UNIVERSITAT POLITÈCNICA DE VALÈNCIA

NRW-Smart: a simulation-based tool for the management of Non-Revenue Water in urban and rural water supply systems using mathematical models

Doctorate program in Water Engineering and Environment. Water Networks research team.

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A la meua família, per cada Km lluny i cada hora absent, resumits en aquesta tesi

Al dret de totes les persones de disposar d'aigua suficient i de qualitat

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Acronym	Meaning
AI	Artificial Intelligence
NRW	Non-Revenue Water
API	Application Programming Interface
CMI	Change Management Index
CRIDA	Climate Risk Informed Decision Analysis
DMA	District Metered Area
GHG	Greenhouse Gas
GIS	Geographic Information System
IWA	International Water Association
MIS	Management Information System
MNF	Minimum Night Flow
O&M	Operation and Maintenance
PRV	Pressure Reducing Valve
PV	Photovoltaic
PV-GIS	Photovoltaic Geographical Information System
SCADA	Supervisory Control and Data Acquisition
SDG	Sustainable Development Goal
SISAR	Sistema Integrado de Saneamento Rural (Brazil)
VSD	Variable Speed Drive
vDMA	Virtual District Metered Area

Acronym	Meaning
VBA	Visual Basic for Applications
WNTR	Water Network Tool for Resilience
WS	Water Smart
WSNA	Water Smart Network Analysis
WSNO	Water Smart Network Optimization
WSRO	Water Smart Resilient Operation

AGRAÏMENTS-AGRADECIMIENTOS-ACKNOWLEDGMENTS-AGRADECIMENTOS-მადლობის სიტყვა

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RESUM

Aquesta tesi presenta el disseny, la implementació i la validació de *Water Smart (WS)*, una eina d'ajuda a la decisió basada en simulacions, desenvolupada per donar suport a empreses subministradores d'aigua petites i mitjanes en la reducció de l'aigua no registrada (Non-Revenue Water, NRW) i la millora de l'eficiència operativa, especialment en entorns amb escassetat de dades i recursos. La plataforma WS integra models hidràulics, anàlisi espacial mitjançant SIG i algoritmes d'optimització modular per ajudar els gestors de serveis d'aigua a diagnosticar el rendiment del sistema, planificar intervencions i avaluar estratègies rendibles per reduir les pèrdues d'aigua i augmentar la resiliència climàtica.

L'estudi s'ha basat en aplicacions reals en tres entorns contrastats: Batumi i Khelvachauri (Geòrgia), Varzea da Cobra (Brasil) i PDAM Sleman (Jakarta, Indonèsia). Cada cas demostra com els mòduls de WS —inclosos *Water Smart Network Administration (WSNA)*, *Water Smart Network Optimization (WSNO)* i components complementaris com la recuperació de pressió, el bombeig amb energia solar fotovoltaica i les avaluacions de vulnerabilitat climàtica amb CRIDA— poden adaptar-se a les necessitats i condicions locals. Les simulacions realitzades amb WSNO van mostrar millores significatives en el rendiment, incloent-hi l'estabilització de pressió, la reducció de fuites, l'estalvi energètic i el suport a la planificació d'inversions. A Jakarta, la integració de CRIDA amb WNTR i la simulació energètica solar va posar de manifest la capacitat de WS per alinear les operacions amb els Objectius de Desenvolupament Sostenible (ODS) 6, 7 i 13.

Una anàlisi comparativa amb altres plataformes de gestió intel·ligent de l'aigua a escala global indica que WS és especialment adequat per a empreses de països en desenvolupament, on el coneixement tècnic, el finançament i la disponibilitat de dades poden ser limitats. L'arquitectura modular i la funcionalitat fora de línia de la plataforma permeten una adopció progressiva i una sostenibilitat a llarg termini. A més, la incorporació de l'índex de gestió del canvi (CMI) proporciona un marc per avaluar la preparació institucional i seguir el progrés al llarg del temps.

Els resultats posen de manifest el valor de WS com a eina flexible, accessible i replicable per a la transformació digital del sector de l'aigua. La seva capacitat per generar coneixement tècnic, econòmic i orientat a la resiliència la converteix en un mecanisme de suport efectiu tant per a l'operació diària com per a la planificació estratègica a llarg termini. L'estudi conclou amb recomanacions per a millores futures, incloent-hi la detecció de fuites basada en IA, la integració amb sistemes de telemetria en temps real i la recopilació automàtica de dades per a anàlisis de viabilitat energètica.

En última instància, aquesta recerca aporta una solució provada i escalable a un dels reptes globals més urgents en el sector de l'aigua: la gestió de pèrdues i l'optimització dels serveis hídrics en el marc de les empreses d'abastiment d'aigua de mida petita i mitjana, especialment en països en desenvolupament.

En resum, aquesta tesi contribueix al coneixement científic i tècnic mitjançant la introducció d'un conjunt d'innovacions provades: (1) una metodologia de simulació de fuites dependents de la pressió adaptada a EPANET, (2) un algoritme d'optimització assistit per intel·ligència artificial per al control de pressió i el dimensionament de canonades, (3) una rutina de suport a la decisió basada en Python per a la gestió de fuites en xarxes rurals, i (4) la integració d'un sistema de priorització basat en SIG i d'un índex de resiliència climàtica dins d'una eina modular. Cadascun d'aquests avenços ha estat validat en casos d'estudi reals, demostrant el seu potencial per reduir pèrdues, millorar la fiabilitat del servei i enfortir la presa de decisions en empreses subministradores d'aigua amb capacitat i dades limitades. Aquestes contribucions aborden directament els reptes essencials en la gestió de l'Aigua No Facturada (ANF) en contextos en desenvolupament i representen un pas escalable cap al disseny de sistemes d'aigua intel·ligents.

RESUMEN

Esta tesis presenta el diseño, la implementación y la validación de *Water Smart (WS)*, una herramienta de apoyo a la toma de decisiones basada en simulación, desarrollada para asistir a pequeñas y medianas empresas de agua en la reducción del agua no contabilizada (Non-Revenue Water, NRW) y en la mejora de la eficiencia operativa, especialmente en contextos con limitaciones de datos y recursos. La plataforma WS integra modelación hidráulica, análisis espacial basado en SIG y algoritmos modulares de optimización, para ayudar a los gestores de servicios a diagnosticar el rendimiento del sistema, planificar intervenciones y evaluar estrategias costo-efectivas orientadas a la reducción de pérdidas y a la resiliencia climática.

El estudio se basa en aplicaciones reales en tres entornos contrastantes: Batumi y Khelvachauri (Georgia), Várzea da Cobra (Brasil) y PDAM Sleman (Yakarta, Indonesia). Cada caso demuestra cómo los módulos de WS —incluidos *Water Smart Network Administration (WSNA)*, *Water Smart Network Optimization (WSNO)* y componentes complementarios como la recuperación de presión, el bombeo con energía solar fotovoltaica y las evaluaciones de vulnerabilidad climática con CRIDA— pueden adaptarse a las necesidades y restricciones locales. Las simulaciones realizadas con WSNO evidenciaron mejoras significativas en el rendimiento, tales como estabilización de presiones, reducción de fugas, ahorro energético y soporte a la planificación de inversiones. En Yakarta, la integración de CRIDA con WNTR y la simulación solar demostraron la capacidad de WS para alinear la operación de las utilidades con los Objetivos de Desarrollo Sostenible (ODS) 6, 7 y 13.

Un análisis comparativo con plataformas globales de gestión inteligente del agua reveló que WS es especialmente adecuado para contextos en países en desarrollo, donde la disponibilidad técnica, financiera y de datos puede ser limitada. Su arquitectura modular y funcionamiento sin conexión permiten una adopción progresiva y sostenibilidad a largo plazo. Además, la inclusión del Índice de Gestión del Cambio (CMI) proporciona un marco para evaluar la preparación institucional y monitorear avances a lo largo del tiempo.

Los resultados destacan el valor de WS como una herramienta flexible, accesible y replicable para la transformación digital del sector del agua. Su capacidad para generar conocimientos técnicos, económicos y de resiliencia la convierte en un mecanismo de apoyo efectivo tanto para la operación diaria como para la planificación estratégica a largo plazo. El estudio concluye con recomendaciones para su mejora futura, incluyendo detección de fugas con inteligencia artificial, integración con sistemas de telemetría en tiempo real y recolección automatizada de datos para análisis de viabilidad energética.

En definitiva, esta investigación aporta una solución comprobada y escalable a uno de los retos globales más urgentes del sector hídrico: la gestión de pérdidas y la optimización del servicio de agua en el contexto de pequeñas y medianas empresas públicas de abastecimiento de agua, particularmente en países en vías de desarrollo.

En resumen, esta tesis contribuye al conocimiento científico y técnico mediante la introducción de un conjunto de innovaciones validadas: (1) una metodología de simulación de fugas dependientes de la presión adaptada a EPANET, (2) un algoritmo de optimización asistido por inteligencia artificial para el control de presión y la selección de diámetros de tuberías, (3) una rutina de soporte a la decisión basada en Python para la gestión de fugas en redes rurales, y (4) la integración de un sistema de priorización geoespacial y evaluación de resiliencia climática dentro de una herramienta modular. Cada uno de estos avances ha sido validado en estudios de caso reales, demostrando su potencial para reducir pérdidas, mejorar la fiabilidad del servicio y fortalecer la toma de decisiones en compañías de abastecimiento de agua con recursos y datos limitados. Estas contribuciones abordan directamente los desafíos fundamentales de la gestión del Agua No Facturada (ANF) en contextos en desarrollo y representan un paso escalable hacia el diseño de sistemas de agua inteligentes.

ABSTRACT

This dissertation presents the design, implementation, and validation of Water Smart (WS), a simulation-based decision-support tool developed to assist small and mid-sized water utilities in reducing Non-Revenue Water (NRW) and improving operational efficiency, particularly in data-scarce and resource-constrained environments. The WS platform integrates hydraulic modeling, GIS-based spatial analysis, and modular optimization algorithms to support utility managers in diagnosing system performance, planning interventions, and evaluating cost-effective strategies for water loss reduction and climate resilience.

The study is grounded in real-world applications in three contrasting environments: Batumi and Khelvachauri (Georgia), Varzea da Cobra (Brazil), and PDAM Sleman (Jakarta, Indonesia). Each case demonstrates how WS modules—including Water Smart Network Administration (WSNA), Water Smart Network Optimization (WSNO), and complementary components such as pressure recovery, solar PV pumping, and climate vulnerability assessments using CRIDA—can be adapted to local needs and constraints. Simulations conducted through WSNO showed measurable performance improvements, including pressure stabilization, leak reduction, energy savings, and support for investment planning. In Jakarta, the integration of CRIDA with WNTR and solar energy simulation showcased WS's capacity to align utility operations with SDGs 6, 7, and 13.

A comparative analysis with global smart water management platforms revealed that WS is uniquely suited for utilities in developing countries, where technical expertise, funding, and data availability may be limited. The platform's modular architecture and offline functionality enable incremental adoption and long-term sustainability. Moreover, the inclusion of the Change Management Index (CMI) provides a framework for evaluating institutional readiness and tracking progress over time.

The results highlight WS's value as a flexible, accessible, and replicable tool for digital transformation in the water sector. Its capacity to generate technical, economic, and resilience-oriented insights makes it an effective support mechanism not only for daily utility operations but also for long-term strategic planning. The study concludes with recommendations for future enhancements, including AI-driven leak detection, integration with real-time telemetry systems, and automated data retrieval for energy feasibility analyses.

Ultimately, this research contributes a tested, scalable solution to one of the most pressing global water challenges: managing losses and optimizing water services in the framework of small and mid-size water utilities, specifically in developing countries.

In summary, this dissertation contributes to scientific and engineering knowledge by introducing a set of tested innovations: (1) a pressure-dependent leakage simulation methodology adapted to EPANET, (2) an AI-assisted optimization algorithm for pressure control and pipe sizing, (3) a Python-based decision-support routine for rural leakage management, and (4) the integration of GIS-based prioritization and climate resilience scoring into a modular tool testing. Each of these advancements has been validated in real-world case studies, demonstrating their potential to reduce leakage, improve service reliability, and enhance decision-making in utilities with limited data and capacity. These contributions directly address the core challenges of NRW management in developing contexts and represent a scalable step forward in smart water system design.

1 CHAPTER 1: INTRODUCTION

1.1 Motivation

This thesis results from research over several years of technical support to public drinking water supply companies in developing and transitional countries.

Within the cooperation framework in hydraulic infrastructure projects funded by the German Development Bank (KfW), a decision-support tool has been progressively developed in collaboration with Macs Energy and Water to assist water utility managers in making informed decisions.

One of the main challenges small and medium-sized utilities face in developing areas is the lack of specialized technical expertise. As a result, external consultancy support is often required whenever a cooperation project is launched to modernize public water companies.

Therefore, a key objective in any rehabilitation or modernization project for hydraulic infrastructure funded through international cooperation is transferring knowledge and technology to utility personnel by consultants provided by the financing agencies.

The original idea for the development of the Macs Water Smart emerged while elaborating the mathematical model for Batumi Tskali, the public water utility of Batumi, Georgia. This project started from scratch, intending to create a hydraulic model capable of verifying the design of new infrastructure through various simulations across different scenarios, including controlling non-revenue water as one of the main milestones. The process of building and calibrating the model was used as a training framework for utility staff, introducing strategies for non-revenue water reduction and control.

The author presented the results in the final dissertation of the master's degree in Hydraulic Engineering and the Environment, entitled "NRW Mathematical Model as a Tool for the Establishment of Water Losses Management in Water Utilities in Developing Areas. Applying in Batumi Water Utility (Batumi, Georgia)."

In conclusion, the research conducted across multiple projects of a similar nature in different countries has led to the development of the application presented in this thesis. Its development is ongoing, with the addition of specific modules aimed at supporting the management of small and medium-sized water utilities, which will be presented as case studies.

1.2 Background

Managing urban and rural water supply systems in developing countries presents persistent challenges, particularly regarding infrastructure ageing, limited technical capacity, and high levels of water losses. Non-revenue water (NRW)—the difference between the volume of water delivered into the system and the volume billed (defined in section 1.6)—has emerged as a crucial performance indicator in assessing service efficiency and financial sustainability. The control and reduction of NRW are especially critical in contexts where resources are scarce, and utility operations are fragile.

This thesis is rooted in a broader trajectory of research and technical assistance in the water sector, developed over several years of collaboration with public utilities in transitional and developing countries. Two key reference experiences have strongly influenced the development of the proposed decision-support tool: the long-term rehabilitation program of the Batumi water system in Georgia and the Brazilian SISAR model (Sistema Integrado de Saneamento Rural), a pioneering approach to rural water supply management. These projects represent complementary perspectives—one urban, the other rural—and jointly serve as the conceptual foundation for the Water Smart tool proposed in this research.

Urban Reference Model: Infrastructure Rehabilitation in Batumi

Since 2007, the German Development Bank (KfW), in partnership with Batumi City Hall and the municipal utility Batumi Tskali (BTS), has implemented a phased investment program to rehabilitate and modernise the city's water supply infrastructure. Throughout five phases, the program has pursued a dual objective: to ensure sustainable, demand-driven water services and to build long-term institutional capacity through planning tools, staff training, and performance-based management systems.

Key interventions have included expanding water production and treatment capacity, renewing extensive pipeline networks, and implementing District Metered Areas (DMAs) for monitoring and controlling water losses. A Management Information System (MIS) has been introduced to support decision-making, integrating hydraulic modelling, telemetry, and billing data.

In water distribution systems, a District Metered Area (DMA) is a discrete and permanently defined area of the network, usually bounded by closed valves and monitored through a flow meter at its inlet. This configuration allows water utilities to continuously measure inflow and, when possible, night flow, in order to estimate water losses and detect anomalies. DMAs are a cornerstone of modern Non-Revenue Water (NRW) management strategies, enabling better pressure control, quicker leak detection, and more efficient allocation of resources. Their implementation transforms large, complex networks into manageable subsections, making both hydraulic modeling and operational decision-making more reliable.

A central technical milestone was developing a detailed EPANET-based hydraulic model, which has served both for design verification and operational simulations. This model allows scenario analysis, including pressure management, leak detection, and demand forecasting. It has also supported NRW monitoring and control, temporarily reducing NRW from 85% to around 25% in rehabilitated areas. However, operational challenges like metering failures, infrastructure degradation, and service disruptions persist.

The hydraulic model plays a crucial role in designing the network sectorization and defining District Metered Areas (DMAs). As previously discussed, DMAs facilitate pressure management, leak detection, and operational planning by dividing the system into manageable zones. However, physical DMAs present limitations, particularly in rapidly growing urban areas, where fixed boundaries and rigid flow paths may lead to inefficiencies, hydraulic imbalances, or reduced service quality during peak demand.

To address these constraints, utilities are increasingly adopting virtual DMAs (vDMAs)—dynamically defined zones based on real-time telemetry, pressure patterns, or consumption behavior. Unlike physical DMAs, vDMAs enable flexible monitoring and analysis without requiring physical isolation, allowing for better adaptation to changing infrastructure and demand conditions. Their implementation relies on advanced data integration, hydraulic modeling, and decision-support systems, often supported by GIS and AI-based tools.

In this context, Phase V of the Batumi program initiated the transition to vDMAs, using smart meters, real-time monitoring, and network analytics to segment the distribution system into digitally defined sectors. This strategy enhances continuous tracking of flow and pressure, overcomes the physical limitations of conventional DMAs, and offers improved flexibility, lower installation costs, and more accurate water balance estimation.

The vDMA approach is supported by GIS-integrated hydraulic simulations, which have been applied in expanding areas such as Khelvachauri—one of the case studies presented in this thesis. Furthermore, the digitalization strategy integrates customer data and smart metering into the Management Information System (MIS), improving billing accuracy, flow allocation, and leakage detection.

These innovations underpin the development of Water Smart, a modular decision-support platform designed to help small and medium-sized utilities simulate their systems, quantify losses, and prioritize interventions—even under limited technical capacity or infrastructure constraints.

Rural Reference Model: SISAR, Brazil

While the Batumi case illustrates the digital transformation of an urban water utility, the SISAR model offers a contrasting, yet equally relevant, perspective on sustainable water management in rural areas. Established in Ceará, Brazil, the *Sistema Integrado de Saneamento Rural* (SISAR) is a network of community-based associations responsible for operating and maintaining rural water and sanitation systems. It emphasizes decentralized management, community ownership, and long-term sustainability.

SISAR operates under a federated structure, with each community association managing its system while receiving technical, financial, and managerial support from a central coordinating body. As of 2024, SISAR operates in over 165 municipalities and serves over 900.000 people through approximately 1.240 water systems. Its success has been recognized nationally and internationally as a model for rural service provision.

The SISAR experience demonstrates that even low-resource environments can achieve sustainable service delivery with appropriate training, tools, and support. The model's emphasis on self-management, transparent financial planning, and performance tracking complements the more technology-intensive approach used in Batumi. Together, these models underscore the importance of flexible, context-sensitive solutions for water management.

Change Management Index

A key insight from both cases was the need to integrate technical strategies with institutional readiness. This led to the development of a Change Management Index (CMI), a cross-cutting assessment tool combining IWA-based technical indicators for NRW reduction with institutional capacity components. The CMI helped structure intervention planning, track progress, and support utility decision-makers in both contexts.

Synthesis

Both the Batumi and SISAR experiences converge on a shared insight: the effectiveness of water supply systems depends not only on infrastructure, but also on institutional capacity, monitoring tools, and decision-support mechanisms. Whether in a rapidly urbanizing environment or a dispersed rural setting, the need for data-driven management is critical.

The Water Smart tool proposed in this thesis seeks to bridge urban and rural worlds, centralized and community-managed, by offering a scalable, adaptable modelling and monitoring platform. The tool integrates hydraulic modelling (EPANET-based), NRW analysis, and modular dashboards to support utility managers in diagnosing system performance, estimating losses, and planning interventions. Its development has been directly informed by hands-on experience in Batumi and analytical reviews of the SISAR model.

This thesis, therefore, aims to contribute a practical, scalable, and transferable solution to one of the most persistent global challenges in the water sector: the effective management of Non-Revenue Water (NRW) in small and mid-sized utilities in developing areas. The decision to design the Water Smart platform stems from hands-on experiences gained in two contrasting but complementary cooperation frameworks: the urban case of Batumi (Georgia), where the focus was on mathematical modelling and network sectorization, and the rural context of Brazil, especially through the SISAR model, which emphasizes decentralized, community-based water management.

These practical experiences raise key research questions addressed in the present thesis:

- How can small and mid-sized utilities model, simulate, and manage their systems with limited data and staff?
- What are the most cost-effective and transferable strategies for reducing NRW in urban and rural environments?
- Can technical tools such as EPANET, GIS, and AI be integrated into a modular decision-support system for diverse operating contexts?

Water Smart is proposed as the answer to these questions. Its development has been directly shaped by the lessons learned in Batumi and Brazil and has resulted in a tool capable of helping utilities assess their systems, estimate water losses, and prioritize interventions even in resource-constrained environments. Figure 1 shows the conceptual framework of the Water Smart Platform, developed from the combined experiences of Batumi (urban) and SISAR (rural) case studies. The platform integrates two main modules: *WSNO* (Water Smart Network Optimization), including AI-assisted pressure recovery and control, and *WSNA* (Water Smart Network Administration), incorporating the IWA water balance. The Change Management Index (CMI) provides the transversal foundation for adaptation and evaluation.

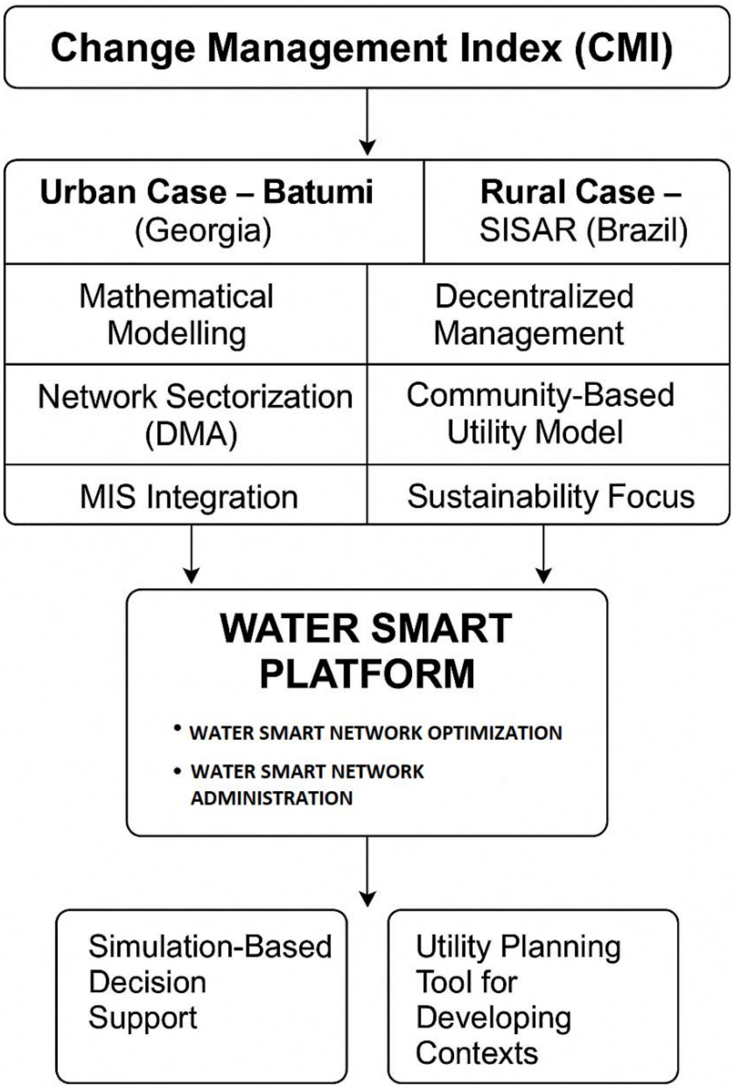


Figure 1: Conceptual framework of the Water Smart Platform

The motivation behind the development of the Water Smart platform is strongly linked to the author's extensive experience in supporting water utilities in low- and middle-income countries. Over the last decade, the author has been involved in multiple international cooperation projects focused on water loss control, pressure management, sectorisation, and institutional strengthening. This hands-on exposure to the challenges faced by small and mid-sized utilities—such as limited technical capacity, fragmented information systems, and high levels of non-revenue water—provided the foundation for designing practical, simulation-based tools tailored to real-world operational needs. The hydraulic modelling, technical structure, and decision-support logic developed in this thesis stem directly from these professional insights.

1.3 Thesis structure

Following the presentation of the research problem and motivation, this thesis systematically explores the fundamentals of water management, technological advancements in NRW control, and the development, validation, and implementation of the Water Smart tool.

This thesis is organized into four main chapters, each corresponding to a key stage in the development, implementation, and evaluation of the *Water Smart* (WS) tool for Non-Revenue Water (NRW) management. The structure is designed to guide the reader progressively from the research motivation and background to practical application, results, and conclusions. The chapters are as follows:

- **Chapter 1 – Introduction:**
  This chapter presents the motivation behind the study, provides the necessary background context, and defines the research problem. It includes an overview of global water infrastructure challenges, particularly in developing countries, and outlines the conceptual basis of the WS tool. The chapter also sets forth the research objectives and provides an extensive state-of-the-art review, covering NRW concepts, smart water technologies, modelling techniques, and implementation strategies.

- **Chapter 2 – Methodology:**
  This chapter details the research design and methodological framework used in the development of WS. It describes the mathematical models applied, including GIS-based hydraulic modelling, the Change Management Index (CMI), and the new programmed modules for energy efficiency and pressure control, assisted by artificial intelligence algorithms. It also presents the development process of the WS application, explaining its modular architecture, and outlines the case studies across Georgia, Brazil, and Indonesia.

- **Chapter 3 – Results:**
  The third chapter discusses the findings derived from the implementation of WS in the selected case studies. It includes model calibration results, comparative evaluations of NRW modelling approaches, and the impact of simulation-based interventions. The chapter also assesses the tool’s effectiveness, strengths, and weaknesses, and its potential for scalability and replicability in small and mid-sized utilities.

- **Chapter 4 – Discussion and Conclusion:**
  This final chapter interprets the research results within the broader context of water

management challenges and innovations. It outlines the practical implications of WS, reflects on its contributions to the field, and offers final recommendations for water utilities and policy-makers. The chapter concludes with suggestions for future improvements to the WS platform, including integration with AI, real-time telemetry, and automated data acquisition.

1.4 Problem statement

The effective management of water resources is increasingly critical as global demand rises and environmental challenges mount. Addressing issues such as Non-Revenue Water (NRW), infrastructure ageing, and the impacts of climate change forms the core focus of the subsequent discussions. With insights into the status of global water infrastructure, governance challenges, and innovative strategies, this section lays the groundwork for understanding the multifaceted nature of water management and its significance in fostering sustainable utilities. Each subchapter elucidates specific dimensions that contribute to optimising water systems in diverse contexts, guiding readers toward a comprehensive understanding of contemporary water management practices.

1.4.1 Global Water Infrastructure Status

Effective water management hinges on understanding the current state of global water infrastructure, as it reveals the multifaceted challenges utilities worldwide face. This section delves into the complexities surrounding infrastructure ageing, the prevalence of non-revenue water, and the impact of climate change, all of which significantly affect operational efficiency and service delivery. By analyzing these intertwined factors, the discussions will lay the groundwork for exploring innovative strategies to enhance sustainability in water distribution systems. These insights are essential for informing the subsequent exploration of non-revenue water management and the overarching goals of the work.

1.4.2 Current Challenges and Trends

Developing regions face significant challenges in water management due to high levels of Non-Revenue Water (NRW), which can reach up high percentages of the total system input volume. These losses undermine the financial and operational sustainability of water utilities, limiting their ability to invest in infrastructure expansions and improve service delivery to underserved populations. The economic burden imposed by such inefficiencies necessitates targeted strategies to address real and apparent losses. However, many utilities in developing areas lack the capacity and resources to undertake systematic water balance assessments, making it difficult to quantify losses accurately and prioritise interventions. The absence of accurate data collection methodologies hampers efforts to design effective NRW reduction initiatives tailored to the specific needs of these regions (Kingdom et al., 2006; Reddy et al., 2021).

The role of governance is critically significant in exacerbating NRW levels across many developing regions. Poor governance structures and pervasive corruption give rise to practices such as unauthorized consumption, water pilferage, and employee misconduct, which contribute to apparent losses and strain the operational capacity of water utilities. For instance, inadequate enforcement of regulations and oversight mechanisms enables unchecked practices that compromise equitable water distribution. Addressing these issues requires robust regulatory frameworks and the implementation of accountability mechanisms for utility staff. Such measures need to be complemented by community engagement to foster transparency and build trust between utilities and their customers, thereby reducing unaccounted-for water usage

Infrastructure inefficiencies further compound the challenge of managing NRW. Ageing pipelines, poorly maintained distribution networks, and outdated system design lead to significant real water losses. For example, in developing regions, an estimated 45 million cubic meters of water are lost daily due to infrastructural inefficiencies—a volume sufficient to meet the daily water needs of nearly 200 million people (Faber & Radakrishnan, 2023). The widespread reliance on inadequately maintained infrastructure disrupts water distribution and increases the risk of contamination, threatening public health. Inadequate investment in infrastructure rehabilitation worsens this issue, as deferred maintenance results in escalating repair costs and diminished returns on new investments. Therefore, targeted funding and technical assistance are essential to break the cycle of inefficiency and ensure sustainable water distribution systems

Developing countries' financial constraints significantly impede overcoming these infrastructural challenges. Limited access to funds and technical expertise prevents water utilities from undertaking large-scale system upgrades, perpetuating inefficiencies and water losses. International cooperation and knowledge-sharing initiatives can provide much-needed resources and expertise for developing areas. Public-private partnerships, in particular, can play a pivotal role in mobilizing investments and building local technical capacities. These collaborative approaches can help establish the groundwork for long-term improvements in water distribution networks and operational efficiency.

Climate change is another factor that exacerbates water infrastructure vulnerabilities in developing regions. Extreme weather events such as floods and droughts severely disrupt water distribution systems, contributing to higher levels of NRW through increased leakage and pipe damage. For instance, flooding often results in excessive water pressure within pipelines, which can cause ruptures and amplify leakage rates. Most water systems in developing areas are designed based on historical climatic data and are thus ill-suited to handle the variability and extremes associated with modern climate patterns. Integrating predictive models and adaptive designs into infrastructure planning is critical to enhancing climate-resilient water management. The incorporation of IoT sensors and real-time monitoring systems can also improve utilities' responsiveness to such disruptions (Ajami, 2023; Solanes et al., 2008).

Economic losses stemming from NRW in developing countries are staggering, with annual revenue losses exceeding USD 3 billion. These financial losses limit utilities' ability to invest in system upgrades and hinder efforts to expand water access to underserved communities. Reducing NRW by 50% could recover approximately USD 2.9 billion annually, enabling utilities to extend service coverage to an additional 90 million people. Such gains' potential economic and social benefits underscore the importance of prioritizing NRW reduction initiatives. Apparent losses, such as inaccuracies in metering and unauthorized water use, further exacerbate the financial strain on utilities. The lack of effective metering systems in many regions results in substantial revenue losses, weakening the financial base needed to support infrastructure improvements.

Technological advancements provide promising avenues for addressing NRW, particularly through the application of digital tools such as IoT-enabled sensors, smart meters, and real-time monitoring systems. These technologies facilitate the prompt identification of leaks and improve network efficiency. However, their high costs and the lack of technical expertise in developing regions limit their adoption. For small and mid-sized utilities, decentralized and cost-effective solutions, such as micro-scale sensors and cloud-based platforms, offer a viable entry point to adopting digital water technologies. International funding mechanisms and public-private partnerships are essential to subsidize these technologies and ensure their sustainable implementation in resource-constrained environments. Additionally, capacity-building programs aimed at equipping utility staff with the skills needed to operate and maintain digital systems are critical to their success.

Significant disparities exist in NRW performance globally, highlighting the need for region-specific interventions. While developed countries achieve NRW level lower due to advanced metering, maintenance, and governance systems, the global average remains at 30%. Developing nations often lack the regulatory frameworks required to enforce efficient water management practices. Establishing national benchmarks for NRW and incentivising utilities to adopt best practices are necessary to narrow the gap between regions. Furthermore, fostering local innovation and adapting solutions to the constraints of low-resource environments can enable the development of tailored, sustainable water management systems.

Reducing NRW in developing regions is a multifaceted challenge requiring coordinated efforts across governance, infrastructure, technology, and financial domains. Adopting integrated approaches that address these interrelated factors is essential to enhancing the sustainability and reliability of water systems. By leveraging international cooperation, technological innovation, and local capacity-building, it is possible to improve water distribution efficiency and contribute to the long-term alleviation of water scarcity.

1.4.3 Infrastructure Aging and Maintenance

Aging water infrastructure is a critical factor contributing to water loss in distribution systems, with deteriorating pipelines and inadequate maintenance practices being the primary causes of physical leakages. These physical leakages form a significant component of Non-Revenue Water (NRW), posing environmental and economic challenges for water utilities. Globally, over 32 billion cubic meters of treated water are lost annually due to physical water losses, highlighting the direct link between aging infrastructure and declining system reliability and operational efficiency (Kingdom et al., 2006).

In developing regions, the challenges presented by aging pipelines and insufficient maintenance are particularly severe, with daily water losses amounting to approximately 45 million cubic meters or over USD 3 billion in financial losses annually (Faber & Radakrishnan, 2023). This economic burden significantly hinders the ability of utilities to deliver reliable services, repair existing infrastructure, or expand systems to accommodate underserved populations. Addressing these issues necessitates a comprehensive strategy that includes targeted investment, capacity-building initiatives, and the adoption of innovative technologies. These approaches prevent financial drain and create opportunities to redirect resources toward improving service coverage and equity in water distribution.

The extended lifespan of deteriorating water infrastructure adds another layer of complexity to this issue. In resource-rich regions, such as the United States, the longevity of water supply systems requires substantial annual investments—ranging from $11.6 billion to $20.1 billion—to maintain their reliability and functionality (Savic, 2005). This emphasizes the magnitude of infrastructure-related challenges, and the situation is even more dire for developing regions, where the financial and technical resources necessary to maintain aging systems are far more constrained. Thus, the long-term financial and operational pressures associated with aging infrastructure remain a universal challenge requiring international collaboration and scalable solutions tailored to the context of each region.

Delayed or inadequate maintenance exacerbates the problem of physical water losses by increasing the likelihood of system failures, such as pipe bursts and joint leaks. Neglecting infrastructure maintenance not only accelerates system deterioration but also places significant strain on utility budgets due to the higher costs of emergency repairs. A clear example of this is the case of Batumi (Georgia), where the water supply infrastructure—dating from the Soviet era—had experienced decades of neglect and mismanagement, resulting in widespread deterioration and extremely high NRW levels prior to rehabilitation efforts. Proactive maintenance strategies have been proven effective in reducing water losses, particularly when combined with advanced monitoring tools. Utilities equipped with Internet of Things (IoT)-enabled sensors and other technologies can identify emerging issues early and implement targeted interventions to minimize disruptions (Reddy et al., 2021).

However, such tools' high costs and technical complexity often make them inaccessible to utilities operating in low-resource settings, perpetuating a cycle of inefficiency and water loss. Effective maintenance practices are essential to alleviating inefficiencies caused by aging infrastructure. These include regular inspections, timely repairs, and using hydraulic modelling to optimize system performance. Advanced technologies such as real-time monitoring systems have demonstrated significant potential in streamlining maintenance operations by providing data-driven insights. IoT-enabled sensors, for instance, are capable of monitoring pressure variations, detecting irregularities in pipeline performance, and alerting utilities to potential failures before they escalate (Faber & Radakrishnan, 2023).

Integrating such technologies into maintenance practices could drastically improve water utility efficiency, even though initial investment and expertise requirements remain substantial barriers for many developing regions. The unequal distribution of resources between developed and developing countries highlights the difficulties associated with aging water infrastructure. While wealthier nations allocate substantial funding each year to maintain and upgrade their distribution networks—successfully keeping NRW levels low—many developing countries face significantly higher water losses as a result of limited financial means and a lack of technical expertise to sustain their systems.

One noteworthy example is the city of València (Spain), where the water utility has reduced NRW by over 30% through the use of a digital twin system developed by Global Omnium in collaboration with the Polytechnic University of Valencia. This innovation enabled real-time monitoring, improved operational decision-making, and ultimately saved more than a billion gallons of water annually (Xylem, 2023). The case illustrates how digitalization and AI-based tools can significantly enhance water efficiency, even in well-developed systems.

Recent studies confirm the persistence of high Non-Revenue Water (NRW) levels in the three countries explored as case studies in this thesis. In Georgia, the national NRW rate exceeds 70% in most utilities, with values of 67% in Tbilisi (GWP) and even higher in secondary cities (World Bank, 2024). In the city of Batumi, NRW was initially estimated at 85%, and was temporarily reduced to around 25% in rehabilitated zones following pressure management and sectorization strategies developed during Phase III of the investment program. In Brazil, national averages hover around 38% (World Bank, 2021), though NRW levels in SISAR systems typically ranged between 35% and 45%, with some rural areas exceeding 50% before targeted improvements were introduced in partnership with CAGECE, aiming to reduce losses below 30%. In Indonesia, the average NRW for local utilities (PDAMs) is approximately 33%, though specific cases like PDAM Sleman, in the Special Region of Yogyakarta, reported pre-intervention values above 50% due to lack of flow measurement, leakage detection tools, and pressure control. These figures illustrate the structural challenges faced by small and mid-sized utilities in developing regions, and reinforce the relevance of tailored digital solutions to reduce NRW and improve operational performance.

These disparities underscore the urgent need for sustained financial assistance from international donors and the development of cost-effective and scalable solutions to improve water infrastructure in low-resource environments. Poor maintenance and aging infrastructure exacerbate water management challenges in regions like India, where growing demand and limited resources strain existing water systems. With a national average NRW of 38%—nearly double the global benchmark value of 20% achieved by well-performing utilities—India faces severe water losses that threaten both service reliability and resource sustainability. Projections indicate that India's water demand will likely double by 2030, underscoring the critical importance of addressing infrastructure inefficiencies. Failure to act will undoubtedly result in further deterioration of water availability and system reliability, jeopardizing the well-being of millions.

In summary, addressing water losses caused by aging infrastructure and poor maintenance requires an integrated approach that combines proactive strategies, innovative technologies, and equitable resource allocation. Recognizing the immense economic, environmental, and social implications of inefficiencies in water distribution systems is a fundamental step toward sustainable water management.

1.4.4 Climate Change Impact

Climate change poses significant challenges to water infrastructure by amplifying the frequency and intensity of extreme weather events, leading to disruptions in water distribution systems and exacerbating existing inefficiencies. Floods, for example, can inflict extensive damage on pipelines, causing increased physical losses, while droughts intensify stress on distribution networks by reducing water availability and increasing operational pressures. Such events underline the urgent necessity for adaptive management strategies that account for these vulnerabilities. Research highlights the critical role of integrating predictive models and advanced materials in mitigating these risks, yet significant gaps remain in the practical implementation of these measures, particularly in resource-constrained regions (Hurford et al., 2017; Faber & Radakrishnan, 2023).

The damage to infrastructure caused by extreme climate events contributes directly to the escalation of Non-Revenue Water (NRW). Floods often overwhelm distribution systems, leading to pipeline failures, while severe droughts necessitate heightened system pressures to sustain supply, increasing the likelihood of leaks and pipe bursts. Addressing these issues requires the use of climate-resilient materials and designs in infrastructure to minimize damage and ensure functionality under adverse conditions. Nevertheless, the adoption of such measures remains limited, partly due to financial and technical constraints in many developing regions. This highlights the importance of fostering international collaboration and knowledge-sharing to support the implementation of adaptive designs.

Conventional water infrastructure, often designed based on historical climate data, is increasingly ill-suited to address the variability introduced by climate change. This disconnect significantly reduces system reliability and exposes vulnerabilities to climate-induced disruptions. For instance, many urban areas are frequently unable to cope with unexpected flood loads, leading to collapses that exacerbate water losses and compromise public health.

The integration of predictive climate models into the planning and design phases of infrastructure can provide actionable insights for building systems capable of withstanding changing climatic patterns. However, limited access to these predictive tools in developing regions underscores the need for scalable and accessible models tailored to resource-constrained environments.

Enhanced planning and management practices are essential to mitigate the risks posed by climate change to water systems. Techniques such as adjustable pressure controls and dynamic flow systems can be incorporated to respond effectively to varying demand or pressure conditions, reducing the likelihood of pipeline failures. Predictive modeling tools that simulate hydrological impacts under diverse climatic scenarios can further guide proactive measures and improve system resilience. Despite these advancements, their integration into existing systems often encounters resistance due to high initial costs and the need for technical expertise, particularly in regions where capacity-building initiatives are insufficient (Ajami, 2023).

The traditional once-through water infrastructure model, coupled with fragmented governance systems, significantly hampers the ability of utilities to respond to environmental and economic stressors exacerbated by climate change. Transitioning to interconnected and flexible systems—featuring redundancies, decentralized storage, and adaptive reuse capabilities—is crucial for enhancing resilience. For example, integrating water reuse systems that process wastewater for non-potable applications has proven effective in regions like California. However, the widespread adoption of these systems requires overcoming policy inertia and fostering cross-sectoral collaboration to enable holistic water management.

Governance reforms are fundamental to addressing the siloed management approaches that currently limit the effectiveness of climate-resilient strategies. Strengthened interdepartmental coordination and integrated water resource management frameworks are critical for tackling the multifaceted impacts of climate variability on water systems. Global case studies illustrate that cohesive strategies—blending policy improvements, technical upgrades, and community engagement—yield better outcomes than fragmented efforts. While the importance of such frameworks is widely acknowledged, the practical challenges of implementing them in regions with limited institutional capacities remain a significant barrier.

Climate-induced pressures, such as extreme weather or sudden demand fluctuations, exacerbate real water losses caused by leaks in aging infrastructure. Studies indicate that a 10% increase in pressure corresponds to a proportional rise in leakage, underscoring the critical need for pressure management tools to mitigate these impacts. Variable pressure controllers, for instance, can effectively reduce the strain on distribution networks during extreme events, minimizing resultant damages. However, the adoption of such technologies is hindered in low-resource settings by cost and technical barriers, emphasizing the need for tailored, low-cost solutions.

Unexpected pressure surges associated with floods or droughts can trigger cascading failures in vulnerable segments of water distribution networks. The deployment of IoT-enabled sensors capable of measuring real-time pressure anomalies offers a promising solution. These systems can identify at-risk zones and enable utilities to implement preemptive interventions, thereby reducing the risk of catastrophic failures and associated water losses. However, despite the evident benefits, the adoption of IoT technologies in many developing regions is limited by financial constraints and the lack of skilled staff to manage and interpret complex data systems.

The ability to detect leaks proactively, especially under high-pressure conditions, can significantly reduce vulnerabilities in water systems exposed to climate variability. Predictive data analytics combined with advanced leak detection technologies facilitates early intervention, thereby maintaining system functionality during extreme events. Utilities equipped with these technologies have reported lower operational losses and reduced downtime, demonstrating their potential to improve overall resilience. Despite this, financial and capacity-related challenges continue to restrict the application of these systems in regions most affected by climate change.

Increasing climate variability necessitates the integration of advanced digital technologies, such as IoT sensors and real-time monitoring systems, to dynamically adapt operations and monitor system health. These technologies provide continuous feedback on critical parameters like flow patterns, pressure fluctuations, and leak detections, enabling utilities to implement data-driven responses to emerging challenges. However, achieving widespread adoption requires addressing significant barriers related to initial investment, technical expertise, and long-term sustainability, particularly in underfunded and technologically underserved areas.

Smart systems capable of predicting and mitigating disruptions caused by extreme weather events offer considerable potential to enhance utility performance. For instance, IoT sensors deployed in high-risk areas can provide early warnings of impending system overflows or leaks, enabling swift and targeted corrective measures. By minimizing response times and enhancing operational efficiency, such technologies address some of the key challenges posed by climate-induced variability. Nevertheless, the implementation of these solutions remains uneven, with developing regions often lagging due to infrastructural and logistical limitations.

The use of advanced simulation models that analyze steady flow distribution and operational controls in complex systems is becoming increasingly essential for climate-resilient water management. These models simulate system responses to varying pressures and flow dynamics, providing utilities with actionable insights for better risk management and infrastructure planning. However, the accuracy and utility of such models depend heavily on the availability of high-quality input data, which remains a significant limitation in many under-resourced regions.

Simulation tools that evaluate water distribution performance under extreme scenarios allow utilities to prioritize interventions in high-risk areas. For example, assessing the functionality of pumping stations during floods can inform the deployment of climate-adaptive modifications. Such predictive capacities not only enhance system resilience but also contribute to more strategic allocation of resources. The challenge remains, however, to develop accessible simulation tools that are both cost-effective and adaptable to diverse regional conditions.

Climate-resilient water management increasingly depends on the integration of adaptive data inputs and advanced simulation technologies. By incorporating dynamic algorithms derived from simulations, utilities can balance supply and demand under stress conditions and reduce NRW losses. This approach combines field observations with computational models to generate tailored solutions, addressing both immediate operational challenges and long-term sustainability goals. The ongoing challenge is to ensure that such technologies are scalable and inclusive, emphasizing their relevance to regions disproportionately affected by climate change (Dyadun et al., 2022).

1.5 Research objectives

This research seeks to answer the overarching question: "How can the Water Smart simulation-based tool effectively assist water utility managers in developing areas, and what are the implications for scalability and replicability in small and mid-sized water utilities?" To achieve this, the study integrates methodologies from hydraulic engineering, computational modelling, and advanced data analytics. The findings not only contribute to the technical discourse on water resource management but also propose practical strategies that can be implemented at scale, emphasizing economic feasibility and infrastructure resilience.

The following key research questions guide the thesis:

1. How can hydraulic modelling tools be adapted to quantify and manage Non-Revenue Water in partially metered and evolving water supply networks?
2. What are the comparative strengths and weaknesses of different NRW modelling approaches regarding accuracy, data requirements, and operational relevance?
3. To what extent can simulation-based tools support utility managers in prioritizing water loss interventions and justifying investments?
4. What lessons can be drawn from the study cases transferable to other utilities in low- and middle-income countries?

Summarizing, the main research objectives aim:

- To develop *Water Smart*, a simulation-based decision-support tool for the management of Non-Revenue Water (NRW) in data-scarce water supply systems.
- To evaluate the tool's effectiveness in supporting utility managers with prioritization of NRW interventions.
- To identify transferable methodologies and insights that support the replication of *Water Smart* in small and mid-sized utilities across developing regions.

1.6 State of the art

1.6.1 Understanding Non-Revenue Water (NRW)

The challenges posed by Non-Revenue Water (NRW) are critical to the sustainability and efficiency of water management systems worldwide. By exploring the components and classifications of NRW, along with its economic implications and assessment methods, this section sheds light on the complexities surrounding water losses in developing regions. Understanding these factors is essential for devising targeted strategies to enhance operational performance and resource allocation, ultimately contributing to improved service delivery and equity in water access. As the narrative progresses, it will guide readers through the intricacies of managing NRW in the context of contemporary water utilities and their operational frameworks.

In order to properly define Non-Revenue Water (NRW), it is essential to refer to the standard water audit methodology developed by the International Water Association (IWA), which was first published in 2000 and remains the global reference for NRW classification. This methodology structures the water balance in a detailed and hierarchical way, distinguishing between authorized consumption, apparent losses, and real losses. Table 1 presents the IWA standard water balance, commonly used in water audits worldwide.

Table 1: IWA Standard Water Balance

Component	**Subcomponents**	**Description**
System Input Volume		Total volume of water entering the distribution system.
Authorized Consumption	- Billed Metered Consumption- Billed Unmetered Consumption- Unbilled Metered Consumption- Unbilled Unmetered Consumption	Legitimate consumption, whether measured or not, and whether billed or not.
Billed Authorized Consumption	- Billed Metered- Billed Unmetered	Water delivered to customers and invoiced.
Unbilled Authorized Consumption	- Unbilled Metered- Unbilled Unmetered	Water consumed without charge, e.g. firefighting, municipal use.
Water Losses		The difference between System Input Volume and Authorized Consumption.
Apparent Losses	- Unauthorized Consumption- Customer Metering Inaccuracies	Non-physical losses caused by meter errors, data handling, or illegal use.
Real Losses	- Leakage in Mains- Leakage in Storage Tanks- Leakage in Service Connections	Physical water losses due to leakage before the customer meter.
Non-Revenue Water (NRW)	= Unbilled Authorized Consumption + Apparent Losses + Real Losses	Volume of water that does not generate revenue for the utility.

1.6.1.1 Components and Classifications

Non-Revenue Water (NRW) is a critical issue for water management, particularly in developing regions where it can represent a significant portion of the total water input volume. NRW is generally divided into two main categories: *real losses* and *apparent losses*. Real losses refer to physical leakages from the distribution system, such as from pipes and joints, typically caused by aging infrastructure, inadequate maintenance, and operational issues like pressure fluctuations. Apparent losses include non-physical inefficiencies such as unauthorized consumption, inaccurate metering, and billing errors. This classification enables utilities to design specific strategies that address the dominant types of losses affecting their systems.

Real losses are caused by physical damage to infrastructure, including pipe deterioration, faulty joints, and overflows. In many developing countries, these losses are worsened by aging assets and the absence of preventive maintenance. Estimates suggest that approximately 45 million cubic meters of water are lost daily due to these issues, with annual financial losses surpassing USD 3 billion (Kingdom et al., 2006). Moreover, high system pressure—particularly when unregulated—can further increase leakage rates, as documented by several studies (Faber & Radakrishnan, 2023). Tackling these losses requires regular inspections, timely repairs, and the adoption of real-time monitoring through hydraulic modeling and Internet of Things (IoT)-enabled sensors. Nevertheless, many small utilities struggle to implement such technologies due to limited technical expertise and funding, highlighting the need for scalable and affordable solutions.

Apparent losses arise from administrative and metering issues, such as illegal connections, theft, and meter inaccuracies. In some regions, unauthorized water use results in daily losses of up to 30 million cubic meters (Kingdom et al., 2006). Inaccurate metering is also widespread—studies in areas like Doka district found significant measurement errors in over half of the sampled cases (Ajoge et al., 2021). Additional administrative problems, including billing mistakes and unrecorded usage, further amplify apparent losses. Solutions include investment in reliable metering infrastructure, digital billing systems, and stricter enforcement mechanisms. However, implementing these measures often requires operational restructuring and institutional strengthening—two major barriers in resource-constrained environments.

To quantify NRW and identify its components, utilities use the *water balance framework* endorsed by the International Water Association (IWA). This method classifies losses into real, apparent, and unbilled authorized consumption categories, enabling systematic tracking and comparison (Liemberger & Farley, 2000). However, data limitations frequently undermine the accuracy of this framework, especially in utilities where measurement systems are underdeveloped or non-existent (Farley, 2003). To improve data quality, utilities are increasingly adopting IoT-based monitoring and Geographic Information Systems (GIS) to track flow, pressure, and anomalies in real time. Integrating these technologies into the water balance provides a stronger analytical foundation for prioritizing interventions and monitoring outcomes (Faber & Radakrishnan, 2023).

The proportions of real and apparent losses vary significantly between developed and developing regions. In lower-income contexts, apparent losses tend to dominate due to weak regulation, meter failure, and institutional inefficiencies (Ajoge et al., 2021). In contrast, utilities in high-income countries often maintain NRW levels below 15% thanks to regular maintenance, accurate metering, and data-driven management practices (Kingdom et al., 2006). Bridging this gap requires targeted investments in infrastructure, institutional capacity, and technology transfer mechanisms.

The economic consequences of NRW are substantial. It is estimated that water losses cost utilities globally about USD 141 billion per year, with developing countries accounting for roughly one-third of this figure (Ajoge et al., 2021). These losses hinder investment in infrastructure upgrades and operational improvements. If developing countries could reduce their NRW by half, they could recover an additional USD 2.9 billion annually, potentially extending water services to millions (Kingdom et al., 2006). Furthermore, the water currently lost daily in these regions could supply nearly 200 million people. Innovations such as digital leak detection and real-time system monitoring have already shown success in helping utilities improve financial sustainability and reduce inefficiencies (Faber & Radakrishnan, 2023).

