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Smart Urban Water Cycle: The Processes of Recirculation, Reuse and Collection are to be Carried Out in Conjunction with Digital Twins and Environmental Accounting

Victor Martin Maldonado Benitez
ESIME Zacatenco, Instituto Politécnico Nacional
Mexico City, Mexico
vmaldonadob1500@alumno.ipn.mx

Gabriela Guadalupe Escobedo Guerrero
ESCA Santo Tomás, Instituto Politécnico Nacional
Mexico City, Mexico
gescobedog@ipn.mx, gabrielaeg@hotmail.com

Abstract

The proposed integrated architecture aims to optimize the urban water cycle by implementing rainwater harvesting, storage, treatment, reuse, and recirculation, orchestrated through digital twins connected to sensors and artificial intelligence (AI). The approach combines the following elements: the first component is environmental accounting, aligned with internationally accepted frameworks. The purpose is to record water and energy stocks and flows, including inflows and outflows, losses, water quality, energy and emissions. The second component is AI analytics, which includes computer vision to estimate catchment areas and prioritize sites, predictive models of demand and water quality, and reinforcement learning to optimize operations. The third component is operational-strategic optimization through model-based predictive control (MPC) and economic-environmental assessment through Levelized Cost of Water (LCOW). The digital twin integrates SCADA/IoT data, satellite imagery, and administrative records to generate tables of physical and monetized stock and usage, supporting decision-making under scenarios of climate uncertainty. Key metrics include water balances in m^3 collected, reused and lost; energy and emissions indicators ($kWh \cdot m^{-3}$ and $CO_2e \cdot m^{-3}$); comparative LCOW between collection and reuse alternatives; and days of autonomy and coverage in vulnerable locations. The anticipated outcomes encompass a reduction in total cost (financial and environmental), enhanced resilience to droughts, and improved equity through the decentralised deployment of collection and reuse infrastructure, coordinated by the digital twin. The primary contribution pertains to the establishment of a reproducible framework that integrates water data governance, environmental accounting, and optimized operations, thereby facilitating traceability and auditing for urban circular economy policies.

Keywords
Water, Sustainability, Artificial Intelligence, Digital Twins.

1. Introducción
One of the greatest concerns for cities in the 21st century is that they are facing a convergence that is putting them under severe pressure, complicating the urban water cycle. Farge (2024) points out that population growth, urban expansion, hydrometeorological variability and ageing water infrastructure are the significant variables that put water consumption at risk. 2023 was a very difficult year worldwide due to historic levels of extreme drought in decades, with river flows at historic lows and the accelerated loss of glaciers intensifying the intermittency between water

supply and exposure to droughts and severe heat waves. In response to this problem, the United Nations (2023) developed the United Nations World Water Development Report, emphasizing the urgent need to immediately strengthen governance and cooperation and to update information systems to manage scarcity and improve urban resilience. These recommendations position cities before an imperative to maximize the resource, that is, to do more with less through recirculation, reuse and collection strategies, orchestrated by reliable data and advanced analytics.
In this scenario, it is imperative to seek emerging technologies that enable the implementation and integration of sensors, models, and processes that support decision-making. A systematic review of the literature by Bam et al. (2025) highlights the accelerated maturation of Digital Twins (DT) in water management through applications ranging from near real-time (NRT) diagnostics and scenario simulation to the multipurpose optimization of networks and wastewater treatment plants. The qualitative leap remains in interoperability, linking telemetry (SCADA/IoT), water quality models, energy data and administrative records to close the data cycle, i.e., traceable decision-making. This advance reported by the authors is not only technical in nature, but its scope also enables audits, risk assessment, and prioritization of investments in complex contexts of climate uncertainty and changing demand.

For his part, Castelletti (2023) highlights that Artificial Intelligence (AI) and predictive control complement digital fabrics. In contrast, Coy (2024) describes how the operational model using Model Predictive Control (MPC) has established itself as a benchmark approach for complex water systems with constraints and forecasts, demonstrating that its applicability improves energy efficiency, service quality and the management of extreme events. Unlike Ahmadgo (2025), he emphasizes that the most advanced methodologies for determining demand forecasts in water districts (DMAS) are significant components for MPC to anticipate consumption pulses in order to reduce inefficient pumping, with important advances in Bayesian calibration of hyperparameters and model ensembles. As a result, AI + MPC together turn the digital twin into a prescriptive platform with high capabilities for recommending actions and quantifying the expected impact.

