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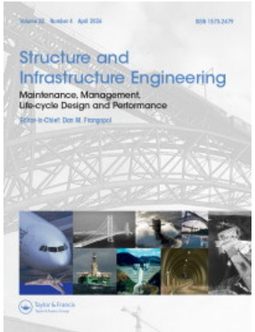

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REVIEW ARTICLE

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A review of monitoring site selection methods for urban drainage networks – the missing link between theory and practice

Spyros Pritsis[a], Francois Clemens-Meyer[b], Sebastian Kerger[c], Abigail Legge[d], Miao Wang[e], Marius Møller Rokstad[a] and Franz Tscheikner-Gratl[a]

[a]Department of Civil and Environmental Engineering, Norwegian University of Science and Technology (NTNU), Trondheim, Norway; [b]SkillsInMotion B.V, Utrecht, The Netherlands; [c]Institute for Water Management and Climate Future, RWTH Aachen University, Aachen, Germany; [d]University of Sheffield, School of Mechanical, Aerospace and Civil Engineering Mappin St, Sheffield City Centre, Sheffield, United Kingdom; [e]Department of Civil and Environmental Engineering, Monash University, Melbourne, Australia

ABSTRACT

This paper presents a critical review of methodologies for monitoring site selection in urban drainage networks, focusing on underground pipe systems. By examining the 35 most relevant publications, trends, strengths, and limitations of their approaches are identified. These methodologies are assessed based on their ability to achieve specific objectives, including model calibration, contaminant detection, and compliance with regulations. In addition to the literature review, the paper presents three case studies that illustrate practical challenges and describe how they were addressed. These case studies highlight how practical constraints such as budget limitations, available data, and accessibility shape decisions during monitoring campaigns. The reliance on expert knowledge emerges as a recurring theme in the practical application of urban drainage monitoring, contrasting with the often theoretical focus of academic research. The findings reveal a gap between theoretical advancements and practical implementation in planning monitoring campaigns, but therein lies an opportunity to better connect the two. To address this gap, we suggest developing standardised benchmarking datasets, modular methodologies, and relevant guidelines tailored to practitioners' needs. This study aims to bridge the divide between research innovations and real-world applications and improve the planning and execution of monitoring campaigns while promoting collaboration between researchers and practitioners.

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1. Introduction

The selection of monitoring sites in urban drainage networks (UDNs) is a critical aspect of effective network management and modelling. Over the past decades, various studies have attempted to address this challenge in research, each with its own strengths and limitations. These publications consider several factors, including network coverage, data quality, cost-effectiveness, and adaptability to real-world conditions, but essentially it boils down to the question of where and what to monitor to create a dataset that will be useful for a certain objective (e.g. calibrating a numerical model, monitoring water quality, fulfilling legal requirements, etc.).

The challenge of monitoring site selection in UDNs aligns conceptually with optimal experimental design (OED), a systematic framework for maximising information gain from data collection efforts. Rooted in statistical theory, OED provides a methodological foundation for determining measurement strategies tailored to specific objectives (Kiefer & Wolfowitz, 1959; Pukelsheim, 2006). While traditionally applied in laboratory settings, OED has been adapted for diverse field applications, including UDN monitoring (Huan et al., 2024). A core tenet of OED is that the optimisation process must be intrinsically linked to the monitoring campaign's purpose, which directly translates to UDNs. This principle underscores that monitoring site selection cannot be separated from the intended use of the data, whether for model calibration, system control, or water quality monitoring.

As we established, the question of where to measure to gather data that will be used for the design, operation, modelling, and evaluation of an urban drainage system cannot be decoupled from its context (e.g. why, how, for how long to measure). Traditionally there are two categories of measurements used in the field of urban drainage: rainfall measurements, taken from above ground locations near the system, and measurements (water quantity and/or quality) taken inside the system (i.e. pipes and manholes). This is

CONTACT Spyros Pritsis spyridon.pritsis@ntnu.no Department of Civil and Environmental Engineering, Norwegian University of Science and Technology (NTNU), S. P. Andersens veg 5, 7031 Trondheim, Norway

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why a main challenge of any urban drainage model (barring models that exclusively focus on dry weather flow) is filling in the gap between the two: converting rainfall into runoff and subsequently transporting this runoff (which we do not measure directly) overland or in the piped systems (Beven, 2011).

As the increased usage of green infrastructure (GI) expanded the boundaries of urban drainage, pledging a shift towards sustainable urban drainage systems (SUDS), the types of measurements that can be taken have also increased (Fletcher et al., 2015, 2024). For example, in a catchment with green roofs and/or rain gardens, measurements of water quantity and/or quality taken from these infrastructures are necessary to evaluate their performance and can also be informative for understanding the behaviour of the UDN downstream. Even though there is research focusing on how to monitor each of these GIs (Mantilla et al., 2025; Zhu et al., 2023), the literature on selecting monitoring site locations in UDNs almost solely focuses on sites located inside manholes and underground pipes. Studies on which GIs to monitor to get a complete picture of the hydrological behaviour of and the diffuse pollution transport in an urban catchment are, to the best of the authors knowledge, still missing.

Another development that is interlinked with urban drainage monitoring is real time control (RTC) systems (Borsányi et al., 2008; Schütze et al., 2004). RTC operates by adjusting actuators – primarily (frequency-controlled) pumps, movable weirs, and orifices in the context of UDN – based on real-time system-state observations to achieve a predefined objective (van der Werf, 2023). Other than the constant monitoring of the system necessary for the operation of RTC, sufficient data is also needed to inform the planning of such an approach (i.e. how to modify the system, where to install actuators). In this context, the decisions made during the planning and implementation of monitoring campaigns can be detrimental to the performance/effectiveness of the RTC strategy (B. P. Wong & Kerkez, 2018; van der Werf, 2023).

The necessity for strategic monitoring site selection in UDNs stems from the topological complexity of these systems (Zischg et al., 2017) and the practical constraints that govern monitoring campaigns. Urban drainage networks are characterised by high spatial and temporal variability in flow patterns, water quality parameters, and system responses to external forcing such as rainfall events (Ochoa-Rodriguez et al., 2015). Without systematic placement strategies, monitoring efforts risk capturing redundant information from closely correlated locations while missing critical system behaviours in other areas. This challenge is exacerbated by the financial and logistical constraints that limit the number of monitoring sites to be deployed and maintained over extended periods of time. The emergence of low-cost sensor technologies has created new opportunities for expanding monitoring coverage within constrained budgets, though their deployment still requires systematic approaches to optimise placement strategies. The optimisation problem is further complicated by the computational complexity involved. Sensor placement in networks is widely recognised as an NP-hard problem, meaning that finding the optimal solution becomes computationally prohibitive as the network size increases (Berger-Wolf et al., 2005). Additionally, the multi-objective nature of most monitoring campaigns requires balancing competing priorities, while accommodating practical constraints including site accessibility and safety, power availability, and maintenance requirements. These factors point towards the necessity of developing systematic methodologies that can efficiently identify near-optimal sensor configurations within reasonable computational timeframes.

The works considered for the literature review as part of this paper are publications that develop a methodology for monitoring site selection in UDNs (i.e. selecting appropriate monitoring sites on a network scale). The type of measurement performed at the sites is not an exclusion criterion (i.e. methodologies aimed at any type of measurement are relevant). In contrast, the type of monitoring sites considered by the methodologies is used as an exclusion criterion. We limit the scope by focusing only on measurements made below ground (i.e. in urban drainage pipe networks). There have been literature reviews of monitoring site selection methodologies for surface waters in natural catchments (Chacon-Hurtado et al., 2017; Mishra & Coulibaly, 2009). Although these systems are very different to UDNs (different scales, components, etc.), there are also similarities between their structure and driving processes (tree topology, free surface flow, driven by rainfall). This makes some methodologies for monitoring site selection transferable between these two fields. Two literature reviews including UDNs are available. Thompson et al. (2011) focussed on monitoring site selection for both UDN and water distribution systems (WDS) with the objective of calibrating models. More recently, Ma et al. (2025) filled the gap since 2011 with a review covering optimal arrangement strategies of Internet of Things (IoT) sensors in UDNs. It primarily focuses on methodological advancements within the sensor placement optimisation domain, proposing a general framework for the sensor arrangement process and emphasising future directions for improving optimisation approaches through dynamic strategies and phased deployment.

In contrast, the present study adopts a fundamentally different perspective and objective. It critically examines the substantial disconnect between the theoretical developments in sensor placement optimisation and their practical implementation in real-world monitoring campaigns. Although we similarly review the available literature on monitoring site selection methodologies, our primary contribution lies in identifying and analysing the barriers that prevent the transfer of research innovations to operational practice. We aim to bridge the gap between academic research (on UDN monitoring site selection) and field applications, investigating why sophisticated optimisation methodologies remain largely confined to academic publications rather than being systematically adopted by other researchers, municipalities, water utilities, and consulting engineers responsible for planning and executing urban drainage monitoring programs. Another distinctive aspect of our work is the inclusion of detailed case studies from research projects that demonstrate the practical challenges encountered when planning and implementing monitoring campaigns in real-world settings. Through these examples, we illustrate barriers and decision-making processes that lead to the under-utilisation of the available literature, offering concrete insights into why the gap between theory and practice persists.

2. Literature review

The present work can be categorised as a narrative literature review (Snyder, 2019; G. Wong et al., 2013). This type of review is well-suited for identifying and analysing trends in a field of research and synthesising a conducive narrative. This aligns with the main goal of this review, which is to identify the trends emerging in UDN monitoring site selection literature and evaluate to which extent they are applied in practice.