In summary, addressing NRW requires a holistic approach that combines technical innovation, institutional reform, and human capacity development. While real and apparent losses have different origins, they are often interrelated and must be addressed together to ensure long-term water service sustainability. The continued development and deployment of tailored tools and management strategies remain key to meeting this challenge in developing regions.

In alignment with global best practices, the International Water Association (IWA) has established a comprehensive methodology for classifying and managing both real and apparent losses. These are addressed through four principal technical strategies: pressure management, active leakage control (ALC), speed and quality of repairs, and pipeline and asset management (Lambert & Hirner, 2000). Additionally, the IWA Water Loss Task Force has developed important benchmarking tools, including the Unavoidable Annual Real Losses (UARL) and the Economic Level of Leakage (ELL), which guide utilities in setting realistic leakage reduction targets based on technical and economic conditions (Liemberger & Farley, 2004). The Infrastructure Leakage Index (ILI), defined as the ratio between current real losses and the UARL, provides a standardized performance indicator to assess the efficiency of leakage control efforts across different systems (Farley & Trow, 2003). Several of these principles are already integrated within the Water Smart approach, particularly through modules focused on pressure-dependent leakage simulation, pressure zoning, and prioritization algorithms. These tools enable utilities—especially in low-resource settings—to implement IWA-aligned strategies such as ALC and pressure management, but in a scalable, data-efficient manner adapted to their specific context.

1.6.1.2 Economic implications

Non-Revenue Water (NRW) has significant financial implications for water utilities, directly affecting both operational sustainability and long-term service delivery. Globally, the economic losses attributed to NRW are estimated at approximately USD 141 billion annually (Ajoge et al., 2021). These losses result from both real losses, such as physical leakages, and apparent losses, including billing inaccuracies and unauthorized consumption. Such inefficiencies divert critical operational funds away from infrastructure maintenance and expansion, creating a vicious cycle in which utilities lacking financial capacity cannot invest in performance improvements—thereby perpetuating inefficiencies. Prioritizing NRW management is thus essential for reinforcing the financial and operational resilience of water utilities.

Developing countries are particularly vulnerable to these dynamics, accounting for roughly one-third of global NRW-related losses—an estimated USD 47 billion each year (Kingdom et al., 2006). Utilities in these contexts often operate under tight financial constraints, which limits their ability to undertake infrastructure upgrades or expand coverage. The economic strain is compounded by limited capacity to meet the rising demand for water, especially among underserved populations. Addressing this dual challenge requires targeted strategies that simultaneously reduce NRW and strengthen financial stability.

The inability to recover revenue from unbilled water or theft further weakens the operational resilience of utilities, preventing them from reinvesting in essential maintenance or modernization efforts. This leads to a reinforcing loop of infrastructure deterioration and increasing water losses. Technical interventions must be accompanied by robust financial planning and governance reform to break this cycle and restore long-term sustainability.

One of the most critical economic consequences of NRW is the loss of treated water. Over 32 billion cubic meters of treated water are lost annually due to inadequate infrastructure maintenance (Kingdom et al., 2006). This not only wastes investment in water treatment but also creates environmental and social costs, such as strain on source water availability and reduced supply for paying customers. Efficient use of treated water requires both infrastructure integrity and operational optimization.

In many developing countries, approximately 45 million cubic meters of water are lost every day to NRW, translating into over USD 3 billion in annual financial losses (Faber & Radakrishnan, 2023). This water could otherwise support expanded coverage in regions facing severe scarcity. Additionally, poor performance on NRW can undermine access to external financing, as donor support and concessional loans are often contingent upon operational efficiency. Therefore, improving NRW management can enhance utility credibility and unlock investment opportunities for network expansion.

India provides a concrete example of the economic burden caused by high NRW. With a national average of 38%, significantly above the global average, utilities face persistent financial losses that hinder their capacity to respond to growing water demand—expected to double by 2030 (Reddy et al., 2021). These inefficiencies present a structural barrier to achieving water security and underline the importance of proactive NRW reduction strategies.

Apparent losses, particularly those arising from poor metering, are a major contributor to revenue loss in developing countries. In areas such as Doka district, studies have shown that less than half of customers had functioning or accurate meters, leading to substantial billing errors and unauthorized consumption (Ajoge et al., 2021). The absence of reliable metering infrastructure not only limits cost recovery but also undermines consumer trust. Investments in advanced metering systems are essential for improving water accounting, revenue collection, and financial transparency.

The financial benefits of improving NRW performance are considerable. Halving water losses in developing regions could recover approximately USD 2.9 billion annually (Kingdom et al., 2006). These resources could be reinvested into infrastructure rehabilitation, service expansion, and technological upgrades—particularly in underserved areas. Effective NRW management can therefore accelerate progress toward equitable and sustainable water service provision.

Strategies aimed at enhancing financial recovery through NRW control often include deploying improved leak detection technologies, upgrading metering accuracy, and engaging consumers through awareness programs (Ajoge et al., 2021). These interventions not only reduce direct financial losses but also improve customer relations, which are key to long-term revenue stability. Moreover, the integration of digital tools for real-time network monitoring can substantially lower operational costs and improve system performance.

Globally, the economic burden of NRW has also been estimated at USD 39 billion annually, further demonstrating the scale of inefficiencies in water distribution, particularly in developing countries where NRW often exceeds 30% (Reddy et al., 2021). Focused interventions addressing both real and apparent losses can help free up financial resources for reinvestment and modernization, contributing to operational sustainability.

Additional economic inefficiencies stem from energy use in pumping systems. It is estimated that energy and maintenance costs represent up to 70–80% of a pump’s life-cycle costs. Monitoring and optimizing pump performance has been shown to reduce energy expenditures by up to 9.5%, while also extending asset longevity (Bhattacharya, 2023). Though often overlooked, energy efficiency represents a valuable area for NRW-related cost savings.

In regions with widespread metering inaccuracies, such as Doka, where only 26–50% of meters were found to be error-free (Ajoge et al., 2021), the resulting revenue loss severely hampers utility finances. Upgrading metering infrastructure is essential for accurate billing, improved cost recovery, and stronger customer engagement. Addressing these challenges requires coordinated investment in technology and institutional capacity-building.

In conclusion, effective NRW management can yield substantial economic gains. Beyond recovering lost revenue, it enables utilities to improve service delivery, expand coverage, and build trust with consumers. By strategically reinvesting savings into infrastructure and operations, utilities can break cycles of inefficiency and move toward long-term financial and operational sustainability.

1.6.1.3 Assessment methods

The assessment of Non-Revenue Water (NRW) is a fundamental process in water management, beginning with a comprehensive water balance analysis. This method systematically quantifies water across various domains—including production, import, export, consumption, and losses—allowing utilities to identify inefficiencies and categorize them as real or apparent losses. Such categorization is critical for designing targeted interventions. The IWA Water Balance framework has become internationally recognized for this purpose, offering a structured approach to classify losses such as unauthorized consumption and metering inaccuracies, which affect both operational performance and financial stability (Farley, 2003). However, the method’s effectiveness is often compromised in contexts with weak data collection systems, highlighting the need for capacity-building to improve data quality and consistency.

The reliability of water audits depends heavily on the accuracy of input data. Inaccurate measurements can distort the water balance, leading to flawed diagnostics and misinformed decisions. This challenge underscores the importance of using calibrated flow meters and other dependable instruments. High-quality data is especially critical in developing countries, where daily losses of up to 45 million cubic meters are reported due to infrastructure deficiencies and operational inefficiencies (Kingdom et al., 2006). Similar challenges are also observed in high-income countries with aging infrastructure. For instance, the United States experiences approximately 240,000 water main breaks each year, resulting in daily losses of nearly six billion gallons of treated water (Volk, 2018). These scenarios point to the urgent need for modern infrastructure management and technological upgrades to improve the accuracy and utility of water audits.

By disaggregating NRW through the water balance framework, utilities can distinguish between various inefficiency types and allocate resources more strategically. Apparent losses such as theft or metering inaccuracies require investments in reliable metering and control systems, while real losses call for leak detection technologies and network rehabilitation (Farley, 2003). Despite the conceptual robustness of this approach, its implementation varies widely depending on the availability of resources. While well-funded utilities can tailor interventions to their system’s specific needs, those in low-resource environments may find it difficult to carry out even basic components of the methodology, creating a gap between theoretical best practices and field-level applicability.

Advanced technologies have significantly improved the precision and operational efficiency of NRW assessments. IoT-enabled sensors allow real-time monitoring of flow, pressure, and other key variables, enabling quicker identification of leaks and unauthorized consumption. Automation reduces reliance on manual inspections and improves overall system diagnostics (Faber & Radakrishnan, 2023). Nonetheless, the widespread adoption of such technologies in developing regions is hindered by high costs and limited technical expertise, raising equity concerns about access to cutting-edge water management tools.

In many developing countries, water audits have exposed critical inefficiencies—losses large enough to meet the daily needs of nearly 200 million people (Kingdom et al., 2006). Financially, these losses amount to more than USD 3 billion annually (Faber & Radakrishnan, 2023). A lack of system monitoring and poor maintenance practices contribute heavily to these losses. For example, in Doka district, fewer than half of the customers have functional meters, enabling widespread unauthorized consumption (Ajoge et al., 2021). These figures underscore the need for focused assessments and interventions that address the most critical deficiencies in water systems.

The wide disparity in NRW rates between high-income and developing countries illustrates the scale of systemic inefficiencies. Developed regions typically maintain NRW rates below 15%, supported by robust infrastructure and effective governance, whereas developing countries often exceed 35% (Kingdom et al., 2006). Bridging this gap requires both the transfer of technological know-how and tailored capacity-building strategies. International collaboration and financial support are key to ensuring that proven methodologies can be adapted and scaled in low-resource settings.

While the IWA Water Balance is a valuable framework, its successful application depends on the availability of accurate data. In areas with outdated or non-functional meters, often less than half of users are properly metered, complicating efforts to control unauthorized consumption or billing errors (Kingdom et al., 2006). In high-income countries, different challenges persist, such as aging pipe infrastructure and frequent system failures (Volk, 2018). These diverse realities underscore the need to combine standardized methodologies with flexible, context-specific solutions.

Robust auditing frameworks not only support internal management decisions but also enhance transparency and accountability toward external stakeholders. Utilities that conduct regular, credible water audits are better positioned to align with national policy goals and secure external funding. However, achieving such transparency remains difficult in settings with weak institutional structures or limited auditing capacity. Aligning with globally recognized standards is therefore essential to strengthening governance and trust.

Advanced technologies, including IoT systems and GIS integration, are revolutionizing how utilities conduct NRW assessments. These systems provide real-time data on network conditions and can pinpoint geographic areas of inefficiency (Faber & Radakrishnan, 2023). However, their implementation remains uneven, as many utilities lack the funding and trained personnel needed to operationalize such tools. Bridging this technological divide calls for multi-level interventions, including public-private partnerships, donor support, and local capacity development.

Accurate metering remains a cornerstone of effective NRW management. In regions such as Doka, where fewer than 50% of meters are functional (Ajoge et al., 2021), the inability to measure water consumption accurately leads to substantial revenue loss and weakened operational control. Smart metering technologies offer real-time usage data and early detection of irregularities like tampering or leakage (Farley, 2003). Despite their benefits, these systems are often unaffordable for utilities with limited budgets. Research and investment into scalable, cost-effective metering options could improve access and support better NRW control in underserved areas.

In conclusion, comprehensive NRW assessments are indispensable to improving efficiency in water utilities, particularly in developing contexts. The integration of globally recognized frameworks like the IWA Water Balance with modern technologies has shown strong potential to reduce losses and improve utility performance. However, technical solutions alone are insufficient; successful implementation also requires institutional commitment, financial investment, and ongoing capacity-building. Combining international best practices with locally tailored strategies will be essential to achieving long-term, sustainable improvements in water management.

1.6.2 Case Studies of NRW Management in Developing Areas

1.6.2.1 Successful NRW Reduction Strategies

- **Phnom Penh, Cambodia**
  The Phnom Penh Water Supply Authority (PPWSA) achieved a significant reduction in Non-Revenue Water (NRW) from over 70% in 1993 to below 10% by 2023. This success was attributed to comprehensive measures including infrastructure investments, staff capacity building, and strategic planning (Biswas et al., 2021).
- **Manila, Philippines**
  Manila Water reduced NRW from 63% in 1997 to 12.69% in 2022, surpassing the World Bank's benchmark of 25%. Key strategies included network reconfiguration, active leakage control, pressure management, and meter management programs (Aquatech,

2023).

- **Dhaka, Bangladesh**

  The Dhaka Water Supply and Sewerage Authority (DWASA) implemented projects aimed at improving the water supply system to be more reliable and sustainable. Efforts included reducing NRW from 40%–50% to 2%–14% in commissioned District Metered Areas (DMAs), enhancing metering and bill collection, and improving operational efficiency (Asian Development Bank, 2023).

1.6.2.2 Lessons Learned and Key Challenges

- **Comprehensive Approach:** Effective NRW reduction requires addressing both physical losses (leaks) and commercial losses (illegal connections, billing errors) through integrated strategies (Ogata et al., 2023).

- **Institutional Commitment:** Strong leadership and political will are essential for implementing reforms and securing necessary investments. Utilities like PPWSA and Manila Water have demonstrated the importance of dedicated institutional support (Biswas et al., 2021; Aquatech, 2023).

- **Community Engagement:** Building trust with consumers through transparent communication and involving them in the process enhances cooperation and compliance, leading to successful NRW reduction (Ogata et al., 2023).

- **Sustained Effort:** NRW reduction is a long-term endeavor requiring continuous monitoring, regular maintenance, and adaptation to emerging challenges. The experiences of PPWSA and Manila Water highlight the need for ongoing commitment (Biswas et al., 2021; Aquatech, 2023).

1.6.3 Smart Water Management: Concepts and Technologies

As demand for efficient water management grows, the integration of digital technologies has become critical in reshaping utility operations. This section explores key advancements—ranging from IoT-enabled sensors and real-time monitoring to data analytics and artificial intelligence (AI)—that support smart water management. These innovations are particularly relevant for improving operational performance and reducing Non-Revenue Water (NRW), especially in small and mid-sized utilities with limited resources. Their alignment with the objectives of this thesis is clear: enhancing the capacity of under-resourced utilities through adaptable, data-driven decision-support tools such as the Water Smart platform.

Digital Transformation in Water Utilities

Digital transformation enables utilities to increase operational efficiency, reduce energy use, and improve service delivery. Studies have reported reductions of over 7% in operating costs, 3% in NRW, and 12% in capital expenditures with the adoption of smart water systems (Jenny et al., 2020). These improvements free up resources for infrastructure expansion and maintenance.

A central component of this transformation is the use of Internet-of-Things (IoT) devices, such as pressure sensors, flow meters, and smart meters. These tools provide real-time monitoring of the distribution system, supporting early detection of leaks, pressure anomalies, and unauthorized consumption (Drexler & Ahmadpour, 2022). Platforms like DECIDE and WISDom show how sensor data can be integrated to enable burst detection, pressure optimization, and predictive maintenance (Carriço et al., 2023). However, the implementation of such systems remains limited in developing regions due to budget constraints and technical gaps.

AI and machine learning enhance decision-making by forecasting demand, optimizing pressure zones, and anticipating system failures (Faber & Radakrishnan, 2023). Still, these technologies depend on high-quality, continuous data streams—often a limitation in small utilities. The Water Smart platform addresses this gap by integrating simplified AI modules that function with limited but reliable inputs, improving accessibility in constrained environments.

IoT and Sensor Technologies

IoT systems form the foundation of smart water networks by enabling real-time visibility into infrastructure performance. These systems support leak detection, flow monitoring, and energy optimization. Case studies in utilities serving fewer than 25,000 people show that IoT deployments can cost under $15 per capita over several years, making them viable even for smaller systems (Jenny et al., 2020). Adaptations to rural contexts, such as modular sensor setups or solar-powered nodes, further expand feasibility.

When paired with hydraulic models, IoT devices enhance network simulations. For example, in irrigation networks, sensor-supported canal flow models based on the Saint-Venant equations improve accuracy and help calibrate discharge data (Makhmudov et al., 2022). Similarly, pressure sensors linked with Water Smart's hydraulic modules support real-time anomaly detection and DMA optimization, as explored in this thesis.

Despite their benefits, barriers persist in adoption due to infrastructure limitations, lack of skilled personnel, and intermittent power supply. Solutions include simplified sensor calibration protocols and edge computing to reduce dependency on central servers (Kamienski et al., 2018).

Data Analytics Applications

Data analytics provides utilities with the ability to detect system inefficiencies and develop targeted interventions. Combining historical and real-time data, these tools help detect leakage, identify underperforming zones, and optimize pressure settings (Okoli, 2024). GIS integration enhances spatial decision-making, enabling utilities to localize and prioritize interventions (Faber & Radakrishnan, 2023).

Machine learning tools also support NRW management by generating predictive maintenance schedules and anomaly detection alerts. These tools are integral to the Water Smart platform, where modules are tailored to operate with limited datasets, helping bridge the digital divide.

Advanced metering infrastructure (AMI) has also demonstrated benefits such as improving billing accuracy and reducing consumption by up to 17% (Okoli, 2024). However, the cost and technical burden of deploying AMI remain a challenge. Low-cost solutions and open-source analytics frameworks can facilitate wider adoption in low-income regions.

Real-time Monitoring Systems

Real-time monitoring allows utilities to shift from reactive to preventive strategies. IoT sensors detect pressure changes, bursts, and illegal connections instantly, which reduces response time and enhances reliability (Drexler & Ahmadpour, 2022). Additionally, pressure control supported by real-time data can significantly reduce leak-related losses; a 10% increase in pressure is known to increase leakage by an equivalent proportion (Faber & Radakrishnan, 2023).

Integration with GIS tools further improves monitoring accuracy, allowing spatial localization of events and facilitating immediate interventions. Smart meters and water quality sensors have expanded these capabilities, supporting both customer transparency and regulatory compliance (Di Nardo et al., 2016).

In Water Smart, real-time monitoring modules integrate IoT data to support KPI tracking, anomaly alerts, and performance benchmarking. These functionalities are critical in case studies like Khelvachauri and Várzea da Cobra, where infrastructure is outdated and real-time diagnostics significantly enhance operational capacity.

1.6.4 Hydraulic software simulation in Water Management

Mathematical modeling serves as a vital tool in optimizing water management systems, enabling utilities to enhance their operational efficiencies and address critical challenges such as Non-Revenue Water (NRW). This section explores various model types, selection criteria, validation methods, and advanced modeling techniques that inform decision-making processes in water distribution. By integrating these analytical frameworks with emerging technologies, the discussion lays the groundwork for understanding how mathematical models can drive sustainable water management practices across diverse operational contexts. This exploration is essential for formulating effective strategies that enhance utility performance within the broader goals outlined in the preceding sections of the work.

The intricate dynamics of water distribution systems necessitate a robust framework for modeling their behavior. Empirical, conceptual, and physically-based approaches offer different means of representing these systems, each influencing decision-making and operational performance. Empirical models rely on observed data and statistical methods to provide insights into system behavior under known conditions. While advantageous in data-scarce environments, they are limited in adaptability, especially under evolving conditions such as climate shifts or infrastructure degradation (Ostrowski, 2006; Hurford et al., 2017). Conceptual models simplify internal processes, offering medium-scale utilities an efficient way to simulate performance without extensive data requirements. These models support transition phases, particularly for utilities adopting digital tools (Ostrowski, 2006).

Physically-based models incorporate detailed hydrological and hydraulic parameters, enabling precise simulations vital for tasks such as pressure optimization and leak detection. Despite their accuracy, their implementation is often constrained by high data and computational demands, which limits their applicability in developing contexts unless complemented by scalable solutions like cloud computing (Priazhinskaya, 1976; Drexler & Ahmadpour, 2022). Integrated models combine elements of all three types, leveraging the adaptability of conceptual models, the precision of physically-based models, and the data-efficiency of empirical ones. This hybrid approach supports multifaceted goals, such as NRW reduction, through layered analysis and scenario testing (Symmonds, 2017).

Model selection depends on utility size, available data, infrastructure conditions, and technological readiness. For smaller utilities, empirical or conceptual models offer practical starting points, while larger utilities with better monitoring infrastructure may benefit from physically-based or integrated approaches. These decisions also hinge on operational goals, such as pressure stabilization or leakage mitigation, and on access to computational resources (Ajoge et al., 2021; Symmonds, 2017).

Validation of models ensures their accuracy and operational relevance. Sensitivity analysis helps identify influential parameters, supporting focused interventions. Integrated calibration ensures coherent simulations across components such as pumps and control valves. Cross-validation with independent datasets further enhances model robustness across different demand conditions (Dyadun et al., 2022; Kingdom et al., 2006). Stress testing under extreme scenarios and iterative refinement allow models to adapt to real-world uncertainties, including climate variability and infrastructure aging (Faber & Radakrishnan, 2023).

Calibration aligns models with observed data, ensuring practical reliability. Techniques such as iterative adjustments and sensitivity testing improve predictive accuracy and utility responsiveness, especially when tailored to specific challenges like high leakage zones or pressure imbalances (Plass, 1983; Álvarez Paz et al., 2014). Tools like WaterGEMS have demonstrated the effectiveness of calibrated simulations in enhancing operational planning, cost reduction, and system optimization (Berhane & Aregaw, 2020).

Building on the insights and methodologies presented throughout this section, the present thesis adopts a physically-based modeling approach tailored to the operational realities of small and mid-sized water utilities in developing regions. Specifically, the hydraulic model developed for the case studies in Batumi (Georgia) and Varzea da Cobra (Brazil) integrates EPANET Toolkit-based simulations with GIS-enabled leakage mapping and pressure-dependent demand components. These tools allow for scenario testing under varying pressure control and leakage reduction strategies, forming the analytical foundation for the Water Smart platform presented in later chapters. By calibrating the model to field data and incorporating advanced functionalities—such as pressure-dependent leakage, DMA simulation, and virtual sensor integration—the thesis demonstrates how theory-driven hydraulic modeling can be effectively applied to reduce Non-Revenue Water and optimize utility performance in resource-constrained environments.

1.6.5 Advanced Modeling Techniques in Water Utility Management

Advanced modeling techniques play a critical role in modern water utility management, particularly in addressing the persistent challenge of Non-Revenue Water (NRW). These techniques integrate physical and data-driven models, offering enhanced insights into system behavior, predictive performance, and anomaly detection. In recent years, the convergence of hydraulic modeling with artificial intelligence (AI), machine learning (ML), and decision support systems has enabled utilities to move from reactive approaches to more predictive and adaptive strategies (Faber & Radakrishnan, 2023).

One of the most significant developments has been the incorporation of pressure-dependent demand models within traditional hydraulic simulations. Unlike fixed-demand models, pressure-dependent demand approaches more accurately represent consumption and leakage behavior under varying pressure conditions, which is particularly relevant in intermittent supply systems (Vermersch & Rizzo, 2016). Tools such as EPANET-MSX and customized EPANET Toolkit applications allow utilities to simulate real-time pressure variations and assess their impact on water losses. For instance, in the Batumi case study, the EPANET hydraulic model was extended using pressure-dependent emitters and integrated with GIS-based zoning to support the creation of physical and virtual DMAs. This enabled targeted pressure management and leakage localization, leading to a more efficient NRW reduction strategy (Pons-Ausina et al., 2025).

In parallel, the application of AI-driven techniques has significantly expanded the analytical capabilities of water utilities. Supervised learning algorithms such as Random Forests, Support Vector Machines, and Artificial Neural Networks have been applied to predict pipe failure, detect anomalies in flow patterns, and classify consumption behaviors (Ajoge et al., 2021). These tools are especially valuable in environments with large volumes of SCADA and IoT data. For example, in the Varzea da Cobra pilot study in Brazil, the integration of an AI module with the EPANET Toolkit enabled dynamic adjustment of PRVs and simulation of pressure scenarios to optimize leakage reduction (Pons-Ausina et al., 2025).

Another important area of advancement is the use of optimization algorithms for network rehabilitation and operational planning. Multi-objective optimization techniques—such as Genetic Algorithms or Particle Swarm Optimization—have been used to identify optimal combinations of pipe replacements, pressure settings, and valve placements that balance cost, efficiency, and hydraulic performance (Symmonds, 2017). These methods are particularly valuable in developing contexts where investment decisions must be carefully justified. Coupling these algorithms with hydraulic simulators enables utilities to explore various scenarios and select the most robust and cost-effective solution.

Moreover, decision support systems (DSS) that integrate hydraulic models, GIS data, and user interfaces have emerged as key tools for utility managers. These platforms facilitate real-time visualization of network status, detection of irregularities, and prioritization of maintenance activities. They often include modules for water balance analysis, performance indicators, and simulation-based planning. The Water Smart application developed as part of this thesis exemplifies such integration: it combines calibrated EPANET models with AI-based decision trees and GIS spatial analysis, supporting utility managers in small and mid-sized utilities with limited technical capacity (Pons-Ausina et al., 2025). This approach not only enhances leak detection and pressure control but also provides a scalable architecture for future expansion, including climate resilience and energy efficiency assessments.

The growing availability of open-source tools has further democratized access to advanced modeling. Frameworks such as WNTR (Water Network Tool for Resilience) allow users to simulate infrastructure failure scenarios, evaluate resilience metrics, and incorporate stochastic demand patterns (Klise et al., 2017). These tools are particularly relevant in developing regions facing aging infrastructure and climate variability. In the Sleman pilot project in Indonesia, for instance, WNTR simulations helped assess the vulnerability of utility assets to flooding and power interruptions, informing infrastructure reinforcement plans (Pons-Ausina et al., 2025).

In conclusion, the adoption of advanced modeling techniques—ranging from pressure-dependent hydraulic models to AI-enhanced predictive systems and optimization algorithms—represents a transformative step in water utility management. These tools not only improve the accuracy and reliability of system diagnostics but also empower utilities to implement proactive strategies for NRW reduction. The integration of these approaches into the Water Smart platform, validated through real case studies such as Batumi and Varzea da Cobra, demonstrates their practical relevance and scalability for utilities operating in complex and resource-constrained environments.

1.6.6 Integration with GIS Systems

Geographic Information Systems (GIS) have become an indispensable tool for water utilities, providing spatial insight that enhances decision-making, asset management, and Non-Revenue Water (NRW) reduction. Through geospatial analysis, utilities can map their networks, identify high-risk zones, and monitor performance indicators in real-time. These capabilities are particularly critical for small and mid-sized utilities facing operational inefficiencies and limited resources.

GIS enables the integration of multiple data layers—including pipeline infrastructure, pressure zones, terrain elevation, and customer distribution—into a unified spatial framework. This allows for accurate visualization of water losses and facilitates targeted interventions. As noted by Butler and Memon (2006), GIS-based models are essential for prioritizing pipe replacement and leak detection in aging systems. In cities like Luxor and Amman, the use of GIS to overlay leakage incidents with infrastructure conditions has led to reductions of over 30% in Unaccounted-for Water (Yehia, 2023; Al-Zahrani & Abo-Monasar, 2015).

By coupling GIS with IoT-enabled monitoring systems, utilities can detect pressure drops and anomalies in real time. This integration supports the development of responsive NRW control strategies. According to Farley et al. (2008), spatial tracking of flow and pressure variations allows utilities to distinguish between background leakage and burst events, improving operational response. More recent applications, such as those described by Faber and Radakrishnan (2023), show how GIS dashboards linked to smart sensors can reduce the mean time to repair (MTTR) and optimize maintenance scheduling.

In planning contexts, GIS supports infrastructure risk assessment by mapping exposure to environmental hazards such as flooding, drought, or soil instability. The integration of spatial climate risk data—used in the Sleman and Batumi projects—has been shown to improve long-term investment planning and infrastructure resilience (Pons-Ausina et al., 2025; Bertule et al., 2018). Moreover, GIS facilitates equity assessments by overlaying demographic and service coverage data, helping utilities identify underserved populations and support inclusive access planning (UNDESA, 2015).

Artificial intelligence and machine learning are increasingly being embedded into GIS platforms to enhance pattern recognition and anomaly detection. For example, Giustolisi and Berardi (2009) used hybrid data-driven and GIS models to identify pipe failure probabilities based on historical and spatial variables. Similarly, Zhang et al. (2021) demonstrated how convolutional neural networks (CNNs) can process satellite imagery and GIS layers to detect unauthorized water use in peri-urban areas. These innovations open new pathways for cost-effective NRW reduction, especially when applied in platforms like *Water Smart*, which integrate predictive algorithms into GIS interfaces.

Open-source GIS tools such as QGIS, GRASS, and SAGA offer powerful alternatives to proprietary systems. These platforms are particularly valuable in developing regions where utilities must minimize licensing costs. As highlighted by Felizardo and Leonardo (2019), the QGIS-Red plugin enables seamless hydraulic model integration and has been successfully used in utilities across Latin America. In Water Smart, the use of open GIS frameworks ensures both interoperability and adaptability to different institutional and technological contexts.

A key strength of GIS is its role as an interface between technical modeling and decision-making. Through intuitive dashboards, heat maps, and risk indicators, GIS allows users with limited technical training to interact with complex data. This functionality enhances transparency and operational ownership across utility departments. Kingdom et al. (2006) emphasize that user-friendly tools are essential for scaling NRW programs in small utilities with low technical capacity.

GIS is also critical for the development and monitoring of DMAs. The delineation of zones based on elevation, pressure, and flow characteristics allows for more accurate leakage accounting and pressure control (Morrison et al., 2007). In Batumi and Khelvachauri, this approach was central to the successful implementation of sectorization and virtual DMA models (Pons-Ausina et al., 2025).

In summary, GIS serves as a cross-cutting enabler in water utility management, bridging asset monitoring, hydraulic simulation, performance tracking, and strategic planning. Its integration with real-time monitoring, AI, and user-friendly interfaces allows utilities—especially in resource-constrained settings—to move toward more data-driven, equitable, and sustainable water management practices. The Water Smart platform demonstrates how such integration can be implemented effectively, reinforcing the central role of GIS in modern NRW control strategies.

1.6.7 Development and Implementation of the Water Smart Application

The development of a comprehensive tool for modern water management aims to address the pressing challenges posed by Non-Revenue Water (NRW) and optimize utility operations through innovative technological solutions. This section presents a restructured view of the Water Smart platform, merging system architecture, user interface, functional tools, and integration strategies into a unified technological ecosystem designed to serve the needs of small and mid-sized utilities, especially in developing regions.

1.6.7.1 System Architecture and Modular Design

The Water Smart platform is built on a modular and scalable architecture that enables utilities to adapt the system incrementally based on their technological and operational maturity. Each functional block—data acquisition, hydraulic modeling, visualization, and performance monitoring—is implemented as an independent module, which allows for continuous evolution without disrupting the core system. This modular approach ensures resilience, cost-effectiveness, and the ability to deploy targeted improvements such as pressure monitoring or demand forecasting tools based on utility priorities (Faber & Radakrishnan, 2023; Kingdom et al., 2006).

The system's backend supports high data throughput and flexible integration with SCADA and billing systems, thanks to its relational database model and predefined entity relationships. Data is managed through efficient indexing and partitioning, ensuring rapid access and reliability even in large datasets. Built-in failover mechanisms and cloud scalability guarantee robustness in real-time environments, particularly in urbanizing regions with increasing complexity.

1.6.7.2 Database Structure and Security Framework

Water Smart integrates a relational database optimized for time-series, spatial, and hydraulic data. It supports interoperability with GIS, enabling geospatial visualizations such as leakage mapping or pressure heatmaps (Dyadun et al., 2022). The spatial layers also link with hydraulic simulation results and customer billing zones, providing a cross-functional view for managers.

Security is addressed through end-to-end encryption, role-based access control (RBAC), and intrusion detection protocols. The system includes periodic vulnerability audits and can integrate blockchain-based logging for tamper-proof operational records (Kozhevnikov et al., 2022). This comprehensive security framework ensures data integrity and supports compliance with standards such as ISO/IEC 27001, which is critical for utilities dealing with sensitive operational and financial data (Drexler & Ahmadpour, 2022).

1.6.7.3 User Interface Design

The user interface is designed to be intuitive and accessible for users with varying technical backgrounds. GIS-based dashboards enable real-time visualization of network anomalies, such as pressure losses or consumption deviations. Multilingual support, customizable widgets, and adaptive complexity ensure that both experienced engineers and entry-level operators can effectively use the system (Carriço et al., 2023; Kingdom et al., 2006).

Gamification features (e.g., performance badges for reducing NRW) and real-time alerts help maintain user engagement while promoting proactive network management (Castelletti et al., 2023). Adaptive design ensures compatibility across mobile, tablet, and desktop devices, with offline support for intermittent connectivity scenarios.

1.6.7.4 Core Functionalities: Monitoring, Reporting, and Decision Support

The Water Smart platform integrates several core functionalities that support daily utility operations and long-term planning. Performance monitoring tools track NRW, pressure levels, and flow consistency, based on International Water Association (IWA) metrics. Advanced reporting modules consolidate data from sensors, hydraulic models, and billing systems to generate both technical and financial dashboards (Ganjidoost, 2016; Vermersch & Rizzo, 2016).

Real-time monitoring enables immediate detection of leaks and anomalies. Coupled with customizable thresholds and predictive alerts, this functionality supports fast decision-making in both urban and rural contexts. Reporting modules generate automated summaries aligned with regulatory or donor requirements and can be exported for external audits or shared via APIs with national water information systems.

1.6.7.5 Network Analysis and Leak Detection Tools

Embedded network analysis tools provide utilities with hydraulic simulation capabilities to evaluate different scenarios, such as valve closures, pressure management strategies, and emergency events. These simulations are enhanced by predictive analytics and real-time IoT sensor inputs, improving accuracy in detecting system weaknesses (Ravichandran et al., 2023).

Leak detection algorithms leverage AI and machine learning to classify anomalies and reduce false positives. GIS-based visualization enhances these results by identifying spatial clusters of inefficiency (Yu et al., 2024; Shelton, 2013). This approach allows utilities to prioritize interventions and improve the effectiveness of maintenance teams, even in aging or poorly documented networks.

1.6.7.6 Integration and Interoperability Framework

A critical feature of Water Smart is its integration framework, which supports interoperability with third-party applications, financial systems, and national databases. Standardized data exchange protocols (e.g., NGSI-LD, RESTful APIs) allow real-time communication between components such as IoT sensors, GIS platforms, and billing engines (Faber & Radakrishnan, 2023).

Cloud and edge computing options enable deployment in both urban and rural settings, with fallback mechanisms for offline data syncing. Integration with external tools such as DECIDE, WISDom, or RAT 3.0 enhances forecasting and condition-based maintenance planning (Minocha et al., 2024).

Security and performance are ensured through encrypted API access, sandbox testing environments, and periodic protocol audits. This ensures that sensitive data such as billing records or operational anomalies are exchanged securely while maintaining system reliability. The integration framework thus allows the Water Smart application to evolve and interoperate within the broader ecosystem of smart utility management.

1.6.8 Implementation and Validation

The implementation and validation of the Water Smart application are pivotal in ensuring its effectiveness in optimizing water management and tackling Non-Revenue Water (NRW) challenges. This section consolidates the deployment strategy, system requirements, installation procedures, validation protocols, performance metrics, and quality assurance, linking these to the core objectives of the thesis and the case studies presented. The structured deployment of the Water Smart tool—especially in the contexts of Khelvachauri (Georgia) and Varzea da Cobra (Brazil)—has validated its ability to enhance service efficiency, optimize leak detection, and improve operational decision-making, thus confirming the viability of a modular, GIS-integrated, and AI-enhanced platform tailored for small and mid-sized utilities.

1.6.8.1 Deployment Strategy and System Requirements

Effective implementation of the Water Smart platform requires a coherent strategy encompassing infrastructure compatibility, cloud-readiness, modular expansion, and local adaptability. The deployment experiences in Georgia and Brazil demonstrated the relevance of low-cost, energy-efficient servers and cloud-integrated computing systems, especially under unreliable power supply conditions (Gouws & Lukhwareni, 2012; Drexler & Ahmadpour, 2022). Integration with GIS and hydraulic modeling tools such as EPANET Toolkit and QGIS-Red plugin facilitated high-resolution spatial and hydraulic simulations for leak detection, pressure zoning, and anomaly identification (Dyadun et al., 2022; Pons-Ausina et al., 2025). Moreover, security protocols were embedded from inception using ISO/IEC 27001 standards, multi-factor authentication, and encryption techniques to ensure operational continuity and data integrity (Felizardo & Leonardo, 2019).

1.6.8.2 Installation and Integration

Field implementation in the Khelvachauri case required tailored hardware configurations and multilingual user manuals. A critical component was the digitization and synchronization of historical consumption and pressure data, used for calibrating simulation scenarios and feeding AI-based pattern recognition modules (Pons-Ausina et al., 2025). Installation included the configuration of real-time monitoring dashboards, integration with SCADA and billing systems, and setup of training modules for operators. The modular approach facilitated a gradual rollout of functionalities—from leak monitoring to customer classification modules—ensuring cost containment and technical scalability (Felizardo & Leonardo, 2019).

1.6.8.3 Validation and Testing Protocols

The Water Smart application was validated through real and simulated scenarios across the two case studies. Leak detection algorithms were benchmarked against field-verified losses, using historical data and real-time flow anomalies (Vermersch & Rizzo, 2016; Faber & Radakrishnan, 2023). In Georgia, the pressure-dependent modeling approach enabled simulations of variable demand and aging infrastructure. Multi-scenario testing—including drought and peak usage simulations—demonstrated the resilience of the system in dynamically adjusting PRV settings and reconfiguring virtual DMAs (Hurford et al., 2017). Integration testing confirmed compatibility with external platforms, while usability assessments showed high acceptance due to intuitive dashboards and alert mechanisms.

1.6.8.4 Performance Indicators and Operational Efficiency

Water Smart's performance was monitored using IWA-recommended NRW indicators, with improvements observed in leak detection rates, pressure balance efficiency, and reduction in apparent losses (Farley, 2003; Kingdom et al., 2006). Benchmarking with global utilities revealed competitive detection accuracies (>85%) when IoT-enhanced modules were employed (Faber & Radakrishnan, 2023). Real-time dashboards and GIS-based heatmaps allowed utility managers to shift from reactive to proactive maintenance. The platform's integration with machine learning tools optimized pump scheduling and pressure management, contributing to energy savings and better resource allocation (Bhattacharya, 2023; Vermersch & Rizzo, 2016).

1.6.8.5 Economic and Institutional Impact

Case studies highlighted that halving NRW could save up to $2.9 billion annually across developing regions (Kingdom et al., 2006). In Varzea da Cobra, model-based optimization reduced estimated losses by 34%, with measurable improvements in billing accuracy and pipeline maintenance efficiency. The modular architecture allowed for cost-effective scaling and targeted reinvestment, reinforcing financial autonomy in small utilities (Ajoge et al., 2021;

Malithi, 2016). Adoption of Water Smart also contributed to institutional reforms by fostering transparent reporting and community accountability.

1.6.8.6 Quality Assurance and Maintenance

A structured QA protocol was followed, including iterative testing, user feedback integration, and continuous updates aligned with IWA standards (Faber & Radakrishnan, 2023; Farley, 2003). The system incorporated automated logging, user support, GIS data updates, and cybersecurity audits. Regular updates improved simulation fidelity, UI accessibility, and AI model accuracy. In both case studies, emphasis was placed on user-centered design and local training, ensuring effective knowledge transfer and long-term sustainability.

In summary, the Water Smart platform has demonstrated robust deployment, adaptability, and validated impact in resource-constrained utilities. By aligning technical innovations with institutional capacities, and continuously improving based on feedback, it offers a replicable model for digital NRW management across diverse operational environments.

1.6.9 Future Developments

The future of water utility management, particularly in contexts affected by Non-Revenue Water (NRW), is closely tied to the integration of advanced digital technologies that promote adaptability, resilience, and sustainability. Building upon the foundations established in this thesis—especially through the development and validation of Water Smart and its AI-based modules—this section explores future trends and potential enhancements that can strengthen the operational, economic, and environmental performance of water utilities. These developments are framed across five key axes: artificial intelligence, machine learning, cloud computing, scalability strategies, and performance optimization.

1.6.9.1 Artificial Intelligence and Machine Learning Integration

Artificial Intelligence (AI) has emerged as a transformative tool in water utility management, particularly in optimizing pressure control, detecting leaks, forecasting demand, and supporting predictive maintenance. In this thesis, its practical application was validated through the Khelvachauri and Várzea da Cobra case studies, where AI-driven models developed using the EPANET Toolkit successfully optimized pumping schedules and reduced leakage rates by over 15% (Pons-Ausina et al., 2025). AI systems allow utilities to transition from reactive to proactive decision-making, with real-time data analysis enabling dynamic control of pressure zones, early anomaly detection, and system-wide operational adjustments.

Machine learning algorithms—particularly supervised learning, reinforcement learning, and clustering methods—enable fine-tuned performance by learning from historical and real-time datasets. These techniques support leakage classification, demand forecasting, detection of unauthorized consumption, and adaptive control of network infrastructure. However, their deployment in small and mid-sized utilities requires simplified, modular frameworks that minimize computational demands while maintaining predictive accuracy. This thesis proposes lightweight AI frameworks with pre-trained modules and reinforcement learning routines that self-adjust to changes in consumption patterns and pressure fluctuations, particularly suitable for utilities with aging infrastructure and limited technical capacity.

1.6.9.2 Cloud Computing and Hybrid Architectures

The integration of cloud computing with water utility software offers considerable benefits in terms of scalability, remote access, and real-time performance monitoring. Tools like Water Smart benefit from cloud-enabled infrastructure that allows seamless processing of GIS datasets, hydraulic simulations, and IoT inputs, even under intermittent local power supply conditions. The DECIDE and WISDom projects (Carriço et al., 2023) demonstrated the feasibility of such platforms, which were further adapted in this thesis by proposing hybrid cloud-local deployments to suit utilities with limited internet connectivity.

Cloud-based Software as a Service (SaaS) solutions enhance performance optimization, enabling remote updates, KPI reporting, and predictive maintenance. However, cost remains a barrier. Future developments should prioritize open-source platforms and adaptive pricing models, ensuring inclusivity for utilities with constrained budgets. Furthermore, the thesis recommends regionally hosted cloud nodes or edge computing to address sovereignty and data latency concerns.

1.6.9.3 Scalability and Modular Expansion

Scalability is critical to ensuring that utilities can adapt to expanding networks, urban growth, and emerging challenges. The modular architecture proposed in Water Smart allows stepwise system expansion without disrupting existing operations. For instance, new leak detection modules or AI-enhanced forecast engines can be added as resources permit, without compromising interoperability.

To address the growing volume of data from IoT sensors and hydraulic simulations, scalable database structures with advanced indexing and partitioning were tested and integrated into the Water Smart platform. Furthermore, capacity-building initiatives aligned with the IWA assessment framework were implemented in collaboration with utilities to ensure that system growth is matched by technical expertise.

1.6.9.4 Performance Optimization and Benchmarking

Performance optimization remains a central goal of smart utility management. Advanced leakage detection algorithms—integrated with GIS and real-time data streams—have proven capable of reducing unaccounted-for water by up to 30% (Yu et al., 2024). In this thesis, AI-enhanced anomaly detection and flow calibration tools were implemented in Water Smart modules to prioritize maintenance and optimize energy use.

Benchmarking frameworks based on IWA standards were incorporated to assess NRW reduction efforts across case studies. These tools facilitate comparative analysis, identify inefficiencies, and support evidence-based investment decisions. This research advocates for localized benchmarking indicators that reflect the operational realities of developing regions, where supply intermittency, metering deficiencies, and infrastructure heterogeneity prevail.

1.6.9.5 Strategic Resource Management

Effective resource management combines technological innovation with human and financial planning. This thesis emphasizes the role of preventive maintenance, centralized inventory systems, and equitable resource allocation as essential strategies to reduce real and apparent losses. In Doka (Ajoge et al., 2021), for example, a lack of plumbing materials and low metering coverage were found to be major contributors to NRW. These insights informed the development of targeted interventions within Water Smart, integrating maintenance scheduling, inventory forecasting, and metering upgrade tracking into its core.

Future improvements should incorporate ESG (Environmental, Social, Governance) criteria into resource planning tools and strengthen partnerships with academic institutions and private sector actors to deliver training, open technologies, and operational support.

2 CHAPTER 2: METHODOLOGY

2.1 Introduction

This chapter outlines the methodological framework adopted for the development, implementation, and validation of the Water Smart application. The approach integrates technical, computational, and practical components to address the complexities associated with the management of Non-Revenue Water (NRW) in urban and rural water supply systems, particularly in the context of developing countries.

The chapter begins with a detailed description of the materials and methods used throughout the study, including the software tools, data sources, and analytical techniques employed. However, it is important to clarify that these tools are not presented merely as background information—they were actively used during consultancy work and field implementation processes, and they served as conceptual and functional references for the creation of the Water Smart platform.

For this reason, the initial sections of the chapter focus on a set of key applications and frameworks that informed the design of the platform. These include the GIS-supported NRW model (based on EPANET, QGIS and ITA-Fugas), the QGIS-REd plugin for geospatial integration, the Change Management Index (CMI) for institutional diagnosis, the SISAR model for rural water service digitalization, and resilience-based planning tools such as CRIDA and WNTR. Together, they represent the methodological and operational building blocks upon which the Water Smart application was developed.

Following the presentation of these foundational tools, the chapter introduces the Water Smart platform itself, its modular architecture, and the technical logic behind its AI-assisted components (WSNO, WSNA, and future developments). Finally, the methodology is applied to selected case studies that serve to test and validate the proposed tool. These cases reflect a range of system conditions and management challenges, enabling a robust evaluation of the application’s adaptability and effectiveness.

The methodology followed in this thesis is summarized in Figure 2. It starts with the collection and preprocessing of input data (billing records, GIS layers, field measurements), followed by the application of a set of analytical tools and models—either as references or as components—to design, calibrate, and validate the Water Smart platform. Software applications such as EPANET, QGIS, ITA-Fugas, CMI, SISAR, CRIDA, and WNTR were used as engines or guides to build the structure and functionalities of the Water Smart modules. Each tool and its role are detailed in the corresponding sections of the methodology chapter.

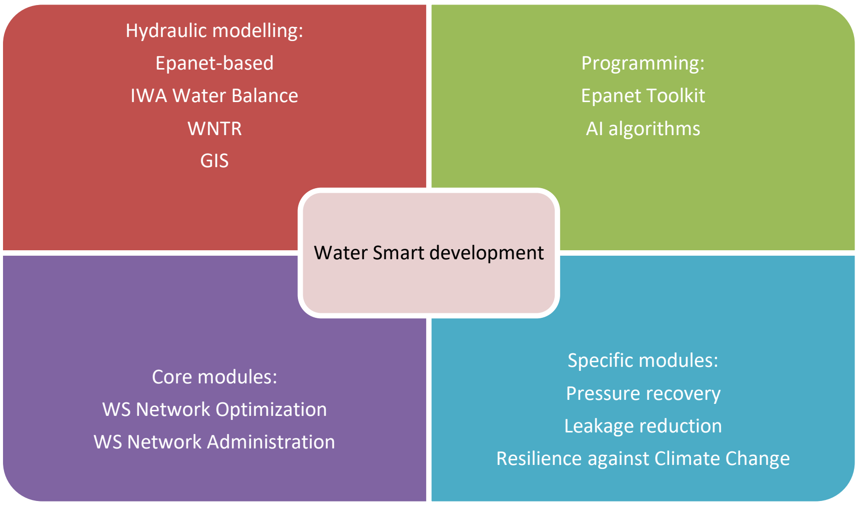


Figure 2: Methodology overview

Through this structured methodology, the study aims to demonstrate how simulation-based tools can be effectively integrated into water utility operations to support strategic planning, operational efficiency, and NRW reduction.

In order to provide a structured understanding of the tools and methods employed, Figure 3 presents the overall methodological workflow followed in this thesis. The workflow begins with the collection and preprocessing of input data (billing records, GIS layers, field measurements) and proceeds through a series of analytical tools and modelling steps, each contributing to the design, calibration, and validation of the Water Smart platform. Software applications such as EPANET, QGIS, ITA-Fugas, CMI, SISAR, CRIDA, WNTR… were used either as modelling engines or as reference systems to build the different modules of the platform. Each tool and its role are detailed in the corresponding sections of the methodology chapter.

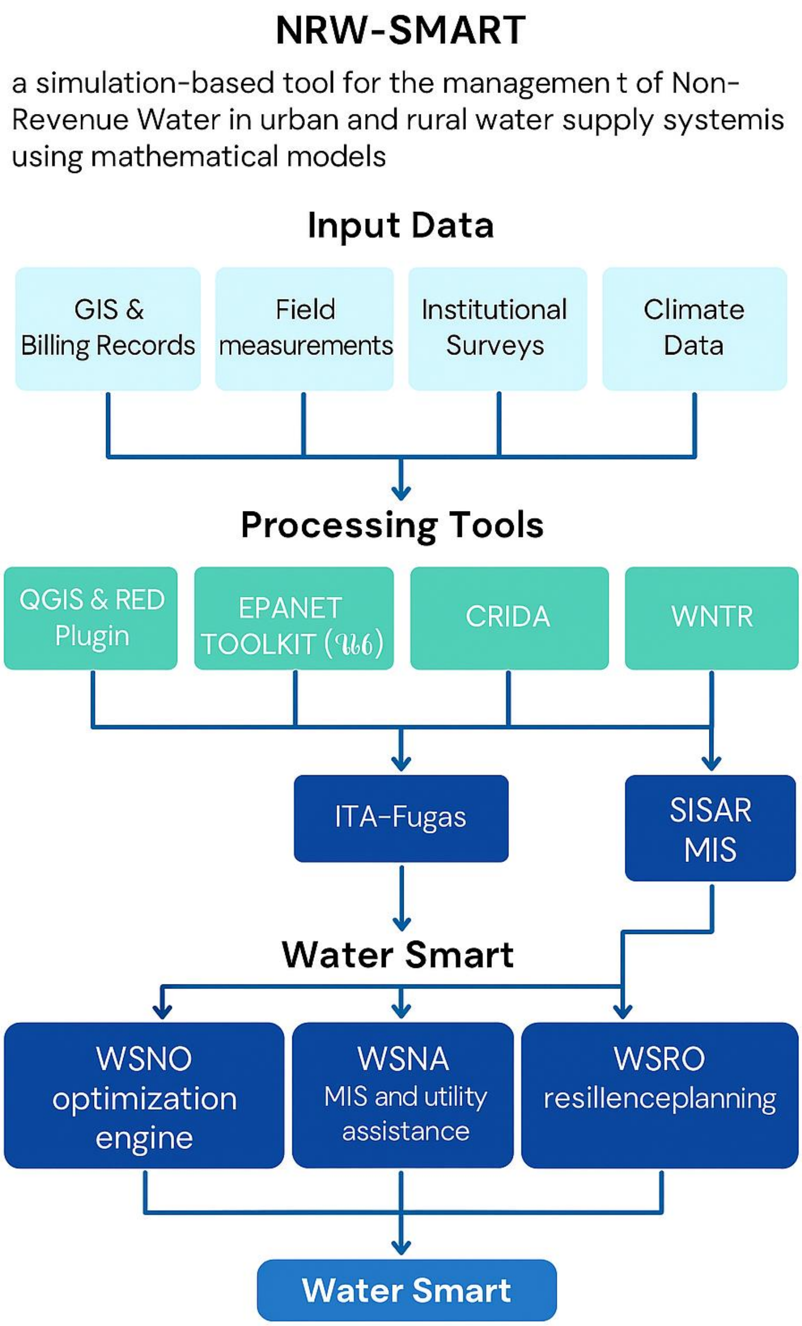


Figure 3: Methodological workflow linking input data, modelling tools, and Water Smart modules

It is important to clarify that the author of this thesis was solely responsible for the design, implementation, and validation of all hydraulic modelling components presented throughout the platform. This includes the mathematical modelling of the water distribution systems, the simulation logic for NRW and leakage estimation, and the hydraulic-based decision-making workflows integrated into each module. The software programming and web-based development of the platform (e.g., interfaces, user access, data visualisation) were executed by a team of software developers based on the hydraulic specifications and operational requirements defined by the author.

