ESTIMATING MAIZE GRAIN YIELD IN SCARCE FIELD-DATA ENVIRONMENT : AN APPROACH COMBINING REMOTE SENSING AND CROP MODELLING IN BURKINA FASO

Leroux L., Baron C., Castets M., Escorihuela M-J., Diouf A.A., Bégué A., Lo Seen D.

AfricaGIS2017, November,2017, Ethiopia

MAIZE (*ZEA MAYS L.*) : KEYSTONE OF FOOD SECURITY

- Most produced crop in the world

- **In West Africa :**
  - Staple crop
  - Providers of health benefits and vital nutrients
  - 30 kg/capita/year

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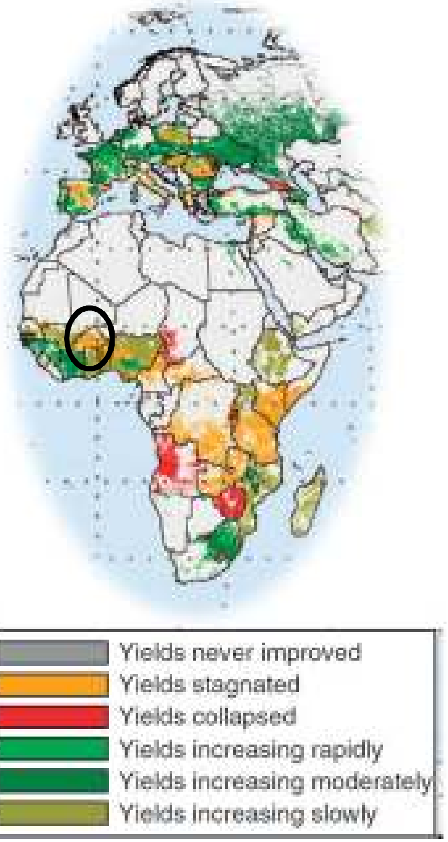

- Stagnation of maize yields
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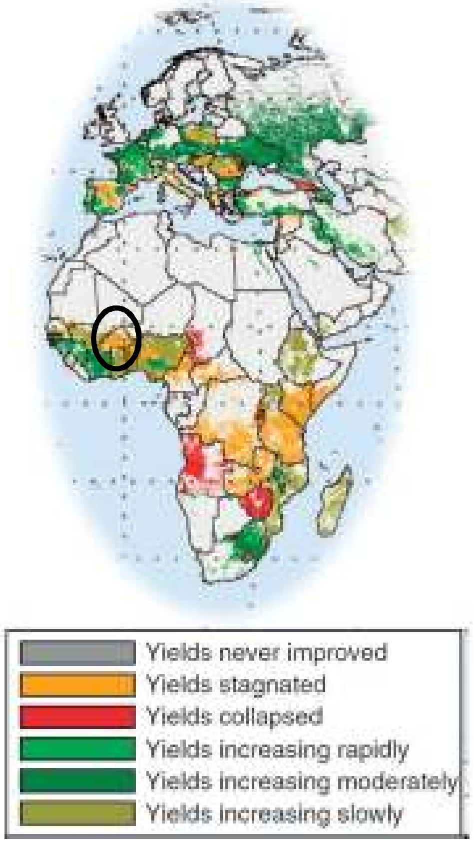

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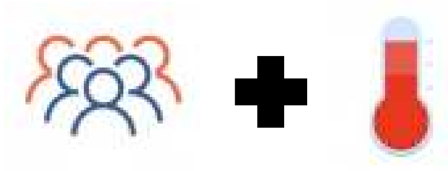

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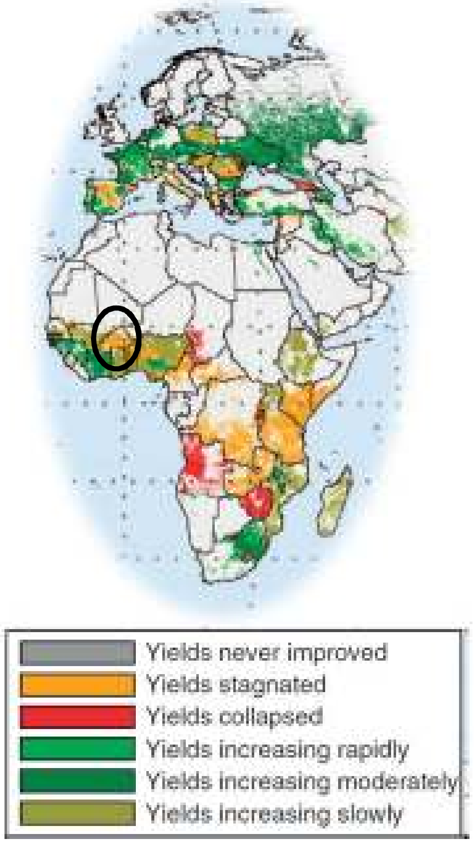

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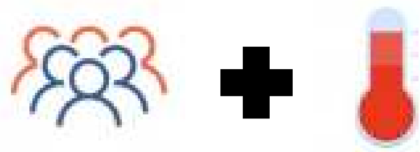
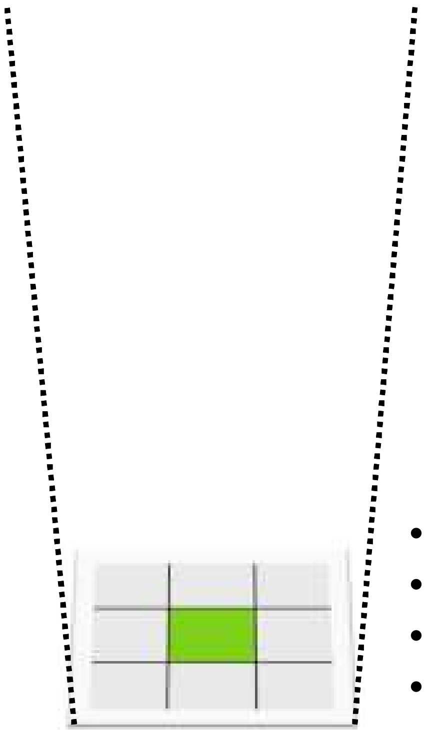


DECLINE IN PER CAPITA FOOD PRODUCTION [RAY ET AL., 2013]

Timely and reliable information on maize crop yields is needed to provide timely estimates of food shortage and support decision-making

YIELD ESTIMATION METHODS



FIELD-BASED SURVEY

- Expensive (time & labor)
- Sampling methods
- Inaccessibility
- Difficulties to upscale to large areas

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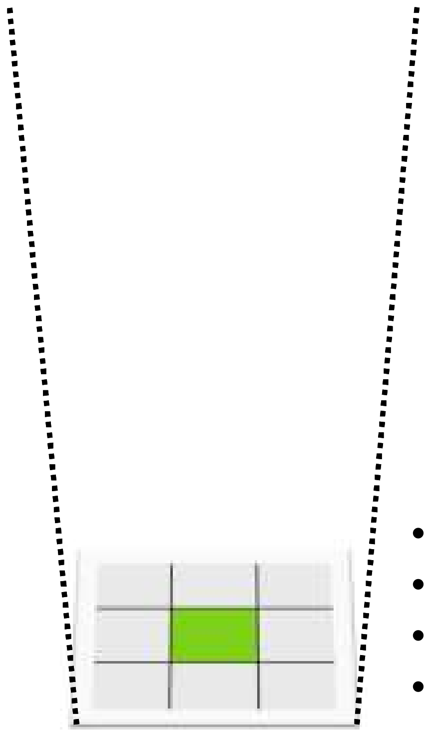

