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Stress-Testing Framework for Urban Water Systems: A Source to Tap Approach for Stochastic Resilience Assessment

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Abstract: Optimizing the design and operation of an Urban Water System (UWS) faces significant challenges over its lifespan to account for the uncertainties of important stressors that arise from population growth rates, climate change factors, or shifting demand patterns. The analysis of a UWS's performance across interdependent subsystems benefits from a multi-model approach where different designs are tested against a variety of metrics and in different times scales for each subsystem. In this work, we present a stress-testing framework for UWSs that assesses the system's resilience, i.e., the degree to which a UWS continues to perform under progressively increasing disturbance (deviation from normal operating conditions). The framework is underpinned by a modeling chain that covers the entire water cycle, in a source-to-tap manner, coupling a water resources management model, a hydraulic water distribution model, and a water demand generation model. An additional stochastic simulation module enables the representation and modeling of uncertainty throughout the water cycle. We demonstrate the framework by "stress-testing" a synthetic UWS case study with an ensemble of scenarios whose parameters are stochastically changing within the UWS simulation timeframe and quantify the uncertainty in the estimation of the system's resilience.

Keywords: Urban Water Systems; resilience; uncertainty; strategic planning; stress-testing; interdependent systems

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1. Introduction

Urban Water Systems (UWSs) are critical infrastructures, which play a key role in sustaining life and welfare. Their sheer size, spatial extent, complexity, construction time, and related costs lead to designs that have a long lifespan (design horizon), typically in the range of 25 to 50 years or more, and carry with them significant investments [1]. As such, water systems designed today must meet a multitude of objectives for a considerable time into the future, balancing water shortage risk, operational costs, and environmental protection [2]. In practice, most water systems serving metropolitan areas, which experience urban sprawl, have been expanding on top of the original systems. In fact, in most industrialized countries (e.g., in the UK, the USA, France, Australia, etc.), the core of the system (and/or significant parts of it) is over a century old, while also in most of the developed world, urban water infrastructure has been fully developed since the 1980s [2]. Thus, water infrastructure typically outlives the original design goal, while being tethered to a technological path dependency and design paradigm for decades [1]. The subsystems, which compose a water system (including water supply works, distribution networks, cyber-physical control and monitoring systems, etc.), interact continuously with each other and the environment. These interactions, along with the long service lifespan, the complexity, and the overall system dependence on exogenous factors (such as climate), make UWSs susceptible to a multitude of changing conditions that can be regarded as system stresses [3]. Some of these stresses change over longer time horizons, such as hydroclimatic stresses (e.g., changes in water resources availability due to climate change [4]) and socioeconomic stresses (e.g., demographic changes, urban growth, increasing water demand and shifting usage patterns, land use change, energy price, etc.) [5–7]. Other stresses manifest themselves over shorter time horizons (e.g., major pipe bursts or cyber-physical attacks to the system's SCADA (its supervisory control and data acquisition [8,9])), resulting in significant impacts on the quality of, or disruption to, the UWS operation. At the design stage of an UWS, quantifying these stresses is challenging [10], and that is despite good knowledge and experience from numerous UWSs because some of the factors driving these stresses are not only unknown but also *unknowable* (see a suggestion in [11]). Furthermore, long-term business and policy decisions within a specific utility or the sector also affect future operations of UWS. Examples include operational rules, pricing, environmental laws, campaigns, and incentives for water conservation to costumers, all of which considerably affect performance. Thus, the resulting deep uncertainty affects the capability of an UWS to deliver its objectives.

The traditional design paradigm of UWSs entails safety factors for demand and supply projections, in order to account for uncertainty [12]. As such, systems are often overdesigned to be 'fail-safe' (i.e., reliable) under all possible future circumstances. In practice though, this proves to be expensive and inevitably futile [13–15], also giving a false expectation of perpetual reliability [14]. A volatile ever-changing global landscape with significant direct and indirect effects on the water sector is fast becoming the 'New Normal' [16] and makes 'fail-safe' aspirations unrealistic. Thus, it is argued that a paradigm shift [17] is needed. This paradigm moves the UWS design logic toward 'safe-to-fail' systems [3,14–16,18], with a focus on anticipating failures and being prepared to overcome them [14,15]. Within this paradigm, it is important to know *how* UWSs fail: how they behave when faced with extreme events and/or with changing conditions, along with the capability of the system to recover quickly from a non-satisfactory state to deliver its goals again.

A desired trait of an engineered system that underpins any 'safe-to-fail' design approach is *resilience*. Despite being used extensively in recent water policy discussions [19], resilience is still an elusive term with different definitions offered according to the context. Holling's seminal definition, stemming from ecological system's analysis [18,20], formalizes resilience as 'the capacity to absorb disturbance so as to still retain essentially the same function, structure, identity, and feedbacks'. This definition gave rise to various alterations, but generally, all interpretations refer to the capacity of a system to absorb, adapt to, or recover from disturbance and cope with stress [19]. Building on past definitions, Makropoulos et al. [3] proposed a resilience metric for UWSs that maps the '*degree of continued performance of the system under disturbance*'. In this work, we adopt this metric to quantify resilience.

In this context, it is important to be able to model not only the individual components/subsystems, which are generally well-modeled and understood, but also interdependencies and cascading effects between them. Uncertainty related to both short- and longer-term stresses needs to be considered using stochastically generated inputs and parameters (e.g., synthetic supply and demand patterns), as well as scenario-based approaches [21]. In a Monte Carlo context, these alternative scenarios can be used as inputs to stress-test alternative system designs under a variety of future conditions, including specific threats, such as cyber-physical attacks (see [9,22–24]). Stochastic computational methods can also be used to generate valid topologies of UWS subsystems and test their designs (such as, for example the approach adopted by Zhang et al. [25] assessing combined sewer systems' resilience). To undertake such an analysis at the level of whole UWSs, several different simulation models are required, with different data needs, computational complexity, spatial and temporal scale, as well as modeler skills and experience required. Moreover, model results need assimilation and aggregation, which is not always straightforward, since different metrics may be employed to measure the capacity of each subsystem.

The need for sophisticated integrated modeling and consistent long-term uncertainty quantification poses a challenge for urban water planners that need to decide between alternative system design options [26], also because of the difficulty to compare these different options within the same practical framework, since alternative designs mean different system topologies, possibly based on different design philosophies (e.g., centralized versus decentralized approaches to infrastructure design), and each option comes with its own operational decisions (e.g., operational rules, goals, and target priorities for different water uses, pricing strategies, strategic planning for new asset deployment and replacements, etc.).

In this work, we provide a remedy to the above challenges by developing and demonstrating a source-to-tap simulation and stress-testing framework for UWSs. We propose a standardized and transferable methodology, which is able to assess the overall system's resilience under long-term uncertainty and stochasticity, aiming to support water utilities to improve evidence-based decision making for long-term infrastructure planning.

