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Performance evaluation of water supply networks and innovative identification of high-risk pipelines: Towards smart governance of public water services

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ABSTRACT

The scarcity of water resources has become a major global issue, exacerbated by the effects of climate change, population growth, and rapid urbanization. This issue is particularly worrying in arid and semi-arid regions, such as Morocco, where renewable water resources per capita are in constant decline, and preserving this existing resource is becoming a strategic priority. One of the essential levers to achieve this lies in reducing losses within drinking water distribution networks. This study is part of this logic and aims to optimize the reduction of technical losses in the drinking water network of the city of Casablanca. The analysis revealed an annual volume of losses exceeding 50 million m³, requiring targeted and prioritized actions. To this end, a two-step methodology was implemented: a water balance according to the standards of the International Water Association (IWA), followed by the development of a decision-making tool based on a multi-criteria risk analysis. The tool was designed in Python in the Visual Studio environment, integrating technical, historical, topographical, and operational criteria to produce a risk index for each network section. Field application helped identify high-risk areas and guide targeted interventions. A concrete case demonstrated the effectiveness of this approach: in an identified critical area, corrective actions resulted in the recovery of 300,000 m³ of water, representing an estimated saving of 1.6 million dirhams. This work confirms the potential of an integrated approach combining technical analysis, modeling, and decision support to improve network performance. The proposed tool is reproducible, scalable, and can be adapted to other urban networks facing the same challenges. It is fully in line with the dynamics of sustainable resource management and smart governance of water services.

Keywords: risk map, water supply, water loss, Python, performance, leak, location, IWA.

INTRODUCTION

Water scarcity is among the most critical socio-economic and environmental issues of the 21st century. According to the UN, in 2023, 2.3 billion people lived in areas affected by high water stress, this figure could reach more than 3.5 billion by 2050, and nearly 4 billion people face water shortages (United Nations [UN-Water], 2023).

This global crisis results from a growing imbalance between the availability and demand for freshwater, exacerbated by various factors. On the environmental level, climate change is altering hydrological regimes, impacting the spatio-temporal distribution of precipitation, intensifying droughts and floods, and accelerating the melting of glaciers (Intergovernmental Panel on Climate Change [IPCC], 2021). Furthermore, water resources are unevenly distributed (Vorosmarty et al., 2010). In addition, there are anthropogenic factors, as population growth puts pressure on available resources, particularly in expanding urban areas. Agriculture, pollution of groundwater and surface water from domestic and industrial wastewater, and poor management of agricultural infrastructure also contribute to the intensification of water scarcity (Food and Agriculture Organization of the United Nations [FAO], 2022).

Faced with this critical situation, several actions have been implemented worldwide to optimize resource management and limit water consumption. Among the most adopted approaches, integrated water resources management (IWRM) aims at a sustainable and equitable distribution of available resources (Global Water Partnership [GWP], 2009). Efforts are also being made to promote water-efficient irrigation, develop wastewater reuse and desalination technologies and encourage transboundary cooperation around shared basin (UNESCO, 2019). Through SDG6, the 2030 Agenda for Sustainable Development enshrines universal access to safe drinking water as a global priority (United Nations [UN], 2015).

Morocco is one of the countries most affected by water stress, with an availability of 600 m^3 per capita, a value below the critical threshold of 1.000 m^3 per capita, considered an indicator of water stress (Ministry of Equipment and Water, 2023). Compared to the 1960s, availability was 2.560 m^3 per capita.

This alarming situation is explained by: Lack of rainfall, inefficient agricultural techniques that consume approximately 85% of the country's water, and a heavy dependence on surface water (Ministry of Equipment and Water, 2023). Furthermore, the pollution of wadis and groundwater by domestic and industrial waste represents an additional obstacle to good management of water resources (Ministry of Equipment and Water, 2023).

To address this crisis, Morocco has implemented several strategies aimed at improving the conservation and management of water resources. The National Program for Drinking Water Supply and Irrigation 2020–2027, with an investment of 115 billion dirhams, includes the interconnection of hydraulic basins, the construction of new dams, as well as desalination and reuse of wastewater (State Secretariat in Charge of Water, 2023). Morocco is also committed to strengthening water governance through institutional reforms and actions to better manage water and combat unrevenue water losses in order to ensure rational and optimized management of resources. Every day, liters of water are wasted in nature. It is therefore essential to put in place an advanced management system.

The objective of this study is to assess water losses in the drinking water distribution system and to develop an application to identify risk areas and pipes most likely to suffer significant losses. This approach is part of a strategy to optimize water resources and effectively plan preventive and corrective actions. To do this, several aspects were addressed, namely: i) Determination of network performance indicators, ii) Use of multi-criteria analysis for predicting the risk of water loss, iii) Development and integration of a decision-making tool in geographic information systems (GIS) that would allow decision-makers to access a dynamic spatial diagnosis, facilitating the planning and proactive management of water losses, which will thus contribute to a more sustainable and efficient use of water resources.

MATERIALS AND METHODS

Presentation of the study area

The study covers the entire city of Greater Casablanca, located in northwest Morocco, along the Atlantic coast, approximately 80 km south of Rabat (High Commission for Planning, 2024). According to the 2024 census, it had a population of over four million, making Casablanca the largest city in the kingdom.

From an administrative point of view, its territory covers an area of 386 km2 (Regional Investment Center Casablanca-Settat, 2017). It is divided into 16 prefectures (Sidi Belyout, Anfa, Maârif, Al Fida, Mers Sultan, Aïn Sebaâ, Hay Mohammadi, Roches Noires, Aïn Chock, Hay Hassani, Ben M'sick, Sbata, Sidi Bernoussi, Sidi Moumen, Moulay Rachid and Sidi Othmane).

Casablanca is located solely in the Chaouia Plain, whose relief is formed by plains and plateaus punctuated by modest hills scattered across the territory neighboring the city of Casablanca, in addition to a coastal strip extending for nearly 35 km. In this area, there is an altitude variation ranging from 0 m to 157 m. The average slope is approximately 12.21%. The soil is sandy in the coastal region, while it is diverse throughout the city (Figure 1) (High Commission for Planning, 2018).

