



From Streamflow Prediction to Water Allocation Policy: A two- phase hackathon

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Capgemini  invent



Hackathon Objectives

Hackathon Water Scarcity
February - may 2025

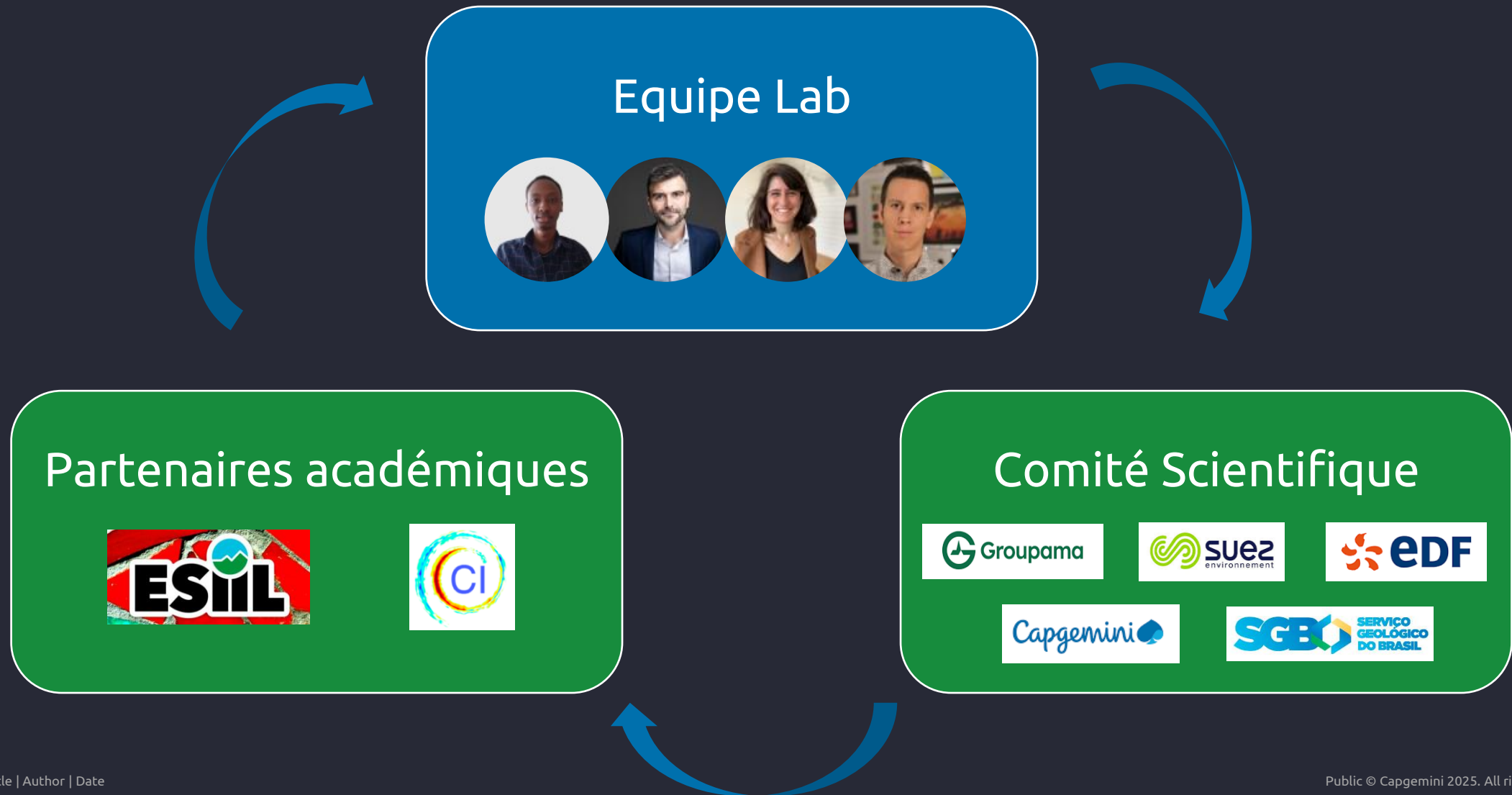
*It's crystal
clear.*

Innovate with data science
to optimize water allocation
in a sustainable way!

Capgemini  invent

Predict water flows and
optimize allocation of
water between different
economic actors, in the
most **sustainable way**.

Un écosystème de partenaires pour soutenir la démarche





A Two Phases Water Scarcity Hackathon



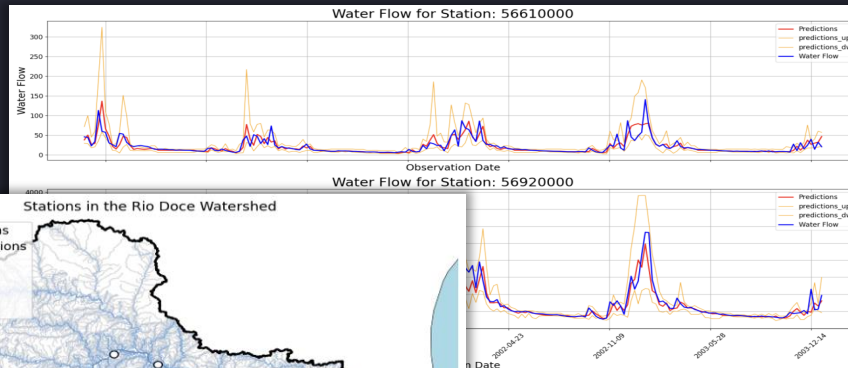
Objective :

Prediction of **water flows** in different **water measuring stations** of a catchment area and management of **water access** in situation of water stress, in the **most sustainable way**.

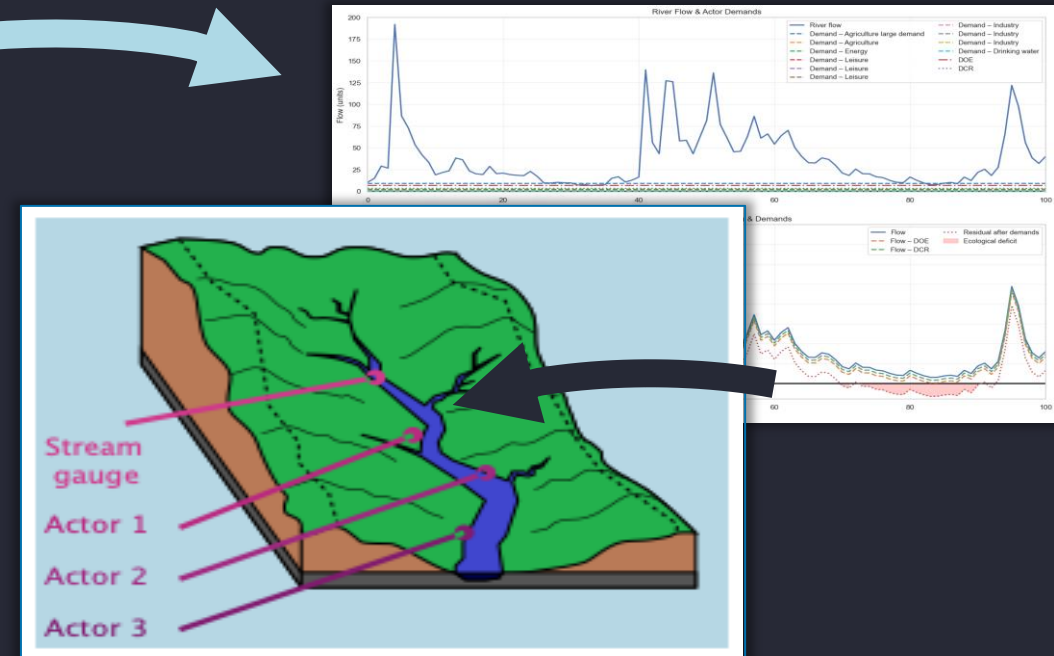
Partners:



Phase 1 : Water flow predictions



Phase 2 : Water allocation strategy





Presentation of the Hackathon

Phase 1 : Water flow predictions (10 weeks)

 **Phase 1** : Creation of a **robust** and **frugal** model for estimating water flows from **open-source data** from measuring stations.

Metrics : Leaderboard on : Gaussian Log Likelihood of the prediction, *coverage* of confidence intervals.