2. UWS Stress-Testing Framework

2.1. From Source to Tap: Coupling State-of-the-Art Tools in a Modeling Chain

The analysis of UWSs from source to tap requires the use and seamless integration of models and tools. Conceptually, this procedure involves models that achieve the following:

- Describe the behavior of groups of consumers at smaller scales, e.g., at a household level, to allow the generation of realistic water demand patterns for various types of consumers and/or uses;
- Simulate the hydraulic distribution of water to consumers in the temporal and spatial dimension, e.g., a model for the water distribution network (WDN) of the UWS, which simulates the behavior of pipes, tanks, valves, pumps, etc.;
- Simulate the hydrologic regime of the system, as well as decisions and operational rules for its extraction and transfer to the WDN. Specifically, a model to simulate the components of the external water supply system and water resources of the UWS (e.g., reservoirs, aqueducts, river intakes, groundwater wells, etc.), along with decision support systems (DSS) for the extraction of operational rules of the systems;
- Generate alternative, yet stochastically consistent, scenarios of model inputs (e.g., rainfall, water demands) and/or parameters to support the encapsulation of uncertainty in all processes.

In this work, the tools selected to play the above-mentioned roles are the *UWOT* [27], *EPANET* [28], *Hydronomeas* [29], and *anySim* [30] model, respectively. These state-of-the art computational tools also have the advantage of easy coupling with each other and hence can be employed in a modeling chain to support a holistic representation of (any) UWS. However, the simulation and stress-testing framework is model-agnostic, and any software solution that meets the above-mentioned requirements can be utilized in their place. A brief presentation of the key elements of the above-mentioned models is provided in the next sections.

2.1.1. *UWOT*

UWOT (Urban Water Optioneering Tool) is a bottom–up urban water cycle model, based on the modeling local micro-components. These include the following:

- Water-consuming household appliances, such as hand basins, toilets, showers, and washing machines;
- Local water treatment or harvesting options, e.g., rainwater harvesting and gray water recycling schemes;
- Regional components such as treatment plants, reservoirs, etc.

Urban water flows (i.e., demand, supply, drainage, and wastewater) are simulated by generating, aggregating, and transmitting demand signals, starting from the household water appliances and moving toward the source [27,31,32].

UWOT has been used in resilience assessment studies involving synthesized and real-world UWSs [3,16]. However, although *UWOT* can simulate the entire source-to-tap urban water cycle, this approach has some limitations in systems where an assessment of performance from a hydraulic perspective is required. In the modeling chain presented here, *UWOT* is utilized to generate daily water demand for various types of consumers, considering household types, demographics (i.e., changes in occupancy throughout the simulation horizon), demand patterns (i.e., seasonality of demands), water-use frequencies of the water appliances, and the technological level of the appliances used (for example, penetration of dual flush toilet systems). *UWOT* employs a recently developed Python wrapper (*pyuwot*) for interoperability with other models.

2.1.2. *EPANET*

The industry standard hydraulic solver *EPANET* is used as the WDN simulator. *EPANET* models the hydraulic distribution of drinking water to consumers downstream of the water sources. The WDNs are represented as graphs with nodes acting as demand junctions, tanks, and reservoirs (which act as infinite water sources), and edges representing pipes, pumps, and valves. Here, we employ the recent *EPANET 2.2* version, which facilitates pressure-driven demand analysis (PDA). The PDA approach can reproduce pressure deficient conditions that may result in service unavailability in a WDN. This approach differs from the demand-driven analysis (DDA) of previous *EPANET* versions [33], where demand is always met without consideration of pressure (even regardless of infeasible negative pressures). Thus, the newer version (2.2) allows capturing the hydraulic failures during simulations, when actual demand is over the WDN's design capacity or when infrastructure fails (e.g., leak occurs or a pipe bursts). *EPANET* is deployed in the modeling chain via the *WNTR* [34] *Python* package.

2.1.3. *Hydronomeas*

Hydronomeas [29,35] is a decision support system (DSS) for water resources management and can simulate and optimize rules for any (raw) water supply system. Reservoirs, pumping stations, aqueducts, borehole groups, river intakes, and other components of water supply systems are represented as a graph network. Targets are employed for water resources allocation of different uses (e.g., drinking water, water for irrigation or industrial needs, etc.), on a daily or monthly time step. Hydrologic variables (such as precipitation, runoff, and evaporation) are model inputs to allow the model to assess water availability. The use of synthetic (stochastically generated) inputs allows for the encapsulation of hydrologic uncertainty in the uncertainty-aware simulation and analysis of the system. Operational rules, pricing strategies, and unit costs can also be assessed and optimized. In particular, a recently developed *Python* version of *Hydronomeas*, *Hydronomomeas2020* [36] is used as the software wrapper to allow interoperability with other models.

2.1.4. *anySim*

In this work, we employ the *anySim* package, developed in *R*, as a generator for synthetic time series, which are used as inputs to drive the above-mentioned water system operation models. *anySim* enables the stochastic simulation of correlated random variables, stochastic processes (at single and multiple temporal scales), and random fields with any marginal distribution and dependence structure. The functionality of the package is tailored to the demanding peculiarities of hydroclimatic (e.g., rainfall, runoff, etc.) and non-physical (e.g., water demand) processes, such as the non-Gaussianity, intermittency, periodicity, as well as the spatiotemporal dependence structures. The package implements a suite of novel stochastic simulation methods that allow the exact preservation of any dependence structure and marginal behavior of processes. The methodology is based on the concept of Nataf's joint distribution [37] according to which the joint distribution of random variables with any target arbitrary marginal distributions can be obtained by mapping an auxiliary multivariate standard Gaussian distribution via the inverse cumulative distribution functions (ICDFs). The implemented methods utilize the link between correlation coefficients in the Gaussian and the target domain, reproducing also the target correlations. Moving to stochastic process simulation, *anySim* employs a similar concept (for more details, see [38–42]) that is based on the mapping (through the ICDF) of an auxiliary Gaussian process (Gp) through the ICDF to establish processes with the target marginal distribution and correlation structure. In this work, the package is employed to generate synthetic hourly water demand patterns, as well as synthetic daily runoff.

2.1.5. Coupling the Models within a Source-to-Tap Framework

The coupling of the models is schematically depicted in Figure 1. Within a design (or simulation) horizon, the daily demand of different types of consumers is simulated by generating household groups with different technological (type of components), demographical (occupancy), and behavioral (frequency of water uses) attributes using UWOT. UWOT can model as many types of consumers/households as the planner needs. The parameters and model inputs can be scenario-based projections or stochastically generated realizations obtained by a suitable tool/model (*anySim* in this case). UWOT's output in this specific scheme is the basic daily water demand for various types of consumers, which varies dynamically within a simulation horizon.

