



Research

Environmental Frontiers for Water–Energy Nexus—Review

A Systematic Review of Greenhouse Gas Emissions Derived From Combined Sewer Overflows and Synergistic Control Strategies Toward Carbon Neutrality



Yilin Xu ^{a,b,c,#}, Cheng Ye ^{a,b,c,#}, Zuxin Xu ^{a,b,c}, Wenhai Chu ^{a,b,c,*}

^a State Key Laboratory of Water Pollution Control and Green Resource Recycling, College of Environmental Science and Engineering, Tongji University, Shanghai 200092, China

^b Ministry of Education Key Laboratory of Yangtze River Water Environment, Tongji University, Shanghai 200092, China

^c Shanghai Institute of Pollution Control and Ecological Security, Shanghai 200092, China

ARTICLE INFO

Article history:

Received 9 July 2024

Revised 24 February 2025

Accepted 19 March 2025

Available online 2 April 2025

Keywords:

Combined sewer overflow

Greenhouse gas emission

Data-driven models

Urban water management

Integrated control strategy

ABSTRACT

Climate change is accelerating globally, raising significant concerns regarding the environmental risks associated with combined sewer overflows (CSOs). These rainfall events lead to the excessive discharge of multiple pollutants into natural waters. However, greenhouse gas (GHG) emissions from CSOs, which are crucial for carbon neutrality in urban water systems, remain fragmented. Using the life-cycle assessment method expansion approach, this study breaks down the formation and discharge processes of CSOs and uncovers the underlying mechanisms driving GHG emissions during each period. Given the complexity and uncertainty in the spatial distribution of GHG emissions from CSOs, the development of standard monitoring and estimation methods is vital. This study identifies the factors influencing GHG emissions within the urban drainage system (UDS) and defines the interactive GHG emission boundaries and accounting framework related to CSOs. This framework is expanded to consider the hybrid nature of urban engineering and hydraulic interactions during the CSO events. Advanced modeling technologies have emerged as essential tools for predicting and managing GHG emissions from CSOs. This review promotes comprehensive data-driven methods for predicting GHG emissions from CSOs, fully considering the inherent heterogeneity of CSOs and the impact of multi-source contaminants discharged into aquatic environments. It emphasizes refining emission boundary definitions, novel accounting practices adapting data-driven methods, and comprehensive management strategies in line with the move toward carbon neutrality in the UDS. It advocates the adoption of solutions including advanced technologies and artificial intelligent methods to mitigate CSO-related GHG emissions, stressing the significance of integrating low-carbon solutions and a comprehensive data-driven management framework in future research directions.

© 2025 THE AUTHORS. Published by Elsevier LTD on behalf of Chinese Academy of Engineering and Higher Education Press Limited Company. This is an open access article under the CC BY-NC-ND license (<http://creativecommons.org/licenses/by-nc-nd/4.0/>).

1. Introduction

Since the industrial revolution, the relationship between global warming and greenhouse gas (GHG) emissions into the atmosphere has attracted considerable attention. Water is involved in many material and energy flows as it passes through the transport, treatment, and discharge processes. Consequently, urban water cycles are complex sources of prominent GHGs, including carbon dioxide (CO₂), methane (CH₄), and nitrous oxide (N₂O). The empha-

sis on GHG emissions parallels the hotspots of wastewater decontamination [1]. Apart from estimating GHG emissions from the wastewater sector, meticulous delineation of system boundaries is also essential for GHG management, as previous carbon accounting may not be absolutely solid and emission boundaries change with external factors such as climate and economic factors [2]. In addition to traditional hotspots (wastewater treatment plants (WWTP), estuary, and riverine ecosystems) in urban water systems, recent concerns have gradually focused on combined sewer overflows (CSOs) [2–6]. Pollutants discharged into urban water systems through unorthodox pathways in the urban drainage system (UDS; including CSOs and sewage leaks) have gradually become the dominant GHG emission sources [7]. Most developed

* Corresponding author.

E-mail address: 1world1water@tongji.edu.cn (W. Chu).

These authors contributed equally to this work.

countries maintain their drainage systems with a high proportion of combined sewer systems (CSSs), thus, CSO pollution is a major concern for wet weather pollution management in most developed countries. Under the pressures of population growth and climate change, particularly in extremely wet weather, CSOs have increased because of the insufficient hydraulic capacity of CSSs to collect water flows [8]. These overflows accumulate from a pollutant array of human activities conducted by rainwater flush, and from untreated wastewater and are then discharged into river bodies [9,10]. Evidence suggests a substantial influence of CSOs on chemical oxygen demand (COD) and total suspended solid (TSS) levels in receiving waters [11]. CSOs present adjacent or even more severe pollutant loads and flow volumes than treated effluents released from municipal treatment plants [12]. Moreover, the formation of CSOs can negatively affect the operations of wastewater collection and treatment systems. Therefore, CSO discharge has the potential to generate direct and indirect GHG emissions in the water sector during extreme weather conditions, negatively affecting the achievement of carbon neutrality in urban water systems.

Resolving the GHG emission challenge posed by active CSOs worldwide requires the definition of boundaries, sources, sinks, and assessment approaches for these emerging GHG emission sources. Previous studies [1,2] have focused on exploring network boundaries, including sewers, WWTPs, and structures. However, influenced by climate change, the frequent interactions between urban water systems and city scales unavoidably increase the complexity of material flows, thus complicating the boundary definition of GHG emissions. In the existing carbon accounting framework, the negative CSO-related impact (e.g., influent concentration, chemical consumption, and energy consumption) is unconsciously included in the actual emission inventory data. However, CSO-related GHG emissions have not been fully investigated, and their impacts, particularly in terms of the carbon footprint within the UDS have not been uncovered. Drawing on the water–energy–carbon nexus framework [5], this review introduces a novel perspective. It integrates the CSO discharge with processes within a wider scale of urban water system management. Similar to the WWTP estimation, GHG emissions from CSOs can be divided into direct and indirect emissions. The direct emissions include CO₂, N₂O, and CH₄. Indirect emissions are life-cycle emissions based on electricity and chemical consumption in interactive urban wastewater management systems in engineering and hydraulics. Previous studies [13–15] identified several operational mechanisms and reactions in various wastewater sectors. The biochemical reaction process in water environments, sewers, and sewer sediment layers, particularly N₂O and CH₄ production, as well as the accumulated volumes of CSOs, are crucial areas of this study [2,16].

Previous studies on GHG emissions from CSOs are only briefly mentioned in this section. Furthermore, researchers [1,8,17] have conducted quantitative estimations of GHG emissions from sewer systems and water environments, emphasizing the isolated influence of these factors on the wastewater sector. Obviously, these studies fall into the misconception of CSO discharge as the sole GHG source, overlooking the complicated processes of CSO formation, transfer, and release. Moreover, the dynamic uncertainty of the urban water cycle driven by increasingly severe extreme weather is a significant factor that influences the accounting process. The variability of this complicated process hampers the generalizability of practical and model-based research. Great uncertainties concerning existing GHG estimations caused by CSO persist: ① lack of guidance for explicit carbon emission sources and boundaries; ② limited availability of mathematical and data-driven models for long-term estimation and monitoring; and ③ lack of integrated CSO control techniques to mitigate the impact of CSOs on the entire environment. Overall, the GHG

emissions from CSOs are of serious concern and require immediate attention.

This review aims to ① uncover the potential for CSO-related GHG emissions from legislative framework development, ② define CSO-related emission boundaries and influencing factors, and ③ explore integrated data-driven pathways that synergize the reduction of pollution and GHG emissions from CSOs. CSO-related policies, regulations, and standards are summarized in three stages aligned with carbon neutrality goals. Key GHG emission sources and boundaries (e.g., riverine ecosystems, pipelines, and external chemical and energy use) are reviewed, along with their mechanisms and influencing factors. Mathematical models from the perspective of CSO prediction as well as GHG production and emission in riverine and sewer systems are also systematically summarized and compared. A comprehensive urban CSO control system that integrates mitigation technologies and data-driven methods across the UDS was proposed, leading to a GHG-focused strategy. This review highlights CSOs as significant GHG sources and emphasizes the need for integrated, low-carbon wastewater management solutions.

2. Involving CSO regulations and recommendations towards sustainability and carbon neutrality

The enactment of CSO-related regulations and recommendations forms a crucial basis for CSO control and management. The timeline (Fig. 1) of historical regulations and policies from the 1950s in the CSO sector can be divided into three phases (Texts S1–S4 in Appendix A). The transition towards a sustainable and carbon-neutral UDS is marked by the integration of traditional and innovative infrastructure (e.g., grey-green infrastructure), which has been driven by CSO-related policies in the past five decades [18–20]. This transition has been recognized for its indirect reduction [21] in energy use, direct [5], and indirect carbon footprints [22,23], spanning initial construction to long-term emissions.

2.1. Global situation of CSO pollution

Following the implementation of policies and regulations to mitigate CSO pollution, CSOs are subject to discharge permissions and treated to remove contaminants that threaten the public environment. However, according to recent reports on urban water systems worldwide [24–26], CSO pollution remains a significant issue and poses an intermittent risk to water quality. Table S1 in Appendix A summarizes the global CSO pollution loads. For example, in the United Kingdom (UK), national monitoring data demonstrate a remarkable rise in CSO numbers in recent years, and the number of CSO events and discharge structures has remained elevated over the past three years [24–26]. These hydraulically overloaded CSOs result in chronic pollution impacts across significant stretches of rivers (owing to widespread elevated ammonia and/or reduced dissolved oxygen) [27]. Although the UK completed the installation of monitoring devices for CSOs by 2023, other countries have not established integral monitoring systems, making them more vulnerable to unassessed overflow risks. Despite these efforts, CSO pollution remains a significant threat to urban water quality worldwide. Furthermore, the frequency of CSO events is likely to increase because of factors that disturb the urban water cycle, such as climate change with more frequent extreme weather events [28,29], aging sewage systems in combination with additional groundwater input, and urbanization combined with increased impermeable surface areas [30–34]. Overall, current efforts towards CSO control have yielded unsatisfactory outcomes and CSOs continue to transport heavy pollutants to urban water bodies.

