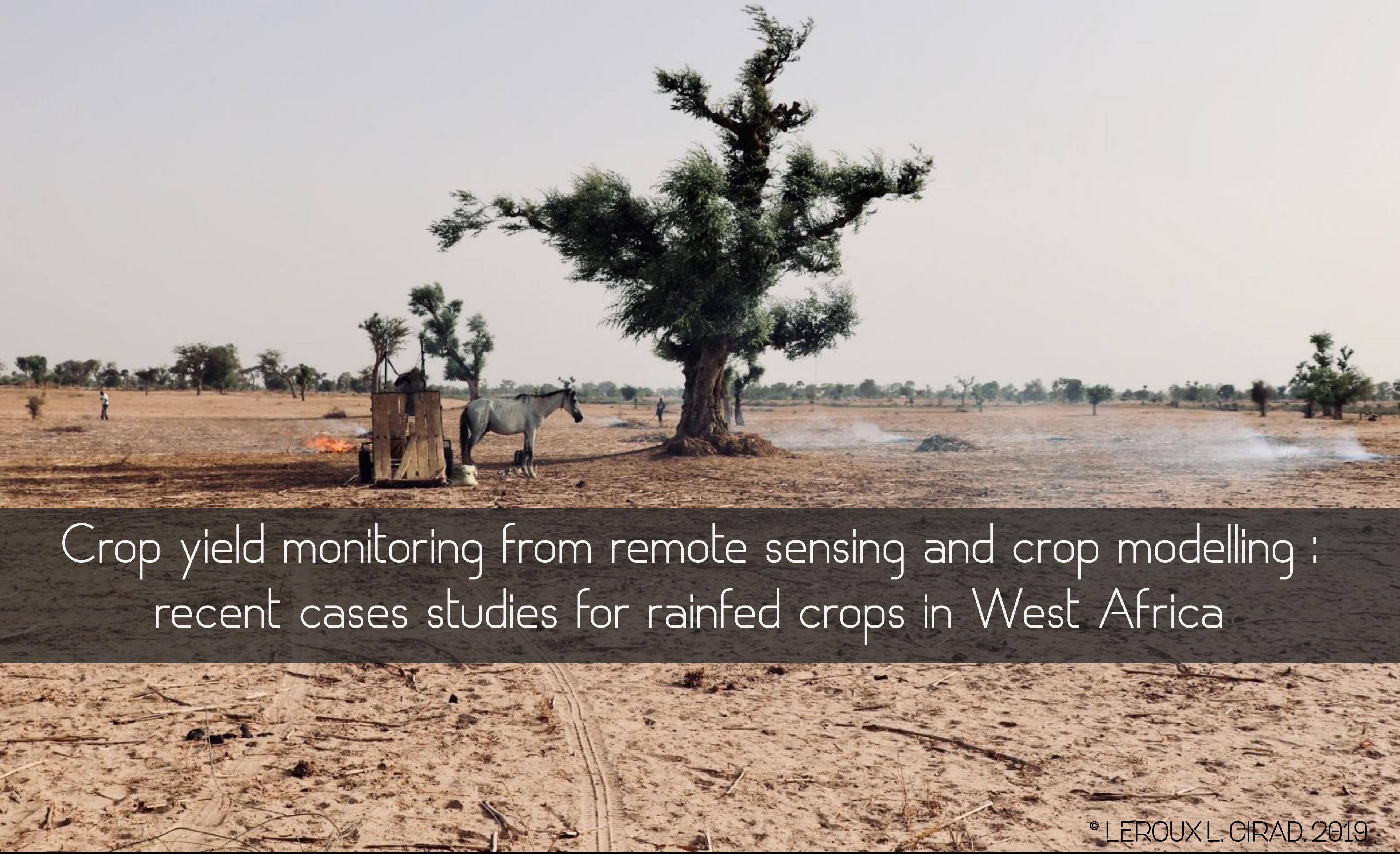
# Crop yield monitoring from remote sensing and crop modelling : recent cases studies for rainfed crops in West Africa





ACCWA

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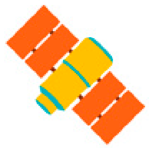
# Yield estimation methods