A systematic search was conducted on the Web of Science database using combinations of the keywords presented in the (Appendix Table A1). The queries yielded 1818 results. The titles and abstracts were then screened to identify the works fitting the selection criteria. More specifically, we consider peer-reviewed publications evaluating the choice of monitoring sites in UDNs (i.e. works developing and/or applying methodologies for selecting monitoring sites in urban drainage pipe networks). Following that, a snowball search method was applied, using the bibliographies of the selected works to more thoroughly explore the existing literature. This resulted in 35 relevant publications being identified for further review (Figure 1 and Table A2 in the Appendix).

2.1. First steps in monitoring site selection methods for water systems

The problem of optimising monitoring site selection in water systems was first addressed in the field of streamflow measurements in the 60s (Fiering, 1965). In the 80s, Walski (1983) developed an approach to assist calibration of water distribution network models. In this work, Walski highlighted the importance of selecting appropriate nodes for fire flow tests – an established practice for extracting hydraulic information from systems under varied conditions. He observed that nodes located at the periphery of the network are generally more informative for such tests than those near the sources and recommended prioritising these peripheral nodes. However, Walski's work did not extend to a formal optimisation of the overall monitoring network. One of the first publications focusing on consciously selecting monitoring locations for an urban water system was published in the 90s by Lee and Deininger (1992). They provided a quantitative framework for evaluating sensor placement choices in WDSs based on the demands of each node.

In the late 90s a series of three papers were published focusing on modelling urban wastewater management (Rauch et al., 1998; Schilling et al., 1997; Vanrolleghem et al., 1999). Specifically, Vanrolleghem et al. (1999) focused on the task of setting up a measurement campaign for integrated wastewater modelling and introduced the sensor placement optimisation challenge in the urban drainage field. Despite focusing on treatment plants and receiving waters, rather than the UDN, it provided a good overview of the different measurement types also used in UDNs. Furthermore, some fundamental ideas were laid down which are a common theme in later publications, such as the application of sensitivity analysis for selecting monitoring locations and the potential benefits of multi-step, iterative approaches.

The first work that focused on optimising a monitoring network for an urban drainage system came three years later by Clemens (2002), where the upper and lower bounds of the sampling frequency were estimated by applying signal analysis on the measured timeseries and calculating Jacobeans to identify (and optimise) model parameter sensitivity to changes in measuring locations. This represented a significant shift from earlier heuristic-based strategies, introducing mathematical rigour to the spatial-temporal design of urban drainage monitoring campaigns.

2.2. Trends in urban drainage systems monitoring site selection literature

Most of the studies presented in Figure 1 are comprised of an objective formulation for the monitoring site selection problem (shapes in the light lime-green shaded area) and a (combination of) method(s) used to reach that objective (shapes in the violet shaded area). Each publication included in this review is presented on the vertical axis of the figure and depending on the objective of the monitoring campaign, corresponding shapes are placed on the categories that are used in the approach proposed in that publication. This information is also presented in the form of a table in the Appendix.

We can discern an evolution of the objectives (model calibration, monitoring water quality, monitoring flooding locations, and information content) that have been popular in the monitoring site selection literature by observing the pattern of the shapes in Figure 1. Starting in the '00s with studies focusing on evaluating monitoring campaigns for numerical model calibration. Since then, water quality monitoring has become the most common objective. Researchers have developed several approaches for efficiently detecting contaminants in the system. Prompted by the global pandemic, studies aiming to pinpoint biological contamination locations have been published in the last five years, bringing more attention to decentralised water quality monitoring in sewage systems. In the last years there has also been an increase in studies that propose a more theoretical monitoring objective, formulating it in terms of information content. These studies aim to maximise the amount of information extracted from the system (given some

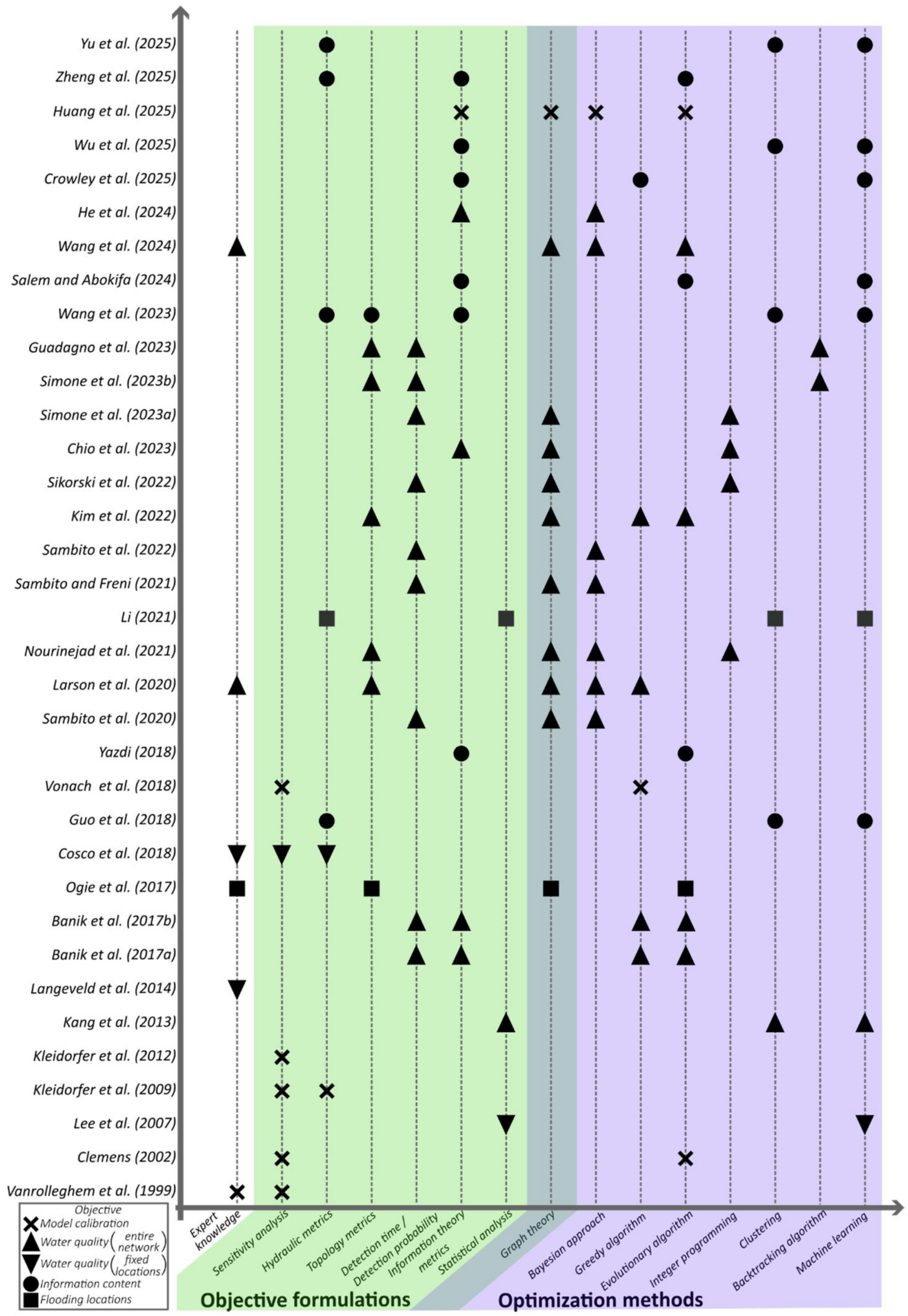

Figure 1. Overview of UDN monitoring site selection literature. Publications are listed on the vertical axis. The light lime-green shaded (left) side of the figure shows the categories of objective formulations. The violet shaded (right) side of the figure shows the different methods used to reach the objective. The different shapes show the general objective of the monitoring campaign for each study (see legend at bottom left). A list of the covered literature and the corresponding categories can also be found in Table A2.

constraints), essentially formalising the sensor placement problem in OED terms.

Regarding methodologies, heuristic methods have remained consistently present throughout the evolution of the field, providing practical solutions when computational complexity becomes prohibitive. In contrast, machine learning techniques represent a more recent development. Graph theoretical approaches tend to use formulations and methods to solve the monitoring site selection problem that are specific to graphs (e.g. centrality metrics, graph partitioning, etc.). For that reason, graph theory is located at the intersection of objective formulations and methods to solve/optimise. This doesn't mean that it cannot be combined with other formulations or methods. Finally, expert knowledge is placed outside these two categories, as its use often does not fit in the paradigm set by them (i.e. formulating an objective function and choosing a method to solve it).

In the following sections, we synthesise the main trends that have emerged in the literature. First, a distinction is made between approaches that exhaustively evaluate the possible monitoring site combinations and the ones that resort to efficiently exploring that solution space with different strategies. Then these strategies and approaches are categorised based on the methodologies they employ, including model parameter sensitivity analysis, machine learning (ML), and various heuristics. Lastly, we consider the publications focusing on monitoring site selection for contaminant detection, a field which expanded rapidly with the need for wastewater-based epidemiology during the global pandemic. The references we have chosen to construe these trends are only a fraction of the works that fall under each category. Figure 1 is intended as a companion to the text for readers wishing to explore a trend or specific approach exhaustively.