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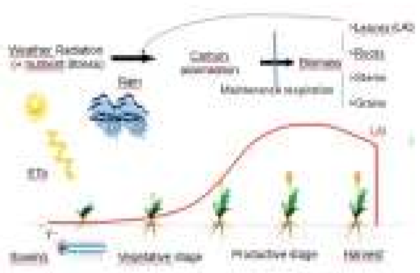
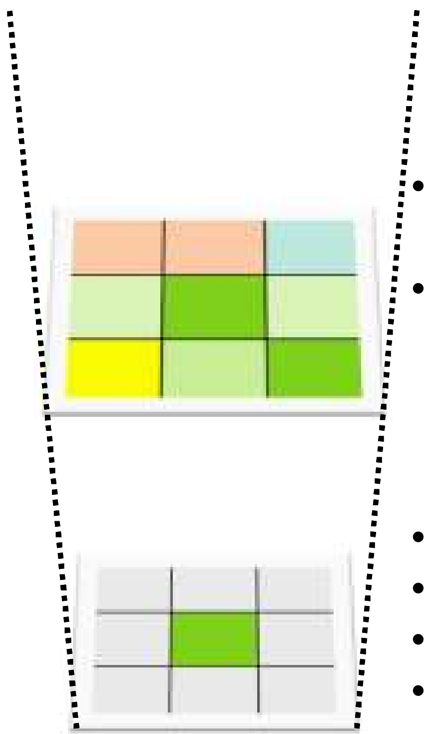
LACK OF GROUND DATA OR UNRELIABLE DATA

YIELD ESTIMATION METHODS

CROP GROWTH MODEL





- Approximation of the reality on the ground
- Potential yields under water or nutrient limitation

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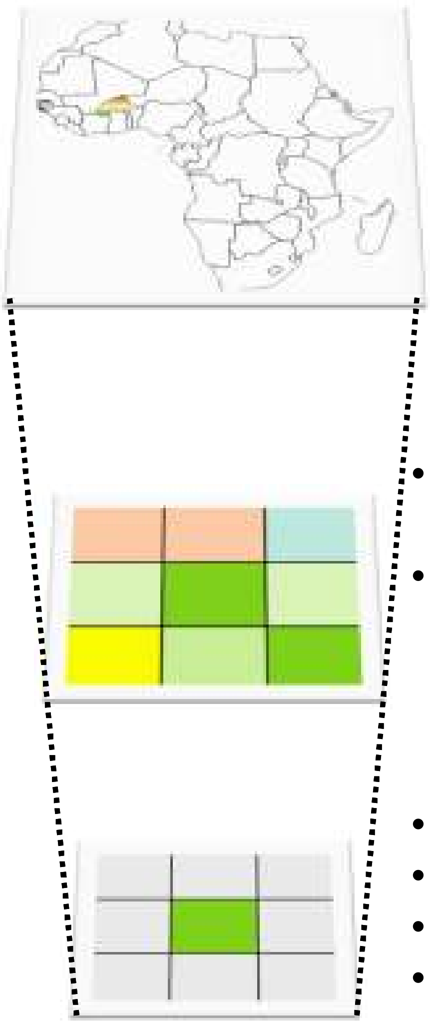
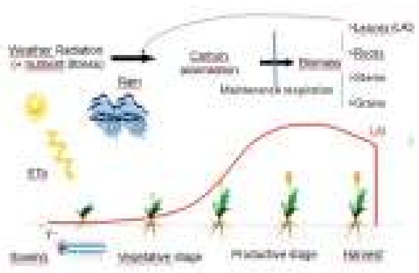


REMOTE SENSING

- Timely and exhaustive information on vegetation cover
- Biomass=f(Vegetation Indices)
- Empirical model calibrated with agricultural statistics **BUT** available ~ 3 months after the end of the cropping season

CROP GROWTH MODEL



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IMPROVE MAIZE YIELDS ESTIMATION USING A CROP MODEL TO GENERATE DIFFERENT COMPONENTS OF YIELDS AS PROXY OF IN SITU OR AGRICULTURAL STATISTICS DATA, AND COMBINING THEM WITH REMOTE SENSING DATA

Uncalibrated approach [Lobell et al., 2015, Burke et al., 2017, Sibley et al., 2014]

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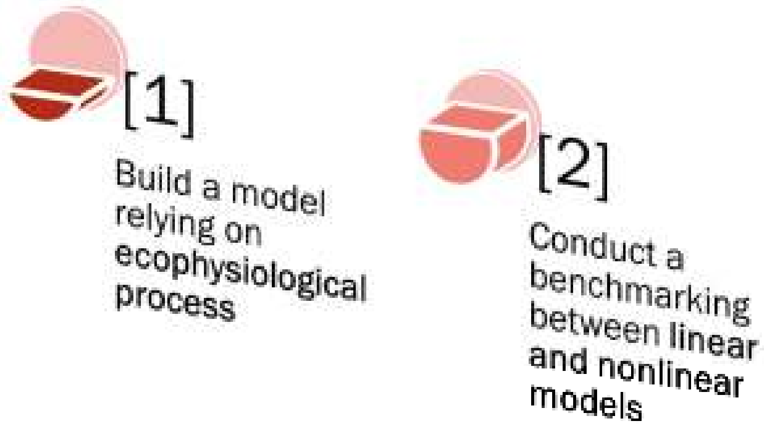