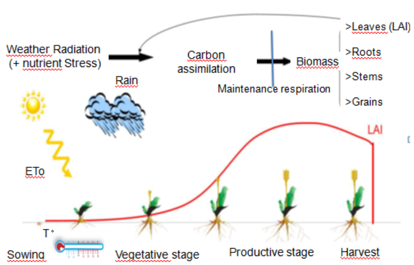

# Yield estimation methods

## 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



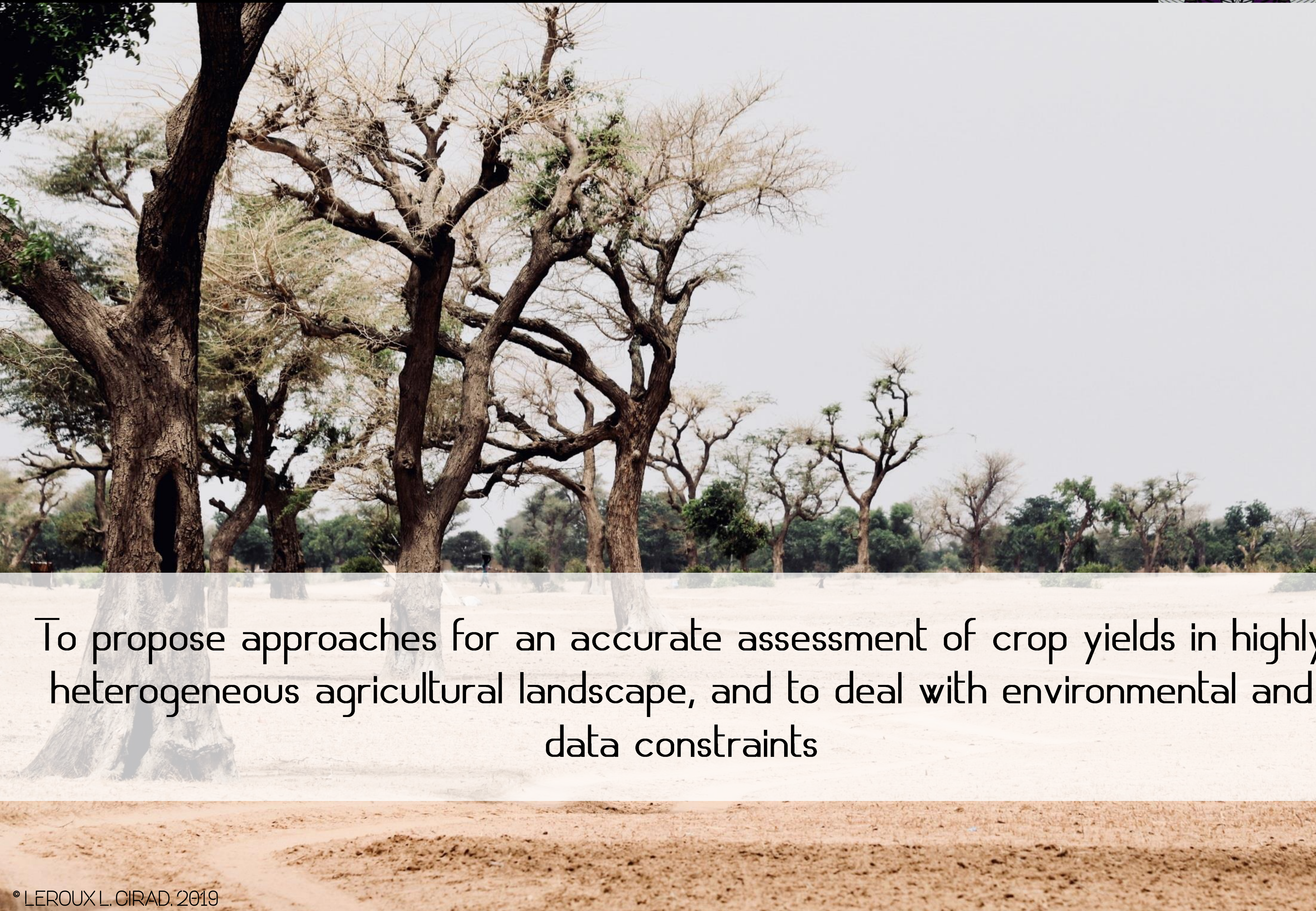

- Approximation of the reality on the ground
- Potential yields under water or nutrient limitation