Phase 2 : Water repartition strategy (4 weeks)

 **Phase 2** : Study of **the optimal management of water demand** via **game theory** based on the outputs of phase 1.

Metrics : Best optimization score and qualitative analysis of the reports, models explainability, overall carbon consumption

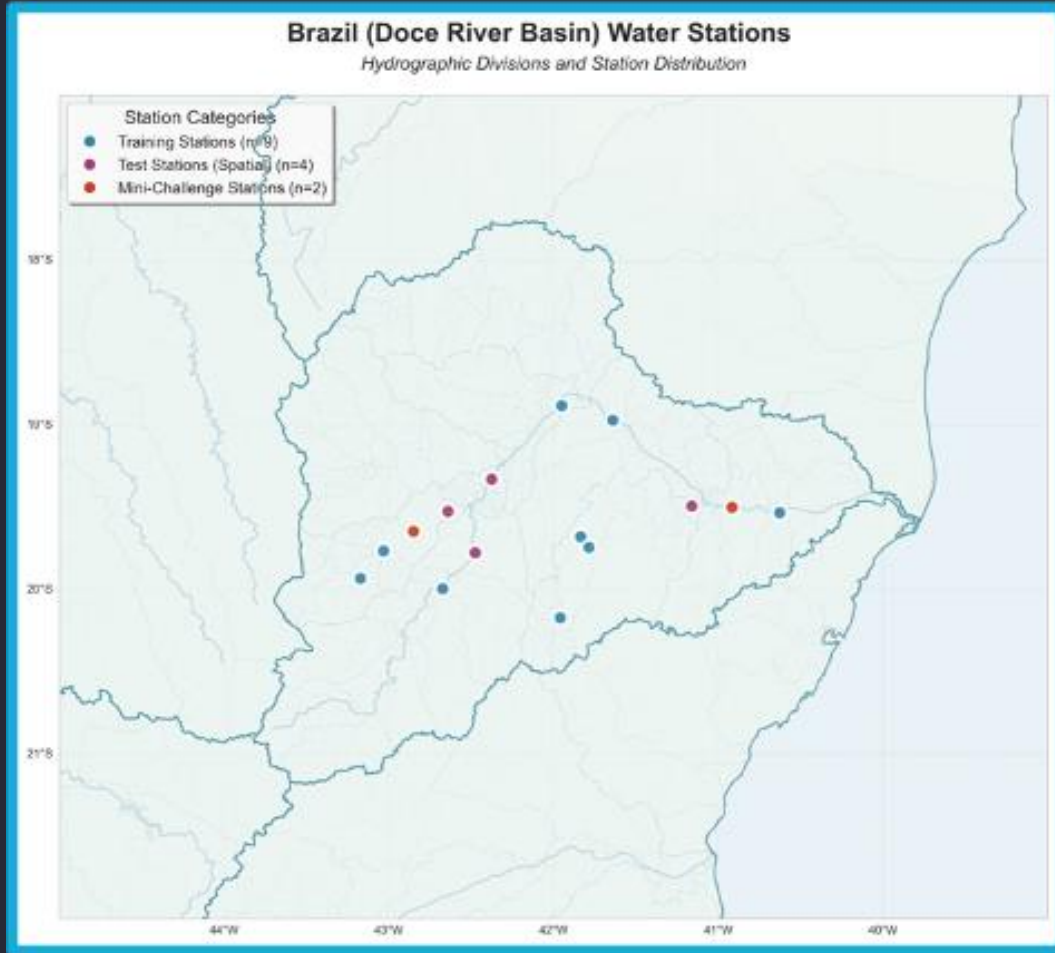
An aerial photograph of a landscape featuring rolling hills, a winding river, and a large lake. A blue line is overlaid on the image, tracing a path that starts from the lake, moves up a hill, and then follows the river's course. The text "Phase 1" is positioned on the left side of the image.

Phase 1

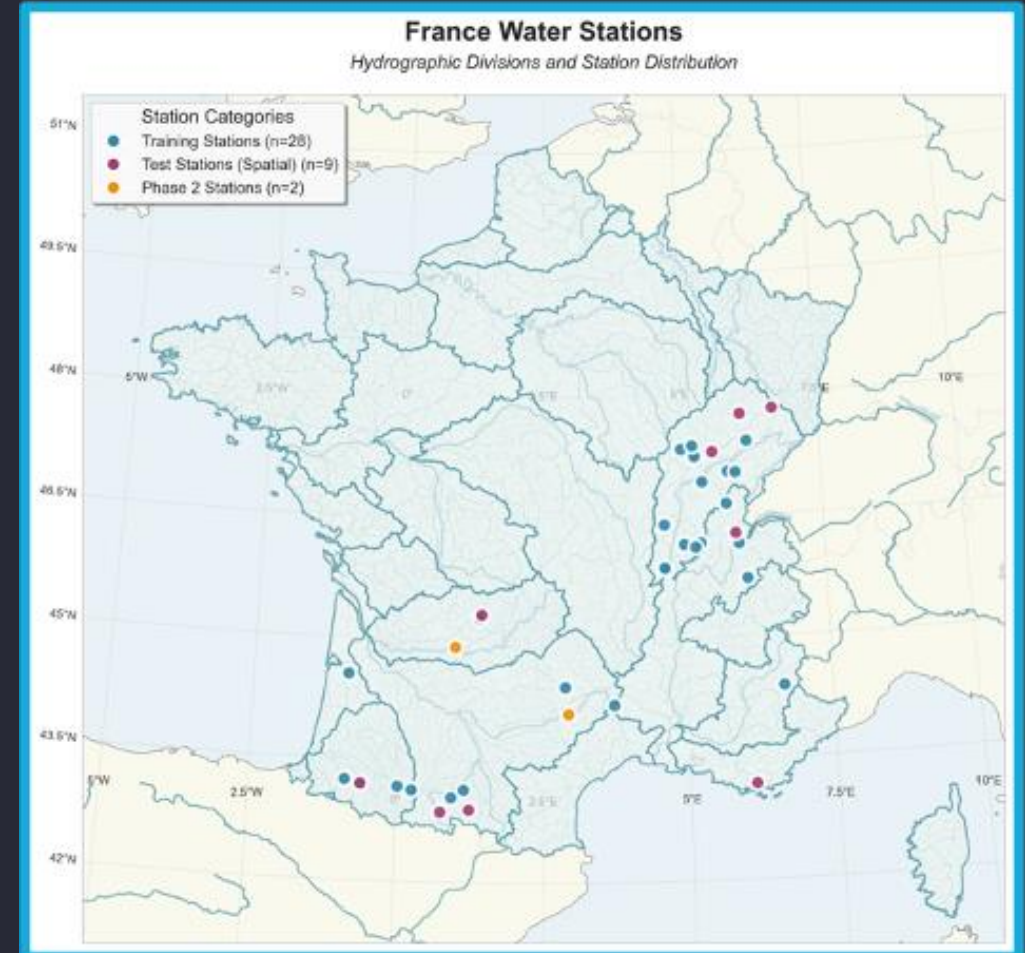
Water flow predictions



River Streamflow Prediction in 52 stations



Brazil (13 stations)

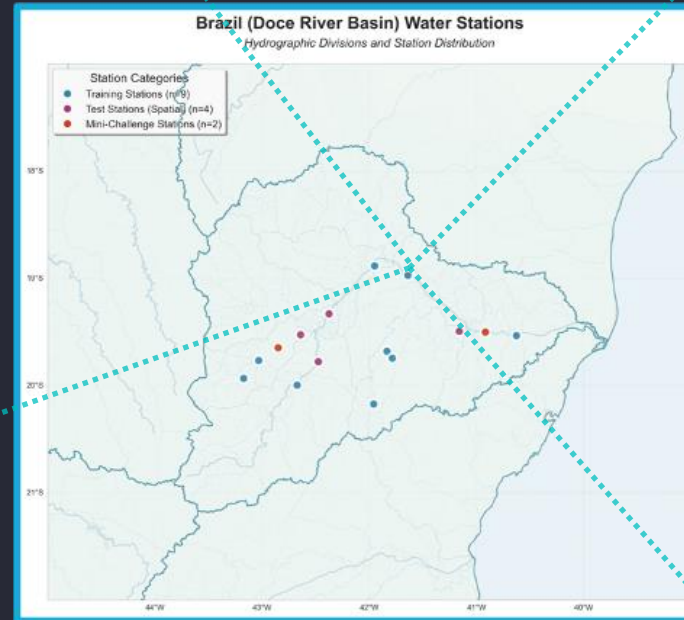


France (39 stations)

Data



Static data : Coordinate

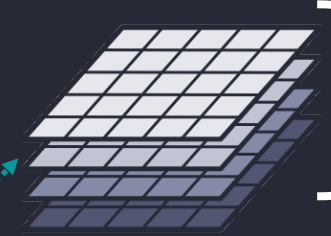


Time Series: (Station water flow)

Frequency : Week.