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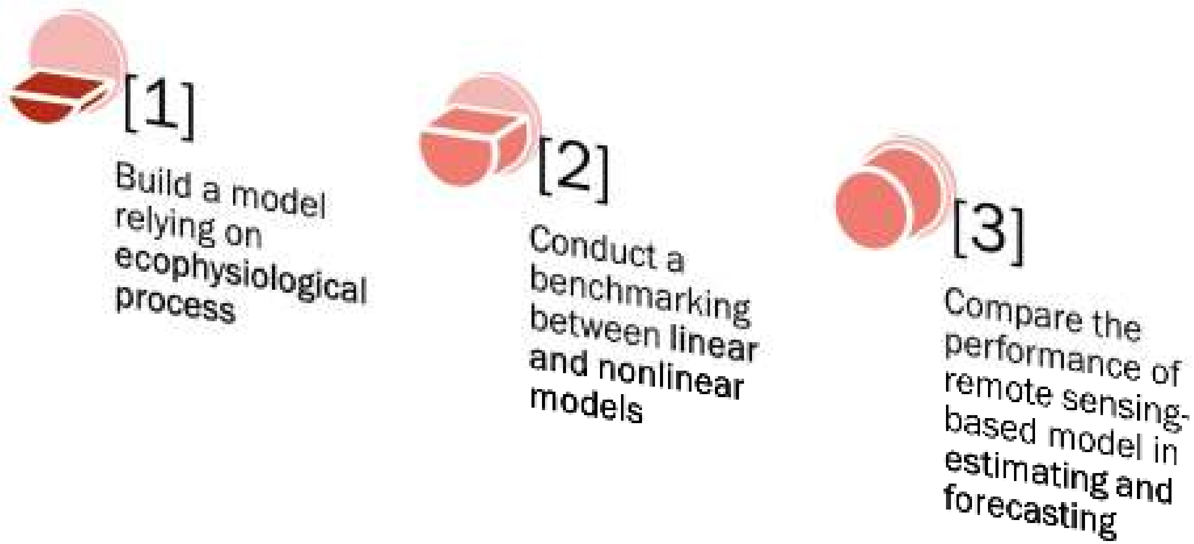
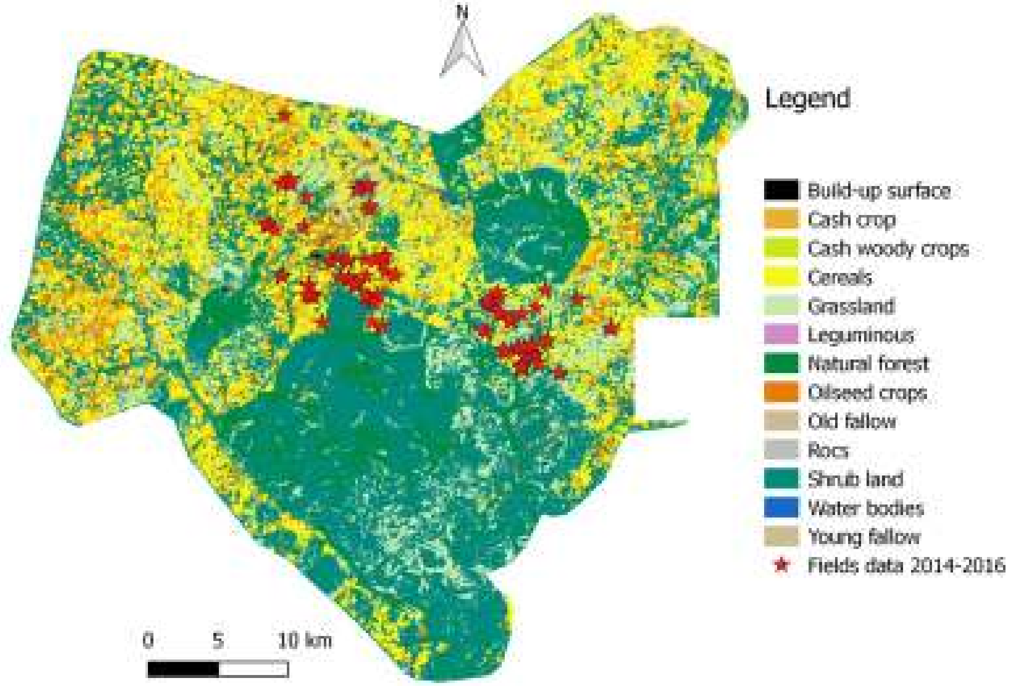


STUDY AREA & FIELDS DATA



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- Sudanian climate
- Rainy season : June-September

- Agropastorale activities
- Rainfed crops : mainly maize and cotton

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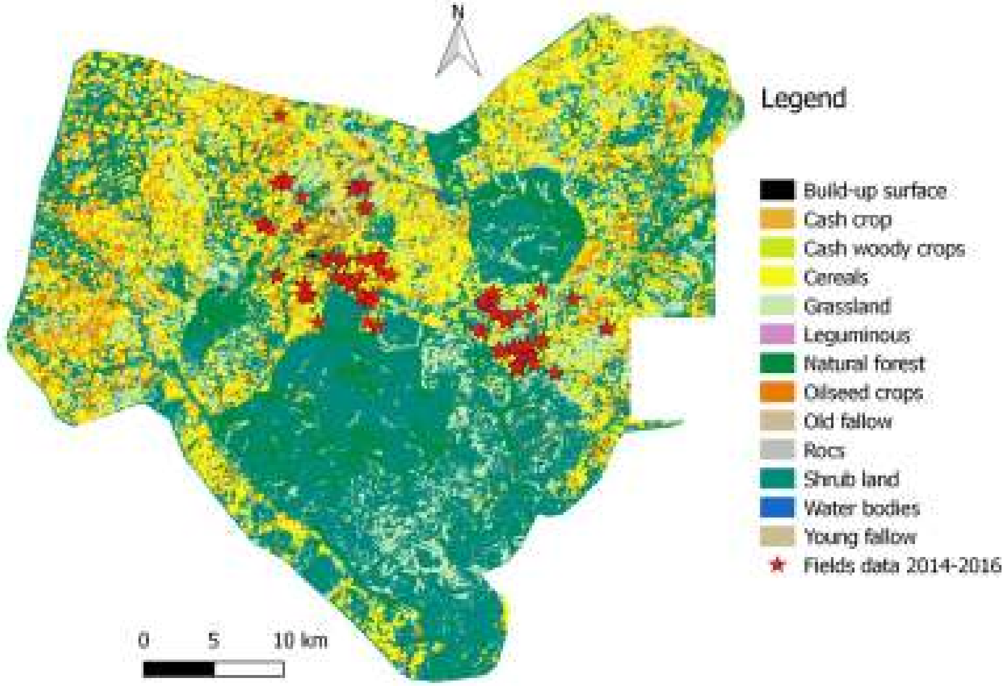

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- 114 maize fields
- Agricultural practices and vegetation parameters

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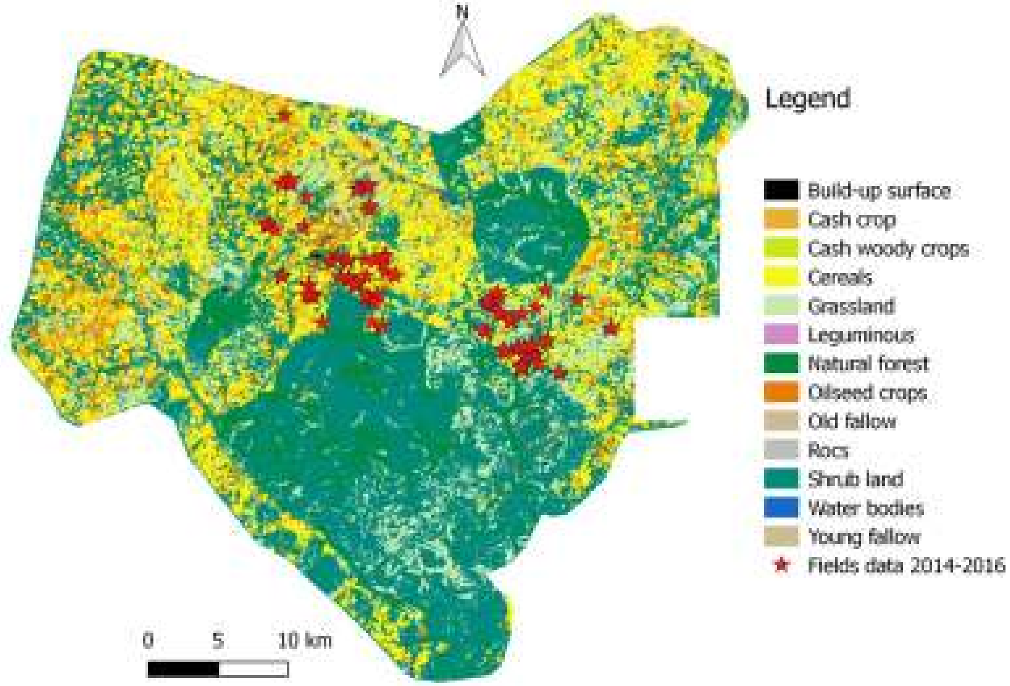

