emphasized additional ecosystem services that can be ensured by CSO-CWs (Rizzo et al., 2020). A comprehensive systematic review on impact of sewer overflow on public health by Sojobi and Zayed (2022) aimed to identify the most significant studies and researchers involved in the study of sewer overflows and public health, and mark significant and emerging research gaps (Sojobi & Zayed, 2022). However, environmental issues are often interrelated, so CSO management should be contemplated as a multi-perspective problem. Therefore, researchers from different disciplines need to work together to tackle the challenge with a holistic approach. Within the context of this approach, building collaboration between key disciplines to identify issues of concern and research gaps plays an important role. Problem characterization and proposing solutions require significant knowledge of management science and engineering which includes a multidisciplinary understanding of hydrology, hydraulics, geographical information systems, meteorology, computer science, and so forth. Therefore, the adopted holistic approach which contemplates the problem from different angles will address the existing gaps in the literature for more sufficient and effective management of CSO.

The primary objective of this study is to present a comprehensive review of the role of mechanistic and data-driven modeling in CSO management. We present a brief historical outlook of sewer systems evolving with the needs of mankind and technological advances starting with simple conduits and extending to artificial intelligence (AI), geographic information systems (GIS), and remote sensing (RS). This review:

- acknowledges CSO characteristics and associated impact on receiving waterbodies;
- evaluates suitable models for CSO management;
- presents GIS and RS applications studies and identifies gaps that could be fulfilled through the use of these cutting-edge technologies; and
- presents studies about CSO and stormwater smart management applications in the context of sustainable urban water management.

2 | MECHANISTIC MODELING

There are many models used for CSO and stormwater modeling including open-source and commercial packages. Commercial models are generally more user-friendly and easier to apply. The main disadvantages of these models are the cost and the lack of flexibility in accommodating users' specific needs. Open-source models can be used in many studies at no cost and the users can access the functions programmatically (being more flexible) and can have a better insight into the processes happening in the background. The advancement in technology over time improved measurements and computational techniques. However, these models still only represent an approximation of physical situations due to the involved complex processes. Within this study, widely used and comprehensive open-source and commercial models are briefly presented. Table 2 provides a summary and comparison of research integrating modeling for CSO and stormwater management.

TABLE 2 Studies integrating modeling for CSO and stormwater management

Objectives of the study	Investigated area	Model	Low-impact development (LID)	Smart management	References
• Identifying the proportion of errors and uncertainty caused by the modeler's discrepancies in the description of specific structures.	Lyon, France	Logiciel Intégré de Conception et de Diagnostic des Réseaux d'Assainissement (CANOE)	–	–	(Garcia-Salas & Chocat, 2006)
• SWMM application to assess hydrological changes in an urbanizing catchment.	Espoo, Southern Finland	SWMM	Rain barrel Porous pavement Storage unit	–	(Guan et al., 2015)
• Carrying on sensitivity analyses of the SWMM and SWMM-H models, and ideal parameter values identification using rainfall-runoff data from a pilot-scale green roof system. • Comparing the two models by simulating soil moisture and capacity assessment of the module in runoff simulation for an urban area-dominated subbasin.	Ulsan, South Korea	SWMM, HYDRUS	Green roof	–	(Baek et al., 2020)
• Pump start-up/shutoff times reduction in multistage drainage pumping stations.	Beijing, China	SWMM	–	Particle swarm optimization (PSO)	(H. Wang, Lei, et al., 2019)
• Employing the storage capability of the sewer system to effectively reduce CSO and flooding.	Cosenza, Italy	SWMM	–	Decentralized real-time system based on a gossip-based algorithm	(Garofalo et al., 2017)
• Stormwater control measures ability evaluation on impact of stormwater flooding in a preurban catchment by integrating a one-dimensional (1D) stormwater drainage model with a two-dimensional (2D) overland flow model	Melbourne, Australia	SWMM, BreZo	Rain tanks Infiltration trenches	–	(Burns et al., 2015)
• Adding new modeling techniques for two best management practices, rain gardens, and rain barrels, to SWMM.	Not mentioned	SWMM	Rain gardens Rain barrels	–	(Abi Aad et al., 2010)
• Investigating the effects of spatial resolution on model predictions in an urban catchment, as well as the mechanism(s) that cause the scale effect.	Not mentioned	SWMM, artificial network generator (ANGel)	–	–	(Ghosh & Hellweger, 2012)
• Presenting a reference for LID measure analyses in highly urbanized areas, including	Shanghai, China	SWMM	Bioretention Infiltration trench Permeable pavements	–	(Liao et al., 2013)

TABLE 2 (Continued)

Objectives of the study	Investigated area	Model	Low-impact development (LID)	Smart management	References
methodology, comparisons, and technical and economic aspects.			Rain Barrels Grass Swale		
• Quantification of water supply from rainwater harvested at a residential parcel and stormwater runoff reduction from a residential drainage catchment for 23 cities in seven climatic areas.	Various Cities in the US	SWMM	Rainwater harvesting	–	(Steffen et al., 2013)
• Assessing the ability of LIDs to restore the water budget of a developed area to a predevelopment level in a semi-arid environment.	Utah, US	SWMM	Green roofs Bioretention	–	(Feng et al., 2016)
• Minimizing peak flow in the sewers, reducing total runoff, and minimizing cost.	Ontario, Canada	SWMM, Borg Multiobjective Evolutionary Algorithm (Borg MOEA)	Bioretention Infiltration trench Permeable pavement Rain barrel	–	(Eckart et al., 2018)
• Simulation of the performance of LIDs in different sections in an urban drainage system.	Longyan, China	SWMM	Rain Garden Green Roof Permeable Pavement Rain Barrel	–	(Luan et al., 2015)
• Introducing a novel optimization model for identifying the number of storage units, their site and size, and the size of their orifices in an existing urban drainage system.	Portugal	SWMM, Optimization model	Storage units	–	(Cunha et al., 2016)
• Minimizing flooding, total suspended solids (TSS) load, and storage cost	China	SWMM	–	• Analytic hierarchy process • Generalized pattern search	(Wang et al., 2017)
• Assessing the effectiveness of GLUE in reducing uncertainties of SWMM inputs and outputs with differed flow types and temporal resolution. • Providing more accurate SWMM parameter estimations. • Identifying SWMM sensitivity to examined control parameters. • Evaluating the effectiveness of various posterior sampling approaches in lowering input control parameter uncertainties.	NY, US	GLUE methodology incorporated in SWMM	–	–	(Sun et al., 2013)

(Continues)

TABLE 2 (Continued)

Objectives of the study	Investigated area	Model	Low-impact development (LID)	Smart management	References
• Constructing an integrated method for prioritizing the placement of LID strategies in marginalized areas and evaluating the effectiveness of LID at the watershed level.	North Carolina, US	SWMM	Bioretention Rainwater harvesting systems	–	(Garcia-Cuerva et al., 2018)
• Investigating the application of LID for maintaining predevelopment hydrology and cost-effective analyses of LID applications.	Colorado, US	SWMM	Rain gardens Infiltration trenches	–	(Simpson & Roesner, 2018)
• Combining dependence metrics in the form of factor and correlation studies with learning classifier systems to develop a flood modeling methodology for sewer systems.	Espoo, Finland	The method was compared with SWMM	–	Machine learning	(Jato-Espino et al., 2019)
• Determining the ideal spatial design of LIDs in a watershed by minimizing downstream peak flow.	Taipei, Taiwan	SWMM coupled with genetic algorithms (GA)	Bioretention Permeable pavement	–	(Liang et al., 2019)
• Investigating challenges in implementing LIDs in urban catchments with highly seasonal rainfall and dry-weather periods of more than 6 months • Identifying and discussing opportunities for stormwater management using LIDs within these challenges.	Chennai, India	SWMM	Green roofs Rainwater harvesting systems	–	(Palanisamy et al., 2020)
• Integrating SWMM and cellular automata DualDraInagE simulation (CADDIES) model to evaluate how LID facilities decrease stormwater runoff in a Zhuhai city neighborhood to quantify the benefits of sponge city construction in flooding reduction.	Zhuhai city, China	SWMM, CADDIES	Rain garden Permeable pavement	–	(Yin et al., 2020)
• Proposing an analytical framework based on the Isochrone and SWMM models for simulating and analyzing the rainfall-runoff process before and after the construction of sponge cities to assess the sponge city infrastructure's performance in managing stormwater outflows.	Fengxi New City, China	Isochrone, SWMM	Rain garden Permeable pavement Planted roof Sunken greenbelt Bio-retention facility Dry well Wet pond Stormwater wetland Stormwater barrel Retention basin Detention pond	–	(Yang et al., 2021)

TABLE 2 (Continued)

