

Physics-Informed Neural Networks for Climate Modeling: A Case Study on Rainfall Prediction in the Blue Nile Basin

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1. Background and Problem Statement

Climate change and rainfall variability present significant issues for Ethiopia, particularly in the Blue Nile Basin, which is essential for agriculture, hydropower, and water resource management. Accurate rainfall projections are essential for irrigation planning, flood prevention, and sustainable development. Traditional physics-based climate models are reliable, but they are often low-resolution and computationally expensive. On the other hand, data-only machine learning methods are uninterpretable and struggle with sparse or noisy data.

Physics-Informed Neural Networks (PINNs) have recently emerged as a promising approach that combines the strength of numerical physics-based models and data-driven deep learning. PINNs embed physical laws (e.g. Conservation of mass, energy, or governing partial differential equations of hydrology and climate dynamics) directly into neural network training. This ensures that predictions remain consistent with physics principles even when data is scarce or noisy.

Although PINNs have been applied in physics and engineering domains, their use in climate and hydrology especially in Africa remains limited. To date, no known studies have employed PINNs for rainfall modeling in Ethiopia or the Blue Nile Basin. This presents an opportunity to explore their potential for climate applications in a local context.

2. Objectives

General Objective:

To develop and evaluate a physics-informed deep learning framework for rainfall prediction in the Blue Nile Basin using reanalysis data and governing climate dynamics.

Specific Objectives:

1. To collect and preprocess rainfall and climate reanalysis datasets.
2. To design a Physics-Informed Neural Network model that incorporates rainfall-related physics constraints.
3. To evaluate the PINN model against standard machine learning approaches and baseline climate models.
4. To analyze the applicability of PINNs for climate modeling in low resource settings.

3. Methodology

- **Data collection:**

- Primary dataset: ERA5 reanalysis rainfall and climate variable (precipitation, temperature, humidity, pressure) for the Blue Nile Basin.

- Supplementary datasets: CHIPRS (Climate Hazard Group InfraRed Precipitation with Station data) or GPM (Global Precipitation Measurement)
- **Model Development:**
 - Implement a PINN that integrates with physical constraints derived from hydrological and atmospheric equations governing rainfall process.
 - Compare performance with conventional ML models like LSTMs, Random Forests and Purely physics-based downscaling methods.
- **Tools:**
 - Python with pyTorch/TensorFlow for deep learning.
 - Numpy for PDE solvers and physical constraints.
 - Google Colab or HPC resources for model training.
- **Evaluation:**
 - Metrics: RMSE, MAE, R^2 for prediction accuracy; physical consistency checks.
 - Baselines: Standard statistical downscaling and LSTM-based rainfall forecasting.

4.Expected Outcomes and Significance

- **Scientific Contribution:**
 - Demonstrate the feasibility of PINNs for climate modeling in Africa.
 - Provide one of the first case studies applying physics-informed AI to Ethiopian rainfall prediction.
- **Practical Contribution:**
 - Support water resource management and agricultural planning in the Blue Nile Basin.
 - Offer Computationally efficient alternatives to high-cost climate simulation.
- **Capacity Building:**
 - Introduce and apply cutting-edge AI methods in the Ethiopian research community.

5.References

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