Data collection and preparation

The reliability of the study depends on the quality of the data collected on the drinking water distribution network of the city of Greater Casablanca. This study consulted several data sources spanning an eight-year period from 2017 to 2024.

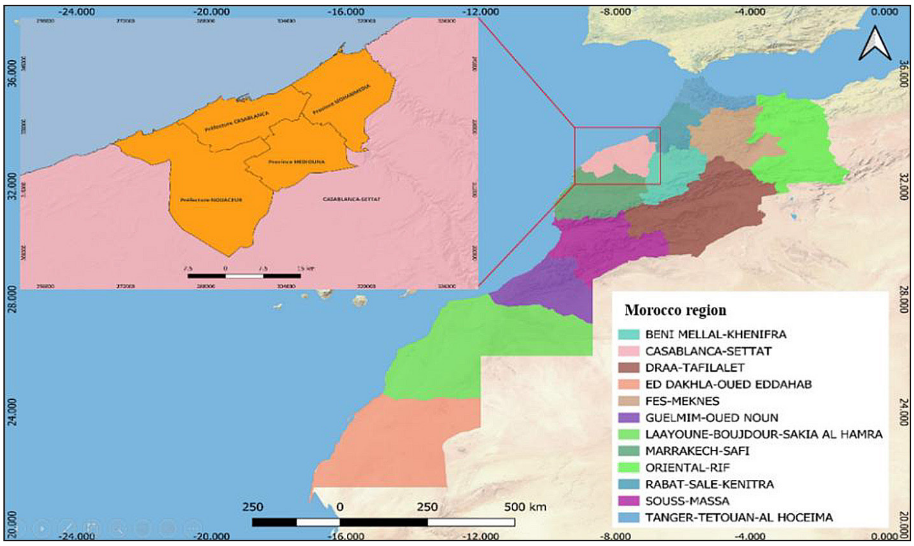

Figure 1. Administrative division of Greater Casablanca

Data sources

Data was collected from the Greater Casablanca drinking water network management services, as well as archival documents, technical reports, and field surveys. The main sources include:
- GIS maps of the drinking water distribution network.
- Databases relating to technical interventions.
- Pressure measurements recorded at various strategic points in the network.
- Leakage histories cover the period from January 2017 to December 2024.

Data collected

Each pipeline segment was characterized using the following criteria:
- Pipe age (calculated from the year of installation).
- Material (grey cast iron, ductile iron, PVC, HDPE, etc.).
- Nominal diameter (in mm).
- Average operating pressure (in m).
- Number of leaks recorded over the period 2017–2024.

These data were chosen in consultation with field engineers, and cross-referenced with scientific literature on network degradation factors.

Data preparation and processing

Data processing was performed using Python in the Visual Studio Code environment, utilizing the following libraries:
- Pandas: tabular database management.
- NumPy: mathematical and statistical operations.
- Matplotlib / Seaborn: initial graphical analyses.
- Geopandas / Folium: cartographic visualization of network segments.

The main data preparation steps were crucial to ensure the quality of the analysis. First, careful cleaning was performed to address missing or outlier values. Then, qualitative variables such as material type were transformed into risk indices to make them usable for the assessment.

The quantitative variables were then standardized to allow for their fair comparison within the multi-criteria model. Finally, a fusion of the geographic data with the technical attributes was carried out, thus allowing a more detailed and relevant spatial analysis of the risk. The results were analyzed and visualized using graphs and histograms, facilitating the interpretation of risk levels across the entire study area.

Determination of network performance indicators

The performance of a drinking water distribution network is essential to ensure reliable and sustainable service. It reflects the system's efficiency in providing water to users while minimizing losses and optimizing resources. This performance is generally measured through various indicators, such as network efficiency, linear loss indices, and leakage rates. These indicators make it possible to assess the reliability, sustainability, and efficiency of the network, and are used as steering tools for asset management and investment planning (Observatoire Sispea, 2024).

To quantify these indicators, the IWA established a water balance for the Casablanca drinking water distribution network. It helps utilities develop loss reduction strategies by distinguishing between three key elements: authorized consumption, apparent losses (measurement errors, fraud), and real losses (network leaks). This balance thus helps optimize water resource management and improve infrastructure efficiency.

Intervention strategies of the International Water Association to reduce water losses (Pilcher, 2003) (Figure 2). The methodology developed by the International Water Association to establish the balance and calculate water losses provides an objective and reliable assessment, based on the following loss indicators:

- The real loss basic index: RLB (real loss basic index).

$$RLB = \frac{V_{loss}}{L_{m+D} \times 365} \tag{1}$$

where: L_{m+D} – network length.

- The non-revenue water basic index (NRWB).

Non-revenue water (NRWB) corresponds to the difference between the quantity of water pumped by a water utility from the distribution network and the quantity of water billed to its consumers (International Water Association [IWA], 2000).

$$NRWB = \frac{V_{produced} - V_{sold}}{V_{produced}} \times 100 \tag{2}$$

- Unavoidable annual real losses (UARL):

These correspond to the minimum volume of water lost that cannot be eliminated, even with the most efficient network management. These unavoidable technical leaks are due to the physical constraints of the network (Hirner and Lambert, 2000).

$$UARL = (18L_{m+D} + 25L_{HC} + 0.8n_{HC}) \cdot 0.365 \cdot P \tag{3}$$

where: P – the average pressure value in the system analyzed, n_{HC} – the number of connections.

- The infrastructure leakage index (ILI).

This is a performance indicator used to assess the effectiveness of managing actual water losses in a distribution network (Hirner and Lambert, 2000).

$$ILI = \frac{V_{loss}}{UARL} \tag{4}$$

The following Table 1 shows the leakage performance categories based on the infrastructure leakage index (ILI) according to the World Bank Institute's banding system (Lambert et al., 2021).