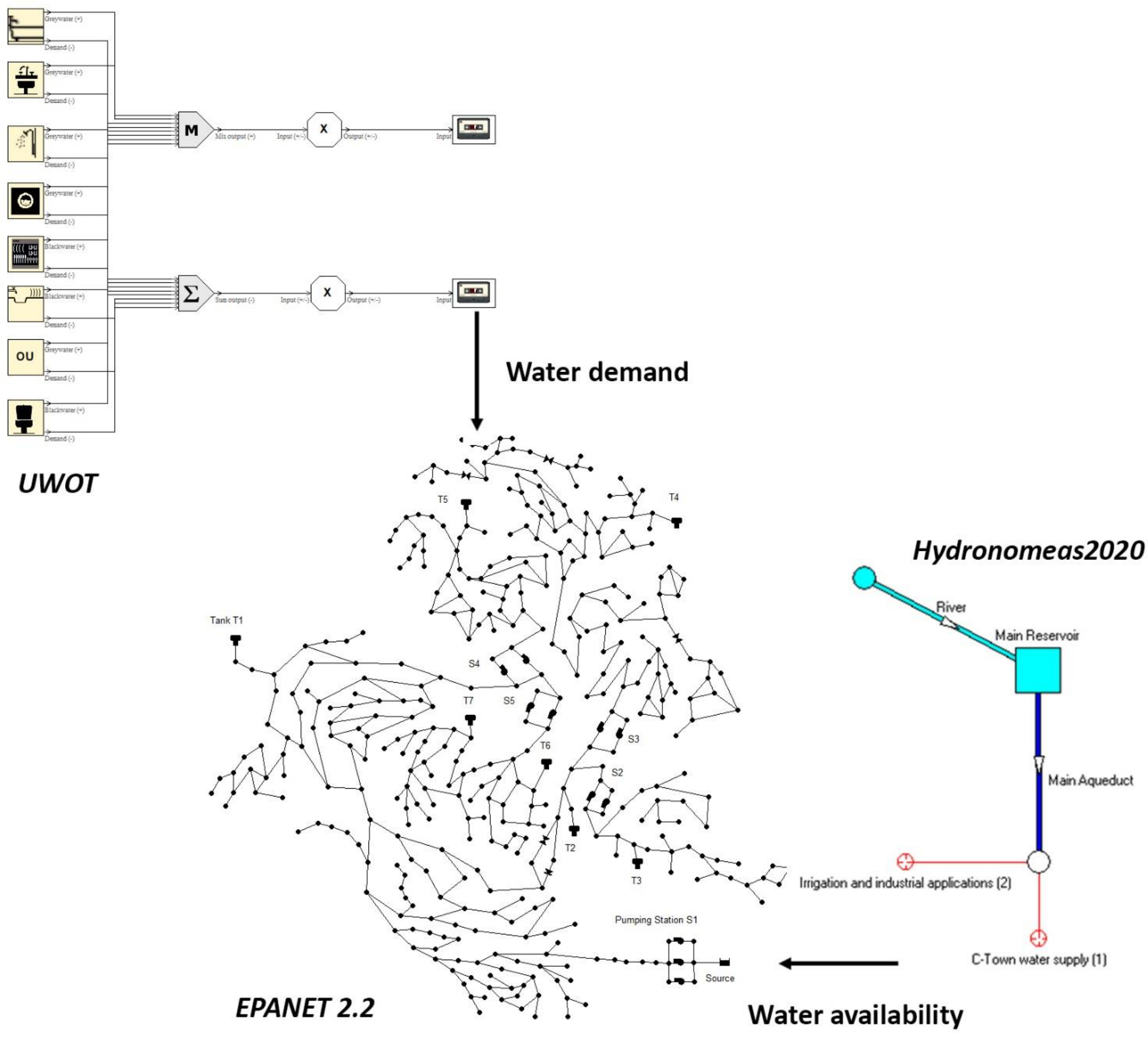

Figure 1. Coupling the computational models within a source-to-tap simulation scheme.

The basic daily demand types need to be spatially distributed to the WDN's junctions, i.e., at the nodes of the *EPANET* model. This can be accomplished by assigning a look-up table of the mix of types at each node (e.g., varying by region or district metered area (DMA)) and dynamically changing the basic daily demand of the model via *WNTR*'s routines; this mix can also vary within the simulation horizon (e.g., starting with high-consumption types and ending with lower consumption household types). The basic daily demand is disaggregated temporally to finer scales via time-varying multiplier patterns. Specifically, here, we generate synthetic yet statistical and stochastic consistent, hourly patterns using *anySim* package. The synthetic series are used as inputs to *EPANET*, thus allowing the hydraulic simulation of the system under time-varying demand loads. Pipe leaks and breaks can also be incorporated, via a probabilistic rule for each day, in the simulation to provide a more realistic representation of the network's operation. The long-period simulation of the WDN employs the PDA solver, capturing instances of inadequate pressure to cover demands. Thus, hydraulic failures in delivering water to consumers are captured. The model generates the water production needs at each reservoir node, which represents a water source, such as a water treatment plant.

Then, water production needs are aggregated to daily time steps and assigned to the respective target node of *Hydronomeas* that models the external raw water supply system of the UWS. Other water uses such as irrigation and industrial needs, which can be part of the UWS but not represented in its WDN subsystem, can also be incorporated. Stochastic inputs for the hydrologic variables (e.g., runoff for catchments) are generated via *anySim*. Properties of components can be set either by the modeler or be scenario-based, such as unit costs for pumping and leakage coefficients for aqueducts. The daily simulation in *Hydronomeas* produces results that show the hydrologic reliability in covering the water target needs.

Results for the UWS reliability are aggregated from both the hydraulic and hydrologic reliability sub-metrics in daily frequency steps. Specifically, a final reliability metric is used, which superpose two objectives: (i) delivering enough water to cover overall needs by the external water supply system on a daily basis and (ii) being able to distribute the water on a daily basis in a hydraulically consistent manner through the WDN simulator. It is noted that since some minor failures may be frequent in a complex system (e.g., a small number of nodes for a limited time within a day in the WDN may have inadequate pressure), a small threshold value of "acceptable" failures within a day can be set to each sub-objective. For example, if 1% of the total water needs is not covered, this can be counted as a "satisfactory" state, lowering the failure sensitivity of the complex UWS. Such a threshold can be determined by the water utility depending on the level of service targeted.

2.2. Stochastic Resilience Assessment Methodology

As discussed above, we adopt a definition of resilience proposed by Makropoulos et al. [3]. In that work, the "disturbance" part of the resilience definition was modeled through scenarios, each representing a future "world view", altering the baseline situation. The scenarios are differentiated on the basis of parameters which, theoretically, could be anything that directly or indirectly affects the UWS: for example, population, demographics, runoff of a river used as a water resource, water price, maintenance capacity of the water utility, public expenditure, behavioral water demand, etc. Then, scenarios could range from mild to extreme, exploratory to speculative, etc., based on: (i) the number of parameters that change in each scenario; (ii) the magnitude of change; and (iii) the rate of change within the stress-testing simulation horizon. After stress-testing different system configurations (i.e., different installed technological assets, design philosophy and/or management decisions), with the same sets of scenarios, configurations' resilience can be compared using resilience profile graphs (similar to that of Figure 2). In such types of graphs, the scenarios are represented on the x-axis, in an ordinal scale by severity, from the least to most stressful to the system, while the y-axis is reserved for the overall performance metric. In the context of UWSs, the performance metric can usually be daily reliability in delivering water to consumer. However, it must be noted that this resilience assessment methodology is also suitable for other performance metrics. For example, in Nikolopoulos et al. [22], the detection ratio of cyber-physical attacks in the context of cyber-physical water systems was used as a performance metric for resilience assessment. In the resilience profile graph (see Figure 2), the area under the (reliability) curve is defined as resilience. This area is compared to the area of an ideal (completely reliable) system, and hence scaling the resilience metric within 0 and 1. In fact, the resilience assessment methodology used in this work defines an ideal system as fully robust, with the degree of robustness of the system defined as the extent to which the system can keep performing within design specifications under increasing stress. The interested reader is referred to Makropoulos et al. [3] for a more detailed explanation of these concepts and terms.