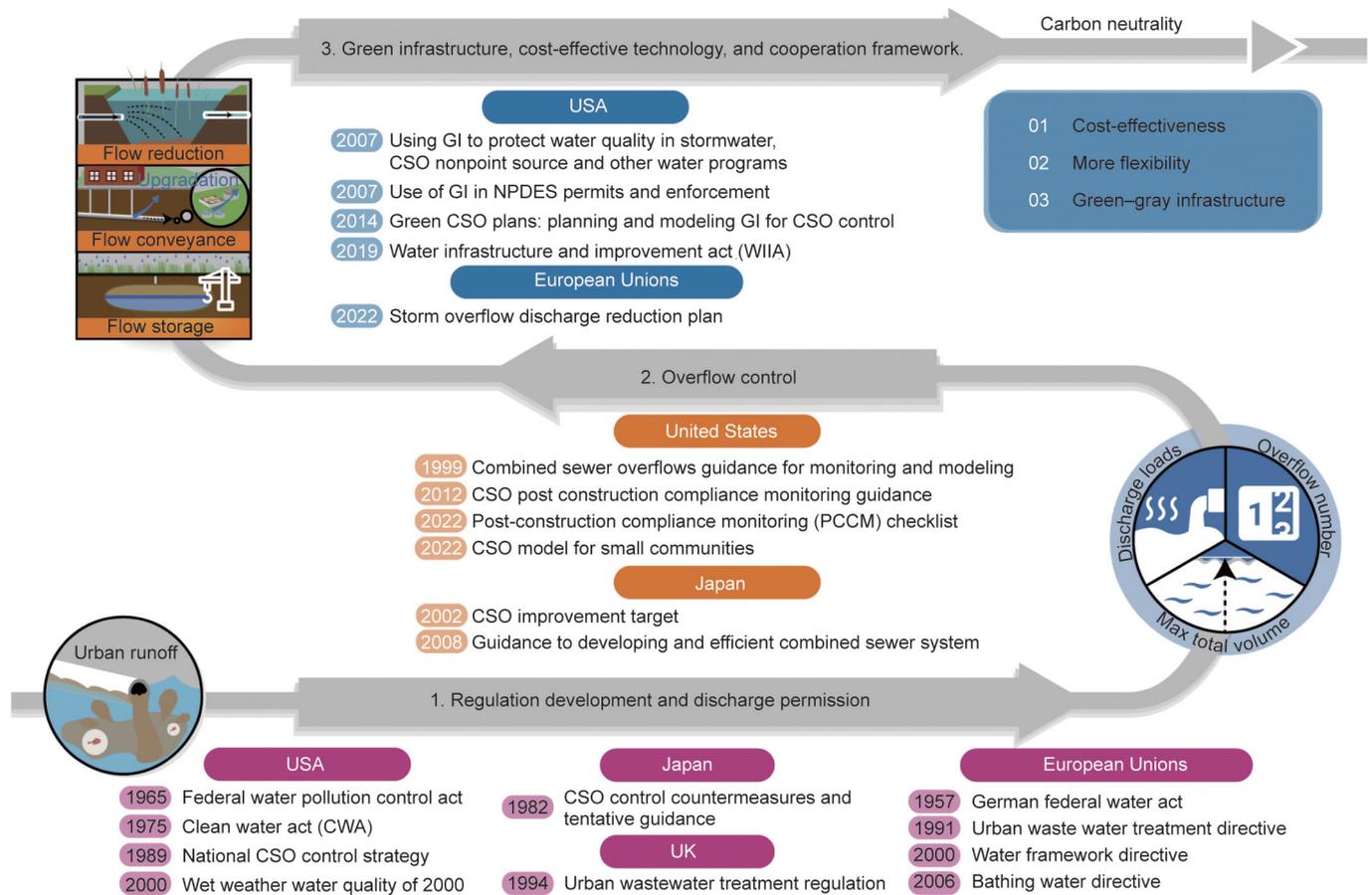


Fig. 1. A summary of historical regulations legislation, and policy in the CSO sector and the recent trends that would affect the carbon neutrality of the sewer system. GI: green infrastructure, NPDES: National Pollutant Discharge Elimination System, Max: maximum.

2.2. Further development

Furthermore, involving CSO control as part of UDS management in carbon-neutral policy [35,36] regimes to mitigate environmental impacts is inevitable. Therefore, developing clean energy technologies and reducing GHG emissions are crucial to achieving CSO control and carbon neutrality [37]. Taking a step toward achieving this milestone in the UDS, CSO-related policies have served as guidance while taking action for CSO management. Furthermore, the recognition of emission potential, identification of clear emission boundaries, and practical engineering solutions are crucial for GHG emission management in the UDS.

3. Identification of emission hotspots from CSOs

Limited by the complex interactive nature of CSO events in the UDS, mechanistic studies of emission boundaries and distribution are scarce. This review can only infer the reasons and extend the emission boundaries from the available literature and engineering experience. In the scope of a UDS, CSOs are often accompanied by pollutant discharges into water bodies, discharges from pumping points in wet weather, and overloaded WWTP operations. Although most countries have identified WWTPs as emission sources in their carbon accounting frameworks, CSOs are currently overlooked as potential emission hotspots in sewer systems [2,38,39]. CSO discharge can be regarded as a special event that disturbs the direction of material and energy flow. Fig. 2 presents a schematic of direct and indirect CSO-related GHG emissions from source to sink in the UDS. These emission boundaries were defined

using the life-cycle assessment (LCA) method expansion approach (Text S5 and Fig. S1 in Appendix A) [40]: ① Urban water systems where CSOs are discharged: mainly riverine ecosystems; ② static urban wastewater management systems: WWTPs and ancillary network infrastructure; and ③ boundaries of urban engineering and hydrology interactions: including sewage conduits, sewer networks, and pumping stations. This review considers interactive boundaries, a crucial concept that encompasses the final destination of CSOs and the activities influenced by them, such as receiving waters and external energy consumption. All of these factors play key roles in CSO management and GHG estimation. Employing a cross-scale approach [41], the following sections discuss CSO-related GHG emission hotspots in the UDS, as well as the corresponding mechanisms and influencing factors within these units.

3.1. GHG emission in sewers

Sewer systems, which are essential components of UDS, are responsible for collecting and transporting wastewater from residential areas to WWTPs. These systems contribute to GHG emissions, particularly CH₄ and N₂O. Although studies [14,17,42–44] on CO₂ and N₂O are scarce, we can only describe the critical processes and factors related to CH₄ formation as emission boundaries in sewer systems. ① Sewer type and operating conditions. Sewer systems are operationally divided into rising main and gravity sewers (the main sewer category of CSSs in dry weather) [17]. In gravity sewers, stagnant wastewater flow creates an anaerobic state and solids deposition, which enhances CH₄ production from the bulk-phase or slime sources [1]. ② Biological mechanisms.

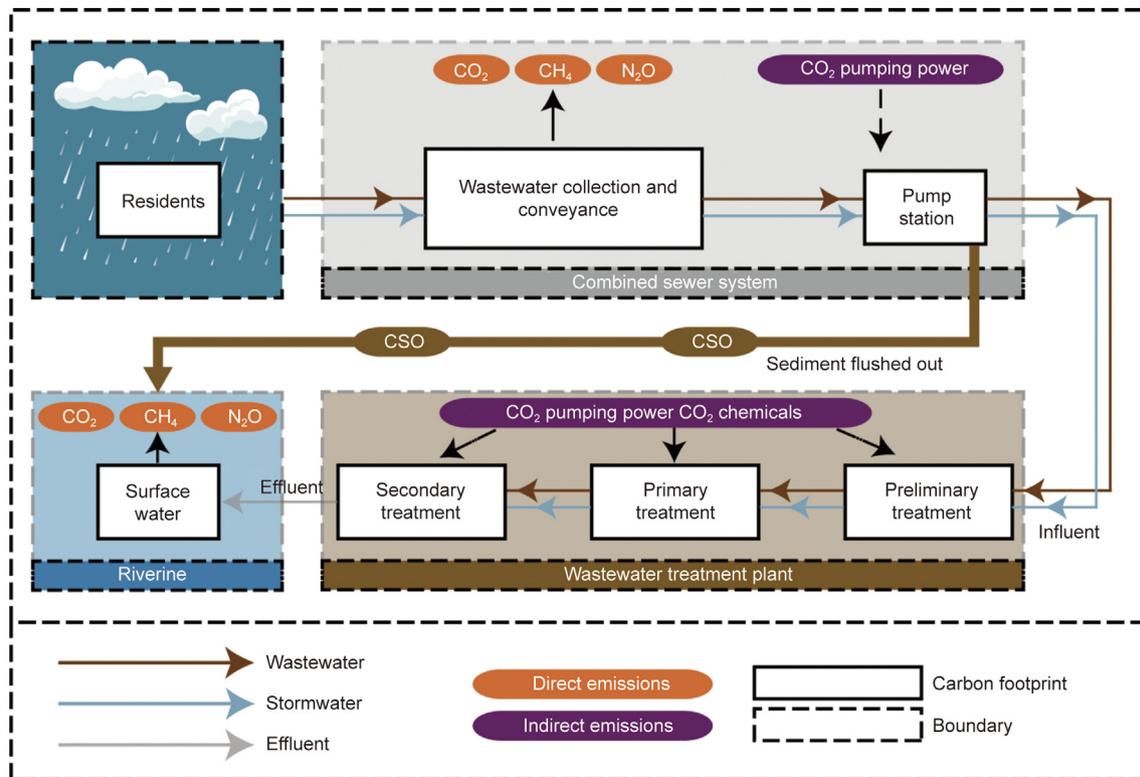


Fig. 2. Schematic of GHG emissions from source to sink due to CSOs in the UDS.

GHG emissions originate from anaerobic, anoxic, or aerobic biological processes that occur in sewer sediments, bulk water, and biofilms that grow on pipe walls [45]. ③ Hydraulic and environmental factors. Water level changes, temperature differences, and pressure differences drive the gas emissions from sewer systems [2]. Driven by the CSO storage effects [46], as the headspace of the sewer system is eliminated, the volume of water filling the sewers moves air upstream to the nearest drop structure, creating high airflow rates during CSO events.

Another key process is that as sewers continue to operate at high water levels during CSO events, their hydraulic parameters approach those of rising main sewers, increasing CH_4 solubility due to pressure changes in the sewers. Consequently, CH_4 trapped in the wastewater and sediment phases within the pipeline enters natural waters with CSO discharge, likely disturbing the spatiotemporal distribution pattern of CH_4 and causing uncontrolled emissions of CH_4 . Based on current laboratory experiments and models, most studies [47] have focused on CH_4 production rather than emissions in sewer systems [2]. Comprehensive hydraulic conditions during CSO events, such as the mixing of water and airflow and complex topologies, make it more difficult to scientifically account for CSO-driven carbon emissions from sewers.

