Artificial Intelligence for Sustainable Water Management: Advances, Challenges, and Future Directions

Speaker: Prof. Ivan Serina
Department of Information Engineering, University of Brescia, Brescia, Italy
ivan.serina@unibs.it

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Overview

1 **Climate Pressure**
How non-stationary extremes and rising demand reshape water management.

2 **Motivation**
Why existing models and EO data aren't enough — bridging the integration gap?

3 **AI Across the Water Cycle**
Forecast, Detect, Optimize, and Act — examples of applied AI models.

4 **Decision Intelligence:**
Linking AI models to policies, dashboards, and robust planning.

5 **Challenges & Future Pathways:**
From data gaps and trust issues to responsible and scalable AI adoption.

This talk offers a broad overview of how AI helps to **address resource-management challenges**, using water systems (stressed by climate change, scarcity, and rising demand) as a guiding example.

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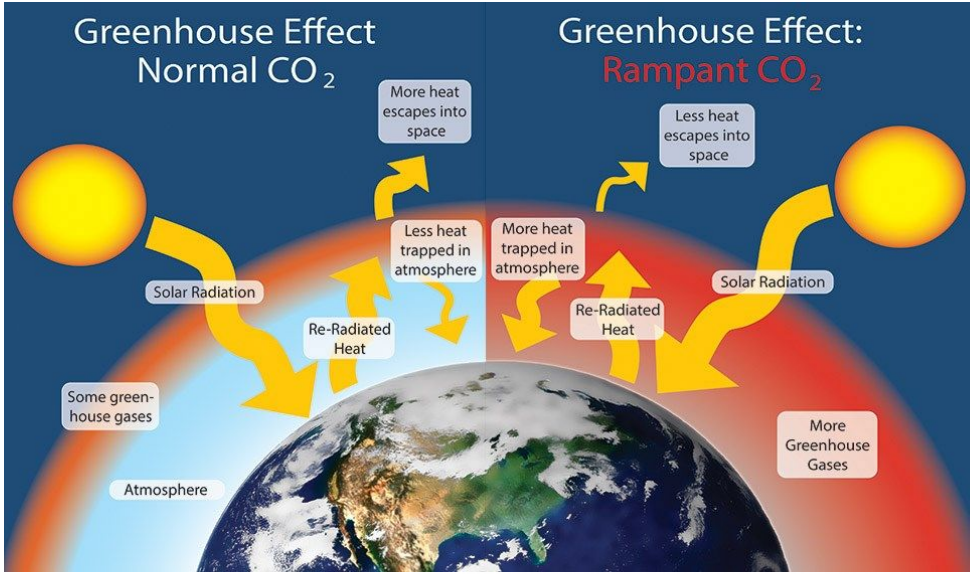
Climate Change

Climate change refers to the **long-term alteration of global weather patterns and environmental conditions,** primarily caused by human activities.

- It **alters rainfall patterns**, evapotranspiration, and water storage
- **Non-stationarity** in extremes (droughts, floods) disrupts traditional water planning
- Managing water under climate change now requires **adaptive**, data-driven, and AI-assisted tools.



(National Park Service,2020)

Climate Change Signals & Water Impacts

Non-stationary Extremes

(IPCC, 2023; WMO,2025)

Compound & Cascading Risks

(IPCC, 2023; WMO,2025)

Cryosphere Changes

(IPCC, 2023)

Heat & Aridification

(Allen, Pereira, Raes, & Smith, 1998; IPCC, 2023)

Water Quality

(IPCC, 2023)

Coasts & Deltas

(Werner et al., 2013; WMO,2025)

Governance & Equity Strain

(IPCC, 2023)

(Source theinvisiblenarad.com and thegeopolitics.com)

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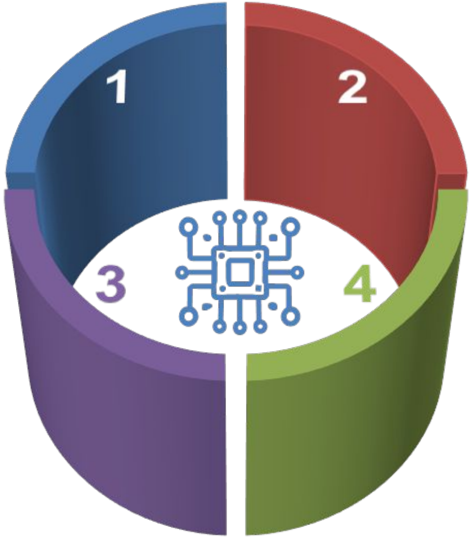
AI Techniques for Water Management



Forecast

Anticipate Demand & Supply
Use AI to forecast ***streamflow, evapotranspiration,*** and demand for smarter planning.

Detect

Monitor & Diagnose
Detect ***anomalies*** in ***water quality, leakage, or operational stress,*** early warning for managers.

Optimize

Plan & Allocate Efficiently
Optimize ***allocation, recharge,*** and ***operational schedules*** under constraints.

Act

Implement & Learn
Turn **model insights into auditable decisions** e.g., for pumping, recharge, or tariff adjustments.

From forecasting to control, AI supports **smarter allocation, demand reduction, recharge, and water-quality protection,** turning data into **auditable, actionable decisions** under scarcity.