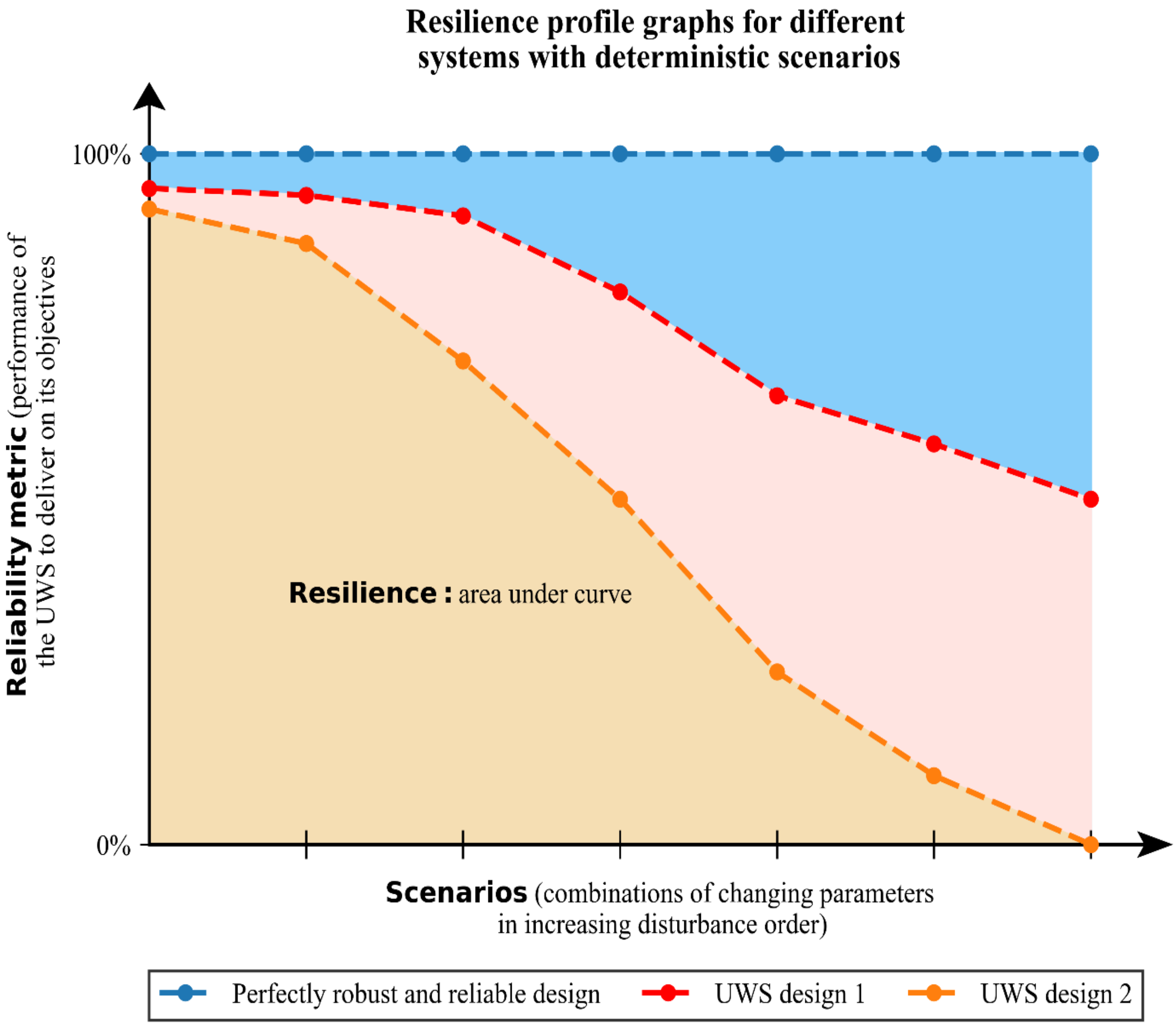

Figure 2. Resilience profile graphs for different UWS designs.

An advantage of the resilience assessment method discussed above is that it naturally incorporates uncertainty in its conceptualization. Projections, parameter estimations, and stochastic variables are mixed in the formulation of scenarios, while it is acknowledged that the behavior of complex systems under the scenario sets is also uncertain. However, as originally formulated, the resilience metric is static. To encapsulate uncertainty in the resilience metric estimation per se, we employ a stochastic procedure: an ensemble of scenario realizations is generated for each scenario that incorporates some stochastically varying inputs or event probabilities. Hence, instead of a performance curve in the resilience profile graph, a cloud of performance points per scenario is generated. Next, we can use these points to generate curves that correspond to the mean performance curve and other confidence intervals (CI), quantifying uncertainty in the resilience estimation. Figure 3 illustrates an example of such an approach.

