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Analyzing and Quantifying Key Sources of Uncertainty in Intermittent Water Supply Simulation: Supply Characteristics, Household Tank Size and Time Series of Water Consumption From the Household Tanks

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Key Points:

- Uncertainty in supply characteristics, household tank size and time series of water consumption from the household tanks were quantified
- Monte Carlo simulations captured the uncertainty range of performance indicators
- Sobol's sensitivity analysis revealed supply characteristics as the most influential parameter

Supporting Information:

Supporting Information may be found in the online version of this article.

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Abstract Many researchers have used deterministic models to address issues in intermittent water supply (IWS) systems, such as inequitable distribution, but these models often overlook key uncertainties. IWS systems vary widely in practices and operations, introducing uncertainties in areas like water consumption pattern, supply characteristics, and household tank sizes. To address these challenges, this study proposes a novel framework for assessing uncertainty in model input parameters and applies it to an IWS network using an EPA-SWMM-based hydraulic simulation. In the first phase, uncertainty analysis (UA) uses probabilistic methods and Monte Carlo simulations to evaluate the impact of uncertainties on performance indicators. The second phase applies global sensitivity analysis (SA) (Sobol's method) to identify the most influential parameters. The findings reveal that system performance is primarily governed by supply characteristics, while household tank size exerts a secondary but nonlinear influence on both pressure and consumption based indicators. Excessive household tank size is shown to reduce the pressure and supply equity, whereas moderate tank size improves the fairness of the water distribution. This work provides a foundation for more accurate and reliable IWS modeling approaches.

1. Introduction

The utilisation of models in the planning, design, and operation of water distribution systems is paramount for anticipating the consequences of various actions taken by engineers and operators. However, these models possess inherent limitations that can potentially distort the representation of the systems they aim to mimic. Understanding and acknowledging these limitations is crucial for the appropriate application of such models. This is particularly important, as uncertainty associated with input parameters lead to inaccurate predictions, thereby affecting the reliability of planning and operational efforts. For effective planning and operation of such systems, it is essential to quantify the output uncertainty resulting from input uncertainty is essential (Filion & Karney, 2003; Kang et al., 2009; Loucks & Eelco, 2016).

In the context of modeling of water distribution networks (WDNs), a highly efficient deterministic model, EPANET, has been widely employed. Various sources of uncertainty associated with EPANET have been identified using different surrogate models to achieve optimal design and resolve rehabilitation problems (Babayan et al., 2005; Fu & Kapelan, 2011; Kapelan et al., 2005), as well as to perform reliability analysis (Wang & Zhu, 2021). These sources of uncertainty are mostly related to demand variability in continuous water supply (CWS) systems in which water is supplied to the network on a 24-hr basis. However, in intermittent WDNs, the focus is mainly on developing a deterministic model that characterizes the behavior of the system, and not much has been done on examining uncertainties.

A typical intermittent water supply (IWS) network is filled and emptied periodically with water, resulting in customers having to store water in their household tanks for use during non-supply times. This makes it challenging to accurately characterize its behavior using conventional software such as EPANET (Rossman, 2000). Although several researchers attempted to use EPANET (Abdy Sayyed et al., 2014; Mohapatra et al., 2014; Taylor et al., 2019) to simulate IWS, the need to model both free-surface and pressurized conditions, that occurs during the filling process, has led to the usage of EPA'S Storm Water Management Model (EPA-SWMM; Rossman, 2017a,

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2017b) for modeling IWS systems (Cabrera-Bejar & Tzatchkov, 2009; Campisano et al., 2019a, 2019b; Dubasik, 2017; Gullotta & Campisano, 2024; Kabaasha, 2012; Sarisen et al., 2024). A thorough critical evaluation of the existing IWS hydraulic analysis methods is detailed in (Sarisen et al., 2022) while a comparison of methods based on EPANET is presented in (Abdelazeem & Meyer, 2024). Recent field based studies (Campisano et al., 2023; Gullotta & Campisano, 2024) have strengthened the credibility of EPA-SWMM for modeling intermittent water supply systems by validating its simulation results against field measurements, thereby demonstrating its applicability in real-world scenarios. More recently, Abdelazeem and Meyer (2025) critically analyzed EPA-SWMM based approaches and identified the most suitable approach for accurately representing real IWS systems.

The supply characteristics (i.e., supply duration, frequency, and timing), household tank size, consumer water consumption pattern, and coping strategies vary between case studies (Danilenko et al., 2014; Kumpel & Nelson, 2016). These factors influence the quantity of water received by a consumer, and they are often highly uncertain. In unpredictable IWS cases, operational characteristics are uncertain, as they depend on various factors including water availability, consumption patterns, and seasonal effects. The presence of domestic tanks in IWS systems affects the characteristics of the system behavior. During the initial stage of water supply, users tend to fill their tanks, which creates peak flow rate in the network resulting in pressure deficiencies at a number of locations (i.e., disadvantaged areas) and creating inequitable distribution of water among consumers (De Marchis et al., 2011; Vairavamoorthy et al., 2007). Although in most IWS cases, standard-sized household tanks are in use, the size and number of household tanks (i.e., total volume of storage) are still unknown for each household, which again should be accounted for in the modeling process. User water consumption from the household tank during supply and non-supply hours is influenced by supply duration, available pressure, and tank size and varies inherently over timescales from minutes to months.

Hydraulic modelling of IWS is a crucial step in analysing and addressing the problems that arise. It has been used for design (Ramani et al., 2023), improvement of equitable supply (Gullotta et al., 2021), conversion to continuous supply (Hastak et al., 2017), and rehabilitation of IWS systems (Mottahehin et al., 2023). In all these applications where the IWS network model is used to support decision-making, understanding the relative magnitude of risk and uncertainty is critical to accurately assessing system behaviour. To simulate realistic scenarios, develop and validate model-based methodologies, and make informed decisions, it is important to better understand the similarities and differences between various IWSs and their operating modes. To develop more representative models, the first step is to analyse all factors affecting the quantity of water a consumer receives over time. The second step is to integrate uncertainties that arise for each case into the modelling processes. Failure to account for uncertainty can lead to incorrect conclusions, which underscores the need for rigorous methods to quantify various sources of uncertainty. In short, the accurate determination of the network model's parameters and the consideration of their uncertainty are essential for developing reliable and effective solutions.

To the best of the author's knowledge, there have been few attempts to address the diverse practices and analyse the unique characteristics of IWS systems through hydraulic modelling. Abhijith et al. (2023) investigated the impacts of two types of consumer behaviours on the performance of IWS systems using their EPyT-IWS simulation tool: Type A, in which water is stored in underground tanks (sumps) and then pumped to overhead (rooftop) tanks for use, and Type B, in which there is no sump storage and water is pumped to overhead tanks. Randeniya et al. (2022) explored the effects of different sizes of domestic water storage tanks on the equity and performance of water supply under rationing scenarios, employing an EPANET-based IWS modelling approach. An issue arises with these modelling techniques, as they were unable to fully simulate the crucial processes of network filling and draining that dictate consumer supply access, and only a select set of uncertain parameters were examined under specific circumstances. A further limitation lies in the numerous simplifying assumptions made about consumer behaviour and the hydraulic model itself, which still awaits calibration and verification against real-world data.