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Motivation (Scarcity & Operations)

Scarcity is intensifying

Hotter baselines, shifting extremes, and rising demand; many basins under high stress; balance reliability, affordability, and environmental flows. *(IPCC,2023; WMO,2025)*

Data & physics models and EO

Strong physics models and rich EO datasets exists but using them together in real time is slow and technically demanding. *(Maurer, 2001; Gochis et al.,2020; Langevin et al.,2022; Liu et al.,2023; Sharifian et al.,2023; Zhao, 2025)*

AI enables faster forecasts

AI enables faster forecasts, hybrid data assimilation, surrogates, and decision optimization with calibrated uncertainty and traceability. (Fraehr et al.,2024; Tripathy et al.,2024; Huynh et al.,2025; Maußner et al.,2025)

Outcome

Proactive, scarcity-aware operations with robust policies, WA+ accounting, and coverage-guaranteed forecasts. (Haasnoot et al., 2013; Karimi et al.,2013; Lempert 2019; Auer et al.,,2024)

The tools exist but the *bottleneck is turning scattered data into timely decisions.*

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Where AI Fits in Water Management

AI Augments Four Decision Layers

Supply	Demand	Allocation	Operations
Reuse, Desalination, MAR	Forecasting, NRW Reduction	Rules, Priorities, Environmental Flows	Networks, Reservoirs, Groundwater

Techniques span forecasting, physics-ML hybrids, data assimilation, optimization/RL, anomaly detection, and decision-under-uncertainty frameworks. *(Tripathy & Mishra 2024; Huynh et al. 2025)*

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Forecasting Demand, Streamflow

Use deep-learning models (including LSTM and Transformers) generate short-term, probabilistic forecasts used to plan pumping, treatment, and irrigation.

(Maußner et al., 2025; Wunsch et al., 2024)

Feature sets: Normalized Water Permeability (NWP), calendar patterns, EO-derived ***ET₀***/Normalized difference vegetation index (NDVI), and network telemetry; report quantiles and coverage guarantees (e.g., conformal prediction) → generate forecasts with uncertainty ranges.

(Kossieris et al., 2024; Ahmadi et al., 2023)

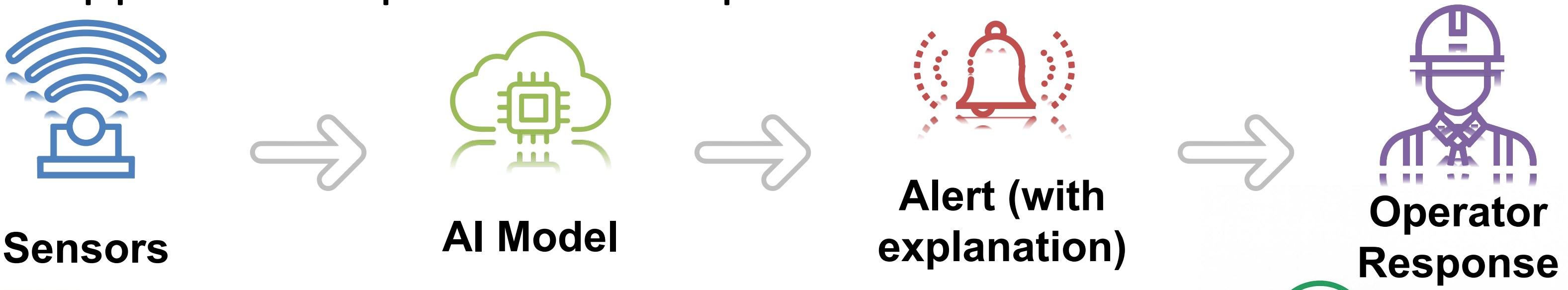
****Definition of*** ET_0*: evapotranspiration from a hypothetical, well-watered reference grass surface under standard conditions; commonly computed with FAO-56 Penman–Monteith; units* $mm \cdot day^{-1}$.

(Allen, Pereira, Raes, & Smith, 1998).

Water-Quality Anomaly Detection and Early Warning

Unsupervised anomaly models (autoencoders, Isolation Forest, one-class SVM) and conformal detection flag deviations in pH, EC, turbidity, residual chlorine, and TOC. *(Kanyama et al., 2024; Hanifa et al., 2025; Prabu et al., 2025).*

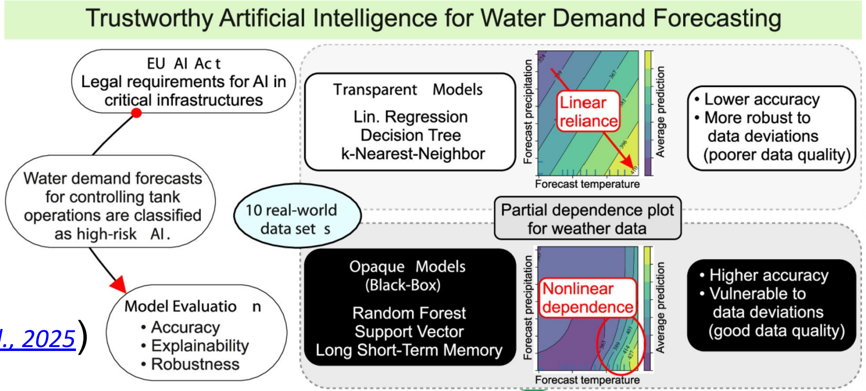
Provide human-readable attributions and dynamic thresholds to support safe operational responses. *(Hanifa et al., 2025).*



Urban Demand Management, Tariffs, and Equity

Interpretable forecasting (SHAP over gradient-boosted or deep models) supports dynamic tariffs, pressure management, and campaign timing (Tripathy & Mishra, 2024)

Causal inference (DID/PSM) estimates policy impacts so utilities scale what truly reduces demand without harming vulnerable users (Maußner et al., 2025; Tripathy & Mishra, 2024).