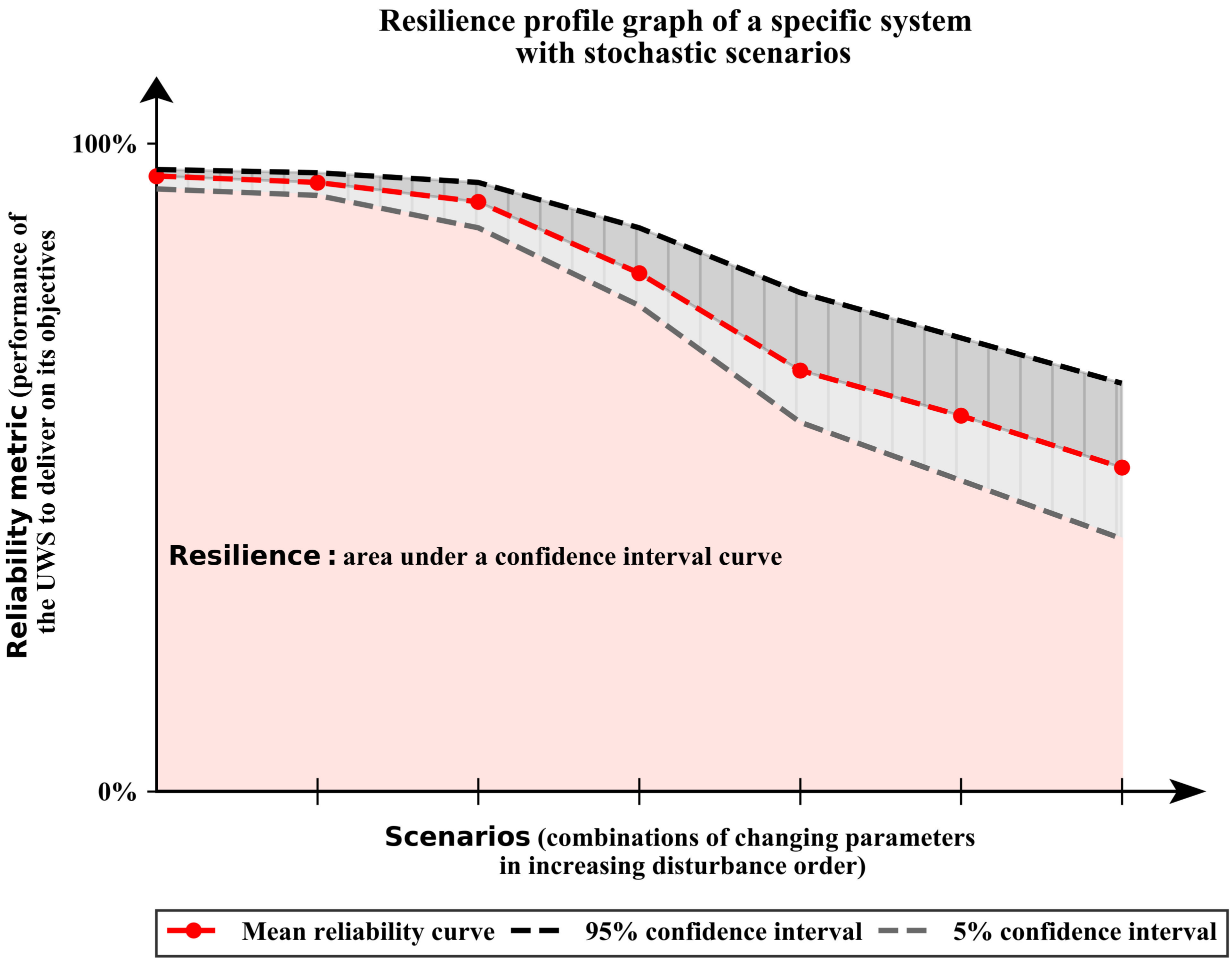

Figure 3. Quantifying uncertainty in resilience estimation of a specific system.

3. Demonstration of the Stress-Testing Framework

3.1. Case Study

To demonstrate the stress-testing framework, we formulated a synthetic, yet realistic in terms of size and complexity, UWS as a case study. The case study is based on the C-Town [43] benchmark WDN model, which represents an anonymized real-world medium-sized city. To alleviate the high computational burden without losing significant spatial and temporal fidelity in the context of a very long simulation, the network is skeletonized using WNTR's functions to 101 nodes (from 388), while the hydraulic time step is set to 4 h. For each of the five DMAs, the given hourly time-varying demand pattern, of a week's length, is used. Taking advantage of this information, synthetic patterns, with a length of 25 years (9131 d), were generated via *anySim*. The generated series preserve the marginal properties of the given series, as well as their spatial and temporal dependencies (i.e., auto- and cross-correlations). Figure 4 shows the skeletonized WDN. For simplicity, in the baseline configuration and at the simulation start, each node of the network consists of the same type of households (Type 1, as modeled in UWOT). The number of households at each node is calculated from the nodal base demand divided by the basic Type 1 household's demand (calculated from an average basic occupancy of 2.3 people per household). At each node, three different household types appear, with a percentage mix that changes through time as a parameter. Household Types 1, 2, and 3 are modeled in UWOT (the schematic topology is shown in Figure 5), as follows:

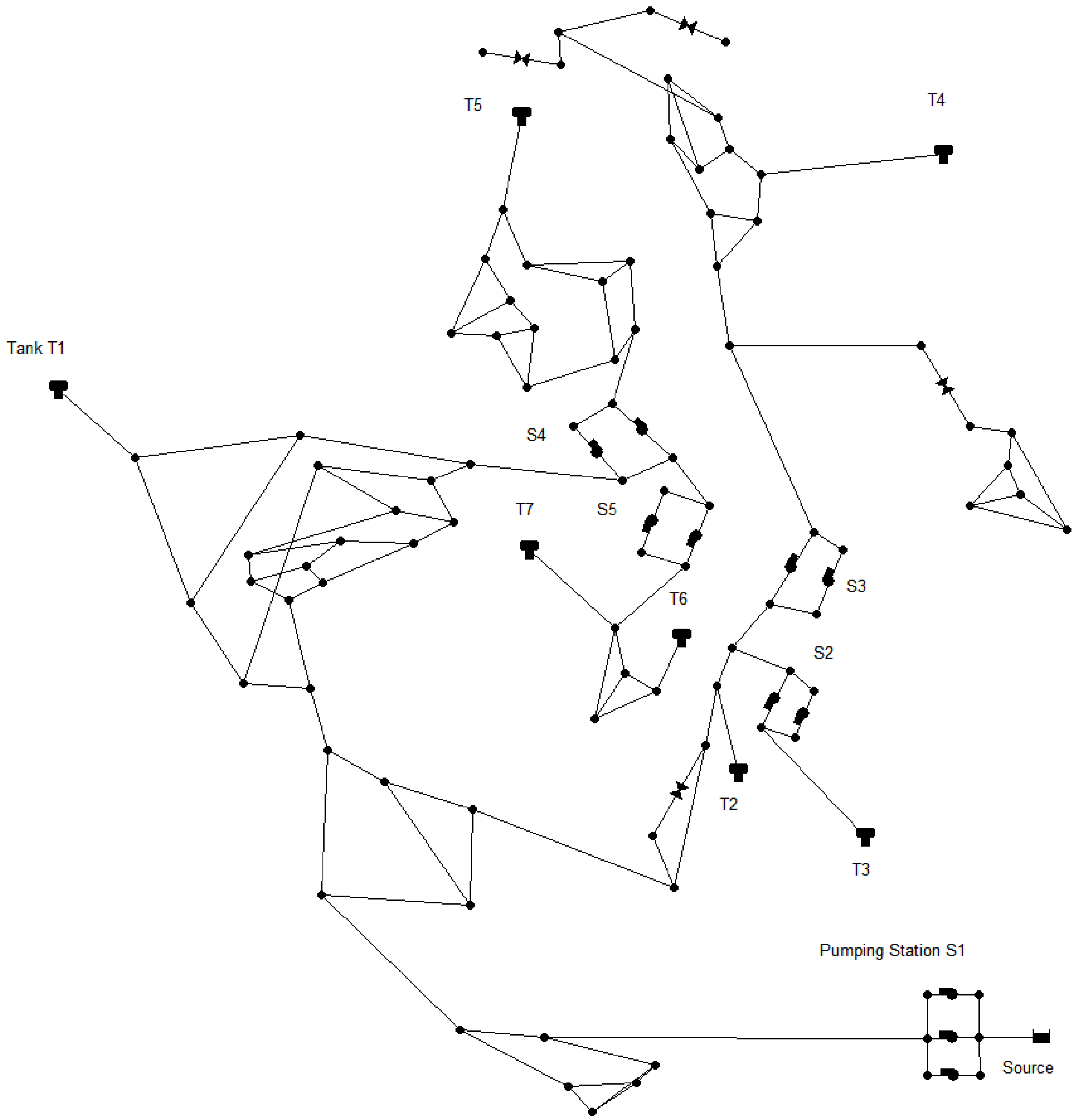

Figure 4. Skeletonized version of C-Town WDN.