2.3. Evaluating a limited number of monitoring points

The studies that solely evaluate combined sewer overflows (CSOs) as monitoring points (Cosco et al., 2018; Kleidorfer et al., 2009, 2012; Langeveld et al., 2014), do not use any of the methods shown on the right side of Figure 1. In these studies, the number of possible monitoring points is relatively small (less than 80). Because of that, it is possible to evaluate them all without a need to efficiently explore the solution space of the formulated monitoring site selection problem.

Similarly, Lee et al. (2007) analyse water quality measurements made in a limited number of outfall points of industrial areas, collected as part of three industrial stormwater general permit programs. Using statistical analysis, they propose sampling frequencies for grab samples but conclude that the high variability in water quality measurements derived by these samples can limit the efficiency of the measurement campaign regardless of the number of measurement locations. Instead of simply increasing the number of locations, they suggest carefully selecting a relatively small number and making more accurate measurements (e.g. flow-weighted composite samplers).

Generally, efficiently reducing the size of the optimisation problem solution space is always beneficial. In cases where computational cost must be reduced, a first step where some sites are selected (using expert knowledge or some other heuristic approach) and not considered as viable monitoring points is often used. Unfortunately, it is not always possible to reduce the number of candidate sites to the level where it is feasible to exhaustively explore the solution space of the monitoring site selection problem.

2.4. Exploring large solution spaces

Often the possible combinations of all monitoring points result in an unrealistically high computational load if they were all to be evaluated for the formulated objective (e.g. minimising detection time for multiple contamination scenarios). In these cases, algorithms must be used to efficiently explore the solution space. Evolutionary algorithms (EAs) are optimisation methods inspired by biological evolution, often applied to non-linear problems with large solution spaces. Many studies (Banik, Alfonso et al., 2017a; Banik et al., 2017b; Salem & Abokifa, 2024; Wang et al., 2024; Zheng et al., 2025) use a Non-dominated Sorting Genetic Algorithm (NSGA-II) (Deb et al., 2002) to approximate Pareto-optimal sensor configurations by iteratively evolving candidate solutions.

Greedy algorithms are a class of heuristic methods frequently used in the context of monitoring site selection for UDNs. The central principle of a greedy algorithm is to make a sequence of locally optimal choices at each step, with the hope that this will lead to a solution that is close to the global optimum. In the presented studies, this typically involves iteratively selecting the next monitoring location that provides the largest marginal improvement in the chosen objective function such as information-theoretic measures (Crowley et al., 2025), detection probability (Banik et al. 2017b), or network coverage (Kim et al., 2022)—until the monitoring budget is exhausted or a stop condition is met.

Banik et al. (2017b) compare combinations of greedy and evolutionary algorithms using the same case studies, with the objective of detecting contaminant intrusions in the system. They found that for a small (31 nodes) artificial network, all their approaches gave similar results. However, when applied to a bigger network (1902 nodes), the evolutionary algorithm is more efficient if the objective function is formulated using entropy metrics. The greedy algorithm also gives adequate results. Furthermore, combining the two algorithms improves the results for their case study.

2.5. Information theory methods

Entropy (Shannon, 1948) metrics have not been used widely with the objective of monitoring site selection for model calibration or contaminant detection/water quality assessment in literature. But mostly in the last few years, entropy, as well as other information theory measures, have been used by many researchers who formulate the problem in more generic terms of maximising information gain/content. These studies (shown with circles in Figure 1) use Shannon's concept of entropy as a measure of uncertainty reduction, where optimal site selection aims to minimise redundant information while capturing system variability.

Yazdi (2018) formulates the optimisation problem as such: the ideal monitoring network must maximise the joint entropy between the measured variables in the chosen monitoring locations. They apply this approach focusing on water quality parameters (more specifically, total nitrogen, total phosphorus, and total suspended solids) derived from a numerical model of Teheran's UDN. They use a differential evolution (DE) algorithm to approximate an optimal solution and show that the result outperforms the monitoring network design proposed by consultant engineers, when evaluated solely on the joint entropy of the simulated 'measured' variables.

Crowley et al. (2025) use the measure of mutual information to identify monitoring locations that maximise the information gain about the state of the system. They apply a greedy algorithm to arrive at near optimal solutions for two case studies and compare their results to other heuristic approaches.

2.6. Expert knowledge and other heuristics

In contrast to the mathematically rigorous approaches discussed in previous sub-chapters, a significant portion of the literature relies heavily on domain expertise and engineering judgement, which is a paradigm more representative of the current practices in monitoring campaigns. The only studies that explicitly rely on expert knowledge of the system are focusing on the selection of critical CSOs. Langeveld et al. (2014) develop a 4-step methodology to aid water authorities when selecting monitoring locations for stormwater quality in UDNs. Their method focuses on applicability in the field; it is practical and relies heavily on the engineers' knowledge of the system.

Other types of heuristics often rely on expert knowledge implicitly. That means that domain knowledge is the main determinant for formulating the heuristic method and prioritising aspects of the optimisation problem. Chio et al. (2023) develop a framework for arriving at optimised sensor locations in a UDN, with the objective of detecting and tracing anomalies. They describe anomalies as transient events which can occur and manifest in the UDN through a set of phenomena (water depth, turbidity, temperature, etc.). The framework utilises historical data of anomalies identified at specific nodes and semantic land uses (i.e. what type of activities are taking place in a given subcatchment) to infer a correlation between the types of anomalies (categorised by the measured phenomena associated with them) and the semantic land uses present upstream of the node where the anomaly occurred. This knowledge is then used to create a realistic set of anticipated anomalies. Subsequently, these anticipated scenarios are simulated and metrics based on graph theory and entropy are calculated on each node. These metrics are used to partition the UDN into subgraphs in order to restrain the optimisation problem. Finally, the location and type of the sensors is obtained/attained by using Mixed Integer Linear Programming (MILP) to maximise the detection and pinpointing of anomalies. The framework also provides decision-makers with an interactive tool to splice/introduce expert knowledge or additional constraints at different stages of the process.

Simone et al. (2023a) compare two approaches tackling the problem of monitoring site selection for contaminant detection in a UDN. The first approach uses a global optimisation solver to maximise the number of simulated contamination events detected by the network of sensors. The second approach is based on graph theory and does not use any information about the hydraulic behaviour of the system (i.e. only information about the network topology and the inflow at each node is used). The In-Relevance-Harmonic centrality of each node is calculated and used as a metric for sensor deployment suitability. They propose combining the two approaches to leverage synergies (i.e. use the graph theory approach to efficiently limit the number of candidate nodes and apply the global optimisation solver to this limited subset).

Guadagno et al. (2023) tackle the same problem by adapting a backtracking algorithm developed by Zierolf et al. (1998). They assume steady-state hydraulic conditions in the network and run simulations of different contamination scenarios (constant concentration of a non-conservative contaminant injected at all nodes, one at a time) to obtain concentration values at all nodes. Based on the concentrations and the flowrate on each node, the backtracking algorithm arrives at an Impact Coefficient for each node, which then defines (in conjunction with a specified threshold of detection value for the sensors) which nodes are 'covered' by the sensors. Finally, for each branch, the first node where the Impact Coefficient falls below the detection threshold is chosen as a new monitoring point until the whole network is 'covered'.

Simone et al. (2023b) follow a very similar approach, but instead of running a simulation to obtain the contaminant concentrations in the network, they use basic hydraulic equations and assume that all pipes are at full capacity and use the results to calculate the Impact Coefficient. Using this augmented approach on the same network as Guadagno et al. (2023), they arrive at an identical monitoring scheme.

2.7. Sensitivity analysis

Among the earliest approaches to monitoring site selection in UDNs, sensitivity analysis has been particularly prominent in studies focused on model calibration objectives. When the monitoring objective is model calibration, most approaches perform a sensitivity analysis to evaluate the relationship between monitoring locations and model parameter values. Kleidorfer et al. (2009) generate a dataset using two calibrated models of urban catchments with UDNs. After an initial screening to limit the number of possible monitoring locations (CSOs) based on the simulated annual overflow volume, they use a stochastic approach to create different calibration scenarios based on different monitoring locations to gather calibration data. By comparing the results of these different scenarios to those of the initial calibrated models, they evaluate the performance of the different measurement campaigns on the model calibration. Kleidorfer et al. (2012) investigate the identifiability of model parameters connected to imperviousness of subcatchments depending on the data available on the system (which is of course conditional on the choice of monitoring locations). They only consider CSO locations as candidates for monitoring.

Sensitivity analysis has also been used in combination with various heuristics. For example, Cosco et al. (2018) propose a method to rank the CSO points of a system based on a weighted average of some chosen 'determinant factors'. These factors can be proxies for any relevant information (quantitative or qualitative) the decision maker might have about these locations. By correctly selecting the factors and weights for each outlet, they aim to identify the 'most convenient [outlets] for the quantification of direct discharge'. Since the influence of selecting these factors is self-evident, they explore three scenarios; basing them on (1) simulation data, (2) expert data, and (3) spatial data. The resulting location rankings vary between scenarios. They also conduct a sensitivity analysis to quantify the effect of the weights used on the factors, showing that, for their case study the rankings are not affected.