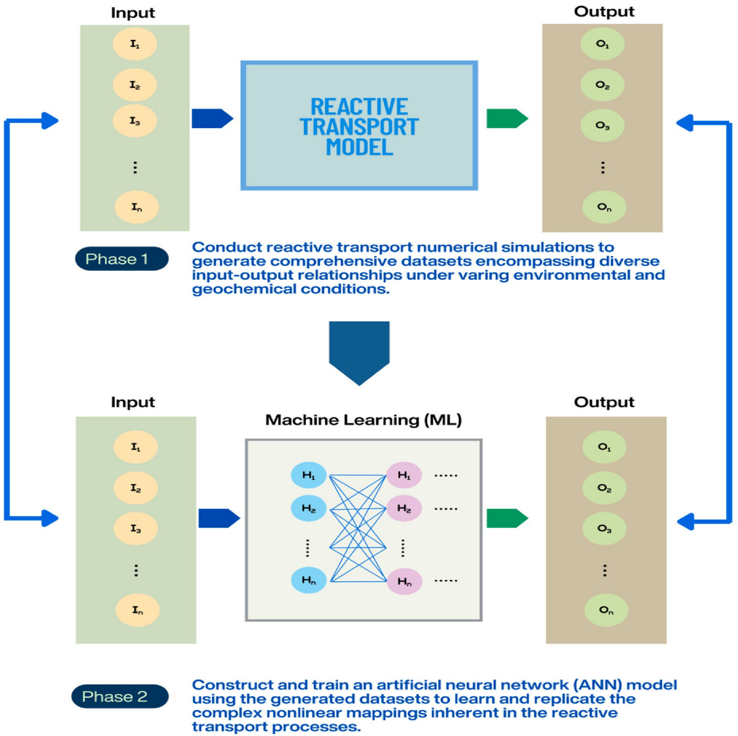


(Maußner et al., 2025)

Physics-Guided Surrogates for Speed and Scale

Train DeepONets/GNNs/… against trusted simulators: SWAT/VIC (flows, nutrients), MODFLOW (heads, storage), HEC-RAS/LISFLOOD-FP (stages, inundation) (Arnold et al., 1998; Liang et al., 1994; Bieger, 2017; HEC 2021).

Enforce mass balance; report uncertainty via ensembles or conformal coverage; typical speedups 10×–1000× (HEC 2021; Diersch, 2014; Auer et al., 2024).



(Nguyen, 2025)

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Conjunctive Use and Managed Aquifer Recharge

Couple MODFLOW-6/OWHM with AI surrogates (PINNs, DeepONets, GNN-mesh) to accelerate scenario sweeps

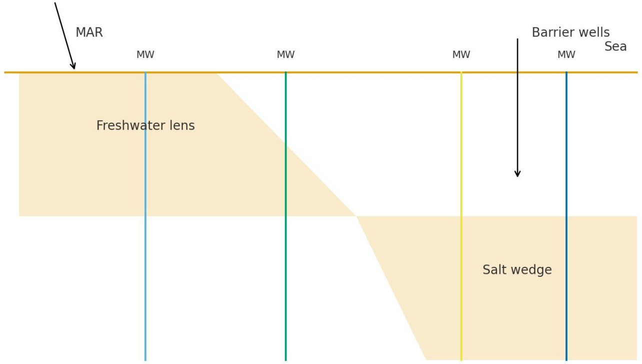
(Alattar, 2020; Langevin, 2022)

Optimize pumping/recharge via safe RL or Bayesian Optimization subject to piezometric, salinity, cost, and equity constraints; implement seasonal rules with triggers and signposts. *(Boyce et al., 2020; Alattar et al., 2020; Kong et al., 2025)*

Coastal Aquifers and Saline Intrusion Control

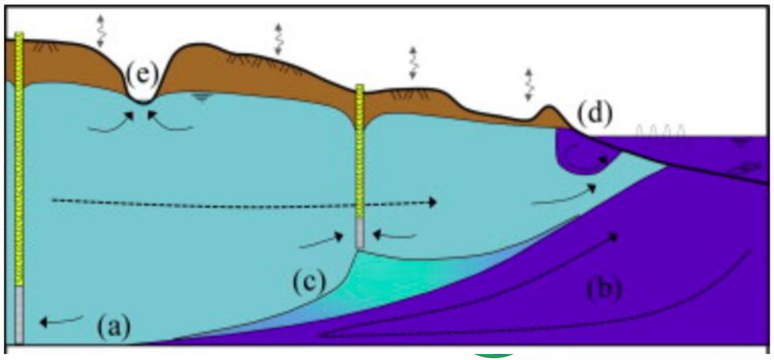
SEAWAT/SUTRA with physics-guided surrogates predicts salt-front dynamics. *(Voss, 1984; Voss, 2002; Werner et al., 2013)*

Policies blend MAR, barrier wells, and well-rotation, triggered by chloride and head thresholds with risk horizons for critical users. *(Langevin & Guo, 2006; Werner et al., 2013; Voss, 1984).*



(Jiang,2025)

(*Werner et al., 2013*)



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Decision Intelligence and Robust Planning

Use robust decision methods (such as RDM and DAPP) to test policies across many possible climate and demand uncertainties *(Lempert 2019; Haasnoot et al., 2013)..*

Communicate trade-offs using visual tools (like Pareto fronts) and define ‘triggers’ for adaptive pathways. *(Haasnoot et al., 2013).*

Build stress-test ensembles (weather generators, socio-economic pathways) and evaluate reliability, resilience, and vulnerability metrics under multiple futures *(Lempert 2019).*

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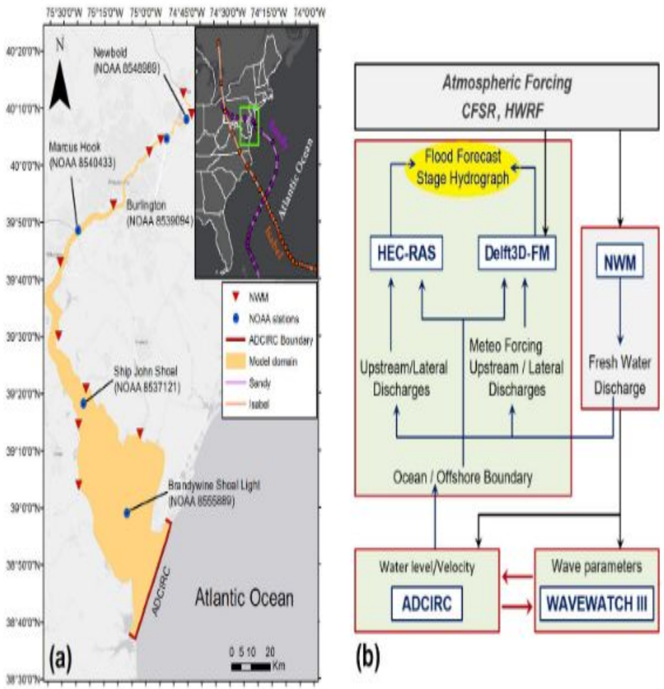
Reservoir and Network Operations