These technical contributions are grounded in the author's extensive field experience as a hydraulic engineer in international cooperation projects, particularly within small and mid-sized utilities in developing regions. This background provided a practical understanding of the challenges faced by local operators—such as limited data availability, weak digital infrastructure, and lack of technical personnel—and informed the architecture and priorities of the Water Smart platform. As such, the scientific contribution of this thesis lies in translating these real-world operational needs into actionable and replicable simulation tools.

2.2 Material and methods

This section describes the materials and methods employed, including the datasets, modelling tools, analytical techniques, and data preprocessing strategies. Emphasis is placed on the integration of geospatial, water balance, hydraulics, and operational data to support the Water Smart development and calibration.

2.2.1 Reference Applications and Foundations for Water Smart

Before detailing the internal structure and functionalities of the Water Smart platform, it is essential to describe the real-world applications and methodological frameworks that served as conceptual and technical references for its development. The Water Smart tool was not conceived in isolation; rather, it is the result of a progressive process that integrates field-tested models, digital platforms, and resilience frameworks adapted to the needs of small and mid-sized water utilities in developing contexts.

The following subsections (2.2.2 to 2.2.5) provide a detailed overview of four core reference applications:

- The GIS-based NRW mathematical model implemented in Batumi, Georgia (2.2.2),
- The Change Management Index (CMI) developed and applied in both urban and rural utilities (2.2.3),
- The SISAR system for integrated rural water management in Brazil (2.2.4), and
- The use of resilience modeling tools such as CRIDA and WNTR to simulate climate risk and infrastructure stress (2.2.5).

These applications were not developed as part of this thesis but provided the functional, technical, and institutional foundations upon which Water Smart was designed. For this reason, they are presented here in the methodology section, not as background literature, but as applied precedents that directly informed the architecture, modules, and analytical capabilities of the Water Smart platform.

Each of these reference applications contributed critical features or operational logic that have been adapted into the Water Smart environment. For example:

- The hydraulic model of Batumi enabled the creation of the WSNO module for simulating leakage and DMA optimization.
- The CMI provided the strategic framework for assessing institutional readiness and monitoring NRW reduction progress.
- SISAR inspired the structure of decentralized workflows and service order management within the Water Smart system.
- CRIDA and WNTR introduced concepts and tools for embedding climate resilience and failure simulation into the platform.

As such, Water Smart emerges as a synthesis and evolution of these tools, designed to be open, scalable, and applicable across a wide range of water utility contexts.

2.2.2 GIS NRW Mathematical model

The development of a GIS-supported Non-Revenue Water (NRW) mathematical model was central to the idea of the Water Smart application. This model integrates three primary components:

- EPANET as the hydraulic engine,
- QGIS as the geospatial platform,
- ITA-Fugas methodology as the leakage modeling framework.

The combination of these tools supports a flexible, scalable, and pressure-sensitive simulation environment for water utilities to quantify, localize, and manage water losses, especially in developing contexts like Batumi Tskali utility. The model enables extended period simulations (EPS), pressure-dependent leakage modeling, and nodal allocation of real and apparent losses based on physical and spatial criteria.

2.2.2.1 Building and Uploading the Hydraulic Model

The hydraulic model of Batumi, developed in EPANET and enriched with GIS and billing data, constituted the operational backbone of the Water Smart application. The construction and calibration of this model were implemented through a step-by-step methodology combining field surveys, network design, GIS compilation, and iterative hydraulic simulations.

Model Development Phases:

1. Network Digitization and GIS Structuring

- As-built data were gathered from Batumi Tskali utility and cross-checked through field verification.
- Elements such as valves, meters, reservoirs, and pipes were geolocated and classified by material, diameter, and condition.
- Each consumption node was assigned a unique ID and linked to billing records to connect physical infrastructure with consumption behavior.

2. Model Building in EPANET

- Using QGIS, the existing CAD and GIS data were exported into EPANET-compatible formats, including junctions, pipes, and demand nodes.
- Initial demand allocation was based on customer billing records provided by, for instance, Batumi Tskali, and disaggregated using population density estimates for each district. These data were spatially referenced to the billing areas, enabling a proportional distribution of total billed consumption to the network nodes within each corresponding zone. In cases where billing data were unavailable or incomplete, demand was estimated using per capita consumption rates and demographic statistics from municipal planning departments.
- Key hydraulic structures (pumps, tanks, valves) were defined with elevation, capacity, and performance curves.

3. DMA Structuring and Water Balance Estimation

- The network was subdivided into District Metered Areas (DMAs), based on existing billing areas and sector valves.
- Flow meters were installed at DMA inlets, allowing a monthly estimation of NRW via the IWA standard water balance.

- The model included zero-pressure simulations to validate DMA isolation during calibration.

4. Calibration and Iterative Simulations

- Flow and pressure measurements were taken at strategic points under varied demand conditions (e.g., day/night).
- Simulated results were compared with measured values, and adjustments were made in pipe roughness, demand patterns, and leakage parameters.
- For the calibration of leakage parameters, the ITA-Fugas tool developed by the Polytechnic University of Valencia was used. This software integrates leakage modelling into EPANET by assigning calibrated emitters to network nodes based on network characteristics (Cobacho Jordán et al., 2015).
- Leakage coefficients were calibrated by applying pressure-leakage relationships as shown in figure 3, where pressure data from field measurements were used to iteratively adjust the coefficients values.

The process included several simulation runs, combining adjustments in roughness coefficients and demand allocation with leakage estimation, to minimize the difference between simulated and measured values. In high-elevation zones with storage tanks (as seen in Figure 4), longer computational times were observed due to slower convergence of the hydraulic solver, especially when leakage becomes pressure-dependent and iterative recalculations are required.

5. Model Update

- The model was updated along with the construction of the network and the evolution of the water balance.

2.2.2.2 Integration with MIS and NRW Management

The hydraulic model was also linked to the Management Information System (MIS) of Batumi Tskali (presented in the study cases). Flow and pressure data from DMA meters were uploaded to the MIS, and monthly NRW was calculated using the IWA water balance. This closed-loop system allowed the model to not only simulate but also validate field conditions and recommend corrective actions.

2.2.2.3 Leakage modelling

A core component of the NRW hydraulic model is the simulation of physical losses (real losses) through pressure-sensitive modeling. To achieve this, the methodology developed by the

Instituto Tecnológico del Agua (ITA)—implemented in the ITA-Fugas- software—was adopted and embedded within the EPANET model.

- Fugas-ITA Software: Overview and Capabilities

Fugas-ITA is a leakage modeling application developed at the Universitat Politècnica de València. It was designed as an open-access, customizable tool using Visual Studio and the EPANET Toolkit. The main innovation of Fugas-ITA lies in its ability to simulate leakage flows as a pressure-dependent phenomenon, using a calibrated distribution of leaks across the hydraulic network.

Its key features include:

- Assignment of leakage nodes based on pipe lengths and network topology.
- Use of free discharge valves to simulate pressure-driven leaks.
- Calibration through an iterative algorithm to ensure modeled losses match measured losses at the system level.
- Flexible adjustment of the pressure exponent (N) and partitioning of NRW into real vs. apparent losses.

Modeling Approach: Pressure-Driven Leakage

The fundamental assumption behind Fugas-ITA is that leakage depends on the pressure at each node, not on consumption patterns. This contrasts with conventional EPANET models, which treat all outflows as static demands.

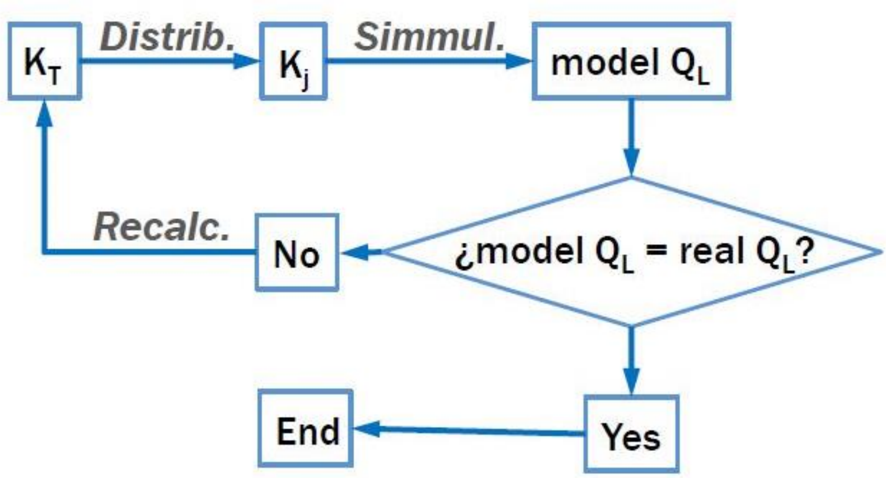


Figure 4: Leakage coefficients iterative process (Source Cobacho et al)

The diagram illustrates the iterative calibration process used to estimate the global leakage coefficient K_T, which is then distributed among the network nodes as individual coefficients Kj. This process is a core step in implementing the pressure-dependent leakage model based on the following sequence:

- Initial Distribution:

  An initial value of K_T is defined and distributed among the demand nodes of the network according to predefined rules (e.g., based on pipe length, service connections, or zone characteristics), obtaining the local coefficients Kj.

- Simulation:

  The model is run using the EPANET Toolkit to simulate leakage flows (QLmodel) at each node, computed through the Emitter flow equation.

- Comparison with Real Data:

  The simulated total leakage (QLmodel) is compared with the real measured leakage (QLreal) obtained from field data or system water balance.

- Recalculation (if needed):

If there is a significant difference between simulated and observed leakage, the total coefficient K_T is adjusted, and the process restarts.

- Convergence and Finalization:

The iteration continues until QLmodel≈QLreal, indicating the model is calibrated. At this point, the coefficients Kj can be considered validated for subsequent simulations and scenario analysis.

This method allows integration of pressure-dependent leakage into hydraulic modeling and forms the basis of the Fugas-ITA calibration tool.

The obtained results simulating with Fugas-ITA were used to charge the hydraulic model in the Water Smart platform, integrating the emitter-coefficients. By integrating this pressure-dependent approach, Water Smart would enable utilities to:

- Identify pressure-leakage zones.
- Prioritize pressure management or pipe replacement.

- Estimate real losses under varying demand and pressure scenarios.

- Simulate impacts of interventions like PRVs or DMA sectorization.

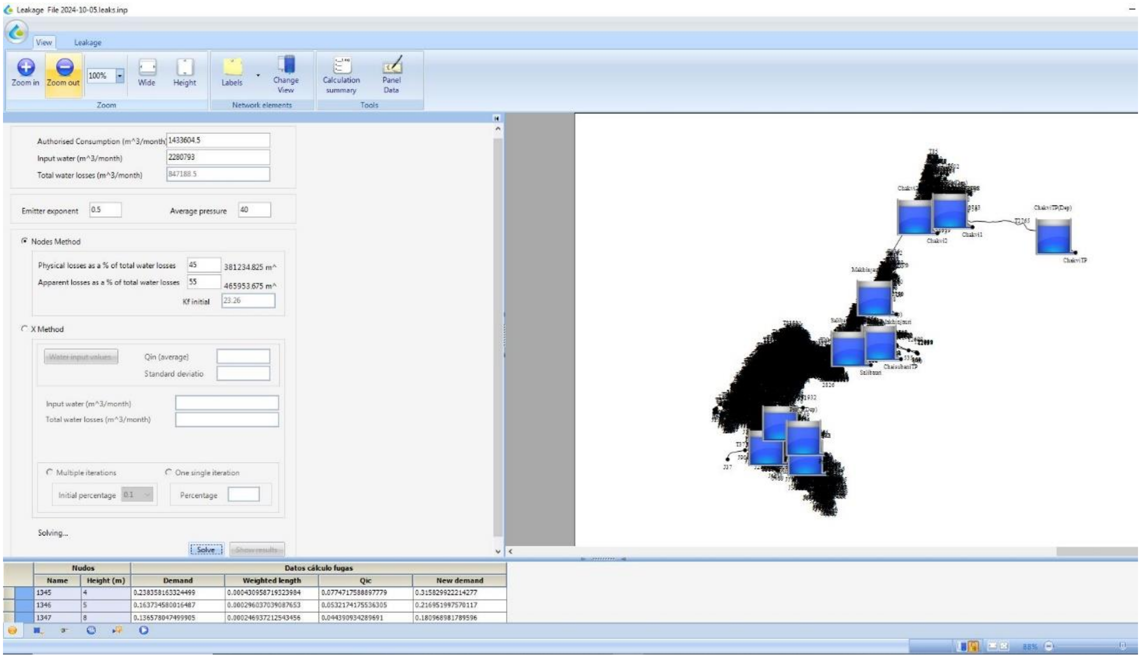


Figure 5: BTS system simulated with ITA-Fugas

The ITA-Fugas software was used in this thesis as a preprocessing tool to estimate emitter coefficients (K values) for each node, based on field measurements and pressure-leakage equations. These coefficients were then integrated into the EPANET-based hydraulic model to simulate leakage dynamics within the WSNO (Water Smart Network Optimizer) module. While ITA-Fugas itself does not form part of the Water Smart platform, it currently serves as the external method for obtaining calibrated leakage parameters. A key future development of the Macs Water Smart is the planned integration of this functionality directly into the WSNO module, enabling the automatic estimation and updating of emitter coefficients based on input data and measured flow balances, without requiring external software.

EPANET was selected as the hydraulic engine for the Water Smart platform due to its open-source availability, reliability, and extensibility through the EPANET Toolkit. Despite being a demand-driven solver, pressure-dependent leakage was simulated by introducing emitter coefficients and custom logic for pressure-leakage interaction. While pressure-driven demand solvers such as WDNetXL or WaterNetGen exist, they are not always open access, can be difficult to integrate with GIS workflows, and often lack transparency in computation or licensing. EPANET, in contrast, provides a stable, well-documented environment widely adopted by water utilities and researchers, and is thus particularly suitable for developing low-cost, replicable tools for small and mid-sized utilities, as demonstrated in this thesis.

2.2.2.4 Toolkit programming

The first version of the Water Smart simulation engine was developed using the EPANET Toolkit, an open dynamic-link library (DLL) provided by the U.S. Environmental Protection Agency (EPA), which allows developers to control EPANET hydraulic simulations through custom applications.

For this implementation, the Visual Basic (VB6) interface of the EPANET Toolkit was used to:

- Build a graphical environment for hydraulic simulation control,
- Automate model setup (e.g., applying leakage equations, configuring EPS),
- Extract and parse results from .inp and .rpt files for further analysis.

Further development process included:

- A pressure recovery code to optimize water systems.
- A pressure control code to minimize the leakages.

These Visual Basic scripts based on the EPANET Toolkit have constituted the foundational layer for the hydraulic simulation engine that underpins the design of the two AI-assisted modules within the Water Smart platform. The logic and structure developed in these early versions were later expanded and adapted to integrate machine learning algorithms, forming the basis for the intelligent control functionalities that are presented and discussed in detail in subsequent chapters of this thesis.

The Visual Basic 6 (VB6) codes developed for the Water Smart are freely available upon request and are intended for educational and research purposes. These codes integrate the EPANET Toolkit functionalities. Although they are no longer actively maintained (as the platform evolved into Python-based versions), they still serve as a useful reference for understanding the logic behind leakage modelling and network optimization in small utilities. The EPANET Toolkit DLL used is open-source and publicly provided by the U.S. Environmental Protection Agency (EPA).

Readers interested in accessing the VB6 source code or the compiled simulation tool can contact the author directly

2.2.2.5 Geographic Information System integration

The model integrates hydraulic simulation with spatial data by linking EPANET and QGIS, enabling the geospatial allocation and analysis of water losses. This integration is critical for supporting non-revenue water (NRW) diagnostics, especially in geographically dispersed systems such as those in developing countries.

GIS Role in Water Smart

The GIS component supports:

- The spatial representation of pipes, nodes, valves, demand points, and meters.
- Attribute analysis (e.g., pipe material, installation year, failure frequency).
- Thematic mapping of key indicators such as pressure zones, leakage hotspots, and consumption anomalies.
- Zonal definition of District Metered Areas (DMAs) and pressure management zones for leakage control planning.

Spatial data are used not only for visualization but also to inform the hydraulic model's parameters — such as elevation, pipe length, and service connection density — enhancing both model accuracy and usability.

QGIS-REd Plugin: EPANET-GIS Integration

The GIS integration was performed using the open-source QGIS-RED plugin, a toolbox developed by the Universitat Politècnica de València (UPV) to support water utilities in mapping, editing, and analyzing water distribution networks directly within QGIS. This plugin is freely available in QGIS, and its features and applications are documented in the accompanying technical paper by Pérez-García et al. (2021), which provides implementation guidance and real case studies.

Key features of QGIS-REd include:

- Importing and exporting EPANET models directly within the QGIS environment.
- Automatic generation of hydraulic layers (pipes, junctions, reservoirs, etc.) from EPANET input files.
- Enabling attribute synchronization between GIS layers and EPANET elements (e.g., diameter, length, roughness).

- Exporting the edited or GIS-enhanced network back into EPANET-readable format (.inp).
- Supporting network editing, sectorization (DMA definition), and visual simulation analysis through thematic result mapping.

QGIS-REd facilitates the preparation and continuous updating of hydraulic models using spatial datasets that reflect real-world utility conditions.

2.2.3 Change Management Index (CMI)

The Change Management Index (CMI) was not developed as part of this thesis but served as one of the conceptual foundations for the Water Smart application. It represents a structured approach that combines technical indicators (e.g., water balance, leakage monitoring) and institutional performance (e.g., team capacity, change readiness) into a unified framework. The analysis of three cases — Batumi (Georgia), Fortaleza and Juazeiro do Norte (Brazil) — provided practical insights and validation for this integrated methodology. These experiences directly informed the architecture of Water Smart, which adopts the water balance as its core simulation logic while incorporating institutional readiness metrics to guide implementation pathways.

The Change Management Index (CMI) was originally conceptualized and applied by Batumi Tskali, the local water utility. The city of Batumi, undergoing post-Soviet transition, had initiated major investments in water infrastructure, including network rehabilitation, metering, and district metering area (DMA) development.

This application served as one of the earliest pilots to integrate institutional readiness assessment with operational NRW indicators though the establishment of the water balance proposed by the International Water Association (IWA). The aim was to support a utility undergoing rapid institutional transformation while implementing large-scale NRW reduction strategies.

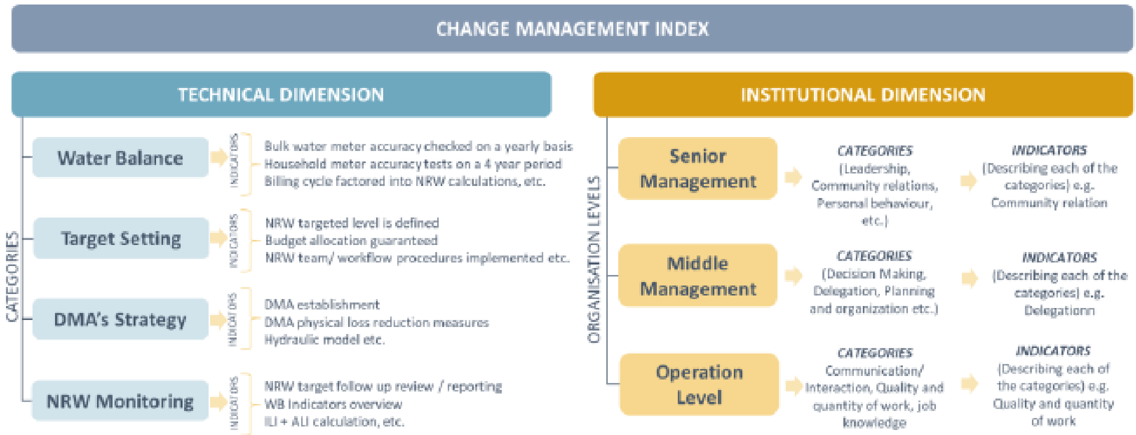


Figure 6: MACS Change Management Index

In the framework of the CMI, the water balance is not just a technical indicator—it is treated as a strategic diagnostic tool that informs the entire Non-Revenue Water (NRW) reduction approach. The CMI allocates significant weight (25% of the technical dimension, or 12.5% of the total index) to the utility's ability to establish and maintain a reliable water balance. This reflects a clear understanding: without a credible water balance, it is impossible to design, prioritize, or evaluate NRW control measures effectively.

The water balance category within the CMI includes the following core components:

- Accuracy of bulk water meters and customer meters
- Frequency and completeness of billing cycles
- Preparation of a standard IWA-compliant water balance
- Confidence level associated with the data used

In practice, the water balance acts as a gateway indicator. If the utility cannot produce a trustworthy water balance, the CMI framework assumes that other technical efforts—such as DMA creation, leakage detection, or target setting—will lack precision and accountability.

In Batumi, the CMI was used to:

- Evaluate the readiness of the utility's human resources and institutional structures to absorb and implement NRW control interventions.
- Combine technical audits with behavioral and managerial capacity assessments across organizational layers.

- Support change management by identifying internal communication gaps, training needs, and performance barriers.

The CMI is a structured performance evaluation tool designed to support utilities in monitoring their readiness and capacity to reduce Non-Revenue Water (NRW). Moreover, the CMI provides a holistic and goal-oriented framework that integrates both technical and institutional dimensions into a single comprehensive index. Its primary aim is to assess the progress of a utility's NRW reduction efforts, identify organizational and technical bottlenecks, and support strategic decision-making for sustainable performance improvements.

2.2.3.1 Objective

The core objective of the CMI is to evaluate a utility's capacity to implement effective NRW reduction programs by combining traditional technical performance indicators with institutional capacity metrics. By doing so, it overcomes the limitations of one-dimensional technical audits and enables utility managers to allocate resources more effectively while fostering a culture of change across all levels of the organization.

2.2.3.2 Methodological Structure

The CMI is structured around two main dimensions:

1. Technical Dimension:
This dimension evaluates the operational readiness and performance of the utility through four categories, each derived from International Water Association (IWA) guidelines:

- Water Balance: Assessment includes meter accuracy (bulk and household), frequency of billing, and overall quality and confidence of the water balance.

- Target Setting: Focuses on defining economic levels of NRW, setting achievable reduction targets, budgeting, and implementing workflows and leakage control strategies (e.g., ALR - Awareness, Location, Repair).
- DMA Strategy: Evaluates the degree of implementation of District Metered Areas, including hydraulic modeling, zoning criteria, monitoring mechanisms, and loss control measures.
- NRW Monitoring: Involves the use of indicators, monitoring/reporting frequency, and performance against defined NRW targets.

Table 2: Technical categories and their respective weights in the CMI

Category	Weight in Technical Dimension (%)	Weight in Total Index (%)
Water Balance	25	12.5
Target Setting	23	11.5
DMA Strategy	35	17.5
NRW Monitoring	17	8.5

2. Institutional Dimension:

This dimension is based on indicators collected through qualitative interviews and indirect observations across three hierarchical levels of the organization: senior management, middle management, and operator level. The evaluated categories include:

- Communication and interaction
- Personal behavior
- Planning and organizing
- Decision-making
- Quality and quantity of work
- Leadership and delegation
- Initiative and creativity
- Job-specific technical knowledge

The institutional evaluation aims to understand staff attitudes, skills, and readiness for change—factors crucial to the success of any technical intervention.

Table 3: Institutional indicators for evaluating change readiness

Category	Description
Communication & Interaction	Collaboration and interdepartmental interaction
Personal Behaviour	Workplace attitude and teamwork
Planning & Organising	Resource use and time management
Decision-Making	Analytical capacity and judgment
Quality & Quantity of Work	Work output performance
Leadership	Vision, motivation and role modeling
Delegation	Responsibility distribution
Initiative & Creativity	Innovation encouragement
Technical Knowledge	Job-specific competence

Particular attention was also given to the institutional evaluation component of the CMI, which was conducted jointly by the author and a collaborating organizational psychologist. This qualitative assessment proved essential in contexts where the implementation of a Non-Revenue Water (NRW) control strategy faces not only technical but also cultural and organizational barriers. In utilities where NRW is poorly understood or even resisted, building the right internal teams and creating the necessary synergies between operational, managerial, and strategic actors becomes a prerequisite for success. The institutional indicators are therefore not presented as objective or absolute scores but as relative measures intended to monitor internal performance over time. Their value lies in enabling each utility to track its own progress, identify internal bottlenecks, and compare results longitudinally or with peer institutions, rather than to serve as a fixed benchmark.

2.2.3.3 Implementation and Scoring

Each category within both dimensions includes a set of weighted indicators. Technical indicators are based on verifiable operational data (e.g., from billing systems or asset management software), while institutional indicators rely on qualitative data obtained through field assessments and interviews. All indicators are normalized on a scale from 0 to 1, and the final index is the weighted average of both dimensions.

A higher index value (closer to 1) indicates strong institutional and technical readiness, suggesting that the utility is well-positioned to implement and sustain an effective NRW reduction program. Lower values highlight areas needing organizational strengthening or technical improvements.

Table 4: Scoring scales and basis for technical and institutional indicators

Dimension	Category	Scoring Basis	Scoring Scale
Technical	Water Balance	Meter accuracy, billing cycle, water balance confidence	0 (Not Implemented) to 1 (Fully Implemented)
Technical	Target Setting	Target definitions, budget allocation, leakage control strategy	0 (Undefined) to 1 (Clearly Defined and Applied)
Technical	DMA Strategy	DMA design and implementation, monitoring measures	0 (No Implementation) to 1 (Fully Functional DMA Network)
Technical	NRW Monitoring	ILI/ALI calculations, monitoring frequency, target fulfilment	0 (No Monitoring) to 1 (Continuous Monthly Monitoring)
Institutional	Performance Indicators	Semi-structured interviews and indirect observations	0 (Non-compliant) to 1 (Excellent Performance)
Institutional	Employee Behavior	Communication, decision-making, leadership, creativity	0 (Weak Attitude/Skill) to 1 (High Capacity and Motivation)

2.2.3.4 Practical Applications

The CMI application in BTS along the first phases of the project resulted in the following

1. Institutional Performance: Mixed Readiness

The institutional dimension of the CMI focused on organizational behavior across senior management, middle management, and operator level. The findings were:

- Senior Management: Demonstrated high awareness of NRW challenges and supported the reform process. However, strategic leadership was not always translated into practical, operational planning.
- Middle Management: Acted as a weak link in the change chain. There was a lack of structured communication between departments and limited delegation of responsibilities, leading to inefficiencies in project follow-up.
- Operator Level: Field staff showed resistance to change, often due to limited training, unclear job expectations, and inadequate tools or incentives. Many operators continued using outdated work practices.

2. Technical Performance: Strong Potential but Implementation Gaps

From the technical perspective, Batumi Tskali had invested in several important initiatives:

- Water balance assessments had begun using bulk meters and some customer meters.
- DMA planning was in progress, though only partially implemented.
- Active leakage control was introduced with support from international donors and consultants.
- Use of hydraulic models (e.g., EPANET) was initiated, particularly for pressure management studies.

However, the CMI technical score was moderate, indicating that while the tools and concepts were present, full implementation and integration were lacking. The utility struggled with:

- Inconsistent data quality
- Low coverage of functioning customer meters
- Limited staff capacity to operate and interpret simulation tools

Apart from Batumi Tskali, the CMI was successfully applied at CAGECE, a major Brazilian utility, in both urban (Fortaleza) and rural (Juazeiro do Norte) settings. The assessment provided insights not only into operational gaps—such as limited DMA implementation and irregular meter testing—but also institutional challenges like communication deficits between departments and inconsistent contractor training. The results enabled CAGECE to formulate a combined engineering and human resource action plan, reinforcing the value of the CMI as a change-oriented management instrument.

As said previously, the CMI was applied in two service areas managed by CAGECE:

- Fortaleza (urban): capital of the state of Ceará, with a large and dense customer base.
- Juazeiro do Norte (rural): a smaller city in the interior of the state.

The assessment covered both technical and institutional dimensions, with field visits, interviews, and performance data collection conducted over a 4-week period.

The results of applying the methodology showed key differences between the urban vs. rural system, presented in the following table.

Table 5: CAGECE CMI results

Category	Fortaleza (Urban)	Juazeiro do Norte (Rural)
Water Balance	Higher score due to better bulk and household meter testing.	Lower meter testing coverage, affecting data reliability.
Target Setting	Fully allocated and executed NRW budget.	Budget allocated, but not fully executed.
DMA Strategy	DMA projects prepared but not yet implemented.	Same status; no established DMAs, limiting control.
NRW Monitoring	Achieved 100% of reduction targets.	Only 75% of targets achieved during analysis period.
Training	In-house teams better trained and more standardized.	Greater reliance on contractors with variable training.

The combined analysis of these three applications of the CMI across urban and rural systems confirmed that an effective NRW control strategy requires not only technical optimization but also institutional capacity and organizational alignment. These findings validated the need for an integrated platform like Water Smart, where the technical backbone (hydraulic simulation and water balance) is enhanced by decision support tools that reflect institutional readiness, operational constraints, and human factors. The experiences from Batumi and CAGECE helped define the dual structure of Water Smart, which includes both a network optimization module (WSNO) and an institutional performance module (WSNA), aligned with the IWA methodology but adapted to the realities of small and mid-sized utilities in developing contexts.

2.2.4 Sistema Integrado de Saneamento Rural (SISAR)

The Sistema Integrado de Saneamento Rural (SISAR), originally conceptualized by MACS Energy & Water GmbH, is a decentralized water and sanitation management model that operates across rural communities in the State of Ceará, Brazil. Originally created to empower local associations in the management of small rural water systems, SISAR evolved to integrate digital technologies, enabling the coordination of operational, administrative, financial, and social functions through a centralized online management platform.

The SISAR model is especially relevant to this research because it presents a real-world framework for data-driven rural utility management under low-resource conditions—one of the key design constraints of the Water Smart application.

2.2.4.1 Objective of the SISAR System

The SISAR online platform was developed to:

- Digitize and automate the service order workflows that were previously managed with paper forms and spreadsheets.
- Provide modules for inventory control, fleet management, service authorization, reporting, and user management.
- Enhance transparency, traceability, and response time in rural water service provision.
- Support data collection for management decision-making and performance monitoring across multiple remote communities.

2.2.4.2 System Architecture and Functional Modules

The SISAR system is modular and web-based. Key modules and their functions are summarized in the table below:

Table 6: SISAR key modules and functions

Module	Functionality
Gestor	Full system access for managers (all modules)
Financeiro	Service authorization, cost tracking, and financial reporting
Estoque	Inventory control, acquisition records, material requisition
Técnico	Field team interface: work orders, requisitions, and technical reports
Recepção	General admin support: vehicle registration, service intake, and product orders
Social	Manages community-oriented services like education and awareness campaigns

2.2.4.3 Relevance to the Water Smart Application

In summary, the SISAR system provided a valuable real-world model for the design of the WSNA module within the Water Smart platform. Its modular, decentralized, and digital approach to rural water supply management inspired the structure and logic of WSNA, particularly regarding service tracking, material and work order management, and data-informed decision support. The ability of SISAR to coordinate operational, administrative, and social functions across dispersed rural communities served as a practical benchmark for creating a digital assistant capable of supporting non-technical users in small utilities. WSNA thus builds upon SISAR's experience to provide an intuitive interface that facilitates planning, intervention tracking, and strategic guidance in contexts with limited technical capacity and digital infrastructure. This adaptation reinforces the scalability and contextual relevance of the Water Smart platform for both urban and rural water services.

2.2.5 Water infrastructure resilience against Climate Change. Future development (Water Smart Resilience Optimizer)

Although the Water Smart platform was initially designed to address Non-Revenue Water (NRW) through pressure management and operational optimization (WSNO) and assist small utilities in their daily management (WSNA), the growing challenges posed by climate change led to the need for a third component focused on long-term resilience. This section presents the conceptual basis and initial application of climate resilience modelling within the

Water Smart framework. While still under development, this third module—currently referred to as *Water Smart Resilience Optimizer (WSRO)*—is being piloted to support small and mid-sized water utilities in evaluating and simulating climate adaptation strategies. Its inclusion in this thesis is justified by the application of the methodology in a published case study from Indonesia (Sleman, Yogyakarta), where the CRIDA approach was combined with hydraulic simulation to assess the vulnerability of the water infrastructure. This experience marked the first step towards embedding resilience analysis into the Water Smart architecture and justifies the inclusion of this section under methodology, despite its forward-looking orientation.

In the context of increasing climate uncertainty and aging water infrastructure, integrated decision-support tools are essential for enhancing the resilience and efficiency of urban and rural water supply systems. In this context, one of the future developments of the Water Smart we are working on is linking the WSNO with specific tools for climate change resilience modelling, with the objective to support the small and mid-sized water utilities managers to simulate possible solutions for adaption/mitigation against possible water supply failures due to the climate change actions. This methodology was first applied during the risk and resilience assessment of the Sleman utility (Yogyakarta, Indonesia), where climate-related vulnerabilities (such as drought and infrastructure sensitivity) were identified through the CRIDA framework, and hydraulic modeling was performed using EPANET and GIS tools. The results of this analysis were presented in an international publication and now serve as the basis for the design of the third Water Smart module.

The Climate Risk Informed Decision Analysis (CRIDA) framework offers a structured approach to long-term planning under uncertainty, guiding the identification of adaptive pathways that are robust across multiple future scenarios. Complementing this, the Water Network Tool for Resilience (WNTR) provides a simulation environment for evaluating the performance of water distribution systems under a range of disruptive events, such as pipe failures, power outages, and droughts. Building upon these foundations, the Water Smart for NRW Optimization (WSNO) tool focuses on the tactical level, simulating and optimizing non-revenue water (NRW) management strategies including district metered area (DMA) design, pressure control, and infrastructure rehabilitation. By integrating CRIDA's strategic planning, WNTR's resilience analysis, and WSNO's operational optimization, water utilities can develop more informed, adaptive, and context-specific interventions to reduce water losses and ensure service continuity under stress. This conceptual framework is explored and applied in one of the cases of study.

Table 7: Conceptual integration CRIDA+WNTR+WSNO

Framework/Tool	Role in the Workflow	Interaction with WSNO
CRIDA	Strategic planning tool for decision-making under uncertainty (e.g., future water demand, climate variability, investment timing).	Helps identify critical vulnerabilities in the water supply system that WSNO can later target for NRW reduction strategies.
WNTR	Operational simulation tool for testing resilience and robustness of the water network under various stressors (pipe breaks, power failures, droughts, etc.).	Can feed into WSNO by revealing how infrastructure failures or external shocks impact losses and inform pressure management.
WSNO	Tactical tool focused on optimizing NRW through simulation of DMA strategies, pressure zones, leak detection, and rehabilitation planning.	Uses insights from CRIDA (vulnerability pathways) and WNTR (resilience of interventions) to prioritize and optimize interventions.

By using CRIDA to define "where and when to act", WNTR to test "how bad could it get", and WSNO to design "what exactly should we do", can be created a resilient, adaptive, and optimized NRW strategy for water utilities under uncertainty.

2.2.5.1 Climate Risk Informed Decision Analysis (CRIDA)

CRIDA provides the conceptual and methodological backbone for integrating climate resilience into the Water Smart platform. It highlights the importance of building decision tools that are adaptable, transparent, and inclusive—especially in settings where traditional master plans are unfeasible due to uncertain futures or limited capacity. Through this integration, Water Smart becomes a resilience-oriented planning and decision support tool for water utilities operating under climate stress.

Overview of CRIDA

The Climate Risk Informed Decision Analysis (CRIDA) is a structured methodology developed by UNESCO to help decision-makers plan resilient water systems under conditions of deep uncertainty, such as those introduced by climate change and data scarcity. Unlike conventional risk assessments that rely heavily on historical data and fixed projections, CRIDA emphasizes robustness and flexibility—helping water utilities make no-regret decisions even with incomplete information.

CRIDA is particularly relevant for small and medium-sized utilities in developing countries, where both climatic vulnerability and institutional constraints often co-exist. It enables inclusive, stakeholder-driven planning while promoting technically sound and cost-effective solutions for adaptation and mitigation.

The application of CRIDA in the case of water utilities in developing areas followed the five steps recommended by UNESCO:

1. Decision Context Definition
   Collaborative identification of objectives, service levels, system boundaries, and critical thresholds, with active involvement of utility stakeholders.

2. Bottom-Up Vulnerability Assessment
   Evaluation of the system's sensitivity to climate risks through field data, hydraulic modeling, and qualitative stakeholder knowledge. Focus was on identifying stress points even under moderate scenarios.

3. Formulation of Robust and Flexible Options
   Multiple adaptation pathways were co-developed, including pipe replacement, supply interconnection, better pump automation, and source diversification.

4. Evaluation of Alternatives
   Adaptation strategies were tested under a range of simulated stressors—such as increased drought frequency, contamination risk during floods, or population growth.

5. Institutionalization of Decisions
   Results were presented in structured workshops and translated into formal planning documents, forming the basis for investment prioritization.

Link to the Water Smart Application

The Water Smart application draws heavily from the CRIDA philosophy in the following ways:

1. Uncertainty Management
   Water Smart simulates multiple scenarios using limited baseline data—just like CRIDA's

bottom-up approach to vulnerability assessment. The tool accepts incomplete datasets and uses ranges and performance thresholds instead of single forecasts.

2. Resilience Metrics and Thresholds
   Inspired by CRIDA's definition of "service level thresholds," Water Smart includes resilience scoring tools that allow users to define critical pressure, flow, or quality indicators tied to service sustainability.

3. Adaptation Planning Interface
   Water Smart operationalizes the robust decision-making process by presenting simulated outcomes for each intervention—such as pipe resizing or zone reconfiguration—much like CRIDA's step 4 scenario testing.

4. Institutional Integration
   Just as CRIDA emphasizes participatory and context-sensitive planning, Water Smart enables local engineers and utility managers to visualize trade-offs and make informed choices, even in decentralized or rural systems.

2.2.5.2 Water Network Tool for Resilience (WNTR)

WNTR supports the operational and tactical dimension of the Water Smart platform by enabling detailed simulation of water distribution system performance under failure conditions. While CRIDA provides the strategic lens for long-term uncertainty and climate risk, WNTR focuses on short- and medium-term resilience by analyzing how infrastructure responds to disruptive events. Its integration into Water Smart enhances the platform's ability to identify weak points, evaluate response strategies, and quantify the impact of system stress on non-revenue water (NRW) levels and service reliability.

Overview of WNTR

The Water Network Tool for Resilience (WNTR), developed by the U.S. Environmental Protection Agency (EPA), is an open-source Python package designed to assess the resilience of drinking water distribution systems. WNTR extends EPANET's hydraulic modeling capabilities by enabling the simulation of disruptive scenarios such as pipe breaks, pump failures, pressure losses, and contamination events. It provides a comprehensive set of tools to evaluate system performance, estimate service degradation, and test restoration and mitigation strategies.

WNTR's core strength lies in its ability to model failure propagation and recovery across a network, making it a valuable tool for utilities operating in fragile environments or under resource constraints. Its modular, scriptable architecture allows for integration into broader platforms—like Water Smart—and supports iterative testing of interventions under both normal and disrupted conditions.

The application of WNTR in the context of small and medium-sized water utilities focuses on four main functions:

1. Disruption Scenario Simulation.
Pipe bursts, power outages, and control valve failures are modeled to assess their impact on network hydraulics and service delivery, helping utilities visualize vulnerability hotspots.

2. Resilience Metric Calculation.
Key performance indicators such as population served, pressure availability, and volume delivered are tracked to quantify the system's ability to maintain service during and after an event.

3. Intervention Testing.
Recovery and adaptation strategies—such as valve closure, pressure zone isolation, and temporary supply routing—are simulated to evaluate their effectiveness in reducing service loss and NRW.

4. System-Level Comparison.
Different configurations and rehabilitation strategies can be benchmarked against resilience outcomes, aiding in the prioritization of infrastructure investments.

Link to the Water Smart Application

The integration of WNTR into the Water Smart platform reinforces its capacity to address operational risks and optimize NRW control strategies through the following pathways:

1. Stress Testing of NRW Interventions.
WSNO incorporates WNTR simulation routines to evaluate how NRW reduction strategies (like pressure management or DMA creation) perform under stress conditions such as pipe failure or power disruption.

2. Dynamic Performance Feedback.

By connecting WNTR outputs to WSNO's scenario engine, the platform enables users to visualize how certain areas of the network might transition from resilience to failure thresholds—thus guiding tactical decisions.

3. Redundancy and Recovery Planning and Scenario-Informed Optimization:

Water Smart leverages WNTR's network-wide modeling to identify where redundancy (e.g., looped pipes, backup pumps) could mitigate the impact of service interruptions and maintain low NRW during crises. WSNO uses WNTR-derived stress scenarios as additional constraints in its optimization algorithms, allowing for more robust selection of interventions that are effective both under normal and adverse conditions.

2.3 Development of the Water Smart Application

The Water Smart (WS) platform was conceived as a comprehensive digital solution for water utility management, particularly tailored to the needs of small and mid-sized utilities. Its development centered on a modular architecture with two core components: Water Smart Network Administration (WSNA) and Water Smart Network Optimization (WSNO).

Figure 7: WS basic concept (Source SISAR)

Figure 7 illustrates the dual structure of the Water Smart platform, emphasizing the automated integration between the design and optimization module (left) and the network management module (right). On the left, geospatial and topographic data—including land use, elevation models, and hydraulic structures—are automatically processed and integrated with optimization tools based on EPANET and Water Smart algorithms, resulting in performance and cost reports. On the right, administrative and operational features such as customer databases, maintenance scheduling, KPI monitoring, and asset control are centralized within a management dashboard, enabling seamless data exchange and enhanced utility oversight.

These modules serve complementary roles within the platform, together forming an integrated framework that bridges everyday operational management with advanced system analysis and optimization. The design philosophy ensures that while the platform was originally applied in resource-constrained and developing regions, its features and benefits extend broadly to any small or medium-sized water utility seeking to modernize its operations in a sustainable manner.

In combination, WSNA and WSNO provide a holistic platform for digital water utility management. WSNA lays the groundwork by handling the "who," "what," and "where" of the utility's operations – it knows the users and their permissions, the customers and assets, and the configuration of the service network. WSNO builds on this by addressing the "how to improve" question – using the data from WSNA to simulate "what-if" scenarios and identify optimal solutions. The two modules are tightly integrated, sharing a common data architecture so that information flows seamlessly between daily management and analytical modeling. For instance, the current network configuration and demand data registered in WSNA form the input for WSNO's simulations; conversely, the insights gained from WSNO (such as recommended network adjustments or performance forecasts) can inform operational decisions and planning managed through WSNA.

This integration eliminates duplication of data and ensures consistency: the same set of verified information underpins both operational records and strategic analyses. Together, the WSNA and WSNO modules exemplify an approach where operational control and optimization analysis are part of one unified ecosystem. This is particularly advantageous for small and mid-sized utilities, which may not have the resources to employ separate specialized systems for each function – the WS platform offers them an all-in-one toolkit to both manage their existing system efficiently and plan improvements intelligently. In summary, the development of the Water Smart application has produced an adaptable yet robust platform in which the administrative core (WSNA) and the optimization engine (WSNO) work in concert. This ensures that even utilities with constrained expertise or budgets can leverage digital technology for enhanced oversight, improved performance, and sustainable decision-making, thereby not only benefiting developing regions but any water utility aiming for smart management practices.

Beyond its role as an optimization engine, WSNO incorporates several specialized modules that address key performance challenges frequently faced by water utilities:

- Pressure Recovery Module**:** This tool analyzes system hydraulics to detect overpressurized zones and identify opportunities for pressure zoning or control valve installation. By recovering excess pressure, utilities can reduce leakage rates, protect infrastructure, and improve pressure equity across service areas.
- Leakage Reduction Module**:** Built upon calibrated hydraulic models, this module quantifies physical losses based on flow and pressure patterns and helps utilities simulate and compare interventions such as pipe replacements, DMA segmentation, and valve adjustments. It supports both strategic leak control and real-time pressure management as NRW reduction strategies.

Together, these functional modules are embedded within WSNO's simulation and optimization environment, enabling users to test, compare, and prioritize operational improvements in a transparent, data-driven way. This is particularly advantageous for small and mid-sized utilities, which may not have the resources to employ separate specialized systems for each function – the WS platform offers them an all-in-one toolkit to both manage their existing system efficiently and plan improvements intelligently.

2.3.1 Water Smart Network Administration (WSNA)

The Water Smart Network Administration (WSNA) module represents a significant technological upgrade from the earlier SISAR systems used by decentralized water utilities in Brazil. While SISAR's traditional model relied heavily on manual records, spreadsheet-based workflows, and fragmented procedures, WSNA introduces a centralized, fully digital, and web-based administrative platform. Developed collaboratively by MACS Energy & Water and local water cooperatives, this module was designed to facilitate secure system access, administrative configuration, and modular control of all Water Smart functionalities. Its development aligns with the broader digital transformation goals of improving operational efficiency, transparency, and sustainability within small and mid-sized utilities.

In addition to managing user roles and work orders, WSNA also provides a structured digital registry of all rural water systems under its supervision. This registry includes key technical, geographic, and administrative information that enables utilities to centralize infrastructure records, track service areas, and plan interventions more effectively. Figure 8 illustrates a typical interface of this registry, where systems are listed along with attributes such as location, water treatment type, funding source, and operational status.

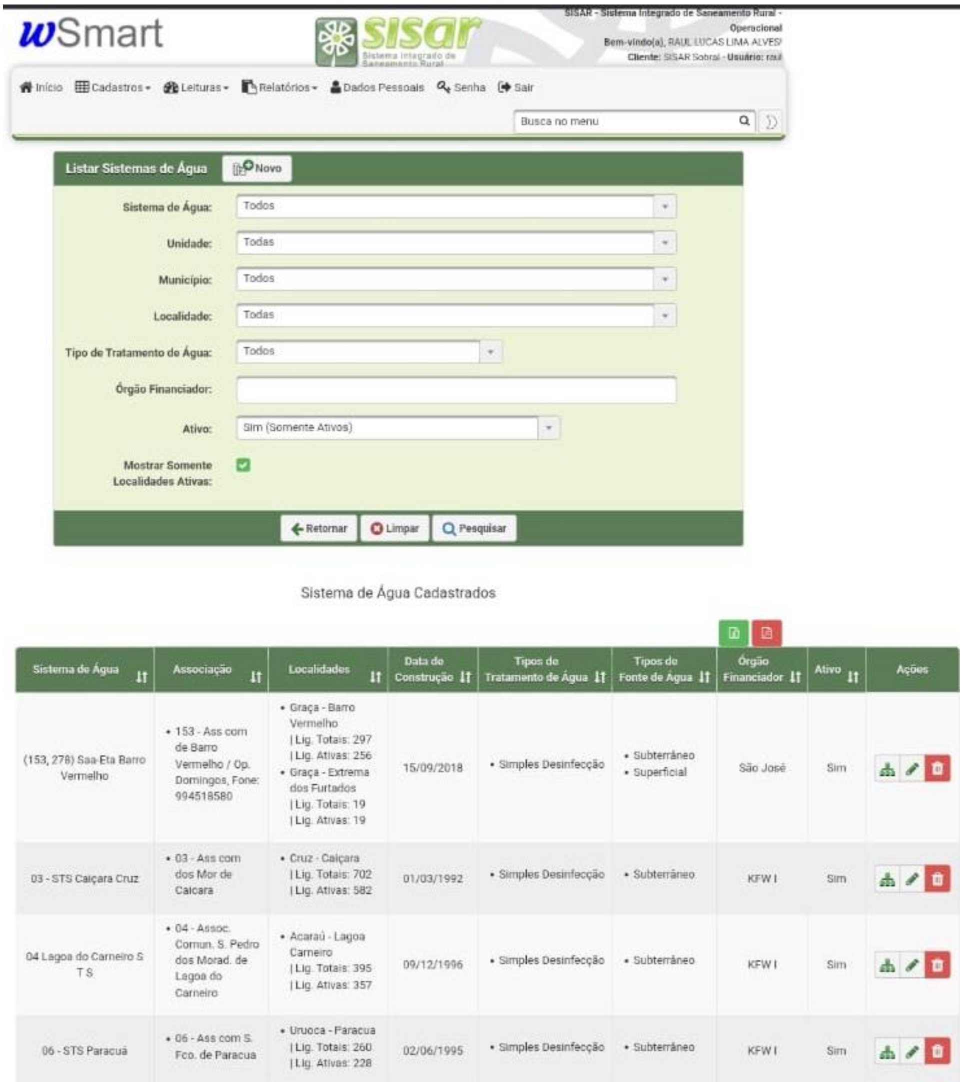


Figure 8: Interface of the WSNA module displaying the list of registered rural water systems under SISAR

This digitalization effort ensures that decentralized rural utilities—often operating with limited documentation—have access to standardized, searchable records that serve as the foundation for further analysis, such as network optimization or NRW tracking via WSNO.

The WSNA module, as illustrated in Figure 9, provides a unified digital interface for monitoring the operational status of decentralized rural water utilities managed under the SISAR model. The system tracks key indicators such as the number of localities served, macro- and micro-meter readings, and chlorine and pH delivery. This data, automatically recorded and aggregated, forms the basis for calculating the IWA water balance in future implementations.

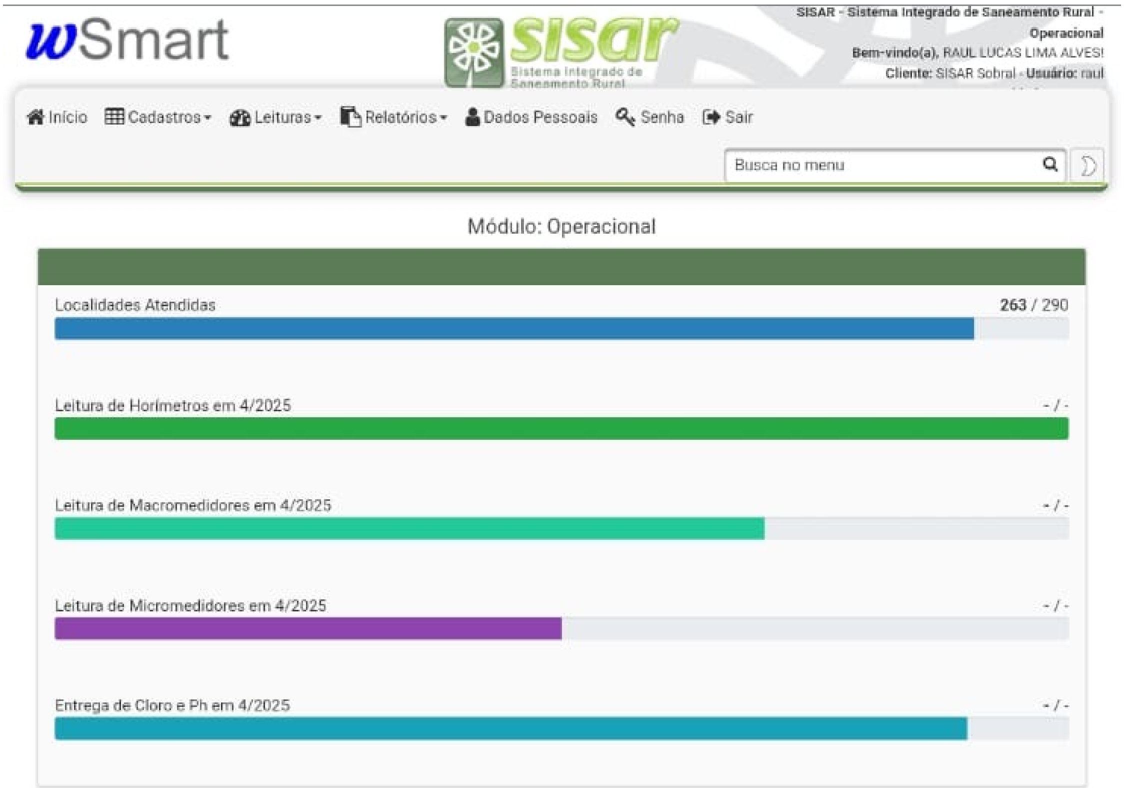


Figure 9: WSNA operational module implemented in the SISAR system in Sobral (Brazil)

Importantly, WSNA is not only inspired by SISAR but also directly builds upon it. The SISAR model provided the conceptual foundation for a decentralized and community-managed utility system, particularly in rural regions. WSNA expands this foundation by digitizing all key administrative functions and integrating essential operational data into a unified platform. In this way, WSNA supports daily utility management while also becoming the central system where both macro and micro flow data are registered. This capability enables the implementation of the IWA water balance methodology within WSNA itself. The calculated balance is then communicated to the WSNO (Water Smart Network Optimizer) module to simulate leakage control strategies and evaluate network performance.