## FIELD-BASED SURVEY

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

# Background & objectives

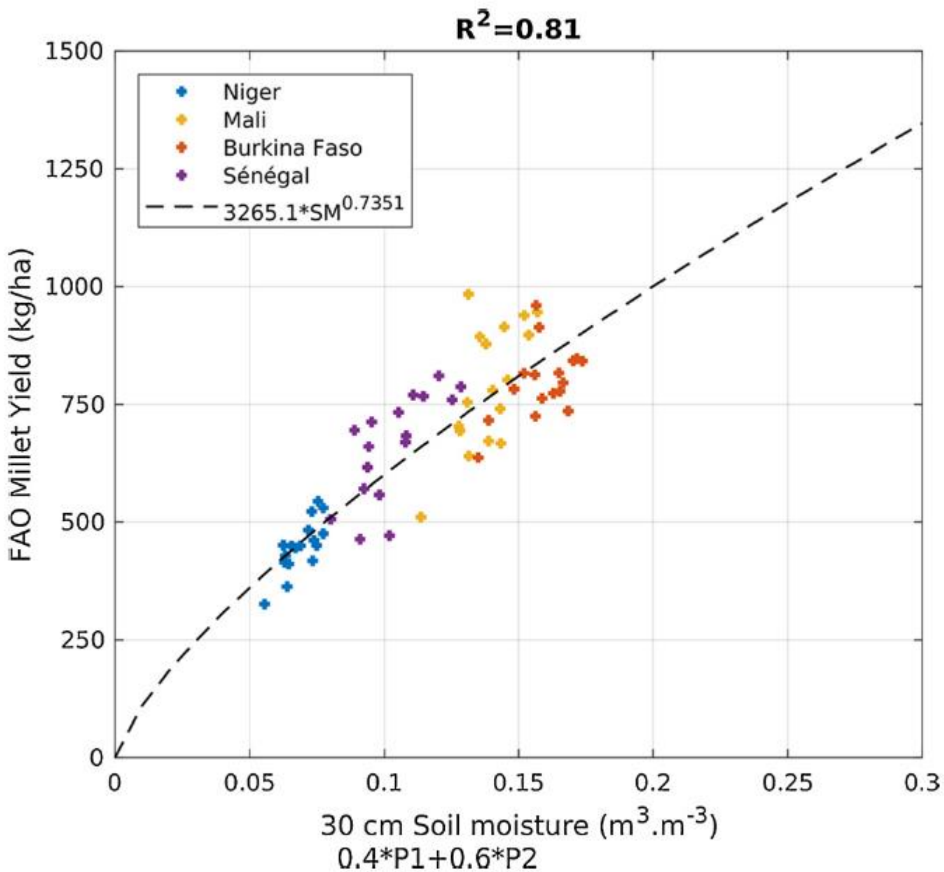
# Objectives




To propose approaches for an accurate assessment of crop yields in highly heterogeneous agricultural landscape, and to deal with environmental and data constraints

## Background

*Quality of rainfall amounts estimations : major problem of RFEs
*Several studies have shown a good potential surface soil moisture for cereal yield estimates (Leroux et al., 2019 , Gibon et al., 2018)




Soil moisture derived from CMORPH adjusted precipitation product

For more information : christian.baron@cirad.fr or thierry.pellarin@univ-grenoble-alpes.fr

