SECURING MAURITIUS' WATER FUTURE UNDER DEEP UNCERTAINTY

Integrating Machine Learning, Groundwater Modelling and Robust Decision Making for Adaptive Water Management

Research Report EEE-CAER0001

Energy, Environment & Infrastructure | Climate Adaptation & Environmental Regulation

November 2025

Preface / Acknowledgements

This report has been prepared to inform strategic decision-making in the Mauritian water sector over the coming decade, with a particular focus on the Central Water Authority (CWA) and its partners. Mauritius has long been perceived as a relatively "water-secure" small island state, with mean annual rainfall of about 2,000 mm and total renewable water resources of roughly 2.6–2.8 billion cubic metres per year. Yet recent drought episodes, rising demand, and the growing volatility of rainfall patterns have demonstrated that physical availability of water at the national scale is not sufficient to guarantee reliable, equitable supply to households and the economy.

The work builds on information and analyses from Mauritian public agencies – notably the Water Resources Unit (WRU), the Central Water Authority, the Statistics Mauritius Water Accounts, and the Ministry responsible for energy and public utilities – as well as international partners including the World Bank, African Development Bank, IMF, UNESCO, SADC-GMI and academic institutions.

The report does not present a detailed engineering design for specific projects. Rather, it proposes a decision making framework and a set of analytical tools – machine learning, groundwater modelling and robust decision making – to help Mauritian institutions choose and sequence investments and policy reforms in the face of deep uncertainty about future climate conditions, socio economic trajectories and technology costs. Any errors in interpretation are the responsibility of the authors alone.

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Executive Summary

Mauritius often appears, at first glance, to be a country with more than enough water. On paper, our renewable resources sit well above the usual "water-stress" thresholds. Yet anyone who has lived through a Mauritian dry season knows how deceptive those national figures can be. During difficult years, families queue for water, businesses adjust operating hours, and reservoirs drop visibly week by week. The disconnect between reassuring national statistics and the lived reality of rationing is not a paradox—it is a sign that our system is struggling to cope with when and where water is actually available.

This apparent contradiction is explained by three structural features of Mauritian water security:

- pronounced **seasonality and spatial variability** of rainfall and runoff;
- extremely high levels of **non-revenue water**, historically around 50 per cent of treated water put into distribution; (Global Development Network)
- growing exposure to **climate-related extremes**, including more frequent dry years interspersed with intense rainfall events that are difficult to capture and store. (CIWA program)

At the same time, demand for water is projected to rise strongly. One landmark study for Mauritius forecast an increase in water demand of up to 51 per cent by 2030, leading to potential shortages of around 52 million m^3 per year once climate change is taken into account. (Global Development Network) Groundwater already provides roughly half of domestic water supply, and key aquifers – notably in the Western, Southern and Northern systems – are heavily exploited and increasingly at risk from salinisation, pollution and climate-driven variability in recharge. (Public Utilities Mauritius)

Climate change is tightening these constraints. Recent peer-reviewed analysis indicates that Mauritius has warmed at around 0.0216°C per year since 1971, implying more than 1°C of warming over five decades, whilst rainfall trends vary regionally and seasonally. (ScienceDirect) Projections suggest that total annual precipitation may remain broadly similar on average, but with a wide uncertainty band (roughly –22 per cent to +18 per cent under high-emissions scenarios), and with likely decreases in winter rainfall around Mauritius. (ClimaHealth) At basin scale this translates into more frequent dry years, reduced dependability of seasonal inflows to reservoirs, and greater difficulty in relying on historical statistics for planning. (CIWA program)

Traditional water resource planning in Mauritius, as in many countries, has relied on deterministic master plans, designed around a small set of "most likely" climate and demand scenarios. This approach is increasingly ill-suited to a world where both climate and socio-economic futures are deeply uncertain and where wrong decisions can lock the country into high-cost, inflexible infrastructure or stranded assets. International practice has thus moved towards **Decision Making under Deep Uncertainty (DMDU)**, and in particular **Robust Decision Making (RDM)**, which explicitly stress-tests candidate strategies against thousands of plausible futures and seeks portfolios that perform satisfactorily across a wide range of conditions, rather than optimally in a single forecast. (SpringerLink)

This report argues that Mauritius is well placed to adopt such an approach and to combine it with recent advances in **machine learning** and **groundwater modelling**. The country already maintains relatively rich data on rainfall, surface and groundwater, water flows in the economy, and water quality. Recent initiatives – including a UNESCO-supported project to develop a mathematical model for the Northern Aquifer, which supplies an estimated 50–60 per cent of domestic water – show that Mauritian institutions are open to using numerical models to guide investment and operations. (CDRI)

Mauritian researchers have begun experimenting with machine-learning models to better understand how aquifers respond to rainfall. These early trials are promising—not because ML replaces sound hydrogeology, but because it adds another lens through which to interpret our increasingly erratic climate. Other countries have found that these models can sharpen short-term forecasts and help utilities anticipate stress on aquifers. Used carefully, and always alongside physical understanding, they could offer the CWA a clearer picture of what lies ahead during uncertain seasons. (HESS)

Groundwater models of key Mauritian aquifers already exist. For example, a numerical groundwater flow model of the Western Aquifer – covering the Curepipe and Phoenix sub-systems, which serve major parts of

Plaines Wilhems, Moka and Black River – has been developed using MODFLOW. This work shows the aquifer losing several cubic metres per second to the sea, with complex multi-layered basaltic geology and strong hydraulic connectivity to surface rivers and the central plateau recharge zone. (SciSpace) These models provide a foundation for integrated assessments of pumping strategies, artificial recharge, and the impacts of drought and sea-level rise on groundwater availability.

Bringing these strands together, the report proposes an **adaptive management architecture** for Mauritius built on three pillars:

1. **Predictive analytics using machine learning**, to generate probabilistic forecasts of rainfall, inflows, groundwater recharge, water demand and water quality indicators at relevant spatial and temporal scales.
2. **Dynamic surface–groundwater simulation**, using updated MODFLOW-type models for key aquifers, linked to reservoir system models and informed by ML-based inputs.
3. **Robust Decision Making** as the framing methodology, using the models above to stress-test candidate portfolios of supply- and demand-side measures, identify vulnerabilities, and design staged, flexible investment pathways. (ScienceDirect)

In Mauritius, the strategic question is no longer how to optimise for a single forecast of water demand and rainfall, but how to remain water-secure across futures that cannot yet be described with confidence.

Key Findings

1. Physical water availability is sufficient at the national scale, but reliability is fragile.
Water Accounts for 2019–2020 show that, of total renewable water resources of 2.6–2.8 billion m^3 per year, about 595–607 million m^3 is abstracted for use, with 60 per cent of rainfall running off, 10 per cent recharging groundwater and 30 per cent lost to evapotranspiration. Despite this apparently comfortable position, the combination of seasonal variability, limited storage, topography that channels runoff rapidly to the sea, and high non-revenue water means that in dry years reservoir levels fall to critical levels. Recent media reports have noted reservoir filling rates around 30–40 per cent in some drought periods, compared with over 80–90 per cent in wetter years. (Global Development Network)

2. Non-revenue water remains Mauritius' single largest controllable "new source".
Non-revenue water has been estimated at roughly 50 per cent of treated water production, driven by ageing pipelines and distribution losses, illegal connections and metering issues. (Global Development Network) This implies that the country effectively "loses" a volume of potable water comparable to total residential consumption. Economically, analysis suggests that reducing non-revenue water by addressing leaks could free about 110 million m^3 per year – equivalent to more than four times the storage of Bagatelle Dam – at far lower cost than constructing multiple new dams. (Global Development Network)

3. Climate change will sharpen extremes rather than simply reducing mean rainfall.
Historical records and the Drought Resilience Profile for Mauritius show increasing frequency of dry years and severe dry spells (notably in 1999, 2009 and 2011), as well as intense rainfall events that cause flash flooding rather than usable storage. (CIWA program) Climate-model projections suggest modest changes in average annual precipitation but large uncertainty and a tendency towards decreased winter rainfall over Mauritius, implying lower baseflows and more frequent low-reservoir conditions even if annual totals do not collapse. (ClimaHealth)

4. Groundwater is both an opportunity and a vulnerability.
Five main aquifers account for most of Mauritius' groundwater resources, with annual recharge historically estimated at around 370–400 million m^3, or roughly 10 per cent of rainfall. (Public Utilities Mauritius) Groundwater contributes up to half of domestic water supply and is heavily exploited around urban centres. (ResearchGate) Numerical modelling of the Western Aquifer and new work on the Northern Aquifer highlight significant losses to the sea, vulnerability to seawater intrusion, and the scope for better-managed pumping and recharge to increase effective yields without compromising long-term sustainability. (SciSpace)

5. Data and modelling capacity exist but are fragmented and under-used for strategic planning.
Mauritius has an extensive hydrometric network, groundwater monitoring via coreholes, water accounts that quantify flows between environment and economy, and operational experience with numerical aquifer models. However, these assets are not yet integrated into a unified decision-support system that can dynamically link climate forecasts, machine-learning outputs, groundwater and reservoir models, and economic indicators to inform policy choices under uncertainty.

