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Early forecasting of crop irrigation for sustainable water use with satellite data and machine learning

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Abstract: Early forecasting of crop irrigation demand improves water efficiency and supports food security. Accurate forecasts allow farmers and policymakers to schedule irrigation based on crop type and climate, ensuring timely water application throughout the growing season. Traditional biophysical models rely on fixed delivery schedules and broad hydrological trends, often lacking precision for specific crop stages. While machine learning (ML) has been widely used for yield and biomass prediction, its application in forecasting crop water requirements remains limited. This study bridges that gap by integrating remote sensing with ML to align water supply with crop demand under changing climate conditions, promoting sustainable irrigation. Therefore, in this study we address that gap by using a remote sensing-based approach combined with ML techniques to align water supply with crop requirements under changing climate conditions and to contribute to sustainable water use.

The study focuses on Pakistan's Indus Basin, specifically Chaj Doab, located between the Jhelum and Chenab rivers. The region features flat terrain with coarse-textured alluvial soils and high evapotranspiration. Agriculture depends on a canal-based surface irrigation system. A wide variety of crops including wheat, rice, sugarcane, maize, and high-value horticulture are grown year-round, making timely irrigation crucial. The proposed methodology for estimating irrigation demand uses actual evapotranspiration (ETact) derived from satellite-based biophysical and climatic variables. Landsat imagery with a spatial resolution of 30 m resolution from 2015 to 2025 was used to calculate normalized difference vegetation Index (NDVI), soil adjusted vegetation index (SAVI), land surface temperature (LST), and net radiation (Rn). Climate variables (precipitation, temperature, humidity) were integrated, and crop classification used a Random Forest model on PlanetScope imagery.

The dataset was split with 80% used for training and 20% for validation chronologically, to simulate a continuous forecasting scenario covering full Kharif and Rabi season cycles. The primary objective was to evaluate model performance in an unseen future period, reflecting irrigation forecasts. The 80-20 chronologically split ensured a long historical record for vigorous training and a sufficiently large, continuous block of unseen data that spans entire season irrigation requirement which validation against observed evapotranspiration (ET) and local climate data from the Eddy Covariance Flux Tower, providing reliable ground-truth checks across entire cropping cycle.

The machine learning models tested included CNN, XGBoost, and Random Forest. Among these, CNN achieved the highest performance with an R^2 of 0.89, followed by XGBoost ($R^2 = 0.81$) and Random Forest ($R^2 = 0.76$) on the testing samples. The short-term irrigation forecasting was validated with ground truth observations across two cropping seasons Kharif and Rabi, using observed ET values and local climate data from an Eddy Covariance Flux Tower. CNN accurately forecasted irrigation for rice (6.79 mm/day vs. observed 6.99) and wheat (2.04 mm/day vs. 1.86). It also closely matched peak water demand during wheat growth (29.87 vs. 33.01 mm/day). Overall, CNN showed the highest correlation attributed to its stronger learning capability, to extract complex spatial temporal relationships than other models across multiple crops (maize, potato, guava, and orchards), showing strong spatial accuracy and temporal relevance. The findings also highlight the potential of integrating ML and remote sensing data with climate forecasts to develop data-driven irrigation planning.

Keywords: *Irrigation Demand Forecasting, Evapotranspiration (ET), Remote Sensing, Machine Learning, Eddy Covariance Flux Tower, Climate-Smart Agriculture*