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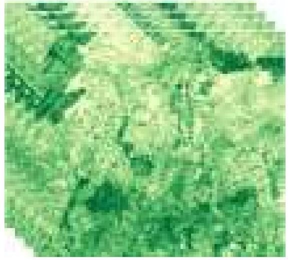
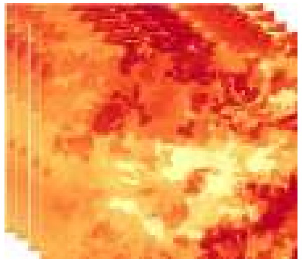
INDEPENDENT DATASET TO TEST THE ROBUSTNESS OF THE APPROACH

DATA

MODIS NDVI TIME SERIES



LAND SURFACE TEMPERATURE TIME SERIES



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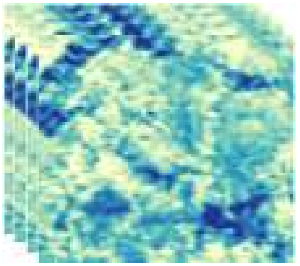

Disaggregated with the DISPATCh method [Merlin et al., 2013]

DATA

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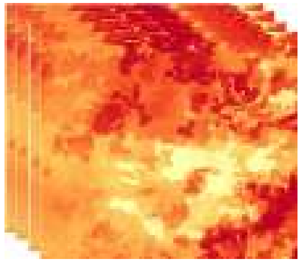

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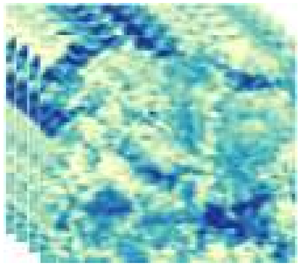

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Phenology, Vegetation vigor and drougth/heat stress related indicators

CWSI | TCI | TVDI | SMADI | NDVI | SSM

DATA

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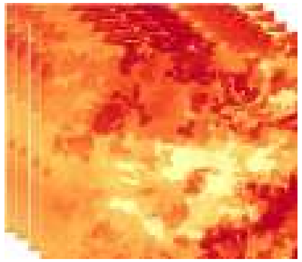

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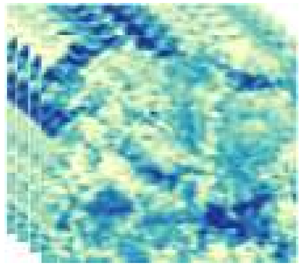

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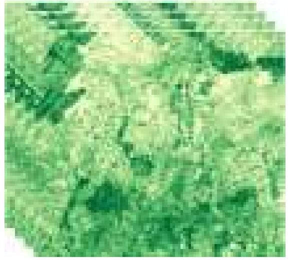
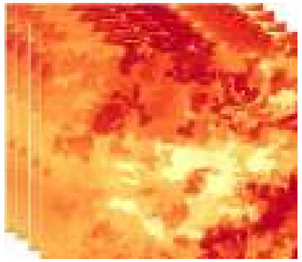
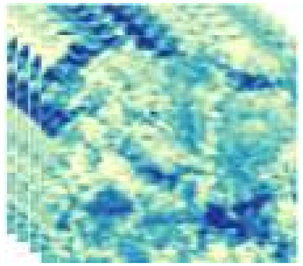


Land Surface Temperature time series



SMOS Soil Moisture time series



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Vegetative period | Productive period

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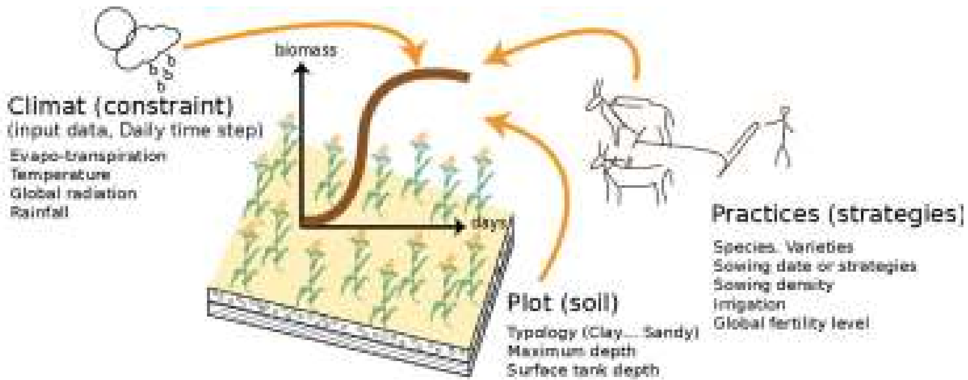

- Sarra-H, a crop model for maize
- Daily time step
- Attainable biomass and yields under **climatic constraints**

- Implementation under the **Ocelet Modelling Plateform**
- **ECMWF** agrometeorological data
- **TAMSAT** rainfall data

- Validated for the Tuy province [Akakpo 2017]

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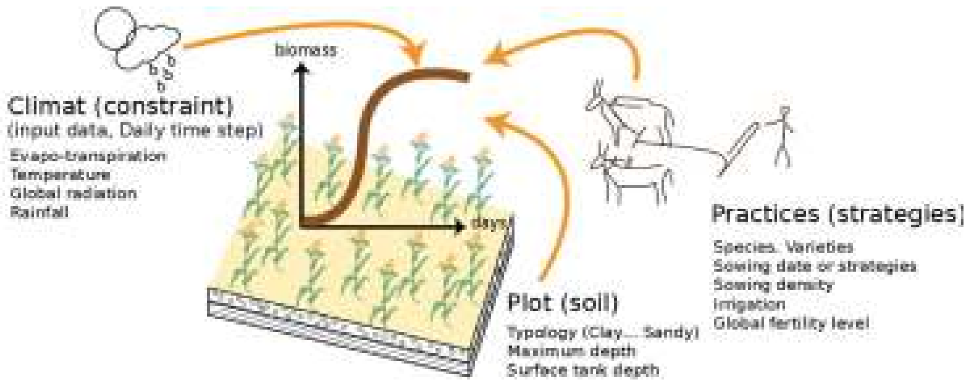

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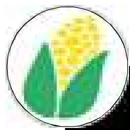
2011-2015

Aboveground biomass at flowering AGB-F

Crop Water stress from flowering to maturation Cstr



Attainable maize final yield

STATISTICAL MODELS AND STRATEGY

- *Above Ground Biomass at flowering (AGB-F) and water stress index (Cstr)*

AGB-F

Vegetation and drought indices – Vegetative period

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AGB-F	Vegetation and drought indices – Vegetative period
Cstr phase 4-5	Vegetation and drought indices – Productive period

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Random Forest Model (RF)

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EVALUATION

- 10-fold cross validation
- Cv-R^2,cv-RMSE …

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IMPORTANCE VARIABLES

- LMG method
- Mean decrease in MSE

STATISTICAL MODELS AND STRATEGY

- *Final maize yield*

STATISTICAL MODELS AND STRATEGY

- ***Final maize yield***

ESTIMATION

Final maize yield $\longrightarrow$ AGB-F x Cstr Phase 4-5

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Final maize yield → AGB-F x Cstr Phase 4-5

FORECASTING

Final maize yield — Vegetation and drought indices – Vegetative period → MLR / RF