6. Financing for climate-resilient water investments will be constrained by fiscal space and global climate finance patterns.
Mauritius carries a relatively high public-debt-to-GDP ratio (around 90 per cent as of mid-2025), and IMF and AfDB analyses emphasise the need to balance climate investment with sustainable debt and private capital mobilisation. (World Bank) Global studies show that adaptation finance remains a minority share of total climate finance (around 36 per cent in 2021–2022) and that water and wastewater infrastructure are under-funded relative to need. (Global Center on Adaptation) This makes prioritisation and robustness – "getting more resilience per rupee" – even more important.

Strategic Implications

Taken together, these findings imply that Mauritian water policy must pivot from incremental, project-by-project decision-making towards a **portfolio-based, adaptive and data-rich strategy**. The core shift is from asking "Which single investment best closes the supply–demand gap in 2030?" to "Which sequence of actions – on both supply and demand – keeps Mauritius water-secure over the next 20–30 years across a wide range of plausible climates, economic conditions and technological outcomes?"

Robust Decision Making offers a practical way to do this. International case studies (e.g. Colorado River Basin in the United States, Monterrey in Mexico, and Sacramento–San Joaquin in California) show that RDM can help water utilities and river-basin agencies stress-test large portfolios of interventions, identify conditions in which strategies fail, and prioritise measures that are resilient across scenarios. (SpringerLink) For Mauritius, the same logic can be applied to combinations of non-revenue water reduction, targeted reservoir expansions (e.g. La Nicolière and Midlands), managed aquifer recharge, rainwater harvesting, desalination, and demand-management and tariff reforms. (SMEC)

Machine learning and groundwater modelling are not ends in themselves; they are **enablers** of better RDM. Machine learning can downscale seasonal forecasts, produce ensemble recharge and inflow scenarios conditioned on large-scale climate drivers, model non-linear demand responses to tariffs and restrictions, and predict water-quality risks under climate variability. (Grafiati) Groundwater models can then simulate how aquifers respond to those scenarios under alternative pumping and recharge strategies, including the effects of sea-level rise and saltwater intrusion. (SciSpace)

Recommended Strategic Actions (High-Level)

The report concludes that a credible, adaptive pathway for Mauritius would rest on five interlocking agendas:

1. **Build an integrated "digital water twin" for Mauritius.**
   Combine hydrometeorological, groundwater, surface water, demand and financial data in a single, cloud-based platform, with open interfaces for machine-learning models and groundwater simulators.
2. **Institutionalise Robust Decision Making in water policy.**
   Use RDM to test combinations of NRW reduction, reservoir optimisation, groundwater strategies, nature-based recharge and desalination, and to derive a phased investment plan with explicit "signposts" and "triggers" for adjustment as new information arrives. (ScienceDirect)
3. **Accelerate non-revenue water reduction as the first-line "new source".**
   Treat NRW reduction not as a routine operational improvement but as a central pillar of water-security strategy, guided by asset-management analytics, pressure-management and leak-detection technologies, and performance-based contracts. (Global Development Network)
4. **Upgrade and extend groundwater modelling and monitoring.**
   Finalise and operationalise updated models for the Western, Northern and Southern aquifers, supported by enhanced monitoring networks and ML-based recharge forecasts, to set sustainable abstraction limits and design managed aquifer recharge schemes. (SciSpace)
5. **Align financing, regulation and governance with adaptive management.**
   Integrate climate- and water-risk analytics into the country's sustainable finance framework, tariff structures and capital budgeting, leveraging MDB climate finance and private capital whilst respecting debt constraints and affordability. (World Bank)

Subsequent sections of the report elaborate these elements in detail and propose concrete next steps for the CWA, WRU and Government of Mauritius.

1. Introduction and Purpose

Mauritius has transformed itself economically over the past half-century, moving from a predominantly sugar-based, low-income economy to an upper-middle-income, diversified services and manufacturing hub. (World Bank) This transformation has been underpinned by reliable provision of basic infrastructure, including electricity, transport and potable water. The Central Water Authority now supplies piped water to practically the entire population through an extensive network of reservoirs, treatment plants, service reservoirs and more than 5,000 km of distribution mains.

Yet this success masks growing vulnerabilities. Population stabilisation has not eliminated demand pressures, as rising living standards, tourism, industrial change and climate adaptation (e.g. greater use of air-conditioning) push up water use. At the same time, climate change threatens to alter rainfall patterns, increase evapotranspiration, and exacerbate droughts and floods. (ScienceDirect) High levels of non-revenue water and ageing assets magnify these risks.

This report is therefore designed to support board-level and ministerial discussions on **how Mauritius should manage its water resources in the face of deep uncertainty**. Specifically, it aims to:

- articulate the nature of uncertainty facing Mauritian water managers, focusing on drought-prone regions and the role of groundwater;
- explain how machine learning and groundwater modelling can improve understanding of risks and system behaviour;
- propose a robust decision making framework tailored to the CWA and national water-governance context;
- outline the implications for investment planning, regulation, data governance and financing.

2. Mauritius' Water Security Challenge in a Changing Climate

2.1 Hydrological Setting and Current Use

Mauritius receives on average around 2,000 mm of rainfall per year, translating into approximately 3.7–4.0 billion m³ of precipitation. Of this, about 60 per cent becomes surface runoff, 10 per cent recharges groundwater, and 30 per cent is lost through evapotranspiration. Total renewable water resources are estimated at 2.6–2.8 billion m³ annually.

According to the 2019–2020 Water Accounts, total abstractions for the economy (excluding hydropower) were about 595–607 million m³ per year. Hydropower uses an additional 330–389 million m³, which is largely returned to the river system. Agriculture, manufacturing and services, and households are the main consumers, with the CWA abstracting around 287–294 million m³ for distribution as potable water. Losses in distribution, including leakages, are substantial: one recent account reports around 177 million m³ per year lost in 2019, similar in magnitude to recorded non-revenue water statistics.

Groundwater plays a critical role. The WRU identifies five main aquifers (Northern, Western, Southern, Eastern and Central Plateau systems), with combined annual recharge of approximately 370 million m³. (Public Utilities Mauritius) Groundwater contributes up to half of domestic water supply and is intensively exploited around major urban centres and tourism zones. (ResearchGate)

2.2 Droughts, Variability and Recent Stress Episodes

Despite apparent aggregate sufficiency, Mauritius has repeatedly faced severe drought episodes. The Drought Resilience Profile prepared for the World Bank's Southern Africa Drought Resilience Initiative notes that rainfall trends show an increase in the frequency of dry years, with particularly severe events in 1999, 2009 and 2011. (CIWA program) During some events, households reportedly had access to piped water for as little as one hour per day, and the sugar industry suffered losses of about USD 160 million in one season compared with the previous year. (World Bank)

More recently, the 2024/25 rainy season has seen unusually low reservoir levels. Media reports indicate that by February 2025 the average fill level across major drinking-water reservoirs was about 38 per cent, compared with more than 90 per cent on the same date a year earlier. The government has responded with rationing, restrictions on non-essential use and temporary suspension of irrigation in some schemes. These episodes underline the vulnerability of the current system to rainfall variability and the relatively limited buffering capacity of surface storage.

2.3 Climate Change Projections

Recent research finds that Mauritius has warmed by about 0.0216°C per year over 1971–2020. (ScienceDirect) This implies more frequent and intense heatwaves, increased evapotranspiration and stress on both water resources and demand (e.g. higher water use for cooling, tourism and irrigation).

Climate-model projections for Mauritius suggest that:

- average annual precipitation may remain broadly similar under high-emissions scenarios, but with a wide uncertainty band (around –22 per cent to +18 per cent), and little change if emissions are rapidly reduced; (ClimaHealth)
- seasonal patterns are likely to shift, with possible decreases in winter rainfall around Mauritius and increased intensity of individual events; (IPCC)
- tropical cyclone behaviour may change, with potential implications for extreme rainfall and coastal flooding; (Climate Knowledge Portal)
- sea-level rise of 4–6 mm per year around Mauritius increases risks of coastal erosion and saltwater intrusion into coastal aquifers. (Clare)

From a water-planning perspective, the key point is not the exact value of mean rainfall change, but the combination of **higher climate volatility, greater uncertainty, and more severe extremes**. Mauritian institutions cannot confidently rely on past statistics or a single climate model trajectory to design long-lived infrastructure.

