KAUST Academy – Summer AI Program
Project Status Report

Evaluating Statistical and Machine Learning Methods for Future Heat Stress Downscaling in Saudi Arabia

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Project Abstract

As global temperatures continue to rise, heat stress is becoming a serious concern, especially in hot and dry regions like Saudi Arabia. Two key indicators of heat stress are Cooling Degree Days (CDD), which estimate energy demands for cooling, and wet-bulb temperature, which measures the danger of extreme heat to human health. Understanding how these indicators may change in the future requires accurate, high-resolution climate data, but global climate models (GCMs) are often too coarse and biased for local analysis. This project focuses on improving projections of CDD and wet-bulb temperature in the cities of Jeddah and Riyadh using statistical downscaling. We will use ERA5 [1]reanalysis data as reference observations and compare traditional approaches, such as Quantile Delta Mapping (QDM), with machine learning methods to evaluate how well they adjust GCM output. Multiple climate models and scenarios from CMIP6 [2]will be used to represent a range of plausible futures. Each method will be tested by its ability to reproduce historical patterns and extremes, and its future projections will be assessed for physical plausibility and consistency with expected climate change trends. The goal is to provide more reliable and localized projections of future heat stress in Saudi Arabia to support planning for public health, energy use, and infrastructure, while also evaluating whether machine learning can improve downscaling performance compared to traditional methods.

ERA5 - Fifth Generation ECMWF Reanalysis [1]
CMIP6- Coupled Model Intercomparison Project Phase 6 [2]

Project Objectives and Goals

- Investigate future heat stress in Saudi Arabia, focusing on Cooling Degree Days (CDD).
- Apply and compare statistical downscaling (e.g., QDM) with machine learning methods to improve spatial resolution and reduce model bias.
- Use downscaled climate data to generate more reliable localized projections for Jeddah and Riyadh.
- Support public health planning, energy management, and infrastructure design through accurate climate projections.

Current Progress and Milestones Achieved

- ERA5 reanalysis data collected and preprocessed.
- CMIP6 climate model data selected for multiple future scenarios.
- Extensive exploratory analysis performed on both historical and future climate datasets.
- Quantile Delta Mapping (QDM) method applied for statistical downscaling of temperature.
- Random Forest and XGBoost machine learning algorithms applied for climate downscaling temperature.
- Evaluating statistical methods against machine learning algorithms.

Methodology and approach

1. Data Sources
   - ERA5 reanalysis (1985–2014) used as observational reference.
   - Three CMIP6 models across emission scenarios SSP1-2.6 to SSP5-8.5.
2. Feature Engineering
   - Physics-based predictors temperature
   - Derived features: climatology, anomalies, seasonal cycles, temporal patterns.
3. Models Applied
   - Quantile Delta Mapping (QDM): baseline statistical method.
   - Random Forest: non-linear ensemble learning.
   - XGBoost (GPU-accelerated): gradient boosting for high-accuracy downscaling.
4. Validation Strategy
   - Time-series cross-validation to preserve temporal structure.
   - Metrics: RMSE, R^2, and bias evaluation.
5. Projection Stage
   - Apply trained models to downscale CMIP6 future scenarios.
   - Generate local-scale projections for Jeddah (coastal) and Riyadh (desert).
6. Pipeline Overview
   - Data → Feature Engineering → Model Training → Validation → Future Projections (as shown in the pipeline diagram).

Challenges and Obstacles Encountered

Data acquisition has presented significant technical challenges over three days. Multiple issues have been encountered with the data download process, including API connectivity failures that interrupt download sessions, corrupted data files that require re-downloading, and datasets containing extensive null values that compromise analysis quality. These data integrity issues are causing delays in the preprocessing phase and requiring additional time for data validation and cleaning procedures.

A methodological challenge arose regarding the downscaling approach for wet-bulb temperature: Should temperature and dewpoint be downscaled separately before computing wet-bulb temperature, or should wet-bulb temperature be computed first and then downscaled? This uncertainty has required extra experimentation and literature review to determine the most appropriate method.

Modeling Difficulties Attempts to downscale dewpoint using machine learning produced persistent errors that could not be resolved within the available timeframe. As a result, the analysis proceeded using temperature-based downscaling only.

Preliminary Results or Findings

XGBoost achieved the highest accuracy (R^2 = 0.995–0.998, RMSE = 0.238–0.370 °C), reducing errors by 83–89% compared to QDM. Random Forest also outperformed QDM but was less accurate than XGBoost. Machine learning methods corrected historical biases, aligning CMIP6 outputs more closely with ERA5 observations.

However, future projections showed limitations: XGBoost produced nearly identical results across scenarios, with maximum temperatures close to ERA5 historical data. This suggests underperformance with out-of-sample climate change conditions, possibly linked to feature engineering choices (e.g., climatology and anomalies) not used in QDM. In contrast, QDM and RF captured more differentiated scenario outcomes. Despite these issues, projections still indicate moderate coastal warming in Jeddah versus stronger amplification in Riyadh, with CDD increases of ~60% and ~75% respectively under SSP5-8.5.

Next Steps and Future Work

To address these limitations, we plan to re-evaluate downscaling using one CMIP6 model across three SSP scenarios with QDM, Random Forest, and XGBoost under a consistent setup. Further work will explore advanced approaches, including Convolutional Neural Networks (CNNs), which may better capture spatial and temporal dynamics. Refining feature engineering and testing additional ML and DL methods will be key to producing more robust and reliable projections for adaptation planning in Saudi Arabia.

Resources and Tools Used

- **Datasets:** ERA5, CMIP6
- **Tools:** Python, xclim, xsdba, scikit-learn, xarray, matplotlib, numpy, cartopy, dask, scipy, siphon

References:

ERA5: is a global climate reanalysis dataset produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) under the Copernicus Climate Change Service.

CMIP6: is the latest phase of the international climate modeling effort coordinated by the World Climate Research Program (WCRP), used for understanding past, present, and future climate changes.

GitHub repo.