

Explainable Machine Learning to Quantify the Value of Proximal Remote Sensing in Latent Energy Flux Estimation

Background/Objective

Latent energy flux (LE), the exchange of energy between the land and atmosphere, is closely linked to crop water use and is an essential metric for crop water management. Traditional process-based models depend on vegetation parameters that change during the growing season. Data driven models using proximal remote sensing data have the potential to address this but require careful predictor selection. This study presents a comprehensive assessment of machine learning (ML) models to assess the utility of meteorological and proximal remote sensing data for LE prediction.

Approach

Half-hourly meteorological variables and proximal remote sensing data were collected with co-located eddy covariance LE measurements at the SABR field site at Iowa State University. We tested 64 deep learning neural network configurations, ranging from one to six predictors across four predictor categories. Model performance and variable importance across crop phenology were evaluated using robust cross-validation and SHAP explainability.

Results

ML models using only three predictors (one meteorological and two proximal remote sensing) captured 81% of LE variability and offered the best trade-off between performance and complexity. A model with four environmental predictors with two proximate remote sensing variables captured 88% of LE variability. An ML model using one proximal remote sensing and one meteorological variable captured 77% of LE variability.

Significance/Impacts

These results demonstrate the power of proximal remote sensing and meteorological observations to estimate land-atmosphere water vapor exchange, providing a solution in cases where more direct methods such as eddy covariance are not available.