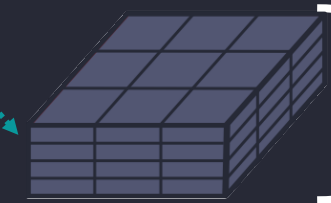
Horizon : 4 predictions weeks over a 6 years period.

Periods : 14 years for training



Geospatial data :

- *Ground composition* from SoilGrids (bulk density, clay content, coarse fragments, sand) at 6 depth levels.
- *DEM* – Nasa SRTM
- *Surface Water & Hydrographic divisions* from Sandre and SNIRH



Spatio-temporal data (ERA5)

- Temperature
- Precipitations
- Evaporation
- Ground humidity



Evaluation Data

Evaluation Splits:

- Temporal split: Assesses performance on seen stations.
- Spatio-temporal split: Tests model on unseen stations.

Dataset Splitting (to prevent cheating):

- Divided into 12-week blocks:
 - 4 weeks of waterflow history.
 - 4 weeks for predictions.
 - 4-week gap.

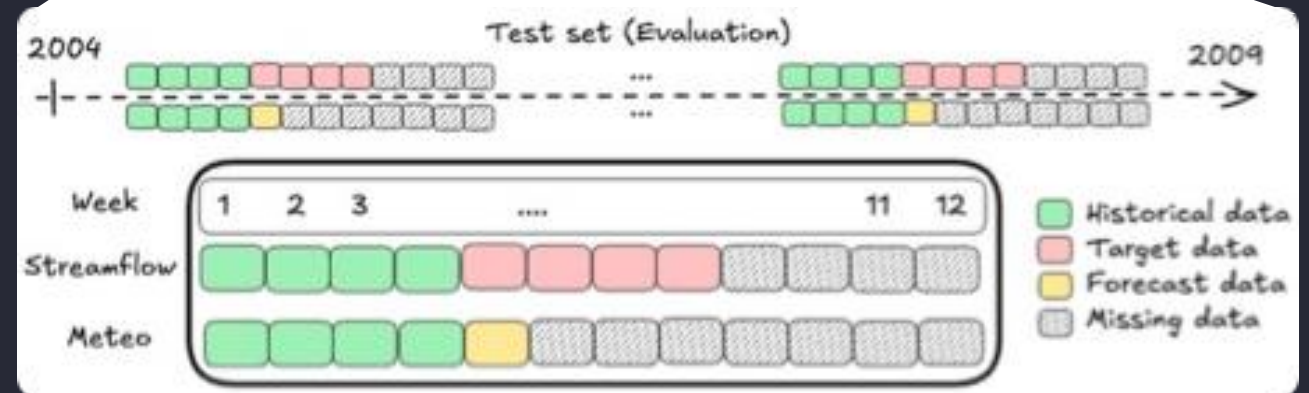
Meteorological Data:

- 4 weeks of meteorological history.
- 1 week of forecast data (given weather forecasts are reliable up to 10 days).
- 7 weeks of gap.



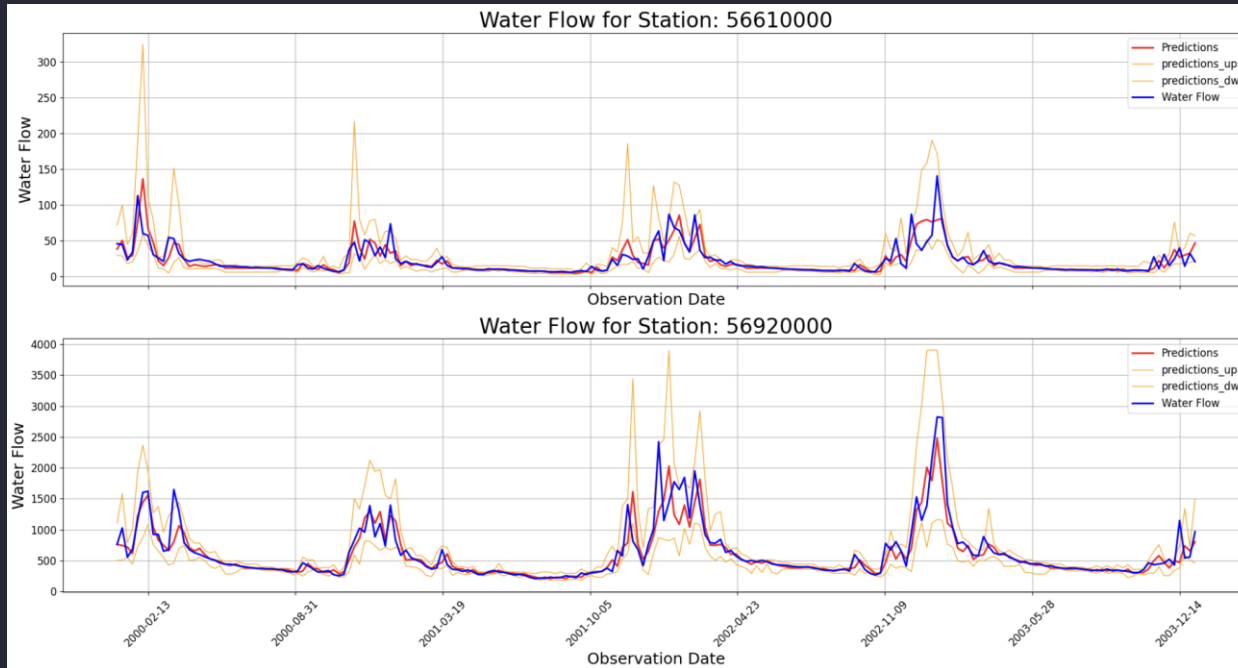
Train Vs Evaluation split

Evaluation data





Evaluation Metrics



To evaluate them fairly,

- we **scale** predictions **per station**,
- use a **log-likelihood-like metric** that minimizes both prediction errors and interval widths
- and ask a minimal average coverage of 90%.

Participants were asked prediction intervals with a coverage of 90% or above.

We used an approximation of gaussian log likelihood as evaluation metrics :

$$NGLL(S_j, T_j) = \frac{1}{n_j} * \sum_{\{t_i \in T\}} \ln(\hat{\sigma}_{\{i,j\}}^*) + \frac{1}{2} * \left(\left| \frac{y_{\{i,j\}}^* - \hat{y}_{\{i,j\}}}{\hat{\sigma}_{\{i,j\}}^*} \right| \right),$$

where $\hat{\sigma}_{\{i,j\}}^$ is a proxy for the standard deviation derived from the normalized prediction intervals.*

An aerial photograph of a landscape featuring rolling hills, a winding river, and a large lake. A blue line graphic is overlaid on the image, starting from the bottom left, curving upwards and to the right, and then curving back down towards the bottom right. The text "Phase 2" is positioned on the left side of the image, and "Water repartition strategy" is positioned below it.