3.2. GHG emission in riverine ecosystem

Increasing evidence has demonstrated that global riverine ecosystems are vital sources of GHG emissions [7,48,49]. Inland waters emit approximately 20% (4.3 petagram carbon per year ($\text{Pg-C}\cdot\text{a}^{-1}$)) of the global carbon budget into the atmosphere [50]. In the study of GHG emissions from riverine systems, research has been conducted on CO_2 , CH_4 , and N_2O emissions [48,51]. The influencing factors are summarized below. ① Extreme weather and hydrological conditions. The intensity and frequency of extreme weather, and hydrological conditions drive the gas emissions from riverine systems. During rainfall events, CSO discharges

are accompanied by pump station drainage and sediment disturbance from pipelines, which input a substantial number of organic pollutants into the receiving water [4]. ② Pollutant inputs, including nutrient loads and dissolved CH_4 . The scoured sewer sediments introduce quantities of nitrogen- and phosphorus-containing materials to the riverine, contributing 20.9%–44.6% and 35.66%–47.3% of total nitrogen (TN) and total phosphorus (TP) mass, respectively, in the receiving water body [52]. Simultaneously, the flashed wastewater mixed with rainwater contains dissolved CH_4 , which can be rapidly released into the atmosphere. ③ Anoxic and anaerobic conditions. Under these circumstances, riverine systems are highly susceptible to rapidly entering anoxic/anaerobic conditions, which promote GHG emissions from the riverine systems. Furthermore, riverine GHG emissions from CSOs may even have a delayed nature compared to CSO events, which requires in-depth exploration due to the temporal-spatial heterogeneity of gases in riverine systems.

3.3. Electrical energy consumption

The dramatic increase in flow over a short period during wet weather puts pressure on the operation of sewer systems, particularly the wastewater collection and transportation systems. The increasing frequency of extreme weather events (e.g., extreme precipitation, catastrophic floods, droughts, heat-cold waves, and storms) has exacerbated this pressure. Electrical energy consumption is becoming a critical hotspot for energy intensity and GHG emissions in UDS. A case study [13] in Delhi, India revealed that wastewater transportation accounted for 45.3% of the total daily energy use in the UDS. The proportion of energy used during the operational phase was 70%, of which 79% was electrical energy. Pumps used for wastewater lifting and transportation in sewers also contribute to indirect GHG emissions, which are calculated using emission factors (EF) [53]. This EF should be optimized according to local realities and situations.

3.4. Chemical consumption

When CSOs occur in the UDS, flows mixed with wastewater and stormwater reach the WWTPs. This leads to an overloaded operation of the WWTPs and lower organic compound concentration in the influent. The most intuitive GHG emissions are the additional chemicals used to treat low-carbon and high-flow wastewater transported to WWTPs [15,54]. Furthermore, it is reasonable to speculate that overflow can render the inefficient operation of WWTPs, necessitating carbon-intensive measures to maintain their functionality.

3.5. Innovations for carbon accounting: clearer boundaries and methodology shift

There is a knowledge and data gap in our understanding of the spatiotemporal distribution and intensity of GHG emissions during CSO events in the UDS. Owing to complexities, monitoring limitations, and costs, GHG estimation remains challenging due to inconsistent and unclear emission boundaries. To define clearer emission boundaries, enhanced research on microscopic processes during CSO events is crucial, as it could increase the clarity of the emission boundaries and facilitate accurate carbon attribution. Improving data monitoring and collection is fundamental to bridging this gap. The requirements for data acquisition include: ① CSO water quality and quantity; ② hydraulic parameters (e.g., water level, flow rate, and even sediment thickness) within the network during CSO events; ③ operational parameters of the ancillary network infrastructure in sewer systems, for example, influent flow and electrical energy consumption per day; ④ monitoring data of water quality and quantity in receiving water bodies before and after the occurrence of CSOs. Carbon accounting methods including the EFs and direct measurement methods, are restricted by data collection and regional differences. By quantifying the EF changes in UDS parameters including specific CSO events in different regions or cities, a global emission inventory can be established based on full-scale measurements and comprehensive data collection. The implementation of this pathway underscores the need to navigate data availability and address the variability in the nature of CSOs, as we explore in the next section.

4. Estimation method and supportive model of CSO-related GHG emission

Although imperfect, the development of mathematical models offers a solution to CSO issues. These models bridge the gap between laboratory experiments and large-scale predictions by establishing reasonable quantitative relationships for CSO-related environmental factors and identifying their correlations with GHG emissions. Therefore, such modeling can serve as a powerful tool to support UDS in the operational management and development of mitigation strategies. Owing to the temporalspatial heterogeneity of GHG emissions during CSO events, researchers have preliminarily explored the modeling framework corresponding to each emission boundary of the CSOs. By varying the key parameters across different types of drainage systems and altering the driving mechanisms of the models, the accuracy and granularity of GHG emission estimations from CSOs were improved. Fig. 3 illustrates the integrated modeling framework proposed in the following sections, as well as its data needs, relevant architecture, and further development potential.

Notably, several studies have investigated CSO models that emulate the overflow volume, duration, and other parameters [55,56]. The impacts of anthropogenic discharge (e.g., urban runoff) on riverine nitrogen and carbon transportation have been pro-

gressively elucidated, along with the GHG generation model in sewer systems [51,57]. In the subsequent sections, existing estimation methods corresponding to GHG emissions caused by CSOs are systematically summarized and discussed to refine the estimation system (Fig. 3) of CSO-related GHG emissions in the UDS.

4.1. CSO models: monitoring data for basic physical and chemical parameters

The first step in mapping full-scale GHG emissions, particularly those without mature models, is a deep dive into hydrological connectivity and micro-scale reactions during CSO events. CSO models provide basic physical and chemical parameters for GHG estimation and serve as essential prediction bridges between sewers and riverine environments. As shown in Fig. 3, the water quantity and quality models mainly constitute the sewer–river water models, which predict the CSO volume and pollutant loads for GHG estimation.

4.1.1. Modeling of CSO volume

These models can be roughly classified into three primary categories: physically-based, statistical, and artificial intelligence (AI)-based models (Texts S6–S8 in Appendix A) [54]. In terms of projecting GHG emissions related to CSOs, models that predict CSO volume can assist in estimating ① direct emissions: how much wastewater mixed with stormwater floods into the riverine ecosystem, and ② indirect emissions: how much stormwater enters the WWTPs, causing inefficiencies. Tables S2 and S3 in Appendix A summarize the studies that utilized these three models to predict overflow volumes. Physically-based models, grounded in the principles of physical processes, describe the relationships among the explanatory parameters of the simulated process [58]. Important input factors include the geometric characteristics and boundary conditions of pipelines, catchment conditions, soil properties, area of impermeable areas, and the digital elevation model of the simulated area [56,59–62]. Statistical models explain the relationship between variables and different overflow characteristics using data-driven techniques, often predicting the probability of CSO occurrence within a certain confidence interval [8,63]. Compared to physically-based models, statistical models are advantageous owing to fewer input data requirements, reduced time consumption, and fewer requirements for physical and chemical knowledge [56]. These models effectively simulate a limited number of CSO events and enhance prediction capabilities through model combinations [64–66]. AI-based models address the inherent uncertainty of datasets, rendering them highly suitable for UDS operation management [56]. Deep learning techniques, such as recurrent neural networks, and long short-term memory, excel at extracting features from raw data using multiple hidden layers [67]. Furthermore, sewage flow in pipelines shows different trends according to social phenomena and climate change factors, such as atmospheric humidity, time of day, and day of the week should be included in the modeling process. By building frameworks that bridge big data algorithms and physics-based numerical models, the accurate prediction of CSO location and time traces in a time frame of seconds can be realized [68].

4.1.2. Modeling of CSO pollutant load

Mathematical water quantity and quality models within sewer systems are typically employed to assess the CSO pollutant loads. Ideally, an integrated modeling method should be applied to estimate the impact of CSOs on current water quantity and quality. These approaches are in synergy with hydrological and hydrodynamic models of the UDS and receiving waters, and consider their interaction [69,70]. Water quantity models (e.g., physically-based models) are elaborated in Section 4.1.1, which allows for a detailed

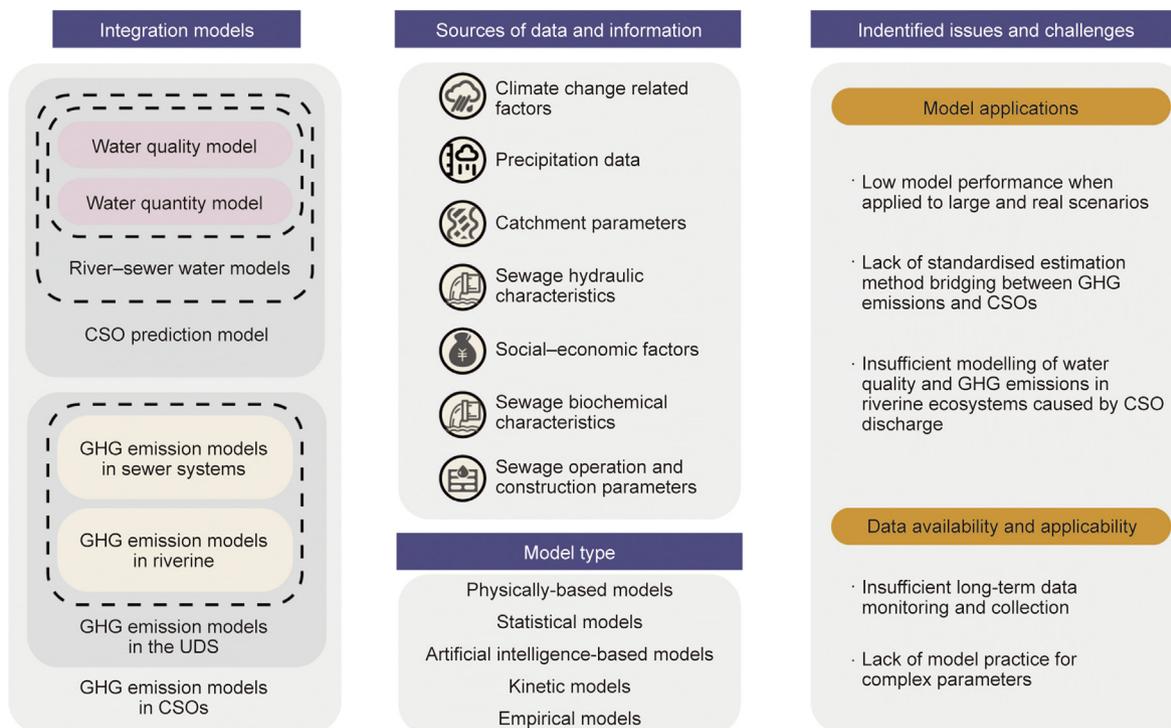


Fig. 3. Integrated models for GHG estimation from CSOs, their data needs, relevant architectures, and potential for further development.