Vonach et al. (2018) also take a heuristic approach to the problem of monitoring site selection for model calibration. They first limit the number of possible measurement sites in a network by only considering pipes that are directly downstream of nodes where there is an inflow (junction or connected subcatchment). They then test two different methodologies on a calibrated model of a combined drainage system. Method 1 ranks the potential measurement sites (pipes) by using the outputs of the calibrated model as a reference scenario and comparing the results of models calibrated on data coming from each pipe (data taken from the reference scenario results). By using this method iteratively, sets of potential measurement sites can be defined. Method 2 ranks the potential measurement sites (pipes) by performing a sensitivity analysis on selected calibration parameters and comparing the results for each individual pipe to the reference scenario. The pipes that more sharply respond to changes in the parameters are prioritised over ones that produce more steady results. As the field evolved beyond these initial model calibration approaches, researchers began to shift their focus towards water quality monitoring objectives, leading to the development of different methodological frameworks.

2.8. Machine learning

Representing a more recent development in the field, ML approaches have begun to emerge as useful alternatives to traditional heuristics. ML approaches have established themselves as important tools in the evolution of urban drainage modelling practices. More specifically, for monitoring site selection, while traditional methods often rely on heuristic optimisation, ML approaches rely on data-driven strategies that adapt to system dynamics. Clustering algorithms are unsupervised machine learning approaches that, 'given a representation of n objects, find K groups based on a measure of similarity such that the similarities between objects in the same group are high while the similarities between objects in different groups are low' (Jain, 2010). By interpreting the possible monitoring locations in a UDN as 'n objects' and representing them in a way that enables meaningful similarity metrics, we can see how clustering algorithms can be applied to address the monitoring site selection problem. In most applications, after the clusters have been identified, a representative node is chosen from each cluster where the sensor should be installed.

Kang et al. (2013) use hierarchical clustering to group nodes based on water quality characteristics derived from simulations of a UDN. To select a representative node from each cluster, they conduct an Analysis of Variance (ANOVA). They apply this approach on different scenarios (varying rainfall intensity, pollutant concentration, and boundary conditions), but the effect on the resulting monitoring schemes is not discussed. Yu et al. (2025) follow a similar approach, highlighting the importance of adapting and refining the methodology depending on the goals of the monitoring campaign and the expected rainfall conditions.

Li (2021) develops a method to choose monitoring points (nodes) in a system for the objective of detecting flooding events. They first limit the examined nodes to those located in the flooded hotspots identified by the municipality. Then they use hierarchical clustering on timeseries, derived from a model, focusing only on water depth. Historical and projected 10-year rainfall timeseries are used with a calibrated model to derive long time-series of water depth for the examined nodes. The number of clusters (i.e. the number of sensors in the monitoring scheme) is determined by setting a threshold for their dissimilarity metric. To select a representative node from each cluster, they conduct ANOVA on the timeseries of each cluster. They reported an influence of the different rainfall scenarios on the resulting monitoring scheme.

Wang et al. (2023) develop an approach that uses k-means clustering on statistical and information theory indexes calculated from water level and quality data generated by a SWMM model. A re-clustering is proposed if the decision-maker wants to introduce additional system-specific knowledge to the process. The representative node (proposed monitoring location) of each cluster is selected based on its distance from the cluster's centroid. Wu et al. (2025) also use a two-stage clustering approach to optimise the location of sensors in a UDN to identify infiltration and inflow (I&I). For the first stage of the clustering, they use the Spectral Clustering method on a similarity matrix constructed for all the nodes in a UDN in such a way that nodes of the same cluster have the minimum joint entropy. The joint entropy of nodes is calculated based on the number of detected I&I events (simulated), so that nodes with low joint entropy have high redundant information. The second stage re-clusters based on topological information; by considering which nodes are in the same branch of the system (i.e. they have the same upstream nodes), the clustering algorithm refines the existing clusters so that the nodes of each one have higher redundant information between them.

Crowley et al. (2025) developed a framework combining multilayer perceptron (MLP) neural networks with genetic algorithms. Their MLP model learned contaminant transport patterns from simulated scenarios, predicting concentrations at potential sensor locations. These predictions informed a genetic algorithm that optimised sensor networks for both observability (detection coverage) and reliability (consistent performance across scenarios). When applied to a midsize sewer network, the hybrid approach revealed critical trade-offs: adding sensors improved reliability but with diminishing returns, while strategic placement proved more impactful than the number of locations. This work highlights ML's ability to navigate multi-objective optimisation in ways that traditional sensitivity analyses cannot. However, both studies stress the dependency of ML methods on high-quality training data, which is a big limitation in systems lacking historical measurements, and the need for interpretability to bridge the gap between data-driven insights and engineering decision-making.

2.9. Contaminant detection and wastewater-based epidemiology

The choice of monitoring locations is important for reliable and timely identification of unwanted inflows in a UDN (e.g. infiltration, illicit connections, or contamination events). Sambito et al. (2020) use a probabilistic approach (Bayesian Decision Network) to optimise sensor locations in two combined UDNs (one artificial and one real) with the objective of reliably detecting an illicit intrusion (contamination event) in the system. To do so, they use a model to simulate an ensemble of random contamination events. They define two metrics; the likelihood of an event being detected by at least one and at least two sensors. The contaminant is modelled as a conservative xenobiotic pollutant (e.g. mercury or lead). The solutions provided by the Bayesian Decision Network are evaluated based on these metrics. Different prior probability distributions for the sensor locations are considered. The resulting posteriors (selected sensor locations) are not affected by the priors, but the computational time to arrive at them is reduced when relevant knowledge is introduced. The monitoring schemes obtained in this study are compared to those of Banik et al.(2017b), for the case of the artificial network, and to the existing monitoring locations, for the case of the real network. Sambito and Freni (2021) use the same approach to detect illicit intrusions of a non-conservative organic contaminant (e.g. total organic carbon or nitrogen). The resulting monitoring schemes in the two studies differ. When the contaminant is modelled as conservative, more downstream (near the outlets) nodes are favoured for monitoring locations.

The COVID-19 pandemic brought renewed attention to the role of urban drainage monitoring, particularly through the application of wastewater-based epidemiology (WBE) for public health surveillance. Since viral genetic material is excreted in human waste, monitoring sewage networks offers a community-scale method to detect and track outbreaks. This approach can provide early warning of infection hotspots, often before clinical cases are reported, due to the temporal lag between infection, symptom onset, and testing (Wurtzer et al., 2020). Several studies have specifically addressed the challenge of optimal monitoring site selection in urban drainage networks for COVID-19 surveillance. Larson et al. (2020) and Nourinejad et al. (2021) developed algorithms that utilise the tree-like structure of sewer networks to represent them using graphs and efficiently locate sources of infection. Their work proposes sequential testing strategies, using Bayesian statistics. Their aim is to sample manholes in a manner that rapidly narrows down the potential source area, by choosing new sampling locations based on the results of each campaign. They use greedy algorithms combined with subjective assessments on the relative importance of each manhole (i.e. each possible monitoring location) to arrive at a monitoring scheme.

Wang et al. (2024) formulate the site selection problem as a multi-objective optimisation task, balancing the number of sensors, network coverage (detection of biological ‘contaminant’), and overall cost of the campaigns. The evolutionary algorithm NSGA-II is used to solve the optimisation task. Using a sewage water network model of a district in Hong Kong, they compare the resulting monitoring schemes with several simple heuristics, showing that their approach clearly outperforms the heuristics (using the objectives defined for the optimisation task as performance metrics).

The operationalisation of these methods depends on the availability of rapid, reliable, and cost-effective in-sewer viral detection technologies. While the mathematical frameworks and algorithms have been validated in simulation, real-world deployment awaits further technological development. Nevertheless, these studies highlight the potential for urban drainage monitoring to serve as a critical tool in pandemic response, offering scalable and adaptive surveillance capabilities that complement traditional clinical testing. However, putting these methods into practice raises a series of ethical and privacy concerns that should not be taken lightly (Doorn, 2022; Jacobs et al., 2021).

3. Case studies

In this chapter, three case studies are presented. The focus is on illuminating the process followed by different researchers and practitioners when faced with the problem of deploying a limited number of sensors in a UDN, given the specific aims and circumstances of each monitoring campaign. The main difference from the type of research discussed in the previous chapter is that the selection of monitoring sites was an auxiliary consideration in these case studies, rather than the main research question. This led, as often is the case also in practice, to the application of expert (or common sense) knowledge and not the application of algorithms such as the ones developed and proposed by the studies reviewed in the previous chapter. Even though the topic and objective formulations of these case studies could be fitting for a number of approaches covered in the aforementioned literature, ad-hoc approaches based on domain knowledge and ‘common sense’ were preferred.

3.1. Case study 1/Rissington monitoring campaign

In a UK based PhD research project (Legge, 2021), it was necessary to create a calibrated hydraulic model of a small new-build residential network to predict shear velocity for each pipe to help assess the risk of blockage (ergo increased risk of sewer flooding) in dry weather flow (DWF) conditions due to introduced organic sediments from food waste disposers (FWD). Due to this, the system was analysed to optimise the location of monitoring sites and achieve a suitably calibrated hydraulic model. The software used was InfoWorks CS, pipe geometry data from as-laid pipe plans was provided by the water utility company, and a hydraulic survey was undertaken to measure water level and velocities to determine flow. The network that was modelled had well defined boundary conditions and was a recently built separate sewer network with 3 points where effluent from an old pre-existing combined sewer network enters the network of interest. The aim was for the diurnal flow patterns, total volumes, flow rates and depths to be consistent between modelled and measured data. The modelled network has 91 pipes with pipe diameters of 100, 150 and 225 mm, pipe lengths ranged from 4.4 m to 80 m with an average length of 30.7 m, and slopes ranging from 0.0043 m/m to 0.15306 m/m and an average slope of 0.0233 m/m. Of the 92 nodes in the network model, representing the new-build residential area in Figure 2, 53 nodes have properties attached (a total of 242 properties) and 3 nodes have wastewater profiles which represent the ∼260 houses from an adjacent pre-existing network.