Objectives of the study	Investigated area	Model	Low-impact development (LID)	Smart management	References
			Grassed swale Infiltration pipe and trench Vegetative filter strip		
• Investigating LID effectiveness in controlling urban waterlogging during various rainfall events in a typical semi-mountainous region in China	Xingtai City, China	SWMM	Green roofs Vegetated swales Concave greenbelts Permeable pavements	–	(Wang et al., 2021)
• Suggesting smart rain barrel (SRB) concept as an IoT-based recommendation for drainage network. • Creating a simulation tool, Smartin, with high resolution that could be used in SRB large-scale implementation and RTC of these barrels within the drainage system. • Demonstrating proof of concept for hypothetically strengthening of existing infrastructure in a case study. • Analyzing the effects of various control strategies, including varied weather forecast conditions, on both the urban water supply and drainage system in an integrated model.	Alpine, Austria	PySWMM, Python EPANET Toolkit	Smart rain barrels	RTC	(Oberascher et al., 2021)
• Developing and testing passive ultrahigh-frequency radio-frequency identification (UHF-RFID) based sensors for monitoring sewer blockages and illicit connections.	Not Mentioned	–	–	RTC Sensors	(Tatiparthi et al., 2021)
• Integrating gray wolf optimizer (GWO) and adaptive neuro-fuzzy inference system (ANFIS) in order to predict multi-ahead influent flow rate.	Isfahan, Iran	Forecast models including GWO, and ANFIS	–	–	(Dehghani et al., 2019)
• Long short-term memory (LSTM) and gated recurrent unit (GRU) performance comparison in forecasting multi-step ahead hydrologic time series data received by the IoT to that of traditional techniques such as multilayer perceptron (MLP) and Wavelet Neural Network (WNN). • Water level simulation and prediction in the CSO structure using developed	Drammen, Norway	MLP, WNN, LSTM, GRU	–	Deep learning	(Zhang et al., 2018)

(Continues)

TABLE 2 (Continued)

Objectives of the study	Investigated area	Model	Low-impact development (LID)	Smart management	References
different neural network models.					
• Building an optimization method that has the same conveniences as a conventional GA but converges to a near-optimal solution faster.	Diest, Belgium	Model predictive control (MPC), reduced genetic algorithm (RGA)	–	RTC	(Vermuyten et al., 2018)
• Developing a stochastic sewer model to be used as input to InfoWorks ICM (InfoWorks Integrated Catchment Modeling) based on SIMulation of water demand, and end-use model wastewater (SIMDEUM WW) household discharge patterns.	Wessex, UK	InfoWorks ICM, SIMDEUM	–	–	(Bailey et al., 2019)
• Developing a unique representation of CSS that is compatible with CityWatStorm which is an integrated and spatially aggregated urban water model. • Validating and assessing the model by comparing with InfoWorks ICM with simulating CSOs and flood volume.	Norwich, UK	CityWatStorm, InfoWorks ICM	Rain garden	–	(Muhandes et al., 2022)
• Analyzing the hydrological and pollution reduction of outfall and storage under various hydrological patterns, vertical parameter setting, and green infrastructure installation locations. Determining the best implementation of the scheme for overflow pollution control.	Fujian, China	InfoWorks ICM	Bio-retention, rain garden, Sunken lawn, Vegetative swale, Permeable pavement, Rain barrel, Storage tank, Green roof	–	(Fan et al., 2022)
• Establishing a 2D drainage model for the investigation site to be further used to optimize the conventional interception-regulation system and assess its overflow COD concentration and COD interception capabilities. • Proposing a pollution-based real-time control (PBRTC) rule-based double-gate control strategy with an emphasis on water quality.	Fuzhou, China	InfoWorks ICM	–	Optimization	(Wei et al., 2021)
		MIKE URBAN	–		

TABLE 2 (Continued)

Objectives of the study	Investigated area	Model	Low-impact development (LID)	Smart management	References
• Ascertain whether logistic regression models that incorporate rainfall event statistics can be an acceptable substitute for producing job lists with fewer extraneous events.	Rudersdal, Denmark			Logistic Regression Models	(Allen et al., 2022)
• Proposing a modeling program called MetroFlow that uses a more simplified representation of interrelated structural layers such catchment hydrology, sewers, linking structures, and CSOs to simulate urban drainage systems.	Chicago, US	Illinois urban hydrologic model (IUHM), InfoWorks ICM	–	RTC	(Luo et al., 2021)
• Developing a methodology for assessing no-dig, LID, and GI as alternatives for enhancing the capacity and quality of the combined sewers.	Oslo, Norway	MIKE URBAN	Infiltration trench, Bioretention cells	–	(Kvitsjoen et al., 2021)

2.1 | Storm water management model

Storm water management model (SWMM; Rossman et al., 2004) is a dynamic urban hydrology and water quality model operating in single event or continuous basis. It is an open-source model which is widely used in research related to combined and separate sewer system planning, analysis, and design applications for stormwater runoff and wastewater management (Niazi et al., 2017). SWMM was used in several studies for runoff and hydrological modeling (Knighton & Walter, 2016; Niemi et al., 2017; Ouyang et al., 2012; Ress et al., 2020; Samouei & Özger, 2020). Runoff simulation is important for CSO management (Field & Cibik, 1980), flood management (Ouyang et al., 2012; Rabori & Ghazavi, 2018), impact of climate change on urban drainage systems (Kovacs & Clement, 2009), sponge city (Jia et al., 2018) and sponge airport (J. Peng, Yu, et al., 2020) applications, and low-impact development (LID) applications (Chui et al., 2016).

SWMM is frequently applied in CSO modeling and control studies (Barone et al., 2019; Crocetti et al., 2021; García et al., 2017; Jean et al., 2018; Liao et al., 2015). In Liao et al. (2015), CSO control scenarios has been designed by using SWMM (Liao et al., 2015). SWMM has also been linked with nondominated sorting genetic algorithm II (NSGA-II) multi-objective optimization module for CSO management (Rathnayake, 2015). This study has evaluated the importance of nonstructural measures combined with structural measures to control CSO. Sun et al. (2014) employed SWMM to evaluate the effect of catchment discretization on model outputs and examined their response and parameter values to different model scales. This work showed the applicability of the parameters calibrated from finer delineation in one catchment to another for better model performance in CSO management. As computational load and simulation time are important factors in modeling studies, application of calibrated parameters of a small catchment with high resolution in a large and complex catchment will be economically reasonable and buys time. However, this methodology might only be efficient for catchments with similar characteristics (Sun et al., 2014). In another study, SWMM was used to investigate the suitability of the distributed storage option over the concentrated storage option for CSO volume control (Piro et al., 2010). The results confirmed that from a sustainable development perspective, a distributed system of storage tanks in series is the preferred method for mitigating the impacts of CSOs from the Liguori Channel Catchment on receiving waters, compared to traditional interventions employing large storage tanks. While applying this methodology, the impact of several factors including the economical factors and land use/land cover (LULC) restrictions should not be ignored. Hence, sometimes traditional interventions may be more feasible.

2.1.1 | Climate change impact assessment

Variation of meteorological and hydrological regimes due to climate change has become a major challenge for the operation of urban wastewater infrastructures which have been often designed and built decades ago. Extensive research indicates that stormwater runoff and flooding have increased due to the increase in rainfall magnitude, intensity, and frequency (Hamouz et al., 2020; Yazdanfar & Sharma, 2015; Zahmatkesh et al., 2015). Changes in climate and land cover significantly increased stormwater runoff in tropical and sub-tropical coastal–urban environments resulting in escalated flooding risks (Huq & Abdul-Aziz, 2021). The adverse effects of climate change on the hydrological cycle need to be accounted for the design and operation of urban drainage systems. In this context, models that incorporate the impact of climate change can play a key role in building resilient infrastructures. SWMM was used in studies on the impacts of climate change on urban drainage systems (Rosenberger et al., 2021; Yazdanfar & Sharma, 2015). Lu and Qin (2020) applied SWMM to evaluate the impact of different general circulation models, namely, MIROC5, EC-EARTH, HadGEM2-ES, GFDL-CM3, and MPI-ESM-MR, and climate model selection on future runoff simulation (Lu & Qin, 2020). Using a variety of statistical and modeling tools, Lu and Qin (2020) developed an integrated framework for assessing climate change impact on excessive rainfall and urban drainage systems. For rainfall disaggregation and design, the simple scaling method and the Huff rainfall design were used, starting with synthetic future climate data generated by the stochastic weather generator. The proposed framework was demonstrated through a case study in a tropical city (Hohhot, Inner Mongolia, China). The approach is applied to a relatively small catchment. However, the stochastic weather generator can be impacted by the size of the study area. Moreover, they did not include prospective LULC changes for hydrological simulations. Climate change also impacts CSO occurrence, duration, and frequency (Tavakol-Davani et al., 2016). SWMM results indicated that climate change will increase CSO occurrence, duration, and frequency by 12%–18% in the City of Toledo, Ohio in the future (2030–2034) under maximum impact scenario. The impact of climate change can vary depending on the subwatershed characteristics such as area, width, slope, and imperviousness (Zahmatkesh et al., 2015). A stormwater climate sensitivity factor (SCSF) was used to further analyze the sensitivity of runoff to climate change in relation to the subwatershed characteristics. SCSF is a positive dimensionless factor with larger values suggesting greater climate change sensitivity of storm water. The SCSF was created by combining subwatershed features by trial-and-error. This factor can be used to analyze sub-watersheds based on their features and anticipate their reaction to climate change in a simple and quick method. SWMM outcomes revealed that climate change resulted in a 40% increase in runoff volume in sub-watersheds with SCSF larger than 0.1. In these sub-watersheds, runoff is sensitive to the slope rather than other characteristics.