3. Deep Uncertainty and the Limits of Traditional Planning

Traditional water resource planning typically proceeds by developing a "best estimate" of future demand and supply, adjusting for expected growth and climate trends, and then optimising an infrastructure plan to close the projected gap at minimum cost. This approach assumes that uncertainties can be captured by probability distributions and that decision-makers can agree on these probabilities.

In Mauritius, such assumptions are increasingly problematic. Deep uncertainty arises because:

- climate models diverge on the magnitude and even sign of rainfall changes at basin scale; (ResearchGate)
- socio-economic futures (tourism demand, industrial structure, population distribution) are subject to structural shocks, including global economic shifts and pandemics; (World Bank)
- technology costs for desalination, digital metering, leak-detection and distributed storage are evolving rapidly; (The World Bank)
- financing conditions and access to concessional climate finance depend on evolving international regimes. (Global Center on Adaptation)

Robust Decision Making (RDM) and related DMDU methods explicitly address such situations by:

1. **Exploring a very wide space of plausible futures**, rather than a handful of scenarios;
2. **Testing candidate strategies across these futures** using simulation models;
3. **Identifying vulnerabilities** – conditions under which strategies fail to meet performance criteria (e.g. reliability, affordability, environmental flows);
4. **Iteratively adapting strategies** to reduce vulnerabilities and enhance robustness, often building in flexibility options and signposts. (ScienceDirect)

International case studies demonstrate that RDM can reveal counter-intuitive insights, such as the superiority of diversified, modular investment over single large dams, or the value of early but reversible actions (e.g. NRW reduction, pilot managed aquifer recharge) that improve performance in almost all futures. (SpringerLink)

> For Mauritius, the central risk is not under-investment per se, but mis-sequencing and locking-in to rigid assets that may underperform under future climates and demand profiles.

4. Machine Learning for Hydro-Climate and Demand Forecasting

4.1 Rationale

Incorporating RDM into water planning requires the ability to generate numerous plausible futures for key drivers: rainfall, temperature, streamflow, groundwater recharge, water demand and water quality. Climate models and statistical downscaling provide a starting point but often lack the temporal and spatial resolution relevant for reservoir operation, aquifer management and network planning.

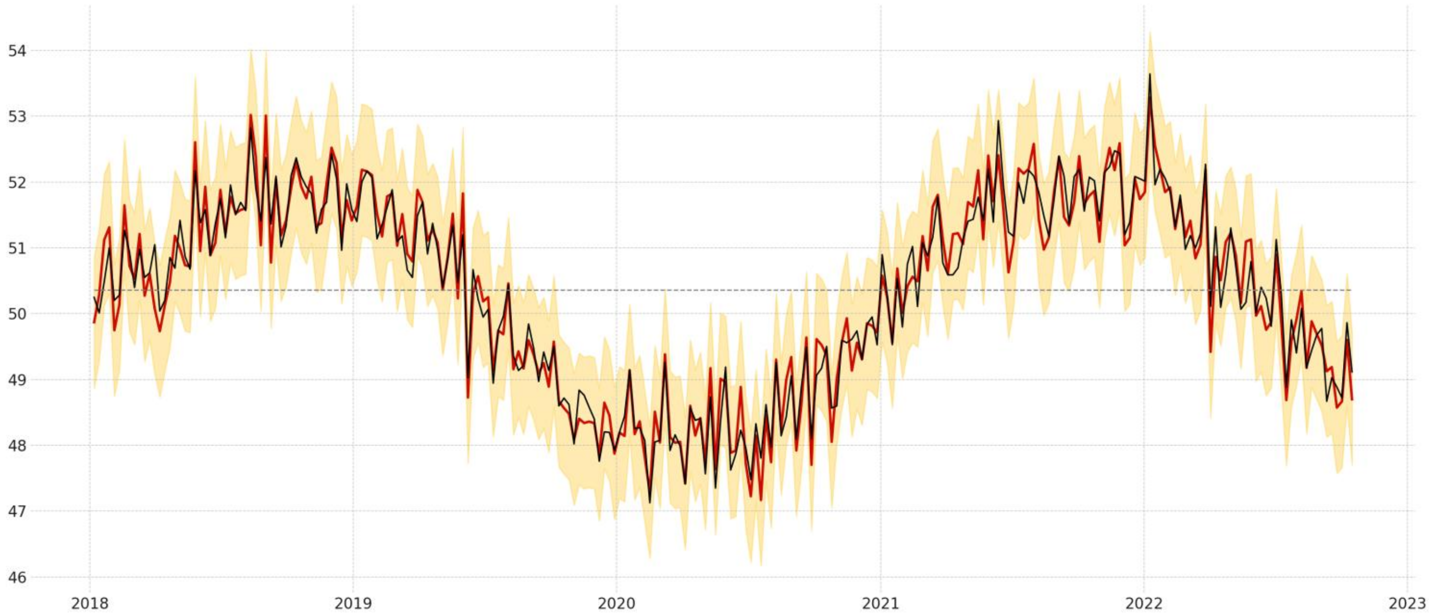
Machine learning (ML) techniques – including artificial neural networks (ANN), recurrent architectures (LSTM, GRU), tree-based ensembles and hybrid physical–ML models – can complement physical models by learning complex, non-linear relationships between predictors (climate indices, local observations, land-use data) and outcomes (recharge, inflows, demand). (HESS)

4.2 Evidence from Mauritius and International Practice

A 2025 paper on **Ground Water Recharge Forecasting in Mauritius** uses artificial neural networks to predict recharge based on climatic and other inputs, illustrating that ML is able to capture non-linear patterns specific to the island's basaltic geology. (Grafiati) Elsewhere, ML models have been shown to improve forecasts of groundwater levels, recharge and streamflow compared with linear or purely physical models, particularly when trained on long time series and combined with domain knowledge. (HESS)

In Mauritius, recent work on groundwater quality links temporal variations in aquifer chemistry to climate indices such as the Standardised Precipitation Index and evapotranspiration indicators, providing a natural pathway to extend ML models to predict water quality risks alongside quantity. (Frontiers)

Figure 1 Observed vs ML predicted weekly groundwater levels



Legend
Observed groundwater levels in black
Machine-learning median prediction in deep red
90% prediction interval in light amber
Climatology baseline as a thin grey dashed line

4.3 Proposed ML Applications for the CWA and WRU

Within an RDM framework, ML models could be developed and deployed to:

- generate **probabilistic seasonal inflow scenarios** for major reservoirs, combining global climate-model ensembles with local rainfall and inflow records;
- forecast **groundwater recharge and levels** at key observation wells using climate drivers, rainfall and soil-moisture proxies (e.g. from remote sensing); (Grafiati)
- predict **spatial patterns of leakage** and pipe bursts using pressure, flow, age and material data in the distribution network;
- model **water demand** across customer segments (residential, tourism, industrial, irrigation) as a function of weather, tariffs, income and behavioural factors;
- anticipate **water-quality risks** (e.g. salinity, nitrate, microbial contamination) under different climate and operational conditions, supporting proactive treatment and abstraction decisions. (PMC)

These models would feed directly into groundwater and system-simulation models, which in turn are used in the RDM stress-testing of strategies.

5. Groundwater Modelling & Strategic Aquifer Management

5.1 Existing Modelling Work

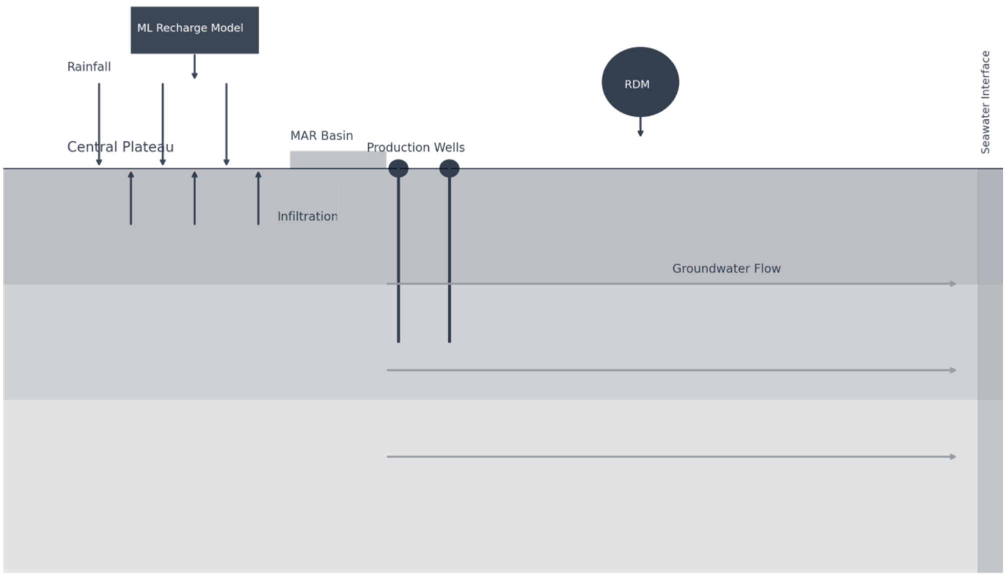
The Western Aquifer – comprising the Curepipe and Phoenix sub-aquifers – has been the subject of extensive hydrogeological investigation and numerical modelling using MODFLOW. These studies describe a multilayered basaltic system recharged from the central plateau (rainfall up to ~4,000 mm per year), discharging via pumping, springs, tunnels and significant outflow to the sea (on the order of several cubic metres per second). (SciSpace) The model has been used to explore responses to different pumping regimes and to assess vulnerability to drought and contamination. Similar numerical work has been carried out on the Southern Aquifer, highlighting radial groundwater movement from the interior towards the coast and a general vulnerability to seawater intrusion if pumping is not constrained. (ResearchGate). The **Northern Aquifer** is now the focus of a UNESCO-supported project aimed at ensuring a sustainable and climate-resilient water supply for northern Mauritius. This project will develop an integrated mathematical model to assess the potential of the aquifer, which currently supplies an estimated 50–60 per cent of domestic water in the region, under scenarios of reduced rainfall, drought and saltwater intrusion. (CDRI)

