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A state-of-the-art review for the prediction of overflow in urban sewer systems

Abstract:

Sewer overflow (SO) is becoming a concerning issue since discharged wastewater contains toxic substances and debris resulting in hazardous pollution to the surrounding environment and water quality degradation; and spilled stormwater may cause localized flooding and even back-up into buildings. Therefore, it is necessary to predict the occurrence of SO in advance, which enables the utilities to post warnings, prioritize the resource allocation and take proactive measures to minimize negative effects on environment and society. This paper aims to provide a state-of-the-art review for the prediction of sewer overflow which is lacking in literature, including bibliometric survey, scientometric analysis, in-depth systematic review, and elucidation of the existing research gaps and the potential future research directions. The findings reveal that the majority focuses on combined sewer overflow (CSO), and artificial intelligence-based models are the most popular ones. The input factors vary widely among three model categories. *Volume*, *likelihood of occurrence* and *water level* are the three mostly adopted output factors. Further research directions are recommended to fill these gaps (e.g., consider socio-economic factors and pipe properties, deploy IoT facilities to reduce false alarms, distinguish between regular and extreme weather conditions). This state-of-the-art review fills the gap of few endeavors focusing on SO prediction, and could provide the scholars and engineers with inclusive hindsight in dealing with harmful incidents.

Keywords: Sewer systems, sewer overflow, prediction, scientometric analysis, systematic review

1. Introduction

The sewer system is one of the critical infrastructures (CIs) to collect and transport domestic, industrial and commercial wastewater, as well as stormwater from the urban areas for public and ecosystem health protection and flooding prevention, which can be classified into combined and separate types (Li et al., 2018). The former conveys wastewater and stormwater jointly to wastewater treatment plants (WWTPs), whereas the latter conveys wastewater through separated pipelines from stormwater. Separate sewer systems (SSSs) have always been recommended, compared with combined sewer systems (CSSs), due to their better ability to solve the problems of discharge of a mixing of untreated wastewater together with stormwater, which may cause overflow and even flooding, exerting negative influences on public health and environment. Nowadays, the proportion of separate type in urban sewer systems keeps rising, for example, Hong Kong's sewer network consists of 1,666 km of sewerage pipes, 1,720 km of stormwater pipes, and only 3 km of combined sewer pipes, since the government began to build the 'separate drainage and sewerage system' in early 20th century (DSD, 2015). However, rapid population growth, intense urbanization, and increased frequency and intensity of extreme rainfall events due to climate change have posed greater risks to sewer systems, and exacerbated the occurrence of sewer overflow (SO). SO can be categorized into two types: combined sewer overflow (CSO) and sanitary sewer overflow (SSO) (Aghdam et al., 2023). CSO happens when the amount of water exceeds the capacity of the system, especially during heavy rainfall events or snowmelt, whereas SSO occurs when the wastewater surcharge is released from manholes due to blockages, pipe breaks, sewer defects, power failures, improper design or vandalism (EPA, 2022). SO has posed great risks to the environment and society, and is becoming a concerning problem and top priority for water utilities because it contains high concentrations of pathogens, toxic substances, bacteria, solids, and debris, resulting in irreversible water contamination and threats to public health (Liu et al., 2018; Su et al., 2020). SO may also lead to water logging/flooding and even worse back-up into buildings, causing severe socio-economic consequences such as obstruction to business, financial losses, damage to the road surface, disruption to traffic, and disturbance to quality of life (Owolabi et al., 2022; Sojobi & Zayed, 2022).

Over the past years, SO has become a worldwide problem where annual cases reach 23,000-75,000 in the United States, and 14,600 in the United Kingdom, leading to 11.4-37.9 million cubic meters and 39 million tons of untreated sewer being discharged into the environment, respectively (DEFRA, 2015; EPA, 2022; EA, 2023). These statistics highlight the criticality of managing SO and emphasize the urgent need for effective strategies and measures to understand and reduce SO. Scholars have made utmost efforts to undertake research related to SO risk modelling and management (Montserrat et al., 2015; Meyers et al., 2021; Gogien et al., 2023). Mechanistic models (e.g., Storm water management model [SWMM], Mike Urban, InfoWorks) and data-driven models (e.g., Model predictive control [MPC], Real-time control [RTC]) have been frequently utilized, further integrated with advanced technologies, such as artificial intelligence (AI), geographic information system (GIS) and remote sensing (RS) (Saddiqi et al., 2023). Additionally, there have been numerous research studies investigating the impacts of SO on the environment and water quality (Even et al., 2007; Madoux-Humery et al., 2016; Quijano et al., 2017). Traditionally, passive measures, such as surveys and regular inspections, are usually conducted by water utilities for aged sewers and stormwater drains in phases or as demanded (DSD, 2021). Additional checks and clearing works are still needed before and after the rainy seasons, which are expensive, time-consuming, and ineffective. If SO can be sufficiently predicted in advance, preventative measures could be employed to mitigate its impact (Joseph-Duran et al., 2014). Hence, it is of paramount importance to predict the SO which enables the decision-makers to post warnings and/or take proactive actions to minimize the negative impacts.

Over the past two decades, a group of theoretical and experimental-based approaches have been developed to predict SO (mostly CSO) in terms of probability, volume and duration. SWMM is one of the commonly used models to predict overflow using hydrological and hydraulic characteristics to simulate runoff conditions in the catchment area (Liu et al., 2018; Su et al., 2020). Machine learning algorithms, e.g., logistic/multi-linear regression, Monte Carlo analysis, artificial neural network (ANN), decision tree (DT), Bayesian network (BN), are used to predict the probability of overflow (Hill et al., 2009; Schellart et al., 2014; Montserrat et al., 2015; Bailey et al., 2016; Allen et al., 2022). Predicting the occurrence of SO is also a time series problem, which needs to use historical data and/or real-time observation data to predict the future state. Long short-term memory (LSTM), gated recurrent unit (GRU), and wavelet neural network (WNN) are examples of advanced deep learning methods for dealing with such problems (Zhang et al., 2018a, b; Jiang et al., 2021; Zhang et al., 2022; Zhang et al., 2023). Most studies consider the precipitation as the main culprit of SO and use the rainfall time series data for prediction, while the impact of structural/operational properties of sewer pipelines on their capacity and SO is lacking due to data unavailability and complexity. Recently, the effect of physical, operational and environmental factors has gained considerable attention in the fields of deterioration of sewer pipelines and SO (Mohandes et al., 2022; Salihu et al., 2022). On the other hand, experimental-based methods usually use ultrasonic sensors to monitor sewage flow and/or level in real-time and integrate hydraulic/rainfall data to predict SO (Rosin et al., 2021), which are usually difficult and expensive to be applied to real and sophisticated sewer networks.

Although a batch of review studies have been conducted related to SO (Botturi et al., 2021; Owolabi et al., 2022; Sojobi & Zayed, 2022; Saddiqi et al., 2023), it can be observed that they focus on either impacts of SO on public health and environment or SO risk management, while there have been quite few review endeavors focusing on the prediction of SO. Hence, this research aims to contribute to the existing literature through a comprehensive and critical review regarding the prediction of overflow in urban sewer system based on the hybridization of scientometric analysis and systematic review. The objectives of this study are listed below:

(1) To bibliometrically retrieve all the relevant literature undertaken on the areas associated with the prediction of SO.
(2) To exhibit a well-rounded scientometric analysis, consisting of publication trends, keyword analysis, contributions of journals and countries, and authorship analysis.
(3) To elaborate an in-depth systematic discussion regarding the reviewed studies categorized into different types of prediction models from the perspectives of methods used, inputs and outputs of the model, study area as well as type of overflow.
(4) To discuss and elaborate on the existing research gaps and make recommendations for future research.

The remainder of this paper is organized as follows. Section 2 describes the steps of the bibliometric survey. Section 3 expounds the results from the scientometric analysis. The findings from an in-depth systematic investigation are explained in section 4. Furthermore, section 5 illustrates the research gaps as well as the future directions. Finally, section 6 presents the concluding remarks of this research.

2. Bibliometric Survey

The flowchart of a comprehensive and proper review process in this study is shown in Figure 1. The bibliometric survey is a critical step at the beginning of any literature review process (Hussein et al., 2021). Once the goal of the review study is set out, keyword selection is the firstly conducted to identify the most relevant documents on the defined research topic. Since this study focuses on sewer overflow prediction, the selected keywords are “sewer overflow” OR “sewer flooding” OR “combined sewer overflow” OR “sanitary sewer overflow” OR “storm overflow” AND “predict*” OR “forecast*”. Secondly, the selected keywords are used to search for relevant publications in two prominent databased repositories, i.e., Scopus and Web of Science (WoS). After keyword searching in scientific databases, filters are applied to eliminate irrelevant studies by setting inclusion and exclusion criteria in terms of subject area, document type and research language. Next, the filtered results from two databases are merged into one file and the duplicates are deleted. Forward and backward snowballing techniques are also used to retrieve more related studies. Finally, the retrieved studies consist of 54 documents (42 articles and 12 conference papers), which are used for the scientometric analysis and systematic review in the following sections.

3. Results of scientometric analysis

3.1. Publication trends

Figure 2 indicates the annual number of publications for the 54 retrieved studies on prediction of SO. It can be seen that the annual number of publications has gradually increased since the 21st century unfolded, and reached its first peak in 2009. A sharp rise can be observed in 2018, which connotes a groundswell of growing interest from the concerned researchers toward this topic. The annual publication trend reached the top with eight annual publications in 2021 and 2022.

3.2. Keyword analysis

The keyword analysis tends to identify the leading area within a certain research field and create awareness of up-to-date research topics to the policymakers and experts in these research areas (Owolabi et al. 2022). In this study, occurrence and co-occurrence analysis of keywords are conducted through VOS viewer 1.6.19. It's worth noting that these imported keywords are curated and some are merged using OpenRefine 3.7.2, since some original keywords with different words have the same meaning. The top keywords occurring at least three times are shown in Table 1 in a descending order based on the occurrence weight, and the co-occurrence of keywords mapping network is shown in Figure 3, where each node represents a certain keyword. The bigger the node size, the more frequently the keyword occurs, and the thickness of lines connecting two nodes indicates the co-occurrence of keywords in the retrieved literature. It can be observed that "Combined sewer overflow" has been a focal point in the field of SO prediction, since it has the highest occurrence and total link strength, and has connections with all the other keywords. Limited success has been achieved in terms of SSO and storm overflow. "Artificial neural network" and "Logistic regression" are both ranked into the top keywords from the perspective of methodology, but belong to different clusters (red and green), which elicits that data-driven models have experienced a considerable popularity in the latest research related to SO prediction and should be further categorized. The inclusion of "Climate change" and "Radar rainfall nowcasts" in the top keywords indicates that the climate change, especially extreme rainfall, are deemed a critical causal factor on SO prediction.

3.3. Contributions of journals and countries

The results of journals' and countries' contributions are collected through VOS viewer software, with the minimum number of documents for a journal/country is set to be 1. There is no limit on the minimum number of citations. 7 out of 36 sources and 5 out of 24 countries meet the thresholds. As for journals' contributions (see Table 2), "Water Science & Technology" is ranked as the most productive research outlet due to the highest number of publications and total link strength, while "Journal of Hydrology" has received the highest recognition from the concerned scholars in terms of citations. This can help guide the researchers toward the important and influential journals in this research area. As for countries' contributions (see Figure 4), it can be found that the United States is the most productive contributor to the domain of SO prediction globally, Denmark comes the second, and United Kingdom the third. China and South Korea are the top contributing countries in Asia. Countries in Europe and North America have made great efforts and the most contributions in this research field.