Phase 2

Water repartition strategy



Phase 2 : Water strategy repartition



Challenge

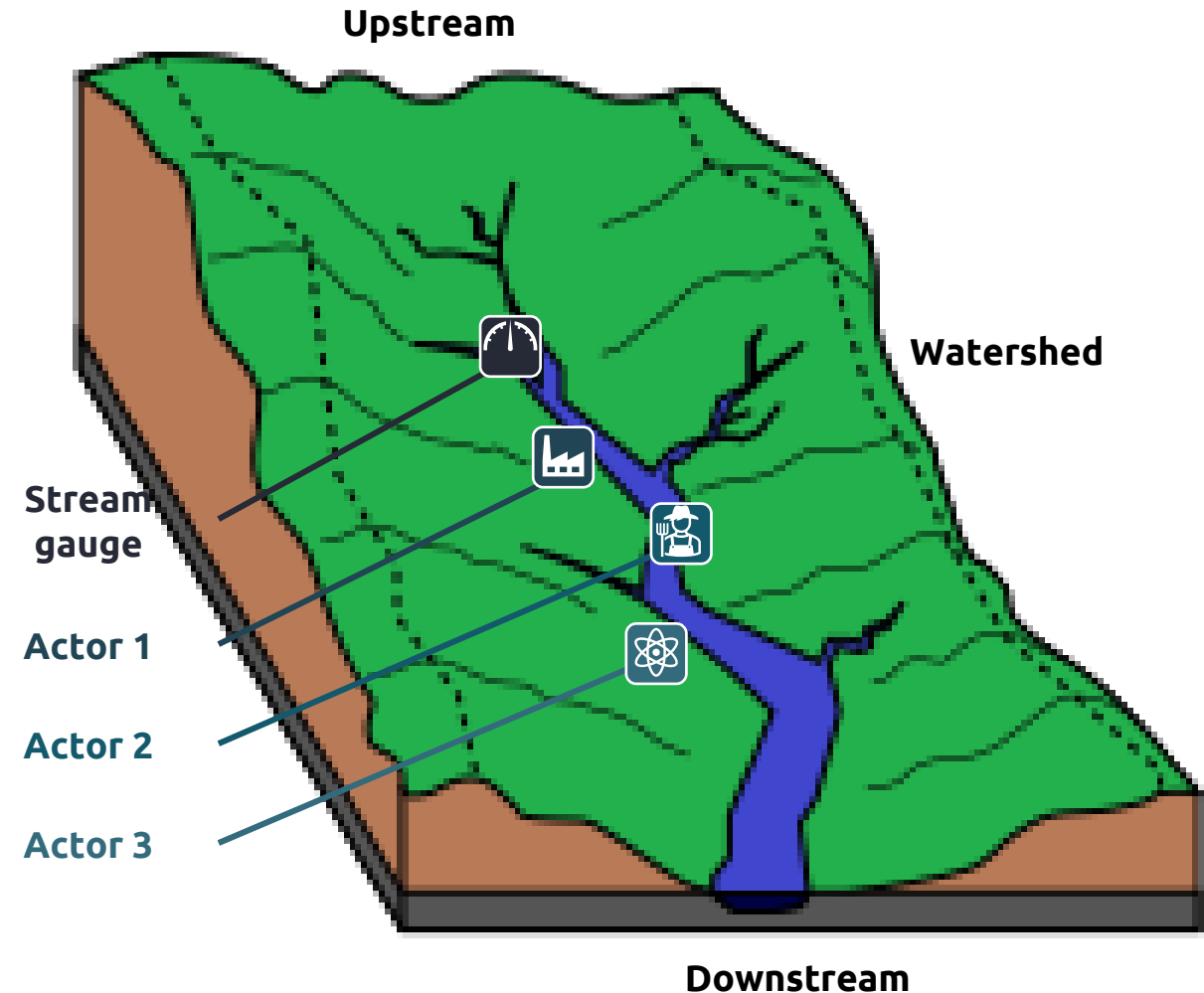
Evaluate **water incentive** and **quota policies** through an agent-based evolutionary game **simulating** withdrawal behaviors at two French monitoring stations.

Minimize environmental impact on *ecological flows* while ensuring strategies are: **fair** for stakeholders, **prioritize essential needs**.



Simulation

Ten stakeholders representing **five user archetypes/personae** (Agriculture, Industry, Energy, Drinking Water, and Leisure). **Leverage Phase 1 forecasts** to determine their water consumption, constrained by usage priorities, storage limitations, sector-specific economic valuations.





Basic principles of the simulation

1. Situation Assessment

- **Crisis Regime** is computed from previous week remaining water.
- Actors get **streamflow forecast** for current week.
- Each actor chooses to **cooperate** or **defect** based on a learned cooperation tendency.



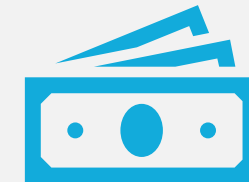
2. Water Allocation

- In **normal regime** : cooperation reduces water usage and therefore crisis risk for next week, based on cooperators forecasts.
- In **alert/crisis regime** : defector maximise their water stock/buffer while cooperator only takes their minimal needs.



3. Outcomes

- Actors **economic benefits** are computed based on real streamflow and **quota / incentive policy**.
- Actors' **cooperation tendencies** are updated by comparing current benefit to alternative benefit.



After 100 iterations of 700 weeks we stop the simulation and compute final score.



Water User Archetypes / Personae

We model five water-user personae / archetypes, each with distinct: demands, economic values, buffer capacities and priorities.

Agriculture

- Medium priority (P_1)
- Low per-unit value
- High consumption
- Medium buffer



Industry

- Low priority (P_0)
- Moderate per-unit value
- Low consumption
- Higher buffer



Energy

- High priority (P_2)
- Critical societal value
- Medium consumption
- No buffer



Drinking Water

- Highest priority (P_2)
- Critical societal value
- Medium consumption
- Small buffer



Leisure

- Low priority (P_0)
- High per-unit value
- Very low consumption
- Small buffer





Crisis regime in simulation

The crisis regime is computed using previous week remaining flow.



- **Normal :**
Remaining flow $\geq$ DOE



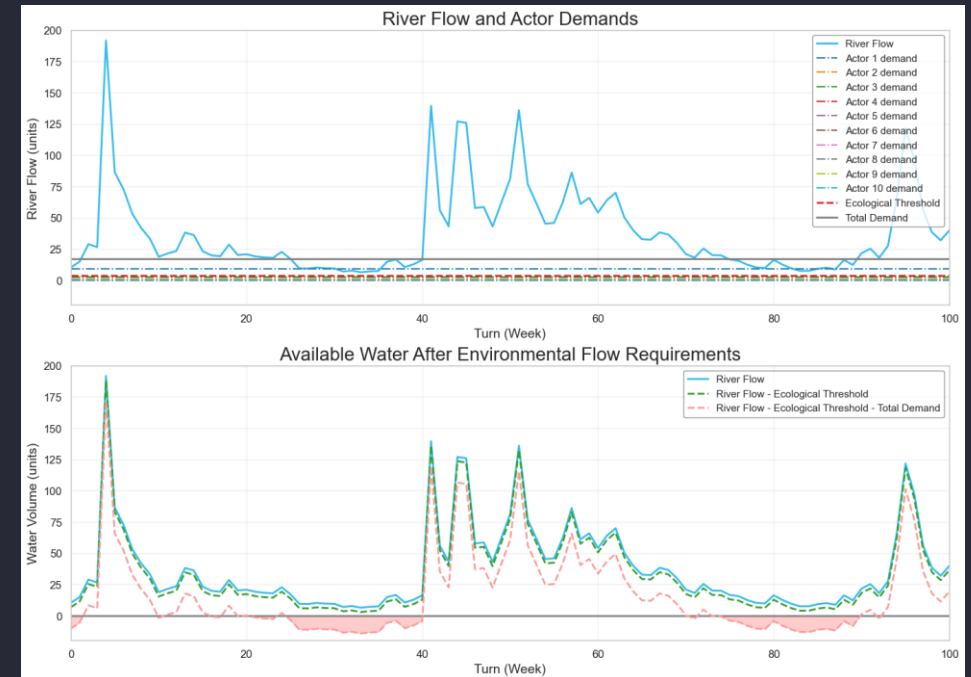
- **Alert:**
DOE > remaining flow $\geq$ (DOE+DCR)/2



- **Moderate Crisis:**
(DOE+DCR)/2 > remaining flow $\geq$ DCR



- **Severe Crisis:**
DCR > remaining flow





Evaluation Metrics and final ranking

Objectives and quantitative metrics used for Phase 2

Ecological Impact: Minimize the **number of weeks** in which flow falls below the Crisis threshold (DCR).

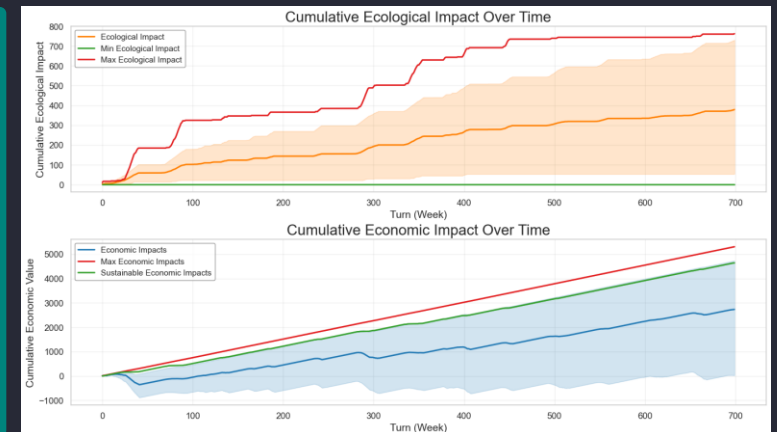
Economic Efficiency: Maximize the **total economic benefit** achieved

Ecological Impact = Weeks below DCR (fewer = better)

Economic Efficiency = Total Benefit Achieved (higher = better)

Priority Rule: Higher priority actors must achieve better satisfaction than lower priority actors. Violators are ranked lower in the final standings.