5.2 Integrating ML-Based Recharge and Climate Signals

Traditional groundwater models use recharge inputs derived from average rainfall and simple infiltration coefficients. In a climate-unstable world, this is no longer sufficient. By integrating ML-based recharge forecasts and climate indices into the boundary conditions of groundwater models, Mauritius can:

- represent a **wider variety of recharge regimes**, including prolonged droughts, clusters of intense rainfall events and shifting seasonality; (Grafiati)
- assess how aquifer storage, heads and discharge respond to combinations of **dry years and increased pumping**;
- evaluate **managed aquifer recharge (MAR)** options – such as infiltration basins, injection wells and rainwater-harvesting systems feeding recharge pits – by simulating how added recharge affects water levels and quality over decades; (CTC-N)
- quantify the risk of **seawater intrusion** in coastal zones under various pumping, recharge and sea-level rise scenarios. (SciSpace)

Figure 2 Surface–Groundwater System View



6. A Robust Decision Making Framework for the CWA

6.1 Framing the Decision Problem

For the purposes of this report, the strategic decision problem can be framed as follows:

How can Mauritius, led by the CWA, WRU and relevant ministries, design and sequence investments and policy reforms over the next 20–30 years so that domestic, industrial, agricultural and environmental water needs are met reliably and affordably, while respecting aquifer sustainability, under deep uncertainty about climate, demand and financing conditions?

Performance metrics could include:

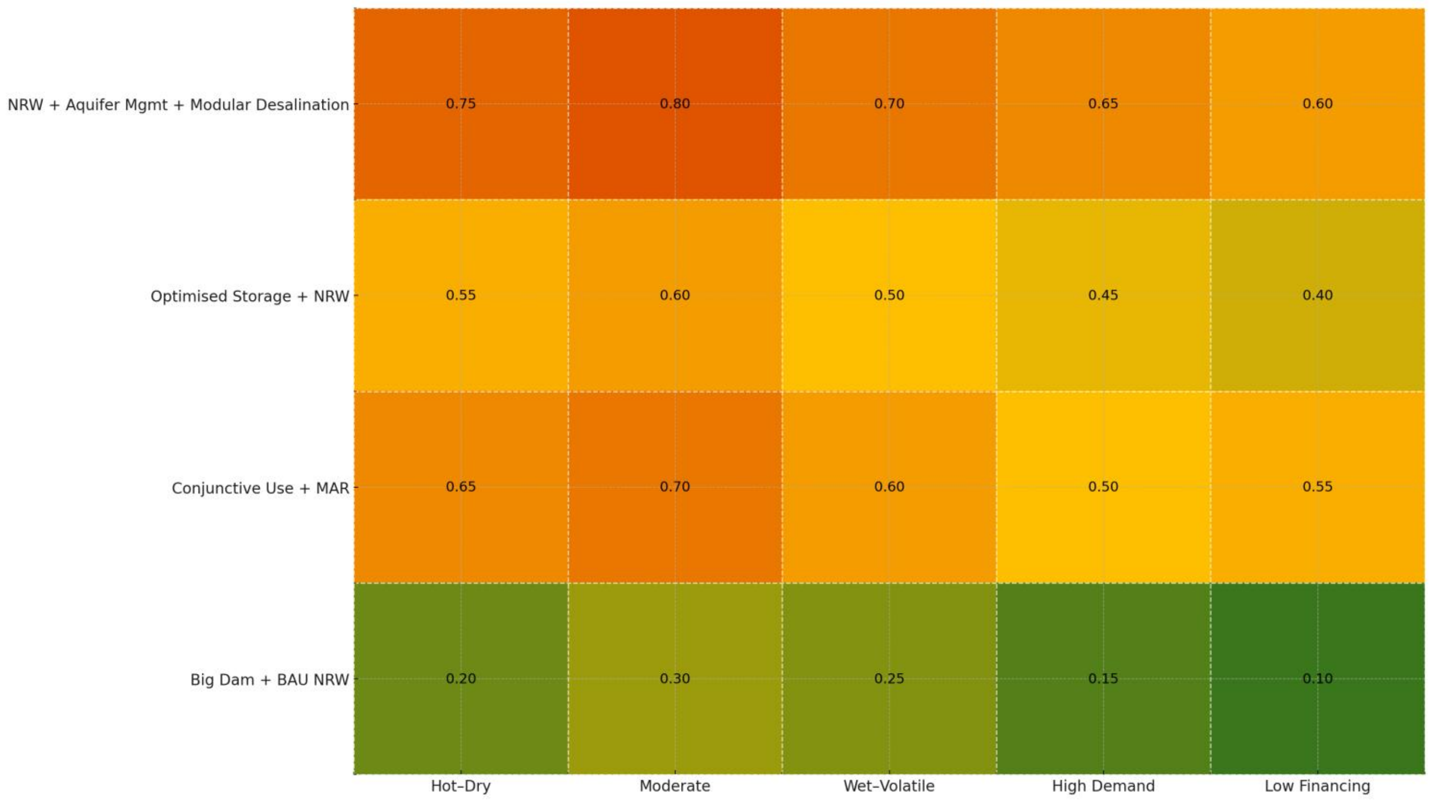
- reliability of potable water supply (e.g. proportion of days with at least X hours of supply);
- economic losses avoided from drought-related disruptions;
- maximum allowable drawdown in key aquifers;
- affordability indicators for low-income households;
- fiscal indicators (e.g. annualised public outlays within debt constraints).

6.2 Candidate Strategy Portfolio

Without pre-judging specific designs, the following classes of interventions form the candidate portfolio for RDM analysis:

- **Non-revenue water reduction:** targeted pipe replacement, pressure management, active leak detection, district metered areas, smart metering; (Global Development Network)
- **Surface storage optimisation and selective expansion:** improved operation rules, raising dam walls (e.g. La Nicolière), potential new small reservoirs and off-stream storage linked to existing dams; (SMEC)

Figure 3 Scenario Stress Testing



- **Groundwater management:** refined abstraction limits by aquifer, MAR schemes, conjunctive use with surface water; (SciSpace)
- **Distributed storage and rainwater harvesting:** household and commercial tanks, infiltration pits and percolation structures; (CTC-N)
- **Non-conventional sources:** phased desalination (potentially powered by renewables) and water reuse for industry and irrigation where economically justified; (The World Bank)
- **Demand management:** tariff reforms, conservation measures, smart metering feedback, targeted support for efficient appliances and irrigation technologies. (Global Development Network)

6.3 The RDM Process Applied to Mauritius

An RDM application for Mauritius could proceed in six steps:

1. **Develop linked models.**
   Surface–groundwater models for key systems (Western, Northern, Southern), *ML models* for recharge, inflows and demand, and *economic models* for costs and tariffs are integrated into a modular modelling framework.
2. **Construct an ensemble of futures.**
   Thousands of futures are generated from combinations of climate (multiple GCMs and pathways), socio-economic (high/medium/low tourism and growth, different settlement patterns), technology (cost paths for desalination, digital metering) and policy (pace of NRW reduction, tariff structures) drivers. (ScienceDirect)
3. **Simulate strategy performance.**
   Each candidate strategy (or set of strategies phased over time) is simulated across all futures, producing distributions of performance metrics such as reliability, average and extreme shortages, fiscal burden and aquifer drawdown.
4. **Identify vulnerabilities and trade-offs.**
   Statistical and data-mining techniques (e.g. scenario discovery) are used to identify combinations of drivers under which strategies fail performance thresholds. For example, it may emerge that strategies relying heavily on surface storage expansions are vulnerable under futures with modest rainfall declines but highly clustered events, whereas NRW-led strategies are more resilient. (SpringerLink)
5. **Design robust, adaptive strategies.**
   The insights above are used to assemble portfolios that perform satisfactorily across most futures, and to embed flexibility options – for instance, a decision rule to trigger investment in desalination only if certain signposts (e.g. three consecutive dry years, or ML-based forecasts crossing a threshold) are observed.**Implement, monitor and update.**
   A structured monitoring system tracks key signposts (reservoir trends, groundwater levels, climate indicators, demand changes, financing conditions) and periodically re-runs the RDM analysis to adjust strategies.