3.4. Authorship analysis

This section describes the results from citation and co-citation analyses of authors, conducted by VOS viewer software. Authors' citation analysis reveals three clusters, as seen in Figure 5(a): cluster 1 (red) is represented by Keedwell E. with 4 items; cluster 2 (green) is represented by Borup M. with 3 items; and cluster 3 (blue) is represented by Kapelan Z. with 2 items. According to Table 3, it has been observed that Kapelan Z. is the most productive scholar, followed by Keedwell E., Thorndahl S., Szeląg B. and Romano M. successively. In terms of citations, Thorndahl S. is the most cited and influential researcher with 64 citations. The co-citation analysis herein refers to two authors cited together by a third author. As shown in Figure 5(b) and Table 4, Thorndahl S. has the largest node size in terms of co-citations and the third highest total link strength (556). However, Mikkelsen P. S. has the largest total link strength of 731 indicating the high frequency of this researcher to collaborate with other researchers.

4. Findings from systematic review

Amid all the retrieved studies, a more-in-depth and meticulous systematic review is carried out, describing the study area, methods and techniques adopted, inputs and outputs of the prediction model, as well as type of overflow. In terms of the methodologies used in the retrieved studies, SO prediction models can be broadly classified into physically-based and data-driven categories, and data-driven group can be further divided into statistical and artificial intelligence-based models. The majority of the researchers are inclined to employ data-driven models (around 70%), compared with traditional physically-based models. The reasons behind might lie in the superiority of data-driven models in terms of handling the complexity, subjectivity, uncertainty and non-linearity of independent covariates, as well as missing data and outliners, and guaranteeing sound and reliable performances. The detailed analysis regarding each category is expounded in the following parts.

4.1. Physically-based models

Table 5 summarizes all the studies related to the utilization of physically-based models in order to predict SO. Physically-based models, built from the principles of physical processes, tend to describe the relationships amidst explanatory parameters pertaining to the simulated process (Nguyen et al., 2021). In general, due to the long transportation of sewage and the inherent dynamic nature of sewage flow, physically-based models have become sought-after tools for predicting SO in both temporal and spatial dimensions, in which researchers typically simulate the runoff conditions in a catchment based on the hydrological-hydraulic characteristics, as exemplified in case studies by Reis et al. (2017) and Quaranta et al. (2022). However, it is a complex process to obtain the catchment parameters of the entire site, thus, the swift model is proposed as alternative to interpret the hydrological-hydraulic states of sewer in real-time, where the application of St. Venant equations is a significant step, as it can effectively simplify the calculation process while ensuring the accuracy and reliability of predictions (Zimmer et al., 2013; Li et al., 2022). In the St. Venant equations, the hydraulic performance graph (HPG) is constructed to describe the flow capacity of an open channel and the volumetric performance graph (VPG) is introduced to obtain the volume stored in the river section under each flow condition described by HPG.

There are numerous open-source and commercial models available for sewer system simulation, analysis and prediction for stormwater runoff and wastewater management (Niazi et al., 2017, Saddiqi et al., 2023). Storm water management model (SWMM) is a typically, open-source software that can model dynamic urban hydrology and water quality in a single event or continuous basis (Rossman et al., 2004). For instance, Roseboro et al. (2021) utilized SWMM to quantify and compare CSO volumes under current and future storms in the city of Buffalo. Accelerated urbanization has led to changing hydrological regimes in cities, specifically as extreme rainfall and the reduction of permeable surfaces exacerbate the risk of urban flooding (Hamouz & Muthanna, 2019). Therefore, reconfiguring the SWMM model by linking different algorithms or programming languages has attracted the attention of scholars, who look forward to improving the practicality of the SWMM model in different management scenarios. For instance, Park et al. (2014) analyzed the characteristics of SO and inundation in a repeatedly flooded zone through an XP-SWMM 2D model which combined 1D SWMM and 2D TUFLOW algorithms. Similarly, Ghodsi et al. (2021) adopted SWMM in conjunction with R-language utilities to predict CSO reductions in city-scale watersheds, which greatly enhanced the utilization of SWMM in assessing the effectiveness of city-scale CSO management strategies and could be generalizable to other cities with similar characteristics.

In addition to SWMM, Mike Urban, InfoWorks and MOUSE are commonly used as physically-based models for predicting SO which typically use the collected extrapolated radar rainfall data to predict SO. Mike Urban is a commercial and flexible system which combines 1D sewer modeling with 2D surface runoff modeling while integrating with GIS (Locatelli et al., 2015). Mike Urban has been applied in numerous studies related to SO prediction and management, for example, Lund et al. (2019) integrated the Mike Urban with a Kalman filter to predict CSO flow rate using continuously updated water level observations. InfoWorks is another common commercial hydrologic-hydraulic model for simulating sewer flow and rainfall-runoff process and has achieved reliable prediction performances regarding SO behaviors. Morales et al. (2017) and Yu et al. (2018) used InfoWorks-CS to simulate and predict CSO occurrence and intensity in Chicago and Tokyo, respectively. During this process, InfoWorks-CS model has been tested and calibrated with data from real rainfall events, thus, the output of the model can be regarded as representative of real data. Additionally, MOUSE, as a catchment and urban drainage model, is used by, for example, Thorndahl and Rasmussen (2013) and Schaarup-Jensen et al. (2009) to predict urban drainage flow, water level and volume with improved prediction performances. At present, to facilitate model updates and interactions, the Danish Hydraulic Institute (DHI) has integrated it into Mike Urban as a module.

Meanwhile, changes in hydrological conditions caused by climate deterioration have identified fields of further enquiry in the realm of SO modelling and prediction, because stormwater runoff increases with the growth of rainfall magnitude, intensity and frequency

(Hamouz et al., 2020). Hence, it is of immense importance to take into account reliable precipitation forecast models and climate models when predicting SO (Schaarup-Jensen et al., 2009). For short-term prediction, extrapolating radar rainfall forecasting models and high-resolution numerical weather forecasting can improve the leading time of SO prediction while maintaining the accuracy, for instance, Schellart et al. (2014) adopted and compared three distinctly different rainfall forecast methods (i.e., HyRaTrac, STEPS and STEPS+MM5) to quantitatively predict sewer flows. For long-term prediction, Abdellatif et al. (2015) adopted three global climate models (GCMs) (i.e., HadCM3, CSIRO and CGCM2 GCMs) to quantify future rainfall and used InfoWorks to predict the spilling volume, duration and frequency of CSOs. Tavakol-Davani et al. (2016) used GCMs (i.e., IPSL-CM5a MRI-RCP6.0 and GFDL-CM3.1-RCP8.5) to estimate future rainfall based on historical records and used SWMM to predict the response of CSO outfalls to future rainfall. By integrating regional climate models (RCMs) to better represent the diversity of future rainfall projections, Gogien et al. (2023) used five GCM/RCM couples (including CNRM/ALADIN, CNRM/RACMO, IPSL/WRF, HadGEM/CCLM and MPIESM/REMO2009) to obtain future rainfall time series and then investigated the evolution of annual CSO volume and frequency. The results exemplify the necessity of building future rainfall time series with a fine time step through appropriate climate models because the changes in rainfall patterns have undeniable impacts on SO occurrence and severity.

Stemming from literature, influential primary factors culminating in CSO in physically-based models consist of precipitation, catchment parameters, sewage hydraulic characteristics, and climate change related factors (Abdellatif et al., 2015; Jean et al., 2018; Balekelayi & Tesfamariam, 2019; Huang et al., 2023). It can be observed from Table 5 that the hydraulic behavior of CSO is greatly affected by rainfall, sewage condition and catchment condition. The frequency, volume, and duration of CSO occurrence are closely related to rainfall characteristics. Researchers have built predictive models to control CSO risks by exploring the relationship between rainfall characteristics and overflow in sewers, in which rainfall intensity, duration, rainfall total depth, and/or combination of these parameters have been used to determine CSO thresholds (Schroeder et al., 2011; Jean et al., 2018; Yu et al., 2018; McGrath et al., 2019). Besides, several physically-based models go a step further in considering the variation of CSO under climate change scenarios. The basis is to use results from global climate models to identify change factors, and apply these change factors to historical rainfall data in a given return period (Gogien et al. 2023). It can be found that these applications could provide flexibility in understanding the response of drainage systems under climate variability.

The hydraulic characteristics of sewage in drainage systems are crucial variables in physically-based models, including flow rate, water level, cross-section flow area, etc., and they are easily affected by geometric characteristics and boundary conditions of pipelines, and basin conditions (Rossman, 2010). In some studies, sewage hydraulic properties are provided by the St. Venant equations and used for network-wide simulation, calibration and detection of hydraulic models (Li et al. 2022). Catchment conditions are also the basis for building hydrologic-hydraulic models, i.e., surface runoff and pipe flow models. The surface runoff model includes hydrological reduction coefficients and mean field radar biases, which are combined into a whole to demonstrate the mass balance between radar precipitation data and actual observation of sewage flow. Catchment conditions also include energy loss parameters such as friction loss in pipes (i.e., Manning index) and head loss, the values of which depend on pipe material and outlet type (Thorndahl & Rasmussen, 2013). Meanwhile, soil properties, the area of impermeable areas and the digital elevation model of the simulated area are also important input factors of the hydrological-hydraulic models (Morales et al., 2017).

Figure 6 shows the percentage of the retrieved studies using physically-based models based on different categories. It can be observed from Figure 6(a) that the overwhelming majority of the researchers have adopted open-source and commercial models instead of traditional hydrological and hydraulic models, and SWMM is the most favorable package among the others. According to Figure 6(b), *Precipitation data* is a primary input factor for physically-based models with presence in 81.3% of the retrieved publications, followed by *Sewage hydraulic characteristics* and *Catchment parameters* with the percentages of 75.0% and 68.8%, respectively. Figure 6(c) illustrates the types of output indicators used to represent the occurrence of SO during prediction, and *Volume* becomes the most popular selection (56.3%), while *Water level* comes second, with the percentage of 43.8%. As seen in Figure 6(d), all the retrieved physically-based models concentrate on predicting CSO, and limited efforts have been made regarding SSO or storm overflow.

4.2. Data-driven models

4.2.1. Statistical models

The retrieved papers which are grouped into statistical models for predicting SO are presented in Table 6. Statistical models, explaining the relationship between variables and different spillover characteristics through data-driven techniques, are often used in the situations where dependent variables have qualitative characteristics and can be bounded by different states (Szeląg et al., 2018a). In terms of SO prediction, statistical models are usually used to predict the probability of SO occurrence within a certain confidence interval, in which the characteristics of rainfall are used as predictor variables, such as rainfall depth, rainfall intensity and total rainfall, and the incidence of SO is regarded as a binary response variable of precipitation conditions (Schroeder et al., 2011; Bizer & Kirchhoff, 2022). This type of modeling method does not require high-precision spatial parameters, so the cost of use is low, which can be suited for an operational use in SO risk management.

The modeling of urban sewer systems on spillage usually relies on long-term rainfall event statistics, hence logistic regression model, multiple linear regression model, generalized linear mixed modeling (GLMM), Bernoulli trail and Monte Carlo simulation are commonly used (Mailhot et al., 2015; Szeląg et al., 2019; Allen et al., 2022; Bizer & Kirchhoff, 2022; Liu et al., 2023). For example, Meyers et al. (2021) used a logistic regression model to predict the risk of SSO events due to compound flooding and to identify the negative impacts of sea level growth on coastal urban wastewater facilities, as shown in Eq. (1)-(3).

$$G\big(E(Y)\big) = X\beta^T + e \tag{1}$$

$$G(\pi) = \ln\left(\frac{\pi}{1-\pi}\right) \tag{2}$$

$$\pi = \frac{\exp(X\beta^T)}{1 + \exp(X\beta^T)} \tag{3}$$

Thorndahl (2009) used the generalized likelihood uncertainty estimation (GLUE) methodology based on long-term Monte Carlo simulations to predict the maximum water level and CSO volume in urban drainage systems. This study also assembled an evaluation model based on drainage system characteristics and rainfall parameters, which could predict the return period of extreme rainfall events with more reliable performances.