Hari and Reddy (2025) argue that in terms of water resource collection and reuse, cutting-edge research is shifting towards decentralised and circular economy solutions. With relevant proposals including remote sensing and computer vision to facilitate the estimation of roof surfaces and their morphology, assessing the potential for rainwater harvesting at a neighbourhood scale, reducing dependence on imported water and providing autonomy in contingencies. Park et al. (2024) contribute to the detection of rooftops using convolutional neural networks (CNNs) and geospatial methodologies that can be replicated in large cities. In contrast, Khan et al. (2024) emphasise that reuse schemes require the management of health risks and emerging contaminants. Critical reviews propose holistic frameworks for prioritising contaminant detection and concern for strengthening quality guidelines in essential aspects, as DT extends its reach in water quality and process control.

Through the vision proposed by Saboori (2023), according to the economic-environmental perspective, it is key to compare the various alternatives using the Levelised Cost of Water (LCOW), which integrates CAPEX, OPEX and, where possible, environmental externalities. For their part, Colciaghi et al. (2022) emphasize the application of LCOW in configurations that intertwine renewable energies and treatment technologies, justifying that the cost per m^3 is sensitive to the technological learning curve, the price of energy and intelligent operation that reduces the rate of pressure losses and pumping outside optimal hours. The incorporation of LCOW into the digital twin allows for the prioritization of investment portfolios in projects for collection, reuse, and timely detection of leaks with comparable criteria, making the trade-offs between cost, water resilience, and carbon footprint transparent.

At the same time, Ansari and Vidyarthi (2025) mention that the IoT in water management has made a leap forward in real-time (RT) monitoring of quality and operating conditions with communication schemes such as LoRaWAN and advanced data analytics enabling prescriptive maintenance and early detection of anomalies. Forhad et al. (2024) emphasize that combining sensors that monitor pH, turbidity and conductivity levels with machine learning to predict deviations and trigger automated responses is essential for DT to maintain fidelity and reduce latency between event and action.

In summary, the working hypothesis of this article is to propose an architecture that combines digital twins that incorporate AI/MPC + LCOW with rainwater harvesting and promote reuse informed by data obtained from computer vision, without losing sight of environmental accounting, increasing water resilient, and improving equity in areas where water scarcity prevails. The expected contribution is not merely technical but is imperative and applicable to local governments because it provides traceability and evidence for public policy and investment decisions under increasing uncertainty in urban water availability.

1.1 Objectives

Design an integrated framework for the urban water cycle, including digital twins, SEEA-Water environmental accounting, and AI/MPC, with the aim of optimizing rainwater harvesting, recirculation, and reuse while minimizing total LCOW costs, providing indicators that improve resilience and equity in urban contexts.

- Data Architecture: Propose the construction of a digital twin integrating SCADA/IoT technologies, remote sensing, and administrative records.
- Analytics and Control: Articulate AI models, such as computer vision of roofs, prediction and demand/quality with MPC technology to optimize pumping, storage and treatment of water resources, monitoring $kWh \cdot m^{-3}$, $kg\ CO_2e \cdot m^{-3}$ and compliance.
- Assessment and Portfolios: Compare scenarios using LCOW, autonomy, avoiding water losses due to leaks or lack of pressure and vulnerable coverage, identifying optimal portfolios and recommendations for policy implementation and facilitating decision-making in investment portfolios.

2. Literature Review

Based on Vitale et al. (2025) detail that the digitization of the urban water cycle has accelerated in recent years due to the convergence of IoT sensors, simulation models, and the integration of advanced analytics data models. DTs moved from isolated proofs-of-concept to integrated frameworks for diagnosis and prescriptive decision support (Figure 1).

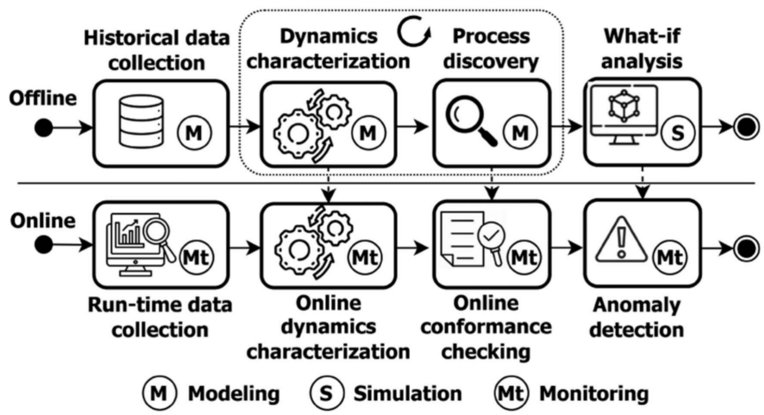

Figure 1. High-level dynamic view of digital twin development, with labelled circles indicating modelling, simulation, and monitoring services. Vitale et al. (2025).