Model-Predictive Control with surrogates of HEC-RAS/LISFLOOD-FP/.. enables real-time set-points that meet flood-risk and environmental-flow constraints. *(Fraehr et al., 2024).*

Safe RL explores Pareto trade-offs between reliability, resilience, vulnerability, and energy costs. *(Besseling et al., 2024).*



(Muñoz, David F., et al. 2022)

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Irrigation Intelligence from Field to District

Smart Irrigation Scheduling

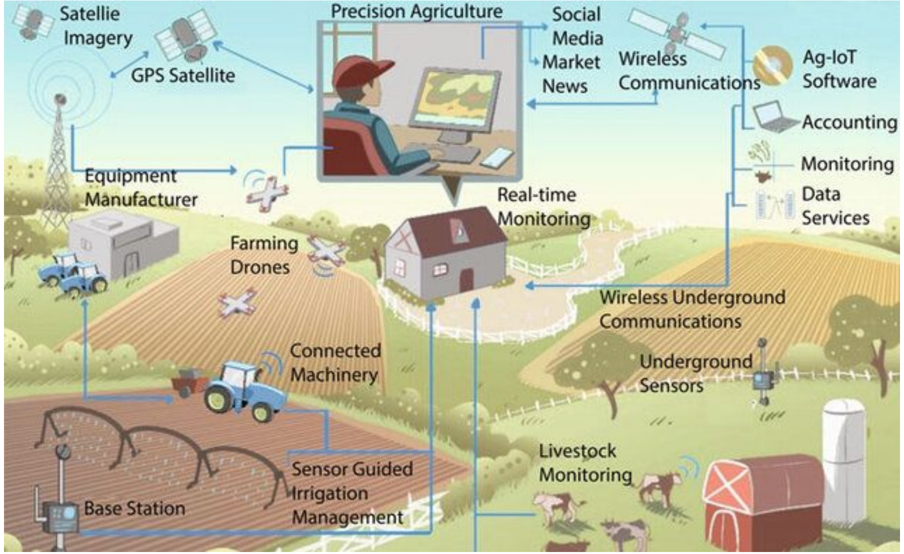
Satellite-based estimates of crop water use to suggest irrigation schedules while respecting water limits ensuring fair distribution among farmers. *(Dong et al., 2024)*

Coordinated Decisions

Coordination among multiple farms to optimize water use, crop yield, and nutrient balance, working together with hydrological models like SWAT/SWAT+. *(Ahmadi et al., 2023)*

Transparent Water Accounting

Maintain transparent basin accounting with WA+ sheets. *(Karimi et al., 2013)*



Salam, A. (2024)

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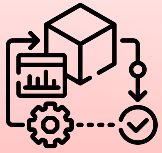
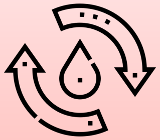
Trust, Auditing, and Responsible MLOps



Adopt model cards and datasheets; track data lineage; monitor drift; provide local/global explanations (SHAP, sensitivity analysis).

Calibrate prediction sets for guaranteed coverage and quantify reliability using conformal prediction (*Auer et al., 2024*; *Yue et al., 2025*).



Report the energy/water footprint of ML workloads and align with procurement/ethics guidelines (*Tripathy & Mishra, 2024*).

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Challenges (Scarcity-Focused)

01

Non-stationarity

shifting extremes break historical patterns; require continual recalibration and uncertainty guarantees

(*WMO, 2025*).

02

Data gaps & fragmentation

uneven observations and siloed systems slow integration; adopt open interfaces and model coupling

(*Tanguy, 2025*)

03

Groundwater blind spot

storage loss and subsidence amplify scarcity; bring subsurface metrics into operations

(*WMO, 2025*).

04

Operational trust

accuracy is not enough—need calibrated prediction sets, drift monitoring, and human-on-the-loop

(*Auer et al., 2024*).

05

Governance & compliance

high-risk obligations under the EU AI Act demand risk management, logging, and transparency by design

((*European Union, 2024–2026*).

Challenges (Data, Ops, Governance)

01

Imbalanced data & extremes

rare events are under-represented, causing biased training and overconfident forecasts; use extreme-aware losses, resampling, and calibrated prediction sets

(WMO, 2025; Auer et al., 2024).

02

Transfer across basins/climates

models don't generalize without domain adaptation and careful validation; avoid data leakage and overfitting

(Tripathy & Mishra, 2024; Du et al., 2025).

03

Ground-truth quality/latency

abstractions, leakage, and illegal wells are noisy or latent; leverage weak supervision and data fusion to triangulate signals

(Karimi et al., 2013; Liu et al., 2023, Romero-Ben, 2023).

04

Reproducibility & benchmarks

inconsistent splits and hidden test leakage undermine claims; adopt open datasets, versioned pipelines, and shared tasks

(Tripathy & Mishra, 2024; Huynh et al.,2025).

Challenges (Data, Ops, Governance)

05

Interoperability & lock-in

proprietary formats/APIs block ops integration; mandate open standards and BMI-style coupling for models and services

(Hutton,2020)

06

Safety, security, & liability

water is critical infrastructure—design fail-safe modes, audit logs, and rollback plans aligned with high-risk obligations

(European Union, 2024–2026)

07

Skills & change management

operators need playbooks, training, and escalation paths to trust and act on ML outputs

(Tripathy & Mishra, 2024).