The investigation of IWS behaviour combined with uncertainty analysis is a relatively new research topic that this paper aims to address. In particular, this study quantifies for the first time the uncertainties in model input parameters stemming from various IWS practices and operations, using the IWS modelling approach recommended by Abdelazeem and Meyer (2025). To achieve this, a novel uncertainty quantification framework is proposed which includes:

1. A brief review of the studies on real IWS systems worldwide to understand and characterize the uncertainties in IWS;
2. Characterizing the uncertain input parameters with a probabilistic approach for the first time;

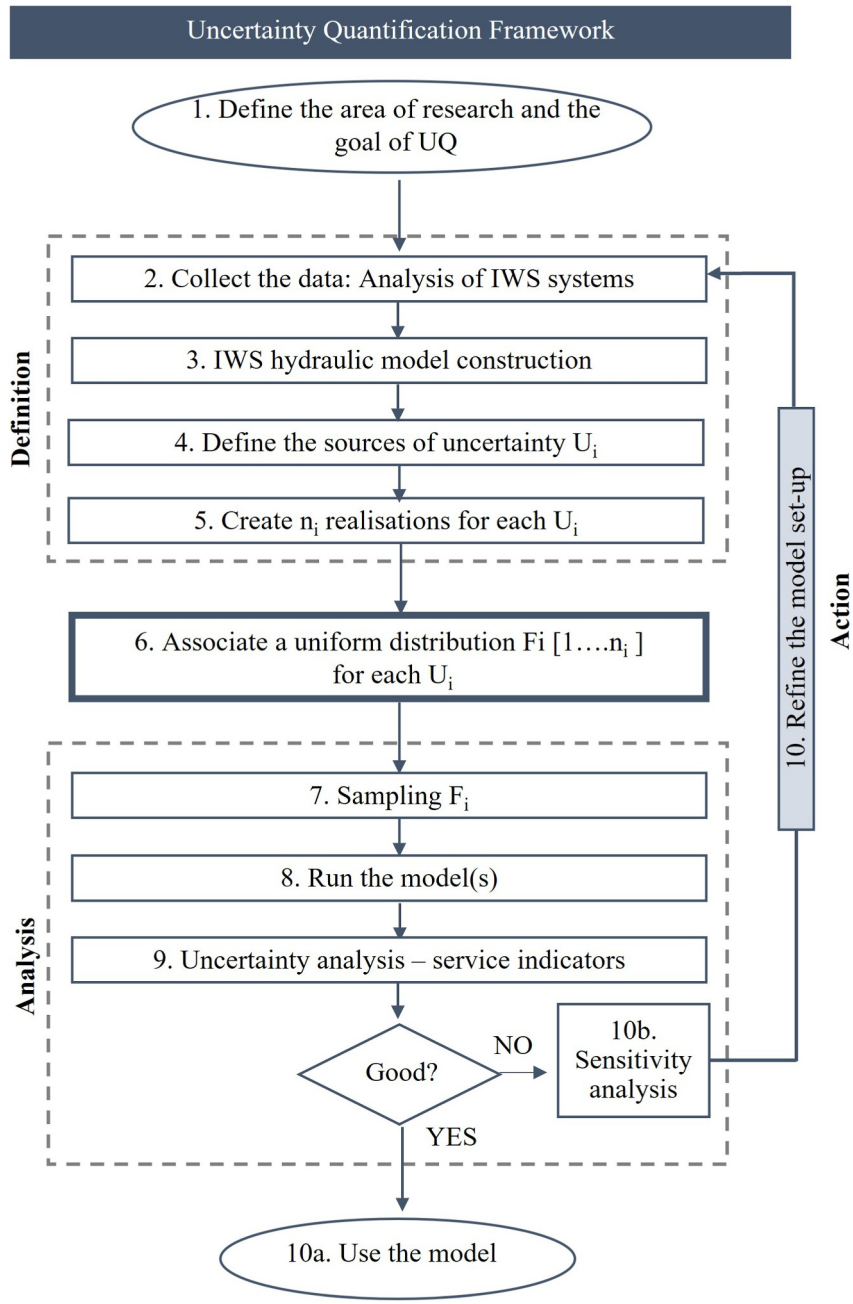

Figure 1. Uncertainty quantification framework steps (adopted from Baroni & Tarantola, 2014).

3. Uncertainty propagation using Monte Carlo (MC) simulations to quantify the uncertainties in performance indicators;
4. Conducting a global sensitivity analysis using Sobol's method (Sobol, 2001) to identify the most influential model input parameters;
5. Considering the influential parameters leading to potential interventions to improve water supply service.

2. Uncertainty Quantification Framework

The proposed uncertainty quantification framework was adapted from (Baroni & Tarantola, 2014) general probabilistic framework for uncertainty and global sensitivity analysis of deterministic models and is presented in Figure 1. The framework consists of three main steps. It begins with the identification of the goal of the

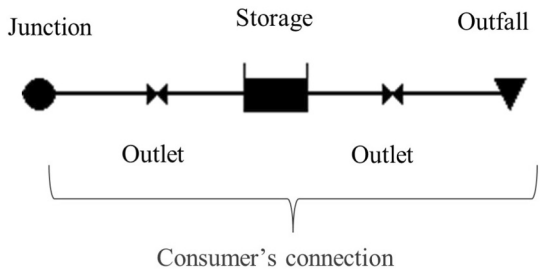

Figure 2. Demand node configuration for IWS simulation.

uncertainty analysis—to quantify the uncertainties arising from various operational practices of IWS systems. Four performance indicators, out of the nine proposed by the WDSA/CCWI Committee (2022), were selected as variables of interest to assess system performance under uncertainty (Section 2.3). A synthesis of relevant IWS literature was conducted and is presented in Text S2 of the Supporting Information S1. This synthesis informed the development of the uncertainty framework and supported the adoption of realistic assumptions for the uncertain input parameters.

Next, the uncertain parameters were characterized using PDFs derived from Delhi, data provided by Meyer (2023), and a representative IWS model was constructed (Section 2.2). Three key sources of uncertainty were incorporated into the model: supply characteristics, household tank size, and the time series of water consumption from the household tanks. The sampling technique proposed by Saltelli (2002a, 2022b) was used to draw samples from the probability distributions of each uncertain parameter and to generate input combinations for the simulations (Section 2.4).

Finally, uncertainty analysis was conducted to quantify the variability in simulation outcomes followed by sensitivity analysis to determine the influence of each parameter on model outcomes. Methodological details, including characterization of the uncertain input parameters, sampling procedures, realisation generation are provided in Text S1 of the Supporting Information S1.

2.1. IWS Practices and Uncertainty: Insights From the Literature

A synthesis of the literature has been conducted and is presented in Text S2 of the Supporting Information S1. Data from the literature from various IWS case studies helped to shape the uncertainty framework methodology and to have more realistic assumptions for the characteristics of the uncertain parameters.

2.2. IWS Modeling With Uncertain Input Parameters

In this study, an analysis of uncertainties that encompass a wide range of practices found in various IWS systems was conducted, as detailed in Section 2.1. A recently recommended EPA-SWMM-based IWS hydraulic modeling approach that could be applied to a diverse array of IWS situations has been chosen (Abdelazeem & Meyer, 2025). EPA-SWMM solves one-dimensional de Saint Venant equations which encompass the conservation of mass and momentum in flow for conduits, as well as the mass continuity equation at network nodes. To calculate friction losses during pressurized flow, the software accommodates the integration of additional equations, such as those formulated by Hazen-Williams or Darcy-Weisbach. A significant feature of EPA-SWMM is its capability to simulate both free-surface and pressurized flow conditions concurrently. The latest version, EPA-SWMM 5.1, employs an iterative algorithm to analyze surcharge processes, updating nodal heads in scenarios where all connecting links are completely filled (Rossman, 2017a, 2017b). EPA-SWMM provides the ability to simulate the network filling process with underlying equations.

EPA-SWMM necessitates the adjustment of the model settings and artificial element incorporation to simulate IWS. Figure 2 illustrates the node configuration of the model used in this study which has the capability to exhibit pressure dependency of the flow, water consumption from the household tank, all of which were introduced sequentially to each outlet from the left. Household tanks represent the size of group of household tanks (equivalent tank) which are connected to each node. Wagner et al.'s (1988) equation was embedded in the outlet element on the left hand side to assign pressure dependency of flow. The model details can be found in Abdelazeem and Meyer (2025) and Sarışen et al. (2026).

The following assumptions were made in the methodology presented here:

1. The network configuration is known (i.e., pipe layout, roughness coefficients, etc.)
2. All demand nodes were assumed to have equivalent consumer tanks with float valves, which is the most common coping strategy in IWS systems and which also makes the analysis applicable to both predictable and irregular intermittent systems, as when water is supplied into the system unexpectedly, the household tanks will start filling automatically.