Moreover, there has been an increasing recognition of the need to conduct comparative experiments in order to verify the reliability of statistical models when predicting SO. For example, Szeląg et al. (2018a) predicted the annual number of storm overflows by constructing basic statistical models, such as logit, probit, Gompertz and linear discriminant analysis models, and Monte Carlo method. The results demonstrate that the precision of logit, probit and Gompertz models are concordant with observations, whereas the linear discriminant analysis model underestimates the frequency of overflow significantly compared with hydrodynamic model. Except for comparing the predicted results from statistical models with the actual observations, some researchers also conduct the comparisons using the simulated prediction results from hydrodynamic models (e.g., SWMM), which is found to be highly consistent (Szeląg & Bąk, 2017; Szeląg et al., 2018b). It can be observed that probabilistic models can serve as an alternative to hydrodynamic models, especially under the circumstances where data availability is limited or catchment model calibration is problematic (Thorndahl et al., 2008). This substitution could reduce much computational effort during the performance analysis phase of the sewer system.

Compared with traditional physically-based models, the novelty of statistical models lies in the ability of overcoming the limitations such as extensive input data requirement, time consuming, and demand for knowledge of physics and chemistry (Saddiqi et al., 2023). Firstly, in terms of scarce data, it has been proven effective to use statistical models to simulate a limited number of CSO events and use the modelling data of rainfall series for prediction (Hamidi et al., 2018; Vezzaro, 2022). Secondly, the combination of different statistical models can improve the prediction ability. For example, Szeląg et al. (2021) proposed a probabilistic methodology to predict storm overflow which both considered changes in precipitation dynamics and the urbanization of the catchment area through logistic regression method, hydrodynamic model, and Monte Carlo method. In this study, the logit model, as shown in Eq. (4), was used to assess the operation of a storm overflow in a precipitation event.

$$\mathrm{p}_e = \frac{\exp\left(a_0 + a_1\hat{A}\cdot x_1 + a_2\hat{A}\cdot x_2 \ldots + a_q\hat{A}\cdot x_q\right)}{1 + \exp\left(a_0 + a_1\hat{A}\cdot x_1 + a_2\hat{A}\cdot x_2 \ldots + a_q\hat{A}\cdot x_q\right)} \tag{4}$$

Thorndahl et al. (2008) analyzed and compared the performances of Monte Carlo Sampling and first order reliability method (FORM) in predicting the frequency of CSO occurrence. The results show that although FORM has no significant advantage in predicting CSO events, it could reduce the time of running traditional models by 80%. A similar performing model is the Gaussian process emulator (GPE), which excels at simulating short-term rainfall events and significantly speeds up simulations (Mahmoodian et al., 2018). These studies exemplify how statistical models can improve the flexibility of the prediction, and save the cost and labor required in data measurement and collection.

As a novel improvement of related research, nonstructural methods, such as model predictive control (MPC) and real-time control (RTC), are widely integrated into SO prediction models. Svensen et al. (2019) evaluated the performance of two MPC methods in the prediction of SO: mixed integer quadratic programming MPC (MIQP-MPC) and quadratic program MPC (QP-MPC). It was found that QP MPC had better performances in predicting the volume of CSO because it had a longer prediction horizon with less computation time. In the subsequent research, they proposed a framework named ensemble-based chance-constrained MPC (ECC-MPC), which outperformed the deterministic MPC with better performances (Svensen et al., 2021). The concept of nonstructural methods enables system-wide optimization by dynamically updating the sewer state and climate data (Lund et al., 2018).

The input variables for statistical models cover a wider range, as can be observed in Table 6. Statistical models mostly focus on rainfall events purely, where the variables include rainfall depth, rainfall duration and rainfall intensity (McGrath et al., 2019). Theoretically, rainfall data can be divided into continuous and event-based groups, and event-based rainfall data can be derived into two sub-groups: historical rainfall events and synthetic rainfall events (Jean et al., 2018). Continuous rainfall data consists of detailed chronological records of precipitation events, which can be used to model rainfall runoff and analyze runoff frequency distributions (Akan & Houghtalen, 2003). Historical rainfall data can be used as alternative to simulate historical rainfall events. Synthetic rainfall events are usually constructed directly from intensity-duration-frequency (IDF) curves, where rainfall depth can be derived from any point on the IDF curve. Furthermore, the uncertainty of overflow volume caused by the variables of synthetic rainfall events will limit the corresponding interpretation of synthetic storm models, which further confirms that there is a relationship between rainfall statistics and SO (Dirckx et al., 2018).

Catchment parameters and sewage hydraulic characteristics are also included by certain statistical models. For example, the proportion of impervious surfaces in catchment areas is considered when constructing logit models to predict volume of stormwater overflow (Szeląg et al., 2019; Szeląg et al., 2021). Soil properties are selected for predicting SO, including soil type, soil storage depth, soil water holding capacity, etc., which play a significant role in calculating runoff in a watershed (Abdellatif et al., 2015; Morales et al., 2017). In addition, sewage water level or flow rate in the manhole are also collected to analyze the overflow operations, which are measured using ultrasonic probs with certain frequency (Szeląg et al. 2018b). Generally, pipelines located within a specific geographic area may be affected by surrounding socio-economic conditions, such as plant distribution, surrounding utilities, and consumer behaviors (Balekelayi & Tesfamariam, 2019). According to Liu et al. (2023), hotel and food service densities, nighttime light, and tree density were chosen as input variables to build a predictive model. Meanwhile, climate change and special geographical location have an indispensable impact on sewage facilities, such as sea level rise, season change and extreme storms. Meyers et al. (2021) considered changes in coastal water levels when using a logistic regression model to predict the likelihood of SSO occurrence. The results show that a sea level rise of 0.5 m leads to an approximately 15-fold increase in the number of SSO events. Also， climate change is recognized to change the rainfall patterns， therefore， it is considered into statistical models for predicting the duration of SO. For example, it is generally believed that summer rainfall events have a higher correlation with CSO, so in some studies seasons are transformed into binary variables as input factors for models (Allen et al. 2022).

The percentages of the retrieved studies using statistical models based on different categories are shown in Figure 7. Figure 7(a) reveals that logistic and multiple regression models are most commonly used, by 50% of the retrieved publications, because they are much easier to implement, interpret and efficient to train, while maintaining good accuracy performances. As seen from Figure 7(b), the input factors of statistical models are the most abundant among the three types of models. *Precipitation data* still ranks first, accounting for 94.4%, followed by *Sewage hydraulic characteristic* and *Catchment parameters*, which takes up 38.9% and 33.3% of the total publications, respectively. It can be seen from Figure 7(c) that the number of output factor types from statistical models is less than that from physically-based models. *Likelihood of occurrence* is the most favorable selection (55.6%), followed by *Volume* (33.3%) and *Frequency* (33.3%). It can also be found that *Frequency* and *Likelihood of occurrence* are used as output factors simultaneously by Szeląg B. (2017, 2018a, 2018b, 2019, 2021). According to Figure 7(d), statistical models have been applied for predicting not only CSO, but also SSO and storm overflow, which fills the gaps of physically-based models. The analysis undertaken hitherto indicates that CSO has gained substantial attention in a vast majority of research.

4.2.2. Artificial intelligence-based models

Table 7 summarizes the retrieved studies using artificial intelligence (AI)-based models to predict SO. AI-based models may hamper the inherent uncertainty of datasets, making them sought-after in the management of urban water resources (Zhang et al., 2018b; Daniel et al., 2022). For instance, the neural network (NN) machine learning mode in the study by Sumer et al. (2007) was integrated with time series analysis to predict depths and flows for detecting SSO. Zhao et al. (2019) established an automated CSO predictive model using field monitoring data based on the efficient least absolute shrinkage and selection operator (LASSO) algorithm. Applications of machine learning techniques, such as Bayesian Network (BN) and Decision Tree (DT), are used to predict the likelihood of CSO occurrence in the studies by Hill et al. (2009) and Montserrat et al. (2015). DT method is validated, and the results indicate an accuracy between 70% and 83% based on rainfall information, while BN method is applied to

Chicago by combining hierarchical modeling strategies and multi-source datasets, indicating the superiority of exploring the causes of CSO and querying the relative importance between CSO event features.

Artificial Neural Network (ANN) is one of the typical AI-based models on predicting SO, and it has been proven to be effective in replacing hydraulic model schemes (Li et al., 2010). In a case study in northern Scotland, UK, an ANN model was demonstrated to predict CSO depth with an error of less than 5%, where rainfall radar records and water flow depth in the CSO chambers were used as input factors to build the relationship between model parameters (Mounce et al., 2014). ANN eliminates the need for manual calibration of data and modeling, despite the limited accuracy due to time horizons and rainfall forecast errors. In addition, ANN can also be employed to detect clogging problems in sewer structures by comparing the predicted water level with the actual observed water level at an asset (Bailey et al., 2016). The results show that the historical water levels and rainfall data could develop reliable water level models, and offer potential benefits for asset performance management. Meanwhile, novel extensions have been proposed to improve the performance of ANN models, such as the evolutionary artificial neural network (EANN) and feed-forward ANN (Rosin et al., 2017; Rosin et al., 2022). Rosin et al. (2021) introduced a bi-model committee evolutionary artificial neural network (CEANN) that combined two EANN models considering both wet and dry weather, which could predict the CSO water level up to six hours in advance. Moreover, the model precipitates automatic parameter optimization since it uses the evolutionary strategy algorithm. By comparing with other ANN models, the CEANN model demonstrates excellent performances in terms of not only accurately predicting the climate humidity level, but also predicting the time and intensity of CSO occurrence, which provides a scientific guidance for the management of sewage systems (Achela et al., 2006).

In order to provide a better decision-making system with higher automation and efficiency, deep learning techniques have received considerable attention in the research related to SO. One of the advantages of deep learning techniques is embedded in its outstanding ability of extracting features from raw data using multiple hidden layers (Goodfellow et al., 2016; Jiang et al., 2021; Zhang et al., 2023). Examples of commonly used deep learning models for SO prediction consist of recurrent neural network (RNN), long short-term memory (LSTM), and gate recurrent unit (GRU) (Gudaparthi et al., 2020; Maltbie et al., 2021). The LSTM model has been proven to improve the accuracy in predicting water depth of CSO chamber by introducing additional input features when observational information is limited or missing (Palmitessa et al., 2021). Thus, LSTM has gradually attracted the attention of scholars, and in the process of the algorithm being upgraded, it has also been used to compare with other models to find the one with a better performance. Zhang et al. (2018a) implemented the LSTM, GRU, RNN and feed-forward neural network (FFNN) (see Figure 8) to predict CSO at a citywide level, indicating that GRU and LSTM were more suitable to capture the temporal and spatial evolution of CSO event and superior to other methods. Later, Yin et al. (2022) applied LSTM to predict water depth, overflow volume and compared them with multilayer perception (MLP), where the root mean square error (RMSE) of LSTM models was 19 to 50 times which were smaller than those of MLP models. Moreover, LSTM presents a good accuracy in predicting the duration and start time of SO with maximum differences of 2-3 minutes. Furthermore, Huang et al. (2023) extended the concept of LSTM and designed the sparse autoencoder-based bidirectional long short-term memory (SAE-BLSTM) network model to comprehensively predict the wastewater flow rate in SSSs since it could effectively extract sparse potential features from the original input data. Afterwards, an extensive comparison was conducted between SAE-BLSTM and several advanced algorithms, such as support vector machine (SVM), fully convolutional networks (FCN), GRU, LSTM and BLSTM, in which SAE-BLSTM consistently outperformed the other models. Specifically, SAE-BLSTM network can achieve the lowest RMSE and mean absolute error (MAE), and highest R-squared when simulating data sets within the same period. However, LSTM is not always the best performer. Zhang et al. (2018b) constructed and compared MLP, wavelet neural network (WNN), LSTM and GRU to simulate and predict the water level of the CSO structure. The results indicate that although the LSTM and GRU algorithms have shown excellent capabilities in time series forecasting, considering the accuracy and calculation efficiency, GRU displays a stronger advantage because it has fewer parameters, faster speed, and simpler architecture, which is more suitable for the dataset with a large amount of information.

