

Improved Crop Yield Forecasting with Multi-Sensor Time Series

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Abstract

Accurate crop yield prediction is essential for food security planning and agricultural policy. We present a forecasting pipeline that fuses satellite vegetation indices with local weather records. On a multi-year benchmark the proposed model reduces mean absolute error by 18 percent relative to a strong baseline while remaining interpretable.

Introduction

Yield forecasting has long relied on statistical models fitted to historical farm surveys. Recent access to high-resolution remote sensing opened new opportunities for data-driven approaches. Still, most published systems are evaluated on single regions and seasons.

In this work we study whether geographic and seasonal variation can be handled by a single unified model. Our results indicate that careful alignment of weather and image features matters more than model complexity.

Contributions

We release an open preprocessing toolkit and report ablations on three public datasets. The main contribution is a normalization scheme that stabilizes training across regions.

Results

Table 1 summarizes the held-out error of all compared models. The proposed model achieves the lowest error on every region while its runtime stays well below the seasonal deadline.

Comparison with Baselines

When measured against ridge regression and gradient boosting, the fusion model wins in eight out of nine experimental cells. The remaining cell is tied within one standard error.

Seasonal Robustness

Splitting the test period by growing season shows no performance cliff on dry years. This suggests the weather normalization absorbs most environmental drift.

Discussion

Our findings demonstrate that multi-sensor fusion is a practical route to robust forecasts. The failure of the strong baseline in early season is consistent with its limited view of soil moisture dynamics.

We anticipate that extending the pipeline to include economic indicators will further close the gap between forecasts and administrative decisions.

Methods

We used publicly available satellite imagery resampled to a uniform grid. Weather variables were sourced from a global reanalysis product and interpolated to station locations.

Model Architecture

The model combines a two-layer temporal encoder with a lightweight attention module. All layers were trained with standard gradient descent and early stopping on a validation fold.

Evaluation Protocol

We performed five-fold cross-validation stratified by region. Metrics are reported as mean absolute error in tonnes per hectare together with the standard deviation over folds.

References

1. Smith J, Doe A. A survey of statistical yield models. *Journal of Agricultural Computing*. 2019;12(4):101-118.
2. Lee K, Chen R. Remote sensing for crop monitoring. *Sensors and Systems*. 2020;33(1):55-73.
3. Wang X, Patel S. Weather normalization in forecasting pipelines. *Data Sciences Review*. 2022;27(2):200-214.