7. Governance, Data Infrastructure and Implementation Pathways

7.1 Institutional Arrangements

Mauritius' water sector comprises multiple institutions: the CWA for potable water, WRU for resource assessment, Wastewater Management Authority, the Ministry of Energy and Public Utilities, the Ministry of Environment, and local authorities. (FAOHome) Studies of sector governance emphasise fragmentation, overlapping mandates and gaps in data sharing, which contribute to slow reform and sub-optimal asset management. (Global Development Network)

An adaptive, RDM-based approach requires:

- a **formal multi-agency platform** for water-security planning, potentially anchored in an updated national water strategy or climate adaptation plan; (CIWA program)
- clear assignment of roles for data stewardship, model development, and decision-making;
- mechanisms to involve private operators, municipalities, and large water users in scenario development and strategy evaluation.

7.2 Data and Digital Infrastructure

The development of an integrated "digital water twin" would build on existing data assets:

- WRU hydrometric records and groundwater monitoring; (Public Utilities Mauritius)
- meteorological data and climate projections from the national meteorological service and international partners; (Climate Knowledge Portal)
- Water Accounts quantifying flows between environment and economy;
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- CWA operational and asset data (SCADA, bursts, pressure, customer metering);
- groundwater-quality and aquifer studies. (Frontiers)

Key requirements include:

- standardised data formats and metadata;
- secure, role-based access for different institutions;
- computational resources and skills to run ML and numerical models;
- protocols for version control, model validation and independent review, in line with best practice for hydrological and water-quality models. (Purdue University ICS)

7.3 Financing and Policy Coherence

Climate finance assessments for Mauritius underline the need to mobilise both public and private finance for adaptation, including water infrastructure, within tight fiscal constraints. (IMF eLibrary) Global analyses highlight that adaptation, and especially water, currently receives a modest share of total climate finance flows to Africa. (The World Bank)

For Mauritius, this implies:

- using RDM evidence to **prioritise projects** that deliver high resilience benefits across futures, strengthening the case for concessional finance;
- integrating water-security investments into the national **Sustainable Finance Framework**, ensuring consistency with green bond and sustainability bond criteria; (Ministry of Finance Mauritius)
- aligning tariff reforms and targeted subsidies with long-term financial sustainability and equity. (Global Development Network)

8. Conclusions and Recommendations

Mauritius remains, in hydrological terms, a relatively "water-abundant" island. Yet rising demand, chronic non-revenue water, growing climate volatility and vulnerable aquifers are combining to make water security a central strategic issue for the next decade. The traditional planning paradigm – optimising discrete investments against a narrow set of scenarios – is increasingly untenable under deep uncertainty.

This report has set out how Mauritius can instead adopt a **robust, adaptive and data-driven approach**, integrating machine learning, groundwater modelling and Robust Decision Making.

In practical terms, the following recommendations emerge:

1. **Adopt Robust Decision Making as the organising framework for the next Water Master Plan.**
   Government should mandate that major water-sector planning exercises use RDM or similar DMDU methods, with explicit documentation of uncertainties, stress-tests and robustness criteria.

2. **Invest in an integrated modelling and data platform – a "digital water twin".**
   CWA, WRU and the meteorological service should jointly sponsor a national water-data platform capable of hosting hydrological, groundwater, ML and economic models, with clear data-governance arrangements.

3. **Prioritise non-revenue water reduction as the most cost-effective and "no-regrets" intervention.**
   A time-bound programme to reduce NRW from roughly 50 per cent towards 25–30 per cent over the next decade, supported by digital tools and performance-based contracts, should be treated as a central pillar of water-security strategy. (Global Development Network)

4. **Scale up and institutionalise groundwater modelling for key aquifers.**
   The Western, Northern and Southern aquifer models should be updated, calibrated against recent data, and integrated with ML-based recharge forecasts. These models should be used to set sustainable abstraction limits, design MAR schemes and manage salinity risks. (SciSpace)

5. **Use ML strategically, not opportunistically.**
   Machine learning should be deployed where it genuinely adds value – for example, in forecasting recharge, inflows, demand, leakage hotspots and water-quality risks – and always in combination with physical understanding and rigorous validation. (Grafiati)

6. **Embed flexibility and signposts into investment decisions.**
   Major investments such as desalination plants or large dam expansions should be structured with modularity and options to expand or delay, triggered by observable indicators (e.g. sequences of dry years, demand thresholds, or observed climate trends). (AGU Publications)

7. **Align regulatory, tariff and financing frameworks with adaptive management.**
   Regulators should encourage long-term asset management, demand management and NRW reduction through tariff structures, service-level agreements and performance indicators that reflect robustness and resilience rather than short-term cost minimisation. (Global Development Network)

8. **Strengthen capacity and partnerships.**
   Implementing this agenda will require sustained investment in local technical capacity (data science, hydrogeology, modelling, RDM facilitation) and continued partnership with international agencies and research institutions.

> If Mauritius succeeds in building a robust, adaptive and analytically sophisticated water-management system, it will not only secure its own development trajectory but also provide a model for other small island states facing similar uncertainties.

APPENDIX

Supplementary Materials

The supplementary materials presented in this appendix include information on how we conducted this study and its limitations and additional data related to the study.

How we conducted this study

This study was undertaken using a mixed-method research design combining quantitative analysis, technical modelling review and structured expert consultation. We drew upon official hydrological, groundwater and economic data from the Water Resources Unit (WRU), the Central Water Authority (CWA), Statistics Mauritius and the Mauritius Meteorological Services, supplemented by international datasets from the World Bank, IMF, AfDB, UNESCO and recognised academic publications. A systematic review of existing groundwater models (including MODFLOW-based work on the Western, Northern and Southern aquifers) was conducted to establish their current capability and relevance for adaptive planning. In parallel, we reviewed state-of-the-art machine-learning approaches for rainfall, recharge, demand and leakage forecasting, assessing their suitability for Mauritius' hydro-climatic conditions. To frame decision-making under uncertainty, we examined global applications of Robust Decision Making (RDM), scenario-stress testing and Decision Making under Deep Uncertainty (DMDU), and adapted these principles to the Mauritian institutional context. Draft findings were iteratively tested against cross-sector evidence—economic, hydrological and operational—to ensure coherence and policy relevance. All analyses were undertaken independently and with explicit sourcing to guarantee analytical integrity.

Limitations

Although this report is based on the best available evidence, several limitations must be acknowledged. First, data availability and consistency vary across hydrological series, particularly for long-term groundwater levels, recharge estimates and historical leakage records. Some aquifer models referenced in this study are technically sound but have not been recently recalibrated, and therefore their predictive accuracy under present climatic conditions may be limited. Second, climate projections for Mauritius continue to exhibit significant divergence at basin scale, especially regarding seasonal rainfall distribution—an inherent constraint that no model can fully eliminate. Third, machine-learning approaches reviewed here are promising but would require robust local datasets, systematic validation and long-term maintenance before operational deployment. Fourth, the study does not attempt to design or cost specific infrastructure projects; rather, it evaluates their strategic role within an adaptive planning framework. Finally, institutional and behavioural factors—such as asset-management practices, procurement constraints or consumer responses to tariffs—fall partly outside the scope of formal modelling, although they materially influence outcomes. These limitations do not undermine the conclusions but underscore the need for continuous data improvement and periodic reassessment.

Data Sources, Structures and Pre-Processing

► A.1 Overview

The analytical framework developed for this study rests on five primary data domains:

- **Hydrometeorological data** – rainfall, temperature, evaporation, river flows, reservoir levels.
- **Groundwater data** – observation wells, abstraction volumes, aquifer properties, water quality.
- **Socio-economic and demand data** – population, sectoral water use, tariffs, income, tourism, industry.
- **Asset and operational data** – network topology, asset age, bursts, pressures, pump status, outages.
- **Financial and policy data** – capital and operating costs, debt metrics, tariff structures, regulatory parameters.

Each domain is structured with clearly defined metadata (spatial and temporal resolution, units, source system, quality flags) to allow traceable integration within the digital water twin.