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- *Final maize yield*

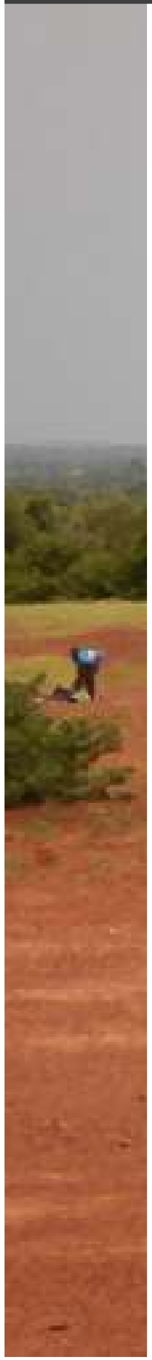
ESTIMATION

Final maize yield → AGB-F x Cstr Phase 4-5

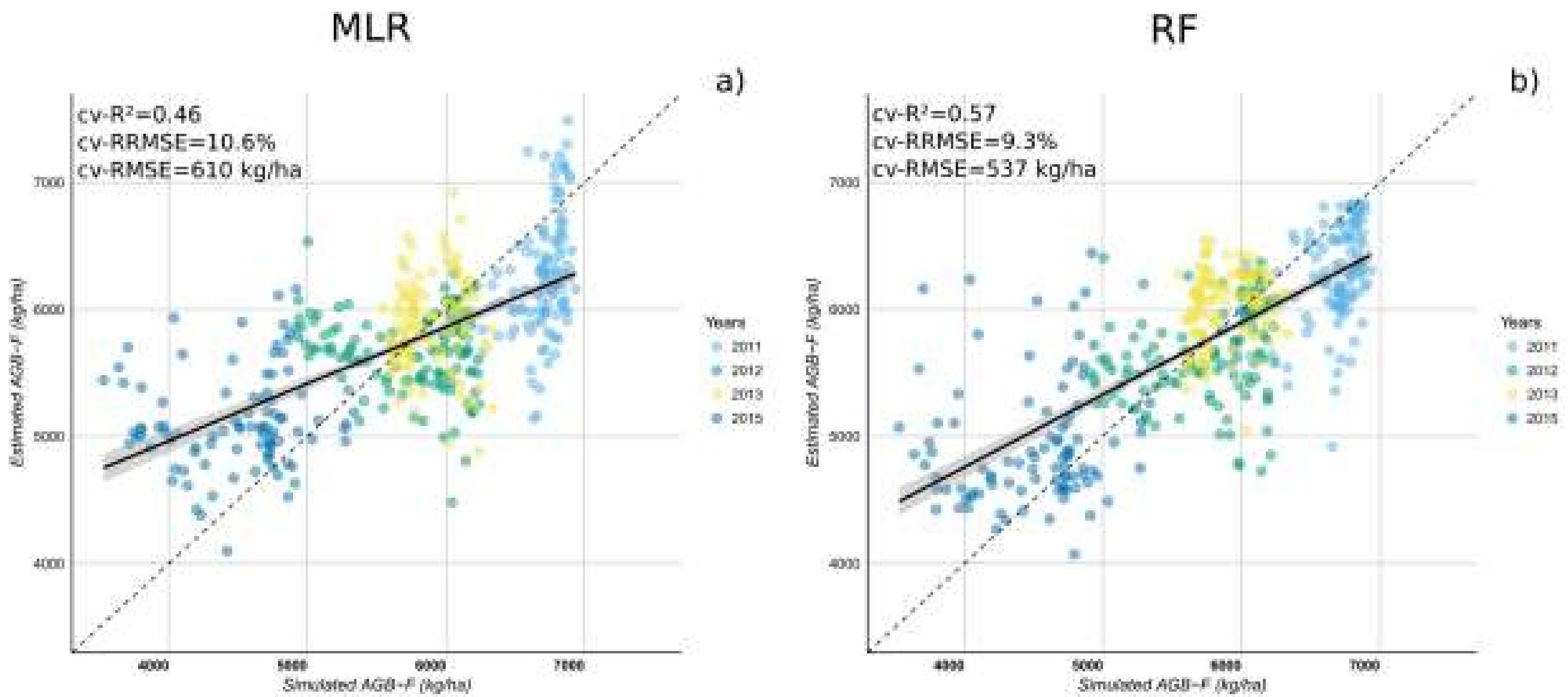
VALIDATION
- Yield from field survey
- Village scale

FORECASTING

Final maize yield — Vegetation and drought indices – Vegetative period → MLR / RF



EVALUATION OF AGB-F ESTIMATION



- Overestimation of low values and underestimation of high values
- RF model significantly better than the MLR model (**57%** of the AGB-F variability)

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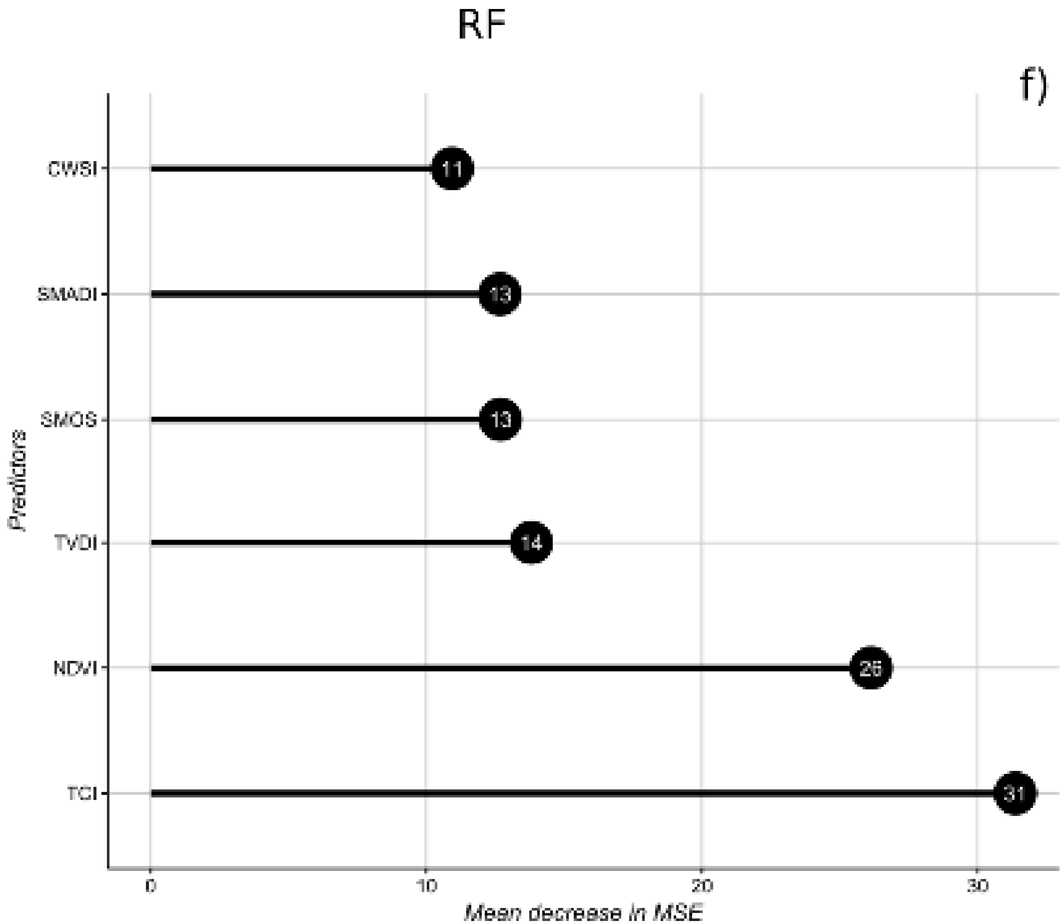

