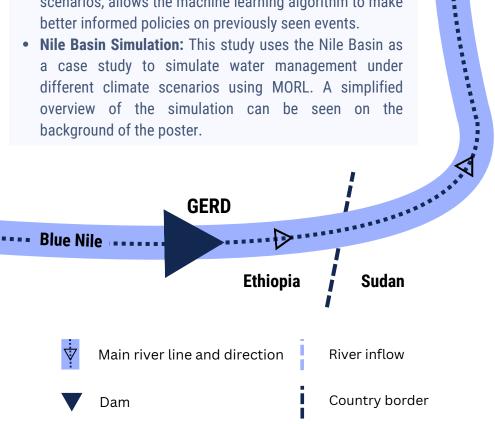
RL4Water: Climate-Resilient Water Management via Reinforcement Learning

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Introduction

- Climate Change Impact: Climate change is causing unpredictable climate conditions, affecting water availability through events like floods or droughts. This calls for effective management of water resources.
- Multi-Objective Reinforcement Learning (MORL):
 - Machine learning can aid in managing water resources more efficiently.
 - Why Reinforcement Learning (RL)? RL algorithms learn and produce optimal policies through iterative actions with the environment, which are suitable for dynamic water management problems.
 - Why Multi-Objective? Considers multiple aims of the problem, which can include environmental and societal factors.
- Data Quality: Ensuring the accuracy and relevancy of the data is necessary to produce effective and robust machine learning-based solutions.
- Adaptive Decision-Making: Considering different climate scenarios, allows the machine learning algorithm to make better informed policies on previously seen events.
- Nile Basin Simulation: This study uses the Nile Basin as a case study to simulate water management under different climate scenarios using MORL. A simplified overview of the simulation can be seen on the background of the poster.



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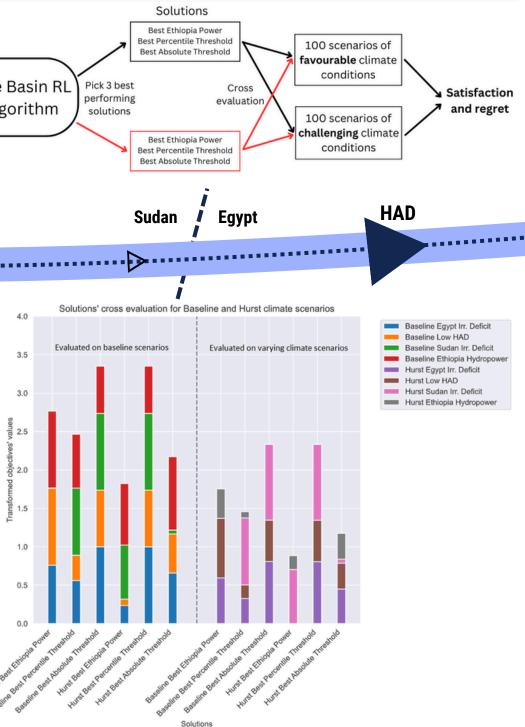
Research question 2

What is the impact of climate-varying data conditions on water management in the Nile **Basin via reinforcement learning?**

White Nile Climate conditioned data Favourable Nile Basin Rl Pick 3 best Training performing algorithm solutions Atbara Challenging Sennar **Roseires**

Results and Conclusion 4

- · Evaluation results: In both testing scenarios, baseline-trained solutions performed better than the climate-varying-trained ones. In climate-varying scenarios, overall optimization was worse than in baseline scenarios. Performance greatly deteriorated in the evaluation stage compared to training results. The graph on the right presents the findings of the evaluation of EMODPS solutions.
- MONES: Successful refactoring of simulation to fit MONES. The algorithm performed worse than EMODPS, possibly due to insufficient training iterations. Further experimentation and hyper-parameter optimization are needed to better evaluate MONES efficiency.
- Data representation: There is a need for accurate, recent data to reflect climate change. Training and testing with diverse climate scenarios is crucial for robust optimization solutions. This will help real-world decision-makers make climateresilient policies in water management.
- Simulation improvements: The current simulation represents a single line of the Nile, lacking a broader context of other parts of the basin. Research that includes a more extensive context, e.g. meteorological factors, could result in more accurate and applicable solutions.



Nile Basin Simulation Model Refactoring and Integration

3 Methodology

Climate-vary Future Data Considerations

EMODPS solutions' analysis

is depicted in the image below.

 Original Limitation: Initially designed only for the Evolutionary Multi-Objective Direct Policy Search (EMODPS) algorithm, it needed to be adaptable to the Multi-Objective Natural Evolution Strategy (MONES) algorithm.

· Refactoring: Developed a comprehensive and adaptive model with the same functionalities. The model can now generalize over similar water-management problems and connect to the MONES algorithm.

 Data Factors: Consider future changes in water inflows, evaporation, and socioeconomic factors like water demand. Uncertainty Projection: Introduced potential more fluctuating climate conditions (droughts, floods) to water inflows, and water evaporation from reservoirs, as well as considered fluctuating population growth on water demand. **Execution**: Ran EMODPS algorithms with scenarios of two climate outcomes: baseline, which is human-favourable, and climate-varying conditions. MONES was only run on climate-varying conditions.

Evaluation: three solutions were picked from each training: best Ethiopia's power, best-exceeding percentile threshold in terms of individual objectives, and best-exceeding absolute threshold considering all objectives combined. The six solutions were assessed on 100 climate scenarios from both baseline and challenging climate conditions, which gave insights according to satisfaction and regret robustness metrics. An overview of this process