and accurate design and analysis of sewerage infrastructure. To model the impact of CSO on surface water quality, only a single pollutant is considered, for example, an indicator of organic matter content such as biological oxygen demand (BOD). This may not be sufficiently comprehensive to define the quality of the receiving water, because other pollutants may also be important. Under these circumstances, water quality models can be used within sewer systems, however, their performance is generally poor [2]. As an option, sample CSO emissions can be applied to the calibration of the regression model for predicting CSO pollutant loads, and this approach is heavily dependent on the high quality of samples and the monitoring of CSOs [71,72]. Another option is to predict the TSS and COD loads of CSO events using the rainfall and CSO volume characteristics [73]. However, these datasets are not always valid; for example, sewer systems worldwide can have various layouts and sources of sewage (e.g., different household and industrial wastewater). Moreover, CSO concentrations often vary over time due to “first flush” or other processes in the overflow events. We found that this requires knowledge and effective data on the relative impact of certain pollutants on receiving waters; however, such knowledge may not be available in data-scarce areas or countries. Furthermore, addressing the impact of CSOs on water quantity and quality in sparsely observed areas has become an urgent problem.

4.2. Sewer GHG models

Detector techniques (the tracer dispersion method and optional gas imaging infrared video camera) are traditional measurement technologies for CH₄ in sewers. However, owing to the complex measurement environment, these techniques exhibit inaccuracies in temporal and spatial variability and are impractical for long-term quantification. Consequently, advanced monitoring methods and mathematical or machine learning (ML)-based models are crucial for CH₄ estimation, providing a robust tool for refining methane EF in sewer systems. Currently, there is no direct model

for the CO₂ and N₂O emission processes in sewers [2]. Although no standardized model for CH₄ emissions from urban drainage pipe systems exists, several studies have developed kinetic or empirical models that consider the main factors influencing CH₄ emissions and biochemical processes, thereby providing preliminary measurement tools. Table S4 in Appendix A summarizes the representative CH₄ models used in previous studies. A detailed analysis of the CH₄ modeling for these two categories is presented in the following two sections.

4.2.1. Kinetic models

As shown in Table S4, the kinetic models describe the primary biochemical processes within the pipeline and predict the changes in CH₄ concentrations based on the measured kinetic parameters. Biological reactions have been modeled as biofilm processes in most sewer models such as the SeweX models [74]. As a dynamic model, the SeweX model (Text S9 in Appendix A) was used to analyze the distribution pattern of CH₄ in the pipeline. However, SeweX is computationally intensive and assumes uniform biofilm activity throughout the pipeline, which may not reflect variations in the wastewater composition and biofilm activity [75,76]. Other kinetic models, such as the first-order kinetic model and modified Gompertz model, have also been applied to monitor CH₄ production. The first-order kinetic model only simulates cumulative CH₄ production after stabilization, because it cannot be calibrated for the acclimatization phase of microorganisms at the beginning of the reaction. Modifying the model (Table S4) by introducing parameter *c* to account for the different reaction kinetics of soluble inert components in wastewater, this model achieves a good fitting effect except for the absolute parameters (e.g., macro-parameters such as initial delay and final CH₄ production) [77]. Including the lag time (λ) as an important indicator of substrate biodegradability and utilization rate, the modified Gompertz model outperforms the predicted and measured CH₄ yields compared to the first-order kinetic model [78]. However, kinetic models can be limited by unknown elements or changes in wastewater composition and

often overlook the biochemical processes that occur in sediments along the pipeline [47]. Therefore, integrating empirical equations that describe parameter changes in sewers would enhance the applicability of these models.

4.2.2. Empirical equations

Empirical equations for CH₄ production and emission in sewers are derived from extensive laboratory-scale data and provide simpler expressions than kinetic models. Table S4 lists the empirical equations developed in previous studies and their performances in simulating CH₄ production. Previous kinetic models have been developed based on the fitted correlation between CH₄ production, pipe area-to-volume ratio, and hydraulic retention time (HRT) in fully pressurized sewers [14]. Owing to less interference from external climatic conditions, most empirical equations fit better with pressurized sewer system performance [79]. A longer HRT and more comprehensive reaction conditions lead to higher CH₄ emissions in gravity sewers [79]. There remains a research gap in addressing the equal potential for CH₄ production and emissions from gravity sewers and monitoring real-time changes in the CH₄ emission procedure when urban runoff and stormwater are flushed into the UDS. Recent studies [1,5] have focused on CH₄ emissions from gravity sewers. These models integrate multiple biochemical and physical processes (e.g., chemical precipitation reaction processes, biochemical reaction processes in different media and their interfaces, and convection processes in sewer up space) [75,77,80]. Collectively, these studies aimed to provide comprehensive models for predicting CH₄ emissions from gravity sewers by incorporating diverse reaction processes and environmental factors. These models offer a foundation for a recognized CH₄ production and emission measurement model. However, further validation using more comprehensive datasets is required to enhance their application.

4.3. Riverine GHG models

Researchers have increasingly emphasized the importance of GHG emissions in riverine ecosystems at a global scale [48,49,81], whereas the crucial work is the establishment of a reliable simulation framework for GHG emissions in such a complicated environment. Existing studies have begun to involve more emission sources in their research network, such as external sources (e.g., surface runoff and groundwater inputs) and sinks (e.g., complete denitrification and atmospheric release during downstream water transport before sampling sites) [81]. However, large uncertainties related to existing simulations have persisted, perhaps because of methodological bias, data scarcity, and an inadequate or uneven understanding of the environmental factors driving riverine GHG emissions. Therefore, there is an urgent need to develop an efficient model that fully considers riverine GHG sources, sinks, and transformation processes during hydrological transport. Previous studies [81,82] have primarily focused on simulating or monitoring single GHG emissions, particularly N₂O emissions, under varying temporal and spatial conditions. Under these circumstances, some researchers have started to monitor GHG emissions driven by climate change, however, enhancing the prediction accuracy of GHG emissions involving anthropogenic nitrogen and carbon emissions from urban runoff and CSOs remains challenging. Table S5 in Appendix A summarizes the quantification methods and models used in various studies to measure GHG emissions from riverine environments. To address GHG emissions from an entire riverine ecosystem, several models have been developed by coupling the river network nitrogen or carbon removal model with measured reaction rates and integrating the GHG emission model with the soil and water assessment tool. Additionally, power-law scaling and dynamic land ecosystem models were employed to assess riverine GHG emissions. How-

ever, most models primarily assume GHG production from instream biogeochemical processes. It is crucial to consider the process of gas exchange across the water–air interface and external nitrogen and carbon sources from urban areas. Only a few methods exist for quantifying GHG emissions from freshwater systems, such as the eddy covariance method [82], floating chamber method [83], flux gradient methods, and diffusion models [84]. The advantages and limitations of these methods are summarized in Table S5. Notably, river characteristics such as flow conditions, water depth, and water level must be considered during modeling. Section 4.1 suggests that data-driven models can be used to estimate these characteristics, as demonstrated by studies simulating global riverine GHG emissions from different streams [85].

4.4. Strategic GHG emission estimation

As shown in Fig. 3, by integrating GHG emission models in sewers and riverines, GHG models in the UDS provide a broad-scale perspective, whereas CSO prediction models serve as detailed analyses for evaluating CSO-related GHG emissions. Therefore, employing a systematic approach to carbon accounting is instrumental in understanding the complex water cycle within the UDS. From the perspective of a comprehensive framework, these approaches share common key parameters and information (Fig. 3). Assessing water quality and quantity in terms of social–economic factors, along with sewer characteristics and geographical conditions is crucial for evaluating GHG potential. Addressing data availability and quality and filling the modeling gaps between GHG estimation and CSOs at the micro- and macro-scales are key points for further development. It is important to consider the impact of extreme weather events within this framework and conduct a thorough assessment of the carbon–nitrogen cycle to clarify control strategies [86,87].

5. Mitigation of GHG emission associated with CSOs

Recognizing the potential for emissions highlights the need for practical engineering solutions. The reduction in CSO volume and pollutant load is expected to be effective in mitigating GHG emissions. To date, different technologies for CSO control have been developed, such as increasing the storage capacity of stormwater, extending detention or retention facilities, and developing sewer separation and treatment technologies. In most regions, changing the existing CSSs into separate drainage systems (i.e., sewer and stormwater systems) is often prohibitive, and the reduction of pollution cannot be guaranteed because of some pipe deficiencies [88]. Therefore, this section only reviews control strategies that do not modify sewer construction. State-of-the-art strategies to mitigate GHG emissions from CSOs are presented in Fig. 4, and the mechanisms of GHG reduction are also summarized. Overall, these strategies can be classified as “Front of the pipe” mitigation, “In the pipe” monitoring, and “End of the pipe” treatment. Furthermore, this chapter emphasizes the potential of employing data-driven technologies for CSO mitigation and proposes an integrated CSO control framework for future research and practical applications.