Water loss risk prediction using multi-criteria analysis

Multi-criteria analysis was chosen because pipe malfunctions in drinking water networks do not depend on a single factor, but result from the interaction of structural, hydraulic, and historical variables. Pipe age, material, pressure conditions, and leak history all contribute to the degradation process. Multi-criteria analysis provides a structured framework for integrating heterogeneous indicators into single composite risk index, thus facilitating the prioritization of interventions in a transparent and quantitative manner. The main objective of water loss risk prediction is to identify the most critical network sections in order to guide preventive maintenance actions. This study

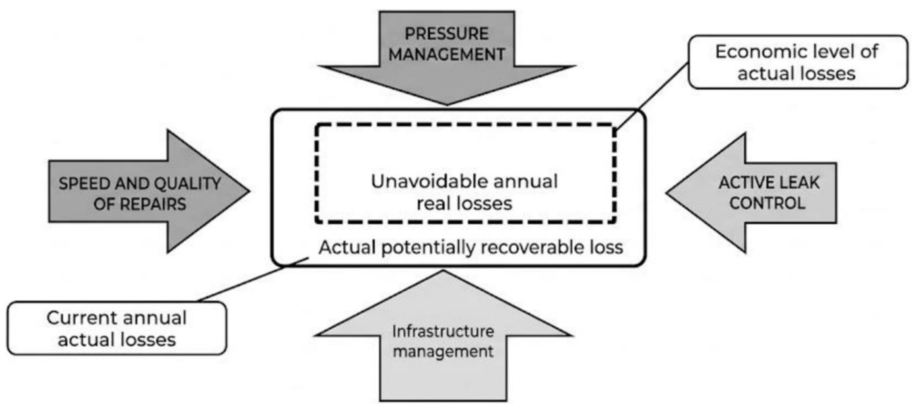

Figure 2. International water association intervention strategies to reduce water losses

Table 1. Water loss performance categories

Category	ILI index	Performance level	Interpretation
1 – Excellent	1 to 2	Excellent leak control	The network is well maintained, and water losses are close to the unavoidable minimum (UARL).
2 – Good	2 to 4	Effective loss management	Losses exist but remain under control, optimizations are possible.
3 – Average	4 to 8	High water loss	The network has significant leaks requiring reduction actions.
4 – Bad	> 8	Critical water loss	Losses are excessive, requiring urgent intervention to improve the network's watertightness.

applies the method of (Hirner and Lambert, 2000). Which defines risk as a set of probable scenarios associated with quantifiable consequences. The overall risk *Ri* for a section *i* is expressed as:

$$Ri = P \times V \times C \tag{5}$$

where: *P* is the probability of occurrence of an event, *V* is the level of vulnerability, *C* is the magnitude of the consequences.

This modeling has been widely used in the analysis of critical infrastructures and is part of modern quantitative approaches to risk management (Aven, 2011).

Based on the results obtained during the risk calculation, a scale with value intervals to determine the level of risk has been proposed, as shown in Table 2 based on several criteria (Tchorzewska-Cieślak et al., 2024):

Two weighting scales were proposed: one for the three parameters P, C, and V, and a risk assessment scale with values ranging from 1 to 27. This approach is consistent with the recommendations of the International Water Association (International Water Association [IWA], 2000).

Regarding probability P represents the estimated frequency of occurrence of an incident (leak or rupture) on a section of the network. It is generally calculated from the intervention history, expressed as the number of leaks per kilometer per year. This approach is consistent with the recommendations of the International Water Association (International Water Association [IWA], 2000) (Table 3). For consequence factor C (Table 4), the assessment criteria were based on the pipe diameter (Hirner and Lambert, 2000).

For vulnerability, V expresses the propensity of a section to fail according to its physical characteristics (age, material, diameter) and its structural condition. Old pipes or those made of fragile material have a higher level of vulnerability. Table 5 presents the classes of risk factors identified for vulnerability analysis. The ranking values were adopted based on research (Sambodja et al., 2020) and our own experience. The type of material, the age of the pipe, and the pressure were selected as factors that have a significant impact on water losses. Table 5 presents a method for estimating the parameter V from the value VI calculated according to formula (5).

In order to determine the vulnerability, the vulnerabilities identifying method (VIM) was used (Tchorzewska-Cieślak et al., 2024). For each factor, rank values R_i and weights w_{ij} should be assigned and then the vulnerability index VI should be calculated.

Table 2. Risk category

Risk value	Risk category
1 ≤ Ri ≤ 6	Low risk
7 ≤ Ri ≤ 17	Moderate risk
18 ≤ Ri ≤ 27	Very high risk

Table 3. Evaluation criteria for parameter P

Parameter	Λ	P
Low	≤0.5	1
Medium	(0.5 ÷ 1)	2
High	≥1	3

Table 4. Evaluation criteria for parameter C

Description	Diameter	C
Small	≤110 mm	1
Medium	110 mm < d < 300 mm	2
Large	≥300 mm	3

Table 5. Evaluation criteria for parameter V

Description	VI	V
Low	1.0 ≤ VI ≤ 1.67	1
Medium	1.67 < VI ≤ 2.33	2
Large	VI > 2.33	3

$$VI = \sum_{\substack{i=1 \\ j=1}}^{n,m} R_i \times w_{ij} \quad (6)$$

where: R_i – rank, w_{ij} – weight, n – number of factors, m – number of weights.

The vulnerability index (*VI*) represents a weighted aggregation of structural and operational factors considered in this study. Higher *VI* values indicate pipelines that are more susceptible to deterioration due to ageing, material characteristics, and adverse hydraulic conditions. To facilitate its integration into the overall risk assessment model, the calculated *VI* was converted into a discrete vulnerability score (V) ranging from 1 (low) to 3 (high), providing a practical and interpretable indicator for asset management and operational decision-making.