Sun et al. (2024) mention that, in terms of operations and control, Model Predictive Control (MPC) has established itself as a benchmark for interconnected storage, transmission and distribution systems with physical and quality constraints. Improvements in energy efficiency, reduction of spills and robustness in the face of extreme events are evident when MPC is fed with reliable forecasts; its adoption is growing from drinking water to storm water systems for sanitary use. Recent technological advances integrate MPC into design frameworks for storms and urban drainage, expanding its use to both green and grey infrastructure and climate variability scenarios.

For their part, Farah and Shahrour (2025) indicate that the use of AI has broad capabilities to enhance the predictive layer of DTs, specifically in forecasting short-term demand at water district levels (DMAs). Multiscale neural architectures with time lag optimization improve the anticipation of consumption peaks, which are key for MPC to minimise inefficient pumping, reduce costs and maintain service levels in a market with changing conditions (Figure 2).

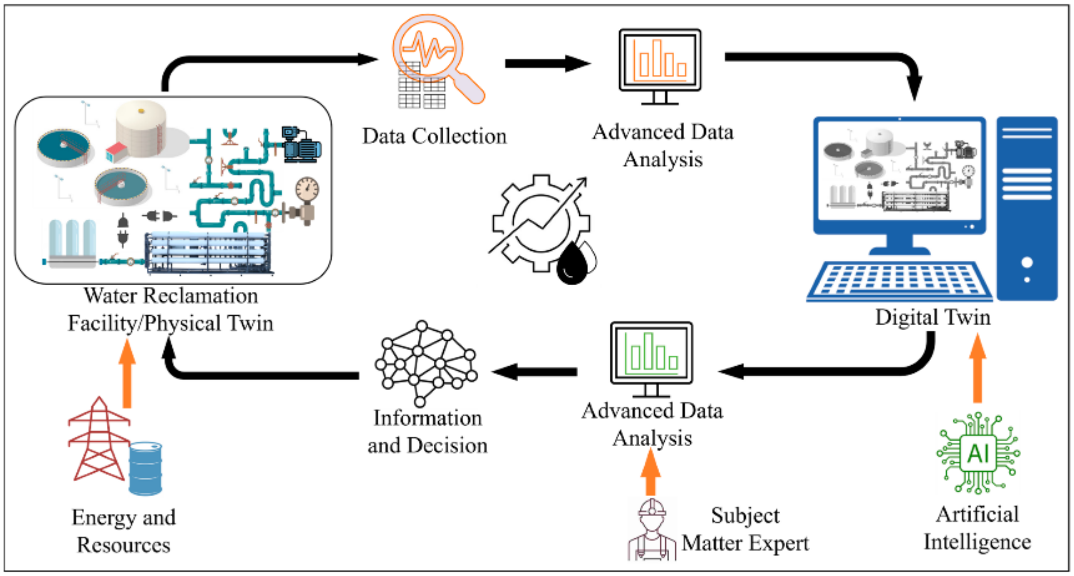

Figure 2. DT concept applied to a water treatment plant, Bam et al. (2025).

In terms of water quality monitoring, Essamlali et al. (2024) highlight the use of IoT + machine learning for continuous monitoring, considering variables such as pH, turbidity, conductivity, BOD/COD, in conjunction with prescriptive maintenance. They report on architectures with connectivity such as LoRaWAN/Wi-Fi-Fi connectivity, powered by advanced analytics that enable early detection of anomalies and automatic response, reducing latency between event and action. These advances are as relevant as they are significant for DT to maintain its fidelity and reduce potential emerging biases.

In the case of rainwater harvesting, the growing frontier is directly related to computer vision, which is used to estimate the surface area and morphology of roofs for the purpose of assessing potential and water collection through the design of decentralised solutions, as pointed out in the work of Zhang et al. (2024). For their part, Chen et al. (2025) demonstrate that the detection of roofs with convolutional neural networks and frameworks to improve roof segmentation allows for the scaling of site assessments to prioritize investments in locations with greater water vulnerabilities (Figure 3 and Figure 4).