Compared with the other two types, the input variables of AI-based models do not involve catchment parameters, as shown in Table 7. Several studies have been conducted on machine learning to predict the relationship between rainfall runoff and overflow levels during heavy rainfall (Yin et al. 2022). To some extent, water levels in drainage system depend on the rainfall characteristics of the surrounding catchment, so classifying rainfall events becomes a good method to improve the performance of machine learning models. Another important influence factor of SO is the rainfall derived inflow and infiltration (RDII). In this case, wastewater flow information structured in time series can reflect the status of wastewater because it can evaluate the inflow and outflow of wastewater in the sewer system (Huang et al., 2023). The condition information of sewage is usually obtained by sensors, mainly including flow rate, flow speed, and water level (Gudaparthi et al., 2020; Li et al., 2022; Maltbie et al., 2021). Some studies have made it possible to easily determine the event, duration, and location of a sewer overflow based solely on the instantaneous water depth at each node (Yin et al., 2022). In addition, the sewage flow in pipes shows different trends according to social phenomena, climate change factors. For example, the discharge of industrial wastewater and domestic sewage has weekday/weekend and day/night characteristics, which are more obvious in dry climates. Therefore, to reduce data bias caused by data imbalance, factors such as atmospheric humidity, time of day, and day of the week should be included in the modeling process (Rosin et al. 2021; Rosin et al., 2022).

Figure 9 shows the percentages of the retrieved studies using AI-based models based on different categories. It can be seen from Figure 9(a) that machine learning techniques, especially ANN, play a dominant role in predicting SO, while deep learning techniques represent a less explored field, where LSTM becomes the mainstay of deep learning models. Figure 9(b) demonstrates that there are four input factors for AI-based models, where *Precipitation data* (85%) and *Sewage hydraulic characteristics* (90%) occupy the dominant positions, while *Socio*-economic factors and *Climate change related factors* only account for 10% and 15% of the total publications, respectively. As observed in Figure 9(c), *Water level* becomes the most popular output factor, applied in 65% of the total publications, because of the application of smart sensing technologies. *Duration* and *Location* are used the least in AI-based models, both accounting for 5%, in contrast with the situation in physically-based and statistical models. According to Figure 9(d), 85% of the retrieved studies using AI-based models focus on the prediction of CSO, while the rest of studies focus on the prediction of SSO.

5. Research gaps and future directions

Although the prediction of SO is thoughtfully substantiated by literature, there appears to be several research gaps and the corresponding future research directions are proposed, as shown in Figure 10.

Relatively little is studied toward predicting overflow in the SSSs, although a vast pool of literature focuses on analyzing CSO risks using physically-based and data-driven models. Along with the upgrading of urban drainage infrastructures, an increasing number of cities and countries tend to build more SSSs by splitting the original combined system into two independent ones. For example, the length of China’s sanitary sewer network, storm sewer network and combined sewer network is 192,100 km, 211,200 km and 107,900 km, respectively, thus, separate sewers account for 78.89% of the total system (Saddiqi et al., 2023). SO prediction in the SSSs still remains an unexplored field and needs further scholarly attention, where SO in the SSSs should be distinguished into wastewater overflow and stormwater overflow under heavy rainfall. The wastewater overflow refers to the unintentional, direct release of untreated wastewater to the environment from the sewerage pipes and manholes, whereas the stormwater overflow occurs when heavy rainfall overloads the stormwater pipes and manholes.

There is lack of consideration for a comprehensive understanding of the critical factors and sub-factors culminating in SO before prediction, although previous studies have identified some culprits of SO sparsely and fragmentally (Mohandes et al., 2022). A considerable number of scholars have studied the effects of precipitation characteristics on the occurrence of SO (Schroeder et al., 2011; Yu et al., 2018). It has been observed that rainfall time series data (e.g., duration, intensity, total depth) could be effectively used to predict SO. However, few studies have taken cognizance of the impacts of factors related to user behavior, land use, structural and operational properties of pipelines on maintaining the capacity they are supposed to have. Recently, the effects of physical, operational and environmental factors have gained considerable attention in the fields of deterioration and defect detection of sewer pipelines (Hawari et al., 2018; Moradi et al., 2020; Daher et al., 2021). Therefore, it is reasonable to propose a hybrid methodological approach to meticulously investigate the factors causing SO based on a comprehensive literature review, experts' interviews, structural equation modeling, and system dynamic modeling (Mohandes et al., 2022). Physical factors may include pipe age, material, diameter, length, depth and slope. Operational factors may include pipe defects (e.g., blockages, debris, deformation, infiltration), and hydraulic conditions (e.g., water level, flow rate, velocity) (Morales et al., 2017; Maltbie et al., 2021; Rosin et al., 2022). Environmental factors may include soil properties, traffic, land use, tree density, population and climate (e.g., precipitation, sea level rise, tidal water, amplitude and speed) (Morales et al., 2017; Reis et al., 2017; Meyers et al., 2021; Liu et al., 2023).

Among the models used for SO prediction, although advanced deep learning algorithms shed light on stronger nonlinear simulation capabilities compared with traditional machine learning algorithms, existing data-driven models still have limitations (Huang et al., 2023). Firstly, the accuracy of the predictive models needs to be improved. Secondly, few modeling methods distinguish between dry and wet weather conditions, which leads to a situation where the trained model can accurately predict SO under daily rainfall, but it performs poorly under extreme weather condition (Rosin et al., 2021). Finally, the model having a short prediction horizon cannot provide sufficient early warnings for impending overflow (Zhang et al., 2018a). Therefore, in order to fill the aforementioned gaps, it is worth incorporating overflow under extreme weather conditions into data-driven models in the future research. Furthermore, in the future research related to water resources, existing algorithms could be improved and certain advanced deep learning algorithms are worthy of further mining, such as stacking depth codes, deep belief networks, which will improve the accuracy, and increase the leading time of forecast meanwhile (Mounce et al., 2014; Zhang et al., 2018a).

Most existing studies on SO prediction solely rely on monitoring drainage infrastructures, collecting data from sensors on a regular basis, and manually transmitting data to computers, including overflow occurrence and overflow duration, etc. (Mailhot et al., 2015; Montserrat et al., 2015). However, this traditional, high-cost data collection and transmission method makes overflow monitoring difficult in application to real and sophisticated sewer systems (Schroeder et al., 2011). Therefore, the water level and flow have become the standards for scholars to calibrate the prediction models. On the one hand, the scarcity of data has led to the fact that almost all research on predicting the state of sewer pipes has focused on the individual level (Mohandes et al., 2022). On the other hand, this may lead to the problem that the real behavior of SO cannot be accurately reflected (Gamerith et al., 2011). Therefore, further research could consider upgrading the model results from the pipeline scale to the watershed scale, and more considerations should be given to the influence relationship between pipeline neighbors. In addition, in order to manage SO risks more efficiently, future research could combine SO monitoring and prediction, such as extending the IoT to environmental monitoring and modelling applications, so as to build an IoT-based smart sewage treatment system (Rahman et al., 2020). In this process, online sensors can be used to collect real-time data and transmit it to an online data storage platform at any time (Montserrat et al., 2015). Meanwhile, telemetry recorders can also be applied to sensor systems to upgrade their monitoring capabilities. Besides, it is also necessary to design a program to analyze raw data online, which can manage SO incidents more proactively and provide a professional guidance to municipalities. As more research is done on this topic, it is hoped that updating operational online urban drainage models with real-time measurements will become the norm (Lund et al, 2018).

Though the utmost efforts to quantify and predict for potential SO to date, integration of real-time monitoring and nowcasting the SO within the detected blackspots of SO risks is relatively immature and indispensable. To address this challenge, there is a dire need to develop an integrated and multi-level approaching framework to long-term predict the potential overflow blackspots using data-driven models and monitor and nowcast the overflow occurrence with reliable accuracy in the short term through smart sensing technologies, given the time and cost constrains.

6. Conclusion

This study presents a state-of-the-art and comprehensive review for the prediction of overflow in urban sewer systems, including bibliometric survey, scientometric analysis, in-depth systematic review, as well as elucidation of the existing research gaps and the potential future research directions. Within the study context, firstly, a thorough bibliometric survey is conducted to collect, clean and sort the most relevant research papers in sewer overflow prediction. Then, based on the scientometric analysis, it can be observed that United States is the most active contributing country on this topic, there exists numerous collaborations among the researchers, e.g., Mikkelsen P.S. and Boruo M. The most frequently used keywords related to SO prediction are CSO, urban drainage system, ANN, wastewater, climate change, and logistic regression. Secondly, an in-depth systematic review is performed to investigate the methodologies used in the retrieved studies. Three categories are considered: physically-based, statistical and AI-based. It can be concluded that the majority of the studies have adopted data-driven models, of which AI-based methods are by far the most adopted ones. In detail, SWMM is the most favorable selection within the context of physically-based models; logistic and multiple regression models are the most commonly used statistical model; and ANN is a dominant contributor to the AI-based models. Moreover, there are mainly five input factors adopted: *Precipitation data*, *Catchment parameters*, *Sewage hydraulic characteristics*, *Socio-economic factors*, and *Climate change related factors*. Regarding the outcome of the predictive models, *Volume* is the most popular selection for physically-based models; *Likelihood of occurrence* is mostly used for statistical models; and *Water level* is the most adopted output factor for AI-based models. Finally, a majority of the retrieved studies focuses on the prediction of CSO, while relatively little is related to SSO prediction. Based on the aforementioned findings, several existing research gaps and potential future research directions are recommended and presented in Section 5. In summary, this state-of-the-art review fills the gap of few endeavors focusing on SO prediction, and could provide the scholars, engineers, experts and utilities with inclusive hindsight in dealing with such issues, which lays the foundation for further preserving the infrastructure, environment, human health and life from such harmful incidents and achieving the goals of providing sustainable and reliable drainage services.

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.

Data availability

All the data used in this study appears in the body of the article.

