Forecasting grain maize yield in sub-Saharan Africa
A hybrid modelling approach

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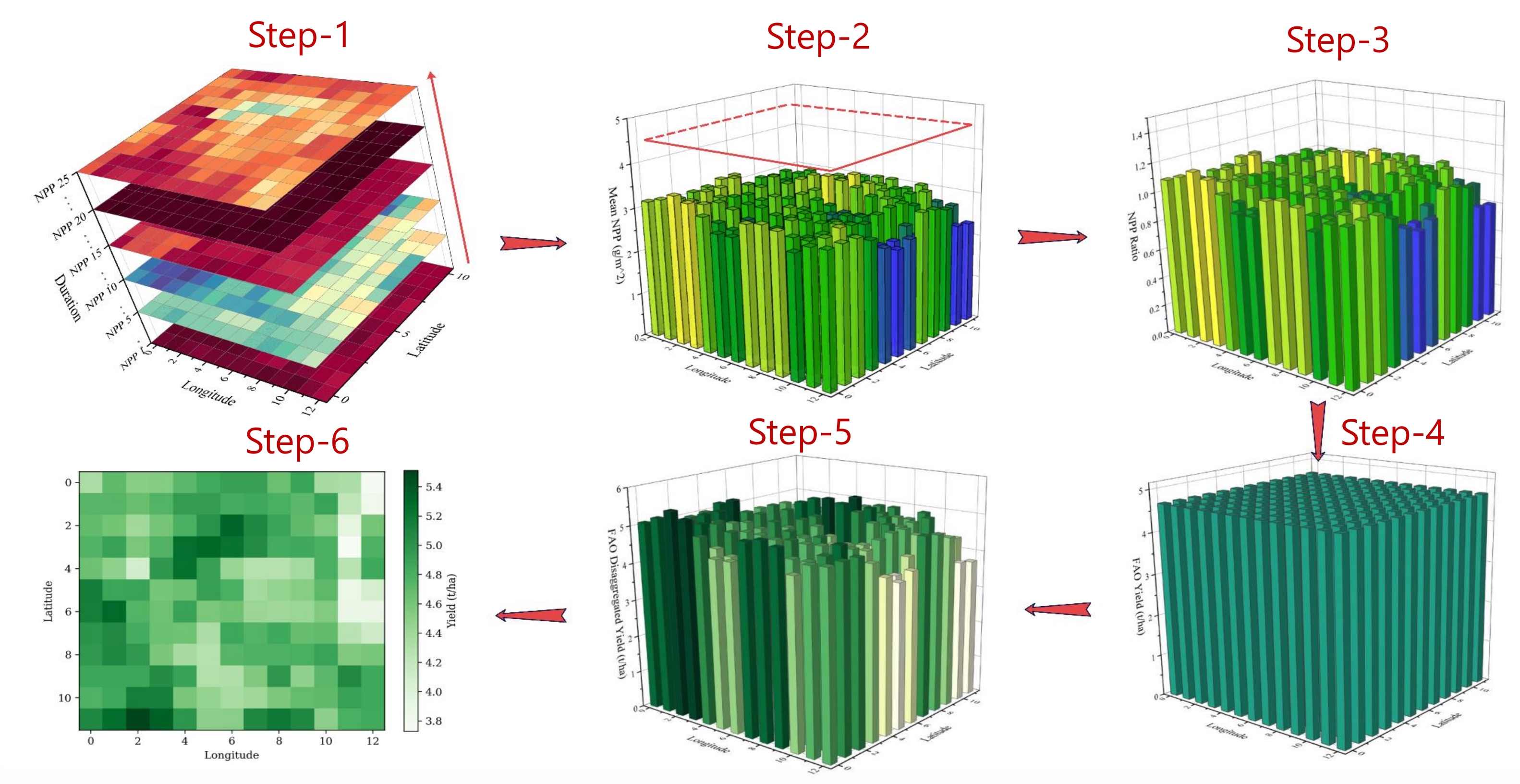
BACKGROUND