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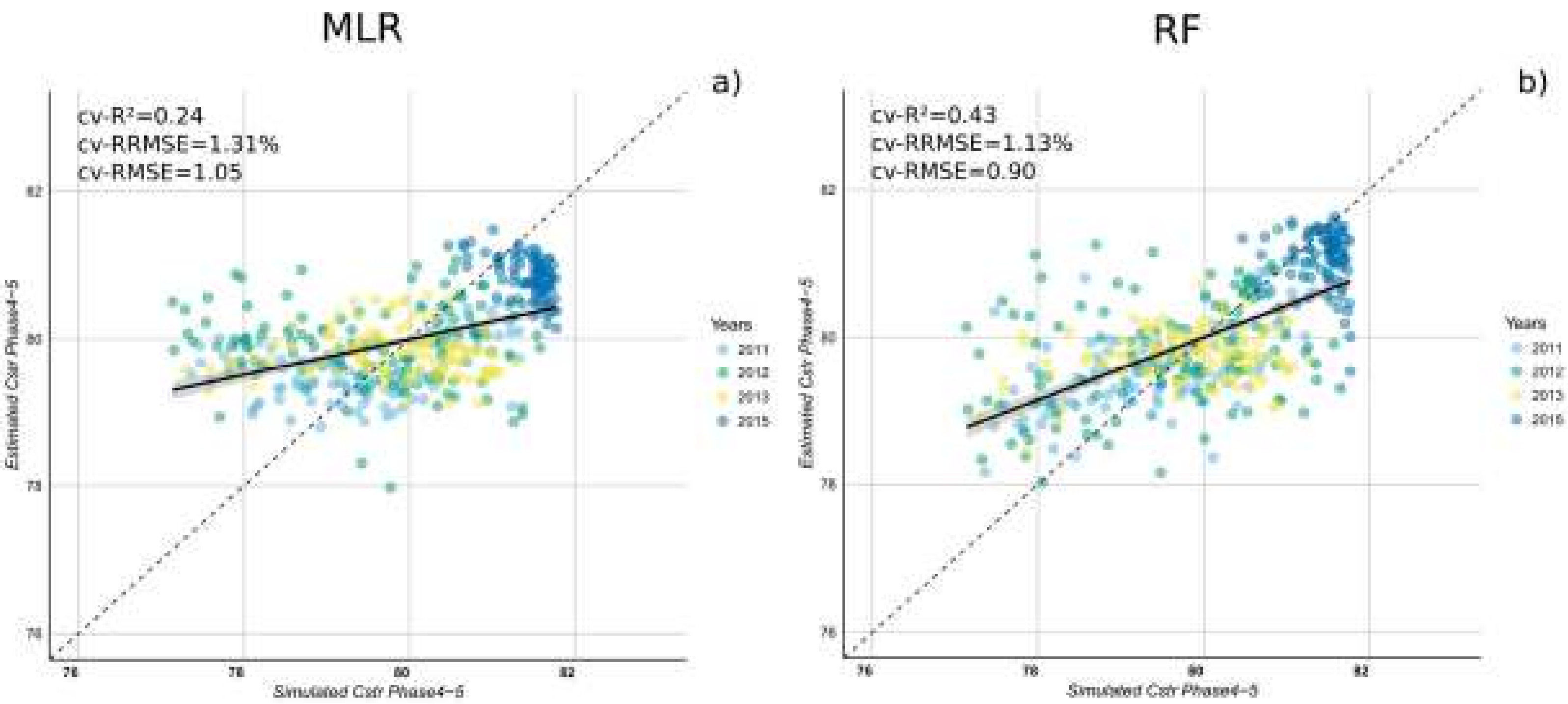
- Importance variable for RF = TCI and NDVI (57%)

EVALUATION OF CSTR PHASE 4-5 ESTIMATION



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- But with cv-RRMSE < 2%? Low variability observed in SARRA-O Cstr!

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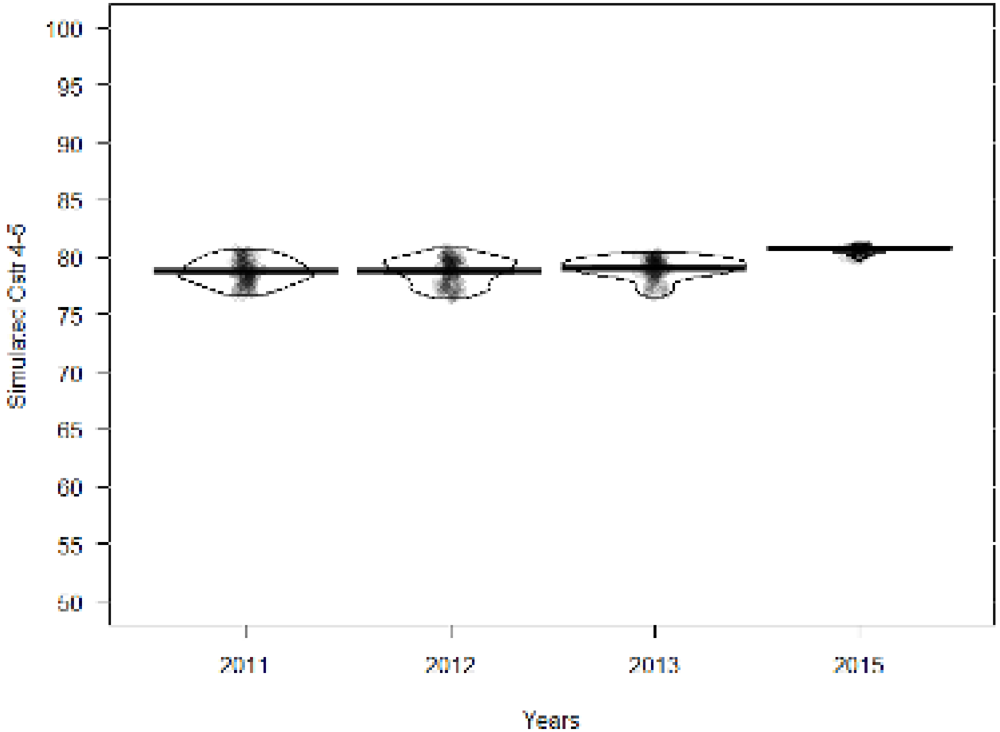