3. The household tanks' maximum level was assumed to be 1 m, and the elevation of the household tanks was chosen as 1 m below the junction node, since tanks are filled from the top of the household tank and it is desired to avoid hydraulic simulation results being affected by the water level in the tank.
4. At the beginning of the simulation, all pipes were assumed to be empty. Multi-day simulations were conducted starting with empty household tanks and an 8-hr supply duration, which corresponds the average duration considered in the uncertainty analysis. Based on the tank water level results, steady-state conditions were reached by the end of the third day. Therefore, each sample in the uncertainty analysis has been simulated over a 4-day period, and the results from the final day have been used for the analysis. To further demonstrate that convergence by Day 3 is neither node nor scenario specific, tank water level behavior was examined for three storage nodes selected based on nodal elevation, representing low, medium, and high-service conditions (Nodes 41, 18, and 9, respectively). To ensure a consistent basis for comparison, all selected nodes have the same demand (0.06 l/s). The analysis was conducted for two representative samples (Sample 1 and Sample 170), which differ in tank size and supply duration: Sample 1 has a tank size of 0.6 m^3 and a supply duration of 2.36 hr, while Sample 170 has a tank size of 1.0 m^3 and a supply duration of 8.15 hr. These contrasting conditions were chosen to clearly illustrate tank water level fluctuations. Day-to-day differences in end-of-day tank water levels were evaluated for both samples, as shown in Figure 3. The negligible differences observed between Days 3 and 4 confirm that steady periodic conditions are achieved by the end of Day 3.
5. Water consumption from the household tanks was permitted once the tank reached 1% of its capacity.

Three key uncertain parameters influencing model outputs were identified and characterized as follows: supply characteristics, household tank size, and time series of water consumption from the household tanks. These are discussed in turn and additional details on the methods used to fit the continuous functions to the data are provided in Text S3 of the Supporting Information S1.

2.2.1. Supply Characteristics

The initial stage of water supply is characterized by users filling their tanks, causing peak flow rates in the network. This, in turn, can create pressure deficiencies in certain areas, particularly in disadvantaged areas, resulting in unequal distribution of water (De Marchis et al., 2011; Vairavamoorthy et al., 2007). Users tend to leave their taps open to collect as much water as possible for use during non-supply hours (Vairavamoorthy, 1994). In such circumstances, the amount of water delivered to each consumer depends on the available pressure in the system, with supply characteristics playing a crucial role in the model outcomes. In unpredictable IWS systems, the supply schedule is unknown and is influenced by factors such as water availability, consumption patterns, and seasonal variations.

The uncertainty in supply characteristics was characterised using probability distribution functions (PDFs). These PDFs were derived from the water supply schedules of Delhi, dated 12th May 2020, as provided by Meyer (2023). Given that Delhi frequently employs IWS systems and has a population estimated at over 32 million (United Nations, Population Division, 2019), it could potentially serve as a suggestive example of IWS practices globally. The three sources of uncertainty associated with supply characteristics are supply duration, supply frequency, and supply timing. Supply duration indicates the total period during which water is released into the system during the day. Supply frequency is the number of times that water is released into the system during the day. Supply timing indicates the hours of the day when water is supplied.

2.2.2. Household Tank Size

Water network analyses typically assume that domestic water usage patterns reflect standard demand models used in network design. However, the presence of domestic storage tanks alters the timing and rate of water withdrawn from the network due to the automated operation of tank valves, disconnecting consumer water consumption from network hydraulics. This discrepancy can lead to significant variances between hydraulic models and actual network performance if storage provisions are not considered. Additionally, network pressure and water availability are influenced by the size and distribution of these storage tanks. Accurately modeling intermittent water supply systems thus requires incorporating domestic storage tanks into analyses to reflect the network's true behavior (Ingeduld et al., 2006; Randeniya et al., 2022). While standard tank sizes are used in most IWS cases, the size of tanks in each household is unknown and should be accounted for in the modeling process.

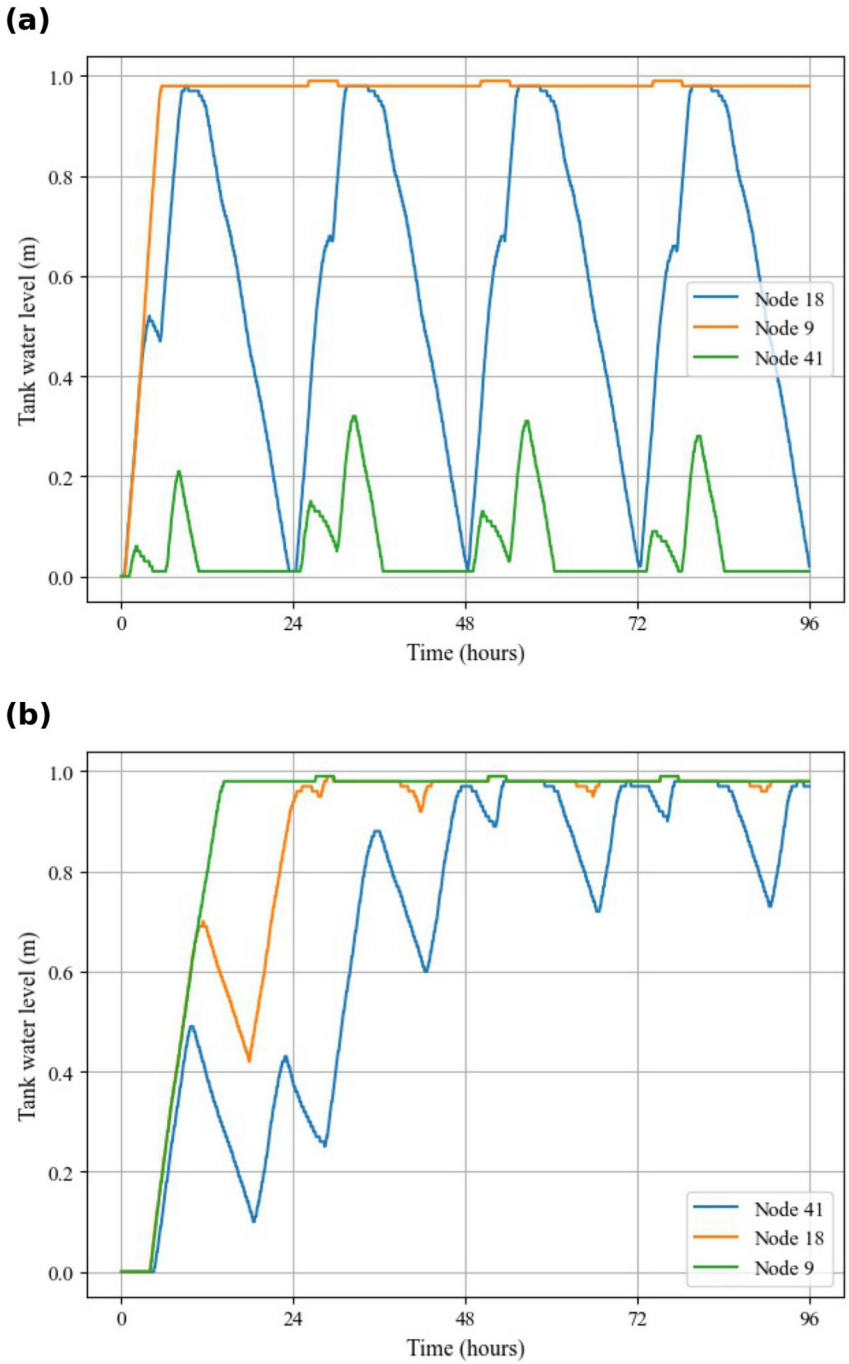

Figure 3. Tank water level time series for three representative storage nodes under high, medium, and low-service conditions, illustrating convergence to steady periodic behavior. (a) Sample 1 (tank size = 0.6 m^3, supply duration = 2.36 hr). (b) Sample 170 (tank size = 1.0 m^3, supply duration = 8.15 hr).