08

Environmental footprint & cost

favor parsimonious models, quantization, and job scheduling; measure and disclose operational KPIs

(Tripathy & Mishra, 2024).

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Take-Home Messages

Water is a stress-test for AI
Nonstationarity, safety constraints, and high stakes expose the limits of current methods.

Hybrid beats pure
The most useful models combine ML with physics, simulators, and domain knowledge.

Decisions over metrics
What ultimately matters is not RMSE, but better, safer decisions under uncertainty.

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Future Directions

01

Physics-guided emulators

with mass-balance checks and conformal coverage for fast, auditable scenario analysis.

(*Auer et al., 2024*; *Tripathy et al., 2024*; *Du et al., 2025*).

02

Hybrid data assimilation at scale

learned operators inside EnKF/ETKF/particle filters with GRACE-FO, InSAR, Sentinel .

(*Liu et al., 2023*).

03

Scarcity-first digital twins

make storage (TWS/groundwater) first-class; pair actions with transparent WA+ accounting.

(*Karimi et al., 2013*; *Ghorbani Bam, 2025*).

04

Robust decision pipelines (not best-forecast):

RDM/DAPP with signposts and triggers baked into tools.

(*Lempert 2019*; *Haasnoot et al., 2013*)

05

Interoperability by default

require open standards for models/data to reduce lock-in.

(*Hutton,2020*)

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Thanks for Your Attention

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ivan.serina@unibs.it

References

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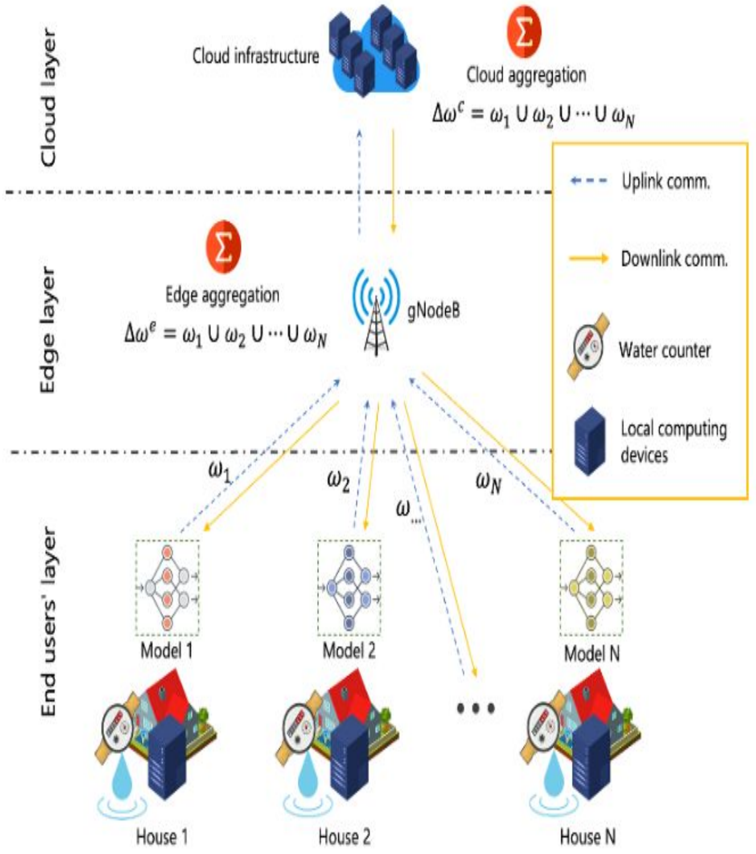
Federated Learning for Collaborative Modeling

A machine learning approach where models are trained across multiple decentralized datasets (e.g. across different utilities or regions) without aggregating the data in one place

(https://arxiv.org/abs/2301.13036).

In water management, data often resides with different stakeholders (utilities, districts) and may be privacy-sensitive (e.g. household water usage).



AI4Water

Edge AI for Real-Time Monitoring and Control

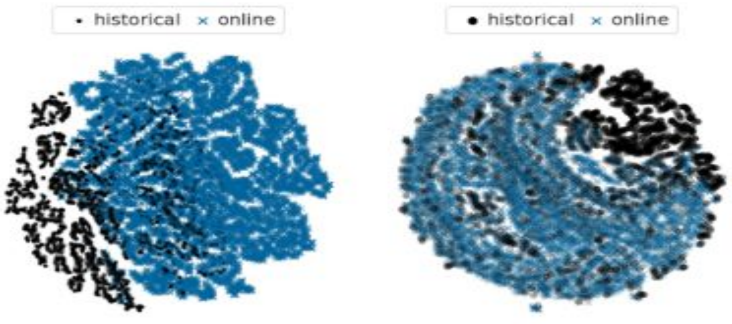
Deploying AI models on edge devices (such as sensor nodes, PLCs, or industrial PCs at pumping stations and treatment plants) so that data is processed locally, near its source (blog.se.com).

Emphasizing edge AI in the presentation would give practitioners a pathway to implement AI in the field for flood control gates, irrigation pivots, or water quality sensors, enhancing reliability and resilience of operations.