The dual challenges of climate change and a burgeoning global population, projected to surpass 9 billion by the year 2030, present unprecedented hurdles for the agricultural sector. These challenges underscore the need for developing precise and timely crop yield forecast (CYF) models. To enhance CYF, various approaches have been explored to reduce uncertainties in model structure, inputs, and parameters, exceeding observed yield variations over time/space. In the present work we tested the Hybrid ML (DNN) modelling concept i.e., LSTM to tackle temporal variables and Dense layer for static variables to improve the accuracy of maize yield predictions compared to gradient boosting algorithms (XGBoost & LightGBM) across 39 sub-Saharan Africa countries.

DATA AND METHODOLOGY

- Climate Data: ERA5-Land Daily Aggregated - ECMWF Climate Reanalysis (Max. & Min. Air Temp, Solar Radiation, & Precipitation)
- Soil Data: Soil Grids 250m v2.0 (Soil texture, Organic carbon, & Total nitrogen)
- Remote Sensing Data: LAI and NDVI
  - MCD15A3H.061 MODIS Leaf Area Index/FPAR 4-Day Global 500m
  - MOD13Q1.061 Terra Vegetation Indices 16-Day Global 250m
- Net Primary Production Data: WAPOR Dekadal Net Primary Production 2.0



Step-1

NPP values for the entire crop duration over croplands were extracted at dekadal intervals, and the mean NPP was calculated for each pixel.

$$\text{Average NPP}_i = \frac{1}{T}\sum_{t=1}^{T}\text{NPP}_i(t)$$

where T is the number of timesteps.

Step-2

The country-level average NPPs were calculated by averaging NPP across all pixels and timesteps.

$$\text{Country Average NPP} = \frac{1}{n \times T}\sum_{i=1}^{n}\sum_{t=1}^{T}\text{NPP}_i(t)$$

where n is the total number of cropland pixels in the country.

Step-3

NPP ratios were calculated by dividing the average NPP of each pixel by the country-level average NPP.

$$\text{NPP Ratio}_i = \frac{\text{Average NPP}_i}{\text{Country Average NPP}}$$

This ratio indicates whether a pixel has higher or lower productivity relative to the country average.

Step-4

FAO country-level yield statistics provide a uniform annual yield (tonnes per hectare) for each pixel across the country.

Step-5

To disaggregate the yield, we multiply the FAO uniform yield by the NPP ratio to adjust the yield based on the pixel's relative productivity.

Step-6

Disaggregated FAO yield based on NPP ratio.

$$\text{Disaggregated Yield}_i = \text{FAO Uniform Yield per Pixel} \times \text{NPP Ratio}_i$$