In this study, the uncertainty in household tank size was characterised by a truncated normal distribution considering the IWS practices synthesised in Section 2.1, with a mean value (μ) of 1.0 m^3 and standard deviation (σ) of 0.8, as shown in Figure S5 of the Supporting Information S1. Each realisation has a minimum tank size restricted to 0.2 m^3, and the sampled tank sizes were rounded to one decimal place. Based on the data provided by Statista (2023), the average household water demand in Italy, where the case study is located, was assumed to be 550 L. Accordingly, the total daily demand at each junction node was divided by 550 L to estimate the number of connected households. In the model, each node was initially assigned an equivalent household tank, assuming

Table 1
Summary of Uncertain Input Parameters and Model Used to Represent Their Range

Parameter		Model	Equation/Key details
Supply characteristics	Supply frequency	Discrete probability mass function	$\Pr(X = 1) = 0.555$, $\Pr(X = 2) = 0.321$, $\Pr(X = 3) = 0.117$, $\Pr(X = 4) = 0.0073$ Figure S1 in Supporting Information S1
	Supply duration	Log-logistic (Fisk) distribution	Equation S1 and Figure S2 in Supporting Information S1
	Supply timing	Bimodal distribution	Equation S2 and Figure S3 in Supporting Information S1
Household tank size		Truncated normal distribution	$\mu = 1.0$, $\sigma = 0.8$; truncated at 0.2–3.0 m^3; rounded to 1 decimal Figure S5 in Supporting Information S1
Time series of water consumption from the household tanks		Gaussian processes	Figure S6 in Supporting Information S1

each household has a 1 m^3 size of household tank. In each simulation, these equivalent tanks were scaled by the sampled household volume.

2.2.3. Time Series of Water Consumption From the Household Tanks

In the later stages of water supply, the flow into tanks might become increasingly complex. While these profiles continue to be influenced by factors such as pressure at the nodes and the sizes of household tanks, they are also expected to be affected by household water consumption. This consumption exhibits aleatory variability, manifesting over diverse timescales ranging from minutes to hours and extending to daily, monthly, and even annual fluctuations. Such variability is heavily contingent on local demand behaviors, making it challenging to formulate generalized conclusions or models (Vairavamoorthy, 1994).

Uncertainties prevail around the time series of water consumption from household tanks, and IWS models may need to account for this. In this study, several demand patterns were generated by employing a Gaussian process (GP) emulators (Rasmussen & Williams, 2006) using a given hourly based demand pattern to account for the correlation between successive demand multipliers. GPs can be regarded as an extension of the multivariate normal distribution to infinite dimensions. More precisely, a GP defines a probability distribution over functions such that any finite collection of function values evaluated at specific points follows a multivariate normal distribution. This distribution is fully specified by its mean and covariance functions (Rasmussen & Williams, 2006). When a given hourly based demand pattern is modeled with GPs, it provides a probability distribution over the entire demand pattern. Realizations from this distribution are then used to reproduce demand patterns.

A summary of the uncertain input parameters, and the model/equation used to represent their range is provided in Table 1. The detail methods used to derive these distributions, including fitting procedures and model configurations, are described in the Text S3 of the Supporting Information S1.

It is worth noting that real-life IWS systems may encompass numerous additional sources of uncertainty, including uncertainties related to input data and parameters, such as pipe roughness coefficients, leakage rates, and uncertainties associated with the models themselves. This work focuses on the analysis of some uncertainties stemming from the input parameters unique to IWS systems, as its rationale was clarified above.

2.3. Performance Indicators

Four of the nine performance indicators proposed by the WDSA/CCWI Committee (2022) were selected in this study to evaluate system performance under uncertainty. These indicators were originally developed to assess how effectively service interventions improve network performance. While the original indicators used in the EPANET model did not account for key features of IWS systems, such as the filling process and the presence of household tanks, they remain applicable within a more realistic IWS model. This is because in both WDSA/CCWI Committee (2022) and in this study, indicator calculations were conducted at the nodal level. In this study, water consumption from household tanks is also incorporated, thereby providing a closer reflection of actual user experience.

Each indicator captures a fundamental aspect of service provision, with values ranging from 0 (poor performance) to 1 (optimal performance). Together, they represent some of the key dimensions of system functionality:

pressure and supply adequacy, continuity and equity which are critical for guiding engineering decisions and planning service improvements. The indicators have been renamed to better reflect their intended purpose and are described in detail below.

1. *Indicator I_1—Pressurized Fraction:* This indicator assesses the ability of each node to receive water, conditional upon the nodal pressure exceeding the specified minimum threshold, reflecting the service hours. It is expressed by the equation below:

$$I_1 = \frac{\sum_{i=1}^{N} n_i}{N.86400} \tag{1}$$

where N is the total number of nodes with demand, and n_i is the total number of seconds per day the node i has pressure above minimum pressure ($p_{\min}$). This indicator captures the basic hydraulic functionality of the network from the user's perspective.

2. *Indicator I_2—System's Supply Ratio (SR):* This indicator quantifies the volume of water consumed from the household tanks in a day relative to the intended daily water consumption.

$$I_2 = \frac{\sum_{p=1}^{N} V_i^s}{\sum_{d=1}^{N} V_i^d} \tag{2}$$

where V_i^s is the volume actually consumed from the household tanks by user i during a day, V_i^d is the volume intended to be used by user i for a day, and N is the total number of users (or nodes with demands). A value of 0 indicates that no intended consumption has occurred, while a value of 1 signifies that all intended consumption has been fully satisfied. Here, intended consumption refers to the volume of water that households aim to withdraw from their household tanks to meet their daily needs. This indicator reflects supply adequacy by directly quantifying whether the system meets users' volumetric demand which is an essential criterion for adequacy of IWS systems.

3. *Indicator I_3—Well-Pressurized Fraction:* This indicator captures the quality of service by assessing the pressure level at consumption nodes throughout a day. It evaluates the adequacy of pressure against a reference pressure p_{ref} established for the case study. The mathematical expression for the I_3 indicator is as follows:

$$I_3 = \frac{\sum_{t=11.3}^{86400} \sum_{i=1}^{N} \max\left(0, \min\left(p_{i,t}, p_{\text{ref}}\right)\right)}{\frac{86400}{t_s}.N.p_{ref}} \tag{3}$$

where t_s is the simulation time step, which is taken as 11.3 s as suggested by Campisano et al. (2019b). N is the number of nodes with demands, and p_{it} [m] is the pressure at node i at simulation time step t. This equation (Equation 3) ensures that the pressure value considered does not exceed a predefined reference pressure (p_{ref}) and does not account for negative pressures. The I_3 value will vary between 0 and a maximum of 1, with the latter occurring when the mean pressures at all nodes exceed p_{ref} over the whole simulation period.

4. *Indicator I_4—Equity:* In IWS systems, inequitable distribution of water is a major concern. I_4 quantifies how fairly the available water is distributed among consumers. This is assessed using the measure developed by (Gottipati & Nanduri, 2014), and it is formulated as follows:

$$I_4 = 1 - \frac{\text{ADEV}}{\text{ASR}} \tag{4}$$

$$\text{SR}_{i,j} = \text{Supply Ratio} = \frac{V_i^s}{V_i^d} \tag{4a}$$

$$\text{ASR} = \text{Average Supply Ratio} = \frac{\sum_{i=1}^{N} \text{SR}_{ij}}{N} \tag{4b}$$

$$\text{ADEV} = \text{Average Deviation} = \frac{\sum_{i=1}^{N} |\text{SR}_{ij} - \text{ASR}|}{N} \quad (4c)$$

where V_i^s represents the volume actually consumed from the household tanks by user i a day, while V_i^d refers to the daily volume intended to be used by the same user, and N stands for the total number of users or demand nodes. When every user obtains their demanded volume, the ASR equals 1, but it drops below 1 if the network fails to meet the demand. A uniform ratio for all users would result in Average deviation (ADEV) being 0 and I_4 achieving the optimal value of 1. Given that the average deviation cannot surpass the mean value, the lowest possible value for I_4 is 0.