2.1.2 | Urban flooding

Hydrology of urban areas has been changing as a result of rapid urbanization in conjunction with climate change (Hamouz & Muthanna, 2019; Leopold, 1968). Consequently, infiltration has decreased due to the transformation of pervious surfaces to impervious surfaces resulting in an increase in runoff. Therefore, flooding may occur in some regions during extreme precipitation. SWMM is among the favored urban models in urban flood management studies (Rabori & Ghazavi, 2018; Sin et al., 2014). The model was integrated with different models and approaches to overcome flooding problems in urban areas. SWMM model outcomes were linked to a proportional integral derivative controller to develop an urban drainage model for flood control in Delhi, India (Chahar et al., 2017). SWMM was linked with a 2D hydrodynamic model named LISFLOOD-FP for modeling urban flooding (Chen et al., 2018). Within this integration, SWMM was used to simulate dynamic flows in 1D sewers, while LISFLOOD-FP was used to simulate 1D river channel flows and 2D overland flow propagation. This model integration was employed to investigate the interaction between sewer flow and surcharge-induced flooding. It was tested against four major historical floods in the Shiqiao Creek District of Dongguan City, South China. The results showed that the integrated model was capable of forecasting urban flooding. The output of the integration is in raster format, an advantage for a GIS integration. However, the approach has not investigated uncertainties and therefore further verification is required prior to application. SWMM was also coupled with a recently built noninertia 2D model to simulate the dynamic and complex bidirectional interaction between sewer system and the urban floodplain (Seyoum et al., 2012). In this study, the water level variations between the sewer network and aboveground flows were used to measure the interacting discharges. The feasibility of SWMM as a river flood simulator was tested by developing a GIS-based SWMM model for Brahmani Delta, which is prone to large-scale flooding (Dhanya et al., 2017). The results showed that, in addition to its use in urban catchments, SWMM could also be used to simulate the response of catchments to flood events in natural systems like rivers. Therefore, rather than investing heavily in flood monitoring stations, SWMM could be used as a low-cost early warning flood prediction tool.

2.1.3 | Sponge city and sponge airport

Sponge city program (SCP) was first announced by the Chinese government in 2013 as a new urban drainage infrastructure building paradigm in order to endorse a sustainable urbanization strategy (Jia et al., 2018). SCP encourages the use of natural systems including soil and vegetation as a part of the urban runoff control strategy. Within the scope of SCP, challenging volume capture rate (VCRa) for annual rainfall was set based on the region. For example, VCRa target in the southernmost regions, where precipitation is high, is 60%–85%. However, this target is 80%–85% in the Beijing area where the region is relatively dry. Given this significant Chinese investment in Sponge Cities, it is important to conduct modeling-based studies to help with planning, while also improving LID representation in hydrologic models and collecting additional data from existing LID installations (Randall et al., 2019). SWMM has been applied in research to promote sound decision-making in the development of sponge cities in urbanized watersheds (Mei et al., 2018). SWMM outcomes have shown that a 75% annual total runoff can be captured using a scenario containing 34.5% of bio-retention facilities and 46% of sunken green spaces for a sports center project in Guangxi, China (Li et al., 2019). According to the continuous SWMM modeling results, the VCRa target of 80%–85% in Beijing can be met with a LID scenario comprising 35% paved areas transformed to the permeable pavement, 30% roofs transformed to green roofs, and 10% green areas transformed to rain gardens (Randall et al., 2019).

Studies have integrated SWMM with other models, applications, and optimization algorithms in sponge city applications (He et al., 2019; She et al., 2021; Zhang et al., 2021). For example, SWMM was coupled with an Isochrone model to create an analytic framework (Yang et al., 2021). This framework was used in simulation and comparison of rainfall-runoff process before and after sponge city construction. An integrated stormwater system called Uwater was designed based on SWMM integrated with computer-aided design (CAD) and GIS applications in the context of the SCP (He et al., 2019). In this study, GIS functions were used to build tools for visual design of LID facilities, visual evaluation of the stormwater pipe system drainage capability, and inundation limits for further optimization of the design plans. Big Data, Internet of Things, and Cloud Computing technologies were used to build the operation and maintenance monitoring information management service system. In various stages of SCP, this integrated framework could be used for simulation, analysis, and decision-making.

Airports are severely impacted by extreme weather conditions including flooding, due to extreme rainfalls which adversely impact operations (J. Peng, Zhong, et al., 2020). Therefore, airport stormwater management has evolved into a significant task requiring careful planning and the application of sophisticated modeling methods. Recently, sponge airport concept, which not only relieves airport flooding but also considers rainwater as a resource, has been considered as a solution through the use of LID facilities (Peng et al., 2021). SWMM has been widely used in simulating rainfall-runoff, flooding, and the effect of LID facilities in sponge airports (Peng et al., 2021; Peng, Ouyang, et al., 2020; Peng, Yu, et al., 2020; J. Peng, Zhong, et al., 2020). SWMM can conceptualize the stormwater drainage performance of an airport and compare the impact of different LID control strategies. However, the lack of monitoring data in airports is adversely impacting model setup, calibration, and validation. Moreover, research into the sensitivity of the parameters is required for more accurate and reliable results (Peng et al., 2021; J. Peng, Zhong, et al., 2020).

2.1.4 | LID hydrologic effectiveness assessment

There is a wide application of SWMM in the assessment of the hydrologic effectiveness of LID (Chui et al., 2016; Joksimovic & Alam, 2014; Zanandrea & de Silveira, 2018; Z. Zhu, Chen, et al., 2019). Zanandrea and de Silveira (2018) studied the effects of LID application on hydrological processes for a consolidated case study in Brazil. In this study, consolidated catchments referred to regions which, despite being heavily occupied, did not have all the necessary urban infrastructure. Through the provision of basic sanitary facilities among other services, these areas began to be incorporated into city planning. Vegetative swales and permeable pavements were chosen as LIDs for the study. The results illustrated that the LID performance was satisfactory and the runoff volume generated by urban area was reduced by 10% (Zanandrea & de Silveira, 2018). SWMM was applied in a study investigating the combined effects of different LIDs including permeable paved surfaces on a parking lot, green roof, infiltration trench, and permeable soil layer in a shopping mall site within the Suewiecki Stream sub-catchment in Warsaw (Barszcz, 2015). A significant reduction in the surface runoff depth (28.0%–29.6%) and maximum flow rate (~20%) was achieved. The scenario analysis revealed that infiltration trenches and permeable soil layers only took in surface runoff from main highways and parking lots within the catchment. Moreover, infiltration trenches resulted in the greatest increase (23%) in the infiltration depth (Barszcz, 2015). Figure 2 presents a generic graphical illustration of an infiltration trench. The figure presents details about the materials used in the construction of the LID and the mechanism which LID uses to manage runoff and inflow. SWMM was also implemented in a study evaluating the behavior of rain gardens and rain barrels under steady-state and unsteady-state situations (Abi Aad et al., 2010). The rain garden had the best response in terms of peak flow and volume mitigation. The volume reduction was as high as 38% despite the fact its area was only 3.9% of the total rooftop area. According to Dussaillant Alejandro et al. (2004), the size of the rain garden must be between 10% and 20% of the impervious surface to achieve some level of groundwater recharge (Dussaillant Alejandro et al., 2004). Therefore, if the surface area of the rain garden was three times larger in the study by Abi Aad et al. (2010), it would not only remove the impact on sewer system but also some level of groundwater recharge could be anticipated.

Permeable pavements are resilient structures which can help reduce runoff and peak flows while also increasing landscape perviousness (Monrose & Tota-Maharaj, 2018). Permeable pavements have been successfully employed in many studies all over the world largely in the United States, the United Kingdom, China, Japan, and Australia (Ahiablame et al., 2013; Chen et al., 2021; Imran et al., 2013; Monrose & Tota-Maharaj, 2018; Takahashi, 2013; H. Zhu, Yu, et al., 2019). SWMM was implemented to model the effect of different pavement structures under varying rainfall conditions on reducing surface runoff and urban stormwater on a two-way, six-lane road in Nanjing (H. Zhu, Yu, et al., 2019). The findings showed that the permeable road had a greater impact on lowering the runoff coefficient and peak flood flow. Moreover, the permeable pavement could reduce surface runoff by more than 50% and reduced flood peak and hysteresis of flood peak. SWMM was applied to evaluate the performance of porous pavements and bioretention cells in a high-density urban catchment in response to anticipated climatic changes for stormwater management (M. Wang, Zhang, et al., 2019). Porous pavements and bioretention cells were relatively successful at controlling runoff and peak flow volume. Moreover, the storms with a quick return period and shorter length had greater impacts than storms that were less frequent and lasted longer on both LIDs. Bioretention cells improved the hydrologic and water quality performance of urban impermeable areas by reducing runoff volumes, flow rates, and durations (Olszewski & Davis, 2013). In northeast Ohio, the hydrologic performance of three bioretention cells (UC, HA South, and HA North) built on low-conductivity soils was evaluated using SWMM (Winston et al., 2016). The results of the study demonstrated that the UC, HA South, and HA North cells had a 59%, 42%, and 36% reduction in runoff, respectively.