5.1. “Front of the pipe” mitigation

The aim of “Front of the pipe” mitigation is to prevent stormwater from entering sewer systems as much as possible. External storage and treatment of stormwater and runoff prior to entering CSSs during intense rainfall can reduce CSOs, often referred to as stormwater control methods (SCMs), within the urban water management framework [89]. Considering the limited suitable space in

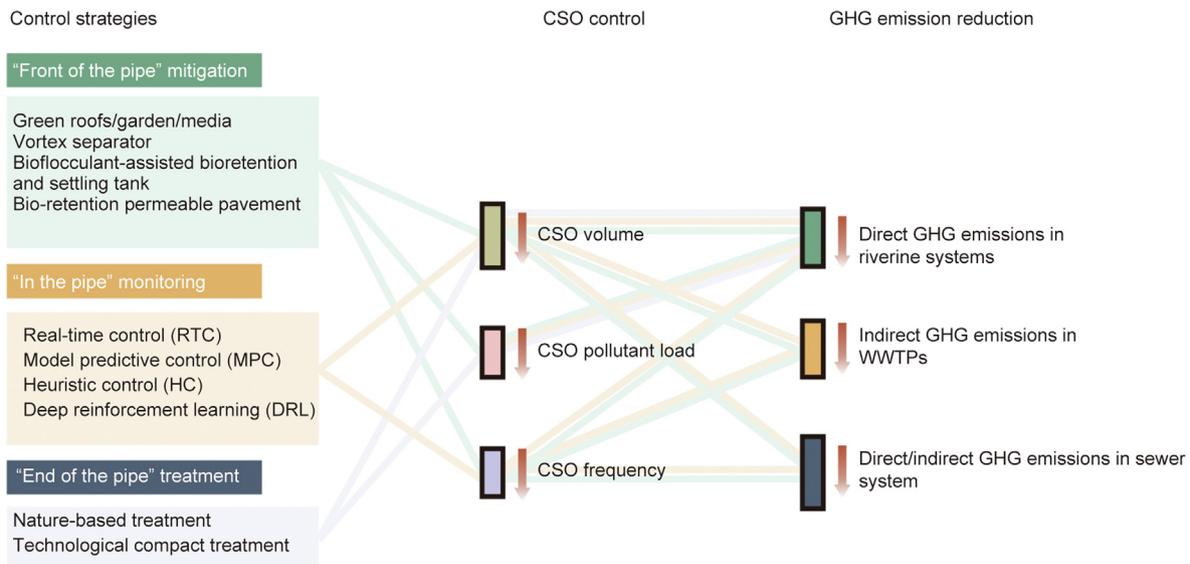


Fig. 4. Mechanisms and strategies involved in different actions to mitigate GHG emissions associated with CSOs from source to “End of pipeline”.

the catchment and the tension in urban land use, these types of SCMs commonly occur as to maximize the use of space within the city. This is known as low-impact development infrastructure in sustainable UDS (SuDS) and sponge cities in other regions [90]. Existing solutions, including hydraulic buffers, physicochemical filtration and adsorption systems, bioretention processes, flocculant-assisted bioretention, and underground separation units based on the gravity of centripetalism, are presented in Fig. 4. Table S6 in Appendix A summarizes the effects of common SCMs and their applicability.

GI in SuDS, including green roofs, infiltration swales, and other nature-based solutions [91], can retain stormwater, mitigate runoff peaks, and further remove specific contaminants associated with stormwater runoff (e.g., suspended loads) [91–93]. That is, SuDS can mitigate the GHG emissions of CSOs by increasing runoff catchment time, reducing the volume, and removing the pollutant loads of runoff [94]. However, despite its promising performance in urban stormwater management, GI cannot completely replace traditional gray infrastructure (e.g., gutters, drains, pipes, and retention basins) in terms of cost-effectiveness. Several comparative studies have illustrated that GI combined with gray infrastructure is a better option for peak flow and pollutant load reduction than individual infrastructure [95,96]. Simultaneously, GI and gray infrastructure were found to have different mechanisms of CSO mitigation. GI with outlet control can better reduce the CSO volume, whereas gray infrastructure is better at reducing the frequency [96]. Furthermore, SuDS can sustain a long-term reduction in CSO volume with a reduction ratio ranging from 50%–90% [94]. The long-term CSO reduction capacity of each GI is vitally important owing to continuous climate change. Apart from increasing stormwater management capacity locally, GI also has a low environmental impact throughout the entire life cycle of the sewer system, owing to the reduced need for the production of construction materials in particular, as well as reduced indirect GHG emissions (e.g., fuel consumption) during the construction process [97]. The rain garden was estimated to have total and net carbon reductions of 1927.41 and 809.99 tonnes CO₂ equivalent (tCO₂e) respectively, using the LCA method, and GI was assessed to improve the annual GHG mitigation level by 45.9% in a city-scale UDS [98,99]. A comprehensive simulation of the interaction between GI and CSO outfalls with continuous, long-term rainfall event data is needed, and integrated GI deployment strate-

gies for reducing CSOs during high-intensity rainfall events require further investigation.

5.2. “In the pipe” monitoring

“In the pipe” monitoring aims to operate the existing infrastructure in the UDS. Along with the digitization of the water sector, real-time control (RTC) has proven to be an efficient method of CSO reduction [89,100,101]. Equipped with sensors and flow control actuators, the RTC can fully utilize the pipeline capacity of storage and conveyance and make real-time operation decisions regarding actuator settlings in the UDS [100,102,103]. The traditional RTC methods include heuristic control (HC) and model predictive control (MPC). HC uses preset rules to control UDS, thus lacking adaptability to changes in environmental conditions (e.g., fluctuations in water quantity and quality during rainfall), resulting in poor CSO mitigation performance [104]. MPC typically outperforms the HC methods, because it uses short-term rainfall prediction, UDS model simulation, and optimization algorithms to optimize the operation strategy at each control time point [100,105,106]. However, the performance of MPC is limited by the accuracy of rainfall prediction and the computing speed of its optimization algorithm [100,102]. Fortunately, MPC applications are facilitated by the use of wireless technologies and autonomous control of gates, valves, and pumps within the pipeline network.

With the widespread use of deep learning (DL) approaches in urban water management [107], RTC methods based on reinforcement learning (RL) and deep RL (DRL) have also been implemented for UDS operation [100,102,104,108–110]. DRL uses experimental trials and relatively simple feedback to train an RL agent to control the UDS in real-time through a closed-loop framework employment [104]. In other words, it is more suitable for RTC scenarios than HC and MPC [110]. Moreover, the performance of the RL controller is sensitive to the formulation of the deep neural network, thereby requiring a large number of computational resources to achieve performance enhancement. Additional efforts have also been made to make communication more robust from the perspective of the control architecture. Zhang et al. [103] proposed a decentralized RTC method for overflow reduction based on multi-agent RL (MARL) to enhance communication robustness, achieving the reduction of CSO volume by 14.39%–21.36% compared to currently-used rule-based control (RBC) in synthetic

rainfalls of the real-world case. More RL strategies, such as centralized and fully decentralized methods, for optimizing control effects and communication robustness, and more robust and fail-safe options for communication failures still have extensive research potential.

5.3. “End of the pipe” treatment

Intercepting and processing CSOs at the end of the pipeline is the final hurdle in mitigating their impact on GHG emissions in urban water systems. Existing strategies regarding end-of-pipe treatment for CSOs and their mechanisms of GHG reduction are shown in Fig. 4. Overall “End of the pipe” treatment strategies can be divided into nature-based treatment (e.g., constructed wetlands (CWs)) and technological compact treatment. Among the CWs used for CSO treatment, vertical flow CWs, also known as retention soil filters (RSFs), are popular and consist of a planted media bed in which water percolates. As shown in Table S7 in Appendix A, RSFs have been extensively studied in terms of their treatment performance for conventional target pollutants including COD, TP, and ammonia nitrogen ($\text{NH}_4^+\text{-N}$), as well as peak flow reduction, showing high removal efficiencies and stability.

The technologically compact treatment can be achieved using in-line treatment methods such as disinfection, adsorption, or chemical coagulation before discharge [89,111]. Table S8 in Appendix A summarizes the alternatives for CSO technological compact treatment and their performance in pollutant load removal. These treatment technologies can remove the total suspended solid (TSS), phosphate, and organic matter from CSOs. Although the removal efficiency of emerging contaminants has been fully investigated (Table S8), studies on their application in the treatment of emerging contaminants in CSO flows are currently lacking. This research gap may be attributed to the lag in the proposal of a technological compact treatment for CSO control and the lagged application of physically-based models such as the stormwater management model (SWMM) in CSO flow modeling. Characterized by intricate sources of pollutants in different phases (e.g., solid and liquid phases), an in-depth analysis of the multi-source pollution of CSOs underpins the development of control processes.

5.4. Calling for integrated CSO control frameworks

Cities have limited resources for controlling CSO-related GHG emissions. Hence, to maximize the cost-effectiveness of existing and future CSO control strategies and mitigate GHG emissions, the proposed solution should be equipped with advanced control technologies and data-driven methods [112,113]. Although previous studies have assessed the impact of RTC methods with different types of GI and other SCMs [105,114–117], there is still a need to apply more complex RTC schemes (e.g., MPC, RBC, or even DL-based RTC scheme) to improve GI controls, analyzing how to implement and distribute GIs gradually based on environmental priority to avoid CSOs. Simultaneously, the need for polishing CSO control strategies to improve storage and conveyance capacities during minor- and medium-sized rainfall events by smart control of stormwater inflows in UDS has also emerged. To compare the performance of different RTC strategies (i.e., MPC and RBC) integrating a large-scale distribution of GIs, Jean et al. [117] proved that the scenario combining GI with MPC is a better strategy to avoid almost all CSO events. Future studies should continue to integrate MPC and other emerging RTC methods with GI and other SCMs to determine how these technologies complement each other. Meanwhile, from the perspective of GHG emission mitigation in the entire life cycle to reduce the CSO discharge impact, an integrated framework involving ① more advanced control processes to reduce CSO volumes and contaminants, ② more comprehensive and emergency-

capable data-driven technologies to manage urban water systems, and ③ larger scale urban facilities such as WWTPs and riverine ecosystems to control CSOs from the whole city perspective is urgently needed, which could provide new and fundamental changes in the way UDSs reduce their GHG emissions.

6. Challenges and limitations while implementing carbon neutrality practices

Based on state-of-the-art research, the current understanding of CSO-related GHG emissions in the UDS contains significant gaps and contradictory findings. The observed limitations and challenges are as follows:

(1) Beyond CSOs in CSSs, sanitary sewer overflow (SSO) caused by illicit connections between pipelines, and structural and functional failures [118] in separate sewer systems pose a serious threat by introducing high concentrations of contaminants into aquatic environments in China. It is common to illegally connect sewage pipes to stormwater pipes in developing countries. Therefore, SSOs also contribute to urban pollution during wet weather [119]. CSOs and SSOs contribute to GHG emissions, however, few studies have comprehensively reviewed this issue. Therefore, a broader focus on carbon emission boundaries, footprints, and verification systems regarding the operational failure of pipelines is urgently required, and the differentiated situations of CSOs and SSOs in urban areas should also be considered.

(2) A clear definition of emission boundaries for CSOs is crucial for effective carbon management. Research on the microscopic physical, chemical, and biological processes can clarify emission boundaries and assess emission dynamics. For instance, it is urgent to uncover regular patterns of GHG emission during CSO formations and discharge and to parse the transformation regulation of pollutants and GHG between different reaction media. Long-term observations of CSO events, including multi-frequency sampling and analysis during CSO events, are essential to accurately quantify their effects on water parameters, hydrological patterns, and GHG emissions. This requires the deployment of additional online monitoring equipment and comprehensive monitoring programs.