2.4. Global Sensitivity Analysis

Sensitivity analysis (SA) is an integral part of uncertainty quantification and involves revealing the proportionate contribution of each uncertain model input parameter to the overall uncertainty in the model's output (Saltelli, 2002b; Saltelli et al., 2008). This analysis is instrumental in enhancing the model, by simplifying it through eliminating non-influential parameters and directing data collection efforts toward the more influential variables.

Sobol's method (Sobol', 1993; Sobol, 2001) was employed in this study to quantify the contribution of each input parameter and its interactions with other parameters to the uncertainty in the model's output. The objective was to understand the behavior of the network in response to the interactions between household water consumption, household tank size, and supply characteristics. This issue is prominent in IWS systems, as the presence of household tanks might lead to a disconnection of consumer water consumption from the network's hydraulics (Randeniya et al., 2022).

Sobol's method (Sobol', 1993, 2001), a variance-based global sensitivity analysis (GSA) approach, has been effectively utilized in numerous applications (Pohya et al., 2022; Pryce et al., 2022; Wang & Zhao, 2023). It offers multiple benefits, including high accuracy, clear interpretation, and ease of implementation, as noted by (Burnaev et al., 2017).

In Section 2, the uncertain model input parameters were first identified and characterized based on all available information. For computational implementation, each uncertain parameter was represented by a finite set of n independent realizations generated from its respective uncertainty distribution and indexed from 1 to n. Discrete uniform distributions over the ranges [1, 50], [1, 150], and [1, 30] were then defined for supply characteristics, household tank size, and time series of water consumption from the household tank, respectively, which were then associated with each realisation. Utilizing the Saltelli sequence, which is specifically designed for Sobol's SA (Herman & Usher, 2017; Saltelli, 2002a), $2^{13} = 8192$ samples were used, adhering to the recommendation of a minimum of 2^{12} samples for three parameters (SciPy Developers, n.d.). This led to a total of $N^*(2D + 2) = 65{,}536$ simulations being executed for each scenario to calculate the Sobol sensitivity indices (where N is the number of samples, and D is the number of uncertain input parameters—here 3).

3. Software Used for Uncertainty Quantification

All IWS simulations were conducted using EPA's Storm Water Management Model (EPA-SWMM). The Python coding platform (Version 3.9) was employed for both UA and SA. This involved setting up simulations and handling pre- and post-processing of the results using the SWMM-toolkit version 0.9.0. For the sensitivity analysis, the SALib library was utilized (Herman & Usher, 2017).

4. Results and Discussions

4.1. Case Study

The methodology proposed in this study was implemented on a WDN detailed in Campisano et al. (2019a, 2019b). This network is responsible for water distribution to a district within the Ragalna municipality, located in the southeastern region of Sicily, Italy. The network, operating on a gravity-fed system, is equipped with a constant head tank of 2.8 m, facilitating water supply to 56 nodes via a network of 58 pipes. A defining characteristic of the system is the pronounced topographic variability, with elevation differences exceeding 100 m across the network. Its daily demand totals around 1151 cubic meters per day (Figure S7 of the Supporting Information S1). Demand

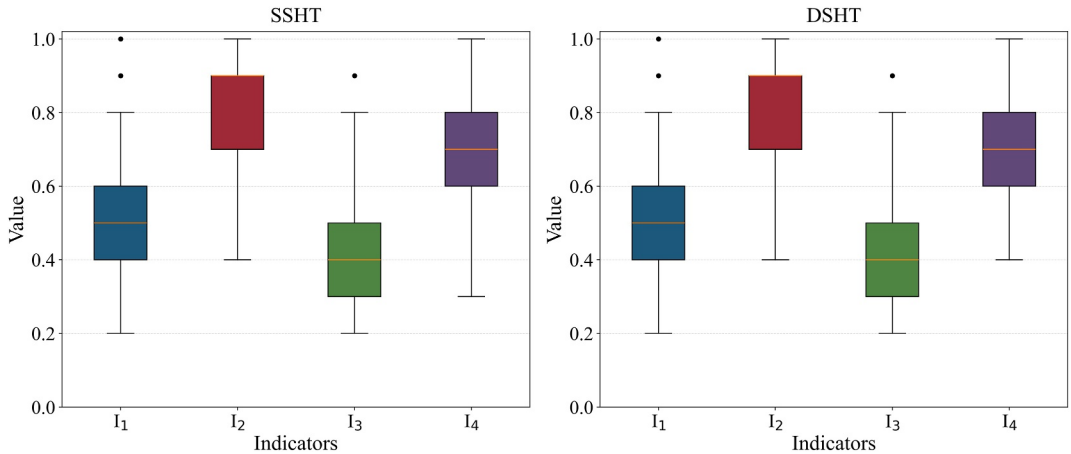

Figure 4. Box plots illustrating the variability and central tendency of each indicator across 12 scenarios: (a) Indicator I_1 (b) Indicator I_2 (c) Indicator I_3 (d) Indicator I_4.

values were estimated using data from flow measurements conducted by an ultrasonic flowmeter situated at the source's outlet, corresponding to a four-hour supply duration, as reported by Campisano et al. (2019a, 2019b). The demand volume at each node was subsequently determined based on these measurements. The consumption rate from the household tanks, referred to as the *base consumption rate* by Abdelazeem and Meyer (2025), was then estimated over a 24-hr period. Key parameters in the network include a minimum pressure (P_{min}) of 5 m and a reference pressure (p_{ref}) of 30 m, in line with recommendations from Campisano et al. (2019a, 2019b). To enhance the numerical accuracy and stability, the network's pipes were discretized such that the length of each segment did not exceed 100 m, following the recommendations of Campisano et al. (2019b). Consistent with this discretization, the hydraulic routing time step was set to 11.3 s. The simulation was run over a total duration of four consecutive

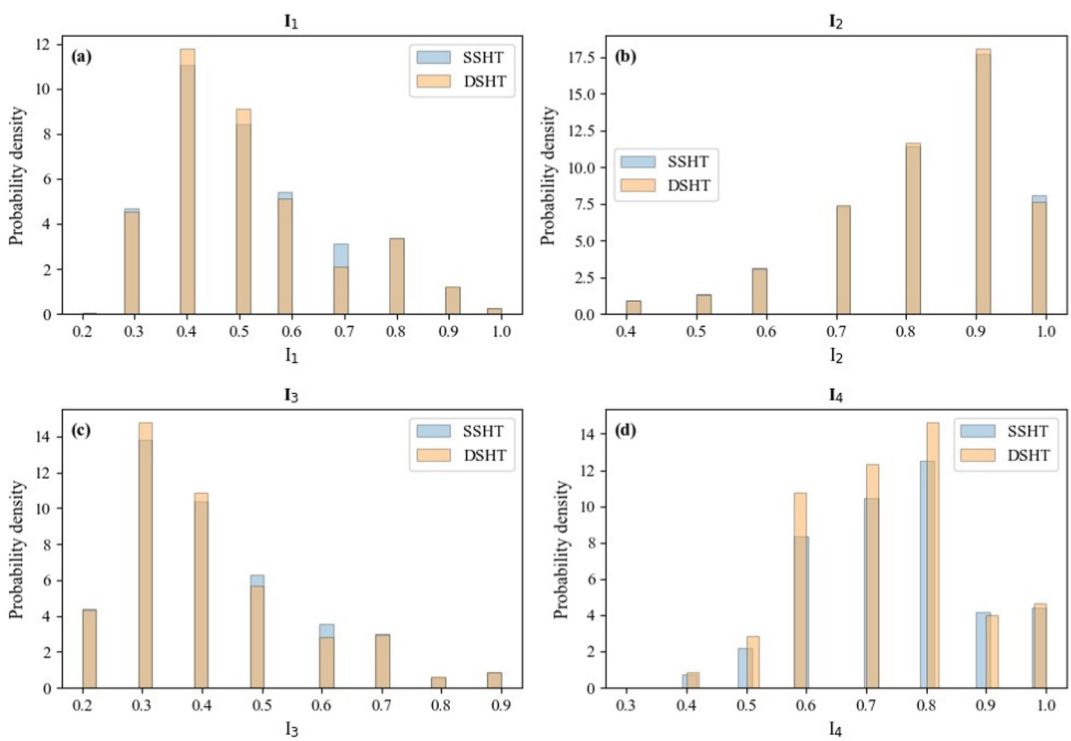

Figure 5. Normalized histograms of performance indicators for the SSHT and DSHT scenarios: (a) I_1 Pressurized Fraction, (b) I_2 System's Supply Ratio, (c) I_3 Well-Pressurized Fraction, and (d) I_4 Equity.