Green roofs allow storm runoff to be delayed and attenuated at the source, resulting in fewer CSO discharges and flooding problems in urban areas (Akther et al., 2018; Burszta-Adamiak & Mrowiec, 2013; Cipolla et al., 2016). However, because of the impact of the layer materials, vegetation, physical features of the substrate, design specification, and climate conditions, their level of performance is site specific. Three different types of green roofs were tested between June and November 2009 and 2010 in Poland employing SWMM. The outcomes confirmed that they had positive impact on volume reduction, peak intensity values, and the occurrence of runoff (Burszta-Adamiak & Mrowiec, 2013). Another study in Colle Ometti, in Genoa (Italy), created a methodological approach for estimating the actual evapotranspiration as climate input data in SWMM (Palla et al., 2018). The suggested methodology was calibrated on a single green roof installation based on one-minute continuous simulations over 26 years of climatic records. Next, a continuous simulation of a small urban catchment, retrofitted with green roofs, was performed. The average peak and volume reduction rate for 1433 rainfall events was 0.3 (with maximum values of 0.96 for peak and 0.86 for volume).

2.2 | Mike Urban

Mike Urban is a flexible system developed by the Danish Hydraulic Institute for independent design and modeling of water supply, wastewater, and stormwater. It is a commercial model which combines 1D sewer modeling with 2D overland-flow modeling and it is integrated with aeronautical reconnaissance coverage geographic information system (ArcGIS) using "geo-database" concept (Locatelli et al., 2015). Mike Urban was implemented in several studies relating to CSO and stormwater management (Abebe & Tesfamariam, 2019; Kourtis & Tsihrintzis, 2021; Zhou et al., 2012).

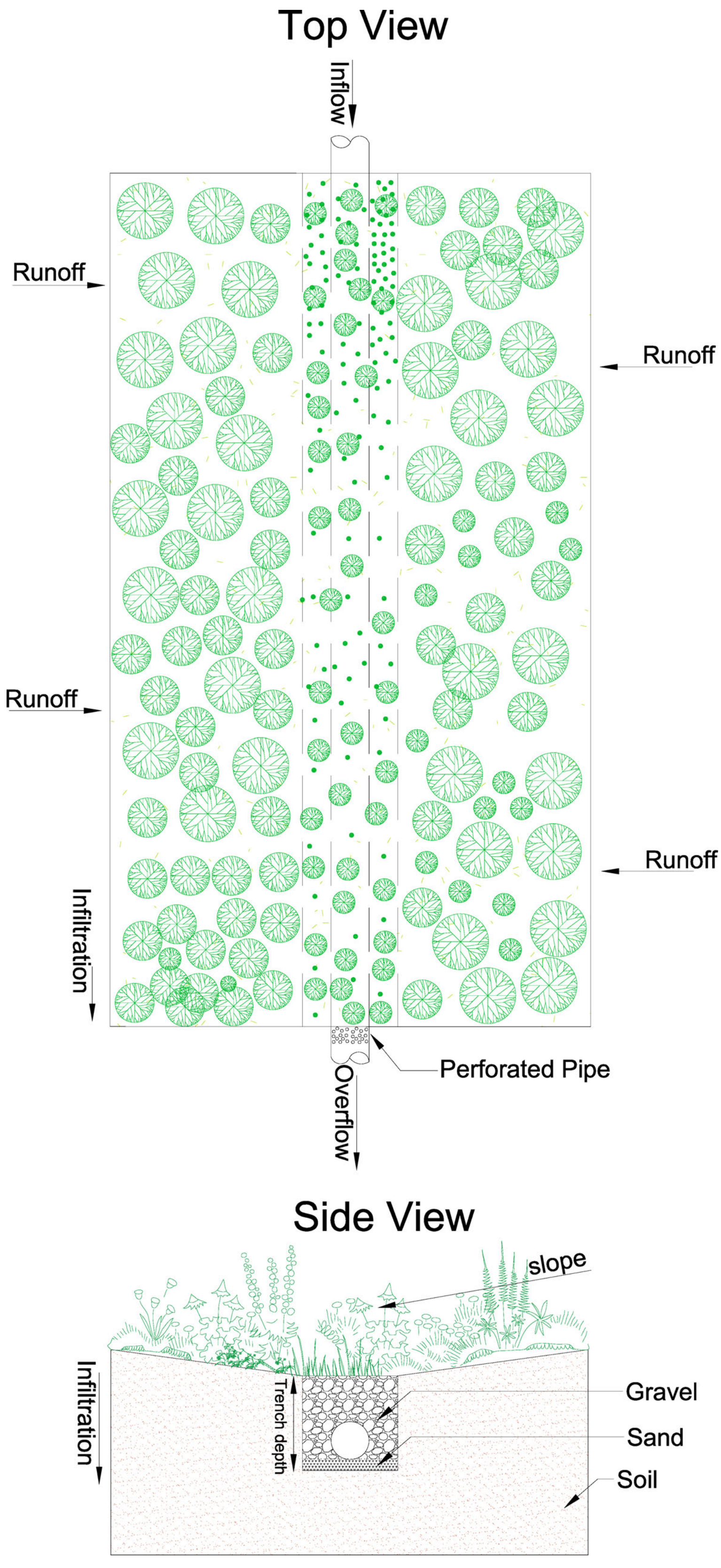

FIGURE 2 Top and side views of infiltration trench

It was used in assessing the effect of sustainable drainage systems (SUDS) scenarios on reducing CSOs volume and duration in a catchment in Norway (Hernes et al., 2020). This study assessed the hydrological performance of green roof and rain garden SUDS control modules of the model and the effect of SUDS scenarios on CSOs employing both event-based and continuous simulations. The results of event-based analyses revealed the superior performance of rain garden in lowering CSOs for large precipitation events, while green roofs benefited smaller incidents. The software was used in a study that predicts infiltration impact on CSO in a 3 km^2 urban catchment in Copenhagen (Roldin et al., 2012). This was done in a three-step scheme including a baseline scenario, a potential infiltration scenario, and a realistic infiltration scenario. The potential infiltration scenario in which soakaways were connected to 65% of the total impervious area, resulted in a 68% reduction in annual CSO volume. The third step included groundwater restraints, resulting in a more realistic scenario in which only 8% of the impervious area was linked to soakaways and CSO volume was reduced by 24%. Locatelli et al. (2015) used Mike Urban to model a retention–detention system in a small catchment in Copenhagen. The retention–detention system prevented flooding for a 10-year rainfall event. For a 22-year period, annual stormwater runoff was reduced by 68%–87%, and the retention volume averaged 53% full at the start of rain events (Locatelli et al., 2015). The authors extended their research to hydrologic impact of urbanization with extensive stormwater infiltration (Locatelli et al., 2017). They used a coupled MIKE SHE-MIKE URBAN groundwater model to explore the impact of urbanization with stormwater infiltration on groundwater height and water balance of a watershed. The hydrologic influence of urbanization with stormwater infiltration was investigated using different land use scenarios. This research found that an increase in urbanization with stormwater infiltration resulted in a rise in groundwater levels as a result of the changes in the water balance, specifically with impervious area construction decreased evapotranspiration, and increased recharge from stormwater infiltration systems. Lund et al. (2019) developed a forecast method by integrating a fast, reservoir-based surrogate forecast model developed by Mike Urban with the Ensemble Kalman filter. They examined this integration on a small catchment in Denmark and validated the model against the monitored flows and overflows. This model updating has advanced the predictions up to 2 hours ahead (Lund et al., 2019).