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Figures and Tables

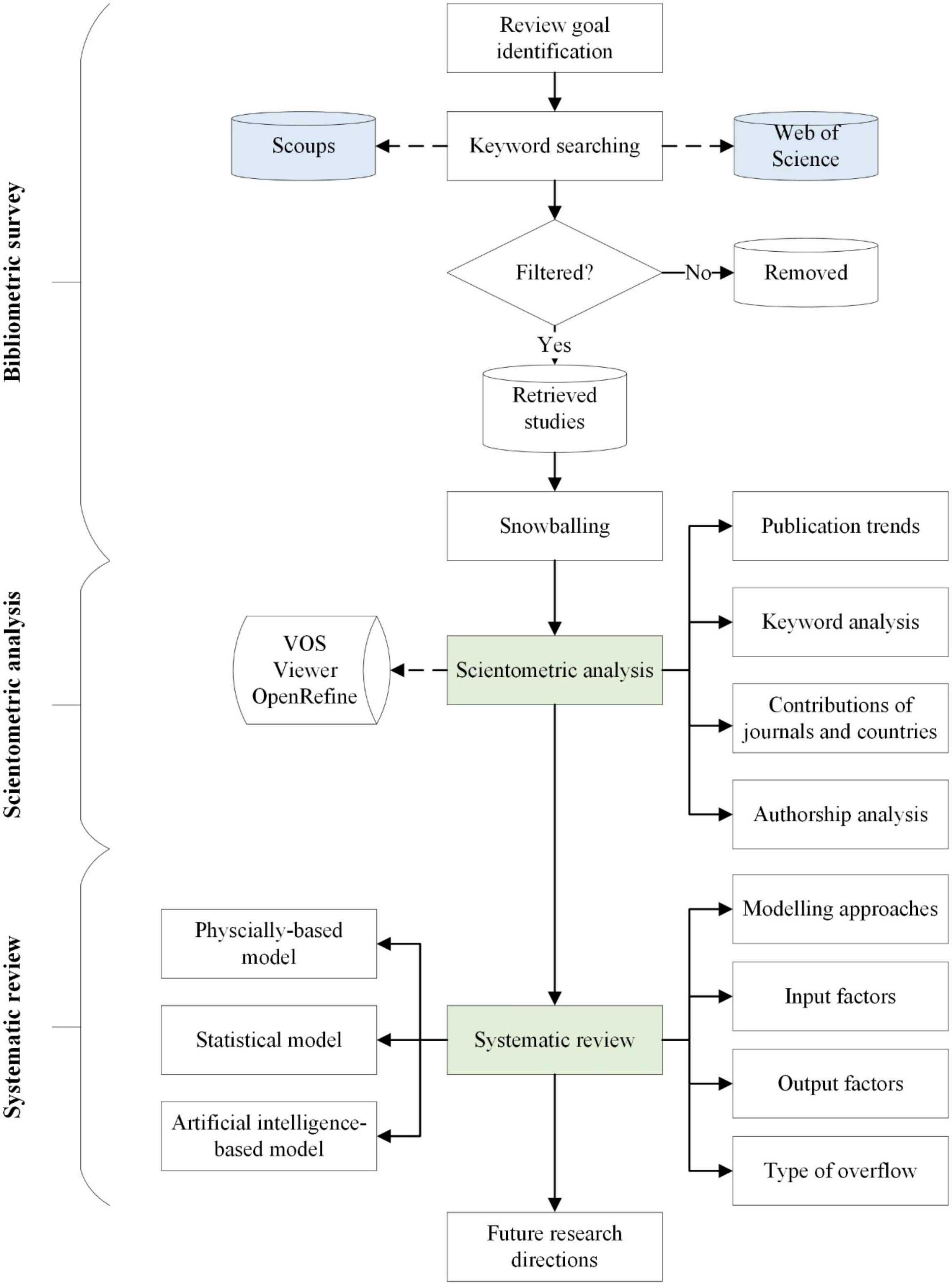


Figure 1. The flowchart of this review study

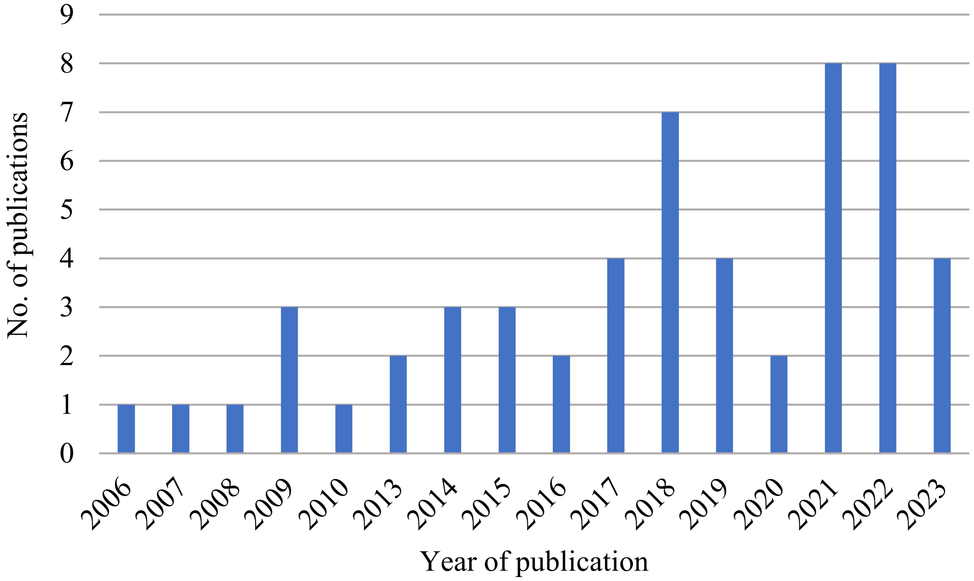


Figure 2. Annual publication trends

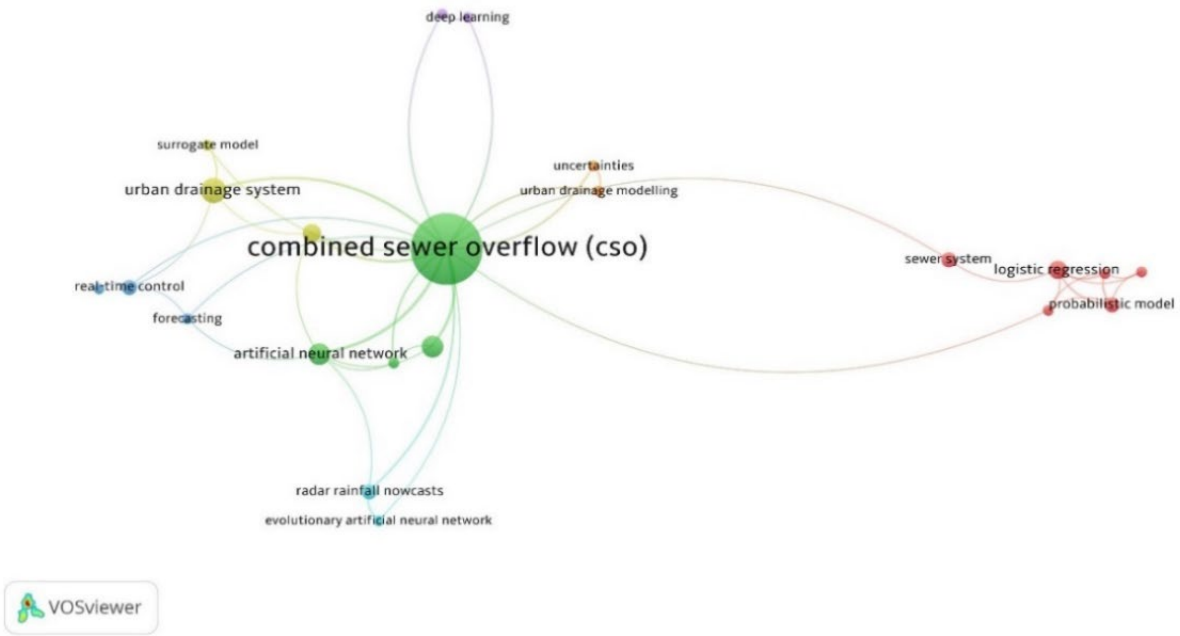


Figure 3. Co-occurrence of keywords mapping network

Table 1. Keyword occurrences

Keyword	Occurrences	Total link strength
Combined sewer overflow (CSO)	26	21
Urban drainage system	6	6
Artificial neural network	5	8
Wastewater	5	5
Climate change	4	6
Logistic regression	4	3
Radar rainfall nowcasts	3	3
Probabilistic model	3	2
Real-time control	3	2
Sewer system	3	2

Table 2. Contribution of journals

Journal	Documents	Citations	Total link strength
Water Science & Technology	9	87	7
Urban Water Journal	4	34	1
Journal of Hydrology	3	222	4
Water Research	3	8	0
Hydrological Sciences Journal	2	39	3
Water Resources Management	2	16	3
Journal of Hydroinformatics	2	20	2

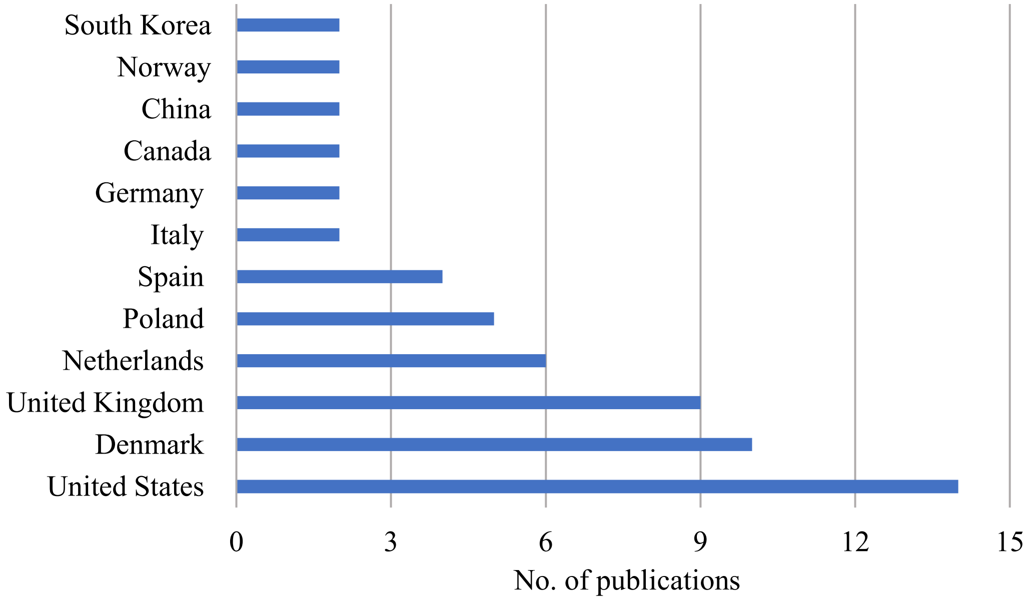
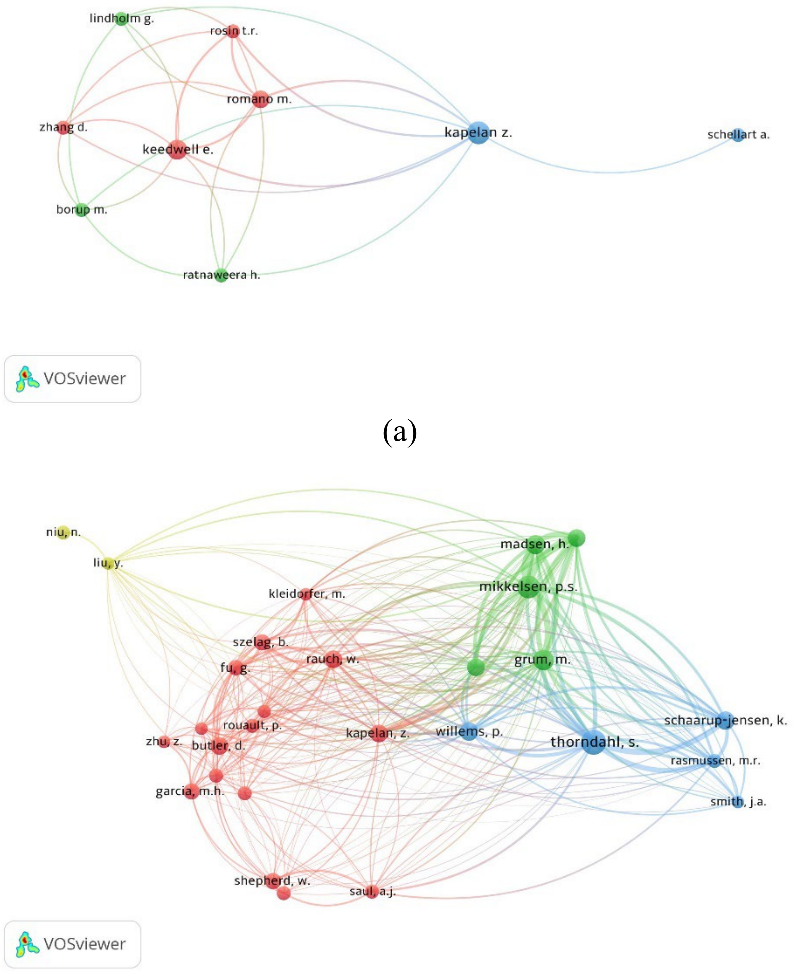


Figure 4. Top contributing countries



(a)

(b)

Figure 5. Results of authorship analysis: (a) citation analysis, and (b) co-citation analysis

Table 3. Citation analysis of authors

Author	Documents	Citations	Total link strength
Kapelan Z.	5	13	11
Keedwell E.	4	13	10
Thorndahl S.	4	64	8
Szeląg B.	4	14	2
Romano M.	3	10	9

Table 4. Co-citation analysis of authors

Author	Citations	Total link strength
Thorndahl S.	40	556
Mikkelsen P. S.	33	731
Grum M.	26	535
Madsen H.	23	548
Schaarup-Jensen K.	21	333
Willems P.	21	228
Borup M.	20	586
Arnbjerg-Nielsen K.	20	318
Rauch W.	20	167