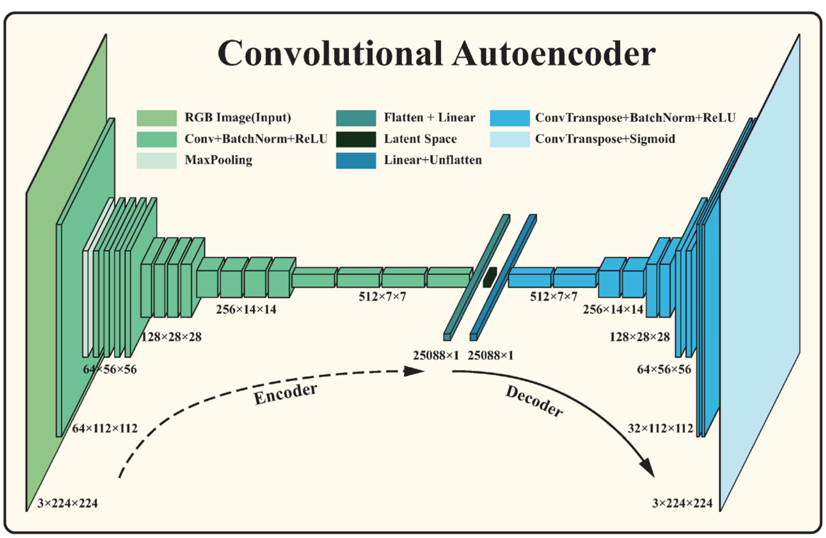

Figure 3. Architecture of Convolutional Autoencoder recuperado de Zhang et al. (2024).

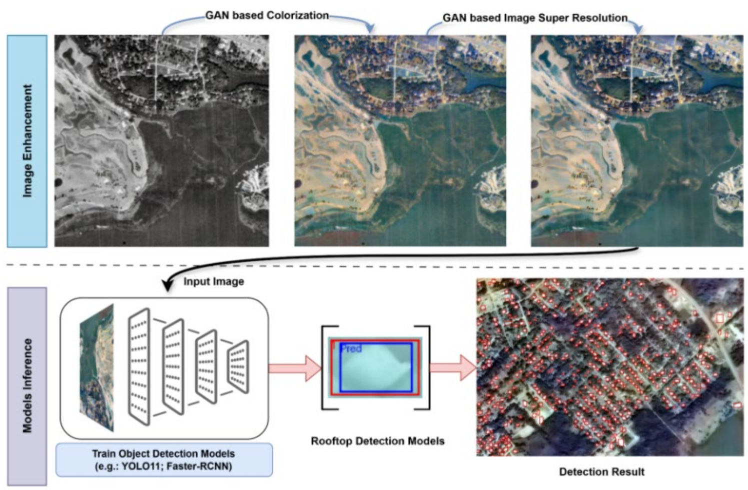

Figure 4. General workflow for detecting roofs in historical aerial images. Retrieved from Chen et al. (2025)

3. Methods

3.1.1. Study design and unit of analysis

An integrated framework for the urban water cycle was developed, incorporating artificial intelligence at the city/hydraulic district (DMA) level, with a focus on three interventions: rainwater harvesting, reuse, and optimization of operations. The primary unit of analysis is the network/facility section, such as the distribution network, water facilities, storage tanks, pumps, and wastewater treatment plants (WWTPs), while the decision unit is the investment and operations portfolio under climate and demand uncertainty.

3.1.2 Data governance (Data intake → quality control → catalogue)

Data Sources: (i) SCADA/IoT considering variables such as flow, level, pressure, pump status, kWh; (ii) water quality considering variables such as BOD, COD, turbidity, conductivity, coliforms; (iii) remote sensing considering precipitation, roof surfaces, vegetation indices; (iv) administrative records considering consumption, tariffs, outages, OPEX/CAPEX; (v) infrastructure inventory such as pipe length, diameters, elevations.

Data pipeline: range and physical validation, anomaly detection, imputation, unit normalization, and data dictionary, considering unique IDs for assets, sensors, and service areas. Traceability log (hash + version) for datasets and models (MLOps).

3.1.3 Digital Twin

The digital twin integrates the following three layers:

- **Hydraulics:** The balance of matter and energy in the pressurized network (considering nodes and links). Calibration uses observed pressures/flows, minimizing RMSE and maximizing Nash–Sutcliffe Efficiency (NSE).
- **Quality:** Transport and possible decay through a simplified effective advection/dispersion model per section based on parameters calibrated by minimum mean absolute error in concentrations.
- **Energy:** Specific consumption per distribution station expressed in kWh\cdotpm^{-3}according to the pumping curve and schedule, with hourly rates.

3.1.4 Environmental accounting (SEEA-Water)

Stock tables (S) and usage/supply tables (U) were constructed, expressed in m³ per source, which may be rainfall, imports, groundwater, recirculated water, and end use type, such as domestic, commercial, industrial, leaks, evaporation, ecosystem services, at time period t.