There were several limitations imposed which impacted certain aspects of the model development and measurement campaign. Budget constraints mean that choices must be made regarding how to make simplifications without negatively impacting the usefulness of the measurements. In this case, ideally a sensor would be installed on the primary school and the small shops too, located in the zone highlighted in blue in Figure 2, however the 3 outputs of the pre-existing residential system had a greater impact on the 'closed system' being studied so were prioritised, along with the key branches of the network and the inlet to the WWTP itself. The sensors were placed at the positions highlighted in Figure 2.

As the model was intended to be applied on DWF this also means that local rain gauge data was obtained to ensure that the flow data was on a dry-weather day. A dry-weather day was considered to be 'dry' if there was no precipitation measured on that day and if the preceding day had received less than 5 mm of rain to mitigate the effects of percolation into the pipes. Stricter requirements could be imposed if budget allowed for longer measurement campaigns or if the data collected happened to be during a very dry period. In this case due to; needing 3 consecutive days of flow data on a weekday to get an average over 3 days for use in the model (3 being the minimum number to calculate variance), combined with the monitoring period having some rain, and also some data being unusable due to ragging, the defined conditions for choosing data were considered acceptable as applying stricter requirements for considering the data to be of a suitable quality would have needed a bigger budget for a longer measurement campaign. In addition to the data used to calibrate the model, data from different days was used to validate the model output and a series of dye tests to check the velocity at different manholes to the sensors were also used as another layer of validation as this gave a velocity at a single point rather than a 24h profile.

Another limitation was that as the development was new, there was not yet any census data available, so it was not possible to model by population, flow was divided per house with an assumed equal population per property, however, using the population would have given a more realistic model. Another assumption was regarding the pipe roughness. In this model it was mostly new pipes, so a roughness value for that particular type of new pipe was used. However, for the short section of old pipe, this was an unknown roughness and this caused a few discrepancies in earlier versions of the model where all pipes had a new pipe roughness. The few sections of upstream pipe from the WWTP, which were original aged pipes, had their roughness changed to better calibrate the model. If not noticed, these details can have a significant impact on the modelling results. A challenge associated with small catchments with low flows in general is that it makes it more difficult to measure in the field and it is also at the limit of what the model is capable of simulating. It needs certain values to be above zero to function. Despite this challenge, small catchments are often uncomplicated and so the model doesn't account for complex structures (pump stations, storage tanks, etc.) and this added stability to the environment can be a benefit.

3.2. Case study 2/Stony Creek monitoring campaign

This case study forms part of the collaborative research program 'Real-time sensing framework for pollution detection and response in the Stony Creek catchment', focusing on the Stony Creek catchment in Melbourne, Australia (Figure 3). The catchment features a natural waterway that collects stormwater runoff before discharging into a larger downstream river and ultimately reaching the estuarine section of a major river. Located in Melbourne's western suburbs, the 25.1 km^2 catchment exhibits mixed land use patterns, with predominant residential and industrial areas complemented by minor commercial development in its upper northern section.

In August 2018, Stony Creek endured what has been called Melbourne's worst waterway pollution event in nearly 30 years. An industrial fire in the catchment caused severe damage when contaminated firewater entered the creek, killing native vegetation and over 2,300 fish. After the initial response and recovery efforts, local authorities and the community developed a rehabilitation plan. This plan outlines several measures to improve water quality and protect the waterway's health. A trial was conducted, implementing various engineering technologies across the Stony Creek catchment, with a focus on enhancing water quality monitoring and identifying high-risk pollution sources. A key aspect of this initiative involved detecting and characterising pollutant sources beyond typical stormwater runoff, particularly illicit discharges in drainage networks, which significantly degrade water quality. To tackle this issue, the case study proposes strategically deploying advanced monitoring methods and detection tools throughout the catchment to identify illicit discharges effectively.

This case study implemented a systematic approach to detect illicit discharges across the stormwater network, following the U.S. Environmental Protection Agency field screening and monitoring framework (Brown & Pitt, 2004). The methodology began with an Outfall Reconnaissance Inventory (ORI). An ORI has the aim of systematically recording the characteristics of storm drain outfalls, potentially identifying affected catchments. Following that, the catchments were segmented, and monitoring devices were installed at stormwater outfalls (Figure 4) to identify

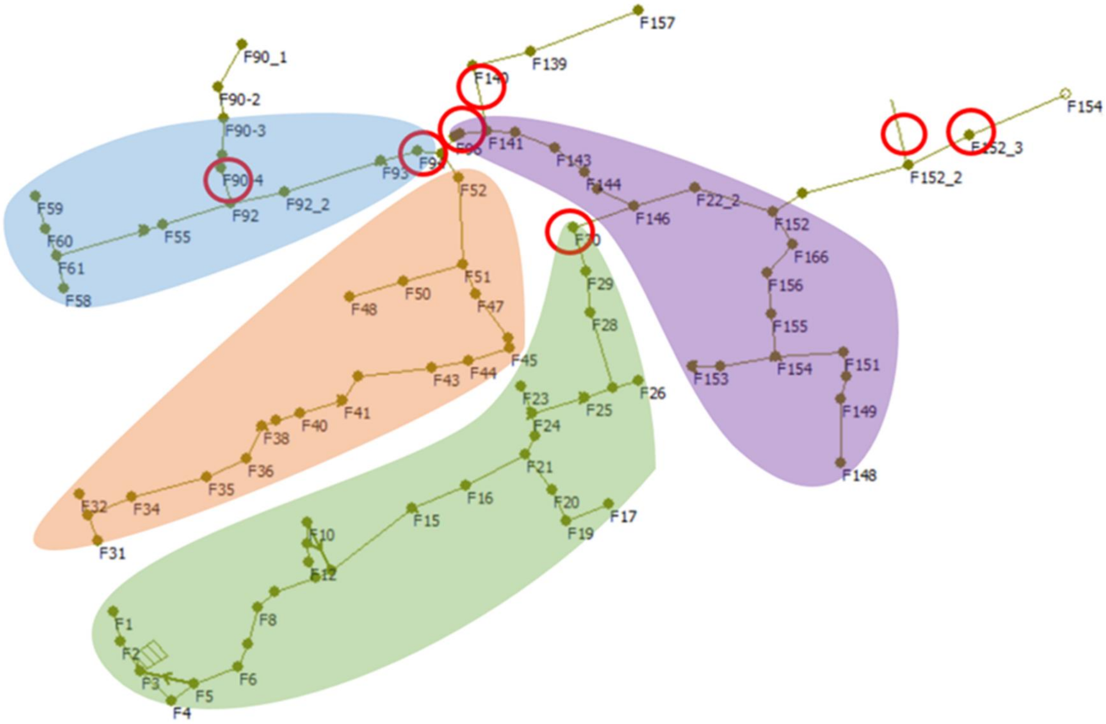

Figure 2. Diagram to show the location of the sensors (red) and also the 4 zones for which this allows flow to be calculated for in the residential area. There are flows from the old network at points F94, F140 and F152_2. The inlet to the WWTP is at F154.