Table 5. Physically-based models

Author(s)	Study area	Methods adopted	Model inputs*				Model outputs**							Overflow type
			(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Quaranta et al. (2022)	European Union + UK (EU28)	Hydrological model	√	√	√		√	√						CSO
Reis et al. (2017)	Philadelphia, US	Hydrological and hydraulic models			√	√	√						√	CSO
Li et al. (2022)	Port Pirie, South Australia	Swift model		√	√					√	√			CSO
Zimmer et al. (2013)	Chicago, US	Storage routing model (SRM)	√	√	√						√			CSO
Roseboro et al. (2021)	Buffalo, New York, US	SWMM	√	√			√							CSO
Park et al. (2014)	Cheongju, Korea	XP-SWMM 2D			√					√	√			CSO
Ghodsi et al. (2021)	Buffalo, New York, US	SWMM, R-language	√	√			√						√	CSO
Schellart et al. (2014)	England	HyRaTrac, STEPS, STEPS+MM5	√		√					√	√			CSO
Lund et al. (2019)	Copenhagen, Denmark	Mike Urban, Ensemble Kalman filter	√		√				√					CSO
Yu et al. (2018)	Tokyo	InfoWorks-CS	√					√			√	√		CSO
Morales et al. (2017)	Chicago, US	IUHM, SWMM, InfoWorks-CS	√	√	√		√	√					√	CSO
Thorndahl and Rasmussen (2013)	Denmark	MOUSE	√	√	√					√	√			CSO
Schaarup-Jensen et al. (2009)	Frejlev, Denmark	MOUSE	√	√	√		√				√			CSO

Abdellatif et al. (2015)	Cheshire, England	GCM, InfoWorks	√	√			√	√					√	CSO
Tavakol-Davani et al. (2016)	Toledo, Ohio	GCMs, SWMM	√	√	√	√	√	√					√	CSO
Gogien et al. (2023)	Valence, France	GCM/RCM, InfoWorks	√	√	√	√	√						√	CSO

*Model inputs: (1) Precipitation data; (2) Catchment parameters; (3) Sewage hydraulic characteristics; and (4) Climate change related factors.
** Model outputs: (1) Volume; (2) Duration; (3) Likelihood of occurrence; (4) Flow rate; (5) Water level; (6) Starting time; and (7) Frequency.

Table 6. Statistical models

Author(s)	**Study area**	**Methods adopted**	**Model inputs***					**Model outputs****				**Overflow type**
			(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	
Allen et al. (2022)	Rudersdal, Denmark	Logistic regression model	√				√		√			CSO
Meyers et al. (2021)	Pinellas County, Florida, US	Logistic regression model	√				√		√			SSO
Bizer and Kirchhoff (2022)	Cumberland, Maryland	Multiple linear regression model	√					√				CSO
Mailhot et al. (2015)	Québec, Canada	Bernoulli trial, binomial distribution, maximum likelihood estimation function, threshold model	√						√			CSO
Szeląg et al. (2019)	Kielce, Poland	Logistic Regression model	√	√					√		√	Storm overflow
Liu et al. (2023)	Wuhan, China	GLMM				√			√			CSO
Thorndahl (2009)	Frejlev, Denmark	GLUE, Monte Carlo simulation	√	√				√		√		CSO
Szeląg et al. (2018a)	Kielce, Poland	Logit model, probit model, Gompertz and linear discriminant analysis mode	√		√				√		√	Storm overflow

Szeląg and Bąk (2017)	Kielce, Poland	Logistic regression model, SWMM	√						√		√	Storm overflow
Szeląg et al. (2018b)	Kielce, Poland	Empirical models, SWMM	√		√				√		√	Storm overflow
Hamidi et al. (2018)	New York, US	Multivariate simulation, Monte Carlo simulation	√	√					√			CSO
Vezzaro (2022)	Copenhagen, Denmark	Extrapolation method	√	√	√			√				CSO
Szeląg et al. (2021)	Kielce city, Poland	Logistic regression model, Monte Carlo simulation	√	√	√				√		√	Storm overflow
Thorndahl et al. (2008)	Aalborg, Denmark	FORM, Monte Carlo simulation	√	√							√	CSO
Mahmoodian et al. (2018)	Grand Duchy, Luxembourg	GPE	√					√				CSO
van der Werf et al. (2023)	Rotterdam, Netherlands	RB-RTC	√		√					√		CSO
Svensen et al. (2019)	Barcelona, Spain	MIQP-MPC, QP-MPC	√		√			√				SSO
Svensen et al. (2021)	Aarhus, Denmark	ECC-MPC	√		√			√				CSO

*Model inputs: (1) Precipitation data; (2) Catchment parameters; (3) Sewage hydraulic characteristics; (4) Socio-economic factors; and (5) Climate change related factors.

** Model outputs: (1) Volume; (2) Likelihood of occurrence; (3) Water level; and (4) Frequency.

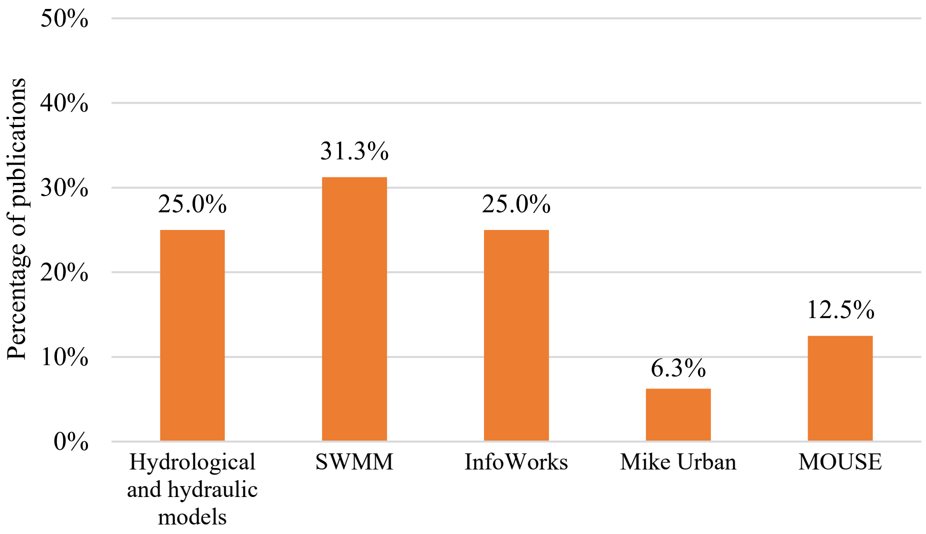
Table 7. Artificial intelligence-based models

Author(s)	**Study area**	**Methods adopted**	**Model inputs***				**Model outputs****							**Overflow type**
			(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	
Sumer et al. (2007)	Pima, Arizona, US	NN, time series analysis		√						√	√			SSO
Hill et al. (2009)	Chicago, US	BN	√	√					√					CSO
Montserrat et al. (2015)	LaGarriga, Spain	DT	√						√					CSO
Zhao et al. (2019)	UK	LASSO, NN, fuzzy models	√	√						√	√			CSO
Li et al. (2010)	Edmonton, Alberta, Canada	ANN	√									√		CSO
Mounce et al. (2014)	Northern Scotland, UK	ANN	√	√							√			CSO
Bailey et al. (2016)	Wales, UK	ANN	√	√							√			CSO
Rosin et al. (2017)	Wirral, England	Feed-forward ANN	√	√		√					√			CSO
Rosin et al. (2022)	Northwest, England	EANN	√	√	√	√					√			CSO
Rosin et al. (2021)	Northern England	CEANN	√	√	√	√					√	√		CSO
Achela et al. (2006)	Avondale, Auckland	Feed-forward back-propagation ANN	√	√			√			√				CSO
Gudaparthi et al. (2020)	Cincinnati, US	LSTM, GRU, IndRNN	√	√					√					CSO
Maltbie et al. (2021)	Cincinnati, US	LSTM, NN, XAI tools	√	√					√					CSO
Palmitessa et al. (2021)	Copenhagen, Denmark	LSTM, NN	√	√							√			CSO

Yin et al. (2022)	Detroit, Michigan, US	LSTM, SWMM, MLP	√	√			√	√			√	√	√	CSO
Huang et al. (2023)	Yangju City, Korea	SAE-BLSTM	√	√						√				CSO
Zhang et al. (2018a)	Drammen, Norway	LSTM, GRU, RNN, FFNN	√	√							√			CSO
Zhang et al. (2018b)	Drammen, Norway	MLP, WNN, LSTM	√	√							√			CSO
Daniel et al. (2022)	Thiruvananthapuram, Kerala	Web-based Real-Time Expert System Shell software		√							√			SSO
Rahman et al. (2020)	Dhaka City, Bangladesh	IoT		√							√			SSO

*Model inputs: (1) Precipitation data; (2) Sewage hydraulic characteristics; (3) Socio-economic factors; and (4) Climate change related factors.

** Model outputs: (1) Volume; (2) Duration; (3) Likelihood of occurrence; (4) Flow rate; (5) Water level; (6) Starting time; and (7) Location.


Percentage of publications
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Hydrological and hydraulic models
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InfoWorks
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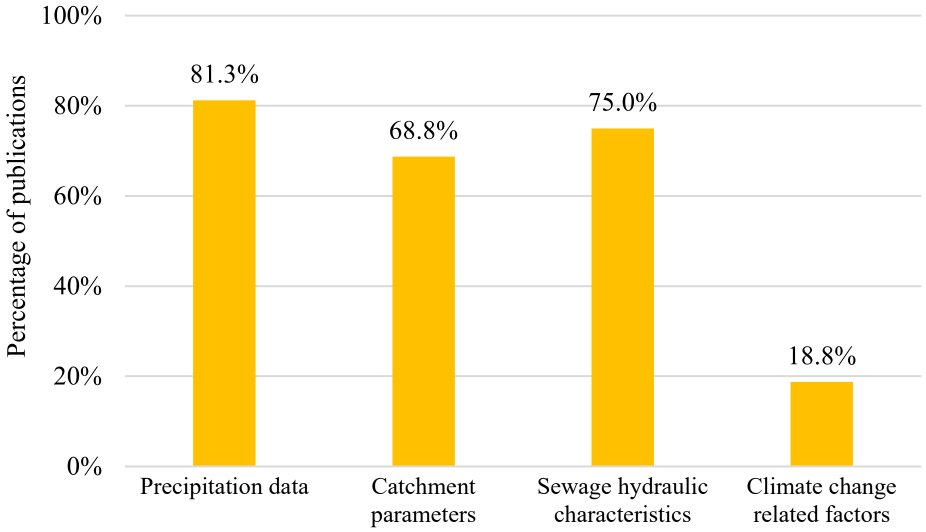
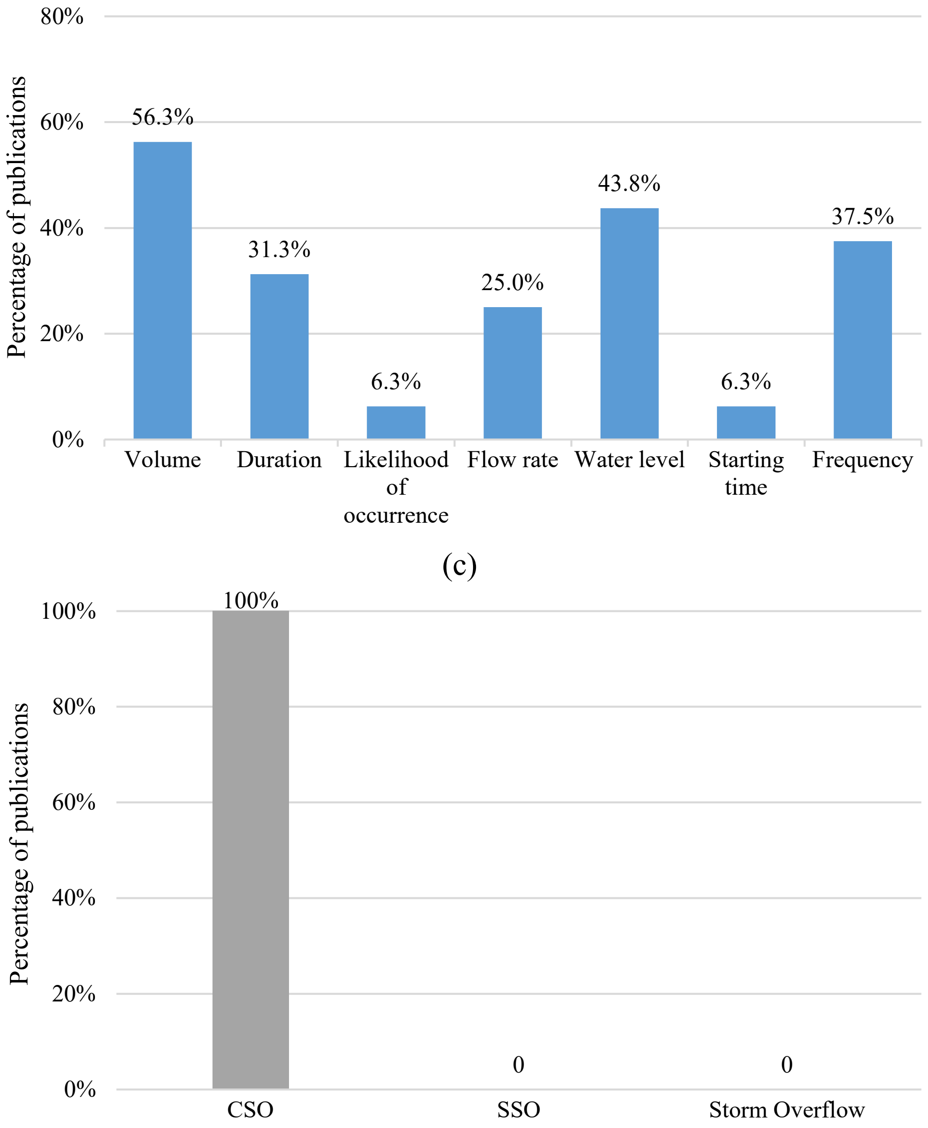
MOUSE