Online Learning and Concept Drift Adaptation

Techniques that enable AI models to update continuously or periodically as new data arrives, instead of being trained once and kept static https://arxiv.org/abs/2412.08435

Research in machine learning shows that traditional batch models can fail under drifting conditions, whereas stream learning methods that continuously update can maintain performance by adapting to new concepts riverml.xyz



(a) Concepts (b) Concept drifts

AI4Water

Climate Change

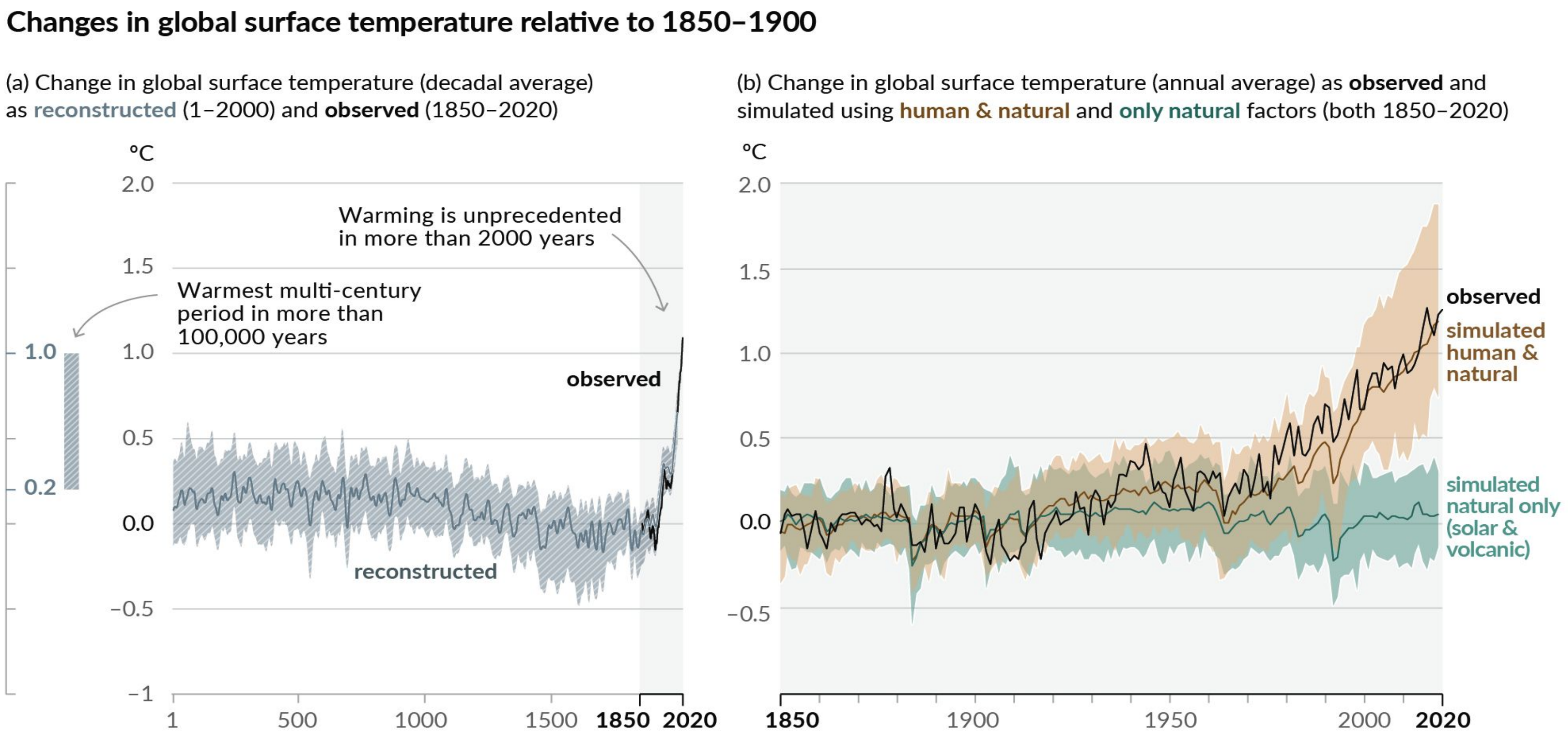
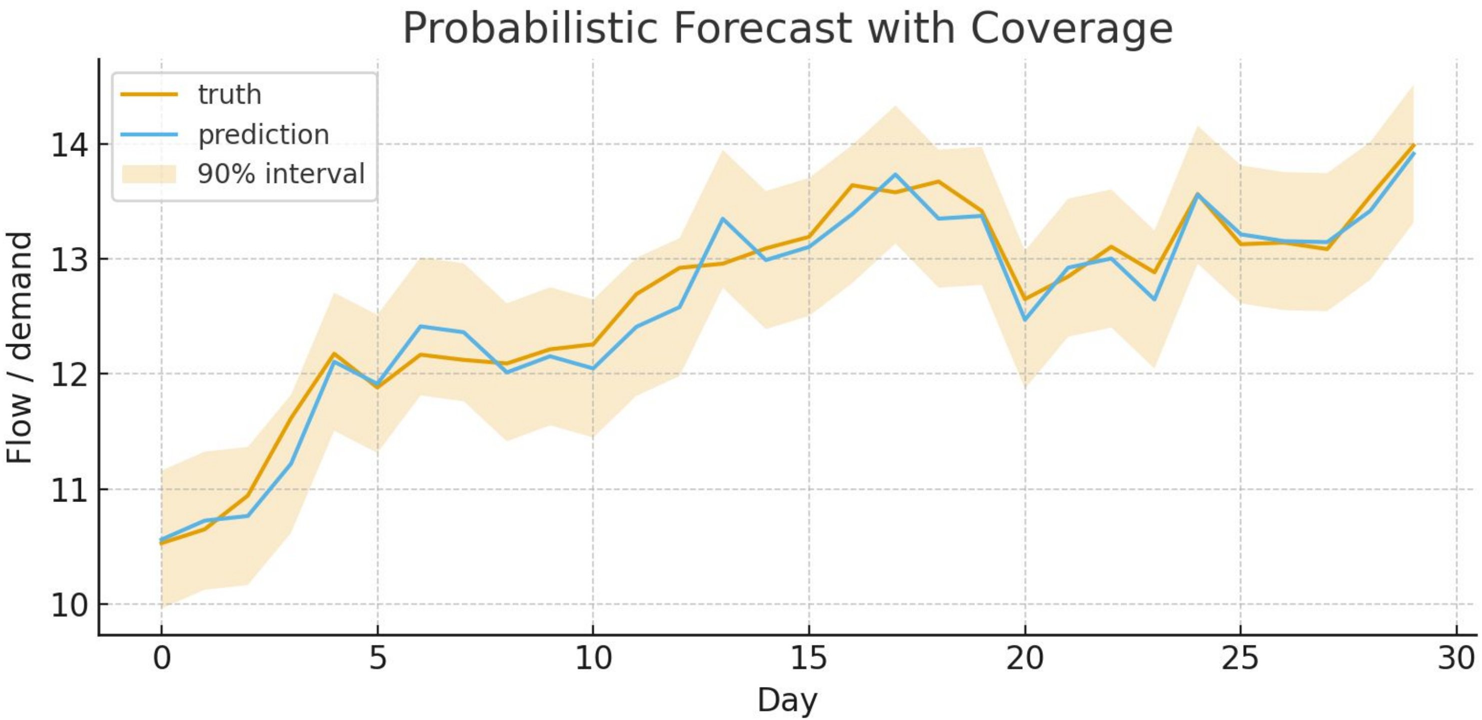


