# Simulating and Predicting Cereal Crop Yields in Ethiopia: Model Calibration and Verification

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## Abstract

Agriculture in developing countries are extremely vulnerable to climate variability and changes. In East Africa, most people live in the rural areas with outdated agriculture techniques and infrastructure. Smallholder agriculture continues to play a key role in this area, and the rate of irrigation is among the lowest of the world. As a result, seasonal and inter-annual weather patterns play an important role in the spatiotemporal variability of crop yields. This study investigates how various climate variables (e.g., temperature, precipitation, sunshine) and agricultural practice (e.g., fertilization, irrigation, planting date) influence cereal crop yields using a process-based model (DSSAT) and statistical analysis, and focuses on the Blue Nile Basin of Ethiopia. The DSSAT model is driven with meteorological forcing from the ECMWF's latest reanalysis product that cover the past 10 years; the statistical model will be developed by linking the same meteorological reanalysis data with harvest data at the woreda level from the Ethiopian national dataset. Results from this study will set the stage for the development of a seasonal prediction system for weather and crop yields in Ethiopia, which will serve multiple sectors in coping with the agricultural impact of climate variability.

## Background

- Agriculture in Ethiopia is the foundation of the country's economy, accounting for half of gross domestic product (GDP), 83.9% of exports, and 80% of total employment.
- Agriculture in Ethiopia is almost entirely rainfed with only 1.4 percent of total cropped area irrigated, less than half of the African average. Droughts is the major risk and source of hardship for rural Ethiopian households.
- The World Bank's Risk and Vulnerability Assessment (2005) found that potential rainfall shocks are the cause of vulnerability for 38 percent of the "vulnerable" population (those with a 50 percent likelihood of falling below the poverty line).

## Research Objective

We developed and applied a crop model in simulating maize yield in Blue Nile Basin, Ethiopia,. Based on the simulated results, we found out the correlation between yield variability and climate factors, and developed a multivariable regression model as supplement and comparison. Those could act as the foundation in revealing seasonal crop growth pattern and predicting yield under future climate situation.

## Study Area

Our research area is Blue Nile River Basin in Ethiopia. The agriculture area accounts for 20% of the total area. Considering the elevation influence on crop growth, the study area can be divided into lowland and highland based on the topographic map. We select 3 sites from each subdivision as our study sites (Fig. 1).

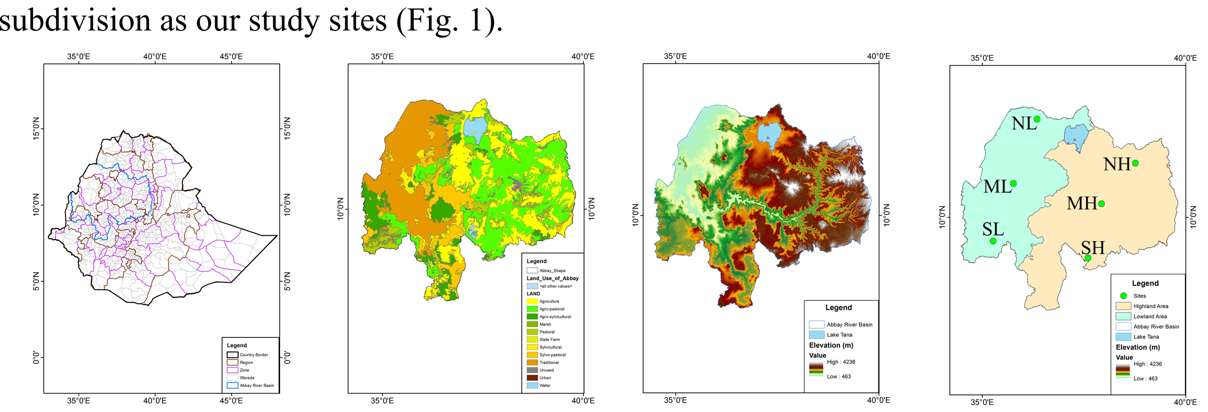


Fig. 1. (1) Location of study area, (2) landuse map, (3) Topographic map, (4) study area division and sites selection

Ethiopia is the fifth largest producer of maize in Africa. In our study area, maize ranks the second in harvest area in both highland and lowland (Fig. 2).