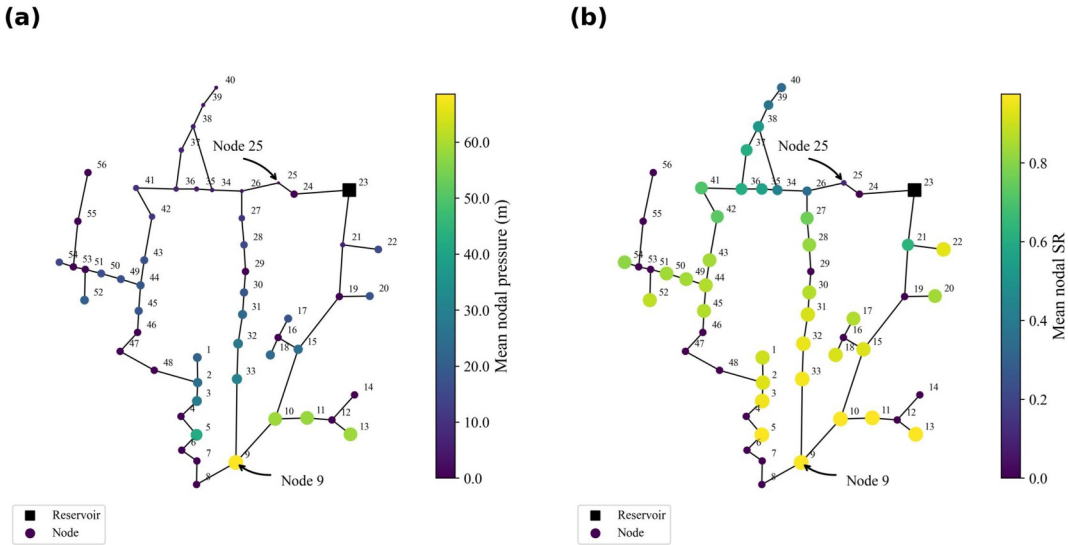

Figure 6. Mean nodal values for scenario SSHT: (a) Mean nodal supply ratio (SR) values (b) Mean nodal pressure (meter) values.

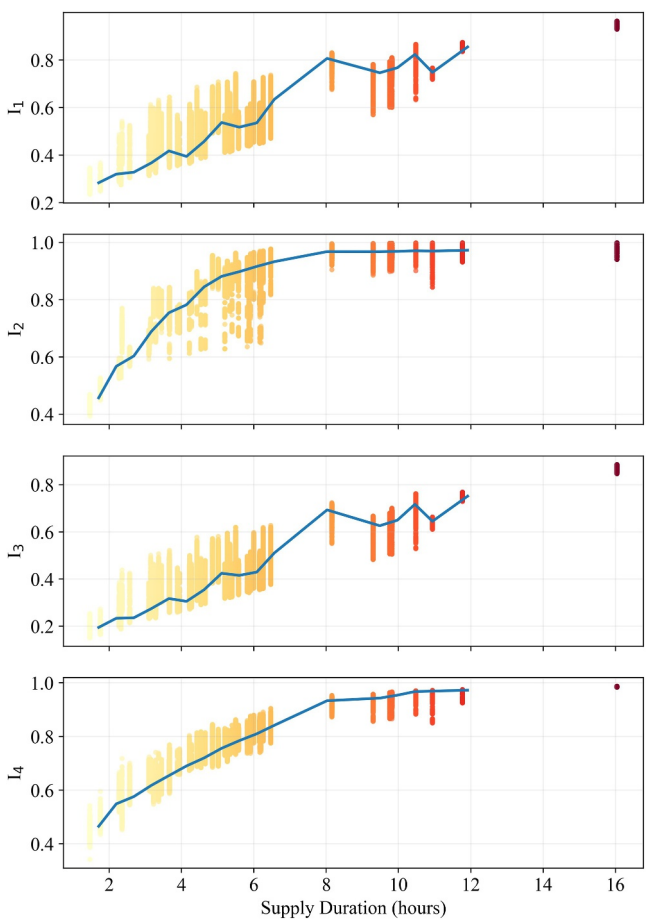

Figure 7. Relationship of the supply duration with each indicator (scenario SSHT).

days to allow the system dynamics to stabilize, particularly with respect to household tank water level. Results from the fourth day were therefore used for both the uncertainty and sensitivity analyses, ensuring that performance indicators were evaluated under stable operating conditions.

The hourly demand multipliers were obtained from Gullotta et al. (2021) for a water distribution network (WDN) in Italy and subsequently varied in accordance with the uncertainty characterization described in Section 2.2.3. The adopted demand pattern is shown in Figure S8 of the Supporting Information S1.

4.2. Uncertainty and Sensitivity Analysis

The simulations described in Section 2.4 were also utilized to analyze uncertainty in an IWS. For both UA and SA, two scenarios were developed, divided into two distinct situations based on the sizes of household tanks at each node:

1. Same size household tank (SSHT) for each node: In this scenario, each simulation used a single sampled household tank volume, which was applied uniformly to scale the equivalent tanks at all nodes.
2. Different size household tank (DSHT) for each node: In this scenario, a different sampled household tank volume was assigned to each node.

Each scenario was executed 65,536 times, as detailed in Section 2.4.

In the scenarios involving varying household tank sizes (DSHTs), spatial variation was introduced at the node level: for each of the 150 realizations, a different tank size was sampled from a truncated normal distribution and assigned independently to each demand node for each simulation.

4.2.1. Uncertainty Analysis (UA)

The first objective is to ascertain the overall uncertainty in the network's performance, considering the uncertain input parameters. Accordingly, Figure 4 shows the variations of the performance indicators outlined in Section 2.3 across the two scenarios. Table S1 in Supporting Information S1

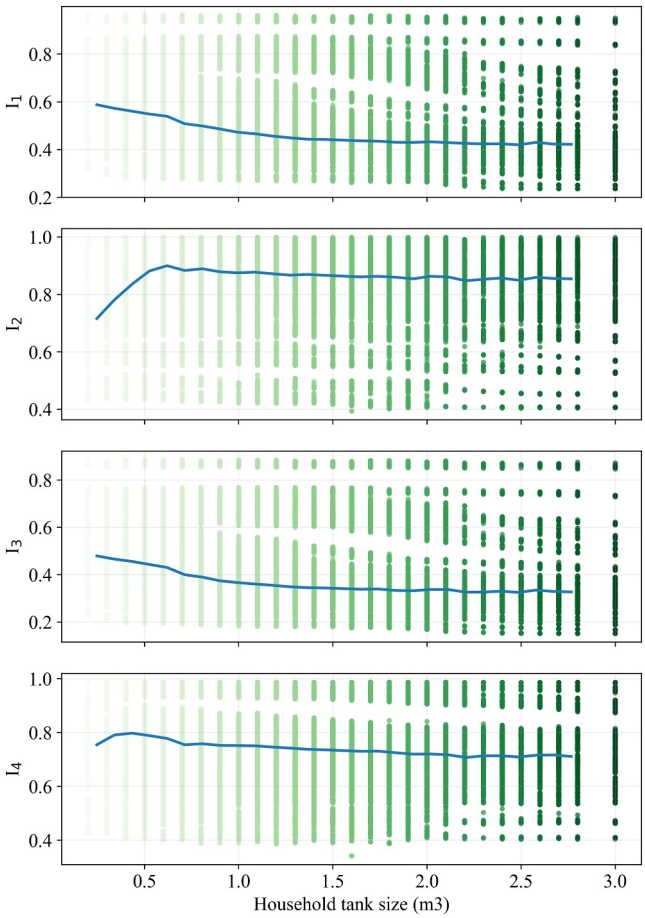

Figure 8. Relationship of the household tank size with each indicator (scenario SSHT).

provides the mean and standard deviation of the performance indicators for each scenario. The boxplots illustrate the variability in system performance under uncertain input parameters. Overall, the indicators show comparable median values across both scenarios, suggesting that the introduction of different household tank sizes in scenario DSHT does not substantially alter the overall network behavior. Evidence provided suggests that MEDIAN performance is relatively insensitive to tank size variability when compared to other uncertain factors such as supply characteristics and consumption patterns.