Final ranking will be the average of your scenarios ranks on these two axes.



Overall ranking for the Hackathon

- **Phase 1 quantitative** evaluation (performance) : 40 %, **report** quality (explainability, computational cost, robustness) : 20 %
- **Phase 2 simulation performance:** 20 %, **report** quality (Policy design, Key insights): 20 %

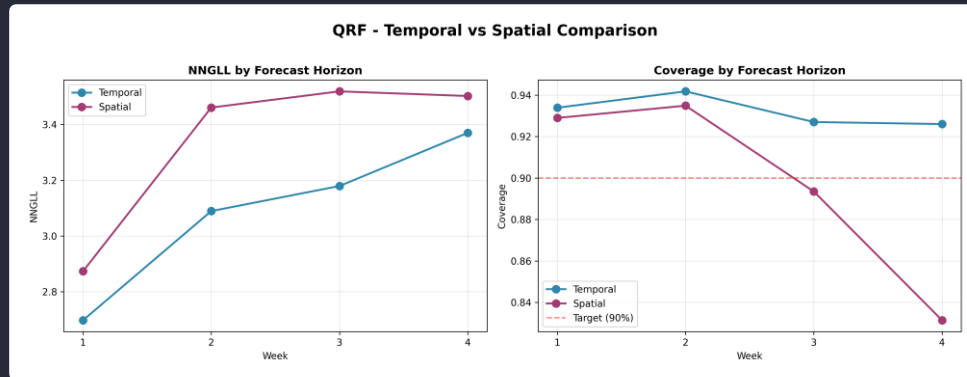
RESULTS





Phase 1 main outputs:

Winning approaches: Frugal models such as Gradient boosting (CatBoost) and QRF dominated over DL



Winning team:

- chained catboost model
- kmeans clustering (based on static features) to approximate historical flow on unseen stations
- Relative Quantile Conformal Calibration (RQCC) to handle heteroscedasticity of streamflow across regions and seasons

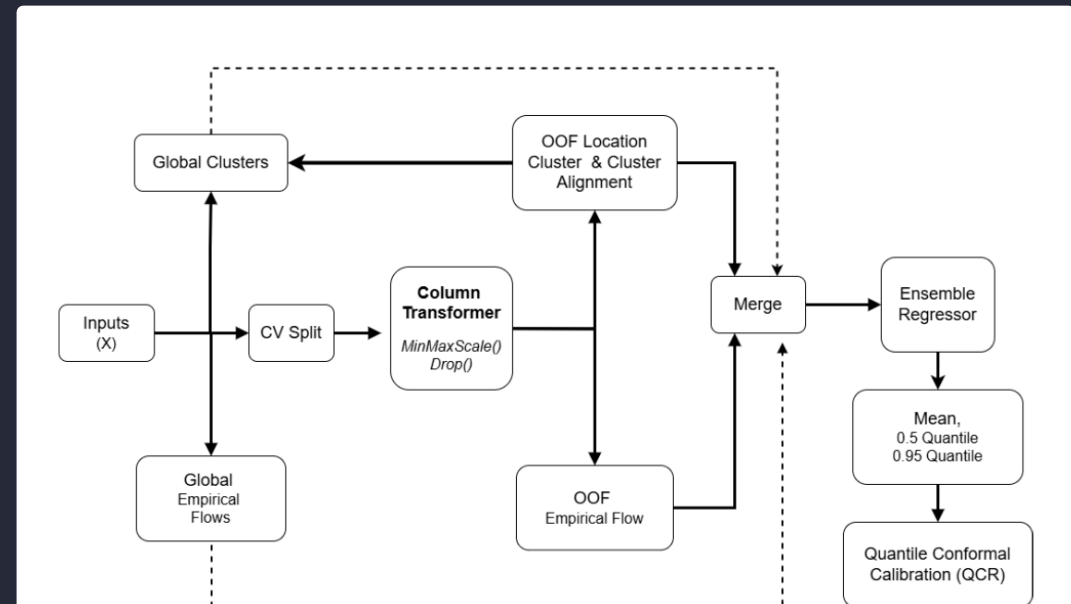
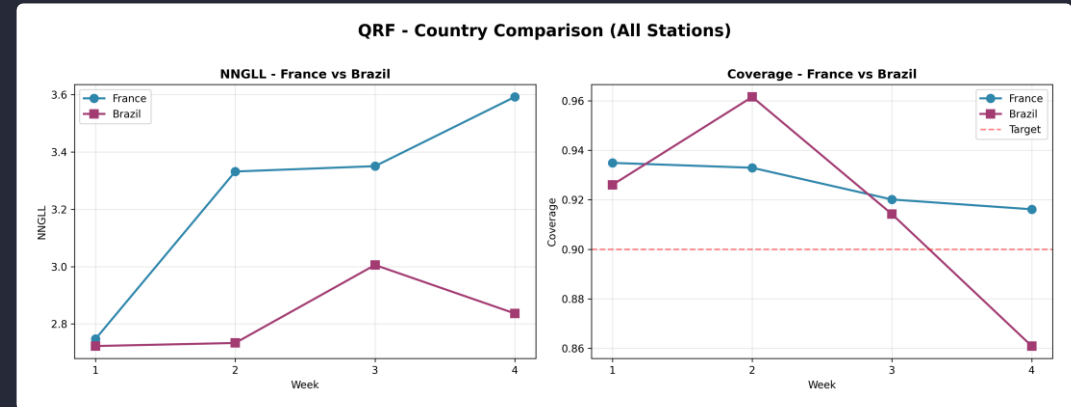