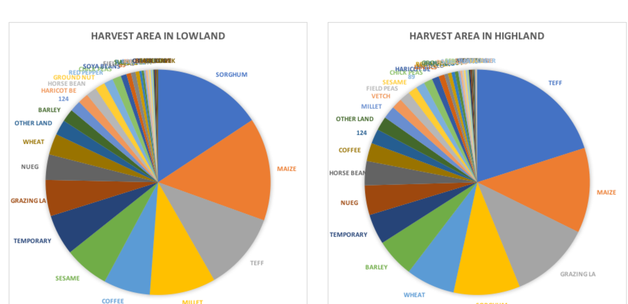


Fig. 2. Crop ranks by harvest area

We divided the crop land into the following 8 situations (Fig. 3):

1) Irrigated and Non-Fertilized Land (INF)
2) Irrigated and Fertilized with Natural Fertilizer Land (IFN)
3) Irrigated and Fertilized with Chemical Fertilizer Land (IFC)
4) Irrigated and Fertilized with Both Natural and Chemical Fertilizer Land (IFB)
5) Rain-fed and Non-Fertilized Land (RNF)
6) Rain-fed and Fertilized with Natural Fertilizer Land (RFN)
7) Rain-fed and Fertilized with Chemical Fertilizer Land (RFC)
8) Rain-fed and Fertilized with Both Natural and Chemical Fertilizer Land (RFB)

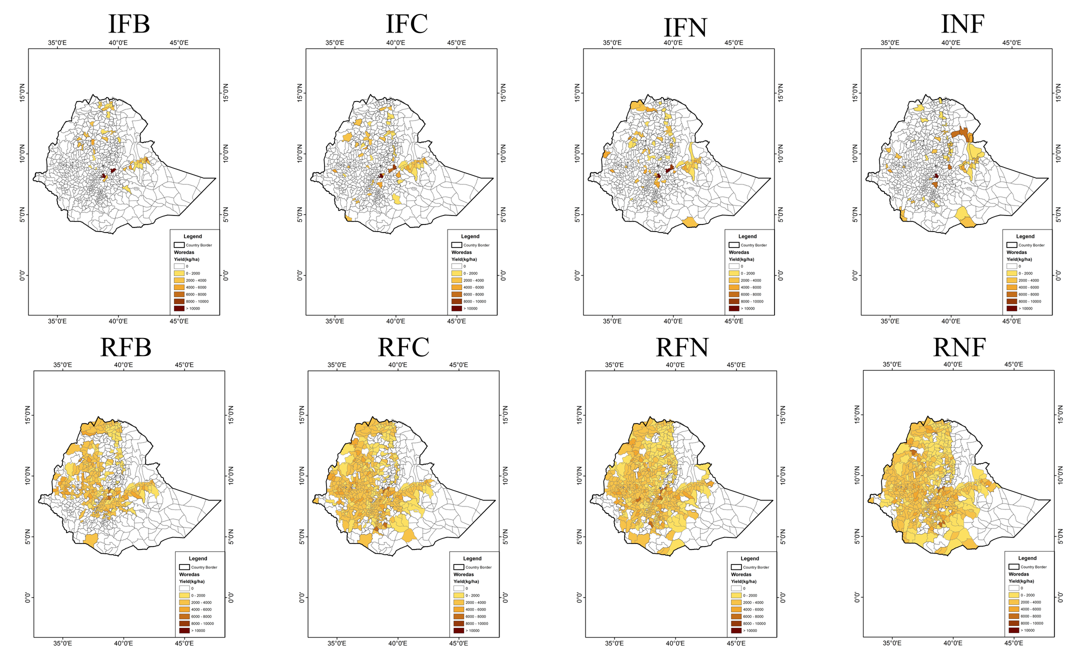


Fig. 3. Maize yield in woreda scale in 2013

## Model Construction

- DSSAT is a process-based crop model that integrates crop physiology and phenotype, weather and soil data, and crop management strategies. It has different modules to perform simulation for different crop types.
- In this research, we collected management data from partner farmers and local research staff. We used 5 min ISRIC-WISE dataset to build the soil database. 0.25 degree MSWEP dataset was used as weather input. For cultivar parameters, we selected a cultivar from DSSAT database that planted most closely to our study area. Finally we used the national crop yield dataset to calibrate model.