(a)


Percentage of publications
100%
80%
60%
40%
20%
0%
81.3%
68.8%
75.0%
18.8%
Precipitation data
Catchment parameters
Sewage hydraulic characteristics
Climate change related factors

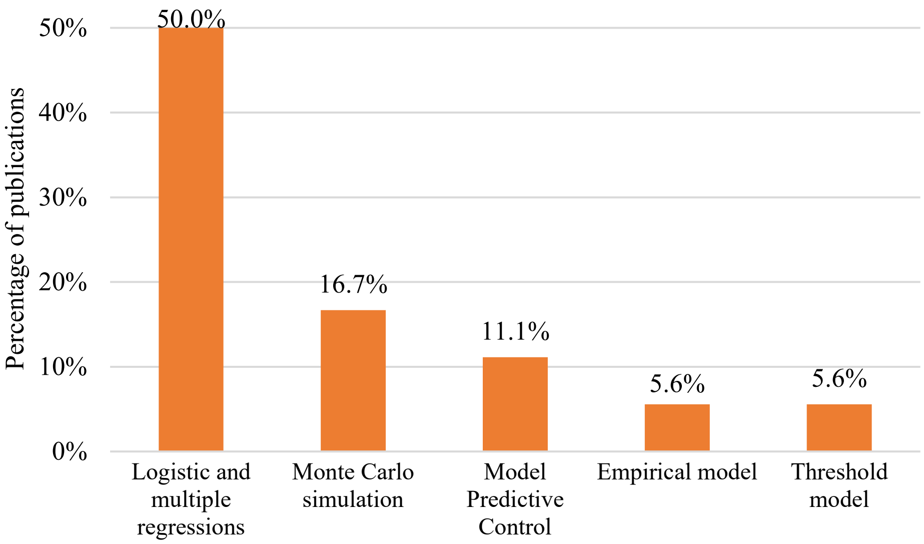
(b)



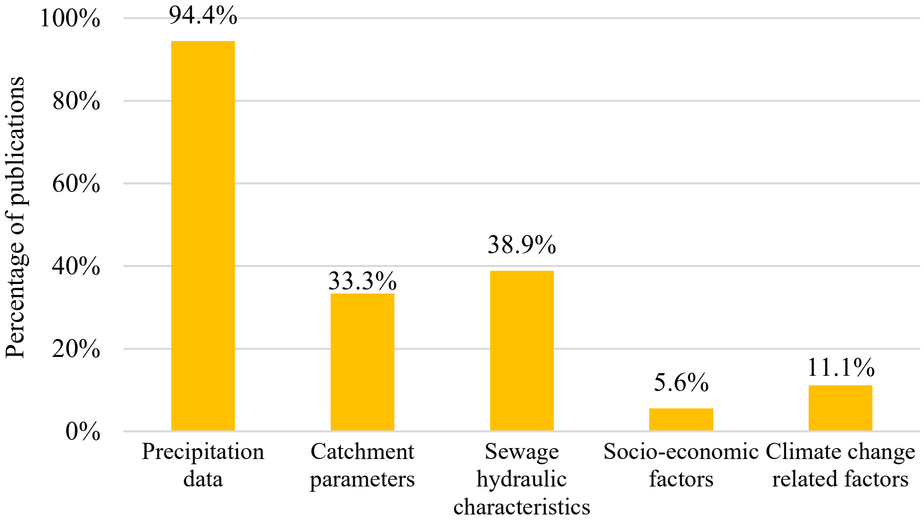
(c)

(d)

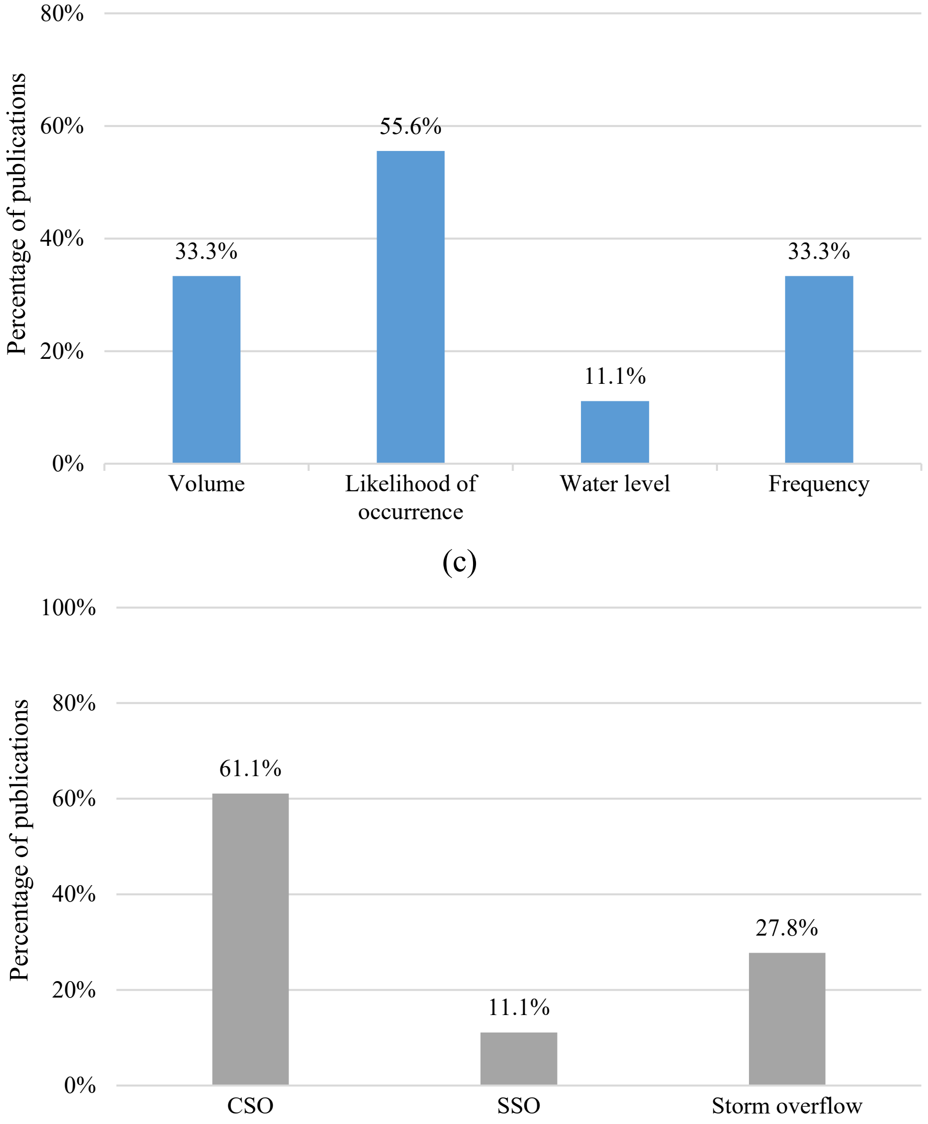
Figure 6. Percentage of the publications using physically-based models based on: (a) type of method adopted, (b) type of inputs, (c) type of outputs, and (d) type of overflow


Percentage of publications
50%
40%
30%
20%
10%
0%
50.0%
16.7%
11.1%
5.6%
5.6%
Logistic and multiple regressions
Monte Carlo simulation
Model Predictive Control
Empirical model
Threshold model

(a)


Percentage of publications
100%
80%
60%
40%
20%
0%
94.4%
33.3%
38.9%
5.6%
11.1%
Precipitation data
Catchment parameters
Sewage hydraulic characteristics
Socio-economic factors
Climate change related factors

(b)



(c)

(d)

Figure 7. Percentage of the publications using statistical models based on: (a) type of method adopted, (b) type of inputs, (c) type of outputs, and (d) type of overflow