Figure 9: Model Architecture

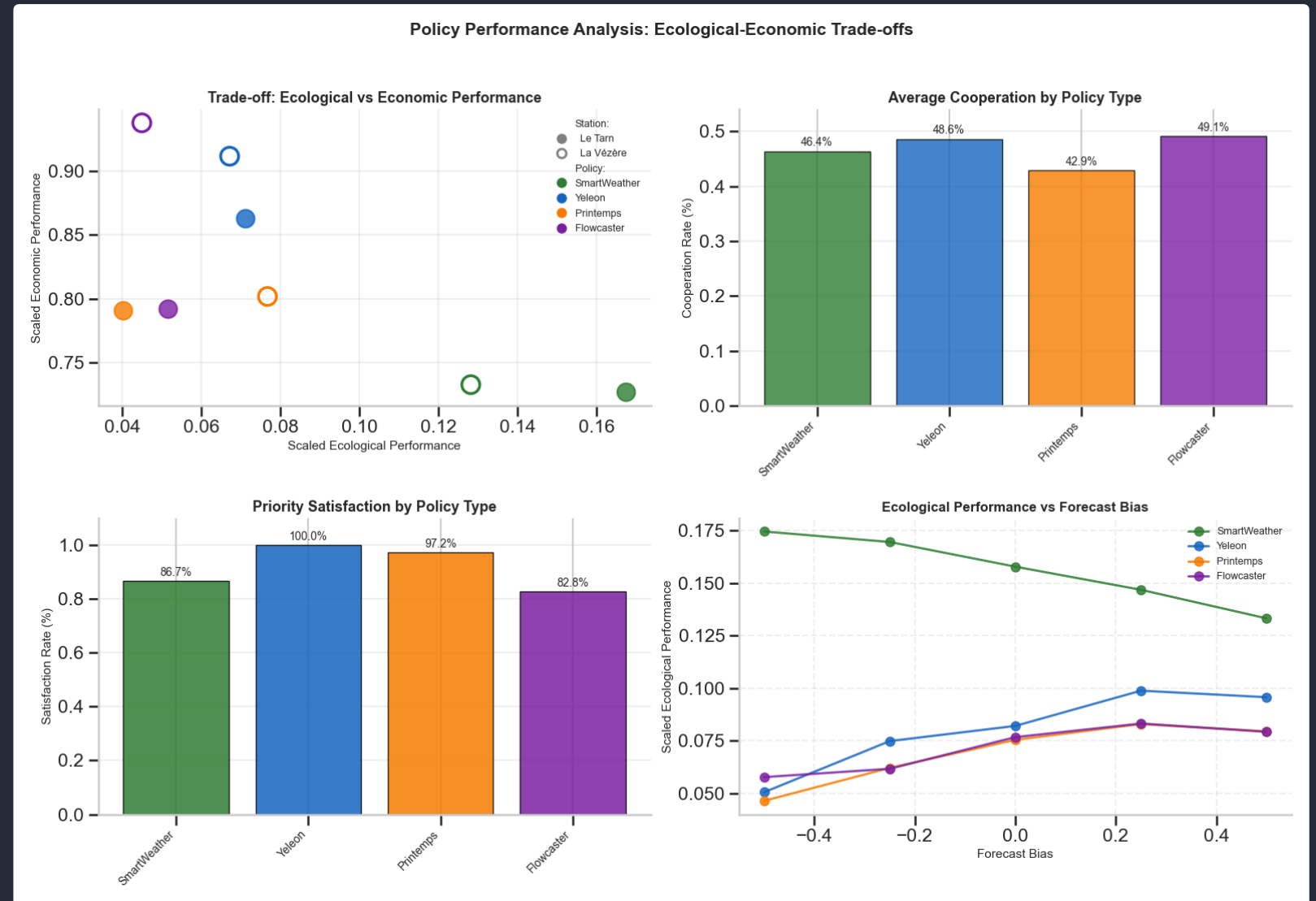
THANK YOU





Phase 2 main outputs:

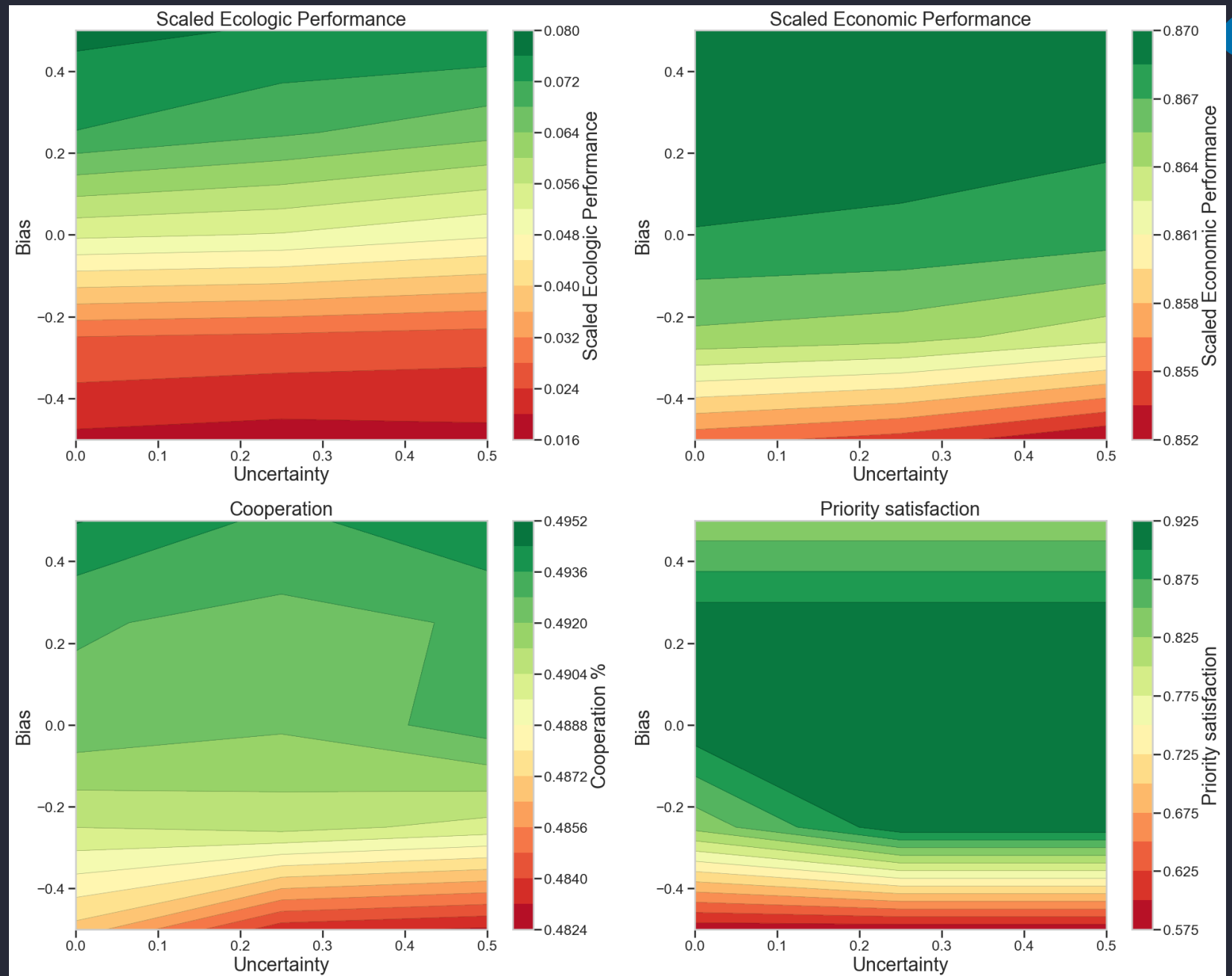
- **Trade-offs** : tension between ecology and economic efficiency
- **Forecast bias effect**: Positive bias increases cooperation but can degrade ecological outcomes—optimistic actors cooperate better but may collectively over-extract water
- **Station-specific adaptation**: Watersheds with frequent historical crises showed greater crisis resilience
- Crisis-focused intervention (minimal regulation until stress)
- Optimization methods: Evolutionary algorithms (NSGA-II, CMA-ES) dominated multi-objective optimization