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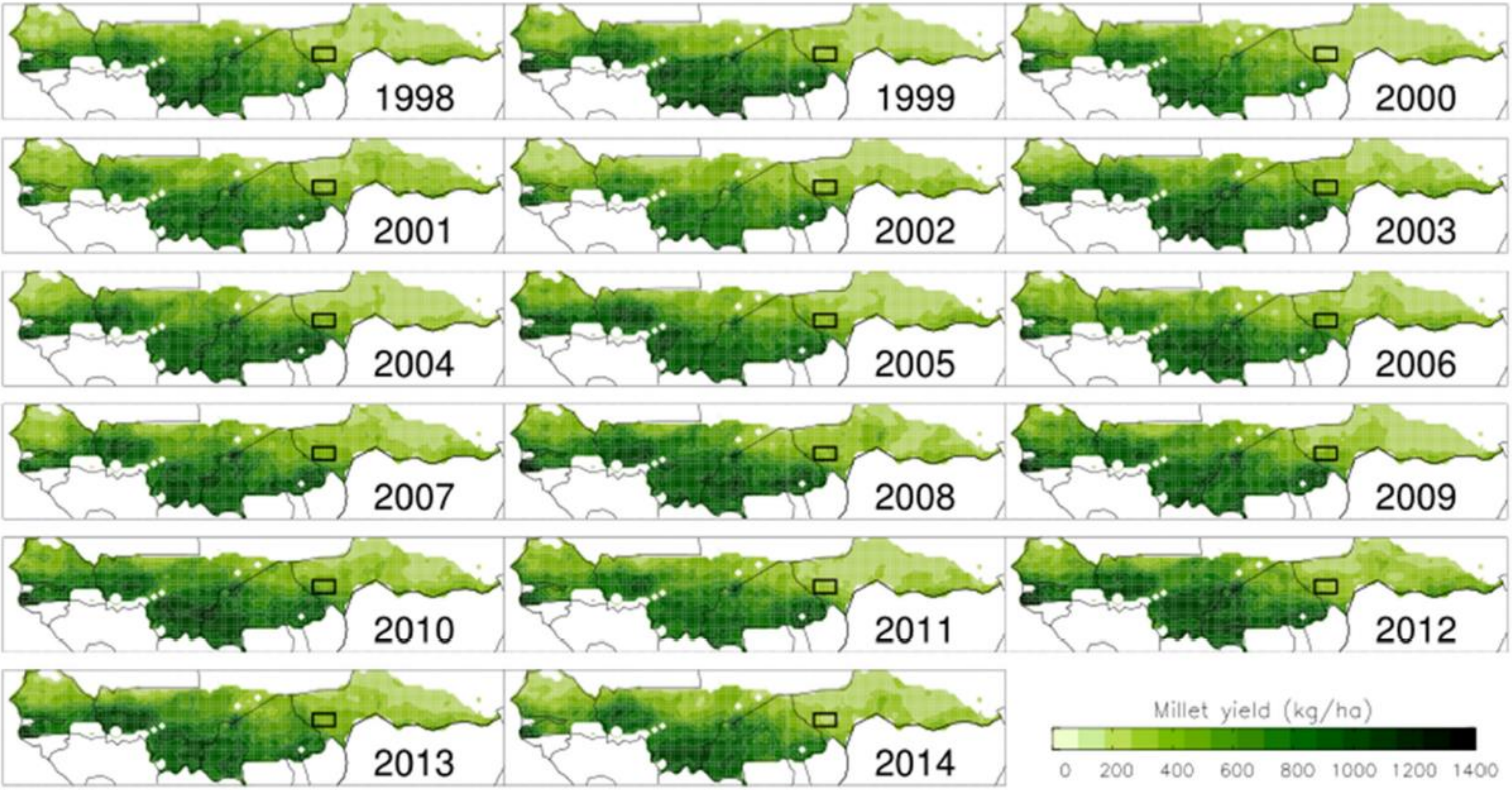


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***Improve crop yields estimation with a crop model using satellite rainfall estimates corrected with surface soil moisture data**

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# Remote sensing contributions to crop-yield simulation at national scale