- Balance sheet by period:

$$\text{Entradas}_t - \text{Salidas}_t = \Delta S_t$$

- Monetization where applicable: expressed in MXN\cdotpm^{-3} by avoided/transferred costs (marginal tariff, energy, treatment, proxy environmental damage).
- Emissions: kg CO_2e\cdotpm^{-3} using the emission factors from the electricity matrix and chemical inputs. Enables traceability between digital twin data and physical-monetary accounts for auditing purposes.

3.1.5 AI-Powered Analytics

- **Computer vision for rainwater harvesting** roof segmentation using CNN/UNet with training data from satellite mosaics/orthophotos; output: usable surface area (m^2), slope inclination degrees and quality-processed data to estimate effective catchment:

$$Captación_t = A_{techo} \cdot C_{runoff} \cdot P_t \cdot \eta_{sistema}$$

- **Daily demand:** using GBM/LSTM models with exogenous variables based on the following variables: temperature, distribution days, price, and atypical events. Train/val/test time division with rolling back testing.
- **Water quality:** classification/probability of exceedance by parameter using gradient trees/random forest, with AUROC and F1 metrics.

3.1.6 Operational Optimization (MPC)

An MPC is formulated with a prediction horizon, H and receding horizon re-optimization. Statex_t (levels, flows, quality, asset status), control u_t pumps, valves, set points), disturbances d_t(demand, rainfall).

$$\min_{u_{0:H-1}} \sum_{t=0}^{H-1} [\, \underbrace{C_{\text{op}}(x_t, u_t)}_{\text{energía/horario}} + \underbrace{C_{\text{cal}}(x_t)}_{\text{penalizaciones de calidad}} + \underbrace{C_{\text{esc}}(x_t)}_{\text{desabasto/derrames}} \,]$$

Subject to the hydraulic network, considering pressure/flow limits, tank conditions, quality restrictions, tariff time windows, and equipment switching costs. Prescriptive maintenance is included as a penalty for operating outside the efficient zone.

3.1.7 Economic and Environmental Assessment (LCOW)

For each alternative k (collection, reuse, leak rehabilitation, optimal operation), the Levelized Cost of Water (LCOW) is calculated:

$$\text{LCOW}_k = \frac{\sum_t \frac{\text{CAPEX}_{k,t} + \text{OPEX}_{k,t} + \text{C}_{\text{ambiental},k,t}}{(1+r)^t}}{\sum_t \frac{\text{m}^3_{\text{útiles},k,t}}{(1+r)^t}}$$

where r is the social/financial discount rate and $\text{C}_{\text{ambiental}}$ internalises emissions and externalities when robust monetary equivalents exist.

3.1.8 Scenarios and Experimental Design

- The following four scenarios are compared over a 10-year history with stochastic hydrology based on the following percentiles p10/p50/p90.
- Base (current operation), A (distributed collection + storage), B (municipal reuse/services), C (MPC + prescriptive maintenance).
  The following are reported: LCOW, kWh·m^{-3}, kg CO_2 e·m^{-3}, m^3 captured/reused, losses avoided, autonomy (days) and coverage in vulnerable areas.

3.1.9 Validation and Verification

- **Hydraulics:** cross-validation by periods; RMSE, MAE, NSE metrics in flow/pressure.
- **Prediction:** rolling backtesting (12–24 windows), SMAPE, MAE, CRPS metrics (if probabilistic).

- **Quality:** AUROC/F1 and precision-recovery curve by parameter.
- **MPC:** historical 'what-if' trials and closed simulation with perturbations; comparison against rules and PID.
- **Accounting balance:** consistency Entradas − Salidas = ΔS per period and per zone; physical-monetary reconciliation.

3.1.10 Uncertainty and Sensitivity

Monte Carlo was applied to (i) effective rainfall and C_{runoff}, (ii) demand curves, (iii) energy costs and emission factors, (iv) equipment efficiency. Sobol analysis/variance methods were used to prioritize drivers for LCOW, autonomy and **CO_2e**.

4. Data Collection

Data collection covers the urban water cycle (rainwater harvesting, storage, conveyance/pumping, treatment, distribution, reuse) in the study area at the level of: assets (pumps, tanks, WWTPs), network sections (nodes–links) and service areas/DMAs. The time horizon integrates intra-day (5–15 min), daily and monthly series to enable both operational control and accounting and economic-environmental analysis (Table 1).