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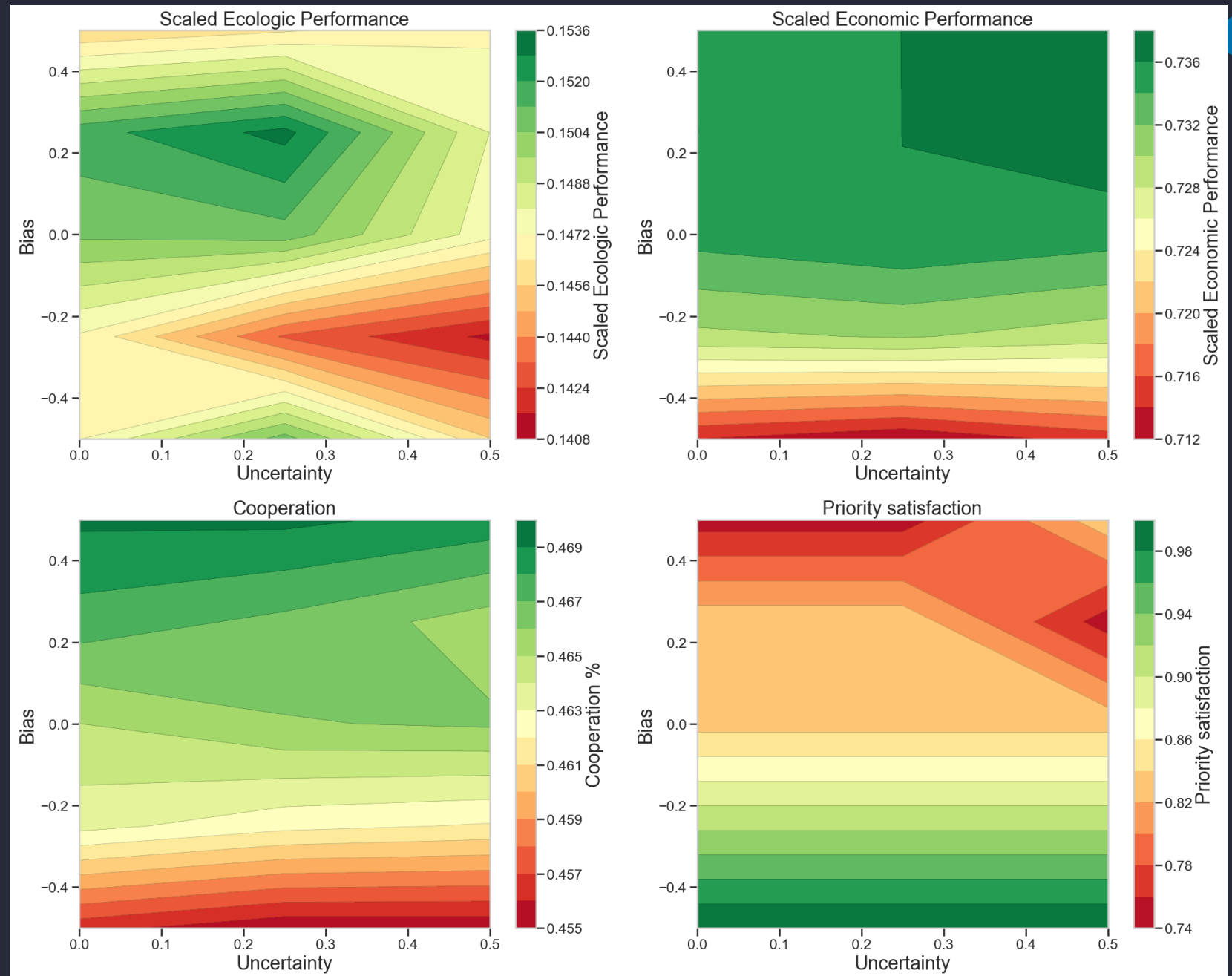
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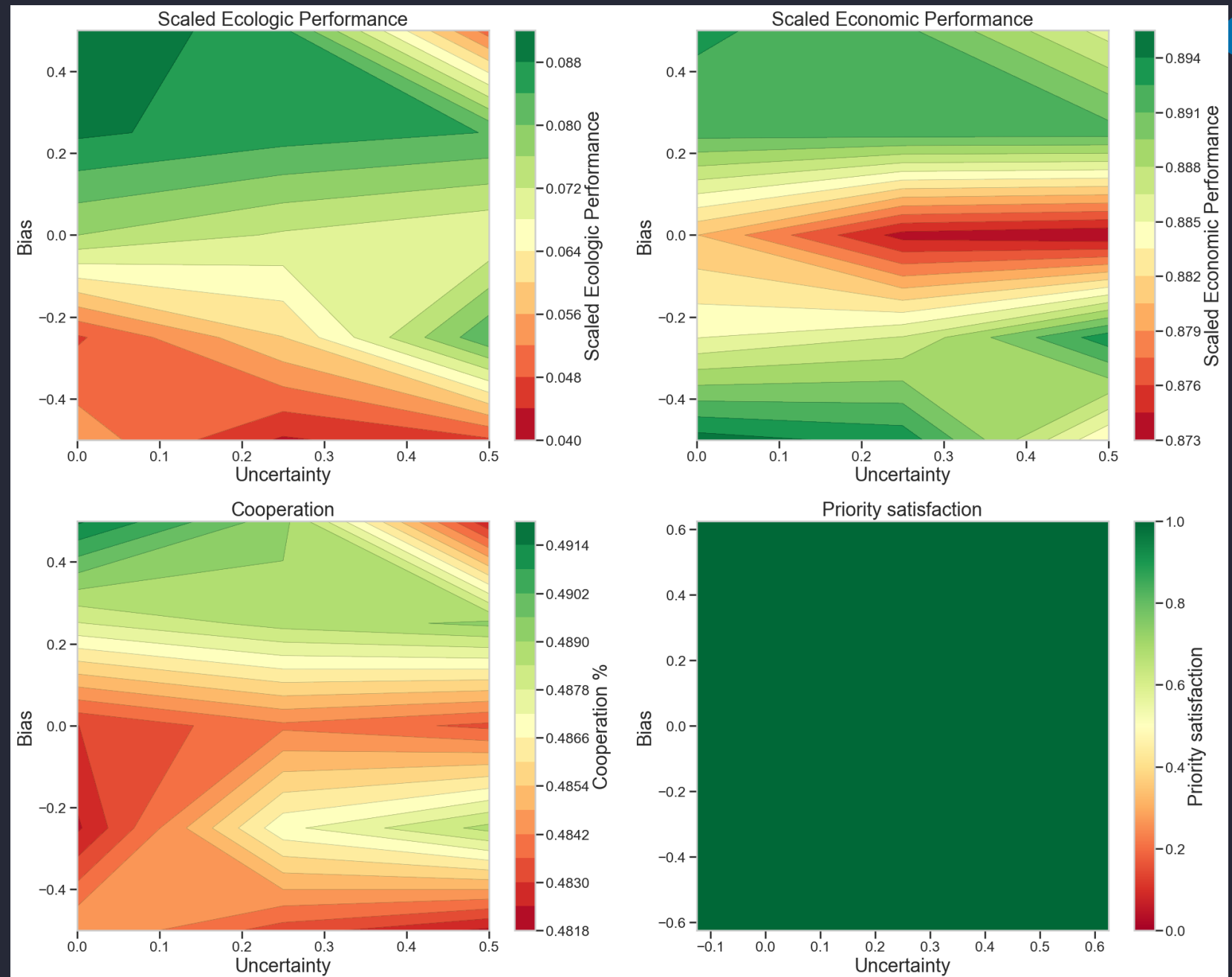
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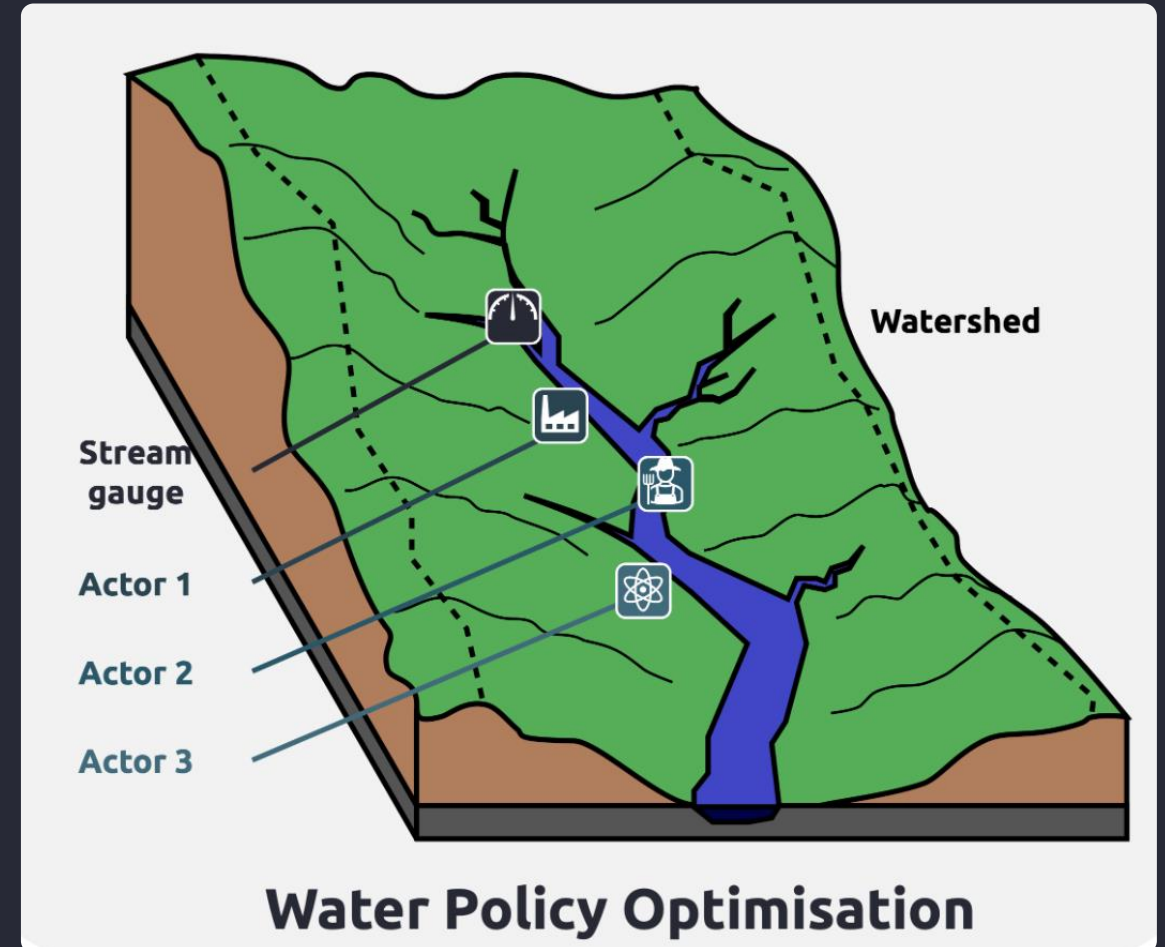
Water allocation

	Normal Regime	Crisis / Alert
Cooperators	1. If no crisis/alert anticipated for next week: withdraw at maximum capacity, 2. if minimal needs are low enough to prevent crisis: withdraw at minimal needs, 3. else: allocate available water based on priorities and demands.	Withdraw only minimal needs up to quota limit.
Defectors	Withdraw at maximum capacity.	1. If minimal needs > quota: withdraw minimal needs, 2. else withdraw at maximum capacity up to quota limit.