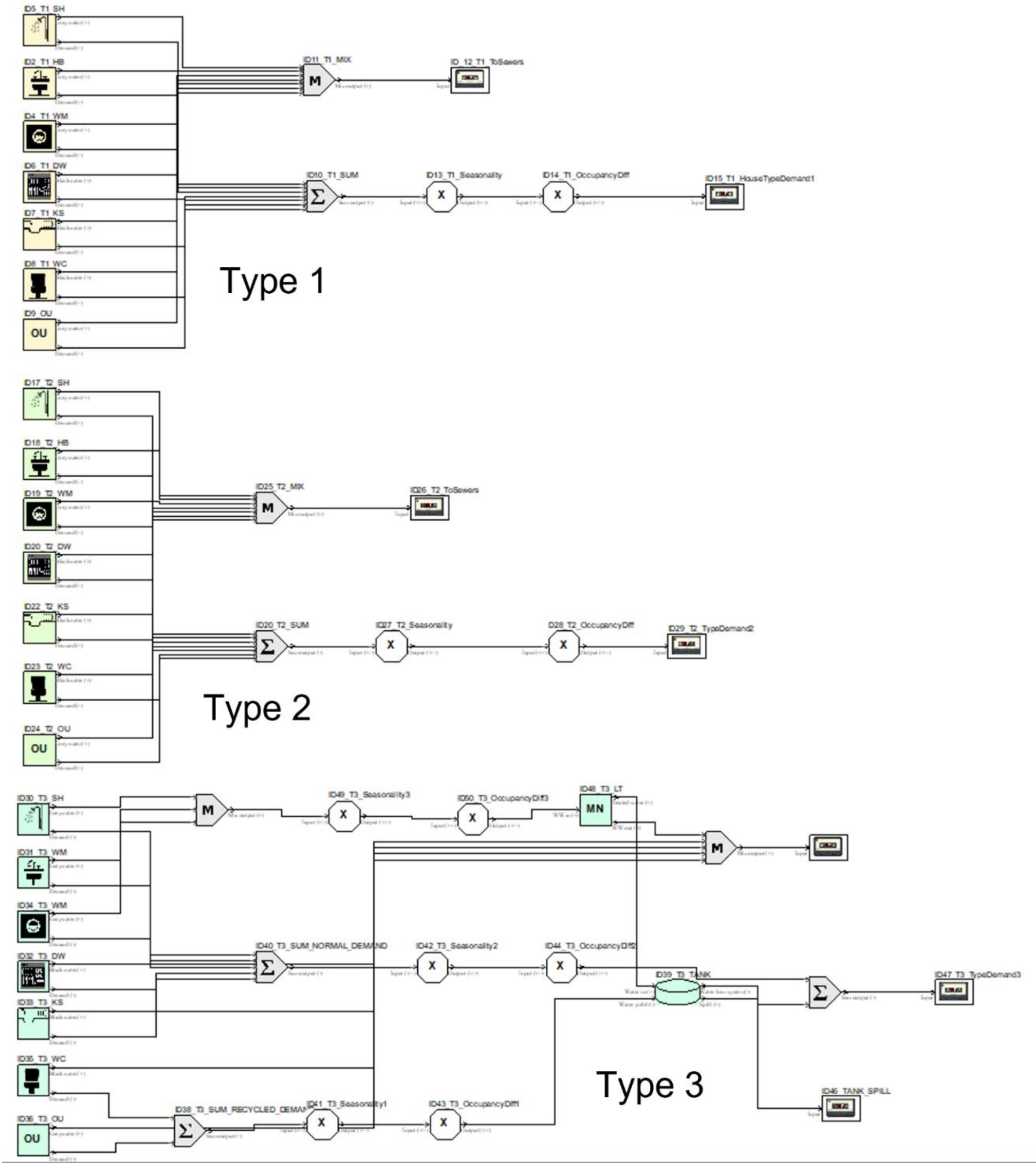

Figure 5. UWOT modeling of the three household types.

- Type 1: Common technological assets, including kitchen sink, hand basin, shower, toilet, washing machine, dishwasher, and a mix of other outside uses, generating a household demand of 606 l/d (263 l/d/pc);
- Type 2: Technological assets that conserve water, with higher efficiency, generating a household demand of 358.8 l/d (155.6 l/d/pc);
- Type 3: Technological assets that conserve water. Specifically, a local graywater recycling scheme and a storage tank, reducing the household demand to 274.6 l/d (107.6 l/d/pc).

Although any parameter in the UWOT model can change dynamically (e.g., the frequency of use for a specific component, seasonality of demands, component properties, etc.), here, we choose to vary only the occupancy of the household, emulating changes in demographics. By varying also the 'number of households' parameter in the WDN, we emulate the population growth within the UWS under study.

The external water supply system of the UWS is a simple set-up consisting of a main reservoir and a main aqueduct, transporting water to C-Town. This system covers the water production needs, and secondarily (i.e., at a second priority level), the green areas irrigation needs, as well as the industrial non-potable needs of the suburban areas. These needs are assumed equal to 2500 m^3/d. The set-up of the external water supply system is depicted in Figure 6. The main aqueduct has a maximum capacity of 1 m^3/s and a leakage coefficient of 5%, which can vary according to the scenario, denoting expenditures for maintenance from the water utility. The small reservoir is assumed to have a catchment of 13 km^2 and a net capacity of 6.93 hm^3. At the beginning of the simulation (initial condition), the reservoir is assumed as half-full. Furthermore, we generate synthetic realizations of daily runoff via *anySim* package on the basis of a benchmark timeseries of 25 years length, with a mean daily runoff of 2.13 mm.

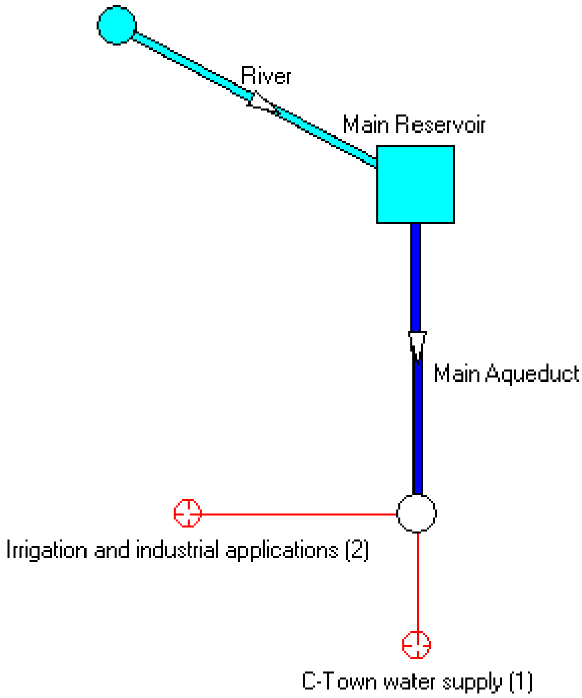

Figure 6. The water supply system of the UWS.