(3) Data-driven UDSs could offer novel methods of CSO mitigation and management, overcoming challenges in carbon accounting, such as data scarcity, low information accuracy [120], and strong spatiotemporal heterogeneity. For example, dynamic data scarcity in real-time water quality and quantity during CSO events hinders the realization of GHG prediction and monitoring. These approaches require advanced computational power for detailed forecasts and improved hardware and mathematical techniques. We believe that ML and DL will fundamentally transform UDS management and operation in response to climate change and environmental challenges. Furthermore, wastewater-based epidemiology can enhance CSO monitoring and provide insights into public health and wellbeing [121].

(4) Implementing integrated CSO control strategies toward carbon neutrality faces resistance and trade-offs. The outcomes of the CSO control, operational costs, and GHG emissions are conflicting. Moreover, quantifying the trade-off between potential benefits and investment necessity remains challenging. Wastewater is dynamically linked to water, energy, and carbon emissions in the urban water cycle [122,123]. Considering CSO control strategies at different scales, their contribution to carbon emission control demonstrates different outcomes. Contractions arise between carbon loss management in wastewater and direct carbon emission control in the UDS [2]. To guide future CSO management, systematic simulations can be implemented to optimize construction programs according to different urban economic and social characteristics, and then seek environmentally friendly and economical control strategies.

These challenges and limitations demonstrate that the application of data-driven CSO control strategies in a UDS is not limited to technological innovation. A whole-system perspective is necessary to transform UDS operations, and technologies should be adapted to local conditions. Simultaneously, it should be realized that the mitigation of GHG emissions caused by pipeline issues (e.g., illicit connections of sewer pipelines to stormwater pipelines or misconnections of stormwater pipelines to sewer pipelines [88]) is a root-based solution for GHG emission reduction in the entire UDS, compared to the utilization of WWTP operation or conducting end-of-pipe control. Therefore, transitioning from CSO emission risk management to comprehensively sustainable GHG management from the source (i.e., drainage pipe network) to the sink (i.e., natural water or WWTPs) in the UDS represents a future direction.

7. Conclusions

This comprehensive review elucidates policies, dynamics, and control strategies for GHG emissions from CSOs. As guidance to deal with CSOs, related policies have gradually identified the reduction of CSO impact on the entire environment as an emerging objective. Concerning the GHG emission sources of CSOs, GHG emissions in riverine ecosystems where CSOs flood during rainfall events are noteworthy. The extra electrical and chemical consumption due to stormwater overflowing also accounts for indirect GHG emissions.

The application of models in CSO-related GHG emission estimation is still at an early stage as most studies focus on modeling specific processes of CSO in the UDS (e.g., CSO volume and frequency), GHG generation in sewer systems, and GHG emissions in riverine ecosystem driven by various factors. Comprehensive process models for carbon emissions have yet to be developed. The application of mathematical technologies, particularly ML and DL have not been fully exploited, despite lessons learned from the innovative use of DL technology in the RTC method. A promising future in which CSO-related GHG emission models are applied with integrated databases in UDS management will help governments capture real-time dynamic data on CSO emissions and their environmental impacts.

Given the potential of AI in the digital and intelligent management of urban water systems, we consider how these transitions can be applied to practical implementation and management strategies. We assert that addressing the GHG emissions challenge cannot be confined to traditional isolated technologies to mitigate CSOs. Integrated control systems incorporating runoff reduction, optimization of sewer operations, and efficient end-of-pipe treatment have been proposed as emerging methods to address the complexity of GHG emissions in networks. If the city is not flooded, using data-driven technologies (e.g., RTC and CSO modeling) could provide a more applicable CSO control strategy that maximizes the impact of a single control method and reduces the negative CSO impact on the entire environment.

We envision a future in which, from the perspective of a safe and smart city, three-step development routes from the full-scale mechanism of GHG dynamics influenced by CSOs, the practical application of data-driven technologies, the trade-off between cost and effectiveness, and finally, achieving active carbon emission control from CSOs will be developed. This approach contributes significantly to achieving carbon neutrality in urban wastewater systems, reinforcing the importance of integrating data-driven technologies with practical urban water system management.

CRedit authorship contribution statement

Yilin Xu: Writing – review & editing, Writing – original draft, Investigation. **Cheng Ye:** Writing – review & editing, Investigation.

Zuxin Xu: Writing – review & editing. **Wenhai Chu:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

This work was supported by the National Natural Science Foundation of China (52325001, 52170009, and 52400114), the National Key Research and Development Program of China (2021YFC3200700 and 2021YFC3200702), the Program of Shanghai Academic Research Leader, China (21XD1424000), and the Fundamental Research Funds for the Central Universities.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.eng.2025.03.027>.

References

- [1] Song CH, Zhu JJ, Willis JL, Moore DP, Zondlo MA, Ren ZJ. Methane emissions from municipal wastewater collection and treatment systems. *Environ Sci Technol* 2023;57(6):2248–61.
- [2] Chen J, Wang H, Yin W, Wang Y, Lv J, Wang A. Deciphering carbon emissions in urban sewer networks: bridging urban sewer networks with city-wide environmental dynamics. *Water Res* 2024;256:121576.
- [3] Aghdam E, Mohandes SR, Zayed T. Evaluating the sensory and health impacts of exposure to sewer overflows on urban population. *J Clean Prod* 2023;413:137498.
- [4] Zhao G, Wang D, Sun T, Ding Y, Chen S, Li Y, et al. Emission of greenhouse gas from urban polluted river during different rainfall events: typhoon and storm will promote stronger evasions. *J Hydrol* 2023;625:130166.
- [5] Su Q, Dai HC, Xie SY, Yu XY, Lin Y, Singh VP, et al. Water–energy–carbon nexus: greenhouse gas emissions from integrated urban drainage systems in China. *Environ Sci Technol* 2023;57(5):2093–104.
- [6] Zhu H, Wang Q, Liu J, Zheng X, Xu M. Closing the gap in methane emission from urban wastewater sewer system in China. *J Clean Prod* 2024;437:140722.
- [7] Xu W, Wang G, Liu S, Wang J, McDowell WH, Huang K, et al. Globally elevated greenhouse gas emissions from polluted urban rivers. *Nat Sustain* 2024;7(7):938–48.
- [8] Bizer M, Kirchhoff CJ. Regression modeling of combined sewer overflows to assess system performance. *Water Sci Technol* 2022;86(11):2848–60.
- [9] Perry WB, Ahmadian R, Munday M, Jones O, Ormerod SJ, Durance I. Addressing the challenges of combined sewer overflows. *Environ Pollut* 2023;343:123225.
- [10] Whelan MJ, Linstead C, Worrall F, Ormerod SJ, Durance I, Johnson AC, et al. Is water quality in British rivers “better than at any time since the end of the Industrial Revolution”? *Sci Total Environ* 2022;843:157014.
- [11] Dirckx G, Vinck E, Kroll S. Stochastic determination of combined sewer overflow loads for decision-making purposes and operational follow-up. *Water* 2022;14(10):1635.
- [12] Bertels D, De Meester J, Dirckx G, Willems P. Estimation of the impact of combined sewer overflows on surface water quality in a sparsely monitored area. *Water Res* 2023;244:120498.
- [13] Singh P, Kansal A. Energy and GHG accounting for wastewater infrastructure. *Resour Conserv Recycl* 2018;128:499–507.
- [14] Guisasola A, de Haas D, Keller J, Yuan Z. Methane formation in sewer systems. *Water Res* 2008;42(6–7):1421–30.
- [15] Zhang X, Hao T, Zhang T, Hu Y, Lu R, Li D, et al. Towards energy conservation and carbon reduction for wastewater treatment processes: a review of carbon-neutral anaerobic biotechnologies. *J Water Process Eng* 2024;59:105026.
- [16] Willis J. GHG methodologies for sewer CH₄, methanol-use CO₂, and biogas-combustion CH₄ and their significance for centralized wastewater treatment [dissertation]. Queensland: University of Queensland; 2017.
- [17] Liu YW, Ni BJ, Sharma KR, Yuan ZG. Methane emission from sewers. *Sci Total Environ* 2015;524–25:40–51.
- [18] Fryd O, Dam T, Jensen MB. A planning framework for sustainable urban drainage systems. *Water Policy* 2012;14(5):865–86.
- [19] Casal-Campos A, Sadr SMK, Fu G, Butler D. Reliable, resilient and sustainable urban drainage systems: an analysis of robustness under deep uncertainty. *Environ Sci Technol* 2018;52(16):9008–21.