To ensure the reproducibility of the VIM, the ranking values (R_i) assigned to each criterion were established based on engineering judgment and the deterioration characteristics commonly reported for water distribution systems. Three criteria were considered in the vulnerability assessment: pipe age, pipe material, and average operating pressure. Pipe age was classified into three categories: pipes younger than 10 years ($R_i = 1$), pipes between 10 and 30 years ($R_i = 2$), and pipes older than 30 years ($R_i = 3$), reflecting the progressive increase in structural deterioration associated with ageing. Pipe materials were ranked according to their expected durability and susceptibility to failures, with PEHD and PVC assigned the lowest rank ($R_i = 1$), ductile iron (FD), asbestos cement (AC), and concrete (BC) assigned an intermediate rank ($R_i = 2$), and grey cast iron (FG) assigned the highest rank ($R_i = 3$) due to its greater susceptibility to corrosion and brittle failure. Average operating pressure was also classified into three levels: pressures below 2 bar ($R_i = 1$), between 2 and 4 bar ($R_i = 2$), and above 4 bar ($R_i = 3$), considering the increasing mechanical stress exerted on the pipeline.

The weighting coefficients (w_{ij}) were established using an expert-based weighting approach to reflect the relative contribution of each criterion to pipeline deterioration. Pipe age was assigned the highest weight ($w_{ij} = 0.40$), followed by pipe material ($w_{ij} = 0.35$) and average operating pressure ($w_{ij} = 0.25$). This weighting scheme reflects the predominant influence of ageing on structural degradation, while material properties and hydraulic operating conditions were considered secondary but significant factors affecting pipeline vulnerability. The resulting vulnerability index (VI) was then calculated using Equation 6 and classified into three vulnerability levels (low, moderate, and high) according to the thresholds presented in Table 5.

Development of the decision support tool

To facilitate the identification and prioritization of leak-risk areas and pipelines in the Casablanca drinking water distribution network, a decision support tool (DSS Decision Support System) was developed in Python, within the Visual Studio Code environment (Savić and Walters, 1997). This tool integrates all analytical processing carried out as part of the multi-criteria risk assessment, from data import to results visualization (Tanyimboh and Templeman, 2000) . It automates the calculation of risk indices based on weighted criteria and displays vulnerability scores by pipeline (Mounce and Boxall, 2010).

The interface, whether command-line or in a simplified graphical version, allows the user to load their own data, run the model, and view the results in the form of tables and maps (Folium Project Contributors, 2022). The code relies on specialized libraries such as Scikit-learn for data processing, matplotlib and seaborn for visualization, and folium for interactive mapping (Python Software Foundation, 2023). The program's modular architecture makes the tool extensible to other urban contexts or datasets (Jabbour et al., 2018).

This tool provides operational support for network managers, helping them direct preventive maintenance investments to the most critical areas, in a proactive and sustainable management approach.

Integrating the multi-criteria model into the decision support tool makes the methodology immediately operational. Managers can update input data and automatically obtain new risk maps, thus ensuring dynamic *prioritization* based on up-to-date, rather than purely reactive management.

Figure 3 illustrates the overall workflow of the decision support tool, from data input to the generation of the risk-classified network map.

Mapping and visualization of risk areas

To facilitate the interpretation of the results of the multi-criteria analysis and support decision-making by network managers, an interactive map of leak risk areas was created. Each pipeline

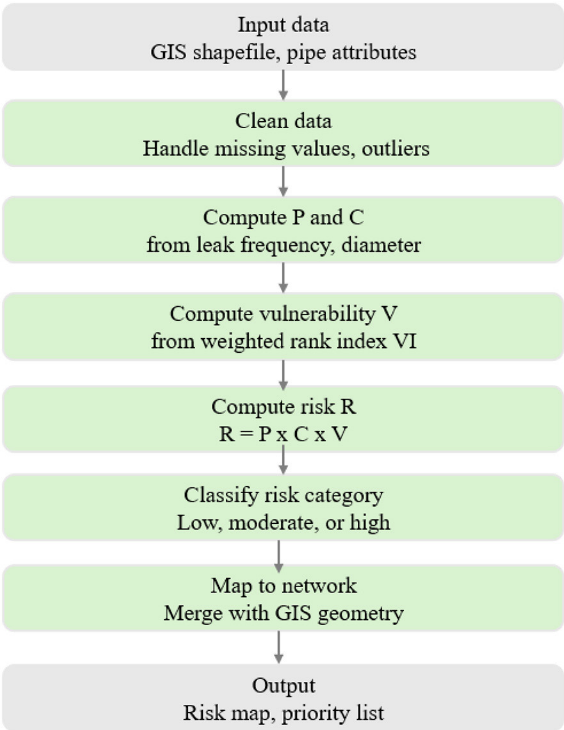

Figure 3. Risk assessment workflow

section was geolocated using GIS data provided by the network manager and then associated with an aggregated risk index, calculated using weighted criteria (age, material, leak frequency, pressure, etc.) (Jabbour et al., 2018).

The tool, developed in Python, integrates the Folium library, which generates dynamic maps based on Leaflet.js. Network segments are represented by polylines colored according to a risk gradient (from green for low-risk areas to red for high-risk areas). This representation facilitates the immediate location of priority sections for maintenance or renewal work (Folium Project Contributors, 2022).

Additional layers of information, such as population density, topography, and high-pressure areas, can be overlaid on the map for more in-depth cross-analysis. The interface also allows each section to be queried to display its detailed attributes (year of installation, material, number of leaks, etc.), thus providing a detailed and interactive spatial diagnosis of the network (Mounce and Boxall, 2010).

This geovisualization approach constitutes a powerful tool for proactive work planning, resource optimization, and communication between technical services, in line with the principles of sustainable and intelligent urban infrastructure management (Jabbour et al., 2018).

RESULTS AND DISCUSSION

Descriptive network analysis

The drinking water supply system of Greater Casablanca covers a length of 7,350 km, supplying water via 256,969 connections. The average daily distribution volume is 607,000 m³. During periods of high demand, a distribution peak can be observed, reaching up to 703,000 m³/d.

Greater Casablanca's water supply comes from two major sources, namely surface water, the Sidi Mohamed Ben Abdellah dam on Oued Bouregreg (107 million m^3 in 2021) and the Daourat and Sidi Saïd Maâchou dams located on Oued Oum Er-Rbia (109 million m^3 in 2021).