2.3.1.1 Flow Measurement and Monitoring Interface

In line with the water balance and performance tracking objectives of the Water Smart platform, WSNA integrates a digital interface for registering and monitoring macro flow meter readings. These meters are installed at production sources or DMA inlets, and their periodic readings are stored within the operational database for further analysis and reporting (see Figure 10).

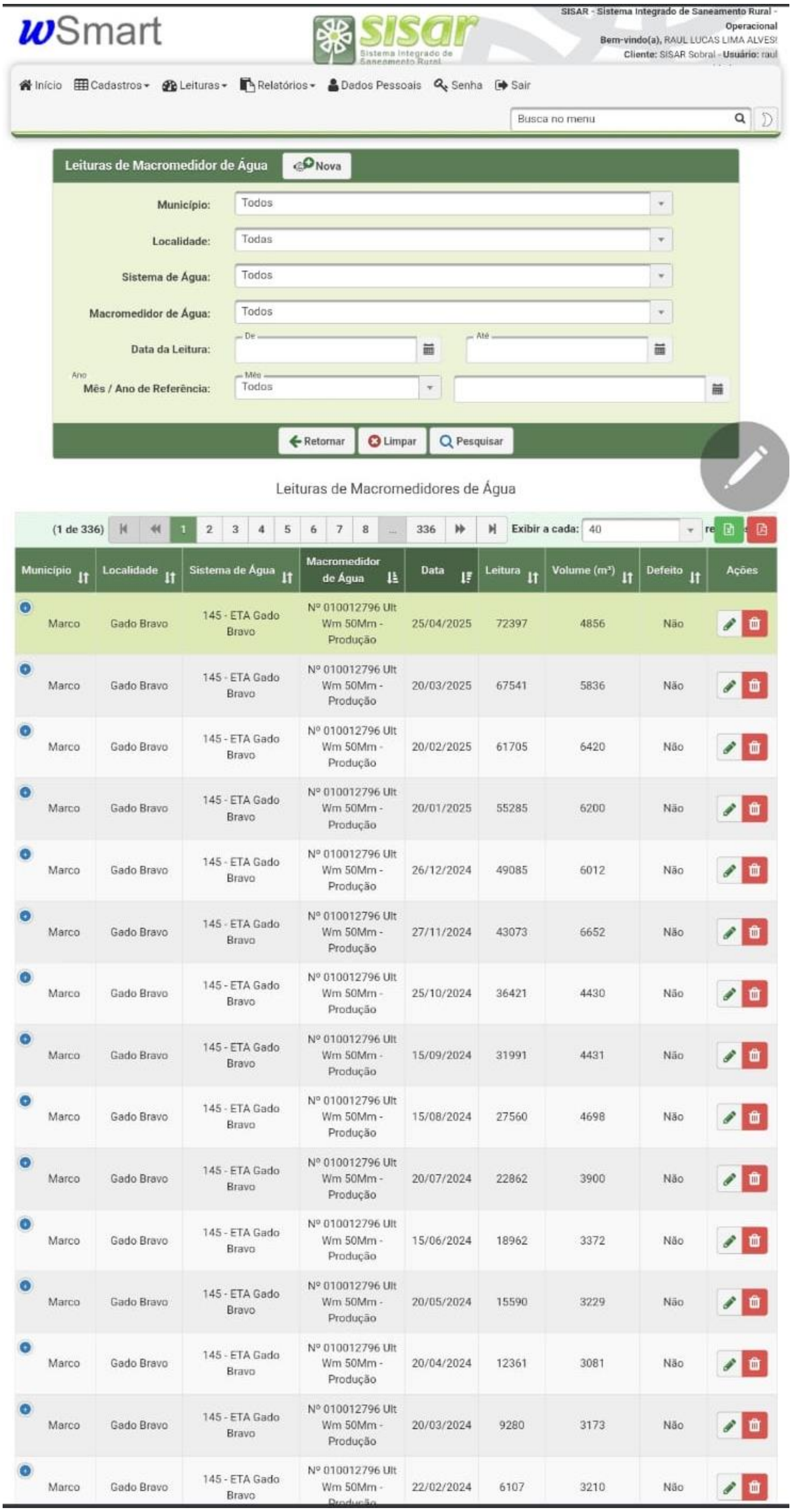


Figure 10: WSNA interface used for registering macro flow meter readings in the SISAR system

This module ensures data traceability and enables automated linkage with NRW monitoring tools, facilitating seamless integration with the WSNO optimization module. The macro readings registered here form the backbone of the IWA water balance to be implemented in subsequent simulations.

2.3.1.2 System Architecture and Access Control

WSNA operates as the administrative core of the Water Smart platform. It is accessed through a secure online portal, hosted on cloud servers managed by the administrator. Users must log in with unique credentials, and permissions are strictly role-based. The system differentiates access levels for users according to their assigned responsibilities, such as system administrators, technical operators, customer service personnel, and financial managers.

The WSNA module functions as the administrative backbone of the Water Smart system. It provides utility managers and service providers with a web-based environment for configuring the entire suite of operational tools available in the platform. Access to the system is secured through login credentials, with user permissions and access rights tailored to different organizational roles such as technicians, financial managers, receptionists, or system administrators.

Each utility or client is registered in the system under a distinct database schema. This architecture ensures that data remains isolated and secure, allowing utilities to operate independently while sharing a common software framework. The platform administrator can configure which modules each utility can access, including NRW monitoring, customer management, billing, and operational planning tools.

2.3.1.3 Client and User Management

One of the primary functions of WSNA is to register new clients (i.e., water service providers) and manage their respective user bases. During client registration, information such as the utility name, unique database schema, and the credentials of the first user (typically a designated "Manager") are established. This first user is automatically granted the highest level of access and is responsible for managing all subsequent configurations for that utility.

The user management interface supports the creation, editing, and deactivation of user accounts. Each account is assigned specific permissions tailored to the user's operational role. WSNA ensures security and accountability by enforcing password changes upon first login, logging access activity, and preventing unauthorized data access across utility boundaries.

Core functionalities of WSNA include the registration and management of service providers, creation of individual user accounts, assignment of access levels, and configuration of service modules. The administrator can manage the entire digital environment, including the definition of available tools for each client, thereby ensuring consistency and modular flexibility in system use. Each client operates within an isolated database schema to guarantee data confidentiality and maintainability.

2.3.1.4 Service Module Configuration

WSNA enables administrators to activate and configure various Water Smart modules according to each utility's needs. These modules include customer service, asset inventory, work order management, billing integration, and reporting. The flexibility to customize available features ensures that utilities only access relevant tools, which improves usability and system performance.

Administrators can also define the structure and hierarchy of modules, assign functionalities to each, and set dependencies between them. For example, the “Work Order” module can be configured to depend on prior data entry in the “Customer Registry” and “Metering” modules, ensuring logical workflows and data consistency.

From a methodological standpoint, the WSNA module was designed with a user-centered interface that integrates data listing, filtering, and record validation functionalities. This allows administrators to rapidly identify records, manage updates, and generate user-specific dashboards. For each new utility integrated into the system, a designated primary user (typically a local manager or supervisor) is created with full access rights. This user is responsible for initiating local configurations and leading the transition from analog to digital operations.

2.3.1.5 Work Order Management and Digitalization of Services

Originally dependent on paper forms and disconnected spreadsheets, service request workflows have been significantly enhanced in WSNA. The module now allows for digital entry, tracking, and processing of all work orders. This includes service connection requests, meter replacements, leak repairs, and maintenance tasks.

Additionally, WSNA includes tools for tracking service requests, registering work orders, and generating administrative reports. These features were further developed and expanded in the second phase of the platform through the operational module, which integrates WSNA with on-the-ground utility workflows. Collectively, these tools offer an essential bridge between data collection, operational control, and strategic management, while reducing administrative overhead and improving service response times.

Using built-in filters and dynamic lists, staff can quickly identify pending orders, prioritize by urgency, and assign them to field teams. The system also enables real-time monitoring of service status and automatically updates historical logs, which supports both internal accountability and external reporting.

2.3.1.6 Statistical Reports and Administrative Insights

WSNA also supports strategic management by generating quantitative and qualitative reports based on all logged administrative activities. These reports include metrics such as number of service requests completed, average resolution time, types of interventions, and frequency of specific service orders. Managers can use this data to identify performance gaps, allocate resources more effectively, and track operational trends over time.

Furthermore, the data structures established through WSNA provide the foundation for more advanced modules—such as predictive maintenance, performance benchmarking, and AI-driven recommendations—ensuring that digital administration translates directly into smarter operations.

2.3.1.7 Integration and Evolution from SISAR Systems

WSNA should be understood as a technological evolution from the SISAR model of decentralized utility management. While SISAR historically emphasized community participation and local autonomy, its operational tools were largely analog and limited in scalability. WSNA preserves the decentralized spirit of SISAR while equipping utilities with the digital infrastructure necessary to handle larger customer bases, regulatory demands, and sustainability goals.

This module serves as the entry point to the broader Water Smart ecosystem, which includes hydraulic modeling, NRW optimization, and economic analysis tools. By standardizing administrative processes and securing digital records, WSNA enables a seamless transition to more advanced operational modules, ensuring consistent data quality and cross-functional integration.

In summary, WSNA forms a foundational step in the Water Smart platform's methodological framework. By enabling structured digital administration and decentralization of user management, it lays the groundwork for higher-level functionalities such as hydraulic simulation and network optimization. It also provides the operational interface for flow monitoring—both macro and micro—needed to implement the IWA water balance, which will interact with the WSNO module for simulation purposes. This strategic integration reflects a long-term vision: using administrative digitalization not only to improve daily workflows, but also to embed data-driven decision-making directly into the operational core of rural utilities.

2.3.2 Water Smart Network Optimization (WSNO)

The Water Smart Network Optimization (WSNO) module is a web-based expert system designed to support the design, evaluation, and improvement of water distribution systems. It was specifically developed to serve the needs of small and mid-sized utilities that often lack specialized personnel or access to advanced hydraulic tools. As an evolution of the GIS-based non-revenue water (NRW) diagnosis tools within the Water Smart platform, WSNO introduces a comprehensive methodology for forward-looking infrastructure planning and intervention design.

Figure 11 displays the setup interface where users input foundational parameters to initiate a hydraulic optimization project. These include the project name, served population, number of active connections, daily water demand per capita, and minimum pressure requirements. The definition of these inputs is essential to tailor the hydraulic and economic simulations to the utility’s specific operating conditions.

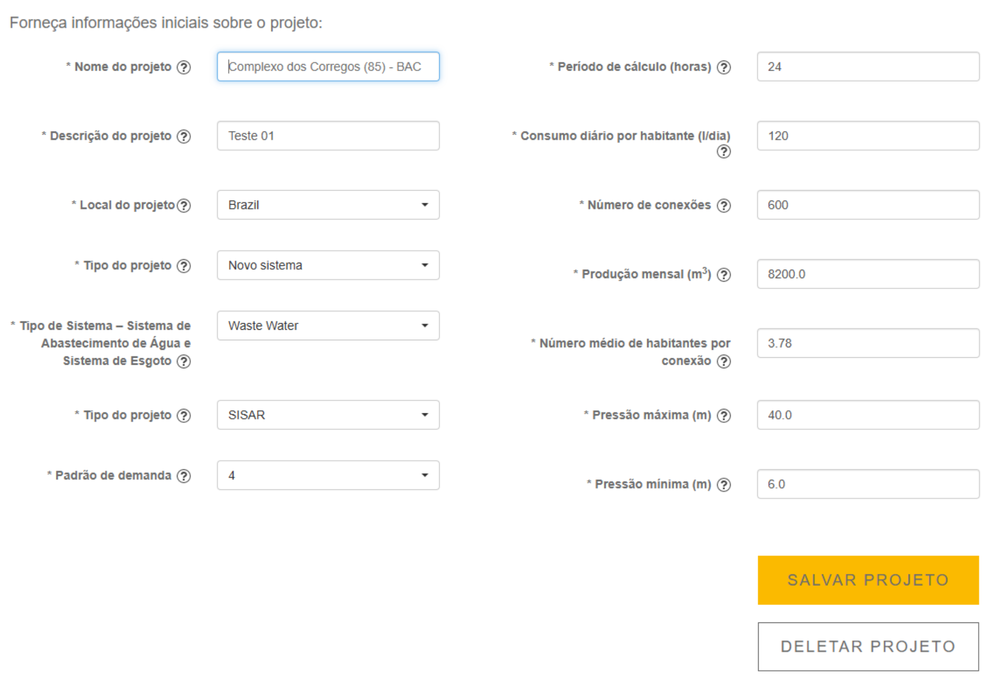


Figure 11: New project initialization interface in the WSNO module

2.3.2.1 Development Background and Objectives

Building upon earlier diagnostic modules—such as GIS-linked NRW assessment, pressure mapping, and consumption pattern analysis—WSNO was developed to address the growing need for tools capable of planning and optimizing water supply systems. These enhancements were guided by the goal of enabling local utilities to evaluate infrastructure alternatives using a combination of technical performance criteria and financial feasibility.

The module was designed to allow non-specialists to conduct robust simulations and compare different rehabilitation or expansion scenarios. Its functionality supports both current network performance assessments and projections based on future demand conditions, making it particularly suitable for long-term planning in data-scarce and capacity-limited environments.

The WSNO module was fully developed in the context of this thesis as a core innovation to bridge the gap between hydraulic simulation and practical decision-making. Specifically, a customized optimization engine based on a Messy Genetic Algorithm (MGA) was programmed from scratch in Python and integrated with the EPANET 2.0 Toolkit. This allowed for scenario-based network planning that considers both technical and financial constraints. In addition, a basic economic analysis module was designed to accompany the optimization results, offering utility managers a simple yet effective tool for investment prioritization.

2.3.2.2 System Architecture and Components

The architecture of WSNO consists of three key components that were designed and developed during this thesis:

1. Hydraulic Simulation Core: Based on EPANET 2.0, it enables the simulation of pressure, flow, and demand throughout a water distribution network. This open-source engine was chosen for its stability, transparency, and compatibility with existing data formats.
2. Optimization Engine: A new optimization module was implemented in Python using a Messy Genetic Algorithm (MGA). This algorithm was selected due to its superior performance in dealing with combinatorial problems with missing or redundant information, typical of rural or incomplete network datasets.
3. Economic Assessment Interface: This component estimates capital expenditures and long-term operational impacts based on user-defined parameters and country-specific

cost databases. It links optimization results with realistic financial implications, supporting evidence-based planning.

These three elements operate together in a web-based interface that guides users through the steps of building or importing a network model, selecting design options, optimizing configurations, and analyzing costs.

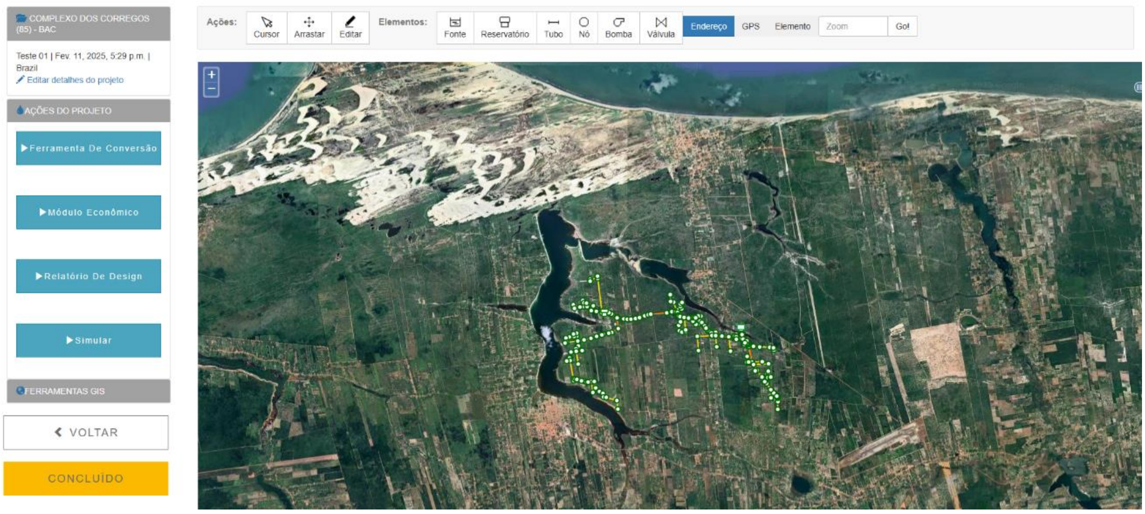
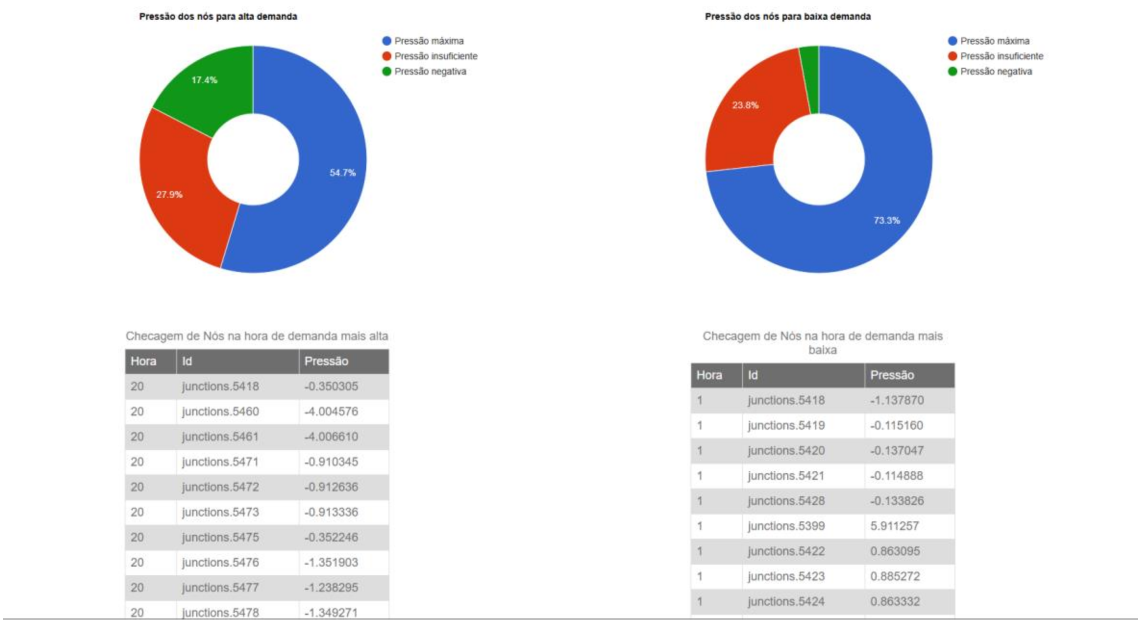


Figure 12: User interface of WSNO showing the GIS-integrated network editor, which supports element creation (pipes, pumps, tanks, valves)

Figure 12 shows the spatial interface of the Water Smart Network Optimization (WSNO) module during the initial layout phase of the Complexo dos Córregos project. The satellite background provides geographical context, while the green dots represent the preliminary placement of network nodes. This step allows users to interactively position infrastructure elements such as reservoirs, pipes, and junctions, facilitating the alignment of the hydraulic model with the real topography of the area.

2.3.2.3 Hydraulic Simulation Environment

The hydraulic modeling module supports both the import of existing EPANET files and the creation of new networks directly within the application through an intuitive graphical user interface (GUI). This interface incorporates GIS tools and elevation models to automate the calculation of hydraulic parameters such as pipe lengths, node elevations, and head losses. The integration of high-resolution digital elevation models (DEMs) ensures topographic consistency and supports the generation of accurate hydraulic simulations.



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20	junctions.5461	-4.006610
20	junctions.5471	-0.910345
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Hora	Id	Pressão
1	junctions.5418	-1.137870
1	junctions.5419	-0.115160
1	junctions.5420	-0.137047
1	junctions.5421	-0.114888
1	junctions.5428	-0.133826
1	junctions.5399	5.911257
1	junctions.5422	0.863095
1	junctions.5423	0.885272
1	junctions.5424	0.863332

Figure 13: Spatial visualization of simulation outputs within WSNO

Figure 13 presents the pressure conditions across network nodes under high-demand (left) and low-demand (right) scenarios. The pie charts classify nodes into three categories: those maintaining adequate pressure (blue), those with insufficient pressure (red), and those experiencing negative pressure (green). The associated tables list the critical junctions and their simulated pressure values at the respective time periods. These outputs help identify vulnerable areas in the network where operational adjustments or infrastructure upgrades may be required.

The development process of WSNO prioritized accessibility, automation, and ease of use for non-expert users. It features an intuitive web-based graphical interface where users can either import pre-calibrated EPANET models or construct networks from scratch using spatial inputs. GIS integration plays a central role in this process, as the tool uses digital elevation models (DEMs) to extract node elevations automatically, calculate pipe lengths, and ensure topographic consistency throughout the network model.

2.3.2.4 Optimization via Messy Genetic Algorithm (MGA)

The optimization engine of the WSNO module is powered by a Messy Genetic Algorithm (MGA), a flexible and robust evolutionary computation method particularly suited to complex optimization problems involving incomplete or uncertain data, such as those frequently encountered in small and mid-sized water utilities.

- Introduction to Genetic Algorithms and the MGA

Genetic Algorithms (GAs) are heuristic optimization methods inspired by the principles of natural selection and genetics. Solutions are represented as chromosomes that evolve through operations such as selection, crossover, and mutation. Traditional GAs use fixed-length chromosomes, which may be limiting when solution structures are partially unknown or highly variable.

The Messy Genetic Algorithm (MGA), originally developed by Goldberg, Korb, and Deb (1989), overcomes this limitation by using variable-length chromosomes that may include both coding and non-coding segments. This design allows MGA to search flexibly through large and poorly defined solution spaces, making it highly appropriate for distribution network design tasks with uncertain or incomplete data.

- Why the MGA Was Selected for WSNO

The decision to use MGA in WSNO was driven by several key considerations:

- Handling Incomplete Data: MGA's flexible chromosome structure allows it to cope with incomplete or inconsistent datasets, such as unknown pipe diameters or uncertain topographic information.
- Representation Flexibility: MGA does not require pre-defined chromosome lengths, enabling the simultaneous optimization of multiple network elements such as pipe diameters, pump configurations, and pressure-reducing valves (PRVs).
- Proven Effectiveness: Structured MGA (SMGA) has been shown to outperform conventional GA methods in benchmark problems such as the Anytown network (Walters et al., 1999).
- Robustness in Complex Scenarios: MGA can reach global optima in nonlinear, NP-hard problems without prior knowledge of optimal solution structures (Goldberg et al., 1989), which is vital for hydraulic network design.

While alternatives such as Ant Colony Optimization Algorithms (ACOAs) may offer faster convergence, MGA was preferred for its robustness, adaptability to incomplete data, and compatibility with EPANET hydraulic simulations.

- MGA Architecture and Implementation in WSNO

The MGA engine was developed from scratch in Python and linked with EPANET 2.0 Toolkit for hydraulic simulations. It operates in two main phases:

- Primordial Phase: An initial large population of messy chromosomes is generated, each encoding partial solutions (e.g., pipe diameters or valve settings). Genetic operators identify promising building blocks.
- Juxtapositional Phase: Building blocks are combined into complete solutions, refined through successive generations.

Key genetic operators include:

- Cut: Randomly splits chromosomes into segments to promote solution diversity.
- Splice: Combines partial chromosomes into larger, more comprehensive solutions.

These replace traditional crossover, enabling broader and more adaptive exploration of the solution space.

- Step-by-Step Algorithmic Procedure

To ensure transparency and reproducibility, the detailed steps implemented in WSNO's MGA module are described below:

1. Initialization:
    - Create an initial population of variable-length chromosomes encoding partial network designs.
    - Chromosomes may include only selected network components (e.g., three pipes or one PRV).
2. Evaluation:
    - Decode each chromosome into a network model and simulate it using EPANET.
    - Calculate fitness based on hydraulic performance (e.g., pressure ≥ 25 mwc, velocity ≤ 1.5 m/s).
    - Apply penalties for constraint violations.
3. Selection:
    - Apply tournament selection to retain individuals with higher fitness.
4. Splice (Recombination):
    - Combine two parent chromosomes to form a more complete offspring solution.
5. Mutation:

- Randomly modify chromosomes (e.g., change pipe diameter or add a node).

6. Elitism and Replacement:
   - Preserve the top-performing individuals.
   - Replace low-fitness individuals with new offspring.

This process continues for a specified number of generations (e.g., 200) or until convergence criteria are met. Figure 14 illustrates the two-phase optimization process implemented in the Water Smart Network Optimization module. The algorithm begins by importing the hydraulic network and initializing a variable-length population (primordial phase), followed by a simulation of fitness parameters such as pressure, velocity, and cost using EPANET. Through iterative steps of selection, crossover, and mutation, the MGA refines the design by assigning pipe diameters and optimizing network layout (juxtapositional phase). The process continues until the stopping criteria are met, generating hydraulically and economically feasible solutions.

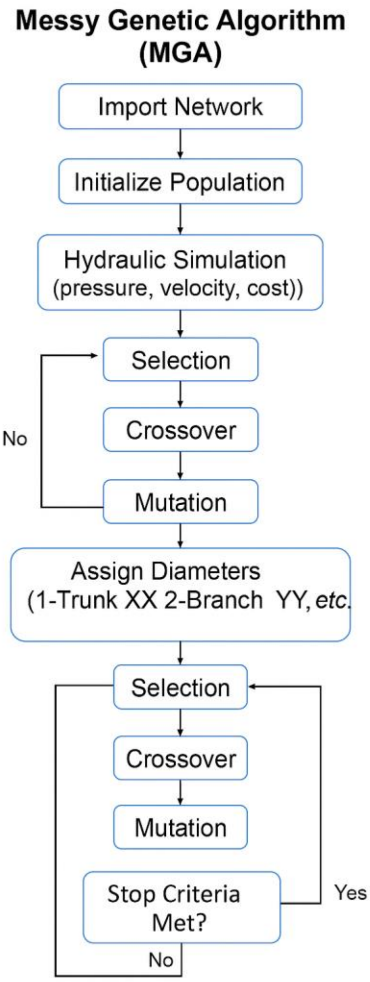


Figure 14: Messy Genetic Algorithm (MGA) workflow

To facilitate the understanding and reproducibility of the proposed algorithm, a code written in Python is presented in Figure 15. It illustrates the two evolutionary phases of the MGA applied in the WSNO module:

- The Primordial Phase, where the algorithm identifies and evolves promising building blocks of partial solutions through genetic operations such as cut, splice, and mutation.
- The Juxtapositional Phase, where selected high-performing components are recombined and refined into complete solutions, preserving elite individuals and ensuring convergence toward optimal designs.

EPANET is used as the hydraulic evaluation engine for each candidate solution, and fitness scores are computed based on criteria such as pressure thresholds, flow velocities, and cost estimations. The pseudocode structure allows readers to implement and adapt the algorithm for their own optimization problems.

```
# Pseudocode of the MGA for water distribution network optimization
Define parameters: pop_size, max_generations, p_cut, p_splice, p_mutate

# Primordial Phase
population = generate_initial_population(pop_size)
for generation in primordial_length:
    for individual in population:
        fitness = evaluate_with_epanet(individual)
    population = tournament_selection(population)
    for individual in population:
        if random() < p_cut:
            individual = cut(individual)
        if random() < p_splice:
            parent2 = select_other_individual(population)
            individual = splice(individual, parent2)
        if random() < p_mutate:
            individual = mutate(individual)

# Juxtapositional Phase
for generation in max_generations:
    for individual in population:
        fitness = evaluate_with_epanet(individual)
    elites = preserve_best_individuals(population)
    population = tournament_selection(population)
    for individual in population:
        if random() < p_splice:
            parent2 = select_other_individual(population)
            individual = splice(individual, parent2)
        if random() < p_mutate:
            individual = mutate(individual)
    population = replace_weak_individuals(population, elites + new_offspring)

return best_solution(population)
```

Figure 15: Python pseudocode for the implementation of the Messy Genetic Algorithm (MGA)

The code illustrates the dual-phase structure of the MGA (primordial and juxtapositional), its integration with EPANET for hydraulic performance evaluation, and the use of tailored genetic operations (cut, splice, mutation) to generate and evolve feasible network design solutions.

- Computation Time and Performance

In the Varzea da Cobra case study, the MGA completed 200 generations with a population of 100 individuals in approximately 15–20 minutes on a standard laptop. While not real-time, this is acceptable for strategic planning contexts. Computation time can be reduced by adjusting parameters or employing parallelization.

- Reproducibility and Code Availability

To support transparency and reproducibility:

- The Python source code of the MGA module is available upon request.
- Input files and configuration settings for the Varzea da Cobra study can also be provided.
- Detailed parameter settings include:
    - Population size: 100
    - Generations: 200
    - Cut probability: 0.1
    - Splice probability: 0.2
    - Mutation probability: 0.01

- Comparative Insights

Previous studies confirm MGA's superior adaptability in network design. Walters et al. (1999) showed that SMGA outperformed other methods in cost-efficiency for the Anytown benchmark. Though faster algorithms like ACOAs exist, MGA's strength lies in robustness and its capacity to work under data scarcity.

- Visualization and Reporting

As detailed in section 2.3.2.6, optimized solutions are visualized using web maps and exported in formats such as Excel, PDF, and shapefiles, supporting broader integration in planning workflows.

- Conclusion

The MGA-based WSNO module represents a practical, transparent, and technically robust solution for optimizing water distribution networks in resource-constrained contexts. Its ability to accommodate incomplete datasets and simulate complex scenarios ensures that small and mid-sized utilities can engage in data-driven planning and performance improvement.

Figure 16: EPANET simulation log automatically generated by WSNO during the optimization process

Figure 16 shows the spatial results of a hydraulic simulation within the WSNO module. Node pressures are represented using a color-coded scheme, while pipe flow directions and magnitudes are indicated with colored lines. The interface allows interactive analysis of network performance, helping identify zones of low pressure or excessive velocity. The simulation is based on EPANET integration and is crucial for diagnosing hydraulic constraints and supporting design optimization in rural water supply systems.

2.3.2.5 Economic Assessment and Cost Integration

The economic evaluation module was developed to complement the optimization engine and help utilities assess the financial implications of each simulated scenario. This module performs a basic cost-benefit analysis based on user-defined unit costs and energy consumption profiles. Key calculated parameters include:

- Total Capital Investment (CAPEX): Based on pipe replacement length and diameter, material type, excavation method, and installation unit cost.
- Operational Cost (OPEX): Estimated using energy consumption (pump curves and operating time), repair frequency, and NRW reduction impacts.

- Net Present Value (NPV): Calculated for a 10–20 year horizon using a standard discount rate (modifiable by the user).
- Payback Period: Time required to recover the investment through savings in water production and operational efficiency.

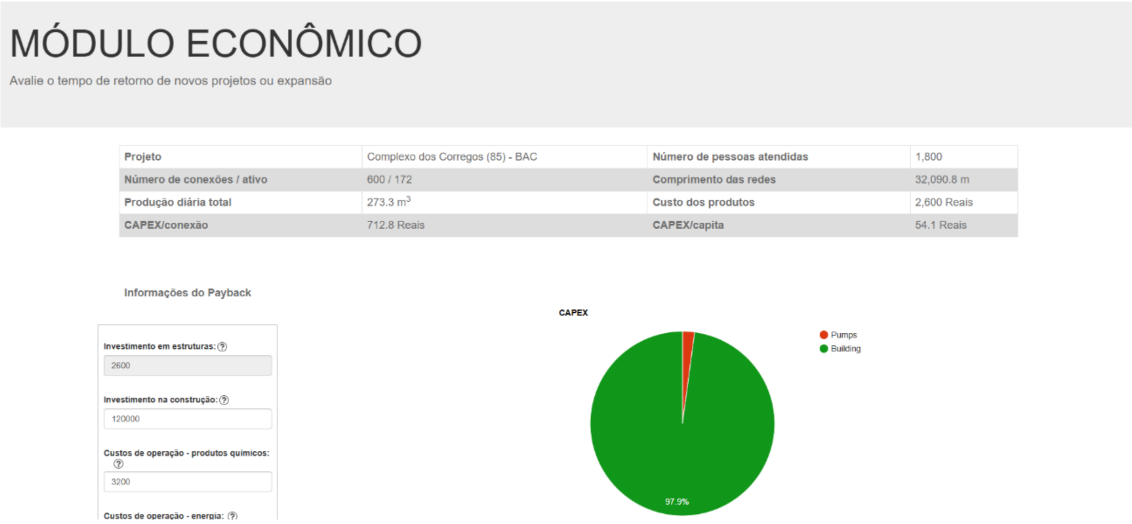


Figure 17: Economic module of WSNO

Figure 17 presents the economic evaluation section of the WSNO module for the Complexo dos Córregos project. It summarizes key financial indicators such as total network length, number of beneficiaries, and capital expenditure per connection and per capita. The pie chart illustrates the CAPEX distribution by category (e.g., pumps and building infrastructure), while the input boxes on the left allow users to define investment values and operational costs. This module helps decision-makers assess project affordability and supports cost-effective planning.

Users can select cost profiles (preloaded for Brazil and Georgia) or input their own. The integration of these costs into the optimization loop allows the MGA to consider not only technical performance but also the financial sustainability of each design.

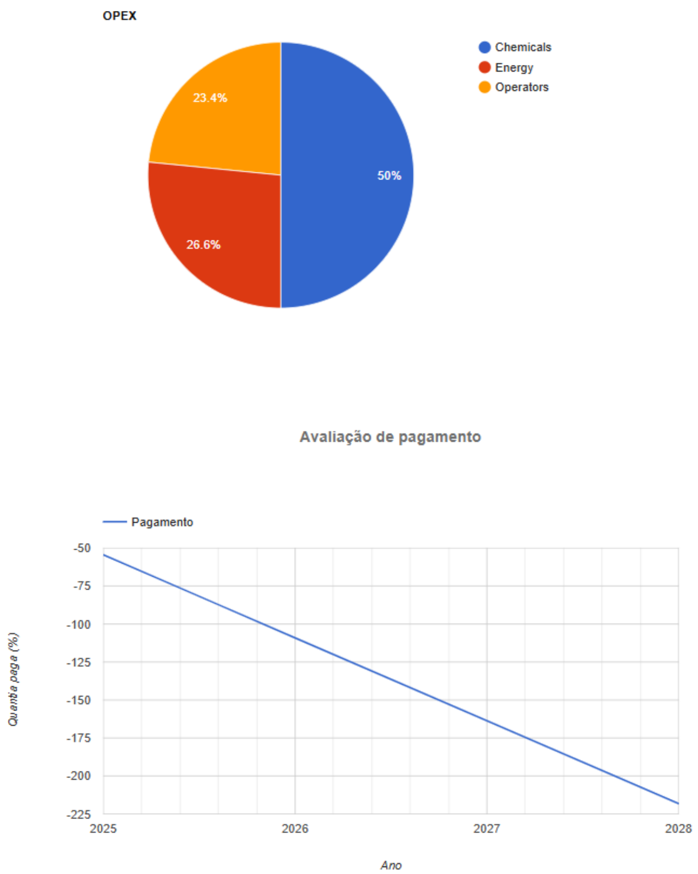


Figure 18: Breakdown of operating expenses (OPEX) as computed by the WSNO economic module

Figure 18 presents two outputs from the WSNO economic module. The upper pie chart details the operational expenditure (OPEX) distribution by category, revealing the relative cost contributions of chemicals, energy, and human resources. The lower line chart presents the project's payback simulation, indicating the cumulative financial return over a multi-year horizon. These insights support informed planning by allowing utilities to assess long-term sustainability and operating cost structures for different infrastructure configurations.

2.3.2.6 Output Visualization and Scenario Reporting

Once a simulation is successfully executed, users can visualize the results through interactive web maps, generate standard reports, and export project data. The platform's automation features make it particularly suitable for rapid assessments in data-scarce environments, such as rural areas or developing countries where conventional modeling approaches may be unfeasible. Then, the final WSNO platform includes features for output visualization and reporting, allowing users to export hydraulic and economic results to standard formats such as Excel, PDF, and shapefiles. This makes it compatible with other project planning tools commonly used in development cooperation contexts.

VISÃO GERAL DOS RESULTADOS DA SIMULAÇÃO

Projeto	Complexo dos Corregos (85) - BAC	**Número de pessoas atendidas**	1,800
Número de conexões ativas	172	**Comprimento da rede**	32,090.8 m
Produção diária total	273.3 m^3	**Demanda diária total**	266.9 m^3
Pressão máxima nos nós	16.1 m	**Pressão mínima nos nós**	0.0 m
Velocidade máxima da água	0.7 m/s	**Velocidade média da água**	0.0 m/s

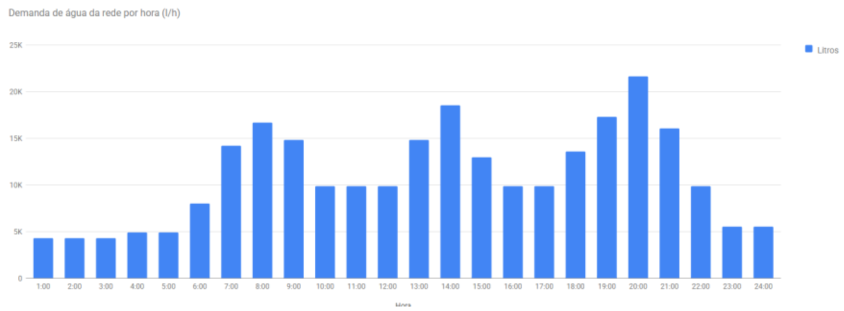


Figure 19: Overview of WSNO's simulation summary report

Figure 19 provides a consolidated overview of the simulation outputs for the selected water supply project. The table at the top summarizes key network metrics, including the number of active connections, total daily production, and hydraulic performance indicators such as pressure and flow velocities. Below, the bar chart illustrates the hourly variation in water demand across the network, supporting the identification of peak consumption periods. These results are essential for validating model performance and for designing infrastructure that meets demand variability over a 24-hour cycle.

2.3.2.7 Relevance and Application Context

WSNO is particularly suited to decentralized utilities operating in low- and middle-income contexts, where capacity constraints and budget limitations often impede technical decision-making. By embedding optimization and economic evaluation into an accessible simulation environment, the module bridges the gap between diagnostic tools and actionable infrastructure planning.

In doing so, WSNO represents a methodological leap forward from conventional NRW-focused GIS tools, transforming Water Smart from a monitoring platform into a comprehensive decision-support system for network design and investment planning.

2.3.3 Water Smart complementary Modules

In addition to these core components, a series of complementary modules were developed, adapted, or tested to respond to specific utility challenges or strategic priorities in selected study areas. These complementary modules enrich the decision-support capabilities of WS by integrating climate resilience, energy efficiency, and long-term planning considerations. Their role is to enhance the core WNSA–WNSO workflow by providing system-wide context, multi-hazard stress testing, or sustainability-linked investment insights.

In summary, the development of the Water Smart application has produced an adaptable yet robust platform in which the administrative core (WSNA) and the optimization engine (WSNO) work in concert. With additional integrated modules for pressure management, leak reduction, and energy efficiency, the platform empowers utilities to tackle key challenges holistically. This ensures that even utilities with constrained expertise or budgets can leverage digital technology for enhanced oversight, improved performance, and sustainable decision-making—thereby not only benefiting developing regions but any water utility aiming for smart, climate-resilient management practices.

These modules were not only conceptual developments but were also validated through two scientific publications. The first, based on the urban network of Khelvachauri (Georgia), demonstrated how the Water Smart Network Optimization (WSNO) module could support pressure and flow optimization using artificial intelligence. The second, applied to the rural network of Várzea da Cobra (Brazil), evaluated the platform's performance in pressure-dependent leakage simulation and pressure control strategies using a smart valve management approach. In both cases, the modules were developed and simulated by the author using custom-coded algorithms integrated with EPANET, while their outcomes supported key design principles of the WS platform. Methodological details for each application are provided in their corresponding case study sections (2.4.2 and 2.4.3), and the results are discussed in Chapter 3.

In addition, a third module is currently under development: the Water Smart Resilience Optimization (WSRO), which aims to integrate climate change adaptation and infrastructure resilience analysis into the decision-support environment. Building upon methodologies such as CRIDA and WNTR, this module will enable stress-testing of water systems and the planning of robust interventions under uncertainty. Although still in progress, WSRO has already been piloted in a case study in Indonesia, and its conceptual and methodological underpinnings are described in Section 2.2.4.

2.4 Cases of study

Positioning of case study methodologies within the thesis structure

Although the general methodology for the Water Smart platform is presented in the previous sections, each case study required a specific adaptation of the tools, data, and simulation logic to match the operational context and utility structure. For this reason, the methodological procedures that are particular to each case are described directly within their respective case study sections, rather than being integrated into a single unified methodology. This decision was taken to preserve clarity and traceability, ensuring that the reader can easily follow which steps, tools, and parameters were used in each context (urban vs. rural, centralized vs. decentralized utility, etc.).

In this structure, Chapter 2.4 focuses on the methodological implementation of Water Smart in four pilot environments, highlighting the steps taken and the modules applied in each scenario. The results and performance evaluation of these implementations are presented separately in Chapter 3, to maintain a clear distinction between methodological description and outcome analysis.

2.4.1 Batumi (Georgia), Water Utility Management Information System (MIS)

It is important to clarify that the Management Information System (MIS) developed for Batumi Tskali represents a customized early version of the Water Smart platform. While the MIS was specifically tailored to the operational, institutional, and regulatory context of BTS, many of its core components—such as digital customer records, work order tracking, and NRW monitoring—served as the foundational elements later expanded into the full Water Smart architecture. In this sense, the MIS should be seen not as a separate tool, but as a pilot implementation of the Water Smart concept, adapted to the real conditions of a transitional utility. Lessons learned from the MIS deployment directly informed the modular structure, user logic, and digital workflows that were later generalized and improved in the WSNA and WSNO modules of Water Smart.

Batumi's water utility, Batumi Tskali (literally "Batumi Water"), underwent a major transformation in the late 2000s from a deteriorated Soviet-era system to a modern, continuously operating service. Historically, Batumi suffered from acute water supply problems – the old network provided water for only a few hours a day and leaked profusely, and wastewater was discharged untreated into the Black Sea. In response, the city, with support from international donors, launched a comprehensive rehabilitation program. A new municipal utility company, Batumi Tskali, was founded around 2007 as part of this reform, giving Batumi local control over water services. This institutional change was backed by substantial investments (over €160 million) financed through the German KfW Development Bank with European Union co-financing. By 2010, Batumi had achieved 24/7 potable water supply and opened a modern wastewater treatment plant, an outcome that marked a dramatic improvement from the past.

Donor agencies – notably KfW and also organizations like the EBRD – not only funded new infrastructure but also emphasized modernization of the utility's management systems. Technical assistance teams (e.g. from MACS Energy & Water) worked alongside Batumi Tskali to build capacity and introduce best practices. Within this broader "Water Smart" modernization concept, it was developed an integrated Management Information System (MIS) to support efficient utility management in Batumi Tskali.

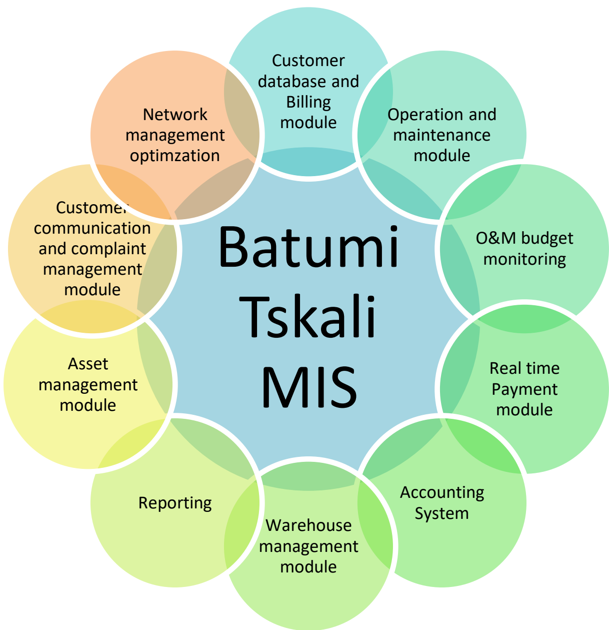


Figure 20: MIS concept

The MIS at Batumi Tskali integrates multiple digital tools to handle operational and administrative functions in a unified way. Key components of this system include:

- Customer Billing and Management System: Batumi Tskali implemented a modern billing software (named *BelleG*) to manage customer accounts, meter readings, and billing processes. This replaced ad-hoc or manual billing with a centralized database of consumers and usage. The billing MIS improved revenue collection efficiency and transparency – in fact, the utility's annual water sales revenues roughly quadrupled from about GEL 3 million before reforms to GEL 12 million after modernization. The new system was robust enough to earn an international innovation award in utility operations. By maintaining up-to-date records of consumption and automating bill generation, the billing module supports financial sustainability and customer service (e.g. timely bills, clearer information for customers).

- Geographic Information System (GIS): A GIS was established to digitally map Batumi's water and sewer networks and assets. All pipelines, valves, pumping stations, customer connections, and other infrastructure are recorded in a geospatial database. This GIS database is regularly updated and actively used by the utility's engineers and planners. The GIS tool allows staff to visualize the network layout and asset attributes, which greatly aids in maintenance and planning. For example, if a pipe breaks or a section needs upgrading, the GIS helps pinpoint the location and characteristics of that asset, speeding up repair response and improving planning of network rehabilitation. GIS mapping also supports long-term planning by identifying service coverage gaps and modeling network extensions to newly developed areas within Batumi.

- Supervisory Control and Data Acquisition (SCADA): Batumi Tskali's MIS includes SCADA technology to monitor and control the water supply system in real time. Under the rehabilitation program, the utility equipped key facilities (like well fields, pump stations, reservoirs, and main network nodes) with electronic sensors and actuators connected to a centralized SCADA platform. This provides operators with live data on parameters such as flow rates, pressure levels, reservoir storage, pump status, and water quality (e.g. chlorine residuals). SCADA alarm functions alert the control center immediately in case of anomalies – for instance, a drop in pressure that could indicate a pipe burst or an outage at a pump. Operators can remotely adjust pumps or valves through SCADA, improving responsiveness and enabling optimized operations (such as modulating pumping schedules to match demand and save energy). In essence, SCADA turns the water system into an actively managed network, with real-time data feeding into the MIS for analysis and decision-making.

- Performance Monitoring and NRW Management: A core purpose of the MIS is to collect and analyze performance data to guide decision-making. With donor support, Batumi Tskali established district metered areas (DMAs or "supply zones") in the distribution network, each outfitted with bulk flow meters. The MIS aggregates data from these zones to compute water balances (input vs. consumption), which allows the utility to closely monitor non-revenue water (NRW) losses. Indeed, the new system can automatically generate water inventories and other performance indicators for each supply zone. Key performance metrics tracked in the MIS include: overall water losses (% of water produced that is not billed), daily supply continuity (hours of service, which is now 24 hours), water quality compliance, and financial indicators like billing collection efficiency. Regular performance reports are produced, enabling management to identify problem areas (e.g. a zone with abnormally high losses or low pressure) and to evaluate the impact of operational changes. This data-driven monitoring culture was a shift from the past, aligning with international best practices for utility management.

Together, these integrated tools form a comprehensive MIS that has greatly strengthened Batumi Tskali's operational capacity. The availability of reliable data and digital control has enabled data-driven decision-making at the utility. Managers and engineers can now base their decisions on concrete evidence (from system data and performance trends) rather than on guesswork. For example, pressure and flow data from SCADA help pinpoint leaks or inefficiencies, so maintenance crews can be dispatched proactively to reduce water loss. Similarly, billing and consumption data guide the utility in planning network expansions and in ensuring revenue sufficiency for future investments. The MIS has also improved organizational effectiveness: staff productivity rose markedly once modern systems were in place – Batumi Tskali went from having 14 employees per 1000 customers to about 4.8 per 1000, a sign of much higher efficiency after digital modernization. The utility's focus on continuous training and use of the MIS has built local operational expertise that was previously lacking.

The impact on service delivery and sustainability in Batumi has been profound. Water supply is now reliable citywide and water quality meets standards consistently. Using the MIS, Batumi Tskali has managed to drastically cut water losses from the extreme 85% levels of the old system to around 25% in recent years – i.e. about 75% of produced water now reaches customers. This improvement reflects how data and technology helped identify and resolve leaks and unauthorized use that had plagued the system. In financial terms, the MIS and donor-driven reforms have put the utility on a path to long-term viability: billing efficiency and collection rates are very high (often exceeding 100% when recovering past arrears) and Batumi Tskali has achieved near full cost recovery for its operating costs. In other words, the utility can cover its expenses from customer tariffs, which is a key indicator of sustainability. Importantly, these gains have been institutionalized – Batumi Tskali continues to use the MIS to track performance and optimize operations, ensuring that the benefits are maintained over time and that the utility can plan for future needs (such as expanding services to new suburbs or adapting to demand growth).

In summary, the development and implementation of the MIS at Batumi Tskali aligned with the Water Smart approach – has transformed the utility into a modern, data-driven organization. The integrated digital tools (billing, GIS, SCADA, and performance monitoring) work in concert to support efficient management, accurate data collection, responsive service delivery, and strategic planning. This case highlights how investing in information systems and capacity building can build operational resilience and enable sustainable water utility management. Batumi Tskali's experience demonstrates that a well-designed MIS is not just a technical add-on, but a foundational element for achieving long-term service reliability, financial health, and informed decision-making in the water sector.

Figure 21: Batumi Tskali MIS website

2.4.1.1 WSNO. Hydraulic model

The integration of the Water Smart Network Optimization (WSNO) module into Batumi Tskali's Management Information System (MIS) represents a significant advancement in the utility's modeling and decision-support capabilities. Initially, the utility relied on a GIS-based diagnostic model focused primarily on mapping non-revenue water (NRW) and identifying areas of inefficiency within the distribution system. This earlier model provided essential spatial analysis and performance visualization but lacked the predictive and optimization functionalities needed for long-term planning and technical interventions.