2.3 | InfoWorks

InfoWorks is also a commercial model and there are different versions of it available for urban water management. For example, Wallingford Software UK developed InfoWorks CS (InfoWorks Combined Sewer), which integrates a relational database with spatial analysis to give a unified platform for asset and network modeling (Koudelak & West, 2008). It allows for accurate and consistent modeling of major components of combined sewer systems, such as backwater effects and reverse flow, open channels, trunk sewers, complex pipe connections, and ancillary structures. Many researchers adopted InfoWorks in a wide variety of studies such as integrated urban hydrologic and hydraulic modeling (Zhu et al., 2016), adaptation of urban drainage networks to climate (Kourtis & Tsihrintzis, 2021), RTC application for CSO impact mitigation (Dirckx et al., 2011), and LID applications for CSO management (Benisi Ghadim et al., 2016). InfoWorks was coupled with TETIS in the CSO impact assessment on a river system in Spain. TETIS is a hydrological model with physically based parameters spread in space that allows for the results to be obtained at any point in the basin while also taking into account the spatial variability of the water cycle (Andrés-Doménech et al., 2010). The results of these two models were combined to determine the final concentration of some pollutants in the river after CSOs. Mantegazza et al. (2010) applied InfoWorks in a study comparing the use of dynamic modeling with "normative criteria" to analyze the impacts of CSOs using a case study on the Lambro River and the Stream Bevera. The normative standards are the current approach in use in Italy for designing first-flush water tanks in order to decrease pollutant discharges. The results showed the existing regulation, which was based on effluent discharge standards, underestimated the size of CSO storage tanks. The authors suggested that the regulation needs to be based on stream standard approach and the CSO tanks need to be designed based on the pollutant concentration and volume of the CSO using a dynamic model (Mantegazza et al., 2010). Another study implemented InfoWorks in cluster analysis for the characterization of rainfalls and CSO behavior in an urban drainage area in Tokyo (Yu et al., 2013). InfoWorks CS was used to simulate all 117 rainfall occurrences recorded in 2007. The rainfall incidents were categorized using two sets of rainfall pattern criteria as well as CSO behavior. Similarity analysis was adopted to link clustered rainfall and CSO groups. The results showed that while small and intense events indicated significant correlations with CSO behavior, moderate events had a weak correlation. This means one can clearly identify patterns of important and negligible rainfalls in CSOs, whereas influences from the drainage area and network had to be included when evaluating moderate rainfall-induced CSO.

InfoWorks ICM (Innovyze Ltd, Oxfordshire) is another version of InfoWorks that was developed to combine natural watersheds and unnatural environment hydrology and hydraulics into a single integrated model (Gong et al., 2017). Peng et al. (2015) adopted InfoWorks ICM in two CSS case studies in Yangpu District, Shanghai. Model calibration and validation were performed using water level measured in the pumping station. They found that to decrease overload in pipelines, prevent manhole overflow, and minimize waterlogging period, conduit diameter, and the green area should be increased (Peng et al., 2015). InfoWorks ICM was integrated with SIMDEUM to establish a stochastic sewer model for hydraulic flow prediction (Bailey et al., 2019). Calibration of the model was performed against metered consumption data. The flow data acquired at the outfall of catchment was used to validate this model. The model was applied in several catchments in the Wessex Water area of the UK. Results showed that the model was more accurate than the classic continuous sewer models in terms of flow, depth, and velocity predictions. Moreover, a low water consumption scenario decreased overnight and daytime flows by up to 80%, but evening flows remained relatively unchanged. Stagnation times in household laterals remained the same while street-scale pipes had longer stagnation times than in the "current" water use scenario.

3 | DATA-DRIVEN MODELING AND OPERATIONAL CONTROL

3.1 | Sewer system smart management

Nonstructural measures in sewer systems management do not entail the use of physical structures, but rather the application of knowledge and experience to establish various policies and control systems for reducing CSOs in existing sewer networks (Rathnayake & Faisal Anwar, 2019). Within the concept of the nonstructural measures; MPC (Abou Rjeily et al., 2018; Zhao et al., 2019), RTC (Edmondson et al., 2018), and optimization techniques (Shishegar et al., 2018) have been widely used in combined sewer systems management. Smart storage tanks (Troutman et al., 2020), smart pipelines (Stoianov et al., 2007), wireless sensors (Montestruque, 2008), smart metering (Lund et al., 2021), smart sensors (Tatiparthi et al., 2021), cloud computing (Troutman et al., 2017), supervisory control, and data acquisition (SCADA; Larry, 2000) have also been used in data collection, control, and operation of sewer systems.

Sensors play an important role in smart management of combined sewer systems (Pu & Lemmon, 2007; Ruggaber & Talley, 2005; See et al., 2021). Montestruque (2008) described a metropolitan scale wireless sensor actuator network that was developed to control the frequency of CSO events in South Bend Indiana (Montestruque, 2008). The system was known as CSOnet comprising 150 wireless sensor nodes that monitored 111 locations in the South Bend sewer system. Figure 3 illustrates the smart elements used in CSS management.

3.1.1 | Model predictive control

MPC is an adaptive control approach for combined sewer systems that recalculates the optimal control iteratively whenever new information about the state of the sewer system and new rainfall forecasts become available (Lund et al., 2018). Pedersen et al. (2017) used MPC to control the Barcelona sewer network system based on the benchmark model developed by Ocampo-Martinez (2010). The results demonstrated the importance of estimating rainfall inflows in order to optimize sewer network control. The MPC approach allowed the network capacity to reduce floods and the flow of wastewater directly into the sea (Pedersen et al., 2017). Lund et al. (2020) used MPC to dynamically control stormwater inlets and a pump to evacuate a retention basin. The MPC decides whether stormwater should be maintained in the gray-green infrastructure or permitted to enter the underground sewer system. A simulated proof-of-concept study was performed using a small-scale watershed in Copenhagen with a cloudburst road and a retention space in an area served by a combined sewer system with one CSO structure. The results showed that when the prediction horizon was longer than the transport period (18.3 min) in the pipe system, MPC of stormwater inflows greatly reduced the number and amount of CSOs. The annual CSO reduction increased from 9.9% to 12.4% when the horizon was increased from 30 to 120 min (Lund et al., 2020).

Ocampo-Martinez et al. (2005) compared active fault tolerant model predictive control (AFTMPC) to passive fault tolerant model predictive control (PFTMPC) in combined sewer system under realistic rain and fault scenarios (Ocampo-Martinez et al., 2005). AFTMPC minimized CSO flooding in all cases and in rain scenarios where the sewer network reached its design capacity; therefore, AFTMPC could prevent or significantly decrease flooding. Zimmer et al. (2015) developed a set of MPC genetic algorithms and tested them offline to see their efficacy in reducing CSO levels in a deep-tunnel sewer system during real-time operation. The GA methods used were micro-GA, probability-based compact GA, and domain-specific GA approaches. These methods limited the number of decision variable values analyzed within the sewage hydraulic model, thus lowering algorithm search space. Of these, the GA approaches that started

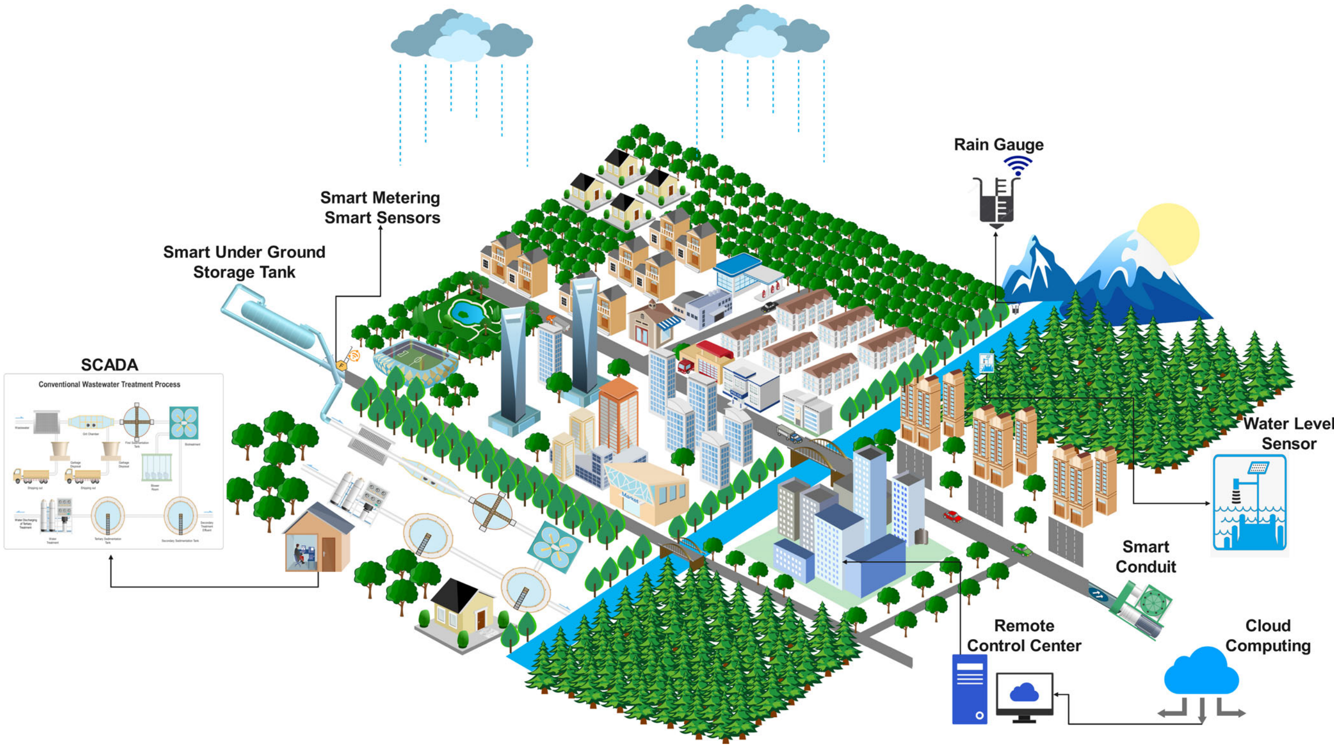

FIGURE 3 Combined sewer system smart management

with a coarse decision variable discretization and then switched to a finer resolution after initial convergence, produced the best control solution with the lowest computational demand. However, more testing on additional applications is required to confirm performance. Further research was needed to see if these results apply to other types of nonlinear optimization algorithms (Zimmer et al., 2015) such as differential evolution and particle swarm optimization. They expanded their research (Zimmer et al., 2018) to investigate the effects of long-term capital investments on CSO frequency. Replacing small-diameter pipes across the network that was creating high hydraulic grade lines could be an alternative strategy to mitigating CSOs in real-time with sluice gates. Conduit replacement was effective but costly, and optimization over a greater spatial extent (without conduit replacement) was demonstrated to minimize CSOs by 14%.