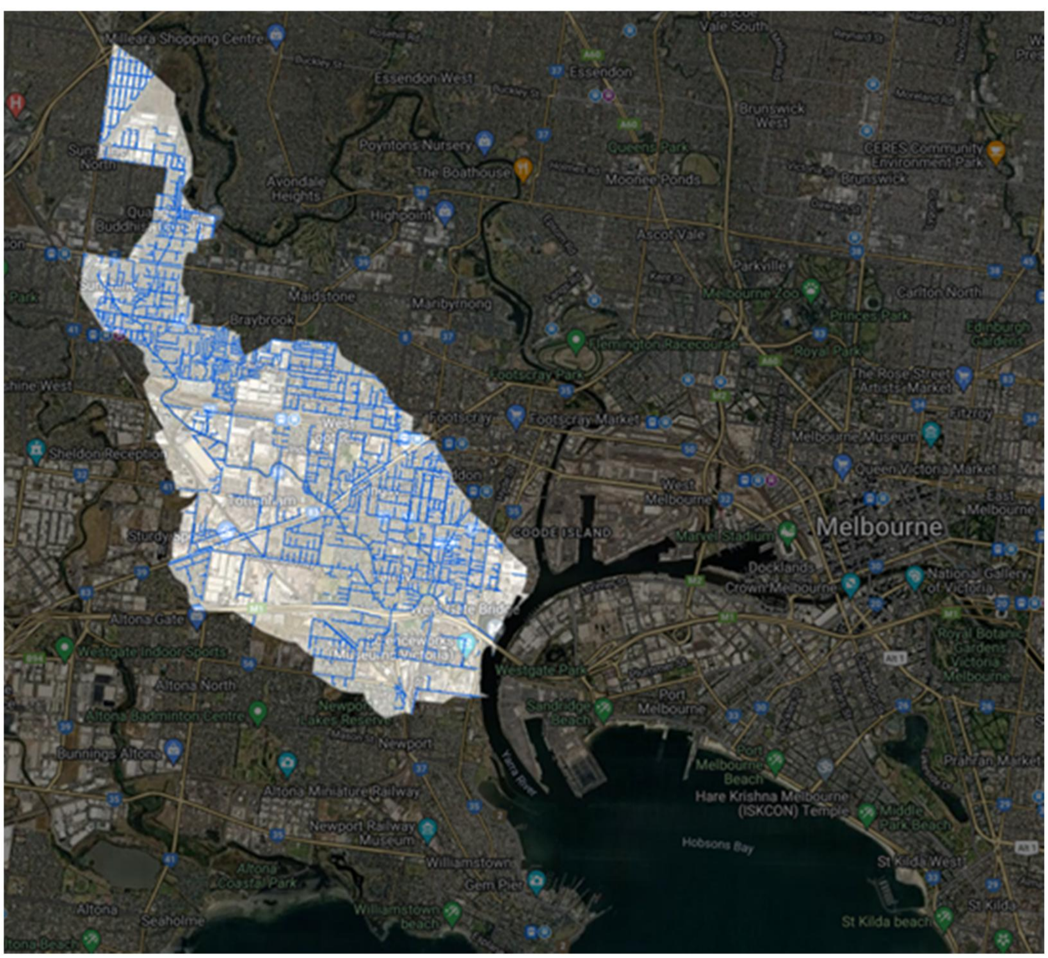

Figure 3. Satellite imagery of the study area showing the stony creek catchment (light-shaded region). The blue lines represent the stormwater drainage network, which discharges into a natural waterway. This waterway flows southeast into a larger river before reaching an estuarine section of a major river (bottom right).

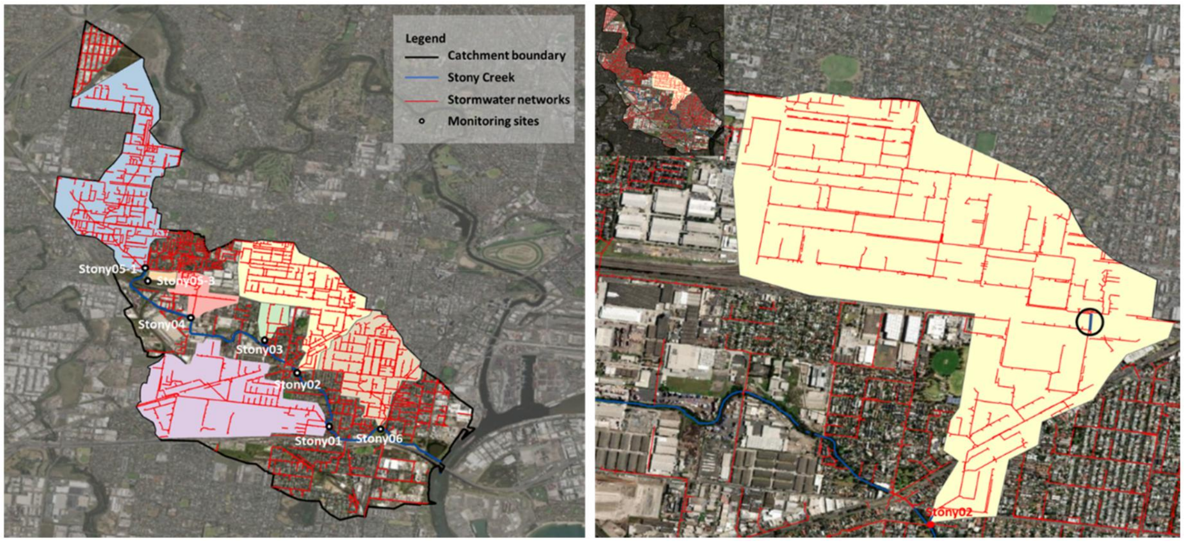

Figure 4. Stony Creek monitoring catchment and monitoring sites. The divided sub-catchments (with different colors) in the Stony Creek catchment (left), the monitoring devices are placed at the outfalls at each sub-catchment before water is discharged to the waterway. The connection pipe in the sub-catchment (right) which is a potential monitoring site diving the sub-catchment into different areas.

problematic sub-catchments. During the monitoring period, outfalls exhibiting abnormal data patterns were flagged as hotspots while stable readings indicated normal sites. After several months of monitoring, results revealed the Stony02 outfall as the most significant contributor of illicit discharges, demonstrating the highest frequency of abnormal signals. This finding prompted detailed investigation within the sub-catchment, where preliminary analysis identified a critical pipeline connecting the northern and southern catchment areas (Figure 4, right) as a strategic monitoring point. The subsequent high-density sensor deployment at this location was designed to precisely trace the source areas of illegal discharges within the problematic sub-catchment. The overall monitoring site selection strategy follows a systematic, stepwise screening approach, where monitoring devices are progressively installed at critical network points to effectively identify and isolate problematic areas contributing to illicit discharges.

3.3. Case study 3/ENTfrachtEN monitoring campaign

In the DBU-funded research project ‘ENTfrachtEN’ monitoring site selection analysis was conducted with the aim of optimising the monitoring locations in a combined sewer system for a combination of water quality and quantity measurements. The objective was to use the sensors for pollution load-based RTC of a combined sewer system and to gain information on the pollutant characteristics in the system (e.g. in overflows). The associated German operator in the project manages several combined sewer systems. The sewer systems were already equipped with water level measurements at all CSO locations for more than 20 years. Hence data was available on the number of CSOs and the calculated CSO discharge at all locations. Furthermore, a hydraulic sewer model was available in MIKE URBAN and a simplified hydrologic pollutant load simulation model in the software KOSMO. The software KOSMO was used in the system for the verification of combined sewer overflows according to German guidelines (DWA, 1994) by calculating the retained chemical oxygen demand (COD) load. The approach can be divided into three main steps. Firstly, the operator selected the most suitable sewer network based on actuator numbers and network size, to accommodate the study size. Secondly, a pre-screening was conducted to analyse the most relevant segments of the system and thirdly a local screening for the selection of the final nodes was conducted. The selected sewer system is shown in Figure 5. The sewer system in the City of Cologne, Germany is mainly a combined system and has a catchment area of 1,372 ha, with 12 overflow structures and 5,104 pipes. The main actuators in the system are pumps and two lifting weirs (at the mustard yellow overflow structures).

The pre-screening was done by analysis of the yearly number of CSOs, CSO volume, and COD pollutant load at each CSO location. A priority list was drawn up of the most relevant CSO locations to monitor. The two highest ranked locations are shown in Figure 5 by the overflows with red arrows above them. Additionally, the hydraulic sewer model was used to rank the proportion of wet weather flow flowing through the branches of the system. From this another priority list was created, with the three main branches of the system shown in Figure 5 with green arrows. Afterwards all data on existing actuators was collected to investigate possible control points. This includes the adjustable flow volume and the storage volume that can be activated by control interventions. From this, a third priority list was created. The three overflow structures with the highest controllable storage volumes are marked with dotted lines. A fourth and final list was drawn up based on strategic considerations of the operator, e.g. a small separate sewer system which drains into the combined sewer system should be investigated regarding water reuse activities (orange overflow structure). All four lists were then compared based on expert knowledge of the operator and from all lists the first

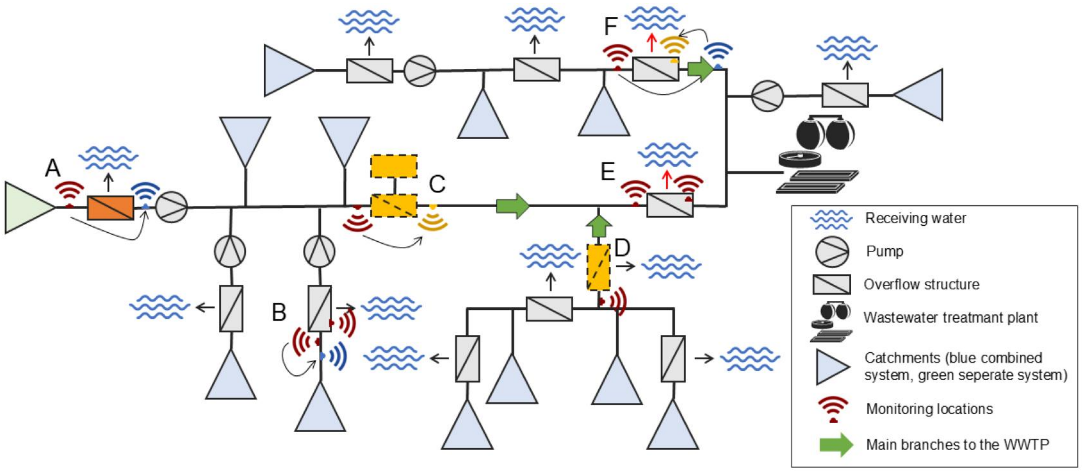

Figure 5. Selected sewer system from the ENTfrachtEN project in the city of Cologne, Germany. The orange overflow structure symbolises the strategic structure. The yellow overflow structures are the structure controlled by lifting weirs. All other overflow structures are regulated by pumps or else by mostly static valves. The overflows with red arrows show the two highest ranked overflow locations. Red monitoring locations are the originally selected, blue adjusted locations due to local constraints, yellow locations due to sensor-induced constraints.

one to three locations were picked. All locations with high priorities from several lists were picked. No limitations were set on the possible number of sensors, but a rough budget was considered.