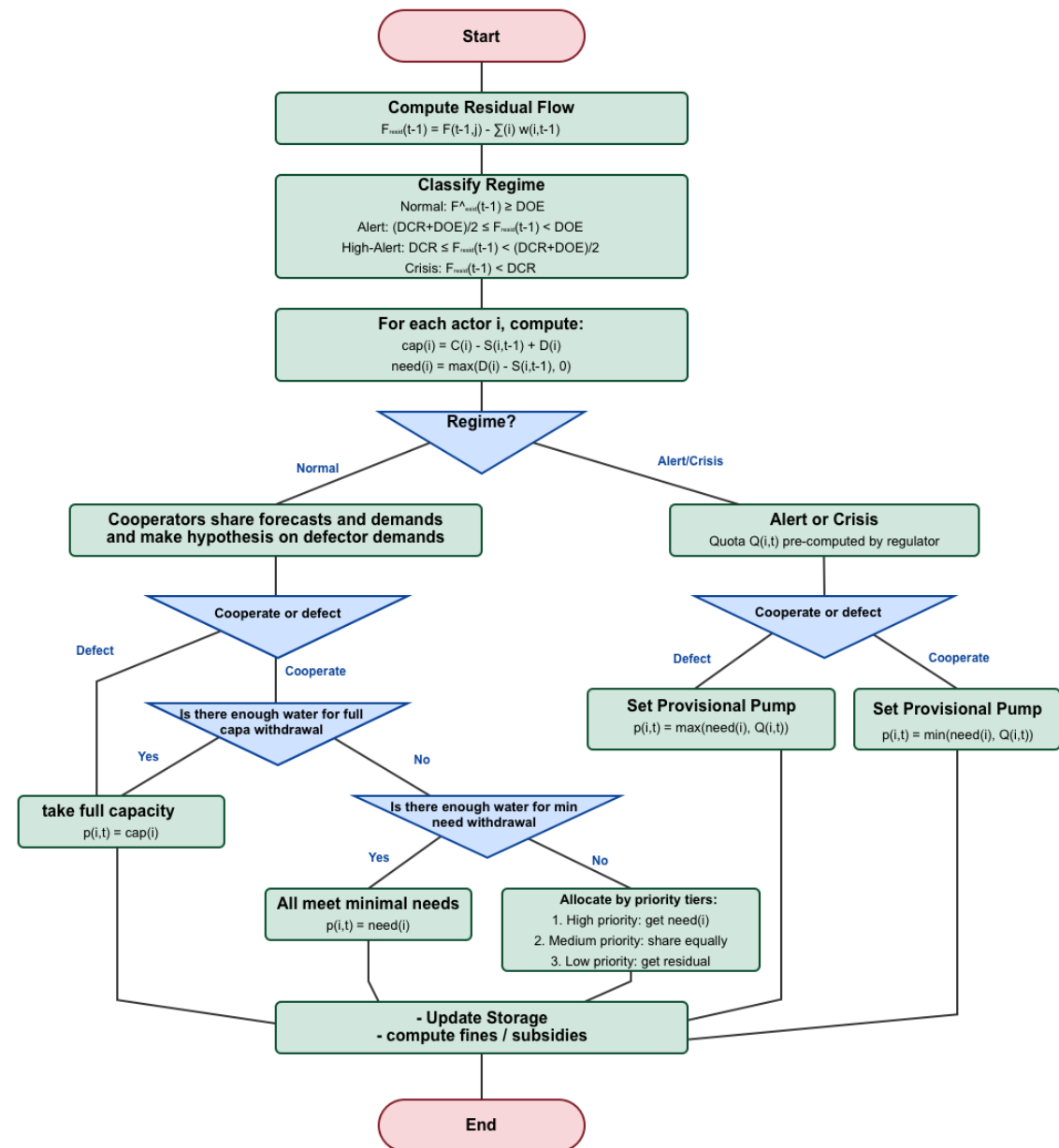


Simulation main parameters

Variable	Description
actors_demands	Baseline water volume each actor "needs" per week
actors_values	Economic benefit per unit of water used
actors_priority	Allocation priority class (0 = low, 1 = med, 2 = high)
actors_storage_capa	Maximum on-site buffer capacity
actors_forecast_bias	Systematic over-/under-prediction factor per actor
actors_forecast_uncertainty	Forecast error variance per actor
DOE, DCR	Ecological thresholds (Optimal vs. Crisis Flow)



Water Allocation Algorithm Flow Chart





- **Winning Approaches**

- **Optimization methods:** Evolutionary algorithms (NSGA-II, CMA-ES) dominated multi-objective optimization
- **Successful archetypes:**
 - Crisis-focused intervention (minimal regulation until stress)
 - Balanced multi-objective optimization
 - Simple robust heuristics (transparent rules)



Final Ranking

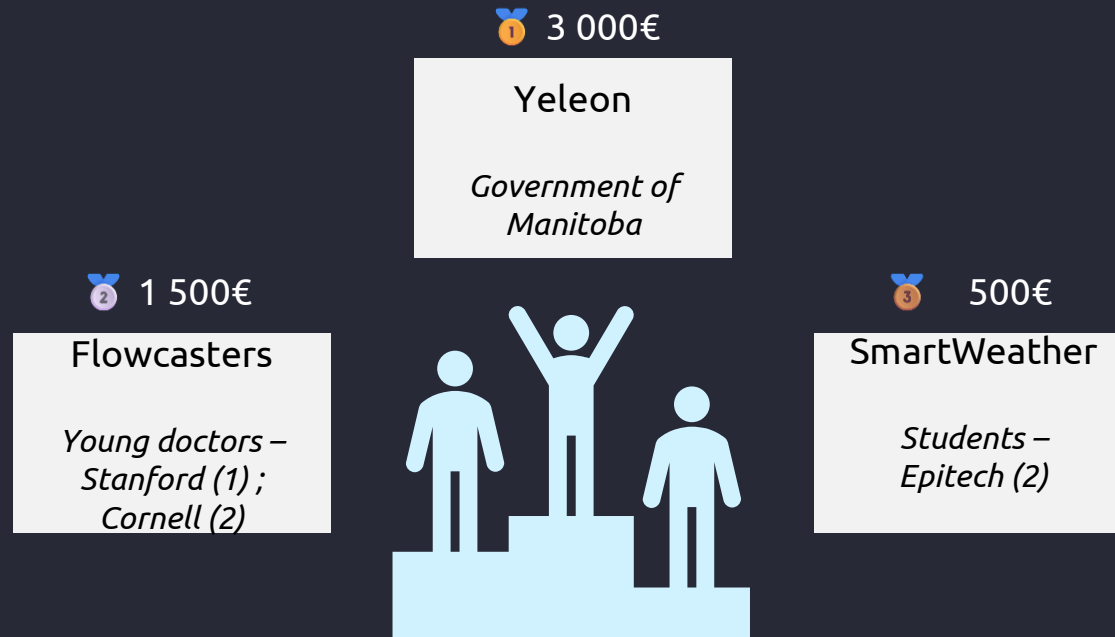
Evaluation criteria

Phase 1

- 40% model performance
- 20% report quality (Clarity of methodology, Scientific Novelty, Explainability, Frugality)

Phase 2

- 20% model performance
- 20% report quality (Policy-design methodology, Optimization rationale, Key insights)



Special Jury prize for the quality of the report and innovative approach :

Printemps - doctorant, ENSIEE