3.1.2 | Real-time control

RTC is associated with interventions on a combined sewer system in the events of stormwater inflow (Weyand, 2002). This can be accomplished by either modifying the stormwater flow direction or controlling the available storage capacity of existing detention facilities. The discharge (e.g., basin outflow, CSO, etc.) in terms of quantity and quality, the storage capacity, and the amount of precipitation are all useful information for the control action. RTC was applied in a wide range of studies related to combined sewer systems (Meng et al., 2017; van Daal et al., 2017; Weyand, 2002). Garofalo et al. (2017) developed a decentralized real-time control (DRTC) system based on a multi-agent paradigm and specifically a gossip-based algorithm and integrated it with the SWMM hydrodynamic simulation model to be applied to the UDS in Cosenza, Italy. Multi-agent systems make it feasible to obtain sophisticated emergent behaviors based on interactions among simple-behaving agents. On the other hand, there are numerous nodes connected through a network in a Gossip-Based Algorithm. Each node has a set of numerical values and can only communicate with a restricted number of peer nodes (i.e., its neighborhood). Despite only being able to communicate locally, the purpose of this type of algorithm is to estimate global aggregate values such as average, variance, maximum, and so on. The UDS in Cosenza has a set of adjustable gates that operate as actuators, as well as sensors that monitor the water level in each conduit. The DRTC algorithm successfully controlled the water level within the UDS, ensuring that the system real storage capacity was fully utilized. The findings showed that the DRTC had a positive impact on the management of the UDS by significantly reducing the risk of flooding and CSO (Garofalo et al., 2017).

Seggelke et al. (2013) presented an integrated RTC for an urban drainage system in Wilhelmshaven, Germany. This fuzzy-based RTC approach was used to control both the sewer system and inflow to the WWTP. The primary goal was to decrease the number and volume of CSO located beside a bathing beach. The monitoring of the integrated RTC during 2011 demonstrated that CSO frequencies decreased by 23% and CSO volumes were lowered by 25%. Moreover, CSO volumes could be reduced by 40% on average in the case of single events (Seggelke et al., 2013). Jafari et al. (2018) coupled RTC applications with a PSO algorithm to compare the performance of two approaches including multi-period and single-period simulation–optimization that were used for regulating controllable elements of an urban drainage system. During heavy rains, the proposed models were used to discover the best pump and gate operating policies at each decision time. The multi-period optimization technique was effective in reducing or eliminating peak water level deviation from the allowable range in front pools of pump stations. It also resulted in a 59% reduction in the pumping station maintenance costs. However, doing multi-period optimization at each decision time adds to the computational load, which could restrict its applicability in larger, more complex urban drainage systems (Jafari et al., 2018).

3.1.3 | Optimization techniques

Optimization techniques were extensively applied within the context of smart management and real-time control of CSS (Shishegar et al., 2018). Wang, Lei, et al. (2019), developed an optimization method based on PSO to achieve a logical pump start-up depth while reducing the number of start-ups/shutoffs (H. Wang, Lei, et al., 2019). SWMM was used to calculate the objective function in assessing different trial solutions, and the PSO iterative computations were used to direct the search and find the optimal solution. The method was adopted in a case study in Beijing comprising nine pumping stations for both multistage pumping station optimization and single pumping station optimization. The multistage method yielded a small number of start-up/shutoff times (from 8 to 114 in different rainfall scenarios) and less pump operating time. However, the developed optimization method did not take pump efficiency into account, which was an important parameter in its operation optimization.

Bachmann-Machnik et al. (2021) optimized static outflow settings of CSO tanks using highly resolved online flow and quality monitoring data and real-time control strategies. The method was tested on two CSO tanks in a conceptual drainage system before six tanks in a case study in Southern Germany. In both the conceptual catchment and the case study, a 6-month measured time series was sufficient for reliable optimization results. An average reduction potential of 2% for the overflow volume and 6% for the overflow duration could be expected for the study area (Bachmann-Machnik et al., 2021).

Optimization techniques were also adopted in smart management of gray–green structures (Boulos, 2017; Oberascher et al., 2021; Paul & Andrew, 2015). A simulation–optimization framework for optimizing urban drainage systems employing hybrid green–blue–gray infrastructures (HGBGIs) and various degrees of centralization was developed and evaluated using a real case study in Ahvaz, Iran (Bakhshipour et al., 2019). HGBGIs of stormwater management systems could challenge the traditional gray-only pipe networks in terms of cost. In centralized networks, green–blue infrastructures (GBIs) were more effective, however, HGBGIs were more costly for decentralized usage compared to traditional solutions. Despite the fact that GBIs were more environmentally friendly and sustainable, system resilience was compromised in the process. Therefore, the optimal DC was determined by the objectives, and it varied in terms of cost, resilience, and sustainability. This suggested that optimal decisions could only be made using a multi-objective optimization framework. For example, a small increase in pipe widths could result in large benefits in resilience at a reasonable cost increase and a minor reduction in sustainability. A multi-objective optimization approach was built by integrating an updated NSGA-II with SWMM to undertake drainage network rehabilitation using pipe substitutions and storage tank placement (Ngamalieu-Nengoue et al., 2019). Flood damages were calculated in monetary terms based on the water level of flood. A collection of Pareto fronts linking both investment and damage costs was obtained. Network managers could use these solutions to make decisions about rehabilitation plans and investments while working within budget limitations of a project.

3.1.4 | Artificial intelligence

AI can be applied as model-based AI or data-driven-based AI depending on the case study. Model-centric AI refers to the development of an AI system that incrementally improves an existing model (algorithm/code), while maintaining the amount and form of the collected data fixed. On the other hand, developers of data-centric AI maintain a fixed model while continually enhancing the quality of the data (Hamid, 2022). Advanced data-driven methods including machine learning (ML; Hadjimichael et al., 2016) and deep learning (DL; Kazaz et al., 2021) were adopted in urban water resources management (Xiang et al., 2021). Artificial network generator (ANN), ANFIS, Gaussian process regression, Wavelet Transform-AI integrated models are among several AI models that have been used in sewer system management (Zhu & Piotrowski, 2020). Although artificial intelligence is applied in many urban water cycle-related studies, limited number of studies related to CSO control and mitigation is reported and further research is required to fill this gap. Furthermore, Additional AI studies are required for the management of stormwater drainage sewers. The following studies present the AI applications on urban waters.

ANN was used to predict CSO performance in a catchment in north of England (Mounce et al., 2014). The depth of flow in the CSO chamber and rainfall radar records were utilized as training data to establish the relationship between the parameters. The outcomes demonstrated that the technique could predict CSO depth for unseen data five-time steps in advance with less than 5% error. The method eliminates the need for manual modeling overheads and calibration data needs, making it a very helpful alternative to creating a full physical-based model of a catchment. Sousa et al. (2014) applied ANN and support vector machines (SVMs) to evaluate the performance of AI in the prediction of sewer systems structural condition (Sousa et al., 2014). This methodology can be useful to estimate probable structural problems and faults within combined sewer systems due to the fact that CSSs have been used for a long time. Therefore, these types of innovative applications would prevent enormous maintenance costs. They compared the performance of these methods with logistic regression in a case study. The uncertainty associated with ANNs and SVMs was defined, as well as the comparative results of a trial-and-error technique versus optimization algorithms to construct SVMs.

Halfawy and Hengmeechai (2014) implemented ML to assess municipal sewer pipes. This study provided a pattern recognition algorithm to automatically detect and classify pipe problems in images generated from traditional closed-circuit television (CCTV) inspection video. To identify pipe faults, the algorithm adopted histograms of oriented gradients (HOG) and SVM. The algorithm used image segmentation to derive suspicious regions of interest which indicated candidate defect areas. These regions of interest were classified using an SVM classifier that was trained using HOG features taken from both positive and negative samples of the defect. The proposed approach was exercised to solve tree root intrusion detection. The performance of SVM classifiers with linear and radial basis functions was tested. The algorithm tested on actual CCTV videos from the Canadian cities of Regina and Calgary. The results demonstrated the algorithm feasibility and resilience (Halfawy & Hengmeechai, 2014). Another study applied ML methodologies to categorize flood versus nonflood events using a rainfall threshold in Shenzhen, China (Ke et al., 2020). ML projected numerous rainfall threshold lines in a plane spanned by two principal components, yielding a binary outcome (flood or no flood). The proposed models, particularly the subspace discriminant analysis, could classify flooding and non-flooding by combinations of multiple-resolution rainfall intensities, increasing the accuracy to 96.5% and lowering the false alert rate to 25% compared to the conventional critical rainfall curve. The crucial indices of accuracy and true positive rate obtained in ML models were 5%–15% higher than in conventional models.