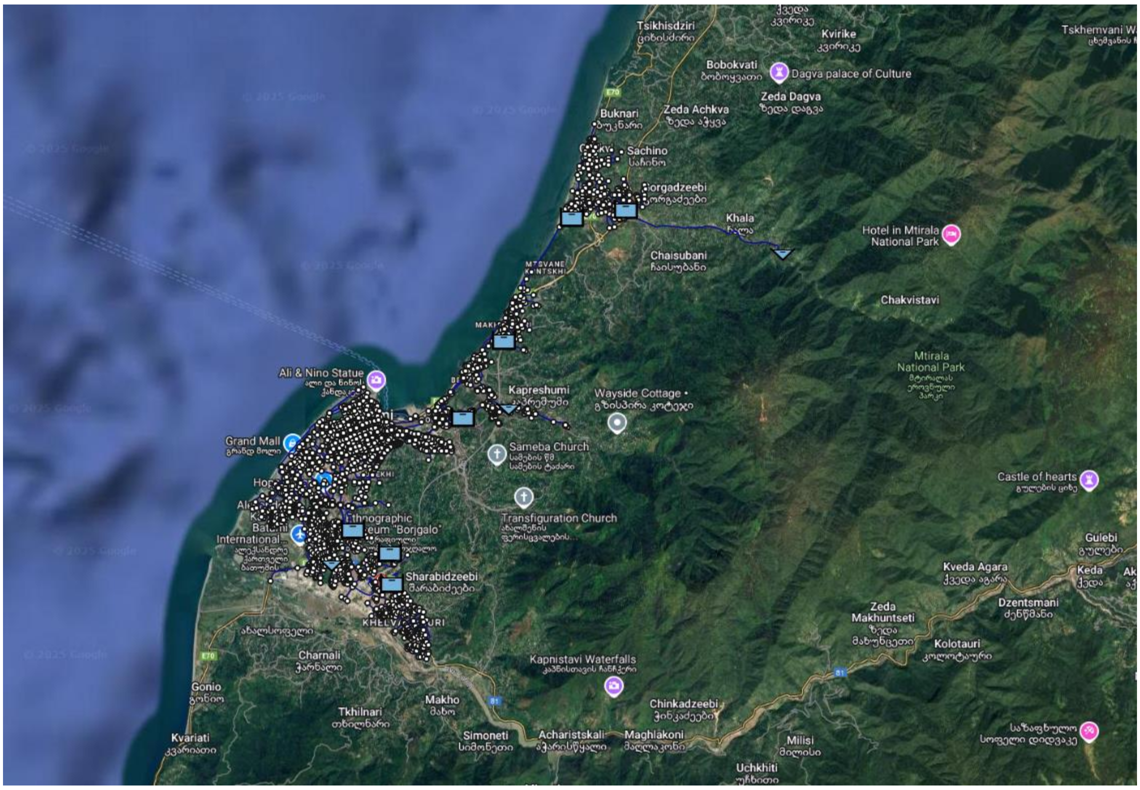


Figure 22: BTS hydraulic model

With the implementation of WSNO, the former NRW GIS model has been expanded and fully incorporated into the MIS as a dynamic hydraulic simulation and optimization tool. Now housed within the digital infrastructure of Batumi Tskali, WSNO enables the utility to not only monitor system performance but also to simulate demand scenarios, evaluate pressure zones, and test network rehabilitation strategies. This integration has allowed the hydraulic model to evolve from a static mapping tool into an active engine for data-driven infrastructure planning, contributing directly to the continuous improvement of water supply services across the city.

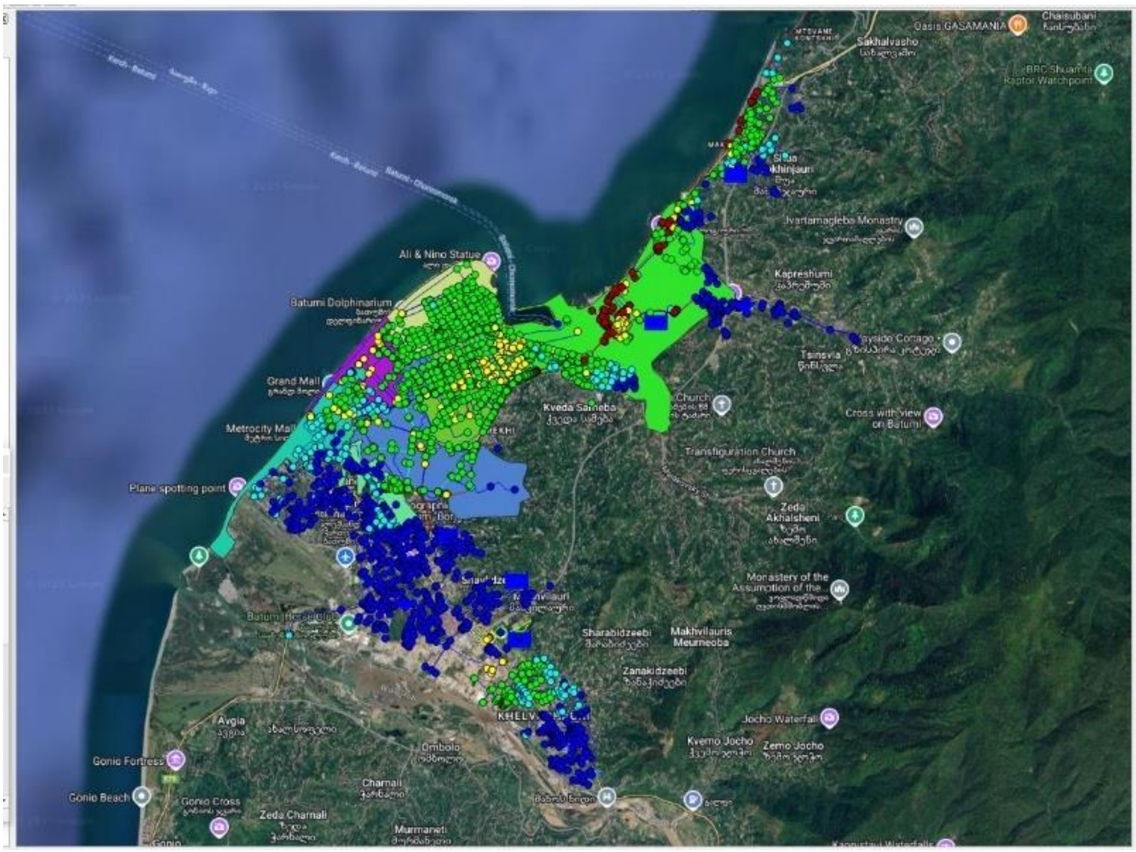


Figure 23: BTS WSNO simulation

2.4.1.2 Sectorization into DMA and Integrated Network Management

Planning the District Metered Areas (DMAs)

Batumi Tskali's water distribution network was strategically divided into District Metered Areas (DMAs) as a core component of the network rehabilitation. Each DMA is a discrete zone of the city's network with controlled inflow points, allowing for isolated monitoring of water supply**.** **I**n the planning phase, engineers followed International Water Association (IWA) guidelines to determine optimal sector boundaries.

These guidelines recommend designing DMAs with minimal elevation variation, robust and easily identifiable boundaries, and appropriately sized meters – all to ensure consistent pressure and reliable flow monitoring. Former billing areas and DMA were used as initial point to stablish the boundaries. An iterative, trial-and-error approach was used in mapping out approximately 7 DMAs**,** balancing each zone's network connectivity and demand patterns in line with international best practices.

Table 8: BTS DMA

Meter-boxes	Monthly Consumption (m^3)	DMA
7258	336198.56	1
5377	158747.34	2
7609	380793.34	3
7818	365404.62	4
4851	172727.3	5
7796	272867.62	6
1118	45893.934	7

Implementing the DMAs in Batumi's network involved substantial physical works. Crews installed isolation valves and flow meters at key junctions to delineate each DMA's inflow and outflow points. In areas where new pipelines were laid during the rehabilitation**,** ultrasonic and electromagnetic flow meters were placed to measure all water entering a DMA. The network was bordered into sectors by closing connecting valves between DMAs and leaving only the metered feed lines open.

After meter installation, each DMA was tested with Zero Pressure Test (ZPT) performing the following methodology.

The Zero Pressure Test is a field-based hydraulic verification procedure used to confirm that a proposed District Metered Area (DMA) is fully isolated from adjacent zones. It is typically conducted during low-demand periods (e.g. at night) and ensures that no unintended cross-connections or leaks exist between sectors.

1. Step-by-Step Procedure:
2. Pre-conditions:
   - All sector boundary valves, as defined in the hydraulic model, must be closed and their status physically confirmed.
   - Inlet flow meters and pressure loggers must be installed and calibrated at DMA entry points.
   - A plan for emergency water supply and public communication must be in place in case prolonged interruptions occur.

3. Isolation Execution:
    - Close all inlets to the target DMA except one (usually the one with metering).
    - Allow the pressure to stabilize and verify inlet flow using the meter.
    - Gradually reduce inflow and observe pressure decay using pressure loggers.
4. Observation Phase:
    - Close the final inlet and wait 10–15 minutes.
    - Record pressure at several key nodes within the DMA. If pressure drops to zero throughout the area, the sector is deemed properly isolated.
5. Leakage Confirmation (optional):
    - If pressure remains above zero, investigate for:
        - Open bypasses or incorrectly mapped valves.
        - Illegal cross-connections.
        - Upstream supply seeping through leaking valves.
6. Restoration and Reporting:
    - Reopen normal supply paths and document all readings, valve status, and anomalies.
    - Update the GIS model and valve layer accordingly.

Zero pressure tests were performed in the early hours (1:00–4:00 AM) to minimize customer disruption.

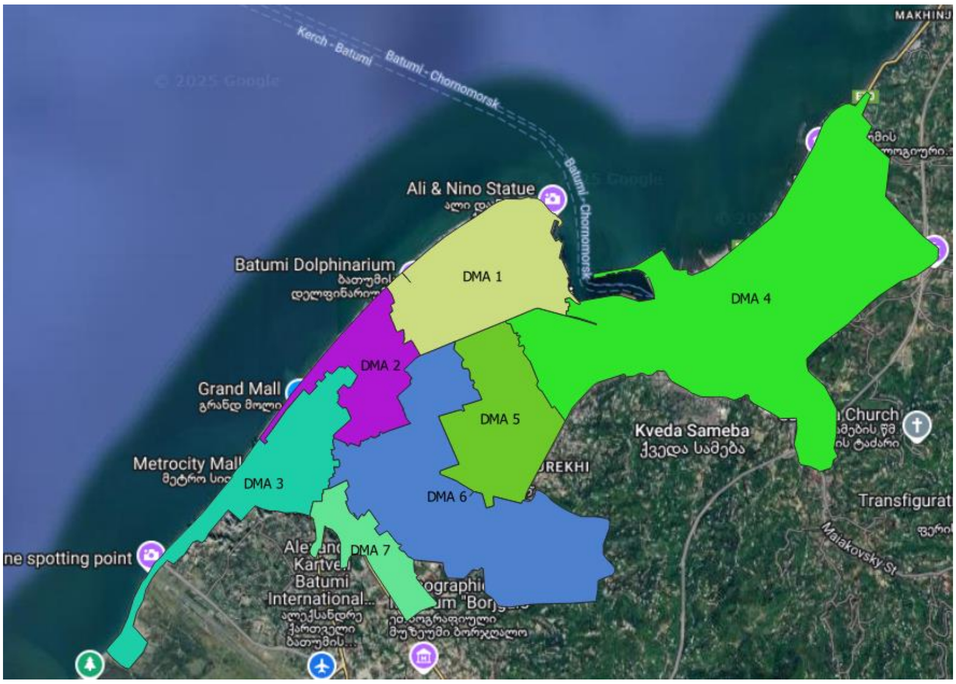


Figure 24: Sectorization into DMAs

Virtual District Metered Areas v(DMAs)

A future development currently being simulated is the establishment of virtual District Metered Areas. This virtual sectorization should be implemented within the physical districts along with the installation of smart water meters in the customers connections.

A virtual DMA (vDMA) is a digital sub-zone within a physical DMA, defined not by physical isolation, but by hydraulic behavior and monitored customer clusters. vDMAs allow utilities to localize issues such as unbalanced pressures or suspected leaks without additional infrastructure.

Conditions for Establishing vDMAs:

- The parent DMA must be physically isolated and stable.
- Continuous monitoring of flow and pressure at DMA inlet(s) must be in place.
- A sufficient number of customer meters must be available—preferably with data loggers or smart meters.
- The network topology should permit estimation of flows into sub-branches based on elevation, pipe characteristics, and usage trends.

Step-by-Step Process:

1. Data Collection:
    - Retrieve flow and pressure time series at the DMA inlet(s).
    - Gather pressure readings at nodes or customer taps (if available).
    - Extract consumption data from customer meters over time.
2. Hydraulic Zoning:
    - Use the calibrated hydraulic model to define pressure zones or logical pipe clusters based on elevation and pipe layout.
    - Cross-check zones with customer distribution patterns (e.g. residential blocks, neighborhoods).
3. Virtual Sub-Zone Allocation:

- Create 2–5 vDMAs per DMA, each containing a group of customer connections and a distinguishable hydraulic footprint (e.g., pressure regime, flow pattern).

4. Water Balance Estimation per vDMA:
   - Estimate expected demand from customer meters.
   - Subtract total from inlet flow to approximate non-revenue volume per sub-zone.
   - Use trend analysis (e.g., minimum night flow, pressure fluctuations) to flag zones with anomalies.
5. Performance Monitoring:
   - Rank vDMAs by apparent losses, pressure variability, or consumption irregularity.
   - Prioritize further field checks or leakage detection in the highest-risk zones.

Benefits of vDMA Integration

- No need for additional valve installations.
- Enables granular NRW tracking within a DMA.
- Supports targeted field investigations, reducing manpower and cost.
- Scalable and adaptable as more smart metering data becomes available.

A simulation for the vDMAs design within the DMA 5 is presented as follows. DMA 5 were selected for this purpose as the sector where the smart meters installation has started, and it is possible extrapolating some results.

The table below presents the needed initial data for sub-zones design.

Table 9: vDMA design

Concept	Description	Purpose in vDMA Analysis
vDMA	The name or ID of the virtual subzone within the physical DMA (e.g., vDMA 3A, 3B, 3C).	Identifies the specific internal zones being analyzed digitally. These are not physically isolated but are monitored using pressure, flow, and customer data.
Elevation Band (m)	The altitude range (in meters above sea level) that defines the zone. This can also be interpreted as pressure head if no pressure control exists.	Used to group properties and pipes that are likely to have similar hydraulic behavior (e.g., zones with higher pressure due to lower elevation). Helps detect if pressure is a factor in water loss.
Estimated HHs (Households)	Approximate number of household connections in the subzone. Based on GIS parcel data or customer billing records.	Important for estimating expected demand and validating if registered consumption aligns with the population served.
Avg Daily Demand (m^3)	The average daily metered water consumption recorded by customers in that vDMA over a recent monitoring period (e.g., 14 days).	Provides a baseline for comparing actual consumption against total inlet flow to detect anomalies like under-registration or losses.
Min Night Flow (L/s)	The lowest recorded flow at the DMA inlet (or sub-zone meter, if available) during the night (usually between 2–4 AM). Expressed in liters per second.	At night, most legitimate consumption ceases, so remaining flow likely represents leaks, illegal use, or storage tank filling. This is a key indicator for detecting potential leakage.
Avg Inlet Pressure (m)	The average pressure at the inlet of the DMA or vDMA, expressed as meters of head (1 m ≈ 0.1	Higher pressure often correlates with higher leakage rates. Comparing pressure between vDMAs helps

	bar). Taken from pressure loggers or modeled values.	explain variations in night flow and overall losses.

Supervisory Control and Data Acquisition (SCADA)

Once the physical DMA structure was in place, Batumi Tskali integrated the DMAs with its Supervisory Control and Data Acquisition (SCADA) system. Each flow meter and pressure sensor at the DMA inlets was connected to SCADA telemetry units, transmitting real-time data on flow rates and pressures to the central control room. This connectivity allowed operators to continuously monitor the water entering and leaving each DMA.

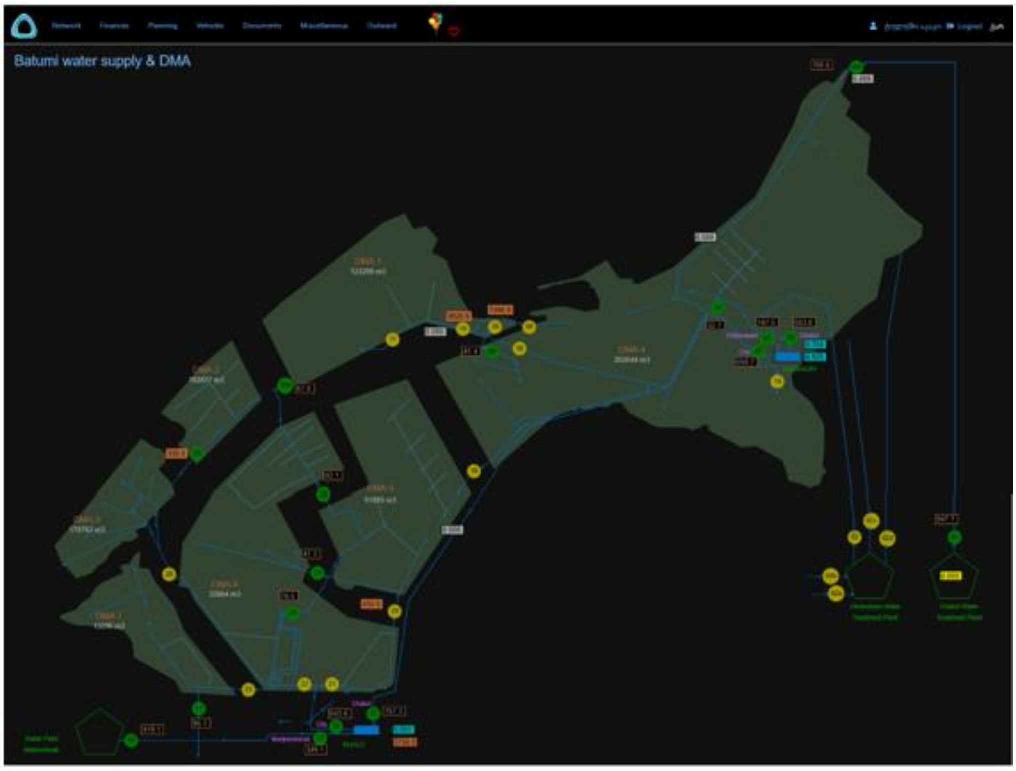


Figure 25: BTS MIS SCADA

In parallel, the utility upgraded its Management Information System (MIS) to assimilate the rich dataset emerging from the DMAs. The MIS was configured to receive SCADA data, including daily volumes fed into each DMA and pressure logs. By integrating SCADA with MIS, Batumi Tskali created a central repository for data-driven decision-making: the MIS automatically calculates water balances by DMA, comparing inflow volumes (from master meters) to customer consumption (from billing meters). These comparisons yield Non-Revenue Water (NRW) percentages per DMA, pinpointing which sectors experience higher losses. The MIS also cross-links with maintenance records and asset management modules. For instance, when SCADA flags a possible leak in a DMA, the MIS can generate a work order for field crews to investigate that specific area, linking the event to asset IDs and maintenance history. Such integration not only streamlines response times but also ensures that knowledge from the field is fed back into the system, improving future event detection and network modeling.

Continuous Performance Monitoring and NRW Reduction

With DMAs established and linked to SCADA/MIS, Batumi Tskali began continuous performance monitoring on a granular level. Each DMA effectively acts as a “mini-network” where water input vs. billed consumption is tracked. The utility’s NRW team meets regularly to review DMA data and make decisions. By examining the network info at the SCADA, staff can identify high-loss areas and prioritize them for active leak detection campaigns. For example, if a particular DMA shows an overnight minimum flow significantly higher than expected, it’s a strong indicator of a hidden leak or unauthorized consumption in that sector. This targeted approach is far more efficient than city-wide averages, allowing Batumi Tskali to reduce NRW in stages. Indeed, Batumi’s network had previously suffered extreme water losses, but the DMA strategy under the KfW-funded rehabilitation program provided a path to systematically bring losses down. Early results showed improved metering and leak response, though success also depended on staff embracing new operational practices.

The SCADA also facilitate pressure information. With clear boundaries, Batumi Tskali could install pressure reducing valves (PRVs) at DMA inlets where needed. This reduces excess pressure that often causes background leakage, further controlling water loss. Overall, continuous DMA monitoring has transformed daily operations into a data-driven regimen, where decisions on repairs, pressure adjustments, and even customer meter checks are guided by real-time evidence from the DMA data.

Optimizing Maintenance and Operations through Data

The sectorized DMA structure has significantly improved maintenance workflows at Batumi Tskali. Work crews are assigned by DMA, meaning that each team develops familiarity with the network subtleties of their zone. When SCADA and MIS data highlight irregularities (like a sudden drop in nightly pressure or an unexplained flow increase), the maintenance team responsible for that DMA is immediately alerted. By localizing issues to a bounded area, the crews can more rapidly pinpoint leaks or operational problems, reducing water outage durations and repair times. This approach exemplifies data-driven maintenance: rather than reacting to customer complaints or catastrophic main breaks, Batumi's teams now often pre-empt issues by interpreting trends in the DMA data. For instance, a gradual uptick in a DMA's minimum night flow over several weeks might prompt proactive leak surveys on that sector's older pipes. Furthermore, maintenance planning (valve exercising, hydrant flushing, meter calibration) is scheduled DMA-by-DMA, optimizing resource allocation by focusing on the most needy sectors first.

Integrating DMAs with the utility's MIS also enhances asset management. Every repair, pipe replacement, or meter change in a DMA is logged and later correlated with the DMA's performance metrics. Over time, Batumi Tskali can analyze which types of interventions yield the greatest NRW reduction or pressure stabilization, refining its maintenance strategies. Additionally, customer service improvements have been observed. Because DMAs allow for isolated shutdowns, when repairs are needed, only the affected sector is taken offline rather than large swathes of the city. This minimizes service disruption and helps the utility adhere to service level standards. All these operational optimizations underscore the primary benefit of DMAs: turning a once "invisible" underground system into a series of transparent, manageable units, each generating data that guides smarter operations.

2.4.1.3 IWA Water Balance

Batumi Tskali (BTS) adopted the IWA water balance methodology within its Management Information System (MIS) to monitor system performance and water loss. In practice, this means that BTS's MIS aggregates data from various sources – production flow meters, zone (DMA) meters, and customer billing databases – and integrates them to produce a continuous water balance for the network. All key components of the IWA water balance are tracked through the MIS:

- System Input Volume Monitoring: BTS uses an array of flow meters at water production sources and at strategic points in the distribution network to capture the total volume of water entering the system. In particular, the network is divided into District Metered Areas (DMAs), each with bulk flow meters that record the water supplied into that zone. These high-precision district meters measure the volume delivered to a defined area of the city. The MIS (through SCADA telemetry) continuously records these inputs. By summing the inputs from all sources (and subtracting any water exported or transferred out, if applicable), the total System Input Volume for the city is computed on a daily and monthly basis. This provides the "top-line" volume against which all consumption is compared.

- Authorized Consumption Tracking: BTS's customer information and billing system is digitally integrated with the MIS, ensuring that all billed consumption data feeds into the water balance calculations. Each customer's metered usage is collected (increasingly via automated meter reading, or otherwise via regular meter readings uploaded to the system) and totalled to give the Billed Authorized Consumption for each billing period. The MIS can pull these totals for each DMA and for the whole system. In parallel, unbilled authorized uses are tracked by operational logs – for instance, when the fire department uses water from hydrants or when line flushing is conducted, the volumes (estimated or metered) are entered into the MIS as unbilled authorized consumption. This comprehensive data integration is crucial: combining SCADA flow data with billing database information allows the MIS to perform a continuous, granular water balance analysis. The system essentially matches the water *input* to each zone with the water *consumed* in that zone (from customer billing records), ensuring that authorized consumption is fully accounted for in the balance.

- Loss Calculation and Analysis: With both input and authorized consumption data in place, the MIS automatically calculates water losses as the difference between the water supplied and the water legitimately used. This is done at multiple levels of detail. For the entire BTS system, the total NRW is computed (monthly, and year-to-date) as the System Input Volume minus billed consumption, with adjustments for any known unbilled authorized usage. More powerfully, at the DMA level the MIS computes an ongoing water balance: for each district, the flow into the DMA (recorded by the district meter) is compared against the sum of all customer consumption in that DMA, revealing the volume of water losses in that sector. This reveals where losses are occurring in the network with a high spatial resolution. Distinguishing the nature of the losses (apparent vs. real) requires further analysis – BTS uses additional data and audits for this purpose. For example, the MIS can incorporate meter testing results to estimate apparent losses due to meter under-registration, and records of theft or illegal connections to quantify unauthorized consumption. Any remaining gap is then attributed to real losses (leakage) in that DMA. Thus, the IWA water balance framework is fully embedded in the MIS analytics: each component (from authorized use to each loss category) can be estimated and tracked.

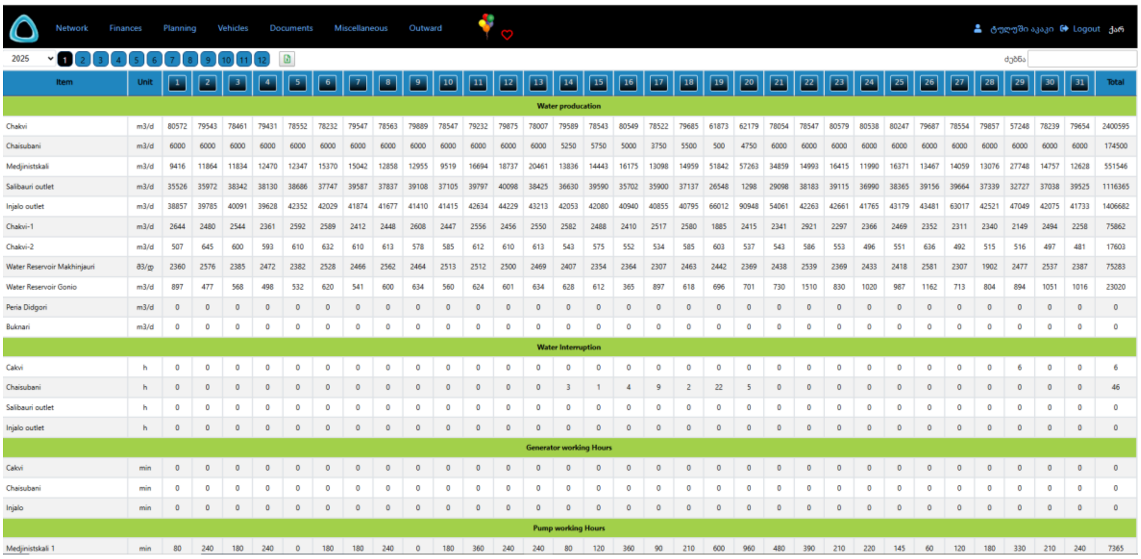
- Reporting and Decision-Making: BTS's MIS generates regular water balance reports for management. Typically, a monthly water balance report is produced for the utility's service area, summarizing System Input, Authorized Consumption (with breakdowns of billed vs. unbilled), and the resulting NRW volume and percentage. These reports may be reviewed in management meetings or submitted to regulators to demonstrate performance. The balance data is also available in near real-time on dashboards, allowing the operations team to see trends in water losses. The frequency of reporting is aligned with operational needs – daily or weekly summaries for quick response, and monthly/annual summaries for strategic evaluation. By having the water balance continuously updated in the MIS, BTS can make data-driven decisions. For instance, if the NRW report highlights that a particular DMA has, say, 40% losses (far higher than the city average), this signals the leakage control team to prioritize that area for active leak detection (e.g. deploying acoustic leak detectors or inspecting for illegal taps). In this way, the water balance is used to target leak detection efforts where they will be most effective. Likewise, if apparent losses are found to be a large portion of NRW in a zone, BTS might initiate a meter replacement program or a customer audit in that area.

The integration of the IWA water balance into BTS's MIS also allows performance tracking over time. By comparing monthly and annual NRW figures, BTS can evaluate the impact of any interventions (for example, pressure management or pipe rehabilitation) on reducing real losses. A declining NRW trend would indicate improvements, while any increase would prompt investigation. Key performance indicators derived from the water balance (such as % NRW, or cubic meters of water lost per km of mains) are used by BTS's management as benchmarks. Moreover, BTS can benchmark itself against international standards using the IWA framework. This outcome, achieved by systematic monitoring and loss reduction, underscores how the MIS-supported water balance guides BTS in operating an efficient system. Overall, the IWA water balance at BTS's MIS is a vital management tool, enabling proactive control of water losses, informed planning of network improvements, and sustained delivery of reliable water service.

2.4.1.4 Water production

Aligned with the water balance calculation explained in the previous section, within Batumi Tskali's Management Information System (MIS), water production monitoring is a fundamental component that supports real-time supervision, operational planning, and strategic resource management. The utility's supply system relies on a combination of deep wells and spring intakes, with production facilities geographically distributed across the service area. These sources are equipped with electromagnetic and ultrasonic flow meters connected to the SCADA system, which continuously transmits data to the MIS. Each production point is configured as a monitored node within the system, allowing the utility to track total production volumes, source-specific outputs, and temporal patterns (e.g., peak extraction hours).

The MIS aggregates this production data to calculate the System Input Volume, a key element of the IWA Water Balance. By maintaining high-frequency measurements, the system enables early detection of production anomalies, such as pump malfunctions, source contamination, or unauthorized abstraction. The data is also used for energy efficiency analysis, particularly when evaluating the performance of pumps and comparing energy consumption against flow output. Monthly and daily production reports generated through the MIS assist decision-makers in aligning supply with demand forecasts and anticipating seasonal variations, particularly important in Batumi's coastal and tourism-driven context.



Item	Unit	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
Water producation																	
Chakvi	m3/d	80572	79543	78461	79431	78552	78232	79547	78563	79889	78547	79232	79875	78007	79589	78543	80549
Chaisubani	m3/d	6000	6000	6000	6000	6000	6000	6000	6000	6000	6000	6000	6000	6000	5250	5750	5000
Medjinistskali	m3/d	9416	11864	11834	12470	12347	15370	15042	12858	12955	9519	16694	18737	20461	13836	14443	16175
Salibauri outlet	m3/d	35526	35972	38342	38130	38686	37747	39587	37837	39108	37105	39797	40098	38425	36630	39590	35702
Injalo outlet	m3/d	38857	39785	40091	39628	42352	42029	41874	41677	41410	41415	42634	44229	43213	42053	42080	40940
Chakvi-1	m3/d	2644	2480	2544	2361	2592	2589	2412	2448	2608	2447	2556	2456	2550	2582	2488	2410
Chakvi-2	m3/d	507	645	600	593	610	632	610	613	578	585	612	610	613	543	575	552
Water Reservoir Makhinjauri	მ3/დ	2360	2576	2385	2472	2382	2528	2466	2562	2464	2513	2512	2500	2469	2407	2354	2364
Water Reservoir Gonio	m3/d	897	477	568	498	532	620	541	600	634	560	624	601	634	628	612	365
Peria Didgori	m3/d	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Buknari	m3/d	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Water Interruption																	
Cakvi	h	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Chaisubani	h	0	0	0	0	0	0	0	0	0	0	0	0	0	3	1	4
Salibauri outlet	h	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Injalo outlet	h	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Generator working Hours																	
Cakvi	min	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Chaisubani	min	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Injalo	min	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Pump working Hours																	
Medjinistskali 1	min	80	240	180	240	0	180	180	240	0	180	360	240	240	80	120	360

Item	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	Total
Water producation																
Chakvi	78522	79685	61873	62179	78054	78547	80579	80538	80247	79687	78554	79857	57248	78239	79654	2400595
Chaisubani	3750	5500	500	4750	6000	6000	6000	6000	6000	6000	6000	6000	6000	6000	6000	174500
Medjinistskali	13098	14959	51842	57263	34859	14993	16415	11990	16371	13467	14059	13076	27748	14757	12628	551546
Salibauri outlet	35900	37137	26548	1298	29098	38183	39115	36990	38365	39156	39664	37339	32727	37038	39525	1116365
Injalo outlet	40855	40795	66012	90948	54061	42263	42661	41765	43179	43481	63017	42521	47049	42075	41733	1406682
Chakvi-1	2517	2580	1885	2415	2341	2921	2297	2366	2469	2352	2311	2340	2149	2494	2258	75862
Chakvi-2	534	585	603	537	543	586	553	496	551	636	492	515	516	497	481	17603
Water Reservoir Makhinjauri	2307	2463	2442	2369	2438	2539	2369	2433	2418	2581	2307	1902	2477	2537	2387	75283
Water Reservoir Gonio	897	618	696	701	730	1510	830	1020	987	1162	713	804	894	1051	1016	23020
Peria Didgori	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Buknari	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Water Interruption																
Cakvi	0	0	0	0	0	0	0	0	0	0	0	0	6	0	0	6
Chaisubani	9	2	22	5	0	0	0	0	0	0	0	0	0	0	0	46
Salibauri outlet	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Injalo outlet	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Generator working Hours																
Cakvi	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Chaisubani	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Injalo	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Pump working Hours																
Medjinistskali 1	90	210	600	960	480	390	210	220	145	60	120	180	330	210	240	7365

Figure 26: BTS MIS Water Production

Additionally, long-term production records stored in the MIS contribute to water resource planning, helping the utility evaluate source sustainability, analyze trends in groundwater drawdown, and support permit compliance with environmental regulations. Through integration with SCADA, hydraulic modeling, and NRW tracking modules, the MIS ensures that water production is not only controlled operationally but also fully aligned with the broader strategic objectives of efficiency and sustainability.

2.4.1.5 Water valves management

The management of water valves within Batumi Tskali is fully integrated into the MIS environment, reflecting the utility's shift toward digitally enabled operational control. Valves are critical for regulating flow, isolating sections for maintenance, and implementing pressure management strategies across the network. Within the MIS, each valve is registered as a geo-referenced asset, complete with attribute data such as type (e.g., gate valve, pressure reducing valve), diameter, installation date, and maintenance history.

This digital registry allows utility staff to locate, identify, and manage valves using both tabular and GIS-based interfaces. Operators and maintenance teams can generate work orders for valve inspection, flushing, or replacement directly from the MIS, which then updates the asset's condition status upon task completion. Integration with the SCADA and DMA monitoring system provides contextual information—such as pressure and flow upstream/downstream of a valve—enabling data-informed decisions on when and how to operate valves during interventions or emergencies.

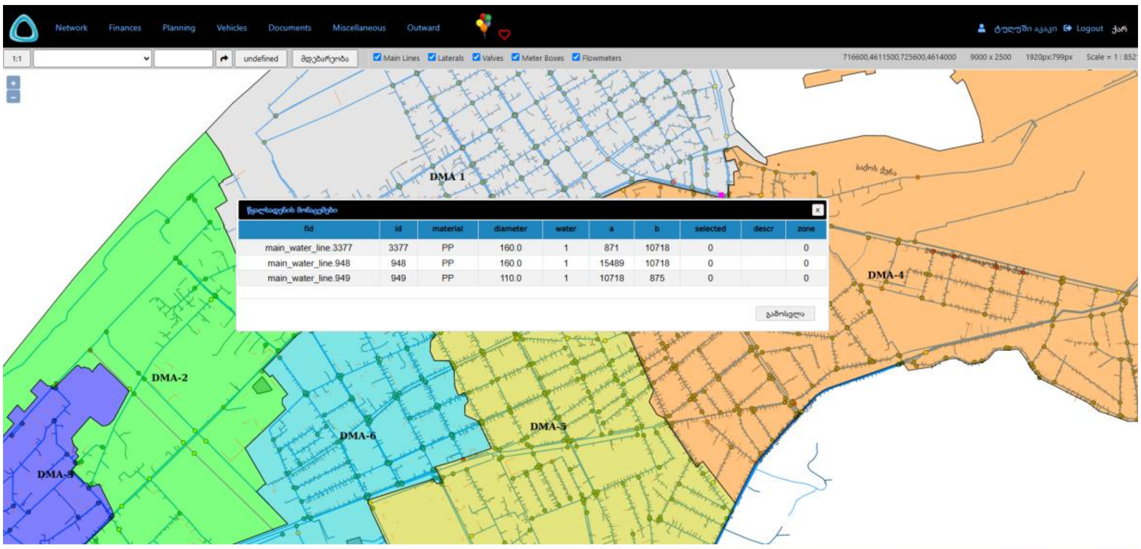


Figure 27: BTS MIS Water Valves

Moreover, the MIS supports preventive maintenance scheduling for critical valves, ensuring they remain functional and accessible when needed. Historical records of valve operations help the utility assess wear and failure risk, contributing to better asset lifecycle planning. For pressure management zones, particularly within DMAs, the MIS also logs valve opening settings and links them to performance indicators, such as minimum pressure levels or leakage reduction trends.

By embedding valve management within the MIS, Batumi Tskali achieves greater coordination across technical teams, reduces service interruptions during repairs, and enhances network resilience. The structured and digital nature of this process not only reduces human error and delays but also ensures traceability and accountability, all in alignment with international utility management practices.

2.4.1.6 Other MIS functionalities

Beyond its core functions in network monitoring, hydraulic modeling, and non-revenue water (NRW) analysis, the Management Information System (MIS) at Batumi Tskali includes a broad suite of modules dedicated to administrative, financial, and strategic utility management. These additional functionalities form an essential part of the utility's digital ecosystem and are key to achieving full operational integration and long-term sustainability.

One of the most prominent features is the billing and financial management system, which allows for the centralized administration of customer accounts, metering data, invoice generation, and revenue tracking. The billing module (e.g., the *BelleG* system previously implemented) maintains a continuously updated registry of active customers, consumption history, and payment records. It automates meter reading processing, applies tariff structures, and generates individualized billing statements. The MIS also tracks overdue accounts and enables targeted follow-up actions such as payment reminders or disconnection notices, all of which contribute to maintaining a high level of collection efficiency. This system has enabled Batumi Tskali to reduce billing errors, enhance transparency, and improve customer trust in the utility's service.

In parallel, the MIS includes financial reporting and budget planning tools that support both day-to-day financial oversight and long-term fiscal planning. Utility managers can access dashboards summarizing revenue flows, operating expenditures, and capital investment needs. Reports can be generated by customer category, service area, or time period, enabling detailed financial analysis. These tools also support multi-year planning and forecasting, which is essential for aligning infrastructure investments with funding availability and expected growth in demand. For example, future rehabilitation projects or expansions can be prioritized based on projected revenues and known service gaps, improving the utility's ability to manage resources efficiently.

Another key area supported by the MIS is service planning and operations reporting. The system aggregates data from various modules—including work order management, customer complaints, and field interventions—to generate periodic reports used for internal audits and external reporting to regulators or donors. Reports can include metrics such as average time to respond to service interruptions, number and type of maintenance activities, employee productivity, and network performance indicators (e.g., pressure zones, burst rates, leakage trends). This functionality enhances institutional accountability and ensures that utility performance can be continuously tracked and communicated.

Moreover, the MIS integrates tools for human resources (HR) and staff management, including shift scheduling, task assignments, and user access logs. This feature supports the efficient coordination of field teams and ensures traceability of operations, particularly when managing distributed workforces across multiple service areas.

In addition to structured data management, the system includes document management capabilities, allowing the utility to store and retrieve technical reports, permits, customer correspondence, and maintenance logs in a centralized digital archive. This reduces the reliance on paper-based systems and facilitates compliance with administrative and regulatory requirements.

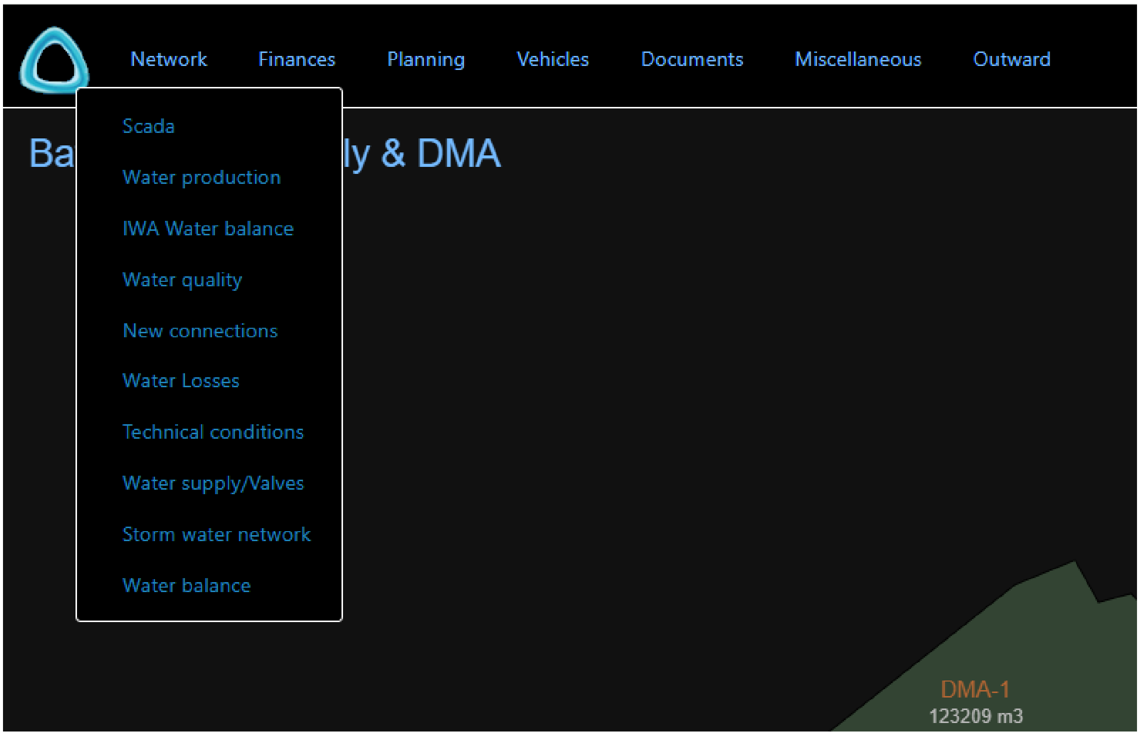


Figure 28: BTS MIS functionalities

In summary, the MIS at Batumi Tskali extends far beyond technical network management. Its functionalities encompass financial control, customer service, operational planning, performance reporting, and organizational coordination, making it a central pillar of the utility's modern management system. This level of integration reflects international best practices and positions Batumi Tskali as a reference for small and mid-sized utilities seeking to digitize not only their infrastructure but also their internal processes and service delivery frameworks.

2.4.2 Khelvachauri (Georgia), Pressure recovery module

2.4.2.1 Introduction

This section presents the implementation of the pressure recovery module of the Water Smart (WS) platform, applied to the potable water distribution system of Khelvachauri, Georgia. The methodology and results presented herein are based on the peer-reviewed article published in *Water* (Pons-Ausina et al., 2025), which validated the tool's performance in a real-world context and highlighted its applicability for pressure optimization and non-revenue water reduction in developing areas.

The module was developed to assist small and mid-sized utilities with limited technical capacity, integrating artificial intelligence (AI) and hydraulic simulation through EPANET Toolkit programming. The selected case study in Khelvachauri was particularly relevant due to its recurrent pressure deficits in the southern sector of the municipality, worsened during peak consumption periods and aggravated by legacy infrastructure inadequately modeled or planned.

Leveraging AI algorithms—specifically a Random Forest regression approach—alongside hydraulic simulation, the module allowed for pipe diameter optimization and pressure enhancement without the need for continuous expert supervision. The results demonstrated clear operational benefits, such as pressure increases above 25 mwc, velocity reductions under 1.5 m/s, and an estimated 8% reduction in leakage rates. The computational time was also significantly reduced, validating the AI-based optimization strategy as a viable alternative to traditional modelling.

The following subsections detail the methodology applied to build the hydraulic model, assess demand and leakage, calibrate the system, and implement the AI-driven optimization. The pressure recovery module, as demonstrated in this case, represents one of the key functional components of the Water Smart platform, bridging diagnostic simulation with actionable infrastructure planning.

2.4.2.2 Process Workflow for Pressure Optimization

To contextualize the development of the pressure recovery module, the following flowchart outlines the structured sequence of steps followed—from field data collection to hydraulic calibration and AI-assisted optimization within the Water Smart platform.

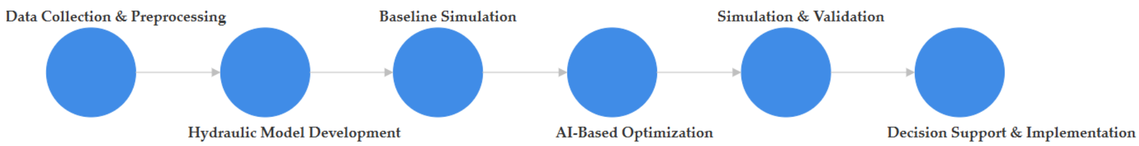


Figure 29: Sequential workflow for the implementation of the pressure recovery module in Khelvachauri

The process began with a comprehensive data collection phase focused on gathering all the necessary information for hydraulic simulation. Geographic Information System (GIS) data was compiled to define the network’s spatial characteristics, including pipeline routes and elevation profiles of the service area. This spatial data was complemented by detailed hydraulic information such as network topology, pipe diameters and materials, node locations, and boundary conditions. Additionally, field campaigns were conducted to measure real-time flow and pressure values at critical points within the distribution system. These measurements were essential for both understanding the current operational state and calibrating the model later.

Once collected, the data underwent a thorough preprocessing stage. This involved cleaning and validating datasets to eliminate inconsistencies, handling missing or incomplete values, and ensuring proper alignment between GIS layers and hydraulic inputs. The processed data was then structured to be compatible with EPANET, a widely used open-source software for simulating water distribution systems. Using this structured input, a baseline hydraulic model of the Khelvachauri network was developed within the MACS Water Smart (WS) platform. The model was calibrated through iterative comparison with the field-measured flow and pressure data, enabling a realistic simulation of current network behavior and helping to highlight zones experiencing operational inefficiencies—particularly low-pressure conditions and excessive flow velocities.

Following calibration, an initial simulation was conducted to evaluate the performance of the existing system. This simulation revealed several underperforming areas, particularly in the southern part of the municipality, where inadequate pipe sizing and long distances from supply points led to insufficient pressure during peak demand hours. High flow velocities in some sections of the network further indicated the risk of head losses and potential structural strain on the pipelines.

In response to these findings, a pressure recovery module was developed as part of the WS tool. This module was programmed using the EPANET Toolkit—a software development kit that allows for custom hydraulic simulations through scripting environments such as Excel VBA. The module's objective was to iteratively adjust pipe diameters to maintain flow velocities within acceptable limits (typically below 1.5 m/s) while restoring pressure to desirable levels throughout the network. Once this functionality was validated, it was further enhanced using artificial intelligence. Specifically, a Random Forest regression model was trained to emulate the optimization logic of the programmed module. By doing so, the system could quickly recommend optimal pipe diameters without relying on repeated hydraulic simulations, significantly reducing computation time and enhancing usability for non-expert users in small utilities.



Case Study

Khelvachauri is a municipality in the southwestern region of Georgia near the Black Sea coast, adjacent to Batumi, the main city of the Adjara region. Currently, the city of Batumi and its region is known as a tourist area in the Black Sea, especially during summertime. The rise of the tourism industry permitted the reactivation of the local economy and the modernization of the area at all levels.

During the last few years, the German Development Bank, in collaboration with the local authorities and with the support of international consultants, rehabilitated all the water supply and wastewater infrastructure, which dated at that moment from the soviet time and had many problems due to the lack of maintenance and management. The project included training the staff of the water public utility at all levels and transferring technology.

The area's geography features mountainous terrain and deep valleys, posing unique challenges for water infrastructure. Its humid subtropical climate, with mild winters and hot summers, significantly influences seasonal water demand.

The history of water supply in Khelvachauri reflects progressive infrastructure development responding to population growth and industrial needs. Initially reliant on natural springs and artisan wells, increasing urbanization necessitated more sophisticated systems.

The water distribution network has recently seen significant improvements, including pipe replacements and integration with Batumi’s modernized hydraulic system. Khelvachauri's potable water supply comes from the "Injalo" reservoir and other additional connections to Batumi’s system. However, these measures have not fully addressed the demand, especially in the southern part of the municipality, where low pressure persists during peak consumption hours. Population growth and urban development continue to increase demand, requiring effective planning and management. This highlights the importance of technological and managerial solutions to optimize water use and ensure availability for all residents.

Initially, Khelvachauri's water network operated with low-pressure pumping from surface water near the MejinisTskali River, requiring consumers to depend on booster pumps and storage tanks. Later, the network operation was transferred to Batumi's public water company, "Batumi Tskali," which integrated it into their infrastructure without conducting hydraulic modelling or simulations. This led to performance challenges, including high non-revenue water (NRW) rates. In response, the German Development Bank (KfW), as the financier of the water infrastructure rehabilitation, commissioned consultants to evaluate the system. Through this evaluation, a comprehensive water supply simulation was conducted to identify solutions and establish a decision-support module as part of a broader knowledge transfer initiative.

Mathematical Network Model Development

First, the as-built plans of the executed network were obtained, and the connections made with the Batumi supply system were checked for the supply to Khelvachauri. There were three connections, one at the outlet of the Injalo tank and two connections to DN355 pipes, all of which are in the northern part of the Khelvachauri network.

The next step was to load the network into the Water Smart to calibrate the hydraulic model. The following figure shows the water system model simulated by the WS.

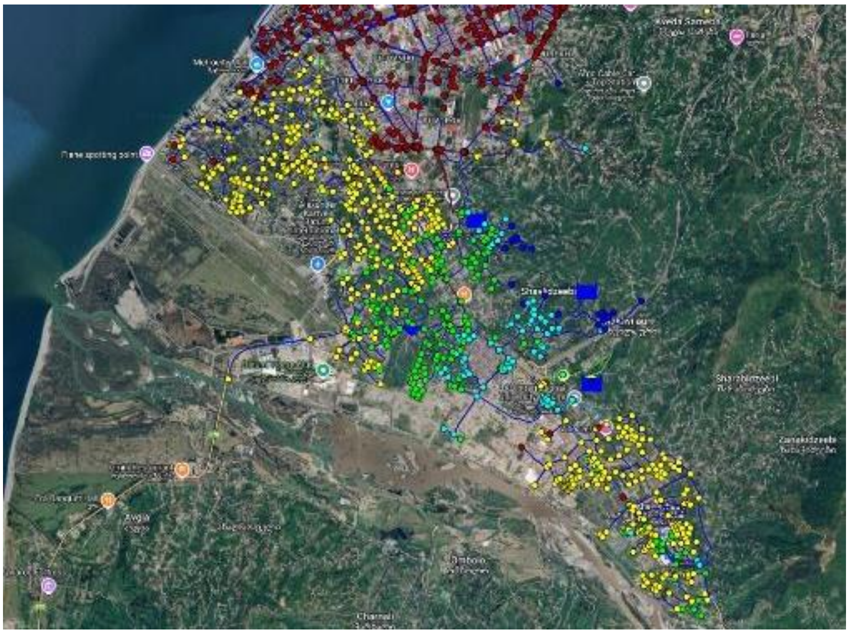


Figure 30: Batumi Tskali hydraulic model

Flow and pressure data were collected through field measurement campaigns carried out at various points across the water distribution network. These empirical observations were essential for validating the calibration of the hydraulic model. Additionally, the recorded data allowed for an estimation of the average water consumption per person, accounting for both actual usage and losses within the system due to leakage.

Figure 31 shows the pressure profiles measured at four critical points across the Khelvachauri water distribution system during a 24-hour monitoring campaign. The 1st point, located at the Mejinistkali Bridge, and the 2nd point, at the Khakhuli Bridge—the main inlet of the network from Batumi—represent two key inflow locations. Both exhibited relatively stable pressures, with peaks around 07:00 h reaching over 40 m w.c., followed by a drop during high demand periods. In contrast, the 1st floor and 7th floor curves correspond to measurements taken within a multi-storey building in the southern neighborhood, a zone known for chronic low-pressure issues. While the 1st floor maintained marginally acceptable pressure levels, the 7th floor experienced critically low conditions, with values dipping below 10 m w.c. during peak hours. These readings confirm the spatial disparity in service levels and highlight the urgent need for targeted pressure recovery interventions in elevated or peripheral areas.