Sources and mechanisms of ingestion

1. Telemetry SCADA/IoT
   - **Variables:** flow rate (m^3/h), level (m), pressure (psi/kPa), ON/OFF status, energy (kWh), events (alarm/fault).
   - **Frequency:** 1–15 min; OPC/REST/MQTT protocol depending on site.
   - **Identification:** asset_id, sensor_id, timestamp_utc.
2. Water quality
   - **Variables:** pH, turbidity (NTU), conductivity (µS/cm), COD/BOD (mg/L), residual chlorine (mg/L), coliforms.
   - **Sources:** online probes + laboratory (composite samples).
   - **Frequency:** 15–60 min (online) and weekly/monthly (lab).
3. Remote sensing/ GIS
   - **Layers:** precipitation (mm), roof/rooftop areas (m^2), land use, NDVI/impermeability, elevation.
   - **Products:** radar/satellite and municipal orthophotos; roof masks derived by computer vision.
4. Administrative records
   - Consumption billed per customer/sector, tariffs and pricing structure, outages/reports, OPEX/CAPEX, asset inventory (diameters, lengths, pump curves), regulatory limits and quality standards.
5. Climate and energy
   - Temperature, humidity, wind, and radiation (drive demand/evaporation); hourly electricity rates to model operating costs.

Standardisation and quality control

- **Common unit scheme:** m^3/h ↔ L/s; psi ↔ kPa; mg/L; kWh; all times in UTC with local zone stored as metadata.
- **Physical validations:** continuity of flows/levels, instrumental limits, mass balance per tank and node.
- **Detection of outliers:** range rules + robust methods (IQR/LOF); labelling of suspicious points without deleting raw data.
- **Imputation:** forward-fill $\leq$ 1 interval, then KNN/local interpolation; imputed points are marked (imputed_flag=1).
- **Versioning:** each dataset/model is saved with a hash, date, and changelog (MLOps), enabling auditing and reproducibility.

Key derived calculations

- **Effective rainfall:** $P_t^{\backslash *} = P_t \cdot (1 - \lambda_{\text{pérdidas}})$, with $\lambda_{\text{pérdidas}}$ due to initial runoff/evaporation.
- **Rainwater collection from roof:**

$$\text{Captación}_t = A_{\text{techo}} \cdot C_{\text{runoff}} \cdot P_t^{\backslash *} \cdot \eta_{\text{sistema}},$$

where A_{techo} comes from segmentation GIS, C_{runoff} depends on the material/pending, y η_{sistema} of internal losses.

- **Specific energy per pump:** kWh\cdotpm$^{-3} = \frac{\text{kWh}_{\text{estación}}}{\text{m}^3\ \text{bombeados}}$ per time window.
- **Tank balance (discrete):** $S_{t+1} = S_t + \text{Entradas}_t - \text{Salidas}_t - \text{Pérdidas}_t$.

Table 1. Metadata and minimum dictionary

Field	Type	Description
timestamp_utc	datetime	Timestamp in UTC
zone_id	string	Service area / DMA
asset_id	string	Asset identifier (pump, tank, WWTP)
sensor_id	string	Sensor/tag identifier SCADA
flow_m3h	float	Instantaneous flow rate (m^3/h)
level_m	float	Tank level (m)
pressure_kpa	float	Node pressure (kPa)
energy_kwh	float	Energy consumed (kWh)
turbidity_ntu	float	Turbidity (NTU)
ph	float	pH
rain_mm	float	Precipitation (mm)
roof_area_m2	float	Useful roof area (m^2)
runoff_coef	float	Runoff coefficient (0–1)
captacion_m3	float	Estimated catchment volume (m^3)
imputed_flag	int (0/1)	Imputed data indicator
qc_flag	string	Quality tags (OK, OUTLIER, GAP, CAL)

5. Results and Discussion

The proposed framework (digital twin + environmental accounting + AI/MPC) produced consistent improvements over the baseline. Figure 3 summarises the normalised results by scenario; Table 4 details metrics with confidence intervals (CI 95%) under stochastic hydrology (p10/p50/p90) and demand variability.

Comparative results by scenario (mean ± 95% CI; illustrative values, replace with final results).