Each indicator exhibits a similar range of uncertainty, reflecting consistent sensitivity levels across performance aspects. As expected, I_2 (System's Supply Ratio) and I_4 (Equity) display similar distributions, since both depend on the volume of water consumed from household tanks. Likewise, I_1 (Pressurized Fraction) and I_3 (Well-Pressurized Fraction) show comparable patterns, being primarily influenced by nodal pressure dynamics. These results indicate that pressure-based and consumption-based indicators respond coherently to the imposed uncertainties, and that tank size heterogeneity introduces only small differences in system reliability and equity under the conditions tested. The relatively low values of I_1 and I_3 can be explained by the skewness of the uncertain input parameter for supply duration, which is concentrated at shorter supply periods (Figure S2 in Supporting Information S1). Because shorter supply durations occur more frequently, the network remains pressurized for limited time intervals in most simulations, resulting in predominantly lower values for the pressure-based indicators.

Figure 5 presents the normalized histograms of the four performance indicators for the SSHT and DSHT scenarios. The substantial overlap of the distributions confirms that introducing spatial variability in household tank sizes does not significantly alter the overall distribution, spread, or central tendency of system-level performance indicators.

To effectively illustrate the network's performance based on location, Figure 6a displays the average supply ratio (SR)—also called the demand satisfaction ratio (Abdelazeem & Meyer, 2024), while Figure 6b presents the mean nodal pressure for the baseline scenario, *SSHT*. In these figures, the color and size of each marker correspond to their mean values. The network has a mean SR of 0.8 and mean pressure of 20.3 m. As indicated in Figure 6a, Node 25 exhibits the lowest average SR (0.1), and Node 9 shows the highest average SR (1.0). This variation can be attributed to the elevation differences between the nodes. Specifically, Node 9 has the lowest elevation among all the demand nodes, whereas Node 40 ranks as the highest in elevation. Although Node 25 is located close to the source, its low elevation difference relative to the source limits the available pressure head, resulting in the lowest supply ratio in the system.

The consistently high SR value (equal to 1.0) for Node 9 across all simulations indicates that consumers at this node were always able to meet their intended consumption from the household tank. This outcome can be explained by the simulation setup, in which results were evaluated at the end of the fourth simulation day; by that time, the household tanks had reached steady-state conditions with relatively high water levels, ensuring that sufficient water was available for withdrawal by the consumers.

4.2.2. Sensitivity Analysis (SA)

After evaluating the uncertainties in performance indicators, the next objective was to identify the influential and non-influential parameters governing the performance of the IWS system. This will show which parameters deserve the most attention during further data collection.

First-order (*S*1), second-order (*S*2), and total-order (*ST*) sensitivity indices were calculated for the two scenarios (SSHT and DSHT). Figure S9 in Supporting Information S1 shows the indices for the SSHT scenario, while Figure

Table 2
Comparison of Performance Indicators (I_1–I_4) for Two Samples With Different Household Tank Sizes (0.6 and 1.4 m^3)

Sample number	I_1	I_2	I_3	I_4
7803	0.65	0.96	0.54	0.85
45674	0.52	0.93	0.41	0.80

S10 in Supporting Information S1 presents those for the DSHT scenario. Although the Sobol uncertainty analysis is illustrated using Indicator I_1, the same sensitivity ranking and parameter dominance were observed for the remaining performance indicators. In both cases, supply characteristics are the most influential uncertain parameter, followed by household tank size, with a substantial difference between their sensitivities. This outcome reflects the dominant control of supply duration on the total volume of water delivered to the system. However, in the SSHT scenario, household tank size exerts a comparatively stronger influence on the pressurized fraction indicator (I_1) than in the DSHT scenario. A detailed discussion of the individual effects of supply characteristics and household tank size is provided in Sections 4.2.3 and 4.2.4, respectively.

4.2.3. Impact of Supply Characteristics

It has been observed that the most influential uncertain parameter pertains to supply characteristics, encompassing three components: supply duration, supply timing, and supply frequency. To delve further into the individual and collective effects of these components on the system dynamics, additional analyses were conducted. The rationale for not treating these components as separate uncertain parameters lies in the fact that they must all be incorporated into the model input file as control rules, specifying the opening and closure times of the pipes connected to the water source. Consequently, they were collectively considered as a single uncertain parameter.

Figure 7 illustrates the comprehensive relationship between supply duration and all indicators, encompassing the base case scenario SSHT. While there appears to be a general linear correlation between supply duration and the magnitude of each indicator (with network performance generally improving as supply duration increases), certain instances deviate from this trend, particularly for I_1 (Pressurized fraction) and I_2 (Well pressurized fraction). For example, in certain cases, a longer supply duration corresponds to a lower indicator value, while in others, different samples yield varying indicator values despite having the same supply duration. These deviations may be associated with variations in household tank dynamics, which vary independently of supply duration. The scattered points at lower durations also reveal the higher uncertainty in the system performance under short supply conditions. Overall, the figure highlights the positive influence of supply duration on network performance, with diminishing improvements at longer durations.

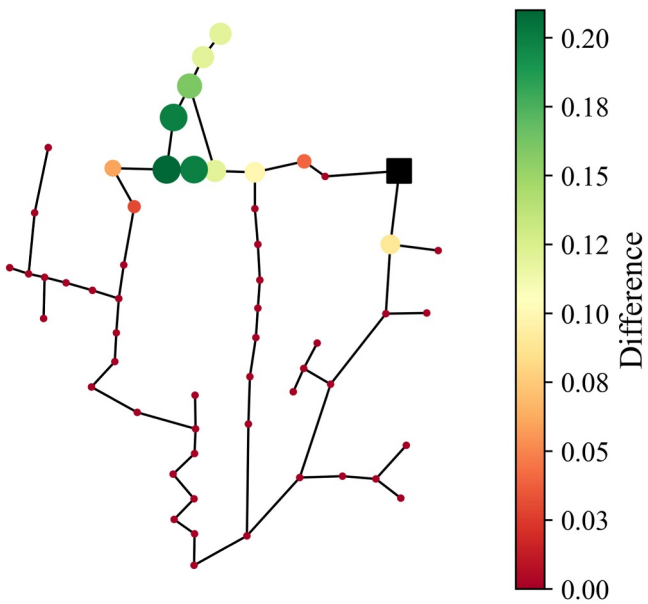

Figure 9. Node-wise difference in nodal supply ratio between samples 7803 (tank size = 0.6 m^3) and 45,674 (tank size = 1.4 m^3).

4.2.4. Impact of Household Tank Size

In Figure 8 the effect of household tank size on the four performance indicators (I_1–I_4) are displayed for scenario SSHT. Unlike the effect of supply duration, the relationship between tank size and system performance appears weak and largely non-monotonic. As tank size increases, I_1 (Pressurized Fraction) and I_3 (Well-Pressurized Fraction) show a gradual decline, suggesting that larger household tanks reduce nodal pressures during supply intervals. Both I_2 (System's Supply Ratio) and I_4 (Equity) improve as tank size increases to a moderate level, but this trend reverses for larger tanks, resulting in inequitable water distribution.