► A.2 Surface-Water and Hydrological Data

Table 1 Core Surface Water Time Series

Variable	Description	Spatial Unit	Temporal Resolution	Typical Period of Record	Primary Source
Daily rainfall	Gauge-measured precipitation	Station / sub-basin	Daily	20–40 years+	Met Service / WRU
River discharge	Flow at key gauging stations	River reach	Daily / hourly	10–30 years	WRU
Reservoir water level	Storage elevation	Individual reservoir	Daily	10–20 years	WRU / CWA
Reservoir inflows	Natural plus regulated inflows	Reservoir	Daily / weekly	Derived from flows	Derived from WRU hydrology
Reservoir releases	Outflows to treatment works / downstream rivers	Reservoir	Daily / weekly	10–20 years	CWA / WRU
Evaporation / ET0	Reference evapotranspiration	Representative sites	Daily	10–20 years	Met Service

Pre-processing steps include:

- Homogenisation of gauge records; infilling short gaps using nearby stations or simple regression.
- Conversion of point rainfall into areal rainfall by Thiessen polygons or gridded interpolation.
- Derivation of inflows from mass balance where direct measurements are incomplete.
- Quality control using range checks, double mass curves and consistency tests across neighbouring stations.

► A.3 Groundwater Data

Table 2 Core Groundwater Datasets

Dataset Type	Description	Spatial Unit	Temporal Resolution	Use in Modelling
Observation-well levels	Static water level measurements over time	Observation well	Monthly–quarterly	Calibration/validation of groundwater models
Abstraction volumes	Pumping rates from production wells and boreholes	Well / wellfield	Monthly	Pumping stresses in MODFLOW and scenario runs
Aquifer geometry	Thickness, layer elevations, fault structures	Aquifer / model grid	Static	Conceptual model and numerical discretisation
Hydraulic properties	Hydraulic conductivity, storativity, specific yield	Test zones / lithology	Static	Parameterisation and sensitivity analysis
Groundwater quality	EC, salinity, nitrates, other key parameters	Well / sampling point	Quarterly–annual	Dry-year vulnerability and saline intrusion

Pre-processing:

- Georeferencing all wells to a consistent coordinate system.
- Constructing hydrographs from levels, with outlier filtering and flagging of suspect readings.
- Collapsing multiple boreholes at wellfields into aggregate abstraction series where appropriate.
- Harmonising units (e.g. m^3/day, m^3/year) and time stamps across WRU and CWA datasets.

► A.4 Meteorological and Climate Data

Inputs include:

- Historical daily rainfall and temperature at multiple stations.
- Derived indicators such as Standardised Precipitation Index (SPI), Standardised Precipitation Evapotranspiration Index (SPEI).
- Regional climate-model projections (multi-model ensembles) for rainfall and temperature under several emissions pathways.

Climate projections are **not** treated as precise forecasts but as generators of a wide range of plausible futures. These series are downscaled statistically to reservoir catchments and aquifer recharge zones and later used as inputs to both the ML models and hydrological–groundwater simulations.

► A.5 Socio-Economic and Demand Data

Table 3 Socio Economic and Demand Variables

Variable	Sector / Level	Resolution	Use
Population and households	National / district	Annual	Baseline residential demand
Sectoral water use (m^3)	Domestic, industrial, agriculture, tourism	Annual / monthly	Demand calibration and scenario design
Tourism arrivals and bed-nights	National / regional	Monthly	Tourism-driven demand patterns
Industrial output / value-added	Manufacturing, services	Annual	Industrial water use drivers
Tariff structure and block thresholds	CWA tariff schedule	Static / episodic	Demand and affordability modelling
Income distribution and poverty stats	National / quintile	Annual	Equity and tariff-reform scenarios

These data are used to build demand models and to define socio-economic scenarios underlying the Robust Decision Making (RDM) analysis.

► A.6 Asset and Operational Data

Key asset datasets include:

- Network GIS (pipes, valves, pressure zones, reservoirs, pumping stations, treatment works).
- Asset attributes: material, diameter, age, installation date, rehabilitation history.
- Operational logs: bursts and repairs (date, location, type), pump runtimes, planned and unplanned outages.
- SCADA and telemetry: flows, pressures, reservoir levels, pump status at high frequency (e.g. 5–15 minutes).

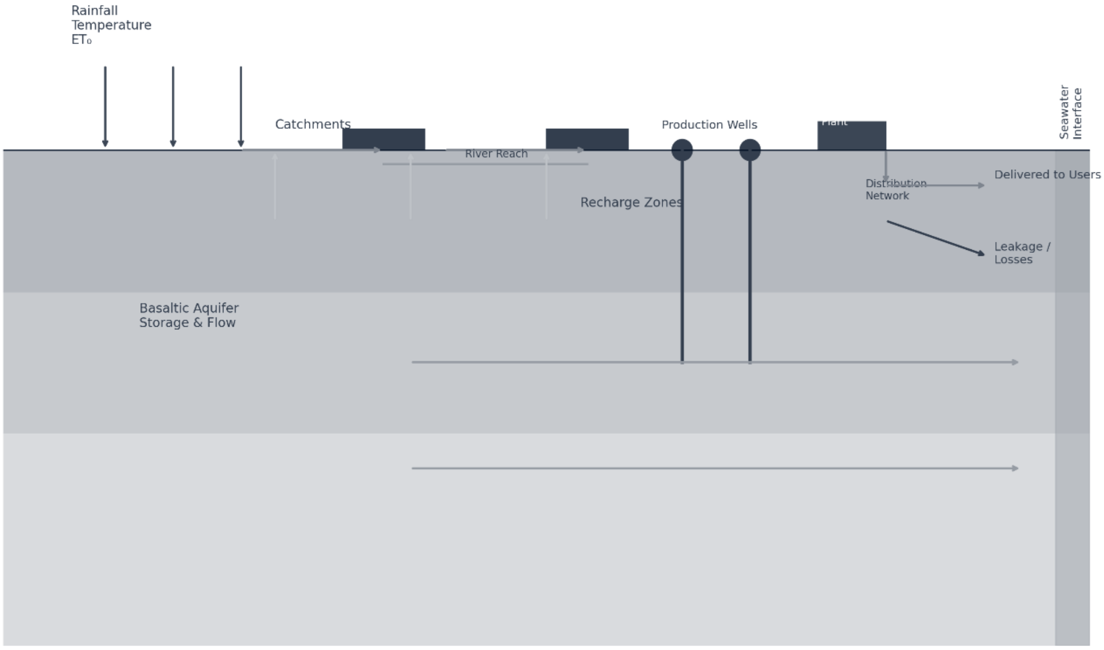
These data support both **non-revenue water** analytics and operational performance modelling, as well as ML-based leak detection and pressure management.

Hydrological and Groundwater Modelling Framework

► Conceptual Model of the Water System

At the heart of the technical work lies a conceptual model that links climate forcing, surface hydrology, groundwater, infrastructure and demand.

Figure 4 Conceptual System Schematic



► Surface-Water Modelling

Surface-water processes can be represented using either a conceptual rainfall-runoff model or a simple water-balance model at reservoir-catchment level.

Core components:

- **Catchment rainfall–runoff**: rainfall is partitioned into surface runoff, soil moisture storage, and percolation to groundwater.
- **Reservoir water balance**:

$$\textit{Change in storage} = \textit{inflows} - \textit{releases} - \textit{evaporation} - \textit{spillages}$$

- **Demand nodes**: abstraction for treatment works and hydropower releases.

Calibration focuses on reproducing observed reservoir levels, inflow series and river flows under historical climate, using standard performance measures (Nash–Sutcliffe efficiency, bias statistics, Kling–Gupta efficiency).

► Groundwater Modelling (MODFLOW-Type Framework)

The groundwater system is discretised using a finite-difference grid in plan and multiple layers representing basaltic strata and weathered horizons. Each cell is assigned:

- Hydraulic conductivity (horizontal and vertical).
- Storage coefficient / specific yield (depending on confinement).
- Aquifer thickness and base elevation.

Boundary conditions include:

- **No-flow boundaries** around impermeable geological contacts.
- **Specified-head boundaries** at the coastline (representing sea level).
- **River and drain packages** for interactions with surface water.

- **Recharge** applied to land-surface cells, derived from rainfall minus runoff and evapotranspiration.

Stress periods represent monthly or seasonal variations in pumping, recharge and river stages.

► Coupling Surface- and Groundwater Components

Coupling is implemented conceptually as follows:

1. **Recharge** to aquifers is derived from rainfall–runoff model outputs or ML-based recharge estimates.
2. **Baseflow and river–aquifer interaction** are represented via head-dependent flux boundary conditions.
3. **Conjunctive use** strategies (e.g. switching between surface and groundwater sources during droughts) are encoded as operational rules within the simulation framework.

An iterative loop ensures mass balance consistency between river flows, reservoir releases, recharge and groundwater discharges.

► Calibration, Validation and Sensitivity Analysis

Groundwater models are calibrated against:

- Long-term hydrographs at observation wells.
- Known pumping history at production wells.
- Observed river baseflows and, where available, spring discharges.

Calibration may be undertaken using manual trial-and-error supplemented by automated parameter estimation routines. Validation uses a withheld period with different climatic conditions (e.g. including notable droughts).