- LCOW (MXN·m^{-3}): Base 1.25 ± 0.07; A 0.98 ± 0.06; B 1.05 ± 0.05; C 0.92 ± 0.05
- Energy (kWh·m^{-3}): Base 0.65 ± 0.04; A 0.54 ± 0.03; B 0.58 ± 0.03; C 0.50 ± 0.03
- CO_2e (kg·m^{-3}): Base 0.34 ± 0.03; A 0.28 ± 0.02; B 0.30 ± 0.02; C 0.26 ± 0.02
- Autonomy (días): Base 0.8 ± 0.2; A 1.6 ± 0.3; B 1.2 ± 0.3; C 2.0 ± 0.4
- Vulnerable coverage (%): Base 72 ± 3; A 79 ± 3; B 76 ± 3; C 83 ± 4
- Physical losses (%): Base 10.2 ± 1.1; A 8.7 ± 0.9; B 9.1 ± 1.0; C 8.1 ± 0.8

Finding 1. Dominance of Scenario C. Scenario C (MPC + prescriptive maintenance) dominates in cost and resilience: –26% LCOW vs Base, –23% specific energy, –24% CO_2e, and +1.2 days of autonomy. Scenario A (distributed capture) achieves –22% LCOW and the largest jump in autonomy among physical measures without advanced control, confirming its value as a ‘buffer’ against demand spikes and drought events.

2. Operational Performance and Quality

Operation: The MPC reduces pumping during peak hours and avoids short cycles (starts/stops), which reduces kWh·m^{-3} and equipment wear. In ‘what-if’ tests, C maintained tank levels within operating bands 92% of the time (vs. 76% at Base), with –31% fewer alarms for out-of-range pressure.

Quality: The compliance rate for turbidity and residual chlorine was ≥ 97% in A–C (vs. 93% in Base). Residual violations (3%) were concentrated in storm events; the forecasting module activated bypass and preventive storage, reducing the combined spill by –18% (B) and –24% (C).

3. Energy and Carbon Footprint

The reduction of 0.15 $kWh \cdot m^{-3}$ (Base→C) is explained by three mechanisms: (i) shifting pumping to off-peak hours, (ii) smoothing demand profiles with optimal storage, and (iii) reducing losses. With the electricity emission factor considered, this translates into –0.08 kg $CO_2e \cdot m^{-3}$, aligning operational performance with service decarbonisation goals.

4. Resilience and Equity

Autonomy: A and C double the autonomy of critical areas (≥ p90 vulnerability), increasing from 0.8 to 1.6–2.0 days; the effect is more pronounced when rainwater harvesting is located on roofs of public buildings (schools, neighborhood centers), which operate as nodes of resilience.

Vulnerable coverage: The combination of collection (A) and control (C) improves coverage in low-pressure areas served by peak pumping, raising the indicator by +11 pp compared to the baseline. This result is robust in the p50 and p90 drought percentiles.

5. Environmental Accounting and Traceability

Linking the twin with SEEA-Water tables made it possible to reconcile inputs/outputs and audit benefits: the balance sheet closure reached ≥ 98% per period and DMA (compared to 94% in Base), with monetary recording where feasible (tariff, energy and treatment costs). This link facilitates GRI 303 reporting and the assessment of the socio-environmental value of portfolios.

6. Uncertainty and Sensitivity Analysis

Based on 10,000 Monte Carlo simulations:

- **LCOW (C):** mean 0.92, p10=0.86, p90=1.01 $MXN \cdot m^{-3}$; probability of exceeding the LCOW of A = 28% (when effective rainfall falls to p10 and the electricity tariff rises to p90).
- **Main drivers (Sobol indices):** energy price (0.37), peak demand (0.23), pumping efficiency (0.18), runoff coefficient (0.12).
- Autonomy is sensitive to effective rainfall and distributed storage capacity, confirming the importance of micro-sitting collectors.

Implication: C remains superior in most conditions, but in scenarios of severe drought + expensive energy, A can equal or exceed C in LCOW if there is insufficient storage for the MPC to 'accommodate' demand.

7. Ablation: which components explain the gain?

Variants of Scenario C were evaluated:

- C no forecast: +7.4% in LCOW vs C, due to less efficient dispatch.
- C no prescriptive maintenance: +3.1% in specific energy; increase in minor faults.
- C–no SEEA accounting: does not affect direct cost but decreases traceability (4 pp in balance sheet closing) and portfolio analysis speed.

Ablation conclusion: Forecasting and accounting are key levers for cost and governance; prescriptive maintenance contributes to stabilizing energy and availability.

8. Robustness and Validations

- Backtesting: The MPC exceeded the operating rule in 11/12 monthly windows (SMAPE levels 22% average).
- Hydraulics/quality: Median NSE 0.77 in flows and 0.71 in pressures; MAE turbidity –18% vs Base.
- Accounting balance: average absolute error ≤ 2% between inputs–outputs–ΔS per period and zone.