Deep learning is an approach to AI that is specifically a form of machine learning, which use multiple hidden layers to extract features from raw data (Goodfellow et al., 2016). Dong et al. (2020) developed and tested a hybrid deep learning model for urban flood prediction and situation awareness using channel network sensor data called fast, accurate, stable, and compact gated recurrent neural network-fully convolutional network (FastGRNN-FCN). They used the data of three historical flood events from 2016 and 2017, which were collected from the channel sensor in the Harris County, Texas to train and validate the hybrid DL model. The hybrid DL model was used to forecast a flood event in 2019 in Houston and the results are comparable with flood modeling using empirical methods. The results showed that the model could accurately forecast spatial–temporal flood propagation and recession, and that it might be used by emergency responders to prioritize flood response and resource allocation strategies (Dong et al., 2020). Additional research proposed a method for automatically detecting and localizing manhole covers using convolutional neural network (CNN) DL approach in very high-resolution aerial and remotely sensed photos (Commandre et al., 2017). This is more extensive than current small object detection/localization approaches because the full image was processed without prior segmentation. More than 49% of the ground truth database was detected with a precision of 75% in the initial experiments using the Prades-Le-Lez and Gigean datasets. Another paper used a DL technique called faster region-based convolutional neural network (faster R-CNN) to develop an automated approach for detecting sewer pipe defects (Cheng & Wang, 2018). 3000 CCTV inspection photos of sewer pipes were used to train the detection model. Using mean average precision, missing rate, detection speed, and training time, the model was evaluated in terms of detection accuracy and computing cost after training. The proposed approach was effective in detecting sewer pipe defects with high accuracy and speed.

3.2 | GIS and RS applications in sewer system management

The integration of GIS and RS data can be a powerful tool for generation of input data in water resources management and specifically CSS management. The first GIS systems and basic spatial data handling techniques made their way into computer technology in 1960s. However, the use of GIS in the field of water management started in 1980s and it is on the rise (Tsihrintzis et al., 1996). Since then GIS has been used as a powerful tool for storing, organizing, and visualizing geographical data, which is common in water management (Wilson et al., 2000). In a pioneering study on GIS applications in urban stormwater management, it was demonstrated that GIS could help with issues like data precision, accuracy, resolution, and degree of aggregation (Meyer et al., 1993). When compared to previous methods, GIS provided a more accurate assessment of the reliability of calculated parameters. In contrast to traditional methodologies, GIS provided a consistent and reliable method of estimating model parameters and input data for stormwater modeling. Sample et al. (2001) reviewed the application of GIS in urban stormwater modeling. A GIS application in urban stormwater management was described. A GIS, a database, a stormwater system design template, and an optimization capability for screening alternatives were included in the neighborhood scale program. Runoff from GIS data was calculated using the soil conservation service (SCS) approach, which is based on area and soil type (Sample et al., 2001). GIS was selected in a preliminary infiltration rating (PIR) calculation that evaluates the possibility of a future surface infiltration based-stormwater control measure at a given location (Tecca et al., 2021). The surface saturated hydraulic conductivity, depth to the water table, slope, and relative elevation were the input variables. Maintenance inspections from 104 rain gardens, done by Minnesota Anoka Conservation District, were used to calibrate and validate the PIR. In 85% of rain gardens, the PIR predicted an accurate or reasonable performance estimation. The PIR can assist in the site-specific investigations and act as an excellent planning tool for future surface infiltration based-stormwater control measures in the land development process.

Likewise, RS technology is also a powerful integration in urban water management. RS technology has been applied in studies such as land use/land cover and impervious surface determination, and other hydrologic parameters like rainfall, temperature, snow cover, elevation, and sewer system physical properties (Abellera & Stenstrom, 2005; Ravagnani et al., 2008; Slonecker et al., 2001). Cermak et al. (1979) used Landsat multispectral scanner (MSS) data in their own developed classification technique and tested it in the Crow Creek and Walnut Creek watersheds near Davenport, Iowa, and Austin, Texas, respectively. The land uses generated as a result of the classification were applied to the stormwater model Hydrologic Engineering Centre (HEC) developed by the US Army Corps of Engineers. Discharge frequency curves based on Landsat MSS were similar to those based on traditional land uses. The flood monitoring and damage estimation relied heavily on these curves (Cermak et al., 1979). In another paper, radial-basis-function neural network (RBF-NN) and the ANN artificial intelligence techniques were applied on panchromatic imageries of Landsat thematic mapper (Landsat TM) and Korea multi-purpose satellite (KOMPSAT) in land use/cover classification in an area in Korea (Ha et al., 2003). The outcome was exerted as input for SWMM to predict stormwater runoff quantity and biological oxygen demand (BOD) loading. Classification accuracy and percentile unit load significantly affected runoff, peak time, and pollutant emissions. Park and Stenstrom (2006) implemented RS to predict stormwater pollutant loadings using Landsat-enhanced thematic mapper Plus (ETM+) images. They presented a Bayesian network to classify RS images of the Marina del Rey area in the Santa Monica Bay watershed. TSS, chemical oxygen demand (COD), nutrients, heavy metals, and oil and grease were among the eight water quality metrics studied. The findings provided thematic maps with spatial predictions of each pollutant load, allowing the highest pollutant loading regions to be identified. These results could be significant in defining the optimal stormwater pollution management techniques at regional and global scales, and determining total maximum daily loads in the watershed (Park & Stenstrom, 2006).

GIS and RS applications have been combined in studies on managing urban water (Svejkovsky & Jones, 2001; Tsihrintzis et al., 1996). In one of the early research in managing stormwater, RS technology was used in automatic inference of elevation and drainage models from a satellite image (Haralick et al., 1985). Thanapura et al. (2007) integrated GIS and RS to determine the runoff coefficient. The goal of this study was to apply an unsupervised classification and the iterative self-organizing data analysis techniques (ISODATA) technique to map impervious area and open space for the determination of runoff coefficient in GIS spatial modeling using 8-bit and 16-bit QuickBird normalized difference vegetation index (NDVI) satellite images. The impervious area and open space were mapped using high spatial resolution NDVI satellite images created with the ISODATA algorithm. This was an efficient and successful information extraction method for reliably predicting spatial representative *C* values. The six QuickBird NDVI thematic maps produced had similar classification accuracies, averaging around 92%. The *C* values were generated in GIS spatial modeling and compared to the industry standard C to investigate high spatial resolution satellite data and to validate the composite runoff index geographic model created by Thanapura in 2005 and 2006. Finally, it was agreed that the greater resolution image and mapping approach improved land cover discrimination and resulted in more accurate C estimation (Thanapura et al., 2007). Aerial images and height data have been used to determine the coefficient of imperviousness (Paul et al., 2018). In this work, random forest (RF) and conditional random fields supervised classification techniques were compared. The outcomes of land cover classification demonstrated that none of the classifiers had an obvious advantage, with both having an overall accuracy of 85.5%. The results required modification to account for the occlusion of the ground surface by trees to calculate the coefficient of imperviousness. This was accomplished using a heuristic approach that employed data from a GIS. The best coefficient of imperviousness result was obtained using the RF classifier with a root mean square error of 3.8%.

GIS and RS have also been integrated into stormwater and flood modeling research (Sytsma et al., 2020; Wang & Xie, 2018). Hong et al. (2017) combined the 2D-surface two-dimensional runoff, erosion, and export (TREX) model and the 1D-sewer CANOE model in the TRENOE platform at a small urban catchment near Paris. The detailed land-use data generated from various information sources was a critical feature for reliable simulations. Khin et al. (2015) used a high-resolution WorldView-2 image in a two-stage classification process and implemented the outcome in hydrologic modeling and performance evaluation of several LIDs. In classifying the same urban region into six land cover classes, the suggested two-stage classification method achieved an overall accuracy of 80.6%, compared to 68.4% for a traditional pixel-based method. The hydrologic parameters of micro-sub-catchments were fed into the SWMM to analyze the performance of LIDs based on the classification results. In a typical low-rise residential area in San Clemente, California, the use of porous pavement and bioretention reduced run-off volume by 18.2% and 37.1%, respectively (Khin et al., 2015). Sytsma et al., (2020) coupled GIS with python stormwater management model (PySWMM) and regression tree analysis to predict hydrological connectivity of impervious surfaces. Impervious areas were separated into directly or physically connected and variably connected including impervious area that drained into pervious area categories. GIS was used via an ArcGIS tool to enable the application of these methods in real life. This was used to, delineate subcatchments, extract the impervious area categories, apply the regression tree algorithm to predict incident rainfall fraction, and summarize the resulting hydrologically connected impervious areas by sub-catchment. The connectivity of the impervious areas were mainly sensitive to the soil type, rainfall depth, area fraction, and antecedent soil moisture conditions of the downslope pervious area parameters (Sytsma et al., 2020).