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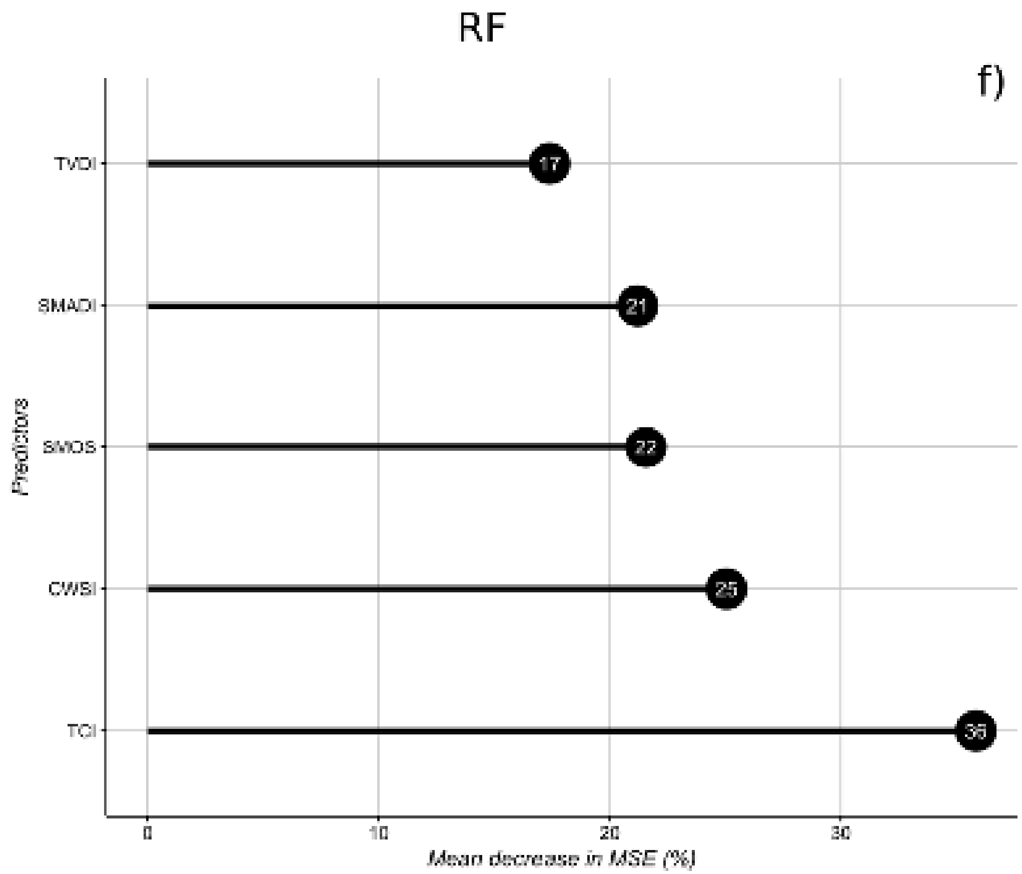
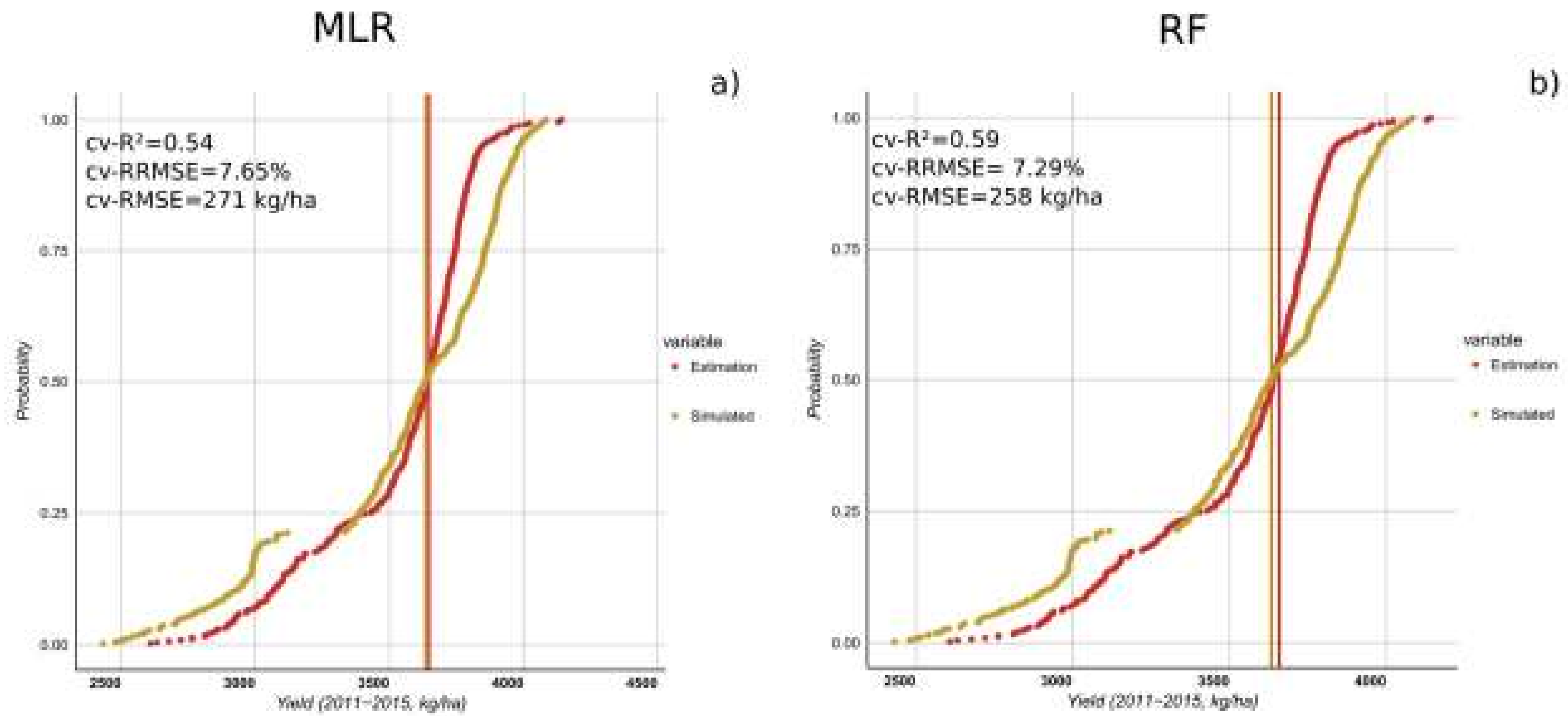


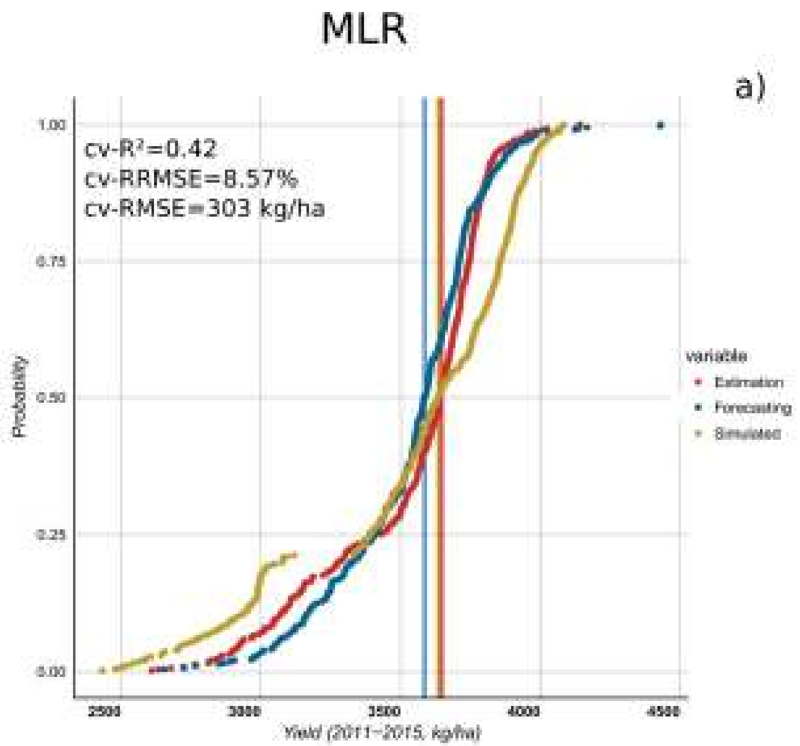
- Temperature Condition Index is the most important driver
- Impact of heat stress on maize : grain number [Eyshi Rezaei et al., 2015]