Figure SPM.1 in IPCC, 2021: Summary for Policymakers

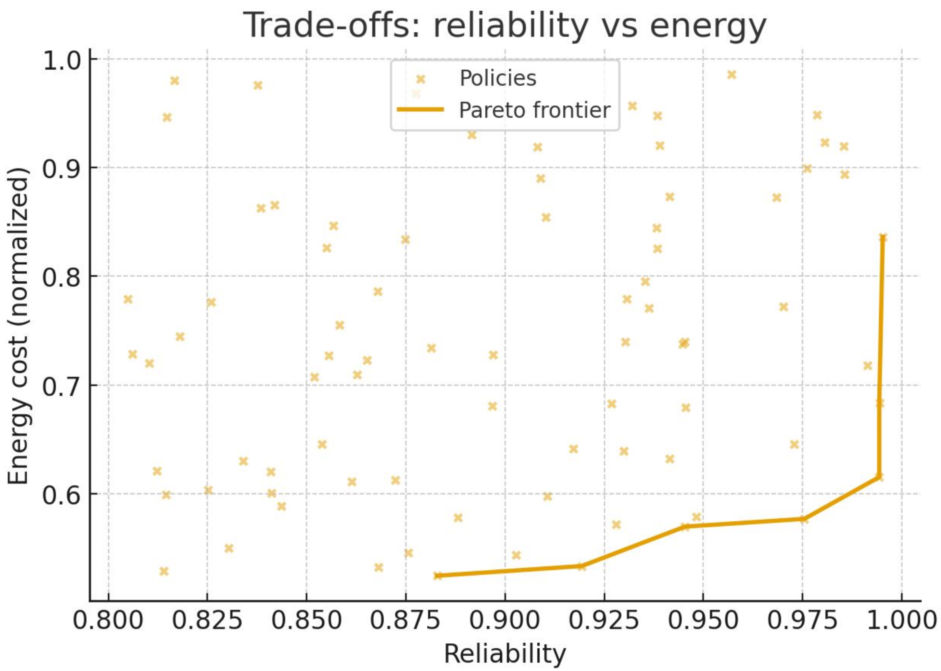
Forecasting Demand, Streamflow, and ET_0



AI-generated forecasts **capture uncertainty through 90% prediction intervals** — allowing safer operational planning.

Decision Intelligence and Robust Planning

Encode equity, environmental-flow, and cost constraints directly in the objective set; present Pareto-efficient choices with stakeholder-friendly labels
([Lempert 2019](#)).

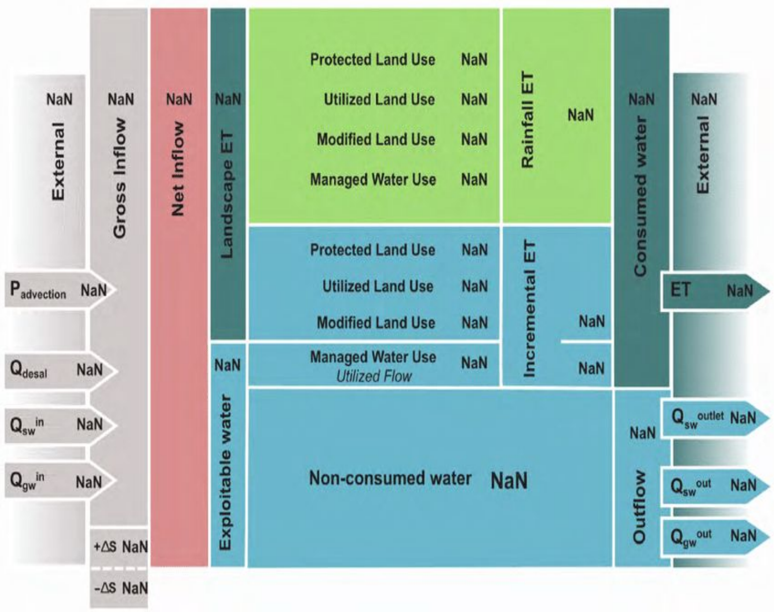


KPIs and Decision Dashboards

Track SDG-6.4 water productivity, service reliability/resilience, NRW, equity metrics, energy/CO_2, and cost-to-serve.

Summarize basin balances with WA+ sheets and display prediction intervals alongside decisions to avoid overconfidence

([Karimi et al., 2013](#))



AI4Water

AI4RedRiver

Next-Quarter Actions (Practical)

1. Stand up an OGC API gateway and BMI wrappers for at least one surface model and one groundwater model (Hutton,2020)

2. Add conformal prediction to one operational forecast (demand or flow) and display coverage metrics on the dashboard (Auer et al.,,2024).