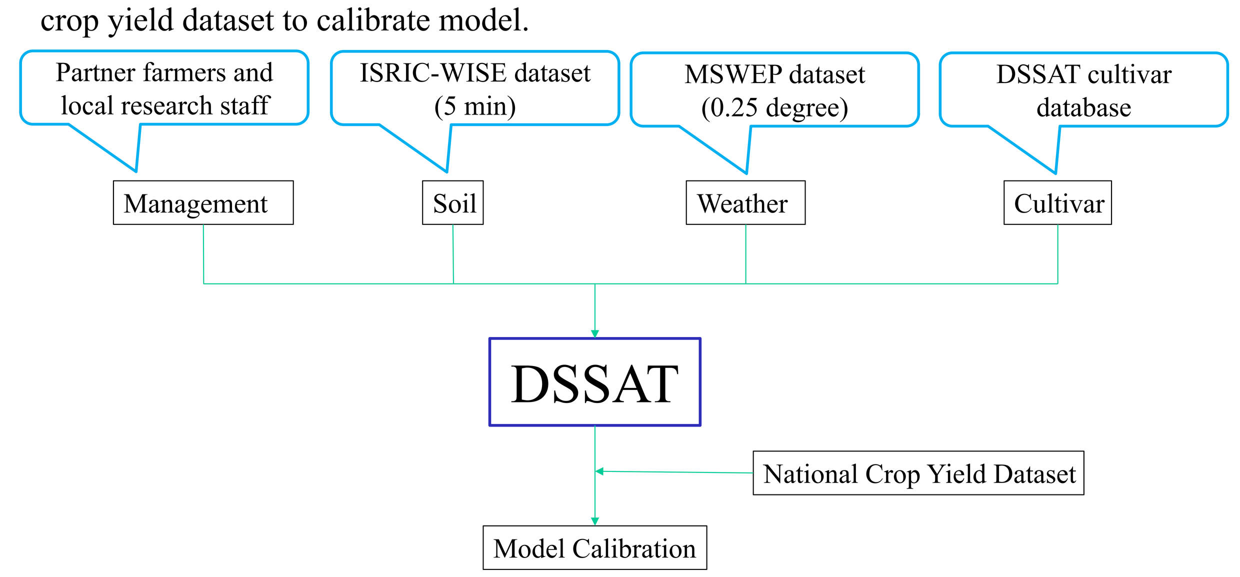


Fig. 4. Model structure and data source

## Results

- The model simulated yields is similar to observed values in average. The increasing of fertilizer application improved the yield in most situation (Fig. 5). However, because the management patterns change from year to year while it's constant in model, it's very difficult for model to capture the real variability.
- In order to know how climate factors affect maize yields, we plotted the interannual variability of simulated yields and climate factors (Fig. 6 - 8). Solar radiation and precipitation are the key factors that influence maize yield.
- In most of the situation, maize yield has a positive correlation with solar radiation and negative correlation with precipitation (Fig. 9, 10)

Fig. 5. Comparison of model simulated yield in two fertilizer application condition with observed value (left to right, top to bottom: NL, ML, SL, NH, MH, SH; the same below)