4 | CHALLENGES AND FUTURE PERSPECTIVES

The management of sewer systems and mitigation of CSOs is a very complex field and there is a need to adopt a case-specific holistic approach. Within the scope of this approach, building partnerships between key stakeholders to develop preliminary goals and identify issues of concern plays an important role. Problem characterization, setting goals, and proposing solutions require significant knowledge of management science and engineering which includes a multidisciplinary understanding of hydrology, hydraulics, geographical information systems, meteorology, computer science, and so forth, to develop holistic solutions. This interdisciplinary approach is needed to build, operate, and optimize climate-resilient and robust wastewater infrastructure that can protect human and ecosystem health under the most challenging conditions. Modeling that integrates catchment properties, climate, and receiving water bodies can help to develop holistic solutions which enable better management and integration of sewer systems and end-of-pipe WWTPs.

The mechanistic stormwater and CSO models comprise the mathematical representation of the relevant real-case situations and generate results based on the principles of physics and chemistry (Al-Amin & Abdul-Aziz, 2013). These models require moderate or extensive input data and most of the time the input data comes with several uncertainties. For instance, digital elevation models (DEMs) are used to delineate the catchment and flow routing. Moreover, satellite imagery is used to generate LULC and soil maps. However, there are several sources of error associated with remote sensing-derived information (Jensen, 2015). Data-driven models analyze data about CSO and stormwater by providing impulse–response type relationships between variables. These models try to correlate and find the connection between variables without considering the principles of physics and chemistry. Whereas, selecting the optimum relationship between variables is a challenge due to complex interactions among different parameters and requires the user to have good knowledge of the physical and chemical processes happening within the system. Another limitation of the data-driven models is that they are mostly constructed based on correlations which are site-specific and can significantly vary from site to site. Data-driven models also suffer from uncertainties related to data. The question of which models should be preferred has always been under the spotlight. Rather than being comparable modeling approaches both mechanistic and data-driven models can complement each other. Mechanistic models can be used to learn the physiochemical correlations of different parameters and variables within a system while data-driven models will complete the missing elements.

Different CSO and stormwater mechanistic models have their own advantages and disadvantages. Some models such as SWMM has kept its application as simple as possible to be able to save time and manage the computational load. Moreover, this simplified representation of the model has made parametrization, sensitivity analysis, calibration, and validation manually doable. However, this simplification sometimes could be a disadvantage due to neglecting some processes happening within the catchment. All these factors bring out the necessity of an automated sensitivity analysis, calibration, and validation method for the model. Moreover, the rapid urbanization has let to expansion in catchment areas and increase in the interaction of rural and urban hydrology while SWMM is being mostly preferred for small catchments (Niazi et al., 2017). This interaction increases the complexity of the processes happening within the urban catchments and the simplified representation of SWMM may become a disadvantage pending on modeling objectives and spatial scale magnitude. Moreover, there is regularly input to urban catchments either in terms of surface runoff or subsurface runoff. Therefore, a simple portrayal would not be enough to effectively model stormwater and CSO. Based on the objectives of the modeling, the aforementioned issues could be dealt through advancing SWMM to deal with moderate to big complex catchments or integrate with a hydrological model such as soil and water assessment tool (SWAT) which can be used for modeling large watersheds.

An urban environment is a set of systems either interconnected to each other or separated from each other. The bigger the systems the more the probability of interaction with other systems. Sewer systems are also a part of this set with a different magnitude based on the urban environment. The larger the magnitude the more need for a tool that is useful for better analyzing, organizing, and decision making. Moreover, most of the time the problems happening within these systems are location based. GIS and RS are the location-based sources of information that could be used to express the reality and connections between different elements of the sewer system. However, integrating GIS and remote sensing with CSO and stormwater models is a big gap identified within this survey. This integration is mostly seen within the commercial models. The integration will not only promote multidisciplinary research but also save time for researchers to focus on other research gaps as well. For example, the open-access SWMM does not have a GIS integration, whereas most of the input data required for model setup are geospatial data. Moreover, one of the factors that may have prevented the SWMM to be preferred for larger catchments is the lack of GIS integration because dealing with that amount of data manually is tiresome. Therefore, GIS and RS integration will make research easier and will open doors for addressing other research gaps such as AI adoption in urban water management. Thanks to the advancements in satellite technology, GIS and RS could be used to create data with high resolution and accuracy which will be used as input for modeling studies.

Adopting data-driven models for CSO and stormwater management is not something recent since RTC, MPC, and several optimization techniques have already been used in different research. However, AI integration is a big gap that has a long way to be closed. Even though this survey mentioned the AI applications in urban water cycle, very limited research about CSO management were encountered. AI can be applied for smart management of urban water network, stormwater and CSO modeling, and automated calibration of the mechanistic models. Despite AI models such as ANN, ANFIS, Gaussian process regression, Wavelet Transform-AI integrated models have been used in sewer system management, applications of reinforcement learning are rare, and it is expected to be a future trend. Reinforcement learning (RL) has evolved as a state-of-the-art methodology for autonomous control and planning systems throughout the AI research areas (Mullapudi et al., 2020). The RL problem is defined as a framework in which an agent seeks to maximize a reward function supplied by an environment by selecting actions from a pool of possible interactions known as a policy (Ochoa et al., 2019). RL specifically can be applied in smart management of sewer network and gray and green infrastructures. Lastly, AI is already a fundamental part of remote sensing technology in terms of DL, and smart city, and digital twin concepts.

Finally, yet importantly, concepts like smart city and digital twin alias Metaverse application in CSO and stormwater management is a cutting-edge of today but expected to be the norm of the near future. In terms of CSO and stormwater management, Metaverse will not only be used for autonomous control of sewer networks but also in tracking the past of the physical environment and predicting the future state to prevent flooding and other disasters related to sewer systems. In Metaverse, the digital copy of the sewer network can be created and synchronized with the physical network. Metaverse can be used to monitor the physical environment and receive operational insights. Moreover, using AI different simulations can be applied to the copies of this digital counterpart to obtain the optimum and cost-effective operational scenarios.

Although calibration and validation are used to verify the proposed approach in both mechanistic and data-driven modeling studies, their accuracy is related to several factors including data and modeling uncertainties, unavailability of critical data for calibration, and validation for both wet and drought periods. However, as metaverse will create a virtual representation of the physical environment and monitor its physical counterpart itself, uncertainties related to data, and unavailability of calibration and validation data for the required period are anticipated to be less effective, therefore more accurate results might be obtained.

5 | CONCLUSION

This study presents a comprehensive survey of combined sewer overflow management research. At first, the history of urban water supply and sanitation, CSO definition in terms of characteristics, problems, and its impact on receiving waterbodies were introduced. Subsequently, the studies utilizing mechanistic and data-driven modeling, and operational controls including RTC, MPC, optimization techniques, and AI for CSO and stormwater management were discussed. Finally, a review of GIS and RS applications in urban water management is given. The following conclusions can be drawn from this work:

- Combined sewer overflow adversely affects human health and aquatic ecosystems, and it is proven to be a significant pollution source.
- Due to the population increase and climate change, sewer systems capacity is not adequate in most cases, and enlarging the infrastructure is not feasible due to economic and land restriction factors. As a result, the need for dynamic and smart management of CSO has increased.
- Mechanistic modeling applications such as SWMM integrated with LIDs can be used to statically control CSO. However, these applications are more effective when urbanization rate and climate change phenomena are considered. Moreover, LID applications not only aid in CSO control but also promote hydrological cycle.
- RTC, MPC, and optimization techniques are significantly used in the context of CSO management. However, only a limited number of studies related to AI and ML applications in CSO control and mitigation is encountered in the literature and further research is required to fill this gap.
- AI and ML can be used in the intelligent management of gray-green infrastructures and sewer networks, and/or applied as data-driven models for CSO modeling and site specification of LIDs. Further research is needed to evaluate the potential of these methods in these two applications.
- GIS and RS applications have the potential to capture, manage, and analyze data related to CSO, but may also provide opportunities for the agile management of CSO.

AUTHOR CONTRIBUTIONS

Mohammad Matin Saddiqi: Conceptualization (lead); visualization (lead); writing – original draft (lead). **Wanqing Zhao:** Conceptualization (supporting); writing – review and editing (equal). **Sarah Cotterill:** Writing – review and editing (equal). **Recep Kaan Dereli:** Conceptualization (lead); supervision (lead); writing – original draft (supporting); writing – review and editing (equal).

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CONFLICT OF INTEREST

The authors have declared no conflicts of interest for this article.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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