After this approach (second step), six segments were identified for the installation of sensors, which are displayed by the letters A to F in Figure 5. For segments B and E, the decision was also made to install two water quality sensors, one preferably in the inflow and one at the overflow weir crest. The next (third) step was choosing the specific location, i.e. at which nodes should the sensors be placed. This local screening was done by the operator and the measuring equipment supplier. The aim was to get as close as possible to the relevant actuators, the inflow of their storage volume, or the CSOs. For this, primarily constraints were considered during on-site inspections. These included hydraulic considerations (curves, cross-connections), available electricity, empty ducts for cable laying, cable length and the possibility of installing samplers (depth of sewer, space for installation, protection against vandalism). Due to the listed constraints, in one case (inflow of B) the identified measurement locations had to be shifted by several pipes upstream. This relocation did not have a relevant effect on the results, as there was no inflow in the sewer between these pipes. In two other cases (A,F) the location had to be shifted from the inlet of a basin to the throttle. In case A into the pipe throttle and in case F behind the throttle. This relocation affected the results considerably as only information of the pollutant load in the throttle instead of the inflow to the overflow structure could be obtained. These relocations are shown in Figure 5 from the selected monitoring locations in red to the blue monitoring locations.

During the initial stage of the monitoring campaign, more restrictions were identified on the choice of measurement locations. These are mainly sensor-induced, as some measuring points are not suitable for the type of measurement used (ultrasound). For example, high entry of air bubbles though household connections or sink traps can make whole pipes unsuitable. Additional sensor-induced restrictions can be frequent sedimentation or insufficient water levels. In this case, the water quality sensors need a minimum water level of 15 cm. The used water quality sensors reacted particularly sensitive to sedimentation. Therefore, the installation sites in front of the lifting weirs were not suitable, as the weir movements led to constant sedimentation and resuspension. Here, different locations in front of the weirs were investigated before moving the sensor in case C behind the lifting weir. In case F the sensor location behind the throttle was categorised as irrelevant, as there was little data available due to low water levels. Hence, the sensor location was relocated to the overflow weir crest, because this location showed generally good measuring results and should provide more meaningful data for the project objective. These relocations are also shown in Figure 5 with the yellow monitoring locations.

4. Discussion

UDNs are complex, dynamic systems, and deploying sensors within them requires addressing a range of technical, financial, and practical constraints. One of the most significant barriers is cost (Pimiento et al., 2025). Municipalities often operate under tight budgets, which limits the scope of the monitoring campaigns they can undertake. Even though the advent of low-cost sensors intends to overcome this barrier, the need for careful planning of monitoring campaigns remains (Hamel et al., 2024). The main reason is that acquiring the necessary sensors is only a part of the total cost of the monitoring campaign (often smaller than operational and maintenance costs). This is especially relevant for long-term or legacy measurements and has also a huge impact on data usability and quality as maintenance of sensors is necessary to provide data of sufficient quality for any objective.

Even though planning and undertaking monitoring campaigns is common in research projects studying UDNs as well as in practice (with projects undertaken by municipalities, water utilities, and consultancy companies), the research on the topic is rarely consulted and existing guidelines are inadequate to ensure a well-planned monitoring campaign. This means there is a lack of knowledge transfer from past research and experience. By leaving the onus of constructing and solving the problem of planning and undertaking a monitoring campaign squarely on the engineer(s) tasked with conducting it, we risk 'reinventing the wheel' for every single campaign.

Incorporating explicit recommendations for the planning phase of monitoring campaigns – such as monitoring site selection – into UDN guidelines could help address these challenges. Such recommendations can take the form of flowcharts or decision maps guiding practitioners to relevant methodologies depending on the details/needs of the project. Unfortunately, this is not happening on a large scale. Some countries are starting to include some considerations of planning such campaigns into guidelines for hydraulic measurements. For example, a new Norwegian guideline was recently published, where this topic is explicitly addressed (Dören & Bratlie, 2023). Also, the German Association for Water, Wastewater and Waste (DWA) guidelines for urban drainage systems outlines strategies for different hydraulic objectives (DWA, 2025). A comprehensive code of practice for UDN modelling published by an independent, international organisation (CIWEM UDG, 2017) also calls attention to the importance of choosing monitoring locations. All strategies outlined in these guidelines focus mainly on expert knowledge of the system, with a lot of information focusing on local restraints (accessibility, safety, etc.). Furthermore, they are explicit about the iterative nature of planning a monitoring campaign. This means that depending on the objectives of the campaign, the specificities of the involved stakeholders, and the knowledge that is gradually acquired during the campaign, the choice of monitoring locations must be evaluated and possibly updated. Particularly in cases where the monitoring campaign results in changes in the system (e.g. implementing RTC measures), the choice of monitoring locations should be re-evaluated as the system dynamics evolve.

While improved guidelines would benefit practitioners in the field, the research community could similarly benefit from standardised benchmarking frameworks that enable systematic comparison of different methodologies. Having benchmark scenarios, consisting of a model and a (set of) rainfall timeseries, could enable studies (and approaches) to be more comparable, as seen in the WDS field (Ostfeld et al., 2012; Walski et al., 1987). This could also accommodate a more modular structure to the approaches, which would be useful considering the benefits of combining approaches. The network used in Example 8 of SWMM's User Manual (Gironás et al., 2010) is used in some of the studies (Banik et al., 2017b; Sambito et al., 2020; Sambito & Freni, 2021; Wang et al., 2023) to demonstrate their approach, usually also accompanied by an application on a real network. Even though the SWMM manual example might be too simple to properly assess these methods, this is a step towards the direction of a systematic benchmarking of different approaches. The next step could be moving towards the use of published datasets from real case studies (e.g. Blumensaat et al., 2023; Pedersen et al., 2021) for this purpose.

It is important that the objectives of a monitoring campaign must be clearly defined, in such a way that the campaign can be evaluated on how well the objectives are achieved. This not only enables the decision-makers to choose an approach for selecting monitoring locations which is aligned/compatible with the objectives but also streamlines the process of evaluating the performance of the campaign. The lack of a connection between policies and guidelines to assure that the policies are followed seems to be a persistent challenge in urban drainage. Policymakers implement system-wide goals and specific requirements to be met, but it's not always clear how these quantities should be monitored (Balmforth et al., 2009; Butler et al., 2018; Lee & Deininger, 1992). Most recently, the UK has been facing a significant challenge, where monitored annual spill frequency and duration is required since the Environment Act (UK Government, 2021). In an effort to combat high levels of illegal CSO spills, pollution, and to regain lost public trust in the UK water industry, the Water (Special Measures) Act demands that all CSOs be monitored and brings greater punishment for lack of compliance. Prior to this, not all CSOs were monitored, but now all must be fitted with event duration monitors (EDM), however this does not indicate the discharge volume making it difficult to anticipate the impact of the event without additional sensors to determine the flow on-site. The EDM data is freely available in an interactive CSO map. Similarly, the EU directive concerning urban wastewater treatment (EU Directive 2024/3019, 2024) requires EU member states to 'carry out representative monitoring, at relevant points, of storm water overflows'. One unintended consequence of these regulations is that by stating that all overflows have to be monitored, also monitoring other critical points in the system might become unfeasible due to budgetary constraints.

Acknowledging the assumptions made in the process of selecting monitoring sites should be done explicitly, as the uncertainty introduced by assumptions will significantly influence the validity and applicability of the resulting monitoring schemes. Current methodologies often rely on implicit assumptions that may not be applicable to many cases. Perhaps most pervasively, expert opinions and choices based on domain knowledge are embedded in numerous studies, even when not explicitly acknowledged. The implicit nature of these subjective judgements makes it difficult to evaluate their impact on the resulting monitoring schemes.

It is inherent in the problem of selecting monitoring locations in a system, especially when no prior monitoring campaigns exist, that an approach aiming to solve it cannot be based on measurements. Most of the approaches require a simulation to generate a dataset to analyse. When taking decisions based on modelling results, we operate under the assumption that the model can replicate the behaviour of the real system for the conditions we are applying, with a level of fidelity that is acceptable for the modelling objective (i.e. taking a specific decision). Even though this is in line with the general paradigm in research around UDNs (i.e. focusing on developing a reliable model of the system in question and using that model to explore scenarios), the underlying assumption that comes with it should be kept in mind (K. Beven, 2002). Being conscious of this is necessary to select the appropriate approach. For example, in cases where a decision-maker does not have a high degree of trust in their system model, approaches that require a low amount of data should be considered first.

Most approaches also fail to explore the effect of different rainfall scenarios on the resulting monitoring schemes, despite evidence that such effects can be substantial. Guo et al. (2018) and Li (2021) showed that the monitoring schemes derived by their approaches are influenced by the rainfall data, using both event-based and long-term simulations. Lee et al. (2007) showed the effect of seasonal patterns in rainfall in the processes captured by monitoring campaigns in historical data. This hints at a need to incorporate varied rainfall inputs into any approach aimed at the challenge of monitoring site selection, as static assumptions about hydrological conditions may lead to suboptimal sensor placement under different weather patterns. Also, while most approaches focus on water quality, few investigate the effect of the dynamics of the considered processes and/or contaminants. Two studies (Sambito et al., 2020; Sambito & Freni, 2021) that use the same approach on the same network, changing only the nature of the modelled contaminant (from conservative to non-conservative), observe a clear effect of the nature of the contaminant on the results of the approach. In the conservative contaminant scenario, more nodes near the outlets are selected as monitoring locations.