A minority contribution (< 1%) is made from two catchment areas located in Tit Mellil and Sidi Moussa Ben Ali (2 million m^3 in 2021). The water stored in the dams is subjected to a treatment process in dedicated facilities to be made potable. This process includes various phases (screening, decantation, filtration and disinfection), carried out by drinking water producers. The drinking water is then transported and stored in reservoirs, where it is checked again before being distributed to residents. The water supplied complies with current standards NM 03.7.001 and NM 03.7.002.

The year 2023 is marked by the context of water stress, and due to the lack of water in the Oum Er-Rabia basin, several actions have been adopted within the framework of the national drinking water supply and irrigation program for the period 2020–2027, among them, establishing a hydraulic link between the northern and southern parts of the city. Currently, most of the city's water supply comes from the Bouregreg (85%), while 15% of the water continues to be supplied by the Oum Er-Rabia basin.

Analysis of actions implemented on the network

Since 2009, the city of Casablanca has implemented a series of initiatives to move toward Smart Water solutions for more efficient water management, thereby supporting its urban development and ensuring good service for its residents.

These actions include improving leak detection capabilities to more quickly identify anomalies and effectively address them. The expansion of the network of fixed pre-locators ensures continuous monitoring of gray cast iron pipes and deteriorated asbestos cement pipes, thus minimizing response times. Furthermore, leak detection on large feeder pipes (DN 400 to 1000) helps limit losses on strategic infrastructure. Pressure modulation and the integration of the expert system for real-time monitoring of the Drinking Water Network allow for optimized distribution. Finally, advanced sectorization, otherwise the Casablanca drinking water network is structured according to a sectorized system, guaranteeing optimized distribution management. It is composed of 13 primary stages, 32 sub-stages and 91 hydraulic zones. This multi-level organization facilitates the monitoring, maintenance and continuous improvement of the network.

Despite numerous measures implemented to optimize drinking water network management, significant water loss persists. The loss rate reaches 23%, representing a volume of over 50 million cubic meters. This amount corresponds to approximately a quarter of the total purchased volume, resulting in an estimated financial loss of 271 million dirhams. These figures highlight the need for an in-depth analysis of performance indicators to identify the areas most affected by water losses and to intensify leak detection and reduction efforts.

IWA's assessment of the performance of the drinking water network

Analysis of the water balance results carried out across all hydraulic zones from 2017 to 2024 highlights heterogeneous trends depending on the performance indicators. Figure 4 and 5 shows the ten most vulnerable «hot zones» which record particularly high volumes of losses.

Nearly 45% of areas show an increase in NRWB, which is consistent with observation reported in other urban contexts in North Africa and the Middle East, where the obsolescence of metering equipment and the lack of structural investment lead to a progressive increase in apparent losses (El Ayoubi et al., 2022). These losses are often linked to metering errors, unauthorized connections or under-billing, and constitute a major obstacle to the economic sustainability of operators (Farley and Trow, 2018). In areas where NRWB remains stable at 55%, the literature shows that this stability often reflects a fragile balance: Current management practices are sufficient to limit degradation, but without real improvement (Kingdom et al., 2006).

The fact that 45% of areas exceed the 23% NRWB threshold is particularly concerning, as international standards recommend a level below 20% for a high-performance network (Alegre et al., 2016). The critical values observed in some central areas of Casablanca, reaching up to 50%, are reminiscent of documented cases in other large, high-density cities, where the lack of sectorization and high pressures promote undetected leaks (Lambert et al., 2021). These results highlight the need for specific strategies for older and highly stressed urban areas.

Regarding actual losses related to distributed volume (RLB), 18% of the areas show a worsening, which corresponds to the trends observed in aging networks subject to high pressures and renewal delays (Thornton et al., 2019). However, the decrease observed in 82% of the areas is encouraging, as it reflects the relative effectiveness of leak detection campaigns, sectorization and pressure modulation, strategies widely recommended by the IWA.

Finally, the evolution of the ILI reveals a worrying situation: in 32% of the areas, the value exceeds 5, a threshold considered critical by the IWA. Similar results have been reported in other contexts where the networks are old, poorly maintained and insufficiently monitored (Frauendorfer and Liemberger, 2010). These high values indicate that losses far exceed the technically unavoidable level (UARL), and confirm the urgency of targeted interventions for pressure renewal and optimization.

Overall, these findings are consistent with recent work on urban water management, which highlights the dual constraints of an aging network and limited financial resources. They also highlight that reducing NRWB and ILI is not only a technical issue, but also a strategic one to ensure water security and the economic viability of operators.

These results confirm that the performance of Casablanca's network *reflects* the typical challenges of large, developing cities, characterized by a combination of aging networks, rapid urbanization, and financial constraints limiting infrastructure renewal. However, the analysis also highlights significant spatial variability between watershed areas, fully justifying the adoption of a differentiated, risk-based approach rather than a uniform renewal strategy. This observation supports the relevance of decision-support tools