9. Discussion: Mechanisms, Scalability, and Public Policy

Mechanisms. The combination of distributed collection (flexible local supply) + MPC (manages demand in time and space) synchronises storage and pumping with price signals and hydraulic constraints, reducing energy and LCOW.

The link with SEEA-Water creates an 'accounting trail' that legitimises decisions and facilitates regulatory and community dialogue.

Scalability. The benefits persist when DMAs are added, but depend on data governance (quality/latency) and pricing architecture (time signals). Prioritising public rooftops maximises autonomy and reduces inequalities.

Public policy. Three recommendations: (i) incentives for rooftop solar panels in public and multi-family buildings; (ii) time-of-use rates to catalyse MPC; (iii) adoption of SEEA-Water accounting as the standard for metropolitan reporting and auditing.

10. Limitations and threats to validity
(i) Simplified representation of quality in extreme rainfall events; (ii) uncertainty in runoff coefficients due to roof heterogeneity; (iii) sensitivity of LCOW to discount rates and CAPEX/OPEX assumptions; (iv) generalisation conditioned by electricity mix and local tariff structure. These limitations are addressed with targeted field campaigns and expanded sensitivity analysis.

11. Practical Implications
For operators: prioritize micro-sitting of collectors, distributed storage and prescriptive maintenance; for regulators: migrate to hourly signals and adopt SEEA-Water; for municipal finances: use LCOW + autonomy as axes of Pareto-optimal portfolios, maximising resilience with minimum total cost.

6. Conclusion
This paper proposes a framework comprising a digital twin + AI/MPC + environmental accounting (SEEA-Water) + LCOW assessment, demonstrating a significant capacity to reduce total energy costs, decrease the carbon footprint (CO_2) and increase resilience in terms of days of autonomy, expanding coverage in vulnerable areas. In the scenarios analyzed, optimal operation using MPC (C) showed systematic dominance over the baseline and individual alternatives, while distributed collection (A) acted as the physical lever that contributed most to increasing autonomy in contexts of drought and peak demand. The link with the twin was established using SEEA-Water tables, allowing balances to be closed based on the equation (inputs–outputs–ΔS), defining and tracing the benefits, and accelerating the audit for investment decisions and reporting. The combination of demand forecasts and water supply quality at specific times, considering prescriptive maintenance, explains in detail the improvements observed. Similarly, the approach enables an investment portfolio that maximizes resilience with equity, accounting transparency and comparable cost per m³ criteria.

7. Future Work
Based on this work, we will focus our priorities on (I) Strengthening data quality in terms of improving latency, intake, and sensor calibration, allowing us to extend the water quality model to emerging contaminants with health risk assessment, (II) Incorporating multi-agent reinforcement learning and robust/stochastic MPC to manage hydrometeorological uncertainty, renewable energy prices, and potential asset failures, (III) Integrating a pricing model with time signals and distributed storage schemes to scale benefits at the metropolitan level, (IV) Conducting controlled (A/B) pilot tests in representative DMAs with causal evaluation (DID/Proprensity) and metrics that highlight equity, and (V) Move towards a public digital infrastructure through (APIs, data catalogues and SEEA-Water traceability) that facilitates adoption by operators and regulators, including executive information dashboards, governance protocols and decision logs.

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Biographies

Victor Martin Maldonado-Benitez is an Industrial Engineer from UPIICSA - IPN and holds an MBA from ESCA UST IPN and a Master's degree in Industrial Engineering specializing in Business Organization and Industrial Projects. In the field of research, he has participated in social projects, so he has a global vision of organizations. Likewise, he has among his main certifications SCRUM Agile Methodologies and Lean Six Sigma Black Belt. He has led Technology projects such as the implementation of RPA's, Artificial Intelligence models, Data Analysis and Visualization, development of projects with blockchain technology, and participation in attracting capital worldwide achieving a fundraising of 1.5 MM Dollars. He currently works as a Data Translator in one of the most important payments companies in Mexico.

Gabriela Guadalupe Escobedo Guerrero. She has a degree in Industrial Administration from UPIICSA-IPN; graduated with a Master's Degree in Politics and Management in Technological Change at CIECAS-IPN and has a

Ph.D. degree in Administrative Sciences obtained from the ESCA UST-IPN; He has a Member of the National Research System (SNI) CONACyT with the distinction: Researcher Candidate. Since 2007 he has been at the ESCAUST, where he has taught undergraduate classes in both modalities (face-to-face and distance). She is currently a researcher and teacher in the Postgraduate Studies Section of the ESCA UST-IPN; He has taught at the Master's degrees in Business Administration (MAN) and in the MAES.