- [20] Wang T, Zhang YH, Li HZ, Xu ZX, Jin W. Policies on combined sewer overflows pollution control: a global perspective to inspire China and less developed countries. *Crit Rev Environ Sci Technol* 2024;54(14):1050–69.
- [21] New York City's Water-Energy Nexus. A tool to measure greenhouse gas emissions for water sustainability initiatives. In: Proceedings of the International Conference on Sustainable Infrastructure; 2017 Oct 26–28; New York City, NY, USA. Washington, DC: American Society of Civil Engineers; 2017.
- [22] Rodríguez-Sinobas L, Zubelzu S, Perales-Momparler S, Canogar S. Techniques and criteria for sustainable urban stormwater management. The case study of Valdebebas (Madrid, Spain). *J Clean Prod* 2018;172:402–16.
- [23] De Sousa MRC, Montalto FA, Spataro S. Using life cycle assessment to evaluate green and grey combined sewer overflow control strategies. *J Ind Ecol* 2012;16(6):901–13.
- [24] Hammond P, Suttie M, Lewis VT, Smith AP, Singer AC. Detection of untreated sewage discharges to watercourses using machine learning. *Npj Clean Water* 2021;4(1):18.
- [25] Environment Agency. Environment Agency publishes storm overflow spill data for 2023 [Internet]. London: GOV.UK; 2024 Mar 21 [cited 2024 Nov 1]. Available from: <https://www.gov.uk/government/news/environment-agency-publishes-storm-overflow-spill-data-for-2023>.
- [26] Environment Agency. Storm overflow-spill frequency portal: event duration monitoring (EDM) [Internet]. London: GOV.UK; undated [cited 2024 Nov 1]. Available from: <https://experience.arcgis.com/experience/c9b8f3ba094c429aa30e0e2b6eaf43ac>.
- [27] Scottish Environment Protection Agency (SEPA). Improving urban waters [Internet]. Aberdeen: Scottish Environment Protection Agency; undated [cited 2024 Nov 1]. Available from: <https://www.sepa.org.uk/environment/water/improving-urban-waters/>.
- [28] Semenza JC. Cascading risks of waterborne diseases from climate change. *Nat Immunol* 2020;21(5):484–7.
- [29] Zhai P, Pörtner HO. Global warming of 1.5 °C. Report. Geneva: The Intergovernmental Panel on Climate Change (IPCC); 2018.
- [30] Dirckx G, Fenu A, Wambecq T, Kroll S, Weemaes M. Dilution of sewage: is it, after all, really worth the bother? *J Hydrol* 2019;571:437–47.
- [31] Liu T, Su X, Prigiobbe V. Groundwater-sewer interaction in Urban Coastal Areas. *Water* 2018;10(12):1774.
- [32] Quaranta E, Fuchs S, Jan Liefing H, Schellart A, Pistocchi A. A hydrological model to estimate pollution from combined sewer overflows at the regional scale: application to Europe. *J Hydrol Reg Stud* 2022;41:101080.
- [33] Su X, Liu T, Beheshti M, Prigiobbe V. Relationship between infiltration, sewer rehabilitation, and groundwater flooding in coastal urban areas. *Environ Sci Pollut Res Int* 2020;27(13):14288–98.
- [34] Environmental Protection Agency (EPA). Report to congress on the impacts and control of combined sewer overflows and sanitary sewer overflows; Availability of public health experts workshop summary (EPA 833-R-02-002). Report. Washington, DC: National Archives; 2004.
- [35] Masson-Delmotte V, Zhai P, Pirani A, Connors SL, Péan C, Berger S, et al. Climate change 2021: the physical science basis. Report. Geneva: Intergovernmental Panel on Climate Change (IPCC); 2021.
- [36] Höhne N, Kuramochi T, Warnecke C, Röser F, Fekete H, Hagemann M, et al. The Paris Agreement: resolving the inconsistency between global goals and national contributions. *Clim Policy* 2017;17(1):16–32.
- [37] Bouckaert S, Pales AF, McGlade C, Remme U, Wanner B, Varro L, et al. Net Zero by 2050: a roadmap for the global energy sector. Report. Paris: International Energy Agency; 2021.
- [38] Shahid MK, Choi Y. Comprehensive analysis of greenhouse gas emissions and emission factors in a Korean domestic wastewater treatment plant: insights into mechanisms and pathways for climate change mitigation. *J Water Process Eng* 2023;56:104476.
- [39] Intergovernmental Panel on Climate Change (IPCC). Guidelines for national greenhouse gas inventories. Report. Geneva: IPCC; 2006.
- [40] Heijungs R, Allacker K, Benetto E, Brandão M, Guinée J, Schaubroeck S, et al. System expansion and substitution in LCA: a lost opportunity of ISO 14044 amendment 2. *Front Sustain* 2021;2:692055.
- [41] Peters GP. Carbon footprints and embodied carbon at multiple scales. *Curr Opin Environ Sustain* 2010;2(4):245–50.
- [42] Sudarjanto G, Gutierrez O, Ren G, Yuan Z. Laboratory assessment of bioproducts for sulphide and methane control in sewer systems. *Sci Total Environ* 2013;443:429–37.
- [43] Jiang G, Sharma KR, Yuan Z. Effects of nitrate dosing on methanogenic activity in a sulfide-producing sewer biofilm reactor. *Water Res* 2013;47(5):1783–92.
- [44] Gutierrez O, Sudarjanto G, Ren G, Ganigüe R, Jiang G, Yuan Z. Assessment of pH shock as a method for controlling sulfide and methane formation in pressure main sewer systems. *Water Res* 2014;48:569–78.
- [45] Mannina G, Butler D, Benedetti L, Deletic A, Fowdar H, Fu G, et al. Greenhouse gas emissions from integrated urban drainage systems: where do we stand? *J Hydrol* 2018;559:307–14.
- [46] Lowe SA. Sewer ventilation: factors affecting airflow and modeling approaches. *J Water Manage Model* 2016:C395.
- [47] Liu Y, Ni BJ, Ganigüe R, Werner U, Sharma KR, Yuan Z. Sulfide and methane production in sewer sediments. *Water Res* 2015;70:350–9.
- [48] Zhang W, Li H, Xiao Q, Li X. Urban rivers are hotspots of riverine greenhouse gas (N₂O, CH₄, CO₂) emissions in the mixed-landscape Chaohu Lake basin. *Water Res* 2021;189:116624.
- [49] Upadhyay P, Prajapati SK, Kumar A. Impacts of riverine pollution on greenhouse gas emissions: a comprehensive review. *Ecol Indic* 2023;154:110649.
- [50] Drake TW, Raymond PA, Spencer RGM. Terrestrial carbon inputs to inland waters: a current synthesis of estimates and uncertainty. *Limnol Oceanogr Lett* 2018;3(3):132–42.
- [51] Sun HH, Tian Y, Zhan W, Zhang HR, Meng YM, Li LP, et al. Estimating Yangtze River basin's riverine N₂O emissions through hybrid modeling of land-river-atmosphere nitrogen flows. *Water Res* 2023;247:120779.
- [52] Yan S, Xu H, Fang Y, Li J, Lv M, Li G, et al. The characteristics and traceability analysis of the overflow pollution during the flood season in an urban area. *Water* 2024;16(22):3159.
- [53] Bhawan S, Puram R. CO₂ baseline database for the Indian power sector. Report. New Delhi: Central Electricity Authority, Ministry of Power, Government on India; 2014.
- [54] Chen S, Liu H. Achieving low-carbon and sustainable wastewater treatment by controlling the flow of pollutants: a pilot scale investigation on reducing greenhouse gas emissions and enhancing resource recovery. *J Water Process Eng* 2024;64:105665.
- [55] Owolabi TA, Mohandes SR, Zayed T. Investigating the impact of sewer overflow on the environment: a comprehensive literature review paper. *J Environ Manage* 2022;301:113810.
- [56] Ma SH, Zayed T, Xing JD, Shao YY. A state-of-the-art review for the prediction of overflow in urban sewer systems. *J Clean Prod* 2024;434:139223.
- [57] Gao X, Ouyang W, Lin CY, Wang KC, Hao FH, Hao X, et al. Considering atmospheric N₂O dynamic in SWAT model avoids the overestimation of N₂O emissions in river networks. *Water Res* 2020;174:115624.
- [58] Nguyen HH, Peche A, Venohr M. Modelling of sewer exfiltration to groundwater in urban wastewater systems: a critical review. *J Hydrol (Amst)* 2021;596:126130.
- [59] Morales VM, Mier JM, Garcia MH. Innovative modeling framework for combined sewer overflows prediction. *Urban Water J* 2017;14(1):97–111.
- [60] Thorndahl S, Rasmussen MR. Short-term forecasting of urban storm water runoff in real-time using extrapolated radar rainfall data. *J Hydroinform* 2013;15(3):897–912.
- [61] Rossman LA. Storm water management model user's manual, version 5.0. Cincinnati: National Risk Management Research Laboratory 2010.
- [62] Schroeder K, Riechel M, Matzinger A, Rouault P, Sonnenberg H, Pawlowsky-Reusing E, et al. Evaluation of effectiveness of combined sewer overflow control measures by operational data. *Water Sci Technol* 2011;63(2):325–30.
- [63] Vezzaro L. Extrapolating performance indicators for annual overflow volume reduction of system-wide real time control strategies. *Urban Water J* 2022;19(1):15–21.
- [64] Szelag B, Suligowski R, Drewnowski J, De Paola F, Fernandez-Morales FJ, Bak L. Simulation of the number of storm overflows considering changes in precipitation dynamics and the urbanisation of the catchment area: a probabilistic approach. *J Hydrol* 2021;598:126275.
- [65] Hamidi A, Farnham DJ, Khanbilvardi R. Uncertainty analysis of urban sewer system using spatial simulation of radar rainfall fields: New York City case study. *Stochastic Environ Res Risk Assess* 2018;32(8):2293–308.
- [66] Zhang YT, Li CL, Duan HP, Yan KF, Wang JH, Wang WH. Deep learning based data-driven model for detecting time-delay water quality indicators of wastewater treatment plant influent. *Chem Eng J* 2023;467:143483.
- [67] Yin Z, Zahedi L, Arturo S, Leon M, Amini H, Bian L. A machine learning framework for overflow prediction in combined sewer systems. In: Proceedings of the World Environmental and Water Resources Congress 2022; 2022 Jun 5–8; Atlanta, GA, USA. Washington, DC: American Society of Civil Engineers; 2022. p. 194–205.
- [68] Keupers I, Wolfs V, Kroll S, Willems P. Impact analysis of CSOs on the receiving river water quality using an integrated conceptual model. In: Proceedings of the 10th International Conference on Urban Drainage Modelling; 2015 Sep 20–23; Mont-Sainte-Anne, QC, Canada. Leuven: KU Leuven; 2015.
- [69] Vaes G, Feyaerts T, Swartenbroeckx P. Influence and modelling of urban runoff on the peak flows in rivers. *Water Sci Technol* 2009;60(7):1919–27.
- [70] Ly DK, Maruejols T, Binet G, Litrico X, Bertrand-Krajewski JL. Evaluation of two statistical approaches for estimating pollutant loads at adjacent combined sewer overflow structures. *Water Sci Technol* 2018;78(3):699–707.
- [71] Maruéjols T, Binet G. Impact of two pollutant fluxes calculation methods along with uncertainties on estimation of combined sewer overflow contribution to environmental pollution at the whole urban catchment scale. *Urban Water J* 2018;15(8):741–9.
- [72] Brzezińska A, Sakson G, Zawilski M. Predictive model of pollutant loads discharged by combined sewer overflows. *Water Sci Technol* 2018;77(7):1819–28.
- [73] Sharma KR, Yuan Z, de Haas D, Hamilton G, Corrie S, Keller J. Dynamics and dynamic modelling of H₂S production in sewer systems. *Water Res* 2008;42(10–11):2527–38.
- [74] Sun J, Ni BJ, Sharma KR, Wang Q, Hu S, Yuan Z. Modelling the long-term effect of wastewater compositions on maximum sulfide and methane production rates of sewer biofilm. *Water Res* 2018;129:58–65.
- [75] Mohanakrishnan J, Sharma KR, Meyer RL, Hamilton G, Keller J, Yuan Z. Variation in biofilm structure and activity along the length of a rising main sewer. *Water Environ Res* 2009;81(8):800–8.