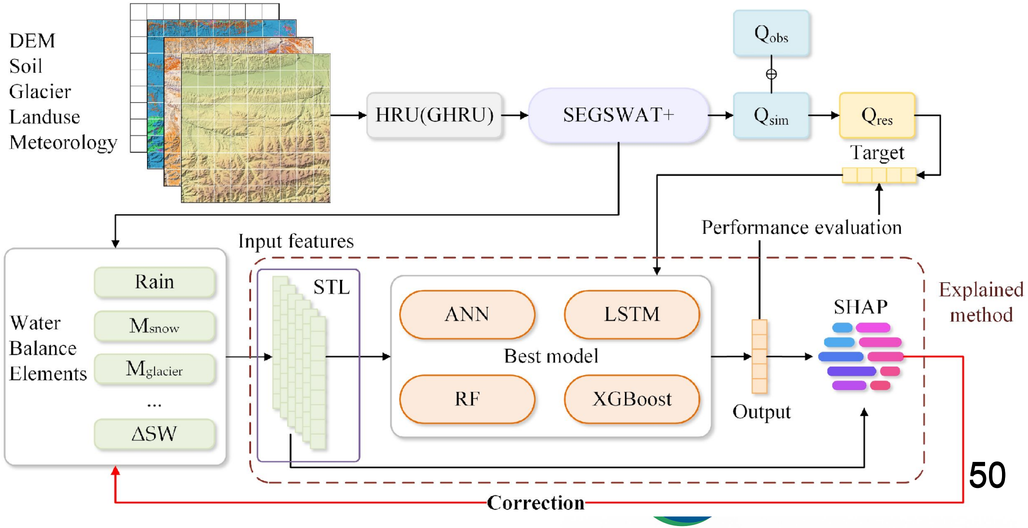
3. Pilot an RDM/DAPP mini-study for a drought allocation rule and predefine triggers for policy pivots (Lempert 2019; Haasnoot et al., 2013).

4. Include a water-use clause in the next AI/cloud procurement (disclosure, WUE, reclaimed water, load shifting) (UNESCO 2021)

Hybrid Data Assimilation with Earth Observation

Fuse GRACE-FO TWS, InSAR subsidence, and Sentinel products into SWAT/VIC/WRF-Hydro/MODFLOW states using EnKF/ETKF/particle filters with learned operators (Liu et al., 2023; Tanguy, 2025)

Bias-correct EO signals with ML and keep auditable basin accounting updated
(Karimi et al., 2013)

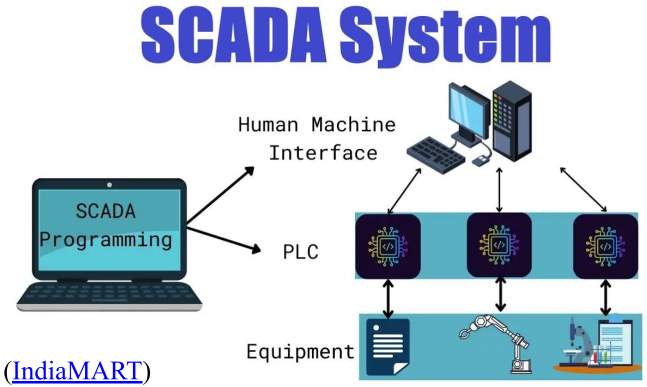


AI4Water

Reference Architecture for AI-Ready Water Ops

Ingest SCADA, IoT, and EO into a feature store; serve forecasting, anomaly, and optimization micro-services; orchestrate actuators via MPC or RL

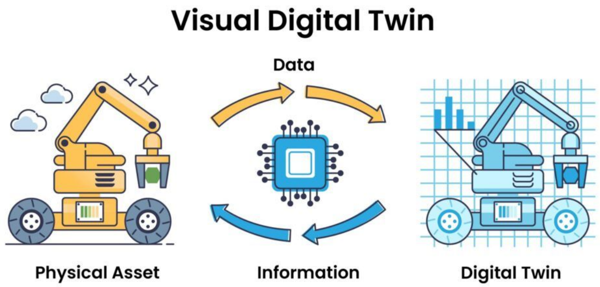
(*Tripathy & Mishra, 2024*).



(IndiaMART)

Maintain a digital twin with physics simulators and surrogates; publish KPIs and accounting dashboards with open standards (BMI, NetCDF/Zarr, OGC-API)

(*Rew,1989*; *Karimi et al., 2013*; *Hutton,2020*; *Ghorbani Bam, 2025*)



(Flagssoftware)

Case Templates You Can Plug In

IRRIGATION DISTRICT

EO-ET plus a weekly scheduler reduces abstractions and preserves yields; fairness rules keep rotations equitable

(Dong et al., 2024; Karimi et al., 2013).

URBAN UTILITY

Demand forecasting and leak localization lower NRW and pressure peaks while maintaining compliance

(Maußner et al., 2025; Liu et al., 2024).

COASTAL PLAIN

MAR and barrier-well policies, triggered by head/chloride thresholds, stabilize the salt front for critical users

(Saad 2022)

AI4Water

AI4RedRiver

Motivation (Scarcity & Operations)

Scarcity is intensifying

Hotter baselines, shifting extremes, and rising demand; many basins under high stress; balance reliability, affordability, and environmental flows. *(IPCC,2023; WMO,2025)*

Data & physics models and EO.

Data & physics models (WRF-Hydro, MODFLOW-6, LISFLOOD-FP) and EO (GRACE-FO, Sentinel, InSAR) exist, but integration is slow and compute-heavy. *(Maurer, 2001; Gochis et al.,2020; Langevin et al.,2022; Liu et al.,2023; Sharifian et al.,2023; Zhao, 2025)*

AI enables faster forecasts

AI enables faster forecasts, hybrid data assimilation, surrogates, and decision optimization with calibrated uncertainty and traceability.

(Fraehr et al.,2024; Tripathy et al.,2024; Huynh et al.,2025; Maußner et al.,2025)

Outcome

Proactive, scarcity-aware operations with robust policies, WA+ accounting, and coverage-guaranteed forecasts.

(Haasnoot et al., 2013; Karimi et al.,2013; Lempert 2019; Auer et al.,,2024)