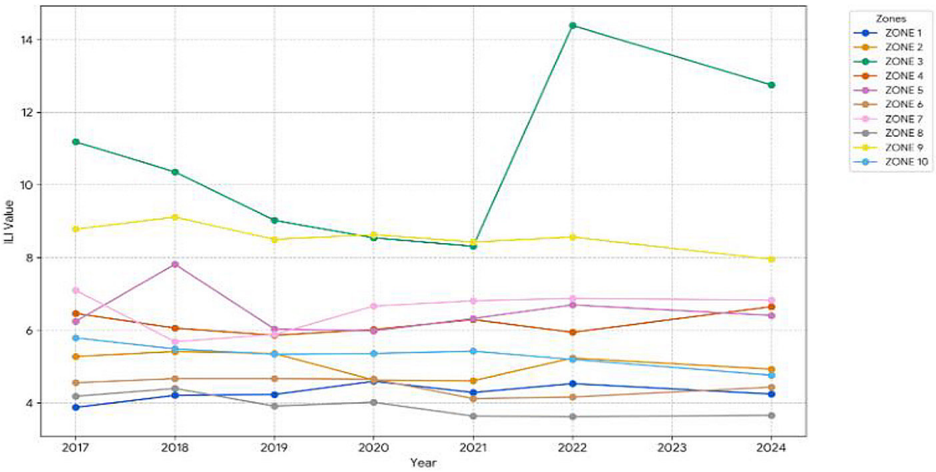

Figure 4. Evolution of infrastructure leakage index per zone

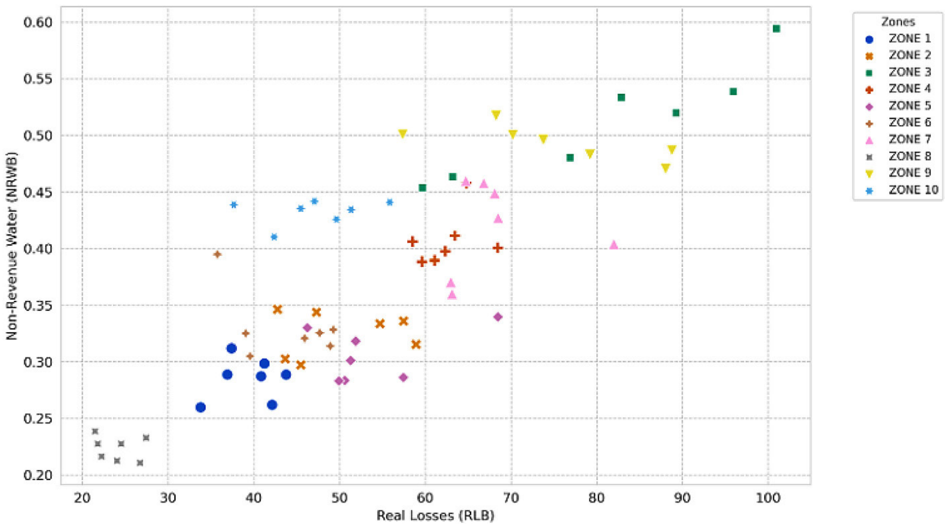

Figure 5. Relationship between real losses (RLB) and non-revenue water (NRWB)

that integrate performance indicators and local vulnerability factors.

Multi-criteria analysis for predicting the risk of water loss in the distribution network

The multi-criteria analysis conducted on the Casablanca drinking water distribution network made it possible to classify the pipeline sections according to their level of vulnerability to leaks, based on a combination of technical, environmental and historical factors (Mutikanga et al., 2013). The criteria used for this study include: the age of the pipes, the material used, the average pressure, the frequency of recorded leaks, urban density, etc. These criteria were selected based on three complementary sources: international scientific literature on pipe degradation and failure models, recommendations from the IWA, and consultation with engineers and technical managers familiar with the operational history of the Casablanca network. This combination ensures that the model reflects both scientific knowledge and real-world conditions.

Each criterion was standardized and weighted according to its relative importance in triggering or aggravating leaks, based on expert opinions and the literature (Mutikanga et al., 2013).

The weighting process was carried out using an expertise-based approach. Engineers and technical managers were asked to rank the relative importance of each factor according to its influence on the occurrence of leaks. The historical frequency of leaks was given the highest weight, as it directly reflects the actual behavior or the network, while age and material were considered major explanatory variables for structural degradation.

The results of the multi-criteria analysis highlight a differentiated vulnerability of the distribution network according to the geographical areas and the technical characteristics of the pipelines (approximately 40% of the sections present a high risk, 14% a moderate risk and 46% a low risk. The sections with a high-risk index are mainly located in sectors with old infrastructures, often combined with materials sensitive to corrosion or pressure, such as gray cast iron or steel pipes installed before the 1980s.

The significant proportion of pipes classified as high-risk confirms that the multi-criteria approach can reveal vulnerabilities that would be identifiable from a single indicator, such as age or the number of leaks. By combining historical, structural, and hydraulic variables, the model provides a systemic view of network degradation. This approach goes beyond traditional methods based solely on breakage histories, which are often limited by the under detection of invisible leaks.

An analysis was also carried out to assess the influence of each criterion on the final index. The results indicate that the frequency of historical leaks is the most determining factor (35%), followed by age (25%) and type of material (15%) (Lambert et al., 2021). This finding is consistent with several previous studies, highlighting that old networks are the most exposed to ruptures and non-visible losses, particularly in dense urban contexts.

Prioritizing the factors highlights that the network's past behavior is the best predictor of future failures, which is consistent with recent work on modeling the reliability of hydraulic infrastructure. However, the significant influence of age and material demonstrates that structural degradation remains a cumulative process, even in the absence of recent incidents. This underscores the value of a preventive rather than a purely corrective approach.

The more moderate impact of pressure nevertheless remains significant, and it shows that operating conditions play a secondary but amplifying role, particularly in areas located downstream or at topographic elevation, where overpressures or hydraulic shocks are frequent. This suggests the need for regular monitoring of pressures and careful management of pumping stations (Figures 6–8).

Mapping of priority pipelines

Based on the results of the multi-criteria risk analysis calculated for each section, a map of priority pipelines was created to visually locate the most vulnerable segments of the network. This map serves as a strategic tool for guiding investment decisions, planning interventions, and optimizing the management of human and material resources. The sections were classified into three priority categories:

High priority: sections with a risk score > 18. These are generally located in high-density hydraulic areas, with a frequent history of leaks and old infrastructure. Medium priority: sections with a score between 7 and 17. These present a moderate risk but may develop into failures if no intervention is carried out in the medium term. Low priority: sections with an index < 6, often more recent or with few recorded incidents.