- [77] Willis J, Brower B, Graf W, Murthy S, Peot C, Regmi P, et al. Manuscript: new GHG methodology to quantify sewer methane. In: Proceedings of Water Environment Federation; 2018 Mar 25–28; Portland, OR, USA. Alexandria: The Water Environment Federation; 2018.
- [78] Zhang W, Wei Q, Wu S, Qi D, Li W, Zuo Z, et al. Batch anaerobic co-digestion of pig manure with dewatered sewage sludge under mesophilic conditions. *Appl Energy* 2014;128:175–83.
- [79] Chaosakul T, Koottatep T, Polprasert C. A model for methane production in sewers. *J Environ Sci Health* 2014;49(11):1316–21.
- [80] Xu J, He Q, Li H, Yang C, Wang Y, Ai H. Modeling of methane formation in gravity sewer system: the impact of microorganism and hydraulic condition. *AMB Express* 2018;8(1):34.
- [81] Hu M, Li B, Wu K, Zhang Y, Wu H, Zhou J, et al. Modeling riverine N₂O sources, fates, and emission factors in a typical river network of Eastern China. *Environ Sci Technol* 2021;55(19):13356–65.
- [82] Guérin F, Abril G, Serça D, Delon C, Richard S, Delmas R, et al. Gas transfer velocities of CO₂ and CH₄ in a tropical reservoir and its river downstream. *J Mar Syst* 2007;66(1–4):161–72.
- [83] Wang R, Zhang H, Zhang W, Zheng X, Butterbach-Bahl K, Li S, et al. An urban polluted river as a significant hotspot for water–atmosphere exchange of CH₄ and N₂O. *Environ Pollut* 2020;264:114770.
- [84] Xiao Q, Zhang M, Hu Z, Gao Y, Hu C, Liu C, et al. Spatial variations of methane emission in a large shallow eutrophic lake in subtropical climate. *J Geophys Res Biogeosci* 2017;122(7):1597–614.
- [85] Marzadri A, Amatulli G, Tonina D, Bellin A, Shen LQ, Allen GH, et al. Global riverine nitrous oxide emissions: the role of small streams and large rivers. *Sci Total Environ* 2021;776:145148.
- [86] Zhou Y, Huang B, Wang J, Chen B, Kong H, Norford L. Climate-conscious urban growth mitigates urban warming: evidence from Shenzhen, China. *Environ Sci Technol* 2019;53(20):11960–8.
- [87] Hui C, Li Y, Zhang W, Yang G, Wang H, Gao Y, et al. Coupling genomics and hydraulic information to predict the nitrogen dynamics in a channel confluence. *Environ Sci Technol* 2021;55(8):4616–28.
- [88] Zhang R, Xiao R, Wang F, Chu W, Hu J, Zhang Y, et al. Direct discharge of sewage to natural water through illicitly connected urban stormwater systems: an overlooked source of dissolved organic matter. *Sci Total Environ* 2023;890:164248.
- [89] Petrie B. A review of combined sewer overflows as a source of wastewater-derived emerging contaminants in the environment and their management. *Environ Sci Pollut Res Int* 2021;28(25):32095–110.
- [90] Hua P, Yang W, Qi X, Jiang S, Xie J, Gu X, et al. Evaluating the effect of urban flooding reduction strategies in response to design rainfall and low impact development. *J Clean Prod* 2020;242:118515.
- [91] Ahiablame LM, Engel BA, Chaubey I. Effectiveness of low impact development practices: literature review and suggestions for future research. *Water Air Soil Pollut* 2012;223(7):4253–73.
- [92] Drake J, Bradford A, van Seters T. Stormwater quality of spring–summer–fall effluent from three partial-infiltration permeable pavement systems and conventional asphalt pavement. *J Environ Manage* 2014;139:69–79.
- [93] Riechel M, Matzinger A, Pallasch M, Joswig K, Pawlowsky-Reusing E, Hinkelmann R, et al. Sustainable urban drainage systems in established city developments: modelling the potential for CSO reduction and river impact mitigation. *J Environ Manage* 2020;274:11207.
- [94] Joshi P, Leitão JP, Maurer M, Bach PM. Not all SuDS are created equal: impact of different approaches on combined sewer overflows. *Water Res* 2021;191:116780.
- [95] Liao ZL, Zhang GQ, Wu ZH, He Y, Chen H. Combined sewer overflow control with LID based on SWMM: an example in Shanghai, China. *Water Sci Technol* 2015;71(8):1136–42.
- [96] Lucas WC, Sample DJ. Reducing combined sewer overflows by using outlet controls for green stormwater infrastructure: case study in Richmond, Virginia. *J Hydrol* 2015;520:473–88.
- [97] Lund NSV, Borup M, Madsen H, Mark O, Arnbjerg-Nielsen K, Mikkelsen PS. Integrated stormwater inflow control for sewers and green structures in urban landscapes. *Nat Sustain* 2019;2(11):1003–10.
- [98] Peng Y, Wang Y, Chen H, Wang L, Luo B, Tong H, et al. Carbon reduction potential of a rain garden: a cradle-to-grave life cycle carbon footprint assessment. *J Clean Prod* 2024;434:139806.
- [99] Liu J, Wang J, Ding X, Shao W, Mei C, Li Z, et al. Assessing the mitigation of greenhouse gas emissions from a green infrastructure-based urban drainage system. *Appl Energy* 2020;278:115686.
- [100] van der Werf JA, Kapelan Z, Langeveld J. Towards the long term implementation of real time control of combined sewer systems: a review of performance and influencing factors. *Water Sci Technol* 2022;85(4):1295–320.
- [101] Balla KM, Bendtsen JD, Schou C, Kalles CS, Ocampo-Martinez C. A learning-based approach towards the data-driven predictive control of combined wastewater networks—an experimental study. *Water Res* 2022;221:118782.
- [102] Tian W, Fu G, Xin K, Zhang Z, Liao Z. Improving the interpretability of deep reinforcement learning in urban drainage system operation. *Water Res* 2024;249:120912.
- [103] Zhang Z, Tian W, Liao Z. Towards coordinated and robust real-time control: a decentralized approach for combined sewer overflow and urban flooding reduction based on multi-agent reinforcement learning. *Water Res* 2023;229:119498.
- [104] Tian W, Liao Z, Zhang Z, Wu H, Xin K. Flooding and overflow mitigation using deep reinforcement learning based on Koopman operator of urban drainage systems. *Water Resour Res* 2022;58(7):e2021WR030939.
- [105] Lund NSV, Falk AKV, Borup M, Madsen H, Steen MP. Model predictive control of urban drainage systems: a review and perspective towards smart real-time water management. *Crit Rev Environ Sci Technol* 2018;48(3):279–339.
- [106] Lund NSV, Borup M, Madsen H, Mark O, Mikkelsen PS. CSO reduction by integrated model predictive control of stormwater inflows: a simulated proof of concept using linear surrogate models. *Water Resour Res* 2020;56(8):e2019WR026272.
- [107] Fu G, Jin Y, Sun S, Yuan Z, Butler D. The role of deep learning in urban water management: a critical review. *Water Res* 2022;223:118973.
- [108] Liao Z, Zhang Z, Tian W, Gu X, Xie J. Comparison of real-time control methods for CSO reduction with two evaluation indices: computing load rate and double baseline normalized distance. *Water Resour Manage* 2022;36(12):4469–84.
- [109] Saliba SM, Bowes BD, Adams S, Beling PA, Goodall JL. Deep reinforcement learning with uncertain data for real-time stormwater system control and flood mitigation. *Water* 2020;12(11):3222.
- [110] Mullanpudi A, Lewis MJ, Gruden CL, Kerkez B. Deep reinforcement learning for the real time control of stormwater systems. *Adv Water Resour* 2020;140:103600.
- [111] Botturi A, Ozbayram EG, Tondera K, Gilbert N, Rouault P, Caradot N, et al. Combined sewer overflows: a critical review on best practice and innovative solutions to mitigate impacts on environment and human health. *Crit Rev Environ Sci Technol* 2021;51(15):1585–618.
- [112] Hino M, Benami E, Brooks N. Machine learning for environmental monitoring. *Nat Sustain* 2018;1(10):583–8.
- [113] Lapointe M, Rochman CM, Tufenkji N. Sustainable strategies to treat urban runoff needed. *Nat Sustain* 2022;5(5):366–9.
- [114] Xu WD, Burns MJ, Cherqui F, Fletcher TD. Enhancing stormwater control measures using real-time control technology: a review. *Urban Water J* 2021;18(2):101–14.
- [115] Jean ME, Morin C, Duchesne S, Pelletier G, Pleau M. Optimization of real-time control with green and gray infrastructure design for a cost-effective mitigation of combined sewer overflows. *Water Resour Res* 2021;57(12):e2021WR030282.
- [116] García L, Barreiro-Gomez J, Escobar E, Tellez D, Quijano N, Ocampo-Martinez C. Modeling and real-time control of urban drainage systems: a review. *Adv Water Resour* 2015;85:120–32.
- [117] Jean ME, Morin C, Duchesne S, Pelletier G, Pleau M. Real-time model predictive and rule-based control with green infrastructures to reduce combined sewer overflows. *Water Res* 2022;221:118753.
- [118] The Environmental Protection Agency (EPA). Report to congress on impacts and control of combined sewer overflows and sanitary sewer overflows. Report. Washington, DC: EPA; 2002.
- [119] Xu Z, Xu J, Yin H, Jin W, Li H, He Z. Urban river pollution control in developing countries. *Nat Sustain* 2019;2(3):158–60.
- [120] Lv J, Du L, Lin H, Wang B, Yin W, Song Y, et al. Enhancing effluent quality prediction in wastewater treatment plants through the integration of factor analysis and machine learning. *Bioresour Technol* 2024;393:130008.
- [121] Wen J, Duan L, Wang B, Dong Q, Liu Y, Chen C, et al. In-sewer stability assessment of 140 pharmaceuticals, personal care products, pesticides and their metabolites: implications for wastewater-based epidemiology biomarker screening. *Environ Int* 2024;184:108465.
- [122] Wang X, Song L, Bai R. Energy consumption evaluation and carbon emission analysis for municipal wastewater treatment plants in Hohhot City. *Environ Sci Technol* 2013;36(2):196–9.
- [123] Hu D, Wang L, Zhou Z. Status and prospects of greenhouse gas emissions in wastewater treatment. *Environ Sci Technol* 2014;37(3):108–12.