3.2. UWS Configurations and Scenarios

To showcase the source-to-tap stochastic resilience assessment framework, we stress-test two alternative configurations of the above-presented UWS, representing different management decisions and policy choices:

- Configuration 1: The baseline system (as described above);
- Configuration 2: The same topology, but with different policy and management decisions throughout the 25-year simulation period:
  - (i) Gradual change of household types from 100% Type 1 to 65%, 35%, and 5% of Types 1, 2, and 3 respectively by the end of the simulation. This scenario represents the case where incentives are given to consumers, through subsidization in water pricing, to alter their technological assets in households.
  - (ii) Leakage coefficient at the main aqueduct is steady at 2% throughout the system's lifespan. This is a scenario where the water utility allocates increased budget for the replacement of parts and repairs.

These scenarios represent future world views and each have their own set of parameters and stochastic variables. Specifically, we focus on the following key parameters, which are modified among scenarios:

1. The average occupancy of household types in *UWOT*;
2. The average percentage of change in the number of households in *EPANET*;
3. The other non-potable uses of the external water supply system in *Hydronomeas*;
4. The river runoff of the external water supply system in Hydronomeas.

Parameters 1–3 are treated as alternative (deterministic) projections, while Parameter 4 is treated as a stochastic variable, and a batch of 100 realizations is generated for each scenario. Specifically, for each configuration, Parameters 1–3 are differentiated according to the following three scenario narratives:

1. Scenario 1 (SC1): Generally, high income allows families to grow (occupancy +10%) and young adults to move to new housing estate (+5% new households). New job opportunities are unfolded, allowing the industrial zone to steadily grow (+10% non-potable water use).
2. Scenario 2 (SC2): Immigration waves, due to ongoing crises and urbanization, leads to population increase (occupancy increase equal to +10% and +25% increase in new households). Additionally, lower-cost labor results in fast growth of the industrial zone (+200% non-potable water use).
3. Scenario 3 (SC3): Extreme urbanization and urban growth imposes a population surge in cities (occupancy increase equal to +10% and +50% increase in new households). Additionally, the production model shifts toward services, with non-potable uses remaining unchanged.

For each of the above scenarios (for Parameters 1–3), four alternative river runoff ensembles are examined. Specifically, we assume shifts in the average runoff of 0%, −5%, −10%, and −15% over 25 years, to account for climatic fluctuations. Thus, in total, 12 future world views are formulated, in addition to the base scenario (no changes). The label that corresponds to each future view, in the analysis presented in the next section, declares the scenario narrative (e.g., SC1) and the runoff scenario (i.e., from 1 up to 4). For example, scenario narrative 2 with a −15% decrease in average runoff is noted as "SC2.4".

4. Results

The results for each of the two configurations examined are presented in Tables 1 and 2, respectively. The hydraulic daily reliability of the WDN subsystem (abbreviated as "WDN rel." in the tables below) is expressed as the percentage of days where hydraulic supply meets demand (within a threshold of 1%). The hydrologic daily reliability of the external water supply (abbreviated as "WS rel.") is expressed as the percentage of days where the water allocation of the water supply system meets the targeted production needs of the WDN, and the median from 100 stochastic realizations is calculated. Note that the production needs may be lower than actual demand, as the WDN may fail hydraulically. The UWS median reliability metric (abbreviated as "UWS Median Rel.") is expressed as percentage of days where neither a hydraulic nor a hydrologic failure occurred and is calculated from the 100 realizations/combinations. Confidence intervals of 95% and 5% are also calculated.

The results in Tables 1 and 2 show that both configurations are reliable (99.98% versus 100% reliability) for the base scenario. A marginal improvement in the performance was gained by the gradual transition to more efficient water appliances (i.e., Configuration 2). In addition, the median performance of WS reliability is identical and equal to 100% in two configurations, masking the effect of lower water losses (due to maintenance) in Configuration 2. Hence, the median performance of both configurations in terms of total UWS reliability is excellent. However, with a closer inspection of the confidence intervals, it becomes apparent that the uncertainty range of Configuration 1 is larger than Configuration 2, with 89.6% UWS reliability versus 93.47%, at the confidence interval 5%.

Table 1. Scenario analysis for Configuration 1.

Scenario	WDN Rel.	WS Rel.	UWS Median Rel.	UWS 95% Rel.	UWS 5% Rel.
Base	99.98%	100.00%	99.98%	99.98%	89.60%
SC1.1	99.91%	96.47%	98.95%	99.91%	84.24%
SC1.2	99.91%	96.59%	98.05%	99.91%	84.13%
SC1.3	99.91%	95.25%	95.17%	99.91%	79.96%
SC1.4	99.91%	93.34%	93.26%	99.91%	75.05%
SC2.1	93.13%	85.21%	79.72%	91.45%	60.37%
SC2.2	93.13%	83.85%	78.48%	89.18%	59.40%
SC2.3	93.13%	80.02%	74.97%	87.36%	55.88%
SC2.4	93.13%	75.60%	70.89%	83.46%	51.86%
SC3.1	56.75%	91.59%	54.06%	56.55%	44.41%
SC3.2	56.75%	90.38%	53.89%	56.55%	43.36%
SC3.3	56.75%	89.74%	53.08%	56.55%	41.85%
SC3.4	56.75%	89.01%	51.71%	56.54%	39.01%

Table 2. Scenario analysis for Configuration 2.

Scenario	WDN Rel.	WS Rel.	UWS Median Rel.	UWS 95% Rel.	UWS 5% Rel.
Base	100.00%	100.00%	100.00%	100.00%	93.47%
SC1.1	99.97%	100.00%	99.97%	99.97%	91.08%
SC1.2	99.97%	100.00%	99.97%	99.97%	89.51%
SC1.3	99.97%	99.44%	99.44%	99.97%	86.54%
SC1.4	99.97%	98.58%	98.55%	99.97%	83.66%
SC2.1	99.23%	93.78%	93.68%	99.90%	73.04%
SC2.2	99.23%	91.05%	90.95%	99.12%	69.85%
SC2.3	99.23%	87.92%	87.82%	97.37%	66.66%
SC2.4	99.23%	84.09%	83.99%	94.97%	62.40%
SC3.1	92.36%	98.09%	90.77%	92.13%	75.73%
SC3.2	92.36%	96.77%	89.27%	92.13%	74.67%
SC3.3	92.36%	95.00%	87.53%	92.13%	70.62%
SC3.4	92.36%	92.55%	85.65%	91.53%	67.42%

The same trend continues to the group of Scenario 1, which is the milder of the three in terms of stress. Although the difference in performance is not marginal anymore between the two configurations, in terms of median (from 1.02 up to 5.26%), the performance of Configuration 1 can be considered acceptable up to SC1.3 (daily UWS reliability higher than 95%). However, the performance gap becomes apparent at the 5% confidence interval with a difference up to 8.61%. In Configuration 1, despite the system being able to cover the demand hydraulically, the increased water production needs, along with the greater losses in the external water supply system, led to a greater range of uncertainty.

In the Scenario 2 group, the increased water demand in Configuration 1 leads to some disruptions in service in the WDN, as signified by the drop in WDN reliability (i.e., 93.13%). On the contrary, the performance of Configuration 2 remains excellent, higher than 99%. In the water supply domain, Configuration 2 fares better than Configuration 1, being able to withstand and absorb more disturbance. It is evident that the 200% increased non-potable demands in this group of scenarios is over the median WS capacity limit to deliver its objective reliably for both configurations. Interestingly, for Configuration 2, the group of Scenario 2 is more stressful than the group of Scenario 3.