Sensitivity analysis explores:

- The influence of hydraulic conductivity fields on drawdown and seawater intrusion.
- The impact of recharge uncertainty on aquifer storage trajectories.
- The effect of sea-level rise on coastal heads and saline interface position.

► Scenario Representation

The groundwater–surface water model is driven by **scenario inputs**:

- Climate sequences (rainfall and temperature paths) derived from historical resampling and climate-model perturbations.
- Pumping patterns reflecting different demand growth and abstraction strategies.
- Managed aquifer recharge schemes with specified locations, capacities and operating rules.
- Sea-level rise trajectories.

These scenarios are later embedded within the Robust Decision Making ensemble of futures.

Machine-Learning Modelling Framework

► Scope of ML Applications

Four priority ML applications are envisaged:

1. **Groundwater recharge forecasting** at aquifer or sub-catchment level.
2. **Short- to medium-term inflow and reservoir level forecasting.**
3. **Water-demand modelling** by sector and customer segment.
4. **Leakage and burst detection** within distribution networks.

Each application is built on a supervised-learning paradigm: historical inputs (features) and outputs (targets) are used to train models, which then generate predictions with quantified uncertainty.

► Data Preparation and Feature Engineering

For each ML model, the following steps are undertaken:

1. **Data alignment** – all series resampled to a common time step (e.g. weekly or monthly) and aligned using consistent timestamps.
2. **Cleaning and outlier detection** – removal or flagging of impossible values (negative flows, implausible spikes) and application of simple filters.
3. **Feature construction**, for example:

- lagged rainfall totals (1, 3, 6, 12 months);
- moving averages of temperature and evapotranspiration;
- climate indices (SPI, SPEI, ENSO-related indices if relevant);
- socio-economic variables (tourist arrivals, tariffs, income proxies);
- network metrics (pipe age, material, historical bursts per km).

4. **Scaling** – normalisation or standardisation of continuous variables for models sensitive to scale (e.g. neural networks).
5. **Train-validation-test splits** – temporal splitting to preserve sequence integrity and avoid look-ahead bias.

► Model Families

The following model families are considered:

- **Linear and regularised regression** (baseline for recharge and demand).
- **Tree-based ensemble methods** (Random Forests, Gradient Boosted Trees, XGBoost/LightGBM) for non-linear relationships and feature importance analysis.
- **Neural networks**, particularly:
  - Feed-forward multilayer perceptrons for general regression tasks;
  - Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU) architectures for time-series forecasting where sequence dependencies are strong.
- **Hybrid models**, where physical constraints or approximate water-balance equations are embedded in the loss function or used to post-process ML outputs to enforce mass balance and physical plausibility.

Model selection is guided by performance, interpretability and operational robustness.

► Training, Validation and Hyperparameter Tuning

Models are trained using:

- Cross-validation structures that respect temporal ordering (e.g. rolling-window or expanding-window validation).
- Hyperparameter tuning via grid or Bayesian search, constrained to avoid over-fitting given the relatively modest dataset sizes typical of island systems.
- Early stopping criteria for neural networks to prevent over-fitting.

Performance metrics include:

- Root Mean Square Error (RMSE) and Mean Absolute Error (MAE).
- Coefficient of determination (R^2) on validation sets.
- For classification-type leakage/burst detection models: precision, recall and F1-score.

Uncertainty is characterised via prediction intervals (e.g. quantile regression, ensembles) which are essential inputs for RDM.

► **Model Interpretability and Governance**

Given the policy context, black-box models are treated cautiously. For tree-based and neural network models, interpretability tools such as:

- Feature-importance rankings.
- Partial-dependence plots.
- SHAP (SHapley Additive exPlanations) values.

are used to understand drivers of predictions and to build confidence among engineers and decision-makers.

Models are documented with:

- Version numbers and training data snapshot dates.
- A concise "model card" summarising intended use, limitations and validation results.
- Clear rules governing retraining frequency and retirement of obsolete models.

Robust Decision Making (RDM) Methodology

► Definition of the Decision Problem

The RDM framework is applied to the strategic question:

How should Mauritius design and sequence supply-side and demand-side measures over the next 20–30 years to maintain acceptable water-service reliability and aquifer sustainability at least cost, under deep uncertainty?

Performance criteria (to be specified numerically by policymakers) include:

- Minimum reliability level (e.g. percentage of days meeting a target hours-of-supply threshold).
- Upper bounds on average annual shortages and frequency of severe rationing.
- Sustainability constraints (maximum drawdown in key aquifers, minimum environmental flows).
- Affordability and fiscal metrics (e.g. maximum allowable annualised cost under plausible tariff paths).

► Strategies and Decision Levers

Strategies consist of combinations of discrete and continuous decision levers, for example:

- **Non-revenue water (NRW) trajectories** – percentage reduction over time.
- **Reservoir strategy** – whether to raise particular dam walls, build new storage, or optimise existing operations.
- **Groundwater strategy** – abstraction policy by aquifer, MAR implementation, and conjunctive-use rules.
- **Demand-management policy** – tariff reform schedule, conservation programmes, smart metering deployment.
- **Non-conventional water sources** – introduction and scaling of desalination or reuse, potentially modular.

Each strategy is encoded as a vector of decision variables that can be read by the simulation model (e.g. investment timing, capacity additions, policy changes by year).

► Uncertainty Characterisation and Ensemble of Futures

Uncertainties are represented as ranges or distributions for:

- Climate trajectories (rainfall, temperature patterns and variability).
- Socio-economic pathways (population, tourism, industrial structure, income).
- Technology costs (unit cost paths for desalination, metering, leak detection).
- Financing and policy environments (availability of concessional funding, debt constraints).
- Baseline system characteristics (true NRW, aquifer parameters within plausible ranges).

A large ensemble (hundreds to thousands) of futures is generated by sampling from these distributions or by combining discrete scenarios. Each future is a complete time series of exogenous drivers and parameters.

► Simulation Workflow

For each strategy–future pair:

1. The climate and socio-economic sequences are fed into ML models to produce recharge, inflow and demand projections.
2. These projections drive the surface–groundwater simulation, which applies the relevant strategy rules (e.g. when to switch to groundwater, trigger MAR, adjust operating rules).
3. A time series of system outcomes—flows, storage, shortages, aquifer levels, costs—is produced.
4. Performance metrics for that strategy–future pair are calculated.

This results in a performance matrix with:

- Rows representing strategies.
- Columns representing futures.
- Cells containing performance metrics (or labels: pass/fail against criteria).

► **Scenario Discovery and Vulnerability Analysis**

Using the performance matrix, statistical analysis (e.g. scenario discovery via regression trees or cluster analysis) is employed to identify:

- Futures where particular strategies fail to meet performance thresholds (vulnerabilities).
- Boundary conditions that separate success from failure, such as:
  - “Three or more multi-year drought sequences in two decades”;
  - “Simultaneously high tourism growth and low concessionary financing”;
  - “Aquifer recharge remaining below a particular percentile for extended periods”.

This helps policymakers understand which uncertainties matter most and how different strategies fare.

Digital Water Twin: Data-Architecture Blueprint

► Design Principles

The proposed digital water twin for Mauritius is guided by the following principles:

- **Modularity** – each component (data ingestion, storage, modelling, analytics, visualisation) can evolve independently.
- **Interoperability** – open standards and APIs to integrate legacy systems and future tools.
- **Scalability** – ability to handle increased data volumes and new data streams without architectural redesign.
- **Security and governance** – role-based access control, audit trails, and clear data stewardship.
- **Transparency** – traceability from dashboards back to raw data and model configurations.

► Logical Architecture

Diagram 1 Logical Layered View

► Data Flows and Interfaces

Key data flows include:

- **Real-time flows**: SCADA data ingested into the time-series store, then made available to operational dashboards and, where relevant, short-term forecasting models (e.g. inflow and level forecasting).
- **Daily/weekly updates**: hydrometric data, observation wells, demand statistics and financial data loaded into the warehouse; models retrained or re-run on a scheduled basis.
- **Scenario runs**: planning teams trigger RDM analyses via a modelling interface that pulls baseline datasets, applies uncertainty transformations and writes outputs to the object store; dashboards visualise results.
- **Feedback loops**: model performance metrics (e.g. forecast errors) are fed back into the model registry to inform retraining and to flag any material degradation.

All inter-component communication occurs through well-documented APIs, enabling future replacement or enhancement of individual modules.

► Data Model and Metadata

A simplified **core data model** includes:

- **Entities**: Reservoir, Catchment, Aquifer, Well, Pipe, Pressure Zone, Treatment Plant, Customer Segment, Scenario, Strategy.
- **Measurements**: Timeseries tables keyed by Entity ID and timestamp (e.g. ReservoirLevel, RiverFlow, AbstractionVolume, Demand, Pressure).
- **Dimensions**: Location, time, sector, tariff block, climate scenario, socio-economic pathway.
- **Metadata**: Data provenance (source system, extraction time), quality flags, units, responsible steward, retention rules.