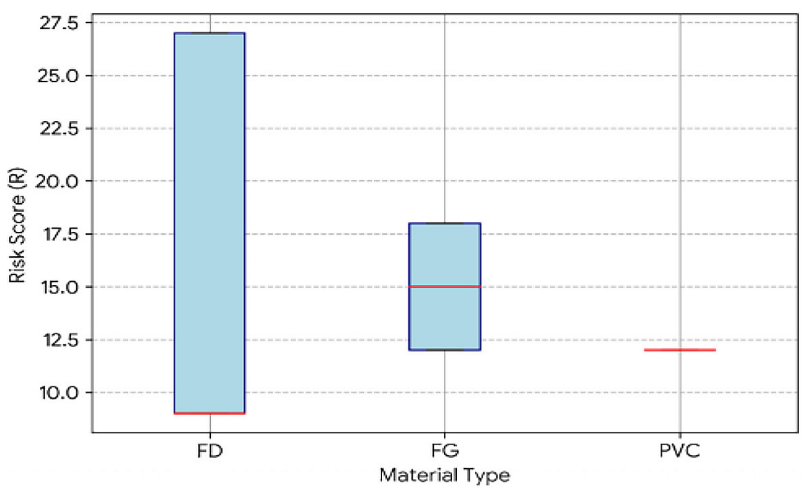

Figure 6. Risk score distribution by pipe material

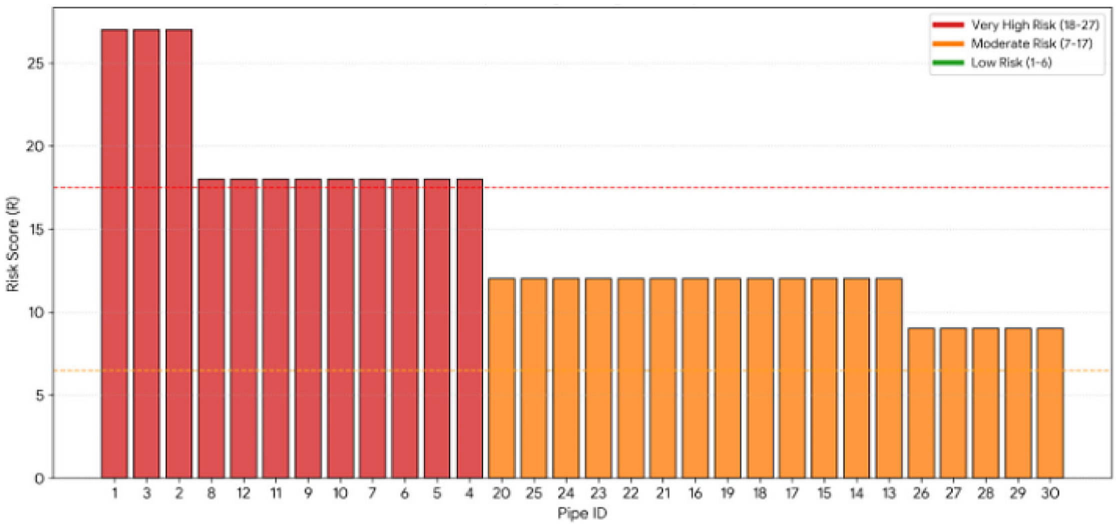

Figure 7. Risk priority ranking

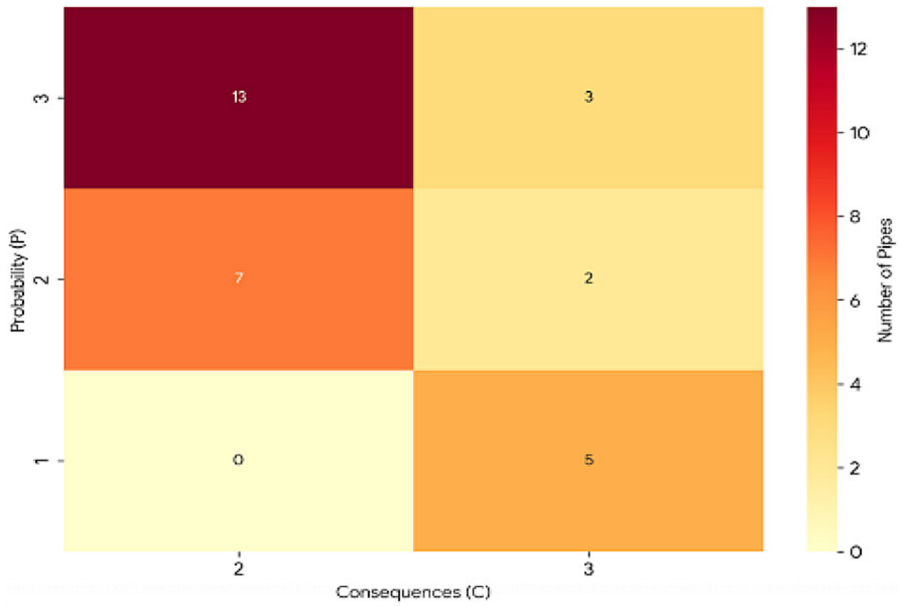

Figure 8. Matrix probability vs consequences

The interactive map developed using Folium (Python) allows these categories to be visualized using an intuitive color code (red, yellow, green).

These layers make it possible to weight the degree of urgency of an intervention not only based on technical risk, but also on the potential socio-economic impact of a failure. For example, a medium-risk section located near a hospital can be treated as a high priority.

This spatial representation of risks therefore makes it possible to guide targeted renewal work, improve the responsiveness of maintenance services, and communicate effectively with stakeholders.

FIELD VALIDATION OF THE DEVELOPED MODEL PREDICTIONS

To validate the effectiveness of the multi-criteria approach and the developed decision-making tool, fieldwork was conducted on several areas identified as high-risk by the model. Among these, an area located in the southwest region of the city drew particular attention due to an abnormal increase in the minimum nighttime flow (MNF) observed over several weeks. MNF, which represents the flow rate measured between 2 a.m. and 6 a.m., is a sensitive indicator for detecting hidden leaks (unreported by users). In this area, MNF exceeded the usual monthly average by more than 30%, which was consistent with a high value for the risk index generated by the model.

Thanks to this cross-linked alert between field data and modeling, a targeted intervention was launched by the technical services, leading to the identification of several hidden leaks, particularly in old gray cast iron pipes and near faulty joints.

