NeuralFAO56: A data-driven Neural Network FAO56 Python Package for Irrigation Demand Estimation

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Introduction

- Accurate estimation of crop evapotranspiration (ETc) and irrigation demands is essential for optimizing water resource management and promoting sustainability in precision agriculture.
- FAO-56 method is a foundational tool for ETc and irrigation prediction but depends on manually collected weather data. This manual acquisition is time-consuming, cost-prohibitive, and prone to errors.
- **NeuralFAO56** is a Python package designed to automate and improve ETc and irrigation scheduling forecasts. It integrates historical, real-time, and forecasted weather data from multiple open-access APIs, providing a unified platform that eliminates the need for users to access multiple data sources. By leveraging advanced machine learning (ML) models, it enhances the accuracy of ETc forecasting.

Objectives

- Dynamically update the FAO-56 model inputs using real-time and forecasted data streams through APIs.
- Incorporate ML models–Long-Short Term Memory (LSTM) and Patch Time Series Transformer (PatchTST)–to generate accurate data-driven ETc forecasts.
- Create a single, modular platform that allows seamless access to data and ETc estimations with minimal user intervention.

Methods

1. Data Collection and Preprocessing:

- **Weather Data:** Historical, real-time, and forecasted weather data will be sourced from the National Weather Service (NWS) and National Centers for Environmental Information (NCEI) APIs.
- **Soil Profile Data:** Key parameters like Field Capacity (FC) and Wilting Point (WP) will be retrieved from the USDA Natural Resources Conservation Service Soil Survey Geographic Database (SSURGO) API.
- **For model validation:**
  - ❖ Ground truth soil moisture and irrigation scheduling data will be collected from field trials at Edisto Research and Education Center (Edisto REC, Clemson University) (since 2023) and Stripling Irrigation Research Park (SIRP, University of Georgia) (since 2019).
  - ❖ Data smoothing will be applied on soil moisture data to detect and address sensor failures. Missing values will be interpolated to maintain continuity and avoid bias.

2. Workflow of NeuralFAO56 (Refer to Figure 1):

Data Retrieval:

- Users input geographical coordinates, and the system retrieves a 7-day weather forecast from the NWS *forecastGrid* endpoint.
- The system selects the nearest weather station and retrieves both historical and real-time weather data using the NWS *observationStations* and *observations* endpoints, as well as the NCEI Data Access API.

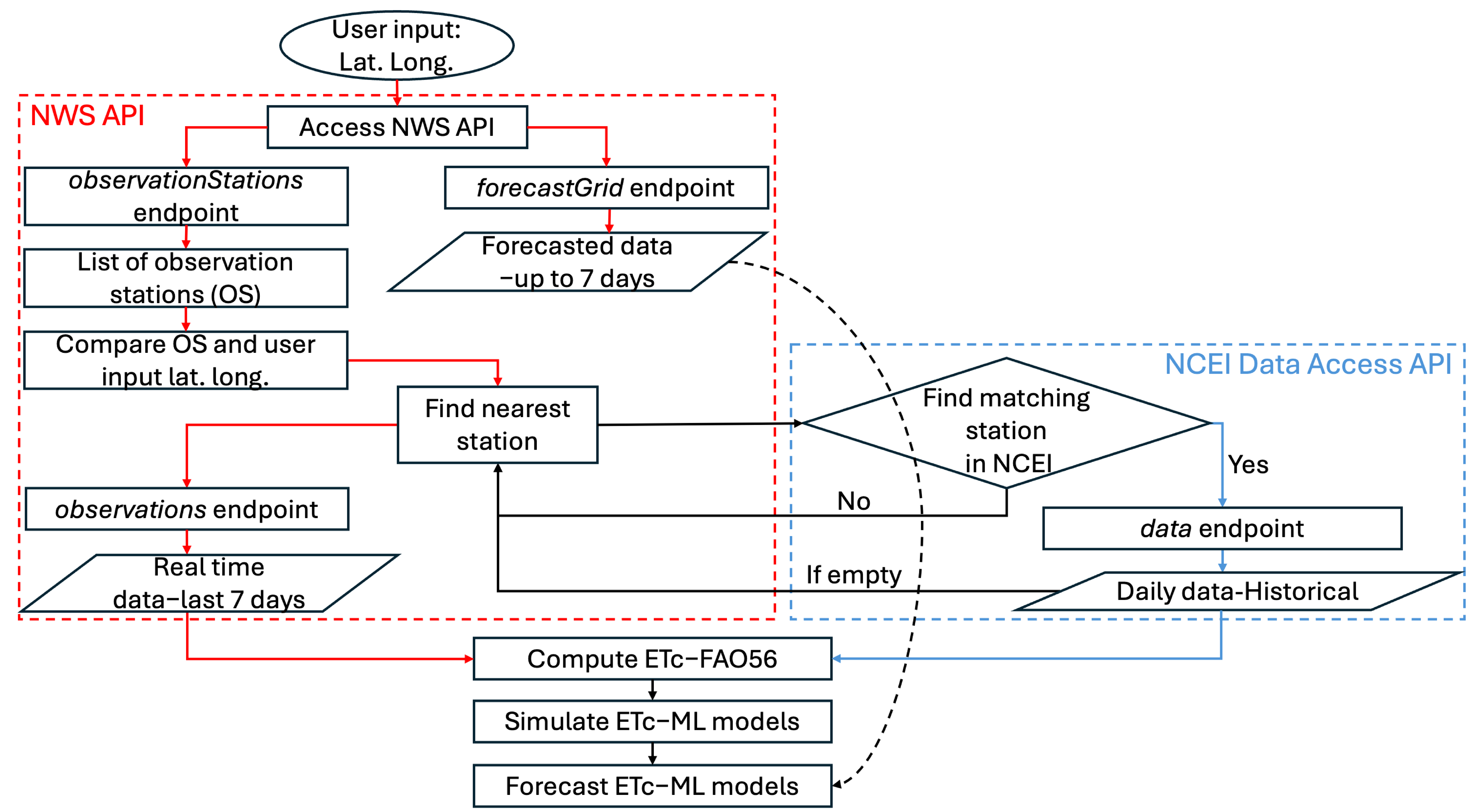

Figure 1. Conceptual framework and workflow of NeuralFAO56

ETc Estimation:

- The FAO56 dual crop coefficient method is used to compute ETc[1], as shown below:

$$ETc = (Kcb + Ke)\ ETo$$

where:

Kcb = Basal crop coefficient, Ke = Evaporative component, and ETo = Reference evapotranspiration

Irrigation Demand Calculation:

- The FAO56 soil water balance equation is used to estimate irrigation need[1], as shown below:

$$D_i = D_{i-1} - (P\text{-}RO)_i - I_i - CR_i + ETc_i + DP_i$$

where:

D_i and D_{i-1} are soil moisture depletion at the end of current and previous day

P = Precipitation, RO = Runoff, I = Irrigation, CR = Capillary rise, ETc = Crop water use, DP = Deep percolation

Machine Learning Models:

1. LSTM (Long Short-Term Memory)[2]
2. PatchTST (Patch Time Series Transformer)[3]

Model Training & Validation:

- Both LSTM and PatchTST models will be trained on historical and real-time data to predict ETc for the next 7 days based on forecasted weather inputs.
- Model performance will be validated using ground truth datasets from Edisto REC and SIRP.

References

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