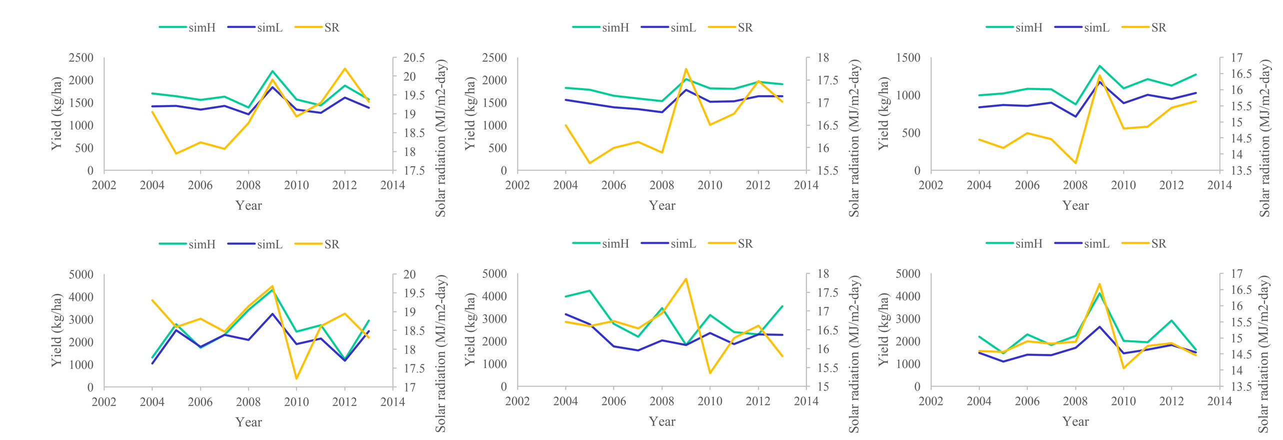

Fig. 6. Variability of simulated yields and solar radiation

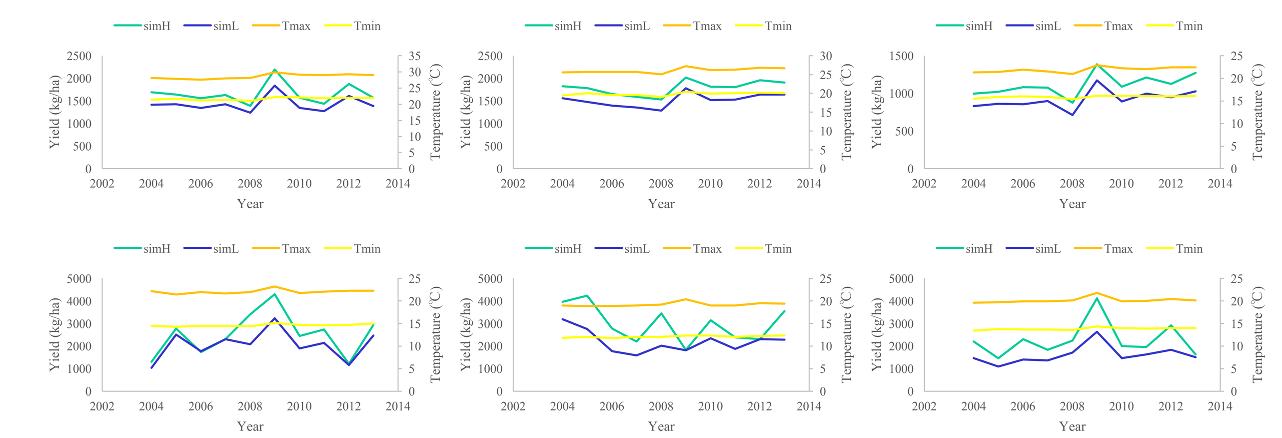

Fig. 7. Variability of simulated yields and temperature

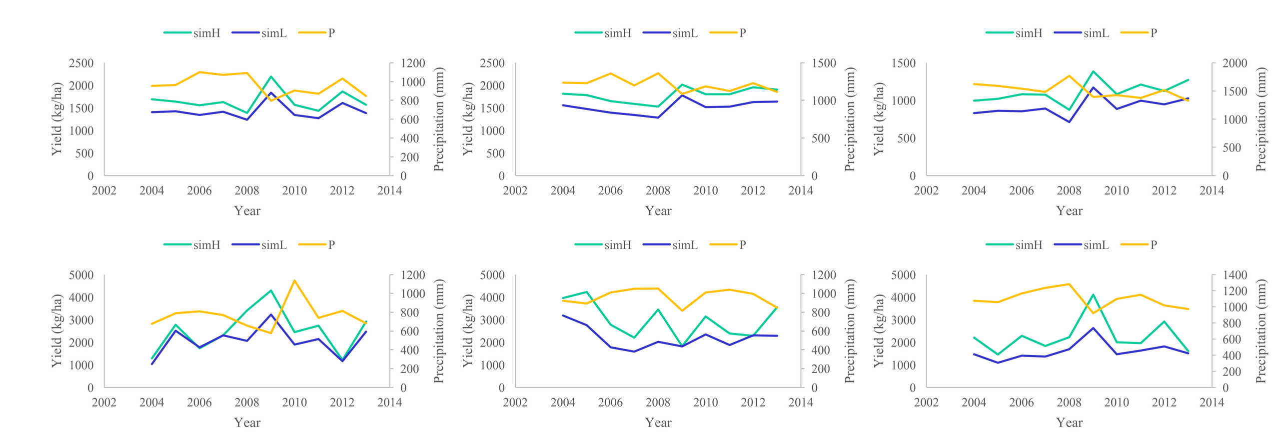

Fig. 8. Variability of simulated yields and precipitation

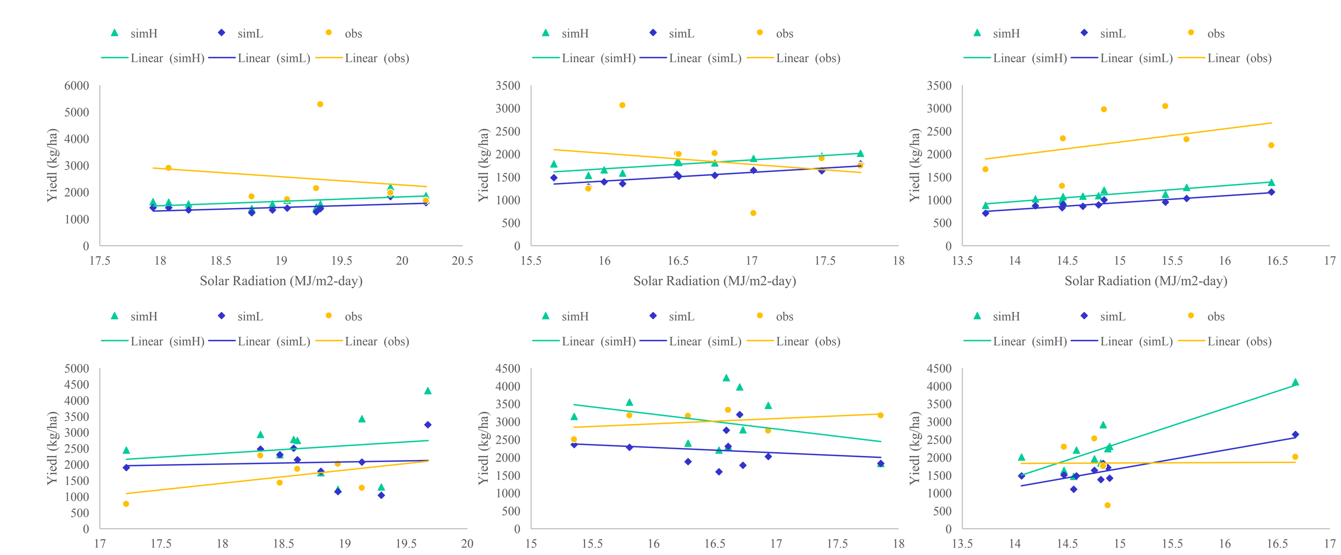

Fig. 9. Correlation between yields and solar radiation