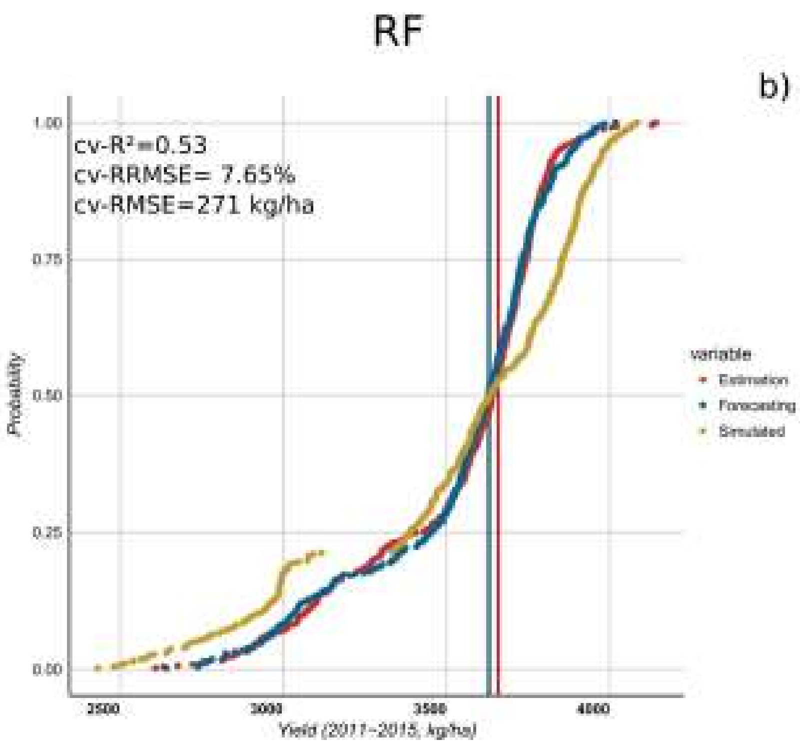
EVALUATION OF MAIZE YIELDS ESTIMATION AT THE END OF THE SEASON



- $Yield = f(AGB - F, Cstr\ Phase\ 4-5)$
- Good potential for maize yield estimation (RMSE<300 kg/ha)
- Good fitting of probability distribution curves :
    - Median SARRA-O : 3634 kg/ha
    - Median MLR : 3648 kg/ha
    - Median RF : 3659 kg/ha

EVALUATION OF EARLY ASSESSMENT OF MAIZE YIELDS





- $Yield = f(Remote\ Sensing\ Indices - Vegetative\ period)$
- Good potential for maize yield forcasting (RMSE<300 kg/ha)
- ~50% of maize yield variability can be explained ~2 months before harvest

VALIDATION OF MAIZE YIELDS WITH GROUND DATA

Independent dataset
*2014, 2015 and **2016***

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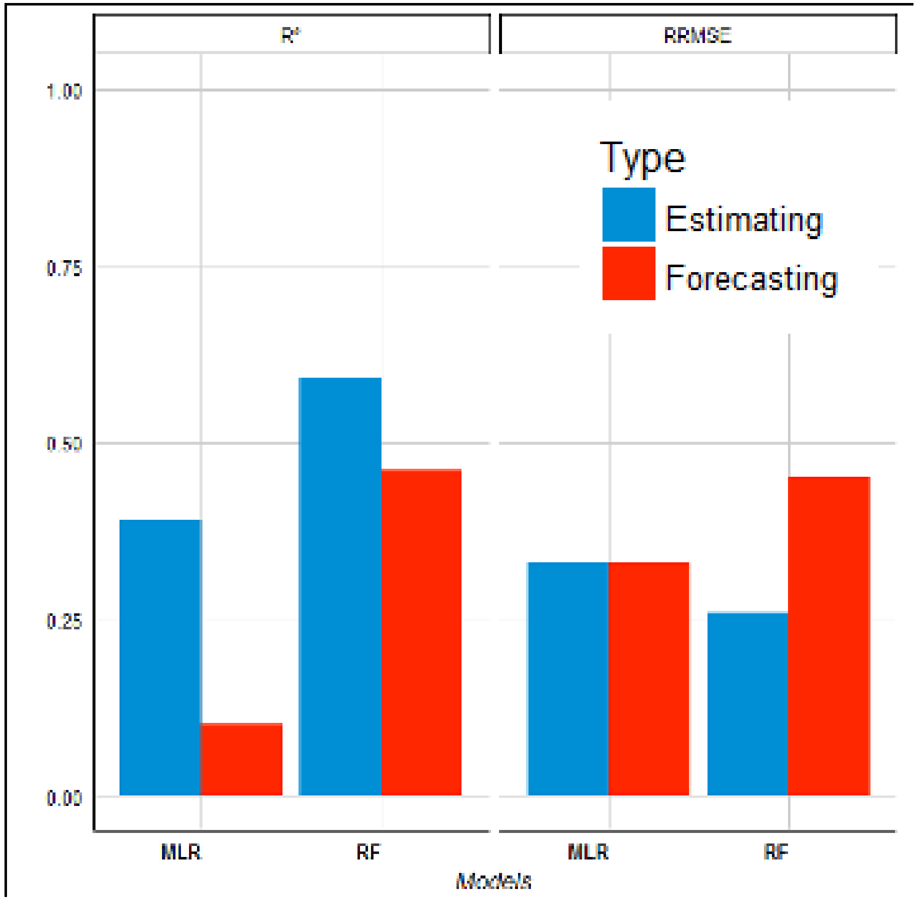

- RF outperforms MLR:
  - Estimation : R^2=0.60
  - Forecasting : R^2=0.46
- High overestimation in forecasting
- MLR : 2016 not accuratly estimated

A GOOD AND EFFECTIVE POTENTIAL OF 'UNCALIBRATED APPROACH' TO ESTIMATE MAIZE YIELD IN SCARCE DATA ENVIRONMENT

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LOOK-BACK ON THE STUDY OBJECTIVES

- Linear *vs* NonLinear models:
  - Higher performance of **RF models** both for estimation and early assessment
  - Complex interaction among biophysical, ecological, physiological and management practices

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- **Estimation vs Early assessment:**
  - Early assessment of maize yields **~ 2 months** before harvesting (RF)
  - Complementary of approaches :
    - **In-season forecasting** : food aids strategies or market and trade information
    - **After harvesting** : agricultural statistics
    - **Both + outputs of crop model** : 'convergence of evidence' in EWS

THANK YOU FOR LISTENING

Leroux Louise – CIRAD UR AÏDA/CSE
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www.louise.leroux.igeo.fr

MORE INFORMATION :

LEROUX ET AL., 2017, *Maize grain yield estimating in a west African agricultural landscape at the cross-roads between remote sensing, crop modelling and statistical methods: Case study in south-west of Burkina Faso*, TO BE SUBMITTED TO AGRIC.FOR.METEOROL