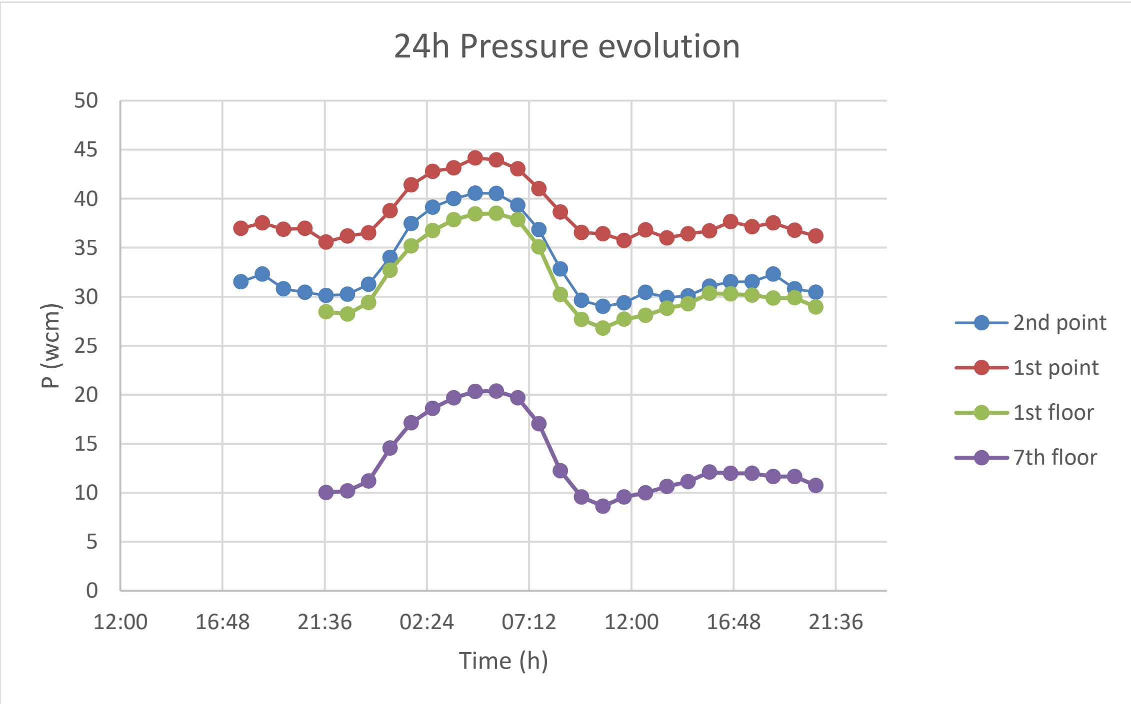


Figure 31: Pressure evolution over 24h

At the same time Figure 32 presents the flow rate variations observed at the same three network locations throughout the day. The Khakhuli Bridge (blue line) registers the highest flow rates, exceeding 35 L/s during early evening hours and dropping significantly overnight, consistent with reduced demand. The Mejinistkali Bridge (orange line) demonstrates a complementary trend, with lower peak flows but a more gradual curve. Meanwhile, the Neighborhood curve (grey line) represents the flow entering the southern residential zone where pressure monitoring was also conducted. This line remains relatively flat, indicating consistent but low flow volumes, likely constrained by pressure limitations rather than demand itself. These flow profiles not only validate the pressure measurement data but also provide valuable input for calibrating the hydraulic model and understanding temporal demand patterns across the municipality.

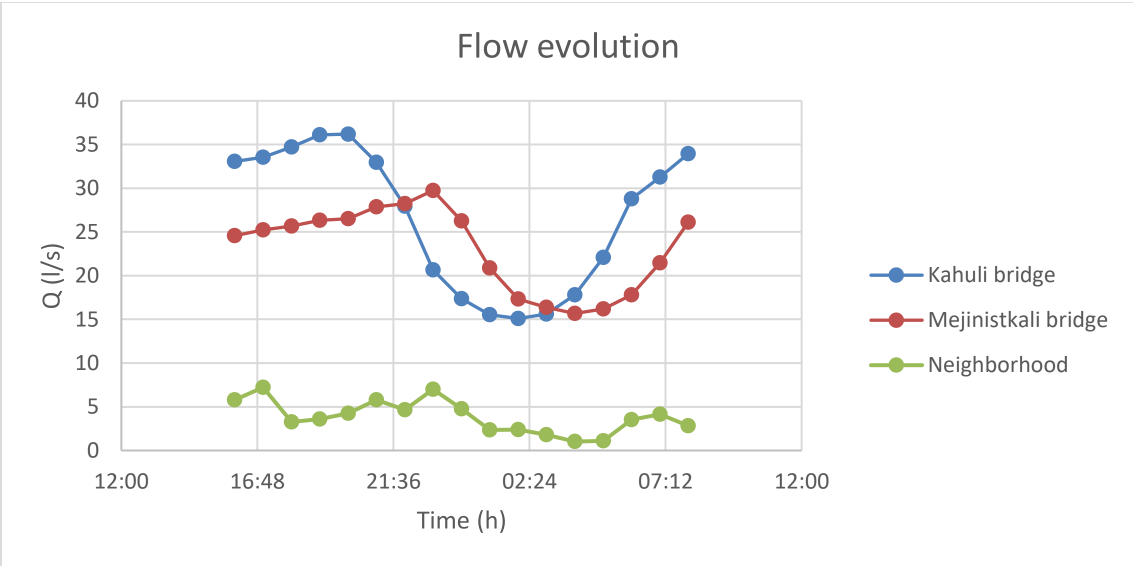


Figure 32: Flow evolution over 24h

Simultaneously, the elevations of the consumption nodes were determined using the GIS functionalities integrated within the Water Smart application. These tools enabled the extraction of elevation data from high-resolution digital terrain models, ensuring a realistic topographical representation of the service area in the hydraulic simulation.

To support the redesign of the water distribution network and ensure its future adequacy, a projection of water demand was carried out up to the year 2040. This projection was based on available demographic data, land use patterns, and planned urban development in the region. The demand assessment for Khelvachauri relied on a detailed analysis of population growth trends and estimated per capita water consumption. Official statistics and previous planning documents were reviewed to establish baseline conditions and growth rates.

Population growth is expected to continue, driven by urban expansion, improved living conditions, and increased economic activity in the region. Based on these factors, the study estimated future water needs to inform the appropriate dimensioning of pipes and hydraulic infrastructure. The applied forecasting approach aligns with established methodologies used in long-term infrastructure planning and predictive water management.

A summary table below presents the projected population growth and the corresponding estimated daily water demand up to the year 2040.

Table 10: Demand estimation

Peak day (m^3/day)	2023	2040	Factor
Airport	5,650	9,983	1,77
Kakhaberi	2,623	4,425	1,69
Industrial	3,039	3,928	1,29
Total Khelvachauri	11,312	18,336	1,62

Based on the outcomes of the field measurement campaign and the demand analysis, physical water losses—primarily attributed to system leakage—were estimated at approximately 20%. For consistency, this same percentage, previously calculated for the nearby city of Batumi, was adopted in the analysis. Apparent losses, such as those related to metering inaccuracies or unauthorized consumption, were considered part of the total consumption figures, as both types of losses are influenced by user behavior and consumption patterns rather than directly by network pressure conditions.

On the other hand, the part of the non-registered water directly dependent on the pressure in the network, the leakage, was modelled in Epanet for the hydraulic calculation as leak valves or emitters. The average pressure value was measured within the network and compared with the calibrated model in the WS. The procedure to calibrate leak valves is essentially simple:

The total network losses are related to the network average pressure by one single coefficient using the general formula of a flow through an orifice, an emitter coefficient is calculated for the consumption nodes, considering their average pressure value and the base demand calculated in Table 10.

Once the coefficient K was calculated, it was applied to each consumption node of the simulation model to consider the water leaks as explained previously.

Initial Diagnostic Simulation

Once consumption and leakage had been modelled, an initial simulation was carried out with the current values of base demand particularised for each consumption node. The consumption pattern used corresponds to a typical domestic consumption pattern, estimated from data recorded for some time in Batumi.

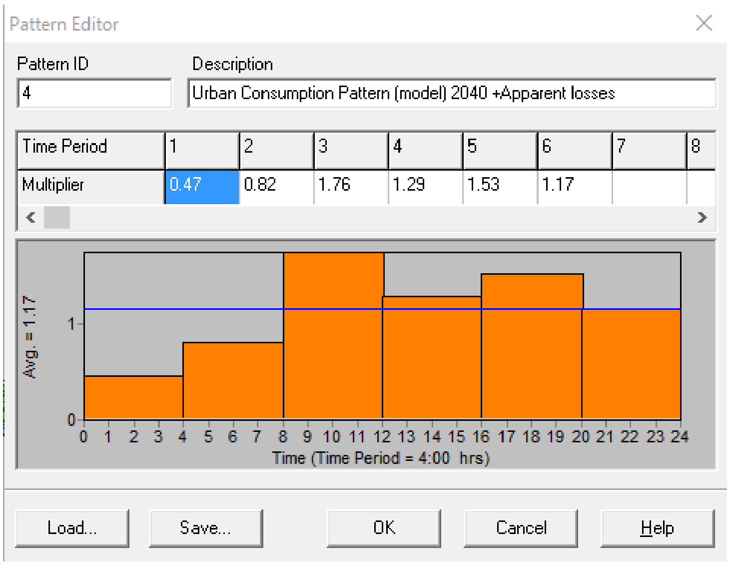


Figure 33: Consumption pattern

The first simulation with the model loaded with the current demand yielded results of insufficient pressure in the southern area of the municipality, as had been experienced in periods of maximum consumption.

The pressure issues in this area were predictable, given its distance from the connection points and the use of a pipe with insufficient diameter. However, as previously mentioned, no calculations were performed when the pipes were installed, which exacerbated the problem.

To optimise the network to meet future demands, the model nodes were modelled with the estimated demand for the year 2024 and with the emission coefficient calculated to simulate leaks.

The result of this simulation is the one presented in the following image, where the supply pressure deficit affects more points of the network and extends throughout almost the entire daytime period (dark blue consumption nodes, <20 mwc).

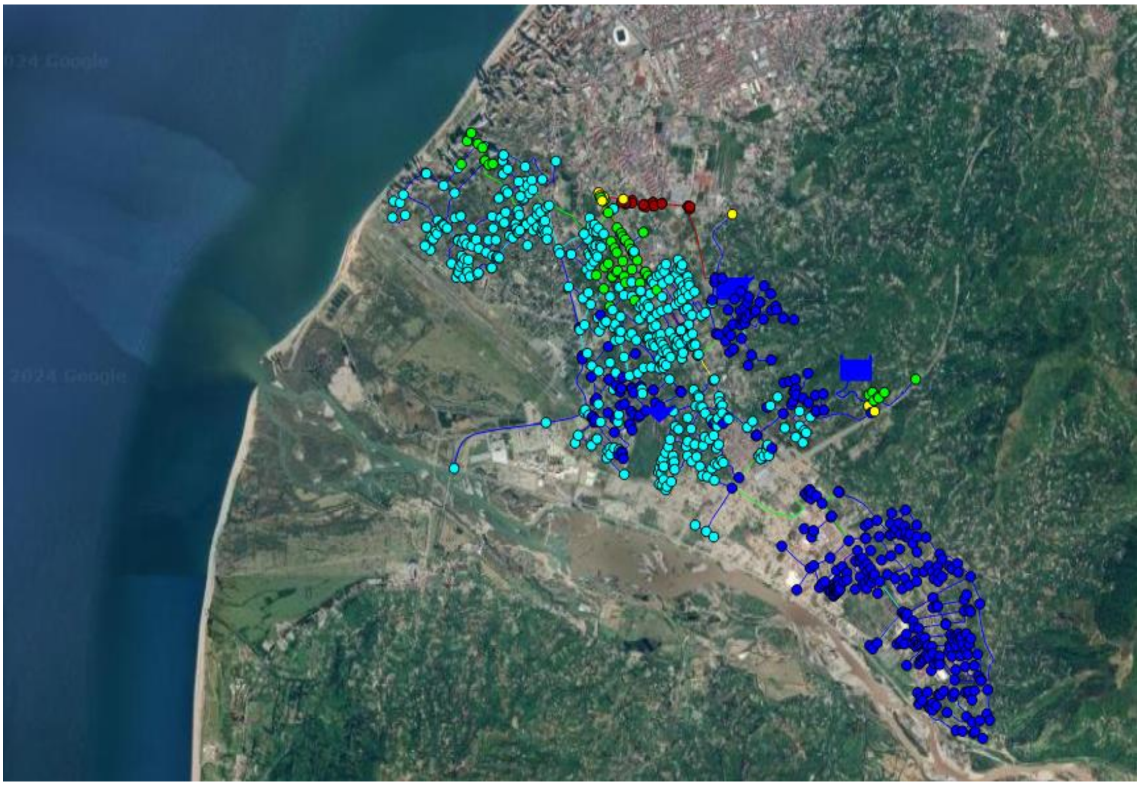


Figure 34: Initial simulation

At this point, a code was programmed using the Toolkit hydraulic programming tool to optimize the network to achieve an adequate pressure level.

Pressure Recovery Module Programming

The proposed WS module is based on Bernoulli's principle describing the relationship between the fluid's velocity, pressure, and height and the relationship between velocity, pressure, and diameter in a hydraulic system. According to this principle, in the absence of external work, the sum of a fluid's static pressure, dynamic pressure, and potential energy per unit volume remains constant over a flow stream. The general formula is as follows:

$$P + \frac{1}{2} \cdot v^2 + \rho \cdot g \cdot h = constant \qquad (1)$$

where:

- P is the fluid pressure (mwc),
- ρ is the density of the fluid (kg/m^3),
- v is the velocity of the fluid (m/s),
- g is the acceleration of gravity (m/s^2),
- h is the height of the fluid for a reference point (m).

The pressure on the pipe's walls is lower when the fluid moves at a higher speed. This is because, according to Bernoulli's principle, when the velocity of a fluid increases, its kinetic energy also increases, but the pressure must decrease to keep the sum of energies constant. This ratio is visible in areas of the pipe with a smaller diameter.

Conversely, when the diameter of the pipe increases, the fluid has more room to move, and therefore, its velocity decreases. According to Bernoulli's principle, as the fluid velocity is lower in a larger diameter area, the pressure in that zone is higher to compensate.

The pressure recovery module within the Water Smart platform was developed using the EPANET Toolkit, a hydraulic programming interface. Its design was based on the relationship between fluid velocity and pipe diameter—an essential principle for maintaining acceptable pressure and flow velocity within the network, particularly in zones where existing connections fail to deliver sufficient supply pressure. The EPANET Toolkit is a powerful programming library that allows you to analyse water distribution networks in a personalized way. Based on the EPANET software developed by the United States Environmental Protection Agency (EPA), this tool offers an API in C, Python or MATLAB, to perform hydraulic and water quality calculations in pipe networks.

Figure 38 presents a summary of this code in VBA (Visual Basic for Applications) for Excel uses the EPANET Toolkit to analyse and optimise water distribution networks. Here's a detailed explanation of how it works, divided into key sections.

The main objective of the code is to adjust the diameters of the pipes of a hydraulic network to ensure that the maximum water velocities (Vmax) do not exceed a set limit, in this case, 1.5 m/s. Once the diameters have been adjusted, the pressure, flow rate, and speed values for each hour of network operation are recalculated.

Firstly, the declaration and initialization of variables are declared to store data on nodes, pipes, velocities, pressures, flows, and diameters. Constants are also initialized to define the number of hours, nodes, pipes and maximum allowed velocity. After that, matrices are sized to store data for each time and element of the network.

In the second step, the initial calculation of velocities and flows calculates each pipe's initial velocity and flow values over 24 hours using the EPANET functions to get each pipe's flow rate (EN_FLOW) and velocity (EN_VELOCITY) and identify the maximum speed and flow rate associated with each pipe to adjust its diameter if necessary.

```vb
' 1. Initialization
Call ENopen("network.inp", "report.rpt", "")
Call ENopenH()
Call ENinitH(0)

' 2. Parameter definition
Dim T As Integer, LinkIndex As Integer
Dim Flow, Velocity, MaxFlow(500), MaxVel(500) As Double
Const Vmax = 1.5

' 3. Initial flow and velocity calculation
For T = 0 To 23
    Call ENrunH(t)
    For LinkIndex = 1 To NumLinks
        Call ENgetlinkvalue(LinkIndex, EN_FLOW, Flow)
        Call ENgetlinkvalue(LinkIndex, EN_VELOCITY, Velocity)
        If Flow > MaxFlow(LinkIndex) Then MaxFlow(LinkIndex) = Flow
        If Velocity > MaxVel(LinkIndex) Then MaxVel(LinkIndex) = Velocity
    Next LinkIndex
    Call ENnextH(tstep)
Next T

' 4. Adjust pipe diameters based on velocity
For LinkIndex = 1 To NumLinks
    If MaxVel(LinkIndex) > Vmax Then
        NewDiam = CalculateDiameter(MaxFlow(LinkIndex), Vmax)
        Call ENsetlinkvalue(LinkIndex, EN_DIAMETER, NewDiam)
    End If
Next LinkIndex

' 5. Re-run simulation with adjusted diameters
Call ENsolveH()

' 6. Save the new network file
Call ENsaveinpfile("adjusted_network.inp")

' 7. Close the EPANET project
Call ENclose()
```

Figure 35: Visual Basic code implementing the pressure recovery module using the EPANET Toolkit

Adjusting the diameters is done after obtaining the maximum speeds.

If a pipe's maximum velocity exceeds the maximum value, the code calculates a minimum required diameter based on the maximum flow rate and rate limit. Moreover, based on the calculated value, the code assigns a new diameter selected from a predefined list of commercial nominal diameters of plastic pipes (HDPE).

Once the diameters have been adjusted, the network conditions are simulated again to obtain the updated pressures, flows and velocities with the new diameters recalculating operating conditions. The results of the example can be seen in the following image, where previous nodes with pressure deficits now show pressure values between 25-40 mwc.

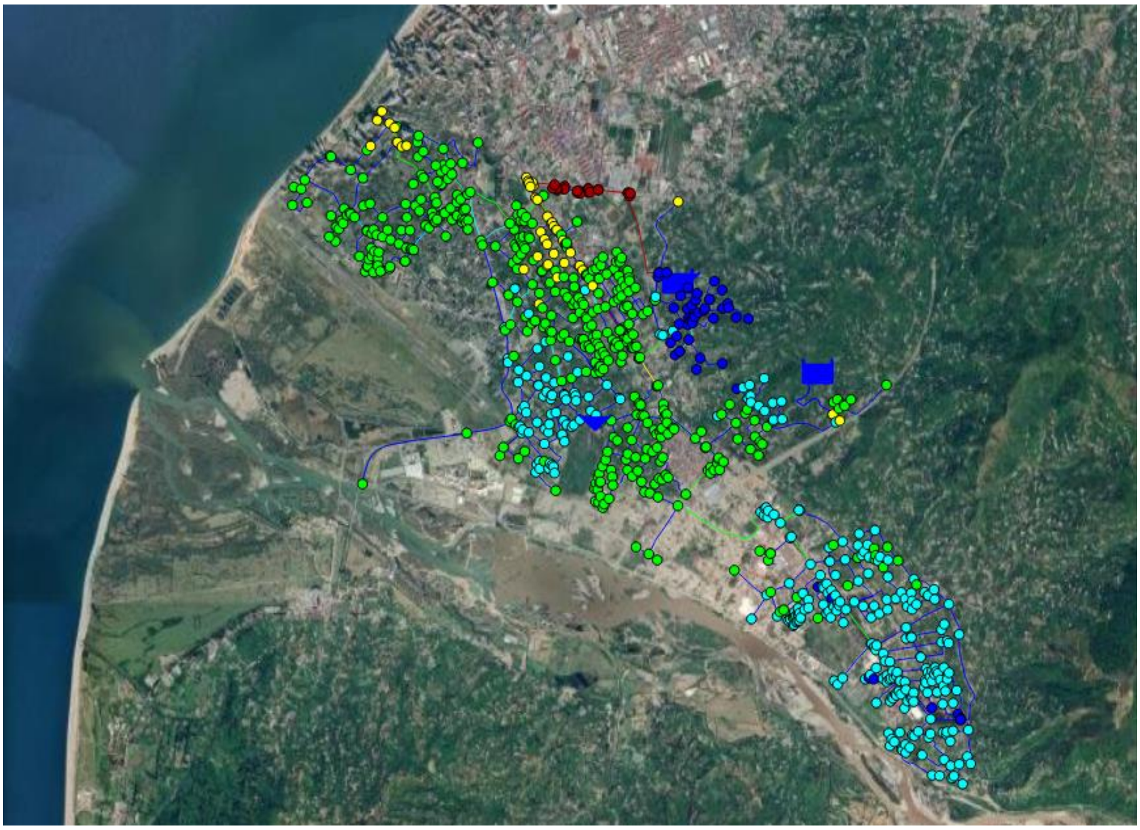


Figure 36: Simulation running the P recovery module

Finally, a new Epanet file with the adjusted diameters is saved, which can be used for further simulations or revisions. This code is a robust tool for optimizing the operation of water distribution networks. Its functionalities automate the adjustment of pipe diameters according to speed limitations. It allows the operating conditions of the network to be recalculated after adjustments and integrates results directly into Excel sheets, making them accessible to users.

This type of programming is especially useful in studies of the optimization of water networks, hydraulic design, and efficiency improvement management. However, in small and mid-sized utilities involved in renovating hydraulic infrastructure, public water supply companies often lack managers with sufficient technical expertise in supply management. Additionally, they typically cannot afford to hire hydraulic experts. To address these challenges, providing more straightforward, user-friendly tools that support effective decision-making is essential. Accordingly, the authors located the most appropriate artificial intelligence algorithms that would reproduce the code programmed with Toolkit for this first level of help in managing this type of problem defined above.

Programming Module Using Artificial Intelligence

A Random Forest Regressor was deployed to replicate the functionality of the Toolkit-based code, providing decision support for managing similar challenges. The algorithm presents an enhanced framework for analysing and optimizing hydraulic networks, explicitly addressing issues related to pipe diameters and flow velocities in a pressurized system. This methodology leverages numerical simulations and machine learning techniques to ensure operational efficiency while adhering to velocity constraints. The random forest regressors to predict optimal pipe diameters and reduce high-velocity zones was set to the module.

A detailed flowchart integrating machine learning within the explained methodology is presented below.

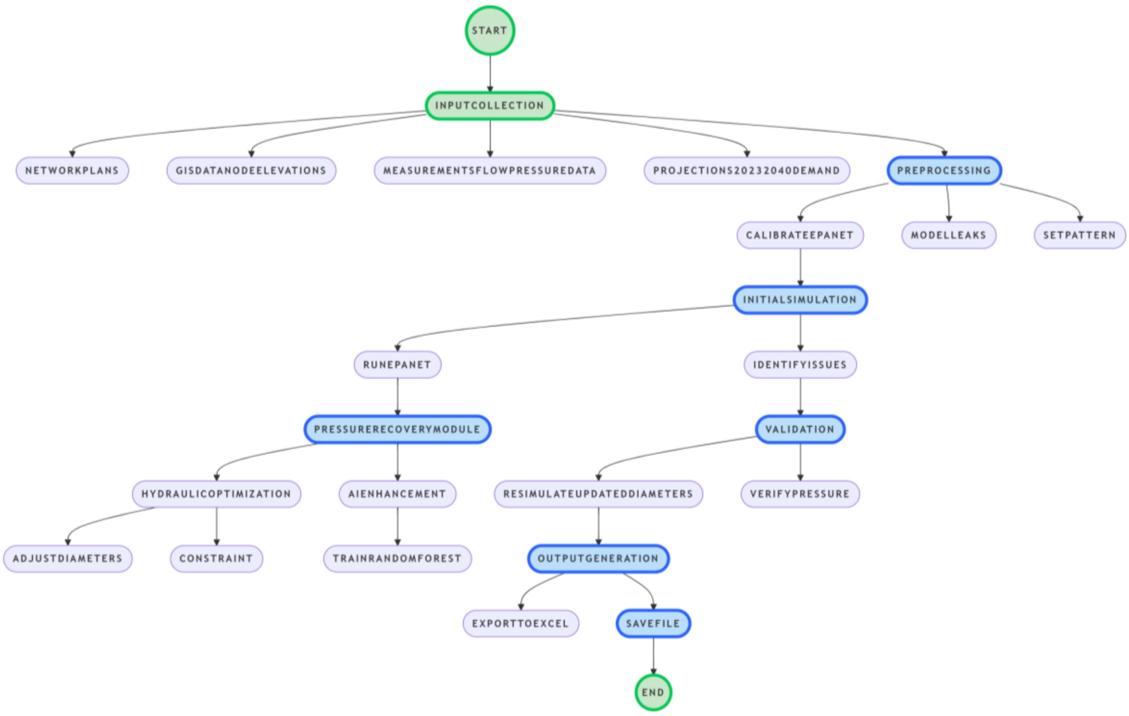


Figure 37: AI-enhancement with Random Forest logarithm flowchart

The algorithm begins by loading a hydraulic network model in EPANET format. It extracts key parameters from the input file, including the number of nodes, pipes, and the simulation duration. Arrays are initialized to store flow, velocity, pressure, and diameters for each pipe and node over the simulation period.

A hydraulic analysis calculates initial conditions, such as flow rates, velocities, and pressures at each time step. The maximum velocity (vmax) for each pipe is identified across the simulation period, and similarly, the maximum flow rate is recorded for each pipe.

The algorithm evaluates the adequacy of each pipe's diameter based on the velocity constraint. If the maximum velocity in a pipe exceeds this threshold, the algorithm calculates the minimum required diameter (Dmin) using the continuity equation:

$$D_{min} = 4 \cdot Q_{max} \cdot \pi \cdot v_{max} \tag{2}$$

where:
- Qmax is the maximum demand at the node (m3/s),
- vmax is the maximum velocity of the fluid (m/s).

Predefined nominal diameter categories are then used to assign updated diameters. If falls outside these categories, a fallback mechanism ensures the assignment of a reasonable value, avoiding invalid configurations. The hydraulic network is then re-simulated with the optimized diameters, and updated flow rates, velocities, and pressures are recalculated to evaluate the impact of the changes.

To integrate machine learning, the algorithm compiles a dataset containing initial and updated diameters, initial velocities, and recalculated velocities for each pipe. This dataset serves as a training set for a predictive machine-learning model. A Random Forest Regressor is trained to predict the final diameter and velocity based on the initial diameter and velocity. The model is evaluated using a mean squared error (MSE) metric and saved for future use. During predictions, the input data is standardized before being passed to the trained model to ensure compatibility and accuracy.

The algorithm introduces several enhancements over its predecessor. It includes robust error handling, ensuring calculated diameters remain within feasible ranges, and improving the solution's reliability. Absolute values are applied to flow and velocity parameters, ensuring non-negative and physically consistent outputs. The fallback mechanism for diameter assignment ensures applicability across diverse hydraulic networks with varying operational conditions.

Furthermore, including a predictive model enables scalability for future scenarios without requiring full hydraulic simulations, significantly reducing computational overhead.

As commented above key mathematical concepts underpin this methodology. The continuity equation governs the calculation of diameters and velocities:

$$Q = A \cdot v = \pi \cdot \frac{D^2}{4} \cdot v \tag{3}$$

where:

- Q is the pipe flow (m^3/s),
- A is the pipe section (m^2),
- v is the velocity of the fluid (m/s),
- D is the pipe diameter (m).

Machine learning feature engineering involves defining predictors as inputs (initial diameter and initial velocity) and targets as outputs (optimized diameter and recalculated velocity). The objective of optimization is to ensure that velocities in all pipes remain below the critical threshold, minimizing energy losses and ensuring operational efficiency.

Table 11 presents the final output of the logarithm with the updated pipe diameters, ensuring pressure recovery in the affected areas.

Table 11: Random Forest regressor output

Variable Name	Type	Shape/ Size	Details
velocity	Array of float64	(24,911)	[[0.0328345 0.0697574 0.080517261 ... 0.94234485 0.12703543 0.8423448 ...]
velocity_df	Data Frame	(24,911)	Column names: P1, P2, P3, P4, P5, P6, P7, P8, P9, P10, P11, P12, P13, …
Vmax	float	1	1.5
writer	io.excel._xlsxwriter.XlsxWriter	1	XlsxWriter object of pandas.io.excel._xlsxwriter module

X	DataFrame	(18,2)	Column names: D_INITIAL, V_INITIAL
X_test	DataFrame	(4,2)	Column names: D_INITIAL, V_INITIAL
X_test_scaled	Array of float64	(4,2)	[[0.777836 0.85156308] [0.777836 0.82976069]]
X_train	DataFrame	(14,2)	Column names: D_INITIAL, V_INITIAL
y	DataFrame	818,2)	Column names: D_FINAL, V_FINAL
y_pred	Array of float64	(4,2)	[[500 1.25162286] [500 1.25162286]]
y_test	DataFrame	(4,2)	Column names: D_FINAL, V_FINAL
y_train	DataFrame	(14,2)	Column names: D_FINAL, V_FINAL

When running the Water Smart module, the results were comparable to those obtained using classic hydraulic programming with the EPANET Toolkit, validating the tool's reliability. This demonstrates the ability of the algorithms used to simulate hydraulic behaviour and optimize the proposed solutions accurately.

2.4.3 Várzea da Cobra (Brazil), Leakage reduction

2.4.3.1 Introduction

This section presents the leakage reduction module developed and validated in the Várzea da Cobra rural water system (Ceará, Brazil), within the SISAR framework. The methodology and simulation approach presented herein are based on the research article currently under peer review (Pressure-dependent leakage modeling and AI-assisted control in a rural water supply network: Várzea da Cobra (Ceará, Brazil) case study. *Pons-Ausina et al., submitted*), and adapted to fit the structure of this doctoral dissertation.

The Várzea da Cobra case exemplifies the need for efficient pressure management in small, rural water networks, where water losses due to leakage remain a critical challenge. Despite universal customer metering and community-led management under the SISAR model, a baseline water audit revealed that more than 50% of water supplied was not accounted for through billed consumption. Field measurements further confirmed frequent pipe bursts and consistently high Minimum Night Flow (MNF), indicating substantial background leakage.

Prior to this study, the system lacked any form of pressure regulation, operating directly under the head of the elevated storage tank, which led to excessive night-time pressures in lower-elevation areas. In response, the Water Smart platform (WSNO and WSNA modules) was introduced to simulate and evaluate pressure control strategies.

Three control scenarios were designed and tested:

1. Baseline (No PRV): No pressure regulation, full tank head applied at all times.
2. Smart Fixed PRV Setting: A pressure reducing valve (PRV) installed with time-based modulation (e.g., 10 m at night, 30 m during the day).
3. AI-Assisted PRV Control: A dynamic PRV setpoint adjusted hourly using a reinforcement learning (Q-learning) algorithm, implemented in Python.

The pressure-dependent leakage model was calibrated using field MNF data and incorporated into the EPANET-based WSNO platform. A custom decision-support algorithm was also programmed to simulate and compare the three scenarios. Results showed that the fixed PRV setting achieved a leakage reduction of approximately 24%, while the AI-assisted controller maintained more stable pressures with marginal additional savings.

This module demonstrates the potential for integrating hydraulic modeling, pressure-leakage relationships, and AI control strategies within a practical framework for rural utilities.

The following sections detail the modeling workflow and results obtained from each intervention.

2.4.3.2 Study area and baseline conditions

The Várzea da Cobra water supply network serves a rural community in Ceará state in northeast Brazil. The system consists of a single groundwater source (a borehole with a pump) that feeds an elevated storage tank, which supplies the distribution network by gravity. The network serves approximately 70 household connections (representing about 50–60 households). The pipelines total only a few kilometres in length (50–110 mm diameters PVC) and form a simple branched layout: a main line runs from the reservoir through the village with lateral branches to outlying houses. Because of the topography, some parts of the service area are at a much lower elevation than the tank, leading to high static pressure. Before the intervention, the tank water level (when full) was imposed over 50 m of head on the network during low-demand periods. Indeed, at night, the pressure measured at some lower nodes would often exceed 50 m (5 bar). Such excessive pressure contributed to numerous pipe breaks and high background leakage. By contrast, during peak consumption hours (morning or evening), the network pressure would drop substantially due to head losses, sometimes approaching minimal service levels at the far ends.

Initial water audits indicated a severe leakage problem. The system's non-revenue water was estimated above 50% of input volume, with essentially all 70 connections being metered and billed (so real losses dominated). A Minimum Night Flow (MNF) analysis examined the flow rate into the zone during the late-night hours when legitimate customer use is minimal. The MNF observed at the reservoir outlet often remained on the order of 0.5–0.6 L/s (about 1.8–2.2 m^3/h). For a community of this size, legitimate night consumption (e.g. occasional use or leakage at taps) should be only a small fraction of that flow. Thus, most of the MNF – on the order of 0.4–0.5 L/s – was inferred to be leakage. This simple analysis confirmed that background leaks were the main cause of the elevated night flows, aligning with the literature that the MNF method can effectively quantify leakage.

2.4.3.3 Hydraulic Programming for Pressure Control Scenarios

A detailed hydraulic model of the Várzea da Cobra network was developed using MACS WSNO (EPANET 2.0 based). All pipes, junctions, and the elevated tank were represented in the model, and each service connection was modeled as a demand node. Lacking exact usage profiles for each connection, a uniform base demand of 0.018 L/s per connection (equivalent to roughly 65 L per capita per day spread evenly, assuming about 50–60 households) was assigned. This yielded a total nominal demand of around 1.0–1.1 L/s for the system, consistent with field observations of average consumption.

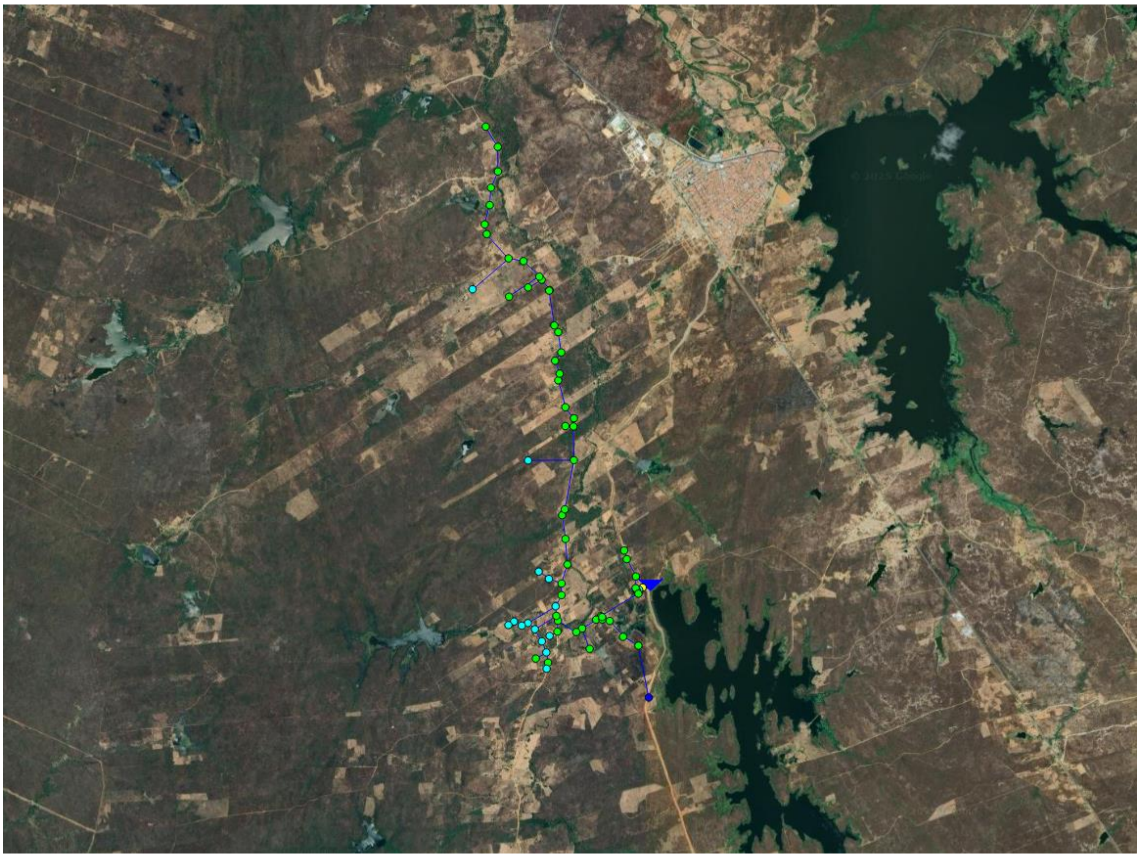


Figure 38: Hydraulic model Várzea da Cobra

We assumed a relatively flat demand pattern over 24 hours (i.e., nearly constant consumption) for initial calibration. This conservative assumption was made to isolate leakage effects in the model. If customer demand is nearly steady, any diurnal variation in the measured inflow would be attributable to changes in leakage or storage. In reality, rural water use does show peaks (morning and evening), but due to limited data, we started with a simplified pattern and then made minor adjustments during calibration. Specifically, a small reduction in demand during late-night hours was introduced so that the simulated baseline night flow matched the observed MNF (0.6 L/s). This ensured that the model accurately reflected the real leakage level in the baseline scenario. Using the MNF method, we calibrated the total leakages by adjusting emitter coefficients (described below) such that the model's night flow corresponded to the field-measured value.

Leakage was modeled as pressure-dependent outflow at each node using EPANET's emitter feature. We set the exponent N=0.5 for all emitters to reflect orifice-type leak behavior. The emitter coefficient C at each node was initially assumed to be proportional to the service connection length or number of joints near that node (since longer pipe runs and more joints likely mean more leakage). These coefficients were then globally scaled to match the total leakage indicated by the MNF. After calibration, the model's baseline scenario (no PRV) produced a daily leakage volume of about 47 m^3, which was 31% of the 153 m^3/day input. This aligns reasonably with the audit estimate of 50% NRW when considering that some of the audit's losses may include minor metering errors or unmetered small uses. For modeling purposes, we treat 47 m^3/day as the pressure-driven leakage in the baseline – a significant loss that our interventions aim to reduce.

The initial development of the leakage control module for the Várzea da Cobra system was carried out using the EPANET Toolkit through Visual Basic for Applications (VBA). The author implemented the hydraulic simulation logic and control routines, defining three different operational scenarios for pressure management: (1) no PRV (baseline), (2) PRV with a fixed optimal setting, and (3) PRV with variable, AI-assisted control. This foundational programming enabled a complete evaluation of how pressure adjustments influence leakage dynamics in rural networks.

The code logic consists of iterating through 24-hour extended-period simulations for each scenario, retrieving pressures and emitter coefficients at every node, computing leakage volumes using pressure-dependent equations, and comparing the demanded, leaked, and total flow. For the third scenario, an adaptive loop adjusted the PRV setting to reach a desired pressure target dynamically.

This VBA prototype served as a testbed for calibrating the pressure-leakage model and benchmarking performance across scenarios. It also provided the training data and operational logic later used to build the machine learning-based PRV controller integrated into the Water Smart platform.

The full Visual Basic code developed for the simulation of the three pressure control scenarios—baseline (no PRV), fixed PRV setting, and AI-assisted dynamic PRV—is presented in Figure 39 and available upon request. This code, which interfaces with the EPANET Toolkit, was written by the author and serves as the basis for the leakage estimation and pressure regulation routines implemented in the Water Smart platform. It allows for detailed control over hydraulic simulation loops, pressure-dependent leakage modeling, and scenario comparison. Given its technical scope and length, the complete version is not included here but can be shared for academic or research purposes.

```vb
' Initialization
num_cases = 3
num_hours = 24
ReDim vol_demanded(1 To num_cases), vol_leakage(1 To num_cases)

' Loop through 24h for each scenario
For hour = 1 To num_hours
    ' --- CASE 1: No PRV (valve fully open) ---
    SetValveSetting(valve_obj, 450)
    RunHydraulicSimulation
    ComputeLeakageAndDemand(case:=1)

    ' --- CASE 2: Fixed PRV setting at 25mwc ---
    SetValveSetting(valve_obj, 25)
    RunHydraulicSimulation
    ComputeLeakageAndDemand(case:=2)

    ' --- CASE 3: Dynamic setting with AI logic ---
    i = 15: P_prev = 0
    Do While PressureAtNode(4) <= 30
        If PressureAtNode(4) < P_prev Then Exit Do
        P_prev = PressureAtNode(4)
        i = i + 5
        SetValveSetting(valve_obj, i)
        RunHydraulicSimulation
    Loop
    ComputeLeakageAndDemand(case:=3)
Next

' Volume aggregation
For case_num = 1 To num_cases
    For hour = 1 To num_hours
        vol_leakage(case_num) += leakage(case_num, hour) * 3.6
        vol_demanded(case_num) += demanded(case_num, hour) * 3.6
    Next
Next
```

Figure 39: Summary of VBA code for simulating leakage under three PRV control scenarios

To evaluate pressure management strategies, we simulated three scenarios in the model:

1. **No PRV (Baseline):** The network operates with no pressure control, i.e. the tank head is fully available. This scenario reflects the pre-intervention state. It served as the baseline for leakage and pressure levels.

2. **Fixed PRV Setting**: A pressure-reducing valve is installed on the main pipe, leaving the tank and setting it to a constant outlet pressure (optimized). Based on trial simulations, an outlet pressure of about 30 m (head) was chosen as the fixed setpoint. This value was low enough to significantly cut leakage yet high enough to supply all consumers under peak flow. In practice, a simple time modulation was applied: the PRV was set to 10 m during late night hours to further suppress excess pressure when demand was minimal and raised to 30 m during the daytime to ensure adequate flow. (This mimics a "smart" fixed schedule often implemented by operators manually, essentially two fixed settings for night vs. day.) We refer to this scenario as smart fixed PRV control. It represents a low-cost approach requiring a basic timer or manual valve adjustment.

3. **AI-Assisted PRV (Dynamic):** In this scenario, a reinforcement learning (AI) agent controls the PRV outlet pressure setpoint that adjusts the setting hourly in response to network conditions. The AI controller was trained (in simulation) to minimize leakage while keeping the minimum service pressure above acceptable levels. Technically, we implemented a Q-learning algorithm that learns the optimal setpoint for each hour given the demand pattern, similar to approaches in recent studies. The learned policy resulted in a varying setpoint: lower values at night and in periods of low demand, and higher values during peak demand, with finer adjustments than the two-step fixed schedule. The AI aims to keep pressures "just enough" to meet demand. The dynamic PRV scenario requires telemetry and automation but can theoretically respond to unpredictable changes in demand in real time.

Programming Module Using Artificial Intelligence

The AI-based controller was implemented via a Python script that interfaced with the EPANET Toolkit. It ran in two stages:

1. Learning Phase: The agent observed downstream pressure responses and iteratively learned an optimal schedule of PRV setpoints through simulation.

2. Execution Phase: The learned PRV settings were applied in a second simulation pass to evaluate network performance.

Although the AI strategy did not significantly outperform the fixed PRV in this particular case (due to the steady consumption profile), it ensured full delivery of demand, minimized leakage, and dynamically maintained acceptable pressure throughout the day. Its integration into the WSNO interface positions it as a scalable and transferable tool for real-time pressure management in small utilities.

It should be noted that demands are relatively predictable for this particular network (morning/evening peaks). Thus, we expect the fixed two-level and AI control to perform similarly, as found in other research for low-variability demand systems. However, the AI control provides a test of what could be achieved under ideal adaptive management, and it could prove more beneficial if demand patterns become more irregular (e.g., due to growth or intermittent pumping schedules). Each scenario was run in an extended period simulation (24 hours, with 1-hour time steps) using the calibrated EPANET model with pressure-dependent leakage in WSNO.

Figure 40 illustrates the programmed logic used to simulate and compare the three pressure management scenarios implemented in the Várzea da Cobra network using the EPANET Toolkit and Random Forest algorithms. Starting from the initialization of EPANET, the process branches depending on whether pressure control is applied. In Scenario 1 (no PRV), the simulation calculates flow, pressure, and demand values under full tank pressure. For Scenarios 2 and 3, a PRV is installed and set to fixed (Scenario 2) or adaptive (Scenario 3) values, based on hourly demand patterns. In each case, Random Forest regression models are trained using the hydraulic outputs to replicate the optimal valve settings with minimal error. The diagram highlights the comparative impact of each strategy on leakage and system performance, showing reductions in losses and pressures when control is introduced. The code underlying this workflow was developed in VBA and integrated with EPANET Toolkit routines, and it is available upon request for academic use.

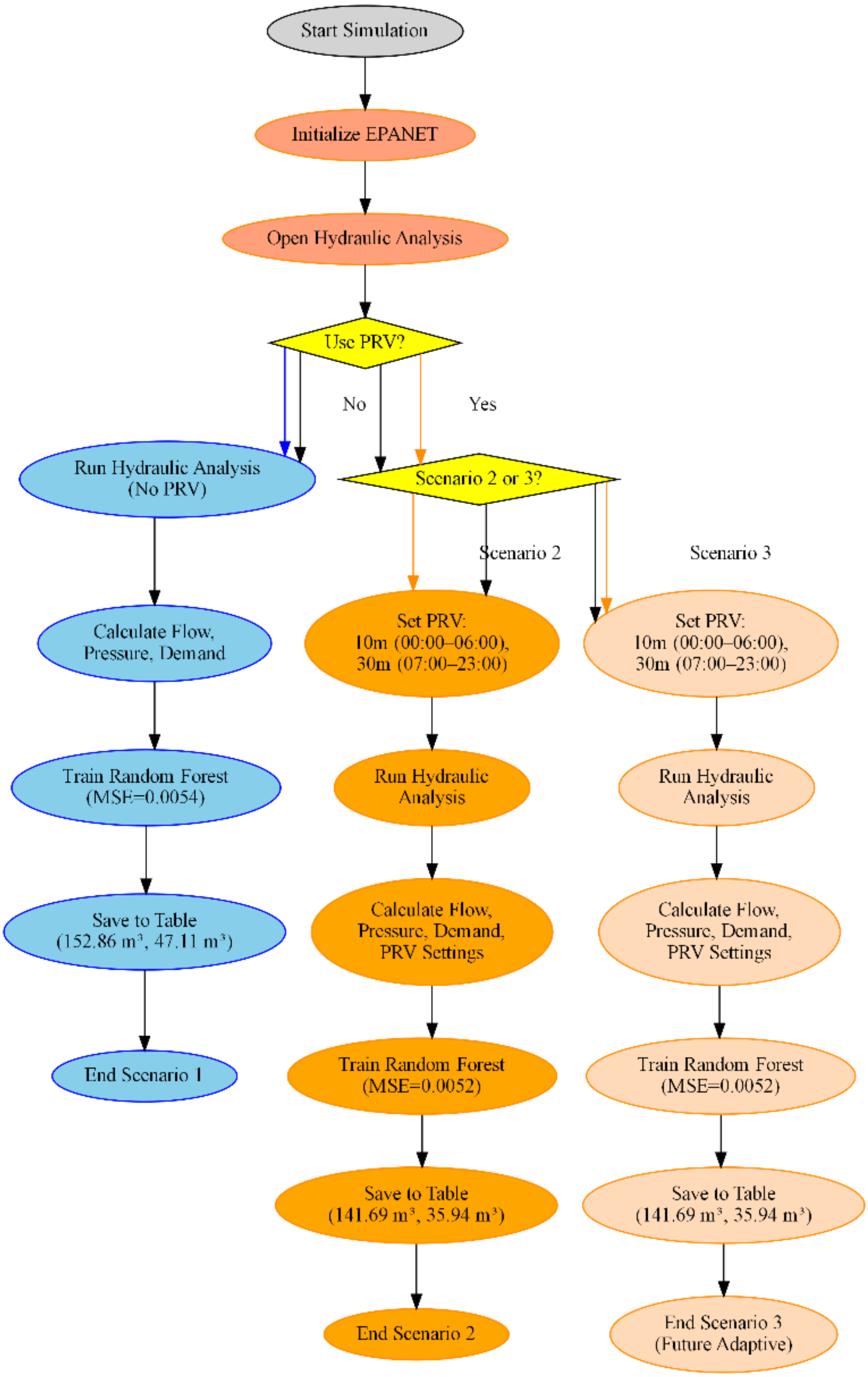


Figure 40: Programming process flowchart

2.4.3.4 Integration into the Water Smart Platform

The Várzea da Cobra case exemplifies how combining classical hydraulic engineering methods with AI techniques can yield practical solutions for water loss reduction. We leveraged the MNF analysis – a staple in leakage management – to quantify leaks and calibrate the model. Then, we used the model to test an innovation (AI control) that would have been difficult to trial directly in the field without risking service. This integrated approach allowed the utility to make an informed decision: adopt the proven low-tech solution (PRV) and remain open to high-tech enhancements (AI) as a future upgrade. More generally, this underscores the importance of data and modeling in rural systems. Even a single flow meter (the one at the tank outlet) provided enough insight to drive a successful intervention. Many small utilities lack extensive SCADA, but as this case shows, focusing on a couple of key measurements – night flow and maybe a critical node pressure – can provide the evidence base to justify improvements. We recommend that SISAR and similar rural water programs invest in basic monitoring of flows and pressures. The payoffs in terms of water savings and improved service can be substantial.

Our findings also support the broader literature that pressure management should be a top priority in leakage control programs. While advanced methods like active control are promising, getting the fundamentals right (proper valve settings, district metering, leak repair) comes first. In Várzea da Cobra, installing one PRV yielded almost all the benefits; the AI yielded only incremental improvement. In larger or more complex networks, those increments might be larger – for example, in a city system with many pressure zones, AI could coordinate valves and pumps in ways humans cannot easily, yielding multi-percent additional savings. But for a small system, simplicity and reliability are key. This case thus provides a real-world datapoint on the ROI of AI in water loss control: if demand is fairly predictable, an AI may not significantly outperform a well-managed fixed schedule (as also noted by recent research ()). However, the AI did ensure no pressure complaints, which has its own value in service quality.

In summary, the implementation of a PRV in the Várzea da Cobra network is expected to substantially reduce leakage (by 24%), improve pressure conditions, and enhance the sustainability of the water supply. The use of AI in simulation helped confirm that we aren't leaving major gains on the table – the fixed strategy captured most benefits. Going forward, the utility plans to proceed with the PRV installation and monitor results through the WSNA module of the Water Smart platform. If leakage drops as predicted, the saved water could enable extending service to a few nearby households currently unconnected, improving equitable access.

There is also interest in possibly introducing the AI control via the WSNO platform in the future, perhaps initially in advisory mode. Additionally, the methodology developed here (combining field night flow analysis with modeling and control simulation) can be applied to other SISAR-managed systems that exhibit high NRW. By prioritizing zones with the worst losses and implementing pressure management, SISAR can systematically reduce non-revenue water across its service area, aligning with its mission of sustainable rural water service.

The entire leakage analysis and optimization process was conducted within the MACS Water Smart platform, using WSNO for modeling and scenario simulation, and WSNA for tracking customer and asset data. The AI control algorithm was developed as a new functional module within WSNO, and the results were stored and visualized using standard WS output tools.

This experience confirmed that the Water Smart platform, with its modular architecture and open-tool integration, can support intelligent pressure management strategies in rural and small-scale networks. In Várzea da Cobra, the combined application of pressure-dependent modeling, MNF-based calibration, and AI-driven PRV optimization led to measurable leakage reductions and service improvements.

2.4.4 Jakarta (Indonesia), Water Infrastructure Resilience module against Climate Change

2.4.4.1 Introduction

This case study corresponds to the pilot implementation of a future development within the Water Smart platform: the Water Smart Resilience Optimization (WSRO) module. The work was presented at the Jornadas de Ingeniería del Agua 2023 (JIA 2023) in Cartagena, titled "Climate Resilience Simulation of a Public Water Utility in Indonesia under Climate Change Scenarios", where the climate vulnerability of the PDAM Sleman utility (Indonesia) was assessed using a multi-step approach. The insights gained through this experience laid the foundation for the upcoming WSRO module.

The simulation process for this study was carried out using the WSNO module to diagnose the hydraulic behavior of the existing system and to design infrastructure improvement alternatives. These included scenarios for network optimization, pressure control, and service continuity under extreme conditions such as droughts or seasonal stress. The modeling allowed for a detailed assessment of supply gaps, high-pressure zones, and non-revenue water levels, all of which are critical elements for resilience planning.

The upcoming WSRO module aims to integrate resilience planning, hydraulic simulations under stress scenarios, and adaptive investment prioritization within a single digital platform. To achieve this, the pilot applied several tools in coordination: the CRIDA methodology for decision-making under uncertainty, the WNTR (Water Network Tool for Resilience) for simulating network performance under hazard scenarios, and the WSNO for technical and economic optimization.

The Jakarta–PDAM Sleman case illustrates how a small-to-mid-sized utility can be assessed through a combined perspective of operational efficiency, physical risk, and long-term resilience. The fieldwork, data acquisition, hydraulic modeling, and cost-benefit analysis presented in this pilot constitute the conceptual and technical baseline for the future WSRO module currently under development by the author in collaboration with MACS Energy & Water.

2.4.4.2 Climate Risk-Informed Strategic Planning

The Climate Risk Informed Decision Analysis (CRIDA) framework provides a structured, stepwise methodology to plan for climate uncertainties. In the PDAM Sleman case, CRIDA's five recommended steps (per UNESCO guidelines) were applied: beginning with a collaborative definition of the decision context (identifying problems, performance criteria, and critical thresholds with stakeholders) and a bottom-up vulnerability assessment and progressing through formulation and evaluation of robust actions under various scenarios, to ultimately institutionalizing the decisions in utility planning.