Repairing these leaks resulted in the recovery of an estimated volume of over 300,000 m³ per year (Figure 4), representing an economic gain of approximately 1.6 million dirhams (MDH). These recovered losses could meet the annual needs of 315 connections. This concrete case illustrates the added value of the developed approach, allowing for faster detection of problem areas without waiting for a major failure. Integrating field indicators, such as the DMN, with the model results strengthens managers' operational intelligence (Figure 9).

In addition, the tool developed in this study, based on Python and GIS visualization libraries, was integrated into the operator's existing geographic information systems (GIS). This would allow engineers and decision-makers to access a dynamic spatial diagnosis, facilitating work planning, communication between departments, and the justification of investments to institutional partners.

This field validation confirms the predictive capacity of the developed model. The correct identification of a risk zone, followed by the effective detection of hidden leaks, demonstrates that the proposed approach is not limited to theoretical analysis but constitutes a reliable operational tool. This ability to anticipate failures before they become critical represents a significant advancement compared to traditional methods based solely on reactive interventions. It is fully aligned with a proactive and intelligent management approach for urban water networks.

Overall, this study demonstrates that integrating IWA performance indicators with spatially explicit multi-criteria analysis is an innovative approach to water loss management. It allows not only for assessing the current state of the network but also for anticipating future critical areas. This dual diagnostic and predictive dimension represents a significant contribution to the intelligent governance of public water services.

CONCLUSIONS

The main objective of this study was to optimize water losses in the distribution network in order to improve its overall performance, both technically and economically. To this end, the first phase was devoted to establishing a water balance in accordance with the recommendations of the IWA, allowing for the precise quantification of actual and apparent losses and the identification of priority areas for intervention.

Based on this diagnosis, a multi-criteria analysis was implemented, combining several technical, historical and contextual indicators to produce a risk index for each section of the network. This analysis was developed using the Python language, relying on the Visual Studio development environment, which made it possible to

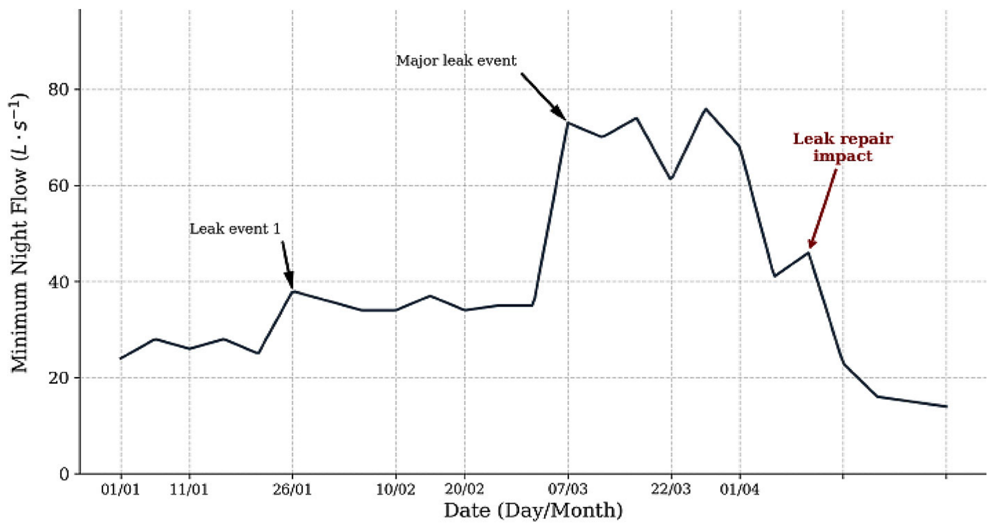

Figure 9. Impact of leak repair on minimum night flow

structure a powerful, modular tool that was easily adaptable to the specificities of the network studied. This approach made it possible to locate the most vulnerable areas and pipes and to guide interventions in a more targeted manner. The effectiveness of this approach was confirmed by field feedback, particularly in an area identified as critical, where the actions undertaken led to the recovery of approximately 300,000 m³ of water, corresponding to an economic gain estimated at 1.6 million dirhams.

The results obtained demonstrate not only the relevance of the applied methodology, but also its potential for adaptation to other urban networks, particularly in similar contexts marked by dilapidated infrastructure, growing demographic pressures, and limited resources. This approach is fully compatible with sustainable development goals, particularly those related to efficient water management and sustainable urban infrastructure.

The recommendations emerging from this study focus on several complementary areas: the implementation of priority targeting of high-risk areas for renewal work, the continuous improvement of the quality of technical data through regular updates of GIS, the installation of smart flow meters to refine loss monitoring, and the strengthening of monitoring of minimum nighttime flow as an early indicator of invisible leaks. In addition, there is ongoing training for technical teams in the use of advanced decision-making tools, the gradual deployment of the tool in other sectors of the network, and the creation of a decision-making dashboard to better inform decision-makers and manage interventions transparently.

To extend this work, several avenues for research and improvement can be considered. It would be interesting to integrate real-time data from smart sensors or SCADA systems to enrich the dynamic leak analysis. Extending the tool to other cities with different network configurations would also allow its transferability to be assessed. Furthermore, the introduction of artificial intelligence techniques, such as machine learning for automatic weighting optimization, could improve the accuracy of the risk zone prediction model. Finally, closer collaboration with local managers and decision-makers would transform the tool into a true strategic lever for water governance, aligned with urban resilience and ecological transition objectives.

In short, this integrated approach paves the way for more proactive, efficient, and sustainable management of urban water networks, by harnessing data, algorithms, and territorial intelligence to drive action.

The raw network data used in this study were provided by the Greater Casablanca drinking water network management services and are subject to confidentiality restrictions; they are therefore not publicly available. Aggregated water balance indicators (NRWB, RLB, UARL, ILI by zone and year) and the per-section risk dataset (probability, diameter, material, age, and risk score) can be provided as supplementary material or obtained from the corresponding author upon reasonable request.

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