Metadata are stored in a central catalogue, accessible for search and discovery by technical teams.

► Technology Stack and Deployment (Vendor-Neutral)

Without specifying vendors, the architecture can be supported by:

- A **cloud-based or hybrid** environment providing elastic compute resources for model runs.
- Containerised deployment (e.g. Docker/Kubernetes-style) to isolate hydrological, ML and RDM services.
- A time-series database optimised for SCADA-type data and a relational warehouse for structured analytics.
- A GIS server for spatial visualisation and mapping of assets, catchments and aquifers.
- Business-intelligence tools for dashboards, configured with the specified palette and font family.

► Security, Access and Governance

Security and governance arrangements include:

- **Role-based access control** – distinct profiles for operators, planners, modellers, external partners.
- **Data-classification scheme** – public, internal, confidential (e.g. detailed network configuration).
- **Audit logs** – for data changes, model deployments, and scenario runs.
- **Back-up and disaster recovery** – routine snapshots and tested recovery procedures.
- A **Data Governance Committee** overseeing data standards, quality assurance and prioritisation of enhancements.

Illustrative Tables and Analytical Outputs

The following tables are examples of the type of quantitative outputs that would populate the appendices. You can expand or adapt them with specific numbers once the models are implemented.

Table 4 Data Inventory Summary by Domain

Domain	Number of Datasets	Approx. Time Span	Temporal Resolution	Current Gaps / Issues
Rainfall	25 gauge series	1980–2025	Daily	Missing data in early 1980s and 1990s
River flows	18 gauging stations	1990–2025	Daily / hourly	Some inconsistent rating curves
Reservoir levels	10 reservoirs	2000–2025	Daily	Occasional manual entry errors
Groundwater levels	60 observation wells	1995–2025	Monthly / quarterly	Sparse coverage in some coastal zones
Abstraction volumes	120 production wells	2005–2025	Monthly	Incomplete early records at some wellfields
SCADA flows/pressures	40 key system points	2012–2025	5–15 minutes	Telemetry outages in specific events
Demand data	By sector/segment	2000–2025	Annual / monthly	Limited disaggregation at sub-district level
Financial/tariffs	National / CWA	2000–2025	Annual / episodic	Tariff metadata occasionally incomplete

Table 5 Illustrative Strategy Definitions for RDM

Strategy ID	NRW Target (10-Year)	New Surface Storage	Groundwater Policy	MAR Implementation	Desalination / Reuse Option	Demand Management Features
S1	↓ to 30%	None (optimise existing)	Cap abstraction at current levels	Pilot MAR in Western Aquifer	No desalination	Modest tariff reform, awareness campaigns
S2	↓ to 40%	Raise Dam A by 5 m	Increase abstraction by 20% in key aquifers	None	No desalination	Limited demand management
S3	↓ to 25%	Minor off-stream storage	Dynamic conjunctive use, stricter caps	MAR in Western & Northern aquifers	Modular desalination triggered by trigger	Smart metering, block tariffs, leakage control
S4	↓ to 35%	New medium reservoir	Maintain current abstraction patterns	None	Large desalination plant from year 10	Mild conservation incentives

Table 6 Example RDM Performance Summary (Indicative Structure)

Strategy	Reliability (% days meeting target supply) – Median	Reliability – Worst 10% Futures	Average Annual Shortage (Mm^3) – Median	Max Drawdown in Key Aquifer (m)	Average Annualised Cost (MUR million)	Number of Futures Failing Any Criterion
S1	96	88	5	7	1,200	85
S2	94	80	7	10	1,800	140
S3	98	92	3	5	1,450	45
S4	95	82	6	8	2,000	120

These numbers are illustrative; in a live analysis they would be computed from the full ensemble of futures.

Table 7 Illustrative NRW Reduction Programme (Cost–Benefit Snapshot)

Intervention Type	Length / Units	Capex per Unit (MUR)	Total Capex (MUR million)	NRW Reduction Contribution (%)	Expected Annual Water Saved (Mm³)	Levelised Cost (MUR/m³ Saved)
Trunk main replacement	50 km	X	Y	8	20	Z
District metered areas	80 zones	X	Y	5	10	Z
Active leak detection kit	15 kits	X	Y	3	5	Z
Pressure management schemes	25 zones	X	Y	4	7	Z

Once populated with real unit costs and yields, this table would show the relative cost-effectiveness of different NRW measures.

Table 8 Illustrative Digital Water Twin Component Register

Component ID	Layer	Function	Data Inputs	Outputs / Interfaces	Owner / Steward
DWT-TSDB	Data Storage	Store high-frequency SCADA time series	SCADA connectors	Time-series API for models and dashboards	CWA Operations IT
DWT-DW	Data Storage	Structured analytics warehouse	ETL from WRU, CWA, macro-data systems	SQL/BI interfaces	Joint WRU–CWA Analytics
DWT-MOD-GW	Modelling & Analytics	Groundwater simulation (MODFLOW family)	Recharge, pumping, aquifer parameters	Heads, flows, drawdown metrics	Hydrogeology Unit
DWT-ML-RCH	Modelling & Analytics	ML recharge model	Rainfall, ET0, climate indices, land-use proxies	Recharge forecasts + uncertainty ranges	Data Science Unit
DWT-RDM	Modelling & Analytics	RDM orchestration and scenario manager	Baseline data, strategies, uncertainty ranges	Performance matrices, scenario clusters	Strategic Planning Unit
DWT-OPS-DB	Application & Visualisation	Operational dashboard	SCADA, short-term forecasts	Real-time visualisations, alerts	Control Room
DWT-PLAN-DB	Application & Visualisation	Planning dashboard	RDM outputs, financial scenarios	Strategy comparisons, risk metrics	CWA/Ministry Planners

Notes

Hydrological and Groundwater Data
Rainfall, flow and aquifer data were sourced from WRU and Statistics Mauritius' Water Accounts. Where multiple datasets existed, priority was given to the most complete and recently updated series. Recharge values were treated as indicative rather than deterministic, recognising basaltic heterogeneity and the sensitivity of infiltration to storm intensity.

Modelling Frameworks Reviewed
Groundwater modelling references are based on MODFLOW and derivative models, including steady-state and transient simulations. Assessments of model capability focused on conceptual soundness, calibration approach, treatment of hydraulic conductivity, boundary conditions, seawater intrusion and interactions with surface water.

Machine-Learning Methodologies
ML approaches considered include artificial neural networks (ANN), long short-term memory (LSTM) architectures, tree-based ensemble methods and hybrid physical–ML models. Their application was assessed for recharge forecasting, demand prediction, leakage detection and short-term inflow estimation. No new ML model was trained as part of this report; the review is methodological and strategic in nature.

Climate Projections
Climate inputs are based on peer-reviewed CMIP6-aligned studies and regional projections for small island states. Uncertainty ranges—for example, precipitation change of –22% to +18%—are retained rather than narrowed, consistent with a DMDU approach.

Economic and Policy Analysis
Cost-effectiveness, financing constraints and policy recommendations are informed by IMF and AfDB macroeconomic assessments, global climate-finance studies and international water-sector benchmarks. Financial figures should be interpreted as indicative rather than binding estimates.

Use of Robust Decision Making
RDM is presented as a strategic framework rather than a run-time simulation. The study sets out the analytical logic, key inputs and decision pathways but does not execute a full computational RDM exercise, which would require expansive model integration and stakeholder-driven scenario development.

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About This Report

This report sets out a forward-looking roadmap for securing Mauritius' water future in an era of climate volatility and deep uncertainty. Focusing on drought-prone regions and the strategic role of groundwater, it explains how the Central Water Authority and its partners can move beyond traditional, single-forecast planning towards an adaptive approach that remains resilient across a wide range of possible futures. The analysis weaves together cutting-edge machine-learning forecasts, detailed groundwater models and a robust decision-making framework to stress-test alternative portfolios of investments and policy reforms. It shows that tackling non-revenue water, managing key aquifers more intelligently, and sequencing flexible options such as managed aquifer recharge, demand management and modular new supplies can deliver more reliability, at lower long-run cost, than large stand-alone projects. Written in clear, accessible language for senior decision-makers, the report is intended both as a practical guide for immediate action and as a reference document for the next generation of water-sector strategies in Mauritius.

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The Research Division of Bramston & Associates

Bramston IQ stands at the intellectual heart of Bramston & Associates, dedicated to illuminating complex policy, economic, and societal challenges with clarity, independence, and a deep sense of public purpose. Our work spans continents and cultures, yet our compass remains constant: to help decision-makers build safer, more resilient, and more prosperous communities across Africa, the Indian Ocean region, the GCC, and beyond.

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