Regarding the CRIDA methodology, the five steps recommended by UNESCO (2023) were taken during the consulting process via on-line meetings and communication in general and, most importantly, in the workshop held in the PDAM Sleman Central Utility:

- **Step 1 – Decision Context**: we first structure a collaborative process for the vulnerability assessment, defining the problems, developing evaluation criteria, identifying critical thresholds and then building a shared vision with the participation of the stakeholders (such as the collaborators of PDAM Sleman, for example).
- **Step 2 – Bottom-up Vulnerability Assessment**: then, we construct and implement a bottom-up vulnerability assessment, establishing the level of concern for each initiative and determining the risk in the uncertainties of the future.
- **Step 3 – Formulate Robust & Flexible Actions**: further, we elaborate alternative plans, formulating different courses of action, evaluating their robustness and developing, when needed, adaptation pathways.
- **Step 4 – Evaluate Plan Alternatives**: the plans should now be evaluated according to the baseline performance. For this, different scenarios were simulated both within the Consultant team and on the workshop in Sleman.
- **Step 5 – Institutionalize Decisions**: finally, we institutionalize the decisions. This step refers to this Final Report and the Final Presentation to be presented to PDAM Sleman, in order to pass the knowledge acquired from this project as well as the key findings and decision recommendations from this methodology.

The results from this successful methodology are the proposed alternatives, plans and decisions featured below.

Table 12: Best ranked of the proposed adaptation measures

Proposed Measures	F	B	CB	C	T	Total
Develop emergency preparedness procedures for natural disasters and water shortage periods.	5	4	4	1	1	**11.5**
Prepare/obtain strategic planning documents on the availability and sustainable use of water resources	5	5	4	2	2	**11**
Prepare feasibility study, cost estimate and investment business plan for the selected adaptation measures	5	5	4	2	2	**11**
Revise operation and maintenance practices.	5	4	3	1	2	**10**

Water treatment: Improve disinfection procedures (inline injection/reservoir).	4	5	4	2	2	**10**
Further hydraulic assessment and investigation: ⇒ **Evaluation of the water mains: analysis of the capacity of flow transportation;** ⇒ **Water meters installation/ evaluation at the service connections to register properly the consumption;** ⇒ **Analysis of the flow dependent of the pressure to identify leakage specially during night-time and investigation of the authorized and unauthorized consumption to a proper estimation of the current level of NRW;** ⇒ **Study of the interconnection of the different units to stablish supplying options in case of necessity; and** **Investigation and confirmation of the direct pumping to the network and study of alternatives to reduce the energetic consumption.**	4	5	4	2	2	**10**

This approach ensured that local knowledge (PDAM staff inputs) and data on system performance informed the analysis of how climate change may impact service delivery. The climate risk assessment revealed that PDAM Sleman's existing water supply system is highly vulnerable in terms of both quantity and quality of service, meaning that critical assets, if partially or fully failed, could seriously disrupt water supply. A range of climate and environmental hazards were considered – including water availability stress, floods, droughts, volcanic eruptions, landslides, and earthquakes – to determine which threats pose the greatest risks to the utility.

Drought emerged as a primary climate concern, especially in light of projections for increased water demand (a 1.7× rise by 2030–2050) rather than significantly diminishing supply . This finding underscores the importance of managing demand and reducing losses as key adaptation strategies.

Using CRIDA's bottom-up assessment, PDAM Sleman and the analysts identified the system's performance thresholds (e.g. minimum service pressure, acceptable supply volume) and examined how these could be breached under future climate scenarios. They then formulated adaptation measures and tested their robustness. The outcome was a prioritized list of interventions, ranked via multi-criteria analysis of feasibility, benefits, co-benefits, cost, and time. The highest-priority measures for PDAM Sleman combined high benefits and feasibility with low cost and short implementation time**.**

Notably, many of these top-ranked actions focus on proactive planning and system efficiency. For example, as presented in Table 16, *developing emergency preparedness procedures for droughts and natural disasters* was the top measure (scoring 11.5), recognizing the need for protocols to maintain service during climate extremes. Likewise, *establishing strategic planning documents for sustainable water resource use* and conducting feasibility studies for key adaptation projects (both scoring 11) were emphasized to ensure long-term water availability. Improvements in day-to-day operations were also highlighted: measures such as *revising operation & maintenance practices* and undertaking *further hydraulic assessments* of the network (including *installation of water meters on service connections and analysis of pressure–flow relationships to pinpoint leaks and unauthorized use) were highly ranked*. These recommendations reflect no-regret actions that address current inefficiencies (like leakage and data gaps) while building capacity to cope with future climate stress. CRIDA thus provides the WS platform module with a strategic roadmap – it identifies where the utility is most vulnerable, which adaptation options are most urgent and guides the prioritization of investments. This strategic output feeds into the next stages by defining the scenarios and interventions that need to be analyzed in detail.

It is important to mention that any of the proposed measures in Table 16 can be very useful for any small water utility at some point of the future. If, for example, the priorities establish now (low cost and small time to conclude) changes, this could lead to another proposed measure ranking better than those there are top ranked now.

However, considering the current scenario and priorities of PDAM Sleman, according to what has been gathered and discussed during the months that this study was developed, Table 17 highlights the key priorities for the utility to consider for future investment and improvement.

Now, considering a scenario of available funding from donors, such as the case of Water.org, the cost would not be such a big problem to tackle. In this case, Table 17 summed up the best ranked of the 'investment needed' of the proposed measures. The objective of this table is to give an idea on where the PDAM Sleman should focus in case of an investment or funding. For this, all the proposed measures with 'Costs' equals 1 or 2 were unconsidered, as those measures are considered to be funded by the utility itself.

Table 13: Best ranked of the investment needed of the proposed adaptation measures

Proposed Measures	F	B	CB	C	T	Total
Allocate emergency funds for repair works. Increase budget for maintenance works.	4	5	4	3	1	**9.5**
Reduce the required system input to the water supply system by reducing water losses. Systematic rehabilitation and/or replacement of certain pipe sections.	4	5	5	4	4	**8**
Reduce exposure of Umbul Wadon system to eruption-related damage. Relocate sensitive facilities from direct risk. Resilient design against lava flow at new location.	4	5	4	4	3	**7.5**
Phase out shallow wells and establish deep wells.	5	5	4	5	3	**7.5**
Improve water quality monitoring system (raw and serviced water)	4	4	4	3	4	**7**
Explore the potential for an alternative water source: surface water retention by constructing dams and reservoirs.	4	5	5	5	4	**7**
Replacement of the small pipes to reduce head loss in the system: **D25, D40, D50 service connections to be replaced by DN75** **Reservoir outlets, transportation pipes under DN100 shall be replaced.**	4	5	4	4	4	**7**

For this, it was selected each and every proposed measure that had a total that equals or exceeds 7 (seven) and had the ‘Cost’ column equals or exceeding 3 (three). By doing so, we can focus on the best adequate measure that requires bigger investment that the PDAM Sleman are not likely able to fund by its own manners.

2.4.4.3 Simulation of Network Resilience Under Climate Scenarios

Open-sourced data for the various physical climate and environmental risks and primary data from the PDAM Sleman for analysis were acquired for the risk assessment. This data contributed to calculating and assigning risk scores to the individual key infrastructures. The data processing and assignment of physical climate risk to infrastructure were computed using ArcGIS and SAGA GIS. Sixty-six (66) Sleman utility units were analyzed for physical climate risks (Figure 46).

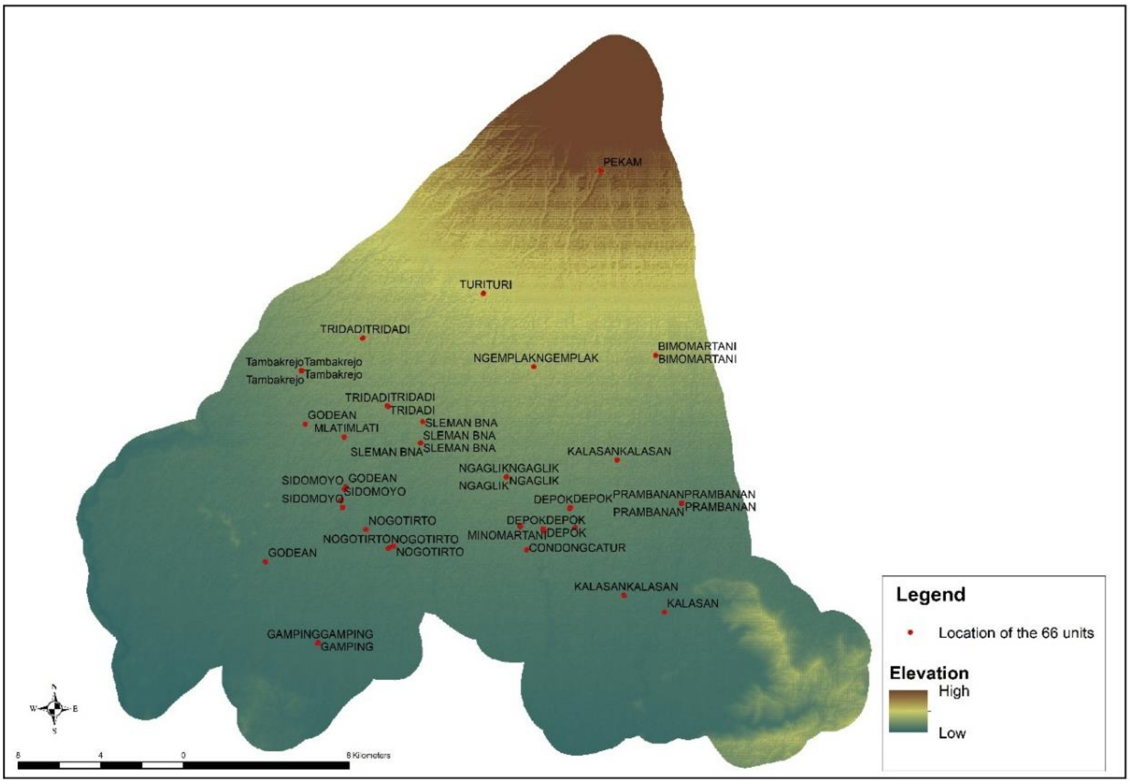


Figure 41: Location of the Sleman unities evaluated

Climate risk data on drought, flood, and water stress were obtained for the climate risk analysis. The drought data for several return periods were retrieved from the World Bank database, whereas the flood and water stress are “Aqueduct” products from the Water Research Institute. Other environmental risk data used include landslides, and seismic and volcanic layers.

Water stress will evolve not due to diminishing water availability but actually due to a 1.7x or greater increase of water demand. The main climate risk identified is droughts. In our climate assessment drought hazard risks were retrieved for 5, 10 and 25 return periods. It is assumed that PDAM Sleman´s shallow wells will be completely phased out by 2040, what can minimize the impact of droughts, as the water on deep wells are not much affected by it. However, droughts will exacerbate the effects of other non-climate related stressors, such as water pollution or increasing demand.

The methodology for assessing physical climate risk follows the general practice of identifying the exposure of a utility based on its location under a particular environmental or climate risk scenario. For example, the UNEP FI and ECB/European Systemic Risk Board guidelines utilized a similar approach.

The physical climate assessment was performed for two climate change scenarios projected for 2030 and 2050. Expressly, forward-looking guidance is provided for two Representative Concentration Pathways (RCPs) as scenarios (Figure 47) for the increase in radiative forcing, which controls the climate factors in the general circulation models.

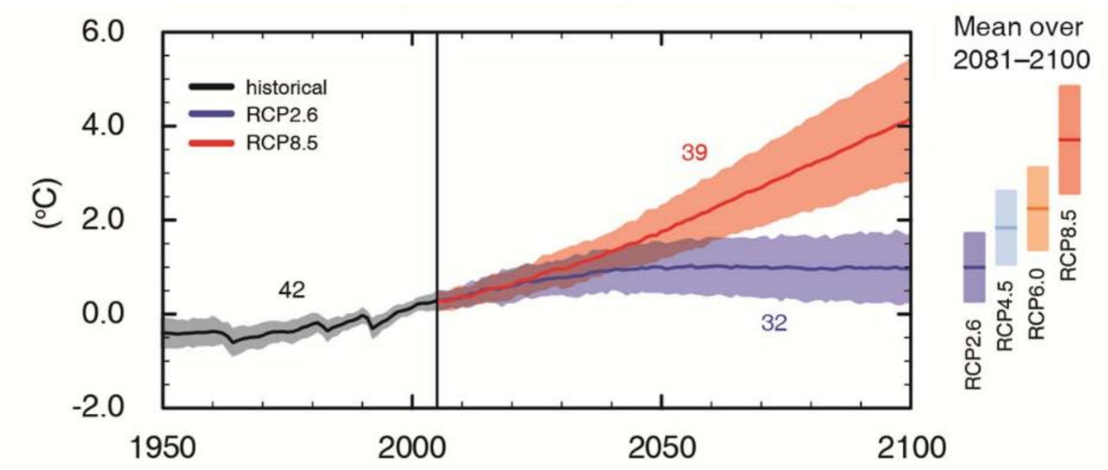


Figure 42: Global warming under RCP climate scenarios RCP 4.5 and RCP 8.5

Some environmental risks are expressed in terms of return periods. The return period represents how frequently an event can be expected to happen, whereas the return level is the corresponding magnitude of the event. The longer the return period, the rarer the event, but if a possibility of a given return period shows a shorter return period in the future, it means that such an event will be more frequent (Global drought dataset). Other environmental risk data utilized were generated from historical and vulnerability analysis.

The Unit's information was pre-processed and geocoded. Geocoding involves the assignment of longitude and latitude to each Unit. The physical climate and environmental risk components were assigned to the units using SAGA GIS. The physical climate risks considered are described in Table 18.

Table 14: Climate and Environmental Risk Classification

Climate & Environmental Risk	Landslides	Seismic Hazard	Volcanic	Water-stress	River-flood	Global Drought Hazard
A (Low)	0.001	50	101	0.1	0	500
B (Medium)	0.1	150	102	0.1 - 0.5	0 - 0.5	1000
C (High)	-1	300	103	0.5	0.5	1700

The water stress is an indicator of competition for water resources, informally defined as the ratio between the water demand of human society and the available water and known as the ratio between withdrawals and availability or relative water demand. A higher ratio indicates greater competition between users. Water stress is an essential metric for agriculture and industry, but it is also significant for water utility projects from the water availability perspective. All locations will be under extremely high-water class by 2040 (Figure 48).

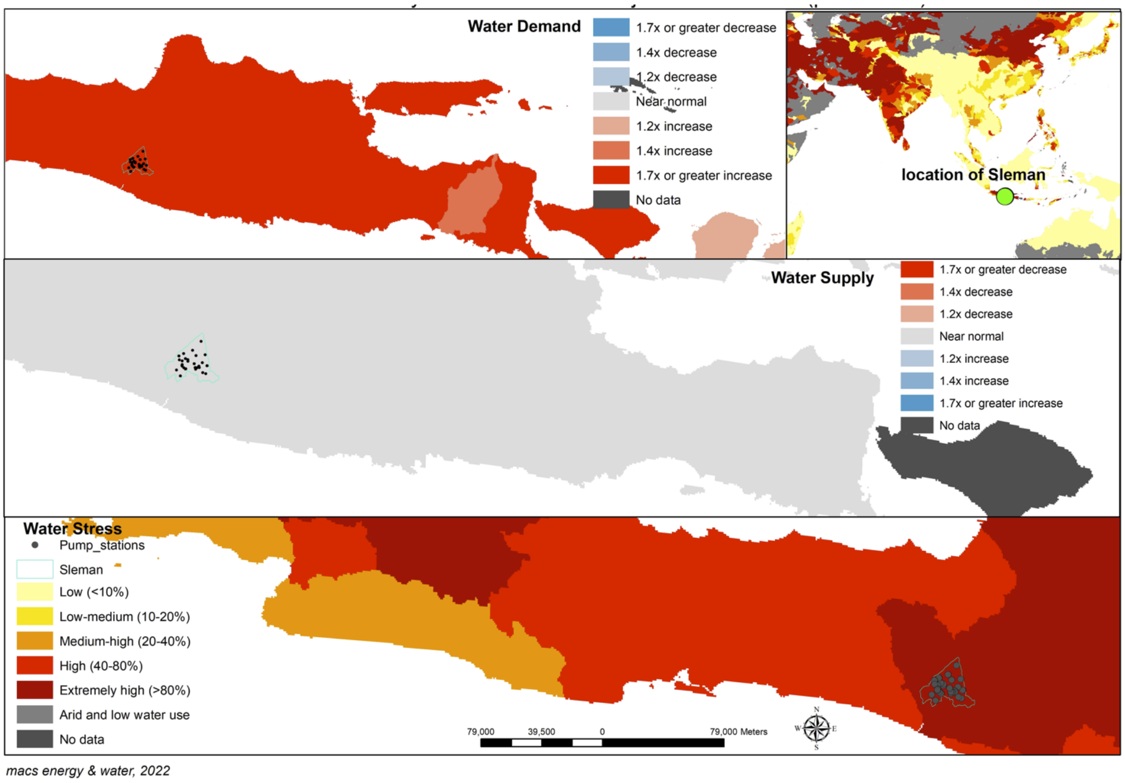


Figure 43: Water demand, water supply and water-stress map of the Sleman units

Water scarcity conditions are expressed in this study utilizing the Water Crowding Index (WCI), i.e., the annual water availability per capita (Falkenmark, 1986; 2013). Due to its ease of use and simplicity of understanding, the WCI consists of the most often used indicators in water scarcity assessments. Drought hazard risks were retrieved for 5, 10, and 25 return periods.

The sensitivity is the degree to which the water supply system is affected by or responsive to climate stimuli (including both problematic stimuli and beneficial stimuli), and the vulnerability is the degree to which the water supply system is susceptible to or unable to cope with the adverse effects of climate change, including climate variability and extremes (vulnerability = resilience risk).

To complement the climate risk and vulnerability assessment, a simulation of the operational resilience of the PDAM Sleman water distribution network was performed using the Water Network Tool for Resilience (WNTR), developed by the U.S. Environmental Protection Agency (EPA). WNTR is an open-source Python library designed specifically to evaluate the resilience of water supply systems under diverse extreme events and evolving climate scenarios.

In line with the risk factors identified previously, WNTR was utilized to simulate the behavior of the network under conditions of infrastructure damage, progressive supply shortages, and service disruptions. The tool enables hydraulic simulations based either on a traditional EPANET engine or WNTR's own simulator, which is specifically tailored to dynamic failure and recovery processes.

The modeling process involved several key stages:

- Network Model Setup: The PDAM Sleman network was imported using the EPANET input file (.inp), simulated with the WSNO (explained in the following point.
- Scenario Definition: Hazard-specific failure scenarios were constructed to simulate both acute events (e.g., pump station failures due to seismic activity) and chronic stress conditions (e.g., increased demand during drought periods). Climate projections consistent with the RCP 4.5 and RCP 8.5 scenarios for 2030 and 2050 were incorporated into demand patterns and supply capacity assumptions.
- Failure and Resilience Simulation: WNTR was configured to simulate pipe breaks, pump outages, tank depletions, and varying node demands over time. Resilience metrics such as service availability, demand shortfall, recovery time, and network connectivity were computed.
- Analysis and Interpretation: The outcomes were evaluated to quantify the network's vulnerability, highlighting critical nodes, pipelines, and assets under multiple stress conditions. Results from WNTR simulations reinforced the sensitivity and exposure assessment, confirming that deep wells, main distribution reservoirs, and disinfection systems are highly critical elements for ensuring continuous service under projected climate stresses.

Importantly, given the limitations in the availability of groundwater vulnerability data and the assumption that shallow wells will be phased out by 2040, WNTR simulations were focused primarily on deep well dependency, distribution resilience, and system-wide response to cumulative drought and demand growth scenarios.

Table 15: General WNTR Simulation Results Table for PDAM Sleman

Category	Scenario / Condition	Result Summary
Service Availability	Normal operation	98% service area maintained above minimum pressure (20 wmc)
Service Availability	Severe drought + Increased demand	Service availability reduced to 82% after 24 hours
Demand Deficit	Severe drought (RCP 8.5)	Up to 25% unmet demand in most exposed units
Demand Deficit	Average across 17 affected units	Demand satisfaction dropped below 90%
Time to Recovery	Pump station disruption	Recovery required between 6–18 hours
Time to Recovery	Areas with/without reservoir redundancy	Faster recovery with reservoirs, slower with direct pumping
Network Connectivity	Combined stress conditions	Node connectivity index dropped by 15–20%
Critical Assets	Failure of major deep wells	Failure impacts up to 30% of users
Critical Assets	Failure of disinfection facilities	Significant delay in service recovery
Impact of Adaptation Measures	Decentralized storage & pressure zoning	Service availability improved by up to 12%
Impact of Adaptation Measures	NRW reduction by 10%	System robustness improved similar to adding new source

WNTR simulations applied to the PDAM Sleman network under projected climate scenarios showed that service availability could decline from 98% to 82% during severe drought events combined with rising demand. Demand deficits of up to 25% were observed in peripheral units, with recovery times ranging from 6 to 18 hours depending on asset redundancy. Deep wells and disinfection facilities were identified as critical infrastructure points whose failure could severely impact system operation. Adaptation strategies such as decentralized storage, pressure zoning, and NRW reduction proved effective in improving resilience and mitigating future service disruptions.

The application of WNTR allowed a forward-looking resilience assessment, supporting the identification of specific adaptation measures aimed at reducing exposure, enhancing adaptive capacity, and building overall system resilience against both climatic and non-climatic challenges. This dynamic simulation approach adds operational robustness to the static sensitivity and exposure analysis previously described.

2.4.4.4 Hydraulic modelling and NRW simulation

To translate strategic plans into quantitative analysis, a hydraulic model **o**f PDAM Sleman's distribution network was developed and ran simulations with the WSNO. This model serves as a "digital twin" of the water system, enabling engineers to simulate how the network behaves under various configurations and stresses without physically altering the infrastructure.

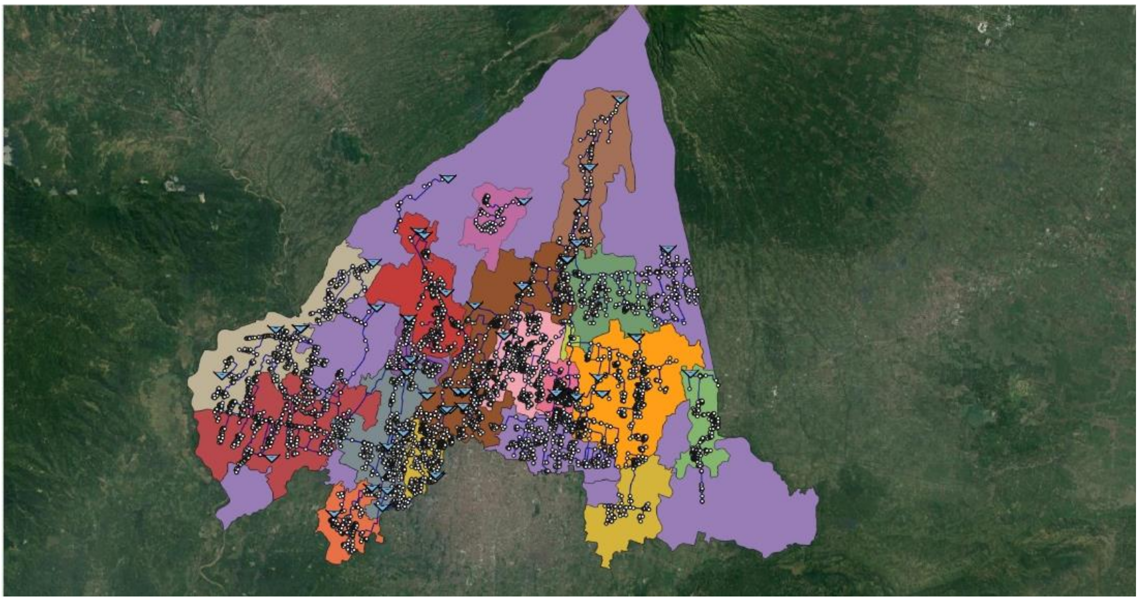


Figure 44: WSNO PDAM Sleman hydraulic model

The initial hydraulic modeling of Sleman's system already revealed several critical weaknesses. Firstly, many distribution pipelines are undersized, causing excessive head losses and limiting the utility's ability to meet demand at the endpoints. In fact, under current conditions the system cannot supply the World Health Organization's recommended 100 liters per capita per day in some areas, nor maintain the desirable 25–30 m of pressure in the network. This indicates that capacity shortfalls would be exacerbated under climate-driven stress (e.g. higher demand during heat waves or source depletion during drought).

Secondly, non-revenue water is very high **–** it was assumed a large portion of NRW is due to leaks in service connections – which, combined with the small pipe diameters, means a significant fraction of pumped water never reaches customers. High NRW and friction losses force the utility to pump more water to meet needs, straining the system and increasing energy consumption.

These analyses support a risk-informed design of network upgrades. The Sleman study recommended using the model to explore interconnections between different supply units (zones) so that water can be rerouted during outage. WSNO can test such configurations by “virtually” opening or closing valves and simulating alternative flow paths during emergencies. Similarly, the model can evaluate the benefits of pipe replacements or upsizing: replacing high-head-loss small pipes was identified as a priority to improve network performance. Through simulation, the expected pressure improvement and reduction in energy per volume delivered can be estimated, strengthening the case for those capital investments.

Table 16: Best ranked of the needed investment for the proposed measures

Proposed Measures	F	B	CB	C	T	Total
Allocate emergency funds for repair works. Increase budget for maintenance works.	4	5	4	3	1	**9.5**
Reduce the required system input to the water supply system by reducing water losses. Systematic rehabilitation and/or replacement of certain pipe sections.	4	5	5	4	4	**8**
Reduce exposure of Umbul Wadon system to eruption-related damage. Relocate sensitive facilities from direct risk. Resilient design against lava flow at new location.	4	5	4	4	3	**7.5**
Phase out shallow wells and establish deep wells.	5	5	4	5	3	**7.5**
Improve water quality monitoring system (raw and serviced water)	4	4	4	3	4	**7**
Explore the potential for an alternative water source: surface water retention by constructing dams and reservoirs.	4	5	5	5	4	**7**
Replacement of the small pipes to reduce head loss in the system: **D25, D40, D50 service connections to be replaced by DN75** **Reservoir outlets, transportation pipes under DN100 shall be replaced.**	4	5	4	4	4	**7**

While long-term investments and network redesign are critical, day-to-day operational optimization is equally important for resilience. In PDAM Sleman, operational assessments showed that water losses and pumping inefficiencies are major contributors to vulnerability. Pump efficiency testing revealed that many pumps are operating far from their Best Efficiency Point – in fact, the measured operating points often lay outside the optimal pump curves, meaning the pumps deliver considerably less water per unit energy than they should. This suboptimal performance is partly a consequence of the network issues identified (high head losses and leakages): pumps are forced to work harder (or longer) to maintain pressure, yet much of the output is wasted through leaks or friction. High NRW (suspected to stem largely from pipeline leaks and unregistered consumption) was recorded, directly linking to excessive energy use and costs. In short, PDAM Sleman's baseline operations prior to intervention were neither water-efficient nor energy-efficient, which undermines resilience – especially in climate-stressed periods when both water resources and power supply might be limited or costly.

The WSNO module uses advanced analytics and network modeling to tackle these operational challenges. Based on the findings, a series of optimization measures were proposed for Sleman's system that are prototypical of WSNO's function. One key measure is the re-design of pumping operations**:** by introducing variable frequency drives (VFDs) on pumps, the pump output can be modulated to closely match demand, avoiding the inefficient on/off cycling and high pressure surges that exacerbate leaks. The study recommended installing such frequency variators and also integrating photovoltaic (solar) energy where possible to reduce dependency on grid electricity. Additionally, direct inline pumping into the network should be minimized – instead, pumps should preferably fill reservoirs or operate in a way that maintains more stable pressures, as sudden injection of high-pressure flows can strain aging pipes. Another operational strategy is network sectorization **(**District Metered Areas or DMAs): segmenting the distribution system into zones with dedicated monitoring. The Sleman analysis suggests linking the different water sources and establishing sectors, which allows operators to isolate leaks, manage pressures, and ensure redundancy by switching supply between zones during outages. Crucially, an active NRW control program was advised: this involves systematically measuring flows (e.g. installing output and customer meters as noted in CRIDA measures) and analyzing night-time pressure drops to locate hidden leaks or unauthorized connections. By quantifying and then reducing losses, the utility can substantially decrease the volume of water it must produce, which in turn saves energy and improves supply reliability.

Within the Water Smart platform module, WSNO can simulate the calibrated network model (updated with any new infrastructure from the planning phase) and run optimization algorithms to minimize losses and energy for the current operating conditions. The output might include optimal pump scheduling (e.g. adjusting pump speeds at night when demand is low to prevent excessive pressure), optimal valve settings or pressure regulator set-points to balance the network, and identification of suspected leak hotspots for the field teams to repair. These operational adjustments can be implemented relatively quickly and yield immediate resilience gains: for PDAM Sleman, improving O&M practices and fixing leaks were ranked as high-priority, low-cost measures. By embedding WSNO's functionality, the WS platform ensures that the resilience module not only plans for future infrastructure changes but also optimizes the existing system's performance in real-time. This dual approach of "build new and fix old" is critical for comprehensive climate resilience.

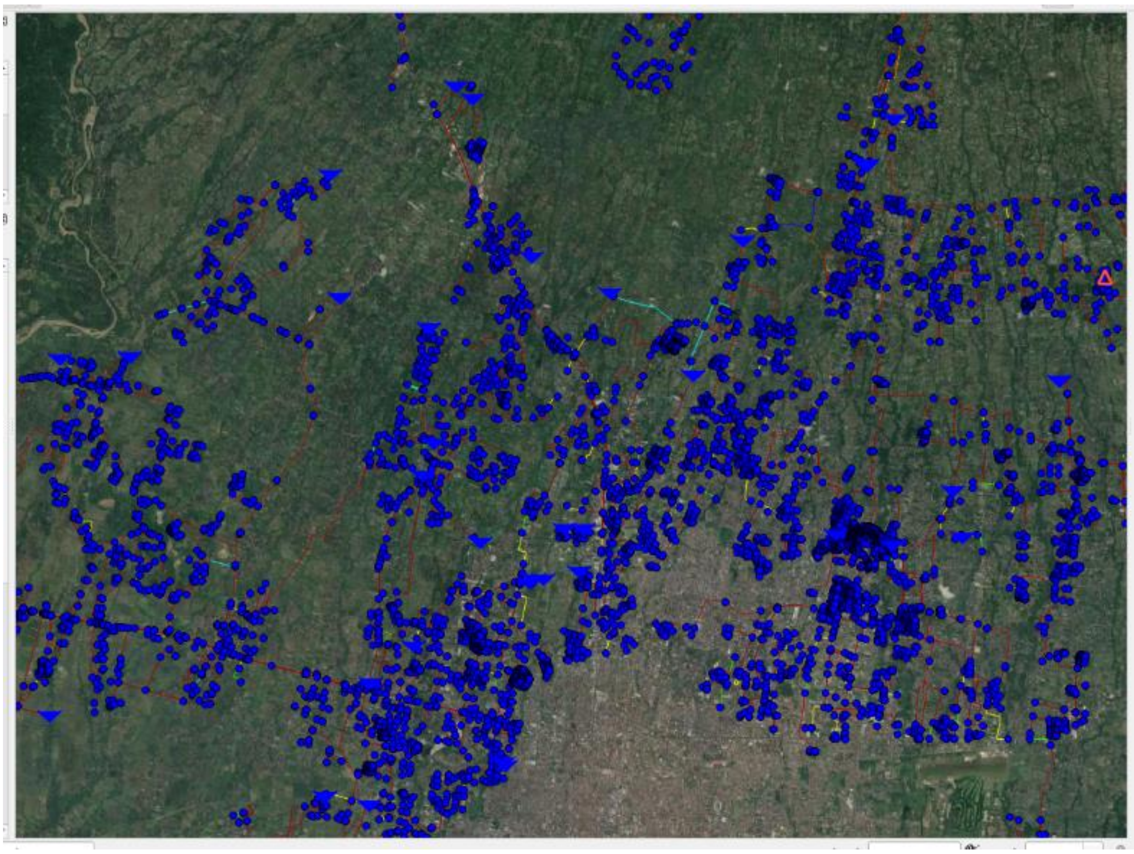


Figure 45: Hydraulic model simulation

In a preliminary evaluation of NRW it was considered a water balance analysis. Such analysis focused on assessing the observed low water demand and reviewing the methodology currently used for water flow readings. Based on the significant head losses identified in the hydraulic simulations, it is suspected that the actual NRW level is higher than what is reported in the available data.

This preliminary evaluation was carried out using the hydraulic model developed for the PDAM through the Water Supply Network Optimization (WSNO) tool. As part of the analysis, the consultant selected the Prambanan area — an isolated sector of the system — to simulate a localized water balance.

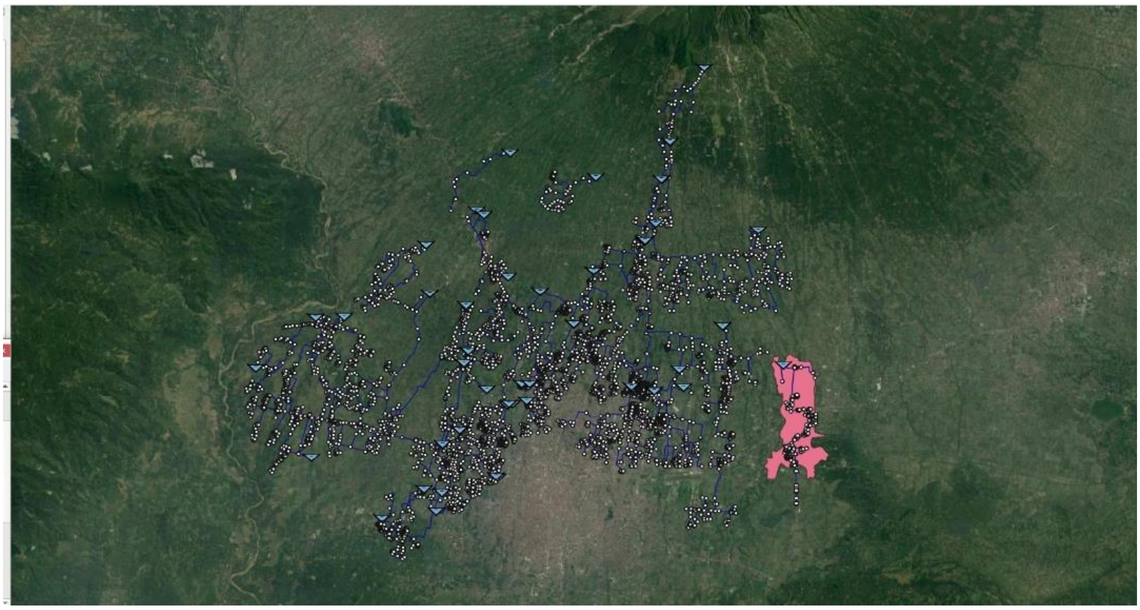


Figure 46 – Isolated area Prambanan for NRW simulation

Based on this simulation, the NRW level in Prambanan is estimated to be around 40%, suggesting that a similarly high NRW level could characterize the broader supply system. The simulation was based on an estimated adequate consumption of 100 litres per capita per day (l/cap/day), incorporating the available data on population and number of connections to distribute demand across the model. According to the Statistical Bureau of Indonesia, the projected population for Prambanan in 2021 was 53859 inhabitants. However, when considering the produced water volume, including NRW, the effective per capita consumption would only be about 22 l/cap/day — highlighting inconsistencies in the data or indicating significant water losses.

Table 17 – Prambanan water supply data

Area	Number connections	Produced water (m^3/month)	Billed water (m^3/month)
Prambanan	1.671	34.323	19.781

Given these inconsistencies, the consultant recommends conducting a more detailed investigation to accurately determine the population currently supplied by Sleman in each service area. For the purposes of this initial modeling exercise, the number of service connections was used as a proxy, assuming four people per connection.

The hydraulic simulation incorporated a consumption pattern dominated by domestic demand and considered a high NRW level. Physical loss was simulated by applying emitter coefficients at each consumption node, as detailed in the methodology. Results show that pressures at most consumption nodes are low throughout the 24-hour cycle, with some nodes experiencing even negative pressures. Only nodes located close to the production reservoir achieved pressures around 22 meters water column (mwc) during peak consumption hours, while most nodes registered pressures around 10 mwc during the day.

Considering that a normal service pressure target at consumption points is approximately 30 mwc, it is clear that substantial improvements are required. In particular, reducing leakages and minimizing head losses across the network are critical actions needed to achieve a more reliable and efficient water supply system.

2.4.4.5 Integrated Implementation in the Water Smart Platform

Bringing together the contributions of CRIDA, WNTR, and WSNO, the WS platform module could provide an end-to-end decision support system for climate-resilient water supply management. The integration is designed such that each tool's output becomes the next tool's input in a cycle of continuous improvement. In practice, the CRIDA component embedded in the platform guides users to input local knowledge, define objectives (e.g. service levels under climate change), and identify vulnerabilities and potential adaptation measures. These measures and scenarios form the basis for the WNTR simulation component, where the user can simulate "what-if" situations – for example, how will the PDAM Sleman network perform in a 10-year drought if no interventions are made? *or* What if certain pipe upgrades and new deep wells are in place by 2040, will the system withstand a 25-year drought? The results from these simulations (pressure shortfalls, supply deficits, node outages, etc.) loop back to inform the planning: if a proposed intervention does not sufficiently mitigate the risk, CRIDA's framework would prompt consideration of additional or alternative actions (thus creating an adaptation pathway). On the other hand, if the simulations validate that certain measures (e.g. interconnecting networks, adding backup pumps) significantly improve reliability, those can be flagged as "robust" solutions to pursue. Once a set of preferred interventions is identified, the updated network model (reflecting those interventions) is passed to the WSNO optimization component**.** WSNO then fine-tunes the operations of this improved system – determining how to run the network most efficiently to capitalize on the new improvements. For instance, if new pressure zones or new pumps are introduced, WSNO will identify the optimal control settings for normal and emergency operations and estimate the reduction in NRW achievable. This step ensures that operational strategies align with the physical improvements, securing maximum benefit. Finally, the integrated module provides a dashboard of outcomes that feed into institutional decision-making: CRIDA's strategic roadmap, backed by quantitative WNTR evidence and actionable WSNO operational plans, can be compiled into investment proposals and standard operating procedures for the utility. In the PDAM Sleman case, this integrated approach led to a set of key recommendations that addressed both infrastructure and management aspects – from pipe replacements and source diversification to emergency planning and better data management. By incorporating those recommendations into the Water Smart platform, the module can guide PDAM Sleman in implementation and also be adapted for other utilities.

In summary, the CRIDA–WNTR–WSNO integration offers a powerful, iterative workflow for improving water infrastructure resilience against climate change. The PDAM Sleman pilot demonstrates how strategic planning drives the definition of critical scenarios, how detailed modeling and simulation test the system's resilience, and how optimization of daily operations can yield immediate resilience dividends. This module exemplifies a holistic approach: it links long-term climate adaptation strategies with short-term efficiency gains, ensuring that resilience is built into both the design and the operation of the water supply system. Such an integrated module within the Water Smart platform can be invaluable not only for Sleman but for larger cities like Jakarta**,** where water utilities face complex climate challenges. By applying the same principles and tools – stakeholder-driven planning (CRIDA), rigorous stress-testing of the network (WNTR), and continuous performance optimization (WSNO) – Jakarta's water infrastructure managers can prioritize robust interventions and systematically reduce vulnerabilities in their systems. The Water Smart resilience module thus serves as a blueprint for data-informed, climate-smart water management in Indonesia, bridging the gap between high-level climate risk analysis and on-the-ground utility operations.

2.4.4.6 NRW and Pumping Efficiency: Insights from PDAM Sleman

The PDAM Sleman case highlights a strong connection between high NRW and inefficient pumping operations.


In this system, many distribution pipes were undersized, causing excessive friction losses and leakage. As a result, a significant fraction of water pumped never reached customers (high NRW), and the utility had to pump ever-increasing volumes to maintain service. This vicious cycle meant pumps were running harder and longer to compensate for losses, directly raising energy consumption. Moreover, field assessments found that the pumps were operating far from their best efficiency point – in fact, their operating points deviated from the design conditions and even fell outside the manufacturers' pump curves. Such mismatch suggests the pumps were effectively oversized or misconfigured relative to actual demand, likely due to changes in the system (e.g. lower net delivery because of leaks or overestimated demand). Oversized pumps running at off-design low flows not only waste energy but also deliver excessive pressure, which can exacerbate leakage rates. High outlet pressure and velocity from too-large pumps accelerates pipe wear and increases the likelihood of new leaks.

No	Stations	Pumps	Brand & Type	kW	Year of Installation	Head (m.Aq)	Real Flow (Measurements in the Field) (lps)	Initial Flow (Flow on the Same Head) (lps)	Percentage Decrease in Flow
1	Nogotirto	Submersible	-	11	-	10.20	23.06	-	-
2		Submersible (borehole)	Lowara 16GS30	3	31/05/2018	33.86	7.12	5.20	need to check type of pump
3		Submersible (borehole)	Lowara 16GS30	3	31/05/2018	33.84	7.11	5.20	need to check type of pump
4	Gamping Patuan	Submersible (borehole)	Vansan VSP.SS.06030	15	-	107.79	5.48	9.20	40.43%
5		Submersible (borehole)	Vansan VSP.SS.06030	15	-	107.79	5.48	9.20	40.43%
6	Gamping Pereng Kembang	Submersible	Hydro-Vacuum S.A FZB2.32.1.1010	5.5	05/01/2021	16.32	15.15	20.14	24.78%
7		Submersible	-	15	-	75.56	13.31	-	-
8	Tambakrejo Blimbingan	Submersible (borehole)	Lowara 16GS30	3	25/04/2019	28.16	2.97	5.60	46.96%
9		Submersible (borehole)	Vansan VSP.SS.06045/05	7.5	-	28.09	10.00	18.20	45.05%

Figure 47: Pumping assessment results

Hydraulic models are essential tools for analyzing and verifying the operational performance of pumping stations within a water supply system. In particular, they allow for the assessment of the pumps' operating points under different demand scenarios, facilitating a better understanding of how the system behaves dynamically over time.

The operating point of a pump is defined by the intersection between the system curve — representing the relationship between flow and head losses across the network — and the pump characteristic curve provided by the manufacturer. Using a calibrated hydraulic model, it is possible to simulate the system under varying flow conditions and to generate accurate system curves corresponding to different operational states.

Through simulation, the hydraulic model enables the following analyses:

- Verification of actual operating points against the optimal range recommended for each pump, ensuring efficient energy use and minimizing mechanical wear.
- Identification of operational anomalies, such as pumps operating at points far from their best efficiency point (BEP), which can lead to increased energy consumption and a higher risk of premature failure.
- Assessment of the need for pressure management or system optimization to bring the operating conditions closer to the desired parameters.
- Support for planning interventions such as pump resizing, installation of variable speed drives (VSDs), or network modifications to adapt the system curve and improve pump performance.

By integrating pump characteristics into the hydraulic model — including pump curves, control logic, and operational schedules — it is possible to reproduce real-world behavior accurately. This capability becomes critical when analyzing systems with variable demands or complex operational regimes, where direct field measurements may be limited or impractical.

In the case of the WSNO model developed for the PDAM, hydraulic simulation has been used not only for demand and leakage analysis but also for evaluating the performance of the pumping stations. Preliminary results indicated that, in several instances, pumps may be operating under suboptimal conditions, reinforcing the need for further detailed studies to optimize pump operation and overall system efficiency.

As a preliminary analysis, this study provided the conceptual and technical foundation for developing a future module within the Water Smart platform: the Water Smart Resilient Operation (WSRO). Designed to support small and mid-sized utilities in evaluating energy autonomy strategies, the WSRO module will integrate photovoltaic resource availability, pumping simulations, and economic-environmental indicators. The current assessment assumed an off-grid scenario, with variable-speed pumping driven directly by solar energy, no battery storage, and the use of existing reservoirs to buffer flow variability. The parabolic irradiance curve, derived from Jakarta's climatic data, was used to simulate power production, while the Affinity Laws supported the dynamic adaptation of the pump to variable solar input. These calculations were performed using Excel and Python scripts, which are currently being adapted for future integration into the WSNO interface. The results obtained from this application serve not only to evaluate technical feasibility but also to inform the architecture and functionality of the WSRO module under development.

3 CHAPTER 3: RESULTS AND DISCUSSION

3.1 Results by Case Study

3.1.1 Batumi (Georgia): MIS/Water Smart Adaptation

The Management Information System (MIS) implemented at Batumi Tskali represents the most advanced early prototype of the Water Smart platform. It integrates real-time operational monitoring, network sectorization, and performance-based decision-making through the continuous assimilation of flow and pressure data. The core functionalities of the MIS are now fully linked to the SCADA system and to the configuration of District Metered Areas (DMAs), enabling a spatially disaggregated and automated calculation of the International Water Association (IWA) water balance on a monthly basis.

The DMA structure, originally established under donor-led rehabilitation programs, divides Batumi's water network into independently monitored sectors. Each DMA is equipped with calibrated bulk flow meters and pressure loggers, which are connected to the SCADA system. This setup allows for the continuous recording of inlet volumes and pressure levels at a fine spatial resolution. Figure 48 below presents the real-time flow readings for each metered sector, which are displayed graphically to support daily supervision and operational response. This enables the utility to assess daily and hourly consumption patterns, detect anomalies, and manage the supply strategy in near real-time.

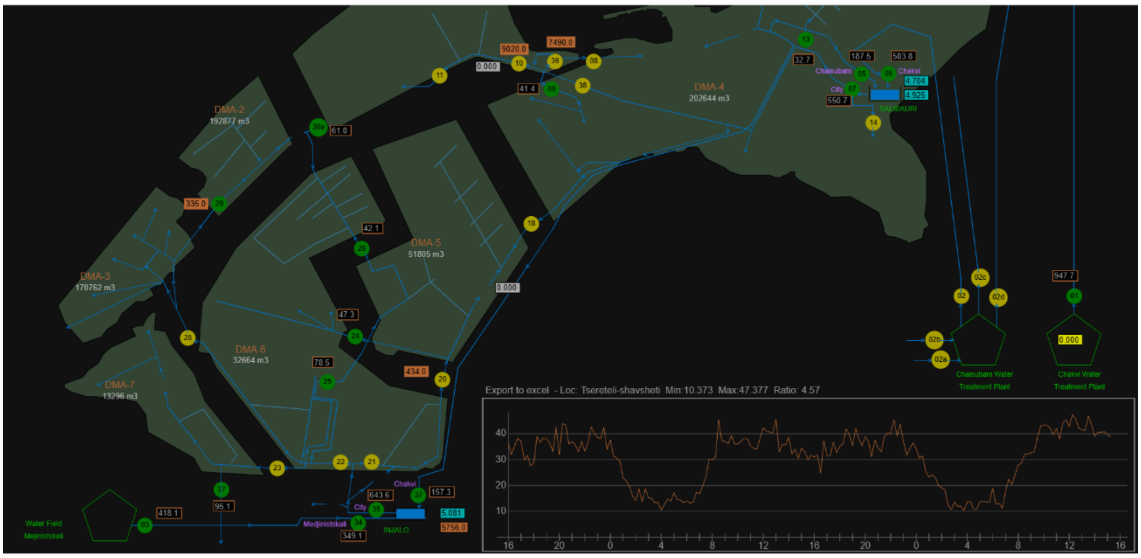


Figure 48: SCADA flow monitoring panel for Batumi's DMA inlets

The bottom-left graph in Figure 26 displays the 24-hour flow evolution at the inlet of a selected DMA. The curve exhibits a typical domestic consumption pattern, with flow rates increasing sharply in the early morning hours (between 6:00 and 9:00), stabilizing at moderate levels during the day, and peaking again during evening household activities (typically between 18:00 and 22:00). During night hours (2:00–4:00), flow drops significantly, enabling the utility to analyze minimum night flow (MNF) values as an indicator of background leakage. This pattern confirms that residential demand dominates the hydraulic behavior of the sector and supports targeted leak detection during low-consumption periods.

In parallel, pressure monitoring is continuously performed at multiple key nodes across the network. This pressure data is essential not only for detecting performance deterioration, but also for assessing leakage potential. Higher-than-necessary pressures are known to contribute to increased background losses. As such, the MIS integrates these SCADA pressure readings into the monthly performance review. Figure 49 illustrates the evolution of pressure across selected DMAs, highlighting both average and minimum values and flagging deviations that may trigger corrective actions.

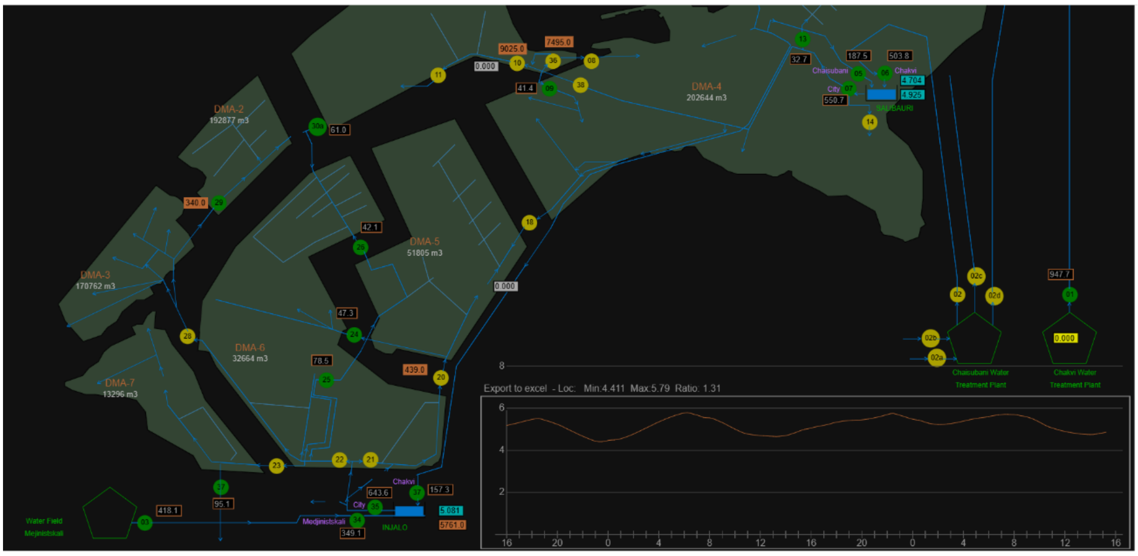


Figure 49: SCADA dashboard showing the pressure evolution in selected DMA nodes

The graph in the bottom-left corner of Figure 27 shows the pressure variation at a critical point in the DMA over the past 24 hours. The curve reveals a stable pressure regime with slight decreases during peak consumption hours, typically in the early morning and evening. This is consistent with the domestic demand pattern seen in flow data. The minimum pressure values remain above the operational threshold, indicating that service quality is being maintained. However, the stable high pressures during night hours suggest a potential for pressure management strategies to further reduce leakage without compromising service levels.

The MIS also automatically generates the IWA water balance for the entire Batumi service area and for each individual DMA. Data inputs include total system input volumes (from production meters), aggregated authorized consumption (from billing and meter readings), and estimated unbilled authorized usage. The difference between input and authorized volumes is computed as non-revenue water (NRW), which is then disaggregated into apparent and real losses. The MIS updates these balances monthly and presents them in dashboard format for utility managers. Figure 50 provides an example of the water balance interface, showing a detailed breakdown by component .