Taking these points into account, in Figure 6 we propose a general framework for selecting appropriate monitoring locations in UDNs. This framework is intended as a coarse guide for any kind of monitoring campaign. Hence, it cannot be used as a detailed step-by-step guide for selecting monitoring locations, but rather it outlines an iterative process – similar to the PDCA cycle (Deming, 1986) – that can be adapted to the characteristics of different monitoring campaigns. This process can enable the correct use of the methodologies we have reviewed in this work, while following good modelling practices (Pons et al., 2023).

The use of autonomous robotic systems for urban drainage monitoring and maintenance heralds a transformative shift in the field, with profound implications for the planning and execution of monitoring campaigns. Emerging initiatives in the field are planning to use advanced robotics to autonomously monitor, map, and maintain sewer networks with minimal human intervention (Worley et al., 2024; Y. Yu et al., 2024). This can be a paradigm shift for datasets, moving from static to dynamic both in spatial and temporal resolution, which will also impact how this data is used for modelling. The first change is one of accuracy, as more accurate geometrical data (collected by robots with better mapping capabilities and more appropriate sensors) will reduce network model uncertainty considerably. Secondly, a moving robot can be the sensor collecting hydraulic data as it moves within a changing system (e.g. registering flows) resulting in a Lagrangian rather than a Eulerian calibration data set. If the future of urban drainage monitoring moves in this direction, the problem of monitoring site selection (or sensor deployment in this new context) will need to be redefined, creating new challenges but also new possibilities.

5. Conclusions

The disconnect between theoretical research and practical application in monitoring site selection becomes evident when examining the current state of guidelines, industry practices, and even research projects that conduct monitoring campaigns. While the academic literature has developed sophisticated methodologies to assist monitoring site selection, these advances have not been systematically integrated into the frameworks used by practitioners. The reliance on expert knowledge highlighted in existing guidelines, while valuable, represents a missed opportunity to utilise decades of research that could provide more structured decision-making tools. The case studies presented in this paper demonstrate that even research projects conducting monitoring campaigns rely predominantly on expert knowledge and practical constraints, rather than using the optimisation methodologies available in the literature. This gap perpetuates a cycle where each monitoring campaign essentially starts from scratch, with practitioners often reinventing solutions rather than building upon established approaches. The persistence of this gap can be attributed to several factors. First, the computational complexity of sensor placement optimisation makes many theoretical approaches impractical for large-scale networks. Second, the formulation of optimisation problems in the literature often assumes full hydraulic model availability and complete system knowledge, conditions that rarely exist in practice where practitioners work with limited data. Third, the lack of modular, adaptable methodologies that can accommodate varying levels of system knowledge and data availability further sustains the gap to implementation.

A critical step towards bridging this divide lies in establishing standardised benchmarking frameworks that enable systematic comparison and validation of different methodologies. Currently, the field lacks comprehensive benchmark datasets that have proven transformative in related domains such as water distribution systems. Applying the principles of FAIR data (Dunning et al., 2018) to urban drainage research is a good step in this path, as datasets will be of sufficient quality to be re-used. Future research should prioritise the development of benchmark scenarios, representing networks of varying scales and complexities, consisting of well-documented models paired with comprehensive rainfall datasets. These benchmarks should incorporate real-world constraints such as site accessibility, maintenance requirements, and budget limitations that practitioners routinely face. Since the nature of the problem of monitoring site selection is objective driven, so are the approaches to a solution. That means that there cannot be a single set of

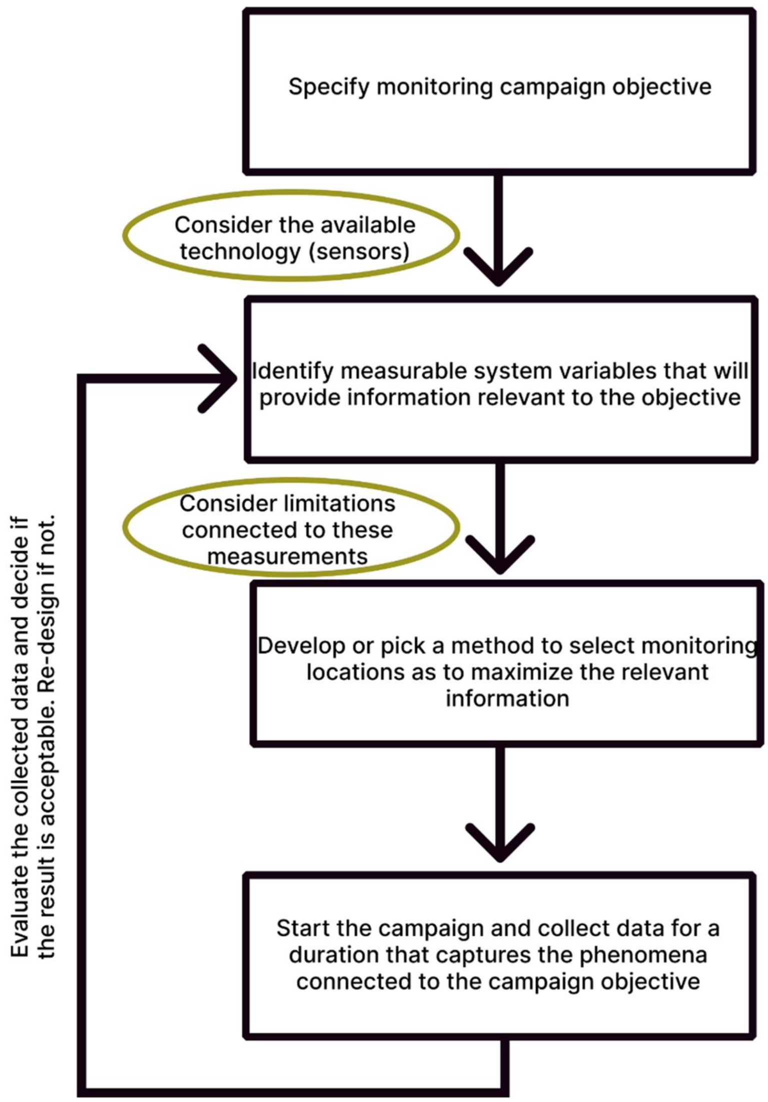

Figure 6. Proposed general framework for selecting appropriate monitoring sites in urban drainage monitoring campaigns. Each step has to be considered under the lens of the uncertainties introduced by assumptions made at each stage (system knowledge, rainfall patterns, contaminant behaviour).

metrics for evaluation. Choosing the metrics should be done so that they represent the performance of the solution (monitoring scheme) in achieving the monitoring objective(s), and not objectives internal to the approach. This is not trivial, as monitoring scheme performance data is not easy to acquire (that requires testing the proposed solution on a real system; for sufficient time in representative conditions, which must be defined). Instead, it is common to evaluate an approach using data created by simulations. Therefore, we should be aware that the uncertainty in the simulated data propagates to the evaluation of solutions.

Such benchmarking frameworks would not only facilitate methodology assessment but also encourage the development of modular approaches that can be combined and adapted to specific project requirements. The benefits of combining approaches highlight the potential for more flexible, hybrid methodologies that can leverage the strengths of different optimisation techniques while accommodating practical constraints. A critical area requiring greater attention in future research is the systematic evaluation of how underlying assumptions propagate through monitoring site selection methodologies and affect the reliability of monitoring schemes. Current approaches often rely on implicit assumptions about rainfall patterns, contaminant behaviour, and runoff processes without adequately assessing their sensitivity or uncertainty propagation effects on the monitoring scheme. The limited exploration of how different rainfall scenarios, seasonal variations, and contaminant dynamics influence optimal placement decisions undermines the robustness of proposed monitoring schemes. To address this, future methodologies should incorporate uncertainty quantification, explicitly accounting for assumption variability, enabling practitioners to make more informed decisions about monitoring site selection under uncertain conditions. This includes developing approaches that can handle incomplete or uncertain system information and provide decision-makers with tools to assess the robustness of monitoring schemes under different scenarios. Only by explicitly addressing uncertainty propagation can the field move towards monitoring strategies that are both theoretically sound and practically reliable.

One recurring theme in this review is the reliance on subjective, expert judgments when making decisions regarding monitoring site selection. Even when sophisticated optimisation methodologies are employed, most authors explicitly stress the importance of critically applying them using domain knowledge and engineering judgement. The way in which different experts will interpret the same information to arrive at conclusions remains a largely unexplored topic in urban drainage monitoring, introducing uncertainty into the monitoring site selection process.

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Author contributions

CRediT: **Spyros Pritsis**: Conceptualization, Methodology, Writing – original draft, Writing – review & editing; **Francois Clemens**: Conceptualization, Supervision, Writing – review & editing; **Sebastian Kerger**: Resources, Writing – original draft, Writing – review & editing; **Abigail Legge**: Resources, Writing – original draft, Writing – review & editing; **Miao Wang**: Resources, Writing – original draft, Writing – review & editing; **Marius Møller Rokstad**: Conceptualization, Supervision, Writing – review & editing; **Franz Tscheikner-Gratl**: Conceptualization, Supervision, Writing – review & editing.

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ORCID

Spyros Pritsis http://orcid.org/0009-0008-7857-0958
Francois Clemens-Meyer http://orcid.org/0000-0002-5731-0582
Sebastian Kerger http://orcid.org/0009-0007-4807-1712
Abigail Legge http://orcid.org/0000-0001-7930-2471
Miao Wang http://orcid.org/0000-0003-3687-0692
Marius Møller Rokstad http://orcid.org/0000-0003-4650-3554
Franz Tscheikner-Gratl http://orcid.org/0000-0002-2545-6683

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