The network achieves its best performance when the supply duration is 16.04 hr and tank sizes range from 0.2 to 2.4 m^3, while the poorest performance occurs for a supply duration of 1.47 hr and a tank size of 1.6 m^3 with respect to all indicators.

To further explore the spatial impact of tank size, two samples (7803 and 45,674) were analyzed in detail, as they exhibit typical system behavior under different household tank size conditions. All uncertain parameters were kept constant except for tank size, which was 0.6 and 1.4 m^3, respectively. As shown in Table 2, the increase in tank size leads to a consistent reduction in all indicators. Figure 9 presents the node-wise differences in Supply Ratio between the two samples. High-elevation nodes (738.75–772 m) are the most

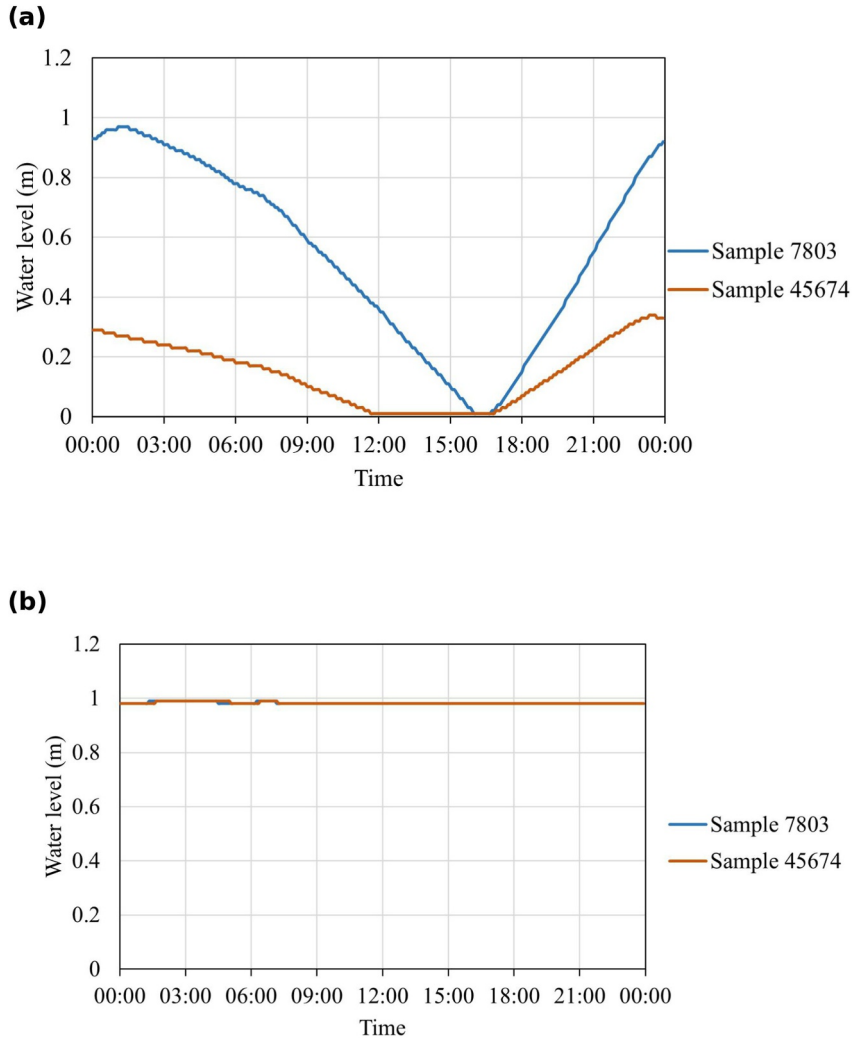

Figure 10. Time series of household tank water level for two nodes under different tank size scenarios: (a) high-elevation Node 37 and (b) low-elevation Node 9, illustrating contrasting temporal responses to increased household tank capacity.

affected, indicating that larger household tanks exacerbate inequitable water distribution by favoring low-elevation areas.

To illustrate how intermittent water supply affects nodes over time, one node most affected by larger household tanks and one least affected node were selected. Node 37 (elevation 746.00 m) and Node 9 (elevation 660.70 m), both with a demand of 0.06 L/s, represent these typical behaviors. Figure 10a shows the tank water level time series for Node 37 under samples 7803 and 45674, while Figure 10b presents the corresponding results for Node 9. For the high-elevation Node 37 (Figure 10a), the larger tank size (sample 45674) results in consistently lower tank water levels throughout the day, indicating reduced effective supply and limited refilling during supply periods. In contrast, the low-elevation Node 9 (Figure 10b) maintains near-full tank levels for both samples, showing minimal sensitivity to tank size.

5. Conclusions and Recommendations

To accurately analyze the behavior of intermittent water supply (IWS) systems, a deep understanding of their operational variability is essential. This necessitates employing suitable models and considering uncertain input parameters. This study introduces a framework designed to identify, characterize, and quantify these uncertain parameters, thereby enhancing IWS modeling. This study marks a pioneering effort in conducting a comprehensive analysis of IWS systems, revealing certain previously unaddressed questions, although some have been

noted by previous studies. While the general framework was derived from existing literature, the proposed methodology is distinct, exploring a variety of unique scenarios. This study serves as a valuable starting point for further research into uncertainty analysis in IWS systems. The key findings yield the following insights:

- It is challenging to anticipate system performance without comprehensive field data, but uncertainty analysis helps reveal the system behavior and leads toward modeling improvements.
- The performance indicators display variability under uncertainties, emphasizing the necessity of incorporating uncertain input parameters in relevant decision-making processes. Further data collection is needed for more accurate modeling, particularly regarding supply characteristics.
- IWS network dynamics are shaped by the combination of uncertain input parameters, which may change the performance of the network and each node's supply ratio.
- The consumer and pipe network relationship depends on the household tank size, outlet coefficient, amount of water consumption from the tank and its demand pattern, and supply characteristics.
- Sensitivity of the model results in terms of system-wide indicators is dominated by the supply characteristics, encompassing three components: supply duration, supply timing, and supply frequency.
- Reducing the sizes of household tanks to an extent enhances the supply ratio of the network, allowing water to reach more disadvantaged nodes, but this ratio also depends on the level of simultaneous water consumption from their tanks by the advantaged nodes.
- As the results of this study suggest, further research can focus on more extensive uncertainty analysis, encompassing additional uncertain parameters, such as leakage; variables like suction pumps and different types of consumer connections; and system characteristics such as required pressure head, minimum and initial household tank levels, and simulation duration

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

1. Modeling
   Software name: EPA-SWMM (EPA'S Storm Water Management Model)
   Version Used: 5.1
   Software Homepage: https://www.epa.gov/water-research/storm-water-management-model-swmm
   License: Public domain software
   Developer(s): United States Environmental Protection Agency (U.S. EPA)
   Documentation: Available on the software homepage
   Program language: Python (Version 3.9).
   Module: SWMM-toolkit 0.9.0
   Availability: https://pypi.org/project/swmm-toolkit/
2. Sensitivity analysis
   SALib library 0.7.1
   Herman, J., & Usher, W. (2017). SALib: Sensitivity Analysis Library in Python (Numpy). Contains Sobol, SALib: An open-source Python library for Sensitivity Analysis. *Journal of Open Source Software*, *2*(9), 97. https://doi.org/10.1016/S0010-1
3. Researcher's experimental environment
   OS: Windows 10
   Operating System(s): Windows 10
   Processor: Intel(R) Core (TN) i7-8700K CPU @3.70GHz
   Installed RAM: 32.0 GB

Data sets from Campisano et al. (2019a, 2019b) and Meyer (2023) were used in this manuscript. All the data, along with Python scripts for generating the results and figures presented in the study are available at Mendeley Data https://data.mendeley.com/preview/c7zc46g3gy?a=14d4ce25-6128-4b6d-b9d7-87b06b5f0d73 (Sarışen et al., 2026).

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