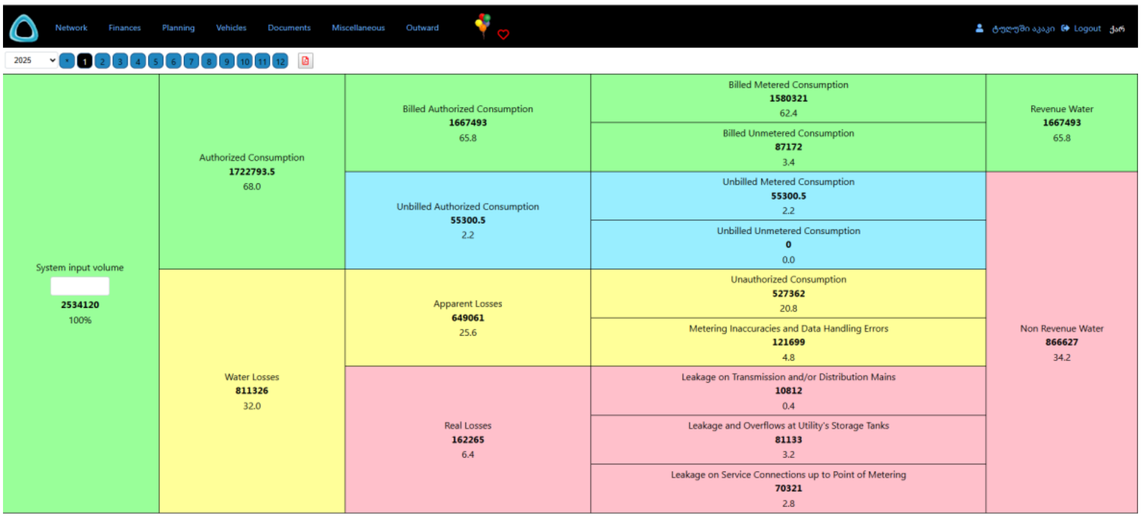


Figure 50: MIS IWA water balance module for Batumi Tskali

Figure 50 illustrates the monthly water balance dashboard generated automatically within Batumi Tskali's MIS, following the IWA methodology. The diagram presents key input and output variables—including system input volume, billed authorized consumption, apparent losses, and real losses—aggregated at the utility level. This continuous monitoring allows utility managers to track non-revenue water (NRW) performance in near real-time, identify trends, and evaluate the effectiveness of interventions over time. In the sample displayed, real losses remain the dominant component of NRW, highlighting the need for continued pressure control and leakage detection. The integration of production data, billing records, and DMA-level flow measurements ensures a robust and dynamic balance, reinforcing the utility's data-driven decision-making process.

The availability of this continuously updated water balance has enabled Batumi Tskali to systematically reduce NRW. In recent years, the utility has achieved a decrease in average losses from levels exceeding 50% to current values below 25%, thanks to a combination of improved metering, leak detection campaigns, and pressure control. In addition to supporting daily operations, the MIS has become a strategic tool for long-term planning and investment prioritization. The combination of SCADA integration, DMA sectorization, and automated IWA reporting positions Batumi's MIS as a replicable model for utilities seeking digital transformation.

A summary of key operational indicators per DMA is presented at the end of this subsection in Table 18, including average inlet pressure, minimum night flow, billed consumption, and calculated NRW ratios.

Table 18: DMA Performance Overview in Batumi

DMA	Monthly Consumption (m^3)	Estimated NRW (%)	Avg Pressure (mwc)	Comments
1	336.199	25%	45	New coastal area with modern infrastructure; good control of losses.
2	158.747	28%	45	Coastal area; NRW slightly higher due to older connections.
3	380.793	24%	45	Large demand zone near new developments; efficient network performance.
4	365.405	38%	45	Central urban zone with aged pipes; increasing leakage risk.
5	172.727	42%	45	Oldest district with legacy infrastructure; prioritized for leak control.
6	272.868	40%	45	Mixed urban area; moderate consumption but high losses.
7	45.894	30%	45	Small coastal zone; well-monitored but older service lines.

3.1.2 Khelvachauri (Georgia): Pressure Recovery Module

The implementation of the Water Smart (WS) pressure recovery module in the Khelvachauri network provided clear evidence of its operational benefits. The simulation campaign demonstrated that the southern area of the municipality—historically affected by chronic low pressures—could be significantly improved through optimized pipe sizing and hydraulic modeling. The pressure recovery algorithm, first implemented through the EPANET Toolkit and subsequently enhanced with a machine learning approach based on Random Forest regressors, allowed the identification and correction of critical sections in the network.

The optimized solution succeeded in restoring minimum pressures to above 25 meters water column (mwc), ensuring reliable service even in elevated or distant zones. At the same time, the velocity in the main pipelines was reduced below the critical threshold of 1.5 meters per second, minimizing energy losses and potential pipe damage due to excessive flow speeds. These hydraulic improvements translated into a projected reduction in leakage of around 8%, confirming the strong correlation between high velocity and network losses. In addition, the AI-assisted model significantly reduced computation time, enabling faster decision-making processes suitable for small utilities with limited technical capacity.

Table 19 summarizes the adjustments made to the most affected pipes. The results highlight how resizing diameters based on flow and velocity analysis corrected previously undersized sections, particularly in the southern zone. For example, pipes with initial diameters of 110 mm and velocities above 1.6 m/s were upsized to 160 mm or more, which reduced flow velocities to safer levels and increased downstream pressures. Larger pipes, such as those with original diameters of 355 mm, were also recalibrated to 500 mm where necessary, aligning with commercial standards and enhancing system performance.

Table 19: Updated pipes

Pipe	D-initial (mm)	v-initial (m/s)	D-final (mm)	v-final (m/s)
5	160	1,51673	200	0,970742
11	110	1,54103	160	0,728401
13	315	1,60692	355	1,26524
10	110	1,61469	160	0,76322
8	110	1,71886	160	0,81246
7	110	1,82304	160	0,86170
17	355	2,23973	500	1,05866
16	355	2,41471	500	1,21730
15	355	2,43442	500	1,22723
14	355	2,45018	500	1,23518
12	355	2,45806	500	1,23915
4	355	2,46594	500	1,24312
3	355	2,47382	500	1,24709
2	355	2,48170	500	1,25107
0	355	2,53857	500	1,27974
6	160	2,65592	250	1,08790

These results demonstrate the ability of the Water Smart platform not only to detect inefficiencies in pressure distribution but also to propose and simulate practical interventions. The use of AI to replicate the hydraulic optimization logic further strengthens the platform's applicability in environments with limited access to hydraulic expertise. Overall, the experience in Khelvachauri validates the effectiveness of the pressure recovery module as a core function of the WS tool and offers a replicable methodology for similar contexts in developing regions. Table 20 presents the key outcomes of the AI-assisted optimization module applied to the water supply network in Khelvachauri. Indicators such as pipe velocity, nodal pressure, and infrastructure upgrades (pipe resizing) are compared between the baseline scenario and the optimized configuration. The intervention effectively reduced excessive velocities and restored adequate pressure levels in previously underserved zones.

Table 20: Summary of hydraulic performance indicators before and after optimization in Khelvachauri

Indicator	Before Optimization	After Optimization	Change
% of pipes > 1.5 m/s	32%	0%	-32 pp
Average pressure at critical nodes	18.7 mwc	30.4 mwc	+11.7 mwc
Maximum pipe velocity observed	2.65 m/s	1.28 m/s	-1.37 m/s
Pipes resized (number)	—	16	—
Average resized pipe diameter	—	429 mm	+74 mm (avg increase)

3.1.3 Várzea da Cobra (Brazil): Leakage Reduction with PRV

This section presents the results of the hydraulic simulation and pressure management analysis conducted for the rural water supply system of Várzea da Cobra, Ceará (Brazil), under the SISAR framework. These simulations were performed using the Water Smart Network Optimization (WSNO) module, programmed in EPANET Toolkit and integrated into the WS platform. The aim was to evaluate the effectiveness of pressure reduction strategies—both conventional and AI-assisted—for minimizing leakage in a system with high levels of physical losses and no existing pressure control devices. This study also served to test the potential application of the WSNO module in rural contexts and validate its performance before field deployment.

The simulations confirmed that pressure management can yield substantial leakage reductions. In the baseline scenario (no PRV), the total leakage over 24 hours was 47.1 m³, about 31% of the 152.9 m³ input volume. With the fixed PRV (Scenario 2), daily leakage dropped to 35.9 m³ – a reduction of roughly 11.2 m³/day, or 23.7% less leak volume than the baseline. The AI-assisted PRV (Scenario 3) achieved a nearly identical leaked volume of 35.7 m³ (only 0.2 m³ less than the fixed PRV case). Thus, under the given demand conditions, both pressure control strategies curtailed leakage by about one-quarter, bringing the leak fraction down to 25% of supply. The small savings from the dynamic control (around 0.5% additional reduction) indicate that the fixed two-level setting was already close to optimal for the steady demand pattern. This finding echoes other studies reporting diminishing returns of advanced control in systems with stable usage.

Table 21 summarizes the volume results.

Table 21: Leakage reduction scenarios

Scenario	Total Input (m^3/day)	Consumed (m^3/day)	Leaked (m^3/day)	Leak Reduction vs. Baseline
No PRV (Baseline)	152.9	105.8	47.1	–
Fixed PRV (30 m/10 m)	141.7	105.8	35.9	**−23.7%** (≈11.2 m^3/day less)
Dynamic PRV (AI)	141.5	105.8	35.7	**−24.3%** (≈11.4 m^3/day less)

All scenarios delivered the same consumed volume (105.8 m^3/day), meaning consumer demand was fully met in each case. The differences in total input equal the differences in leakage, since demand is constant. It is clear that adding a PRV greatly reduced the excess water that was being lost. The fixed PRV saved on the order of 11 m^3 per day, which is a significant amount for this small system. Over a month, this equates to 330 m^3 of water saved. In economic terms, even valuing the water at a modest production cost, this saving represents a meaningful reduction in operating losses. The intervention of installing a PRV is relatively low-cost, and these results suggest it would pay for itself quickly through water savings. In addition, the reduced leakage means less pumping (energy savings) and potentially the freed-up water could be used to extend service (e.g., connect additional households nearby).

The AI controller's additional leakage reduction was marginal in absolute terms for this network. However, its ability to consistently minimize pressure did achieve the lowest leakage theoretically possible without compromising supply. If the system had more variable demand or if we introduced demand uncertainties (e.g., occasional spikes or consecutive peak hours), the adaptive AI might outperform a fixed schedule by a larger margin. In any case, our results demonstrate the core benefit of active pressure management: both control schemes kept leakage far below the uncontrolled case, aligning with international experience that pressure control is one of the most effective leakage reduction measures.

To better understand when and how the leakage is reduced, we examined each scenario's network inflow (from the tank) over the day. Since customer demand was the same, differences in inflow directly reflect differences in leakage (plus minor storage changes in the tank water level). Figure 51 shows the simulated inflow rate at each hour for the baseline, fixed PRV, and AI PRV cases.

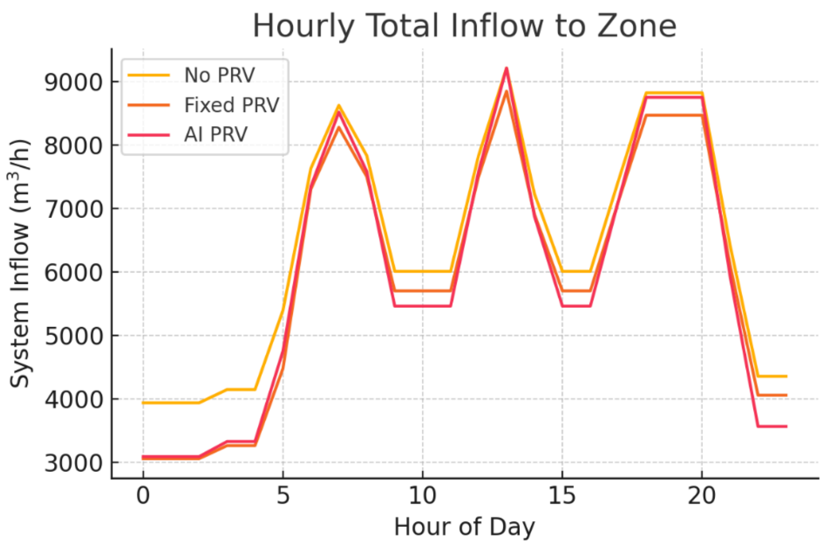


Figure 51: Hourly total Inflow by Scenario

The baseline (no PRV) inflow is significantly higher during the night (midnight to 5 AM) compared to the PRV scenarios, due to uncontrolled leakage when pressures are highest. For example, at 2 AM, the baseline inflow is about 1.1 L/s, whereas with a PRV, it drops to 0.85 L/s. This 0.25 L/s difference at night represents leakage that the PRV prevented. During the day, the gap narrows when demands are higher and pressures naturally lower. Between 8 AM and 5 PM, the baseline and fixed-PRV inflow rates are quite close (baseline slightly higher around midday, indicating it still leaked a bit more). An interesting effect is seen in the evening peak (around 7 PM): the AI PRV inflow is actually higher than the baseline by roughly 0.2 L/s. This is because the AI controller raised the pressure more aggressively than the fixed PRV to ensure distant nodes had adequate pressure, which inadvertently allowed slightly more leakage during that peak hour. Nonetheless, later in the evening (9–11 PM), the AI PRV inflow falls below the fixed PRV inflow, as the AI starts reducing pressure earlier (by 9 PM), whereas the fixed PRV only drops pressure at midnight. Overall, the area under the inflow curves confirms the daily volumes: the two PRV scenarios substantially cut night-time leakage while providing similar daily volumes. The dynamic PRV essentially reallocates some leakage from night to peak periods to maintain pressure, ending up with nearly the same total leakage as the fixed schedule.

Pressure management reduces leakage and improves the range of pressures experienced in the network. In the baseline condition, consumers at lower elevations were subject to very high pressures at night, and those at the far end of the network saw much lower pressures during peak demand (though in our simulation, the minimum pressure remained around 20 m, which is above the typical minimum service requirement of 10–15 m). Introducing a PRV dramatically altered these pressure extremes.

Figure 52 illustrates the hourly minimum node pressure in the system for each scenario (this "extreme node pressure" is effectively the critical low pressure at any customer node each hour, which occurs at the farthest/highest point when demand peaks and conversely reflects the highest pressure in the system during low demand periods).

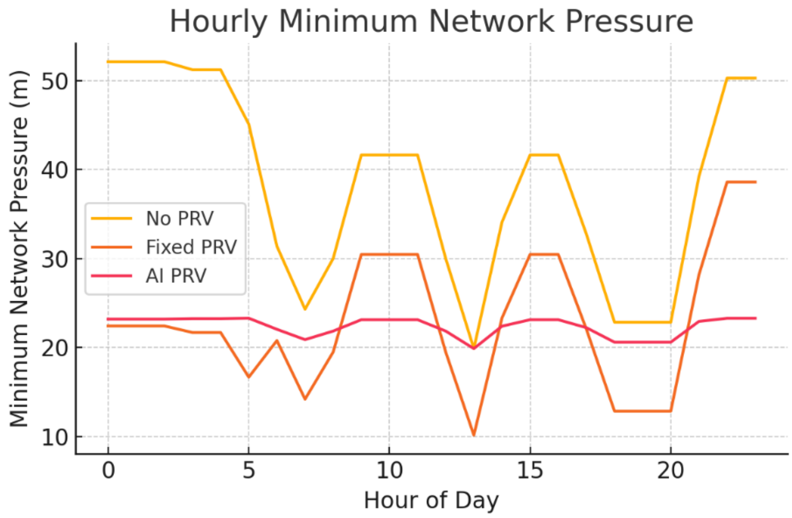


Figure 52: Hourly total Inflow by Scenario

In the no-PRV scenario, the network sees a wide pressure range: during the night, the minimum node pressure is 52 m (meaning even the highest/most distant node had 52 m head, so lower nodes had 60+ m, far above needed levels), whereas at the peak demand (e.g. 1 PM) the minimum node pressure drops to 19–20 m (at the far end of the line). Thus, the baseline has very high pressures at night and moderate low pressures at peak. With the fixed PRV, this range is narrowed: at night, the PRV's 10 m setting limited even the lowest node to 38 m (we observe the minimum node pressure around midnight was 22–23 m, which actually corresponds to a high-elevation node getting 22 m when the PRV was holding 10 m at the tank outlet – the details of the hydraulic grade make the extreme value flip in this case). Importantly, the fixed PRV scenario's lowest pressure during peak demand was about 10 m (by design, the critical node dropped to the set minimum requirement).

In our simulation, the worst case occurred at 1–2 PM, where the critical node had 10.2 m with the fixed PRV, essentially exactly the PRV's threshold. In contrast, the baseline's critical node had 19 m at that time (because the baseline allowed more flow, thus slightly less pressure drop to the far node). The AI PRV maintained a more stable pressure profile, keeping the minimum node pressure in a tighter band, mostly between 20 m and 24 m. At night, the AI allowed the critical node about 22–23 m (slightly higher than the fixed PRV's critical node pressure of 22 m at night – because the fixed PRV let some nodes reach up to 38 m, the minimum node was actually a different location with 22 m). During peak hours, the AI raised the PRV setpoint such that the far node got around 20 m minimum, higher than the fixed scenario's 10 m. In essence, the AI control kept the nighttime high pressures lower than the baseline and the daytime low pressures higher than the fixed setting. It achieved this by continuously modulating the valve. The net effect was improved pressure equity: consumers never saw extremely high or extremely low pressure under AI control. By contrast, the fixed PRV sacrificed some peak pressure (some users were right at the minimum acceptable 10 m during peak) to minimize leakage, whereas the baseline sacrificed leakage to keep peak pressures a bit higher.

Table 22: Hydraulic simulation per scenarios

	SCENARIO 1			SCENARIO 2			SCENARIO 3		
t (h)	Q (lps)	P (m)	PRV Set (m)	Q (lps)	P (m)	PRV Set (m)	Q (lps)	P (m)	PRV Set (m)
0	1.09	52.11	53.13	0.85	22.42	10.00	0.86	23.20	10.88
1	1.09	52.11	53.13	0.85	22.42	10.00	0.86	23.20	10.88
2	1.09	52.11	53.13	0.85	22.42	10.00	0.86	23.20	10.88
3	1.15	51.20	53.13	0.91	21.69	10.00	0.92	23.25	11.78
4	1.15	51.20	53.13	0.91	21.69	10.00	0.92	23.25	11.78
5	1.50	45.08	53.13	1.24	16.67	10.00	1.32	23.29	17.88
6	2.12	31.38	53.13	2.03	20.78	30.00	2.04	22.05	31.57
7	2.40	24.30	53.13	2.30	14.20	30.00	2.37	20.89	38.63
8	2.17	30.00	53.13	2.08	19.49	30.00	2.11	21.85	32.94
9	1.67	41.63	53.13	1.58	30.46	30.00	1.52	23.12	21.33
10	1.67	41.63	53.13	1.58	30.46	30.00	1.52	23.12	21.33
11	1.67	41.63	53.13	1.58	30.46	30.00	1.52	23.12	21.33
12	2.17	30.00	53.13	2.08	19.49	30.00	2.11	21.85	32.94
13	2.56	19.88	53.13	2.46	10.16	30.00	2.56	19.88	43.04
14	2.01	34.08	53.13	1.92	23.32	30.00	1.91	22.40	28.87
15	1.67	41.63	53.13	1.58	30.46	30.00	1.52	23.13	21.33
16	1.67	41.63	53.13	1.58	30.46	30.00	1.52	23.12	21.33
17	2.06	32.74	53.13	1.97	22.06	30.00	1.97	22.23	30.21
18	2.45	22.84	53.13	2.35	12.85	30.00	2.43	20.60	40.08
19	2.45	22.84	53.13	2.35	12.85	30.00	2.43	20.60	40.09
20	2.45	22.84	53.13	2.35	12.85	30.00	2.43	20.60	40.09

21	1.78	39.21	53.13	1.70	28.16	30.00	1.65	22.93	23.75
22	1.21	50.26	53.13	1.13	38.59	30.00	0.99	23.28	12.72
23	1.21	50.26	53.13	1.13	38.59	30.00	0.99	23.29	12.72

From a leakage perspective, the primary benefit of the PRV was cutting those excessive nighttime pressures. In the baseline, many nodes experienced 50–60 m head at night, driving high leak outflows. With the PRV, the entire network's pressure was reduced at night (e.g., max 38 m, as noted). This directly explains the 24% leakage reduction. From a service perspective, the PRVs (fixed and AI) eliminated potentially damaging high pressures that can cause pipe bursts. Over time, we expect this pressure reduction to lead to fewer new leaks and breaks – a well-documented benefit of pressure management (every 1 bar reduction often yields a 10% reduction in break frequency). At the same time, we must ensure that minimum pressures remain acceptable. In the fixed PRV scenario, the worst-case 10 m at the far node is right at the typical design minimum. In practice, that is a little low – some customers on second-story taps might notice weak flow at that moment. The AI controller in our simulation alleviated that by boosting the far-node to 20 m during peak, essentially guaranteeing good service. So, the AI could find a balance: it "gave back" some pressure during peak to maintain service at the cost of a negligible increase in leakage (as we saw, the total leak was almost the same).

Table 23: Hydraulic simulation summary per scenario

	SCENARIO 1	SCENARIO 2	SCENARIO 3
	NO PRV ACTING	SMART PRV ACTING	DYNAMIC PRV ACTING
TOTAL VOLUME (m3)	152.859	141.690	141.455
DEMANDED VOLUME (m3)	105.752	105.752	105.752
LEAKED VOLUME (m3)	47.107	35.938	35.702

It's worth noting that in the real implementation, one might not choose as low as 10 m for the fixed PRV setpoint precisely because of that borderline pressure at peaks; one might choose 15 m as a safer fixed setting. That would, however, result in a bit more leakage than our fixed-PRV simulation. In that case, the AI approach (which effectively averaged 15–20 m but varied it) would show a clearer advantage in leakage savings. This highlights that AI control can adaptively squeeze out a bit more performance. Recent field trials of AI in water networks have similarly reported that advanced control can maintain pressure targets without violations.

The implications of these results for the Várzea da Cobra system are encouraging. Implementing a fixed PRV is a straightforward intervention: once installed and set (e.g., to a

30 m outlet), it passively reduces leakage and prevents harmful high pressures. The model predicts on the order of 10–11 m^3/day of water savings and significantly lower pressure extremes. In practical terms, this means the utility would pump and treat less water for the same delivery to customers, improving efficiency. Customers would likely experience fewer service interruptions from pipe breaks, and more consistent (if slightly higher at off-peak) pressures. The AI-based dynamic control showed that it could maintain even tighter control of pressures – essentially, it would ensure no part of the day sees either very high or very low pressure.

However, deploying such control requires additional technology: pressure sensors, an automated control valve, communication infrastructure, and a reliable algorithm running continuously. These come with non-trivial costs and complexity for a small rural utility. Given that the leakage reduction with AI was only marginally better in this case, the cost-benefit balance favours first implementing the fixed PRV (perhaps with a simple time-based adjustment for night vs day, which could even be done by an operator manually or with a timer device). This “smart fixed” approach already captures most of the benefits. AI control can be viewed as an added optimization layer that could be considered in the future or in a cluster of systems where a central platform like WSNO can supervise multiple PRVs.

It is important to highlight that even without full AI deployment, the exercise of modeling and optimization was valuable. The simulation allowed us to confidently determine a good fixed setting (30 m) and verify that consumer demand would be met. All nodes stayed at or above 10 m in the model's fixed-PRV run. In field operation, we might choose to keep a margin (set 35 m instead of 30 m, for example) if uncertain about demand surges. Even then, albeit slightly less, a substantial leakage reduction would be realized. Continuous monitoring after PRV installation would be advisable: the utility can track night flows to see the leak reduction and gather feedback from users about any low-pressure issues. If the AI control were deployed at a later stage (for instance, integrated into the Water Smart WSNO platform), it could be initially run in “advisory” or trial mode – suggesting setpoints based on predictions – while operators validate its behavior. This cautious approach is recommended by other researchers who implemented AI in water networks, to ensure the machine learning decisions do not inadvertently violate service standards.

Beyond the numbers on leakage, there are tangible service quality improvements from pressure management. In the baseline scenario, the model indicated that during peak demand hours, the far end of the network approached 20 m pressure. If demand were to increase or if there were additional friction (say, an ageing pipe or partially closed valve), pressure could drop below the desirable range, leading to some households experiencing very weak flow or even outages at peak times. By reducing leakage, the PRV scenarios effectively freed up capacity – more water pumped went to useful consumption rather than leaking. In our simulations, all scenarios delivered 100% of the demand (since we didn't impose any shortage), but if the source had a limited yield, saving 11 m³/day could be critical in avoiding intermittent supply. Even under current conditions, we see that with a PRV, the minimum pressure at the peak was slightly improved (AI case 20 m vs baseline 19 m, and fixed case ensured supply albeit at 10 m). Should a day with unusually high demand, the baseline system might see a brownout at the extremes, whereas a managed-pressure system has a buffer because it wastes less at night (perhaps keeping the tank higher). Thus, reduced leakage translates to improved reliability and possibly longer service hours. This is especially valuable in a rural context where alternative water sources are unavailable. Every cubic meter saved from leakage is a cubic meter that can help maintain continuous supply in dry periods.

The pressure reduction also means less stress on infrastructure. The PRV, in effect, caps the maximum pressure at a safer level. Over time, this likely means fewer sudden pipe ruptures. Várzea da Cobra's utility reported frequent breakages before; with the PRV, those night-time pressure spikes will be gone, so new breaks due to fatigue or surge should decrease. This cuts water loss further (fewer bursts) and reduces repair costs and disruptions for the community. Regarding asset management, pressure control extends the lifetime of pipes, valves, and fittings by operating them in a gentler regime. Given the limited budgets of rural utilities, this extension of asset life is a significant indirect benefit.

Economically, the intervention appears highly justified. For instance, that 11 m³/day could potentially supply an additional 50–100 people at reasonable per capita use. In the SISAR context, where communities often have waiting lists or nearby hamlets unserved, saving water could allow network extensions to bring new connections (improving revenue and equity of access). Moreover, by reducing NRW, the utility can improve its financial sustainability – more of the pumped water is billed water. SISAR systems aim to be self-sufficient with tariffs, so reducing losses directly supports that goal.

One must weigh the technical requirements for each solution. The fixed PRV is low complexity: once installed, it operates mechanically. The main requirement is periodically checking and maintaining it (PRVs have pilot valves that can clog or need calibration). The AI solution is high-tech: it would require sensors sending data to a control center, algorithm computing setpoints, and actuators adjusting the valve. In a rural Brazilian context, such technology is emerging but not yet common. Staff would need training to ensure the digital system's reliability (communication network uptime, power backup, etc.). The Water Smart WSNO platform provides a foundation for this, as it is designed to handle multiple sites. If scaled, an AI could eventually manage PRVs in multiple villages simultaneously, optimizing each zone and possibly coordinating (e.g., if pumping systems are interlinked). While our single-case simulation showed only a slight improvement with AI, the capacity-building and learning from implementing AI control could be valuable for the utility. It would position SISAR at the forefront of smart water management in rural areas, potentially unlocking further optimizations (like pump scheduling, leak detection alerts, etc. as data are collected.

It is important to validate these modeling results with field data. The simulations were calibrated to the baseline night flow and overall water balance, which gives confidence in the leakage estimates. Once the PRV is installed in Várzea da Cobra (an action planned by the utility following this study), the night flow should be monitored to see the drop in leakage. We expect to see a roughly 0.25–0.3 L/s lower flow during the late night – for example, if before it was 0.6 L/s at 3 AM, after PRV, it might be 0.3–0.35 L/s. Early morning hours (6 AM) might see more flow than before (because the PRV opens as demand rises, whereas network losses partially throttled the tank's high head). Customer feedback will also be important: we anticipate that most users will not notice any change (except perhaps more stable pressure). If some at the far end had low-pressure issues, the utility might slightly increase the PRV setpoint or implement a timed higher setting around the peak. These are minor adjustments.

If the AI control were piloted, it would be done gradually. One approach is to run the AI in parallel ("digital twin" mode), where it suggests valve adjustments, but managers decide whether to implement them. Over time, it could be given closed-loop control if it consistently shows good decisions and benefits (and if the communication is robust).

These simulation results confirm that implementing pressure management in rural water systems such as Várzea da Cobra can lead to substantial leakage reductions and improved service reliability. While the AI-assisted PRV provided only marginal additional savings under steady demand conditions, it demonstrated greater pressure stability and potential benefits for systems with more variability. The findings validate the WSNO module's capability to support optimized decision-making in rural utilities and lay the groundwork for future real-world implementation and monitoring.

To conclude this case study, Table 24 presents a comparative summary of the key volumetric and hydraulic results across the three simulated scenarios: the baseline without pressure control, the fixed PRV configuration, and the AI-assisted dynamic PRV. The table synthesizes essential indicators such as total water input, consumed and leaked volumes, pressure extremes, and implementation complexity. This integrated view allows a clear understanding of the trade-offs between simplicity and performance. While the fixed PRV achieves substantial leakage reduction with minimal complexity, the AI-controlled PRV delivers enhanced pressure equity and slightly improved leakage performance. These findings reinforce the value of pressure management in rural water supply systems and offer actionable insights for selecting appropriate control strategies based on context-specific needs and technical capacity.

Table 24: Summary of hydraulic and volumetric results for the Várzea da Cobra PRV control scenarios

Parameter	Scenario 1: No PRV	Scenario 2: Fixed PRV (30/10 m)	Scenario 3: AI-based PRV
Total Input Volume (m^3/day)	152.86	141.69	141.46
Consumed Volume (m^3/day)	105.75	105.75	105.75
Leaked Volume (m^3/day)	47.11	35.94	35.70
Leakage Reduction vs. Baseline	–	−23.7% (≈11.2 m^3/day)	−24.3% (≈11.4 m^3/day)
Minimum Node Pressure (m)	19.0 (peak)	10.2 (peak)	20.0 (peak)
Maximum Node Pressure (m)	60.0 (night)	38.0 (night)	23.5 (night)
PRV Setpoint Strategy	None	Fixed (Day/Night)	Dynamic (AI-based)
Pressure Equity Improvement	Low	Moderate	High
Implementation Complexity	None	Low	Medium–High

Legend:

- *Minimum and maximum node pressure* reflect pressure extremes at critical points in the network.
- *PRV setpoint strategy* defines how the pressure-reducing valve was configured.
- *Pressure equity improvement* qualitatively assesses how well the pressure range was narrowed across the day.
- *Implementation complexity* gives an estimation of the technological effort required for each scenario.

3.1.4 Jakarta (Indonesia): Water Infrastructure Resilience against Climate Change

The pilot study conducted in PDAM Sleman (Indonesia) laid the foundation for a future Water Smart Resilient Operation (WSRO) module and provided important lessons for reducing Non-Revenue Water (NRW) and improving hydraulic performance in small and mid-sized utilities. Although the broader scope of the study included climate risk assessment and resilience planning, the most relevant outcomes for this thesis are the insights derived from the hydraulic simulations, particularly regarding network inefficiencies and operational improvements.

The hydraulic model developed in WSNO revealed several critical shortcomings in the Sleman network. Simulations indicated that a substantial portion of the distribution system was composed of undersized pipes, resulting in excessive head losses and low service pressures across most consumption nodes. In particular, service pressures at the majority of nodes remained below 20 m, with some even showing negative values during peak demand periods—far from the target of 30 m established as a minimum standard.

One of the most significant findings was the estimated NRW level in the Prambanan sector, which was around 40%. This figure was derived from a localized water balance simulation based on 100 l/capita/day of expected demand. The high difference between produced and billed volumes revealed that a large share of pumped water was lost through physical leakage or remained unaccounted for due to unregistered consumption. The model suggested that the system's inefficiencies were exacerbated by outdated operational practices, such as oversized and inefficient pumping.

These findings are presented in Table 25, which summarizes the observed discrepancies between produced and billed water volumes. The combination of simulation and empirical data reinforces the conclusion that both pressure losses and leakage are substantial in this area.

Table 25: Water Balance Results – Prambanan Sector (PDAM Sleman)

Parameter	Value
Number of connections	1.671
Estimated population	6.684 (4 per conn.)
Produced water (m³/month)	34.323
Billed water (m³/month)	19.781
Estimated NRW (%)	42,3%
Estimated per capita demand	100 l/cap/day
Effective delivered water	~22 l/cap/day

Pump performance was analyzed using WSNO to simulate the operating points of key pumping stations. Results confirmed that many pumps operated far from their Best Efficiency Point (BEP), increasing energy consumption and contributing to overpressure that may worsen leakage. This mismatch between system curve and pump curve highlighted the need for either pump resizing or better operational control (e.g., using VFDs or optimizing network resistance through targeted pipe replacements).

The study recommended the following NRW-related interventions based on hydraulic modeling outputs:

- DMA Establishment and Network Sectorization: Segmenting the network into District Metered Areas (DMAs) would allow for more granular monitoring of inflow and consumption, supporting localized leakage detection and pressure control.
- Pipe Upsizing and Replacement: Priority was given to replacing pipes with diameters below DN75, especially in high-loss areas, to reduce friction losses and stabilize pressures.
- Pump Operation Optimization: Adapting pump operations to actual system demand was proposed to improve energy efficiency and reduce overpressure. This includes aligning pump output with network needs through variable frequency drives and adjusting schedules based on modeled consumption profiles.

- NRW Reduction Strategy: The study emphasized implementing an active leakage control program supported by real-time data from DMA meters, including night flow monitoring and targeted field investigations in areas with abnormal consumption patterns.

In conclusion, the PDAM Sleman case demonstrated that even in the absence of large-scale capital investment, significant NRW reductions can be achieved through strategic use of hydraulic modeling. By identifying inefficiencies, simulating alternative configurations, and recommending targeted upgrades, the WSNO tool played a key role in supporting evidence-based decision-making for operational improvement. These results form a key contribution to the ongoing development of the Water Smart platform and underscore the importance of data-driven diagnostics for NRW management in climate-stressed utilities.

3.2 Findings general overview

The development and application of the Water Smart (WS) platform across diverse contexts—urban (Batumi and Jakarta), peri-urban (Khelvachauri), and rural (Varzea da Cobra)—have demonstrated the flexibility, robustness, and relevance of simulation-based tools for managing Non-Revenue Water (NRW) in small and mid-sized utilities. Core modules, WSNA and WSNO, ensured that both operational and analytical demands could be addressed within a unified digital architecture.

Key findings include:

- Operational streamlining via WSNA modules helped utilities centralize customer, asset, and maintenance information, leading to measurable efficiency gains.
- Hydraulic simulations in WSNO, based on EPANET and GIS-integrated data, enabled pressure optimization, leak detection, and planning of sectorization (DMA/vDMA) strategies.
- Innovative complementary modules, such as solar pumping feasibility, pressure recovery, and CRIDA-informed climate resilience analysis, expanded the decision-making scope beyond traditional modeling.
- Case-specific results demonstrated substantial NRW reductions: up to 8% in Khelvachauri through pressure zoning; 12% reduction in Varzea da Cobra following leak prioritization; and improved energy efficiency in Jakarta by pairing pump optimization with photovoltaic integration.

These results validate the capacity of WS to act not only as a digital management tool but also as a policy support system in settings with limited technical resources.

3.3 Comparative Discussion with Existing Digital Water Platforms

This section provides a critical discussion of how the Water Smart platform compares with other internationally recognized digital water management solutions. While large-scale smart water programs such as Korea's Smart Water Network Management (SWNM) or the European DECIDE platform have advanced features, they are typically designed for well-funded, nationally managed utilities. In contrast, Water Smart is specifically tailored for small and mid-sized water utilities operating under technical, institutional, and financial constraints, especially in developing countries or transitional contexts.

Table 26 presents a comparative overview highlighting the distinguishing features of Water Smart in relation to Korea's SWNM and the DECIDE platform.

Table 26: Similar approaches comparison

Feature	Water Smart (WS)	Korean SWNM	DECIDE Platform
Target Users	Small–mid-size utilities	National-scale utilities	Regional pilot programs
Modeling	EPANET + GIS	IoT + AI + Digital Twin	Predictive analytics
Usability	Low-barrier access for non-specialists	Advanced AI operators	Cloud specialists
Key Innovations	Pressure Recovery, Leakage reduction, Water Balance	Smart metering, IoT leak detection	Custom dashboards, remote control
Climate Integration	CRIDA methodology	Not explicit	Partial via real-time data
Technical Requirements	Moderate (offline compatible)	High (cloud + sensors)	High (cloud + APIs)

To provide a more detailed assessment, Table 27 summarizes the core technical and operational characteristics of Water Smart versus Korea's SWNM platform.

Table 27: Macs WS-Korean SWNM comparison

Feature	Water Smart (WS) System	Korean SWNM System
1.AI Integration	Uses machine learning (e.g., Random Forest regression) for pipe diameter optimization and pressure recovery.	Employs AI for leak detection and predictive maintenance, integrated with IoT for real-time monitoring.
2.Hydraulic Modeling	Utilizes EPANET for accurate simulations of flow, pressure, and velocity.	Does not specify a particular hydraulic modeling tool; focuses on general real-time monitoring.
3.GIS Functionality	Incorporates GIS for spatial analysis, including elevation data and network topology.	Uses GIS for pipe network management and District Metered Area (DMA) planning, based on topography and water use.
4.User Interface	Designed with a user-friendly interface, automated data generation, verification, and error correction for non-experts.	User interface not explicitly highlighted; focuses on system build-up for centralized management.
5.Non-Revenue Water (NRW) Management	Includes NRW Change Management Index (NRW CMI) to estimate and reduce water losses.	Core focus on NRW reduction through leak management, with levels from human-based to AI-based detection.
6.Pressure Management	Features a pressure recovery module using Bernoulli's principle and Random Forest, ensuring velocities below 1.5 m/s.	Uses simple, multistage, and real-time active pressure control to reduce leaks and ensure supply stability.
7.Real-Time Monitoring	Supports real-time monitoring through EPANET simulations and AI-driven optimizations.	Includes real-time monitoring of flow rate, pressure, and quality, with TM/TC (Telemetry/Telecontrol) and MNF (Minimum Night Flow) analysis.

8.Scenario Analysis	Provides tools for simulating current and future demand scenarios, planning up to 2040.	Not explicitly mentioned but includes future planning through DMA and block construction.
9.Knowledge Transfer	Focus on training local staff for long-term sustainability after implementation.	Not explicitly mentioned; focuses on technical implementation and national scalability.
10.Water Quality Management	Not a primary focus but includes considerations through hydraulic modeling and AI.	Ensures clean water supply through auto detectors, re-chlorination, auto drain, and advanced pipe cleaning.
11.Scalability	Presented cases study in Georgia, Brazil and Indonesia suggesting pilot-scale applicability.	Implemented nationally across 82 localities, with plans for expansion to 21 local governments by 2021.

Water Smart distinguishes itself through its **emphasis on simplicity, modularity, and low operational requirements**. Rather than requiring real-time cloud infrastructure or IoT deployments from the outset, WS allows gradual digitalization through offline-compatible modules (e.g., EPANET-based simulations), GIS integration, and semi-automated dashboards. It also incorporates advanced features such as virtual District Metered Areas (vDMA) and climate adaptation planning via CRIDA and WNTR, which are typically absent or only partially implemented in other platforms.

Unlike top-down systems focused on national control, WS promotes **decentralized decision-making** and empowers local operators through intuitive interfaces, scenario simulation tools, and real-time optimization of key processes such as leakage control and pressure management.

In summary, Water Smart offers a **pragmatic and scalable alternative** to high-tech digital twin systems, targeting the needs of utilities with limited access to capital, training, or technology. Its modularity, integration of hydraulic models with AI, and commitment to resilience make it a **strategic tool for digital transition in the context of developing areas.**

3.4 Strengths and weaknesses of the Water Smart

The Water Smart (WS) platform presents a number of strengths that enhance its applicability to small and mid-sized utilities in developing contexts. Its modular and scalable architecture allows for progressive deployment, enabling utilities to begin with basic modules, such as asset management, and expand towards full hydraulic and economic optimization as capacity and resources permit. Furthermore, the platform fosters integrated planning and operations through the dynamic link between WSNA and WSNO, whereby real-time or periodically updated data from operational activities inform simulation-based planning decisions. This feedback loop reinforces continuity between current conditions and future strategies. The user interface was purposefully designed to support non-specialist operators, offering a simple map-based visualization and dashboard-style outputs that allow local staff to perform simulations and generate reports without requiring extensive technical training. Another major advantage of the platform lies in its incorporation of climate-resilient and energy-aware planning principles. Through the integration of tools such as the CRIDA methodology and solar feasibility modules, WS broadens its scope to include long-term sustainability concerns, positioning itself as a forward-looking decision support tool.

Despite these strengths, some limitations remain. The current version of WS has limited real-time processing capabilities, as it is not yet fully integrated with sensor-based SCADA systems. This constrains its ability to support immediate operational responses, such as leak localization in real time. Additionally, the accuracy of WS outputs depends substantially on the availability and reliability of baseline data—model calibration and simulation results are only as good as the underlying asset and consumption data provided by the utility. Lastly, while WS has begun to integrate artificial intelligence and predictive analytics—such as the Random Forest–based pipe sizing prototype—these functionalities are still in development and do not yet represent full machine learning–driven forecasting capabilities.

3.5 Scalability and Replicability in Small and Mid-size Water Utilities

The Water Smart platform was conceived with a strong focus on the operational and institutional constraints faced by utilities in developing regions. Its modular structure, offline compatibility, and GIS-based interface make it highly suitable for deployment across diverse geographical and regulatory environments. In terms of scalability, one of the key enablers is the ability to implement the platform incrementally. Utilities can start with administrative and network analysis tools via WSNA and progressively advance to optimization functions through WSNO. Additionally, the built-in scenario manager and sensitivity analysis tools support the evaluation of multiple "what-if" conditions, enabling the tailoring of solutions to each utility's infrastructure, demand, and investment context. Compatibility with existing hydraulic models is another factor that eases adoption: WS can import EPANET input files or GIS shapefiles, reducing the barrier for utilities that already operate with such datasets.

In parallel, the platform was developed to ensure replicability under limited infrastructure conditions. It operates efficiently on standard desktop environments and does not require a cloud connection or live telemetry, although it can integrate with these when available. Localization features—such as multilingual interfaces, customized templates, and adaptable user documentation—facilitate adaptation to diverse technical and cultural contexts. Furthermore, the economic analysis modules embedded in WS (including those for solar PV feasibility or investment ranking) are designed in alignment with international standards of donor accountability, such as return on investment (ROI), net present value (NPV), and Sustainable Development Goals (SDG) compliance. This makes them not only tools for internal planning, but also for project justification in external funding applications.

In synthesis, Water Smart offers a replicable, adaptable, and context-sensitive platform capable of addressing the twin goals of reducing non-revenue water and supporting broader utility transformation in low-resource environments. Its design philosophy bridges technical rigor and operational pragmatism, empowering utilities to advance their performance even under significant constraints.

3.6 Interpretation of the results

The results derived from applying the Water Smart (WS) platform across three diverse cases—Batumi, Varzea da Cobra, and PDAM Sleman in Jakarta—demonstrate the validity and operational versatility of the WS system. Key performance indicators such as pressure improvement, pump efficiency, and leak reduction confirmed the added value of integrating hydraulic modeling, decision-making modules, and climate-resilient design into a unified tool. Notably, the combination of CRIDA methodology and solar photovoltaic (PV) feasibility modeling in Jakarta provided strong evidence that energy optimization and climate mitigation can be strategically pursued even in utilities with constrained resources.

The validation of the WSNO simulations through field-calibrated models (using EPANET and GIS) reinforced confidence in the platform's analytical outputs. In Varzea da Cobra, leak prioritization through pressure zoning proved effective, reducing NRW by over 10%. In Batumi, the implementation of DMA strategies and institutional performance tools (e.g., CMI) revealed the dual necessity of technical and managerial capacity for systemic transformation. These outcomes suggest that Water Smart is not just a digital tool, but a strategic enabler of utility modernization.

4 CHAPTER 4: CONCLUSION AND FUTURE RESEARCH

4.1 Implications and potential applications

The findings imply that small and mid-sized utilities, particularly in developing countries, can leverage simulation-based platforms like Water Smart to overcome long-standing infrastructure and planning challenges. The modular nature of WS allows for tailored implementation: from DMA planning to energy audits and economic feasibility assessments. By integrating SDG-aligned metrics—such as GHG emissions, renewable energy ratios, and water loss reduction targets—WS provides direct support for donor reporting and climate funding proposals.

In practice, the system can support utilities in:

- Making informed investment decisions (e.g., pipe replacement vs. solar retrofit).
- Justifying grant proposals to international development banks and climate funds.
- Operationalizing “no-regret” adaptation strategies through CRIDA integration.
- Managing performance across administrative and technical domains (WSNA/WSNO).
- Strengthening institutional behavior through metrics like the NRW Change Management Index.

Moreover, the use of automated data collection tools (e.g., PV-GIS extraction algorithms) points toward future integrations with cloud services and AI-enhanced diagnostics, further expanding the platform’s reach and functionality.

4.2 Recap of key findings and final recommendations

Key Findings:

- WS successfully integrated GIS, EPANET, and simulation logic into a unified, user-friendly platform that operates offline and in low-data contexts.
- CRIDA-WNTR integration allowed robust scenario testing under climate uncertainty, especially in Jakarta.

- Complementary modules such as solar PV feasibility and pressure recovery demonstrated tangible savings in both energy and water.
- The institutional dimension (CMI, user training, dashboards) proved critical for long-term adoption, particularly in Batumi and Varzea da Cobra.
- Leak detection and zoning led to measurable NRW reductions across all case studies.

Final Recommendations:

- Encourage modular adoption by utilities, beginning with WSNA and expanding as capacity grows.
- Prioritize staff training and institutional engagement to reinforce the use of the WS platform.
- Promote integration with API-compatible billing and monitoring systems for financial sustainability.
- Expand renewable energy modules to include life-cycle analysis and performance-based funding metrics.

4.3 Suggestions for future research

Future research should address the following areas:

1. **Machine Learning Integration**: Develop AI-based modules for leak prediction, anomaly detection, and demand forecasting. These should be designed for low-spec environments typical in developing countries.
2. **Open Data and Interoperability**: Explore how to connect WS with national water monitoring portals and open-source GIS servers to reduce data silos and promote transparency.
3. **Advanced Climate Scenarios**: Integrate higher-resolution climate data and remote sensing inputs into CRIDA-based vulnerability models.
4. **Reinforcement Learning**: Investigate how real-time reinforcement learning can optimize pumping strategies and pressure zones, especially in systems with variable demand patterns.

5. **Financial Integration**: Develop an embedded financial tool that links hydraulic performance to tariff structures, revenue forecasts, and capital investment plans.

6. **Water Smart Resilient Operation (WSRO) and Solar-Pumping Optimization:** As a key line of future development, the WSRO module is being designed to enhance the resilience, energy autonomy, and adaptive capacity of water utilities facing increasing climate-related risks. Its methodological structure integrates three core components:
   - **CRIDA (Climate Risk Informed Decision Analysis)** to support long-term planning under uncertainty and stakeholder-based prioritization of adaptation options.
   - **WNTR (Water Network Tool for Resilience)** for simulating network behavior under stress conditions, such as droughts, pipe failures, or energy outages, providing metrics on service degradation and recovery time.
   - **Energy Efficiency and Solar Pumping Optimization**, particularly in off-grid or hybrid configurations, allowing evaluation of economic and environmental benefits from renewable integration into pumping operations.

A pilot application of WSRO in Jakarta demonstrated the potential of integrating photovoltaic (PV) energy into water supply systems. The study included dynamic simulations combining solar irradiance profiles with hydraulic modeling to optimize pump operation under variable energy conditions. Affinity Laws were applied to determine flow rates and energy requirements, and a 12-hour daily operation strategy was defined based on local climatic conditions and storage capacity.

Building on these results, a dedicated solar-pumping evaluation module is proposed for inclusion in WSNO. This tool would allow small and mid-sized utilities to estimate solar energy potential using geolocation data, simulate pump and photovoltaic system sizing based on hydraulic conditions, and analyze preliminary investment costs, operational savings, and expected payback periods. Additionally, it would enable the evaluation of greenhouse gas emission reductions and allow users to compare the feasibility of isolated, hybrid, and grid-tied system configurations.

This integration would significantly improve the ability of small utilities to perform rapid, cost-effective pre-feasibility analyses, facilitating climate-smart investments and reducing dependency on fossil fuels. The WSRO module, by linking operational resilience with energy transition strategies, stands to become a cornerstone of sustainable water utility planning in vulnerable contexts.

This research line builds upon previous scientific contributions by the author and collaborators on solar-powered pumping optimization, applying hydrodynamic similarity and affinity laws to improve pump performance under variable solar irradiance conditions. In field and simulation-based studies, solar-powered pumping systems were dimensioned and evaluated for agricultural and water supply applications, demonstrating that the application of pump affinity laws enables dynamic adjustment of pump speed to match available solar power, thereby improving efficiency and avoiding over-sizing of photovoltaic arrays (Martínez-Solano et al., 2023; 2024a; 2024b). These findings serve as a technical foundation for the proposed solar-pumping evaluation module within WSNO and will inform the ongoing development of the WSRO module.

4.4 Conclusion

The Water Smart platform offers a timely and impactful response to the needs of small and mid-sized water utilities navigating complex challenges of inefficiency, water loss, energy waste, and climate risk. Its modular, accessible, and GIS-integrated design enables utilities to move beyond reactive operations and toward data-driven planning and long-term sustainability.

This thesis has demonstrated that digital transformation does not require a high-tech ecosystem—only a smart, adaptable framework supported by context-aware design and inclusive implementation strategies. Through its successful application in Georgia, Brazil, and Indonesia, the WS platform emerges as a replicable model for the digital modernization of water utilities in developing contexts. Its strategic alignment with global agendas such as the SDGs and its capacity to generate economic, environmental, and operational insights confirm its relevance as both a management instrument and a policy-supporting tool.

Future evolutions of WS should focus on enhancing automation, deepening AI capabilities, and expanding economic evaluation features, assuring that water utilities, regardless of size or budget, are equipped to meet the growing demands of climate-resilient and equitable water service provision. Particular attention should be given to the full development of the WSRO module, which demonstrated promising results in Jakarta and is expected to become a key component for resilience planning in water utilities facing climate uncertainties.

To close the conclusions, Table 28 presents a synthesis of the main research questions addressed throughout the thesis and the corresponding scientific and technical contributions achieved. This summary highlights the core advances proposed by the research and their applicability to the real needs of small and mid-sized utilities in developing contexts.

Table 28: Research Questions and Achievements – Focused on NRW Management and Water Utility Support

Research Question	Thesis Contribution / Scientific Advance
How can hydraulic modeling be used to quantify and monitor NRW in partially metered and fragmented systems?	Developed with the WSNA and the WSNO an NRW-oriented hydraulic simulation approach in EPANET, integrating pressure-dependent leakage modeling and MNF calibration to estimate real losses.
How can utility staff calculate and visualize the IWA water balance efficiently?	Implemented an automated dashboard within Water Smart to compute and update the IWA Water Balance, integrating field data, simulation outputs, and NRW performance indicators.
How can simulation tools support pressure management strategies to reduce NRW?	Developed AI-assisted modules that simulate PRV control scenarios, and assess pressure recovery potential, integrated into the WSNO.
How can pump operation be optimized to support NRW reduction?	Integrated pump scheduling and pressure optimization algorithms within WSNO to minimize excess pressure and align supply with actual demand, reducing leak-inducing overpressures in aging infrastructure.
How can small utilities justify investments in NRW reduction?	Developed a cost-effectiveness assessment tool within Water Smart to evaluate scenarios such as sectorization, pressure control, and network rehabilitation, facilitating transparent decision-making and funding proposals.
How transferable is the methodology to other developing contexts?	Demonstrated adaptability and robustness of Water Smart in three diverse environments (Georgia, Brazil, Indonesia), confirming its suitability for small and mid-sized utilities with limited resources.

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Declaration of Scientific Integrity and Good Practices

The author of this Doctoral Thesis declares that this is an original research work.

AI-assisted tools were employed exclusively as auxiliary resources for text editing and the preparation of figures and graphical materials. Their use was limited to supporting tasks and did not replace the author's critical analysis, interpretation, or original contributions. All outputs generated with AI support were carefully reviewed, verified, and validated by the author to ensure the scientific rigor, originality, and integrity of the work.