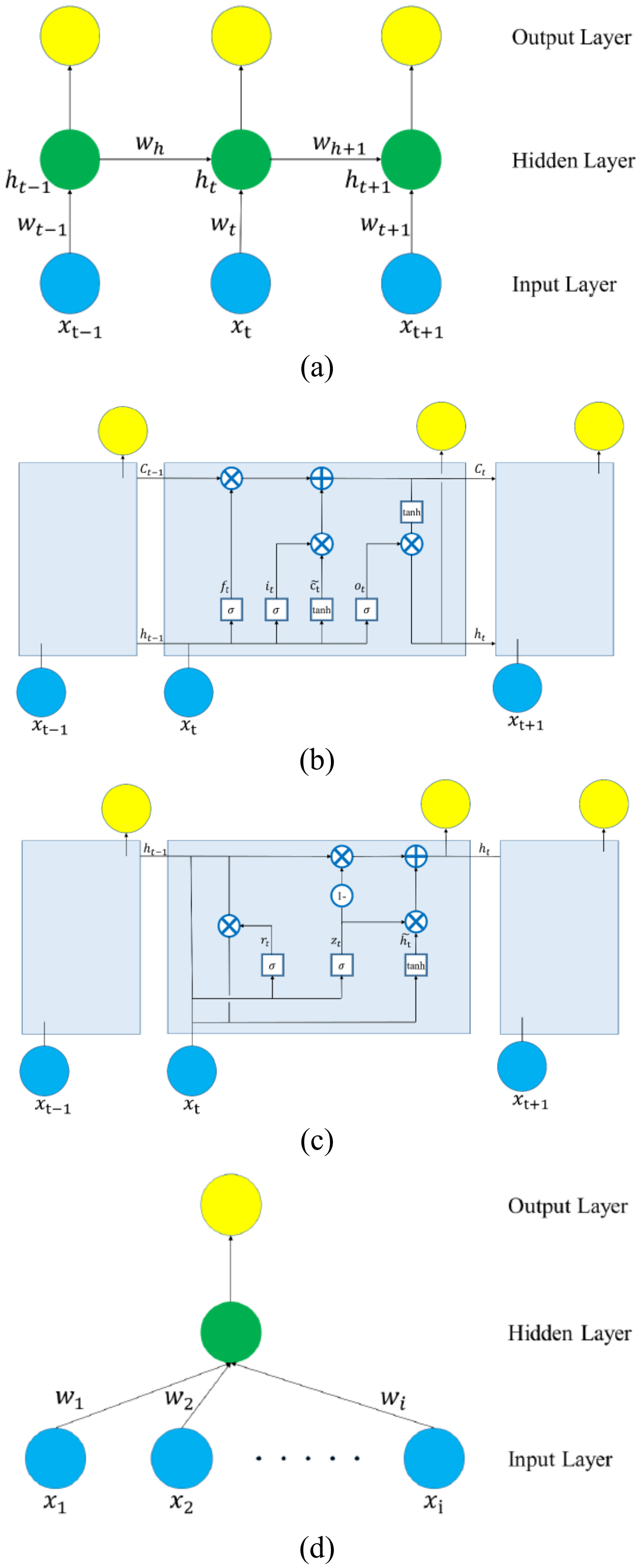
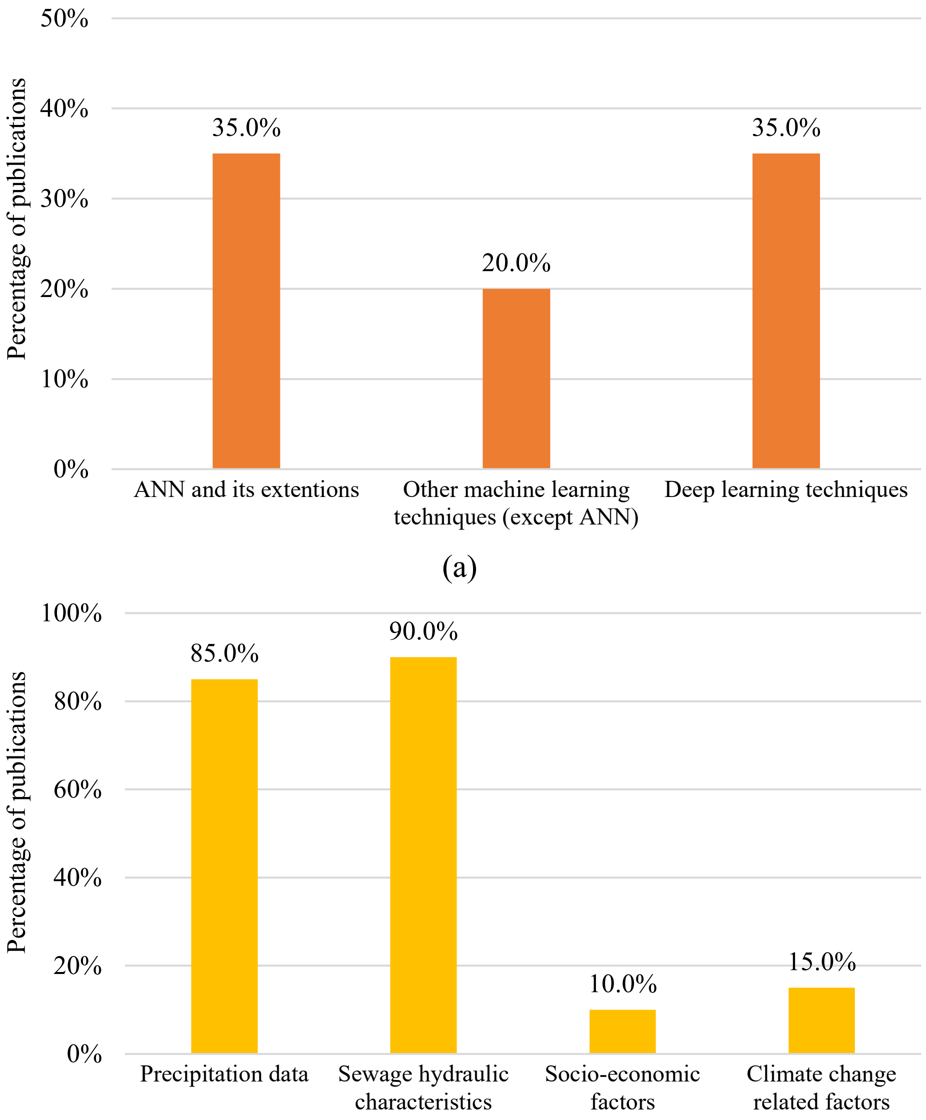
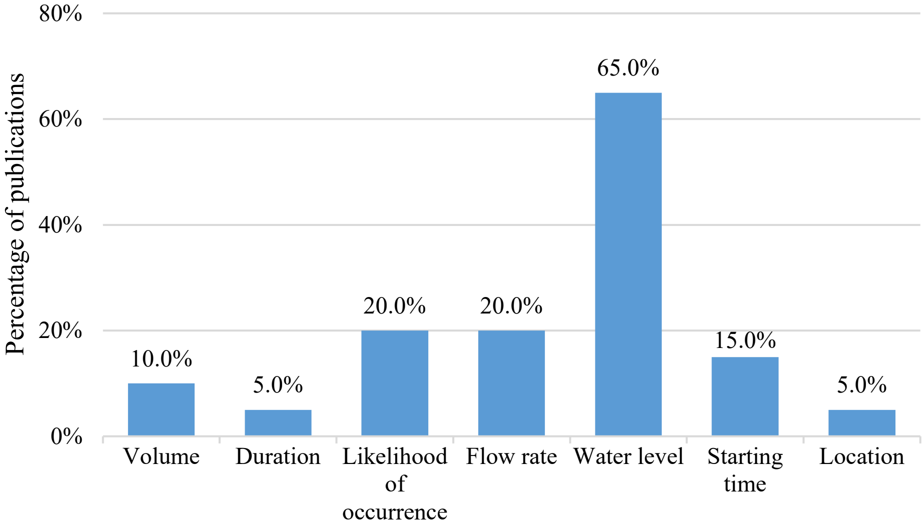


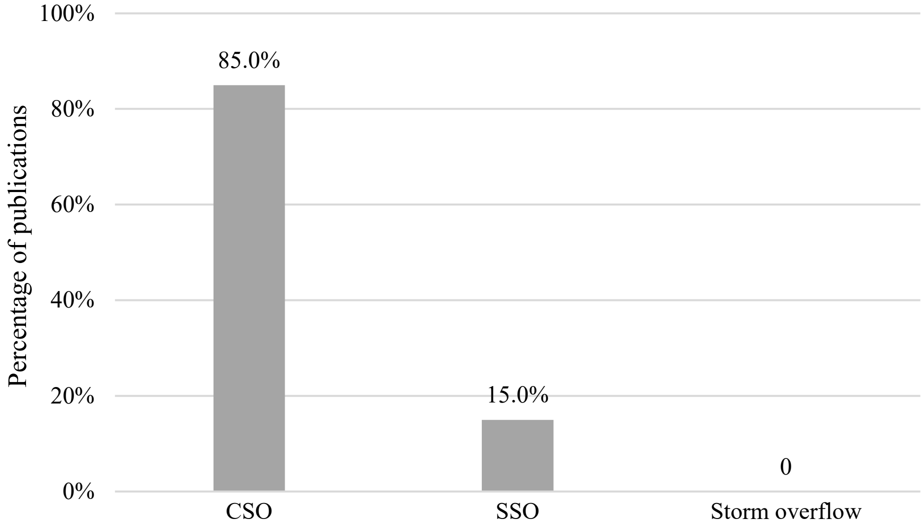
Figure 8. Schematics of (a) RNN, (b) LSTM, (c) GRU, and (d) FFNN (Adopted from Zhang et al., 2018a)


Percentage of publications
50%
40%
30%
20%
10%
0%
35.0%
20.0%
35.0%
ANN and its extentions
Other machine learning techniques (except ANN)
Deep learning techniques
(a)
Percentage of publications
100%
80%
60%
40%
20%
0%
85.0%
90.0%
10.0%
15.0%
Precipitation data
Sewage hydraulic characteristics
Socio-economic factors
Climate change related factors

(b)



(c)



(d)

Figure 9. Percentage of the publications using artificial intelligence-based models based on: (a) type of method adopted, (b) type of inputs, (c) type of outputs, and (d) type of overflow

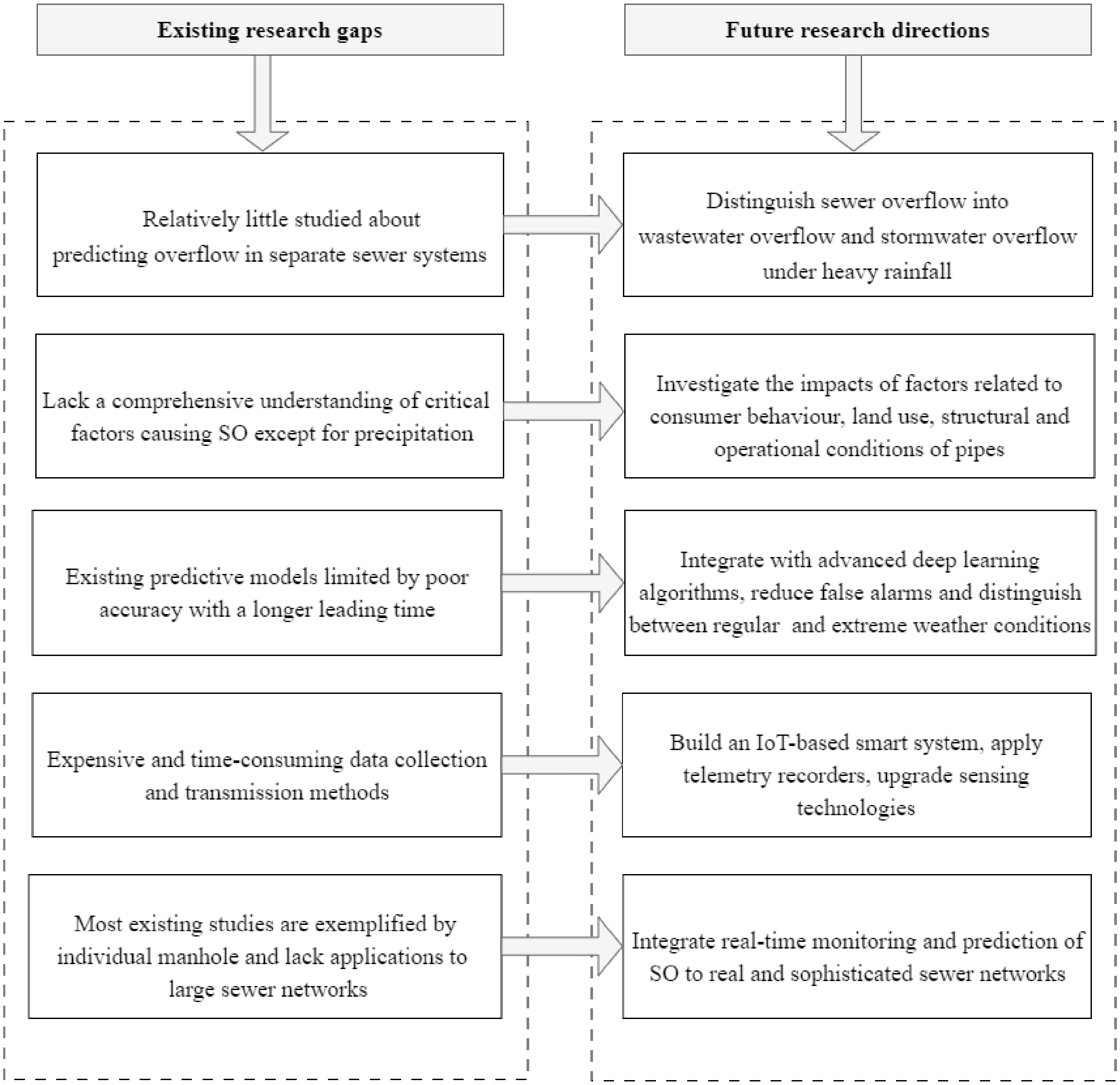


Figure 10. Existing research gaps and future research directions