The WDN subsystem is significantly stressed in the case of Configuration 1 and for the scenarios of the Scenario 3 group. The increased demand cannot be reliably delivered hydraulically to consumers and leads to frequent failures, as WDN reliability drops to 56.75%, dragging the UWS's reliability to low. The water availability is comparably high and can meet the production needs, since the latter ones are lower than the actual demand. On the other hand, Configuration 2 manages to absorb the disturbance and operate with some failures, at 92.36%. The better performance regarding water losses in the WS leads to better performance than Configuration 1 with respect to the median WS reliability. In Configuration 1, production needs are also higher, because they are at the limit of the WDN capacity.

The resilience profile graphs for both configurations are presented in Figure 7. The uncertainty bands stemming from the 5% and 95% CIs are illustrated. The resilience scores for 5%, 50%, and 95% CIs are summarized in Table 3. The graph suggests that overall, Configuration 2 is more reliable. Especially, for the upper bounds, Configuration 2 is close to an ideal system with a score of 0.969 and maintains a wide performance gap in the median and lower bounds. Interestingly, in the group of Scenario 2, while the median reliability curves differ significantly, due to uncertainty, there exist overlapping areas where the performance of both configurations is comparable, but with different probability. As shown, in the 95% CI, Configuration 1 is performing similarly to the median of Configuration 2, while in the 5% CI, Configuration 2 performs worse that the median of Configuration 1. On the contrary, in the group of Scenario 3, there is no overlap of the CIs, signifying the distinctive advantage of Configuration 2, under more extreme stress. This result is also indicative for the added value of the improvements in terms of uncertainty quantification made in this work to the original resilience assessment methodology. By quantifying uncertainty as an integral part of the assessment of the scenarios, a more informed and nuanced decision making is possible.

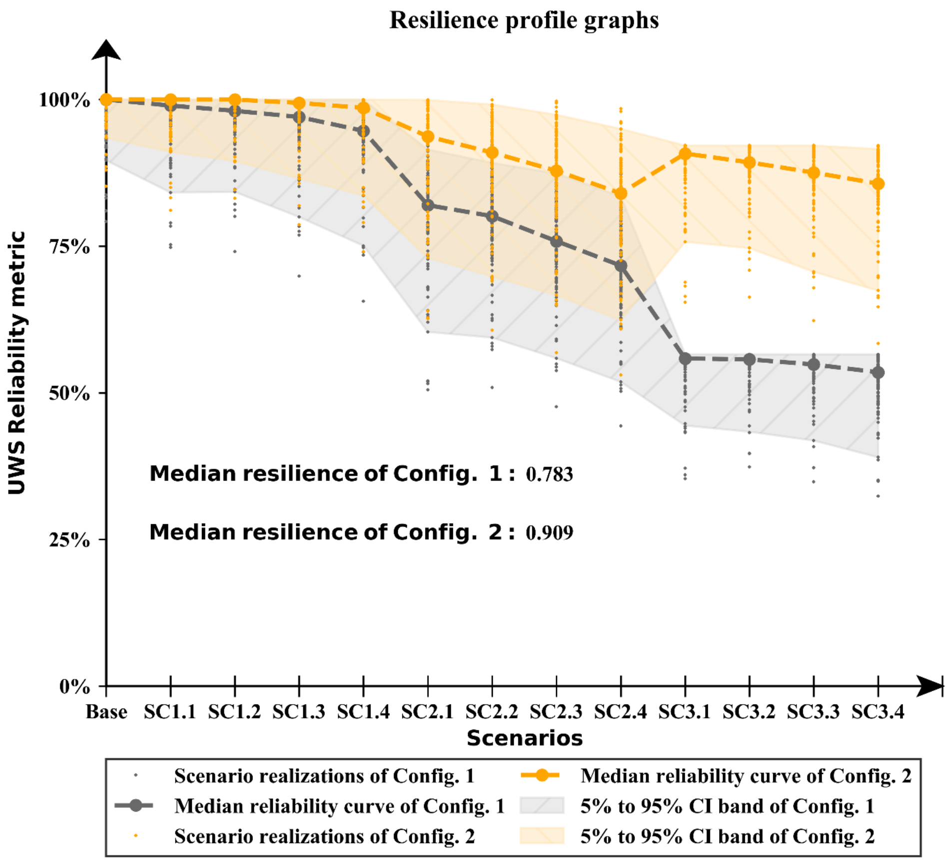

Figure 7. Resilience profile graphs with highlighted uncertainty bands.

Table 3. Resilience scores for Configurations 1 and 2.

Confidence Interval	Configuration 1	Configuration 2
95%	0.829	0.969
50% (median)	0.789	0.909
5%	0.622	0.773

5. Discussion and Conclusions

In this work, we proposed and demonstrated an uncertainty-aware source-to-tap simulation framework that employs a modeling chain that can capture the complex behavior of interdependent subsystems in UWSs. The framework allows us to assess the performance of subsystems independently but also aggregate performance in terms of system-wide resilience. The synthesized case study presented here is a simplified example, but it is not less complex than small real-world systems. The tools employed in the simulation can handle real-world systems and have been implemented for such purposes independently. As such, the stress-testing framework is applicable and transferable to real-world cases, being flexible to account for any type of scenario developed, in collaboration with stakeholders in any of the interdependent subsystems that comprise a UWS. The coupling of different modeling tools into an integrated stress-testing environment can highlight cascading effects and assist in the exploration of conditions that are not straightforward to imagine, even for experienced system planners or operators. Thus, it can enhance strategic planning and decision making of water utilities under deep uncertainty. For real-world uses, scenarios can be comprised of more variables to explore a greater range of uncertainty sources. Beyond water supply and distribution, the stress-testing framework is expandable (equipped with the appropriate subsystem models) to strategic planning for sewer and storm-water collection systems. The same approach can also be applied to shorter periods (i.e., within a tactical or operational context), to estimate resilience in scenarios dealing with medium-term uncertainty, e.g., during economic crises, pandemics, droughts, etc. to test system configuration changes or management decisions against ensembles of rapidly changing parameters and variables. The framework, as presented here, tackles long-term uncertainty and estimates in a probabilistic manner regarding the resilience of the complete water system. To this end, fidelity can be improved by examining a larger number of scenarios both in terms of different types and stochastic synthetic realizations. However, it should be noted that the formulation of scenarios is entirely speculative and up to the modeler. Scenarios do not represent forecasts in any way, and there can be no standardized way to formulate them to be representative of all future conditions. That would be in contrast with the concept of resilience [16]. Rather, these are used as evidence-based comparisons between different topologies, installed technologies, design philosophies, policy, and management decisions. The power of the approach lies in the provision of standardized, evidence-based, uncertainty-aware comparisons between complex decisions in a format (resilience graphs) that is easily communicated to decision makers.

We argue that in the volatile, ever-changing landscape that affects the water sector which increasingly incorporates new technologies (e.g., digitalization of assets and services, cyber-physical systems), along with the growing complexity of UWSs, such a stress-testing resilience-based approach has a key role to play toward the improvement of our understanding of how water systems behave when faced with unknown and (to a large extent) unknowable stresses.

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