RESULTS AND DISCUSSION

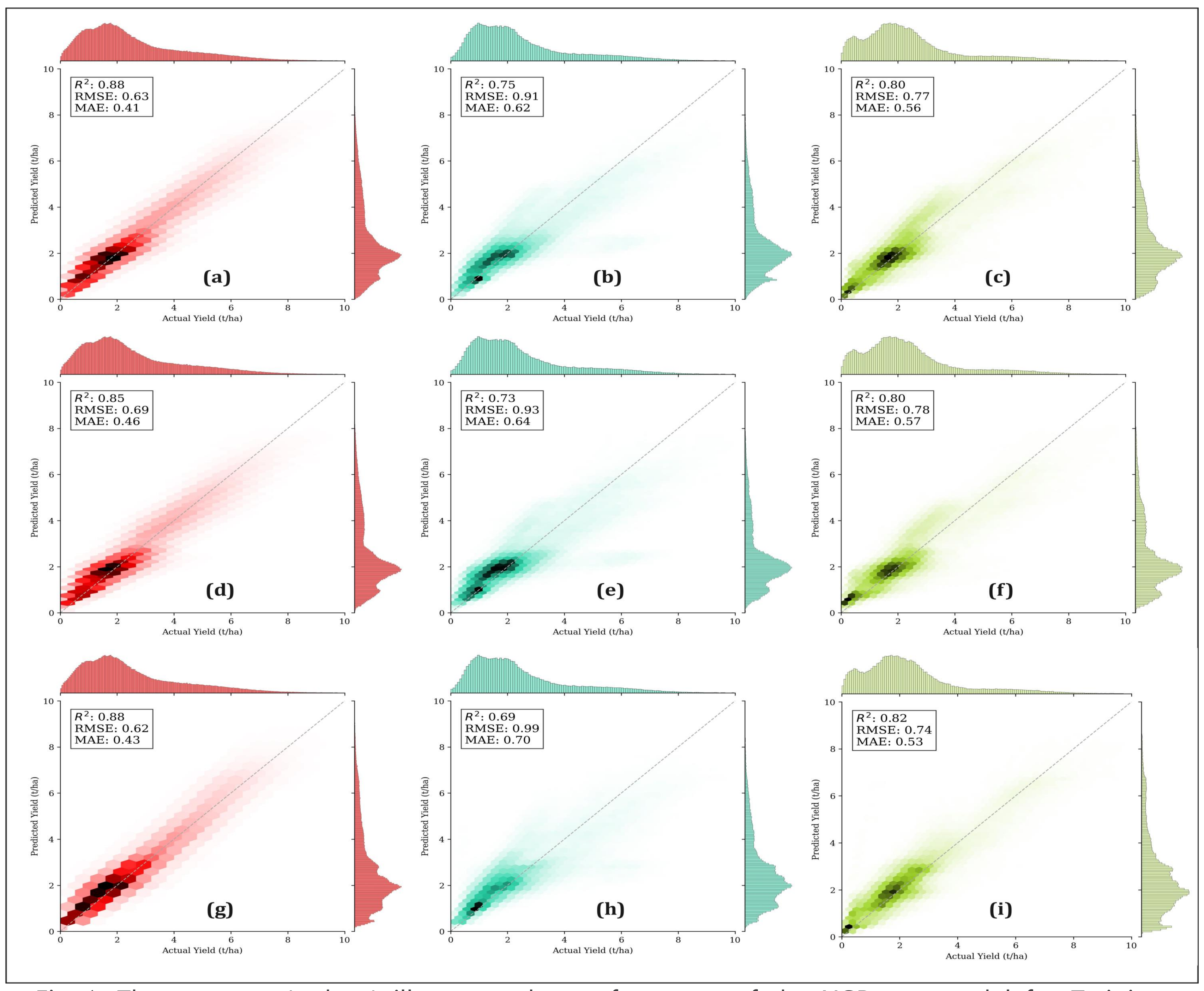
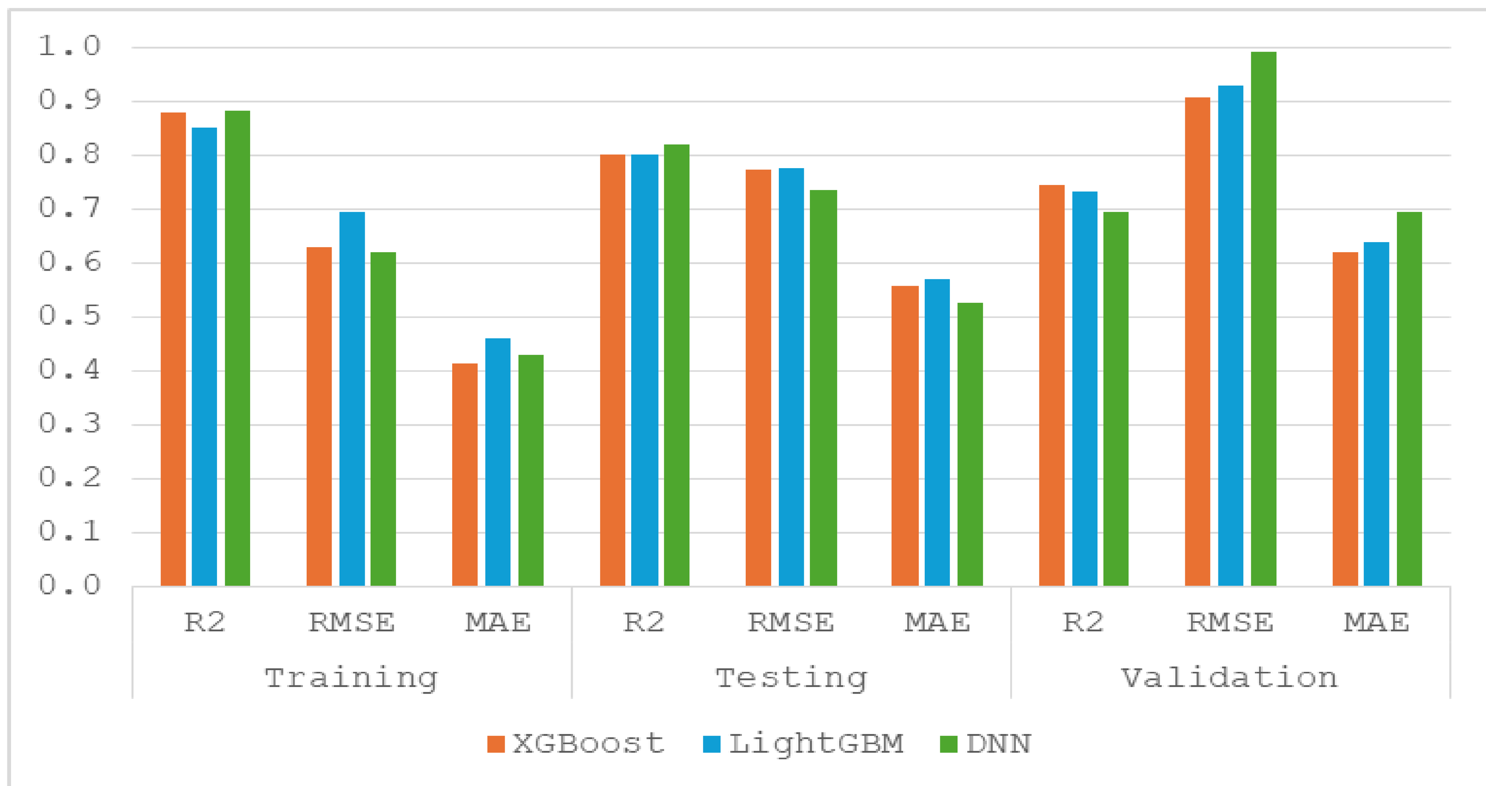


Fig 1: The top row (a, b, c) illustrates the performance of the XGBoost model for Training, Testing, and Validation. The middle row (d, e, f) displays results for the LightGBM model, while the bottom row (g, h, i) shows the performance of the DNN model.



The above bar chart compares the performance (XGBoost, LightGBM, and DNN) across Training, Testing, and Validation dataset using three evaluation metrics: R^2 (coefficient of determination), RMSE (Root Mean Square Error), and MAE (Mean Absolute Error).

- DNN performs best in the Training and Testing phases with higher R^2 and lower RMSE, suggesting it fits well and generalizes across training and test sets.
- XGBoost has the best performance in the Validation phase with the lowest RMSE and MAE, which could mean it's less overfitted compared to DNN.
- LightGBM shows competitive results but slightly lags behind XGBoost and XGBoost, especially in validation.

Conclusion: For overall model performance, DNN is superior for training and testing, but XGBoost shines in validation, which is more critical for real-world prediction accuracy.

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