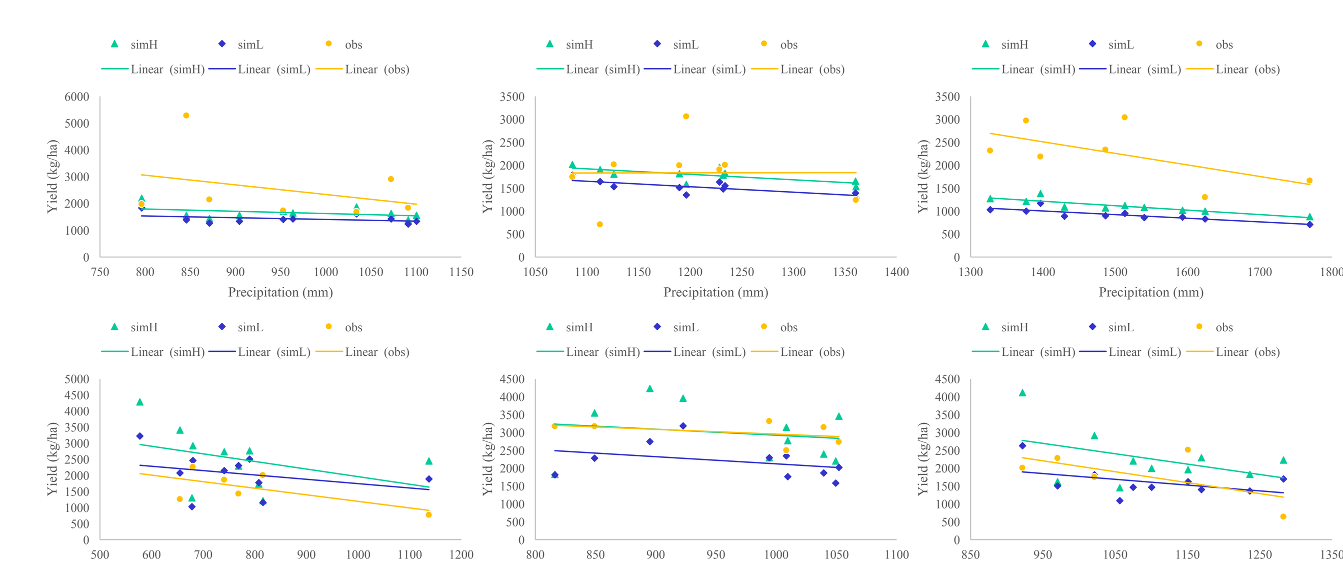

Fig. 10. Correlation between yields and precipitation

We build a multivariable regression model as supplement and comparison to DSSAT.

$$Yield = A \times SR + B \times P + C$$

In high fertilizer application condition (Fig. 11), the multivariable regression model has a good correlation with DSSAT in ML, SL and SH, but not performed well in the other sites.

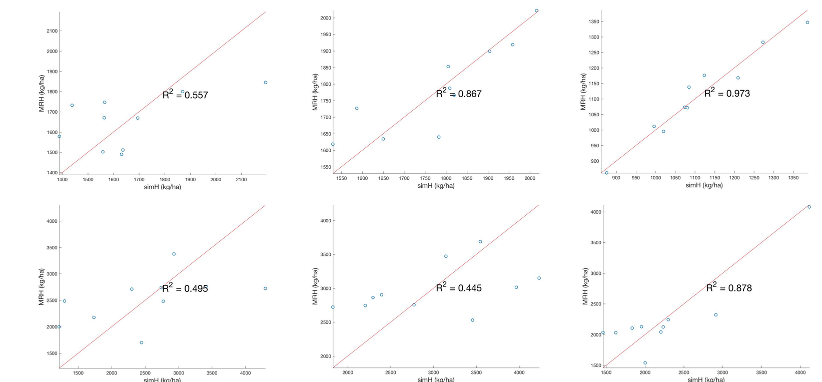

Fig. 11. Correlation between DSSAT simulated yield and multivariable regression model results (high fertilizer)

Similar to high fertilizer application condition, in low fertilizer application condition(Fig. 11), the multivariable regression model well correlated with DSSAT in ML, SL and SH, but not performed well in the other sites.

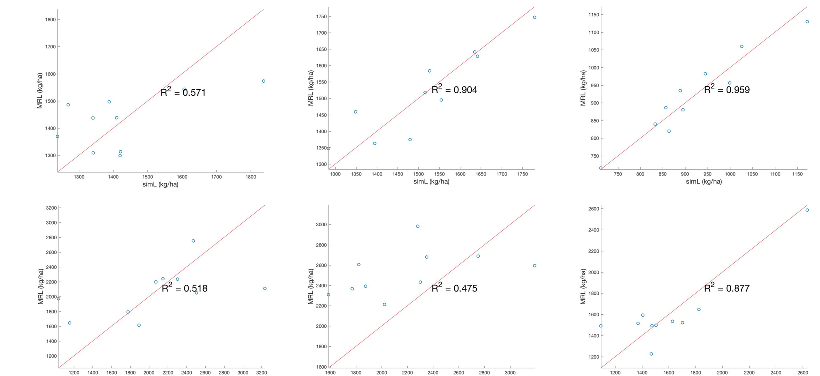

Fig. 12. Correlation between DSSAT simulated yield and multivariable regression model results (low fertilizer)

Compared with the multivariable regression model trained by simulated results, the regression model trained by observed values doesn't have a good performance (Fig. 13). It is poorly correlated with the observed values in every sites.

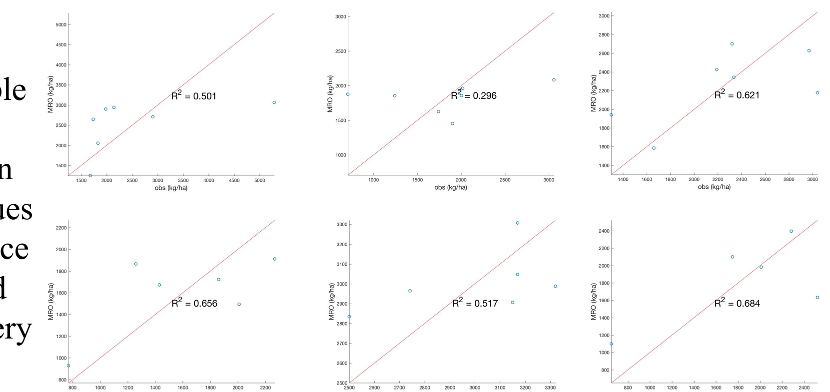

Fig. 13. Correlation between observed yield and multivariable regression model results

## Conclusions

- DSSAT model is applicable in simulating the maize yield in this area.
- Increasing fertilizer application could improve maize yield.
- Yield is positively correlated with solar radiation but negatively correlated with precipitation.
- From 2004 to 2013, the growing season precipitation exceeds the requirement of maize.
- Multivariable regression model could act as a supplemental measure for DSSAT in some sites.

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