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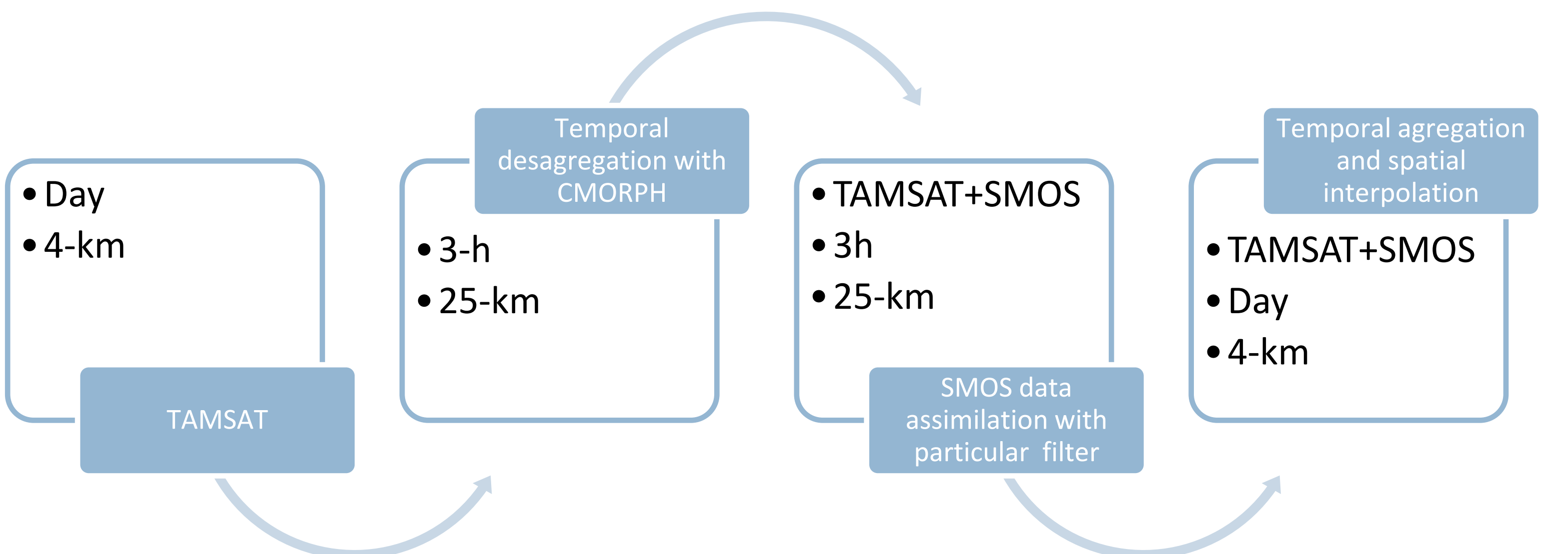
## Bias correction in TAMSAT using CMORPH and SMOS

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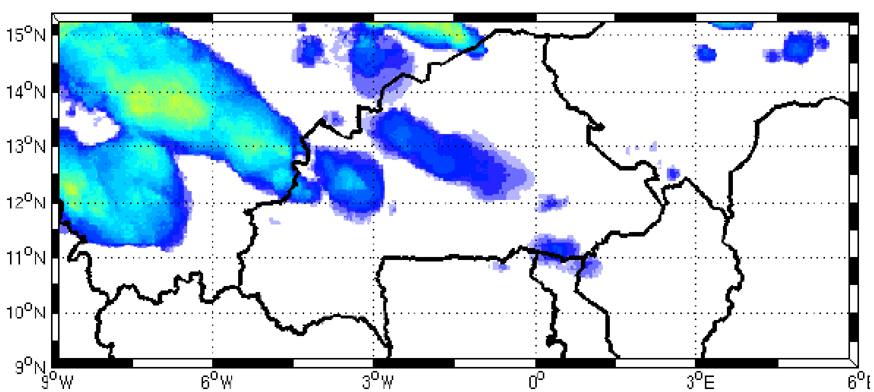
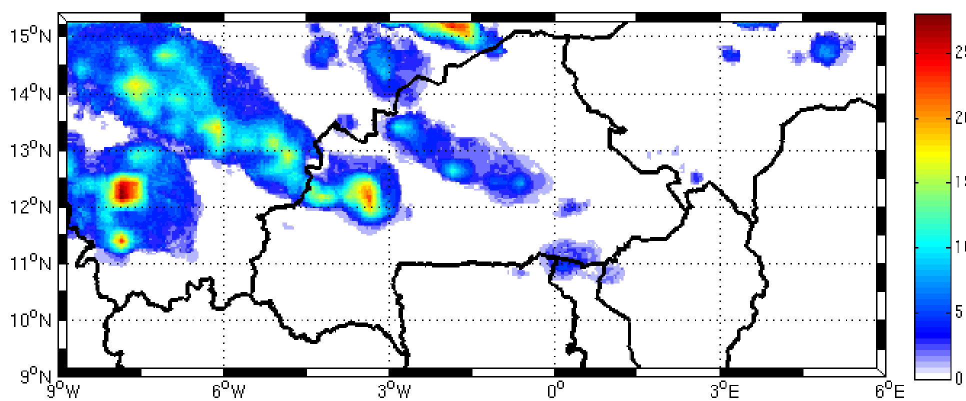
**TAMSAT ORIGINAL – BEFORE ASSIMILATION**




**TAMSAT+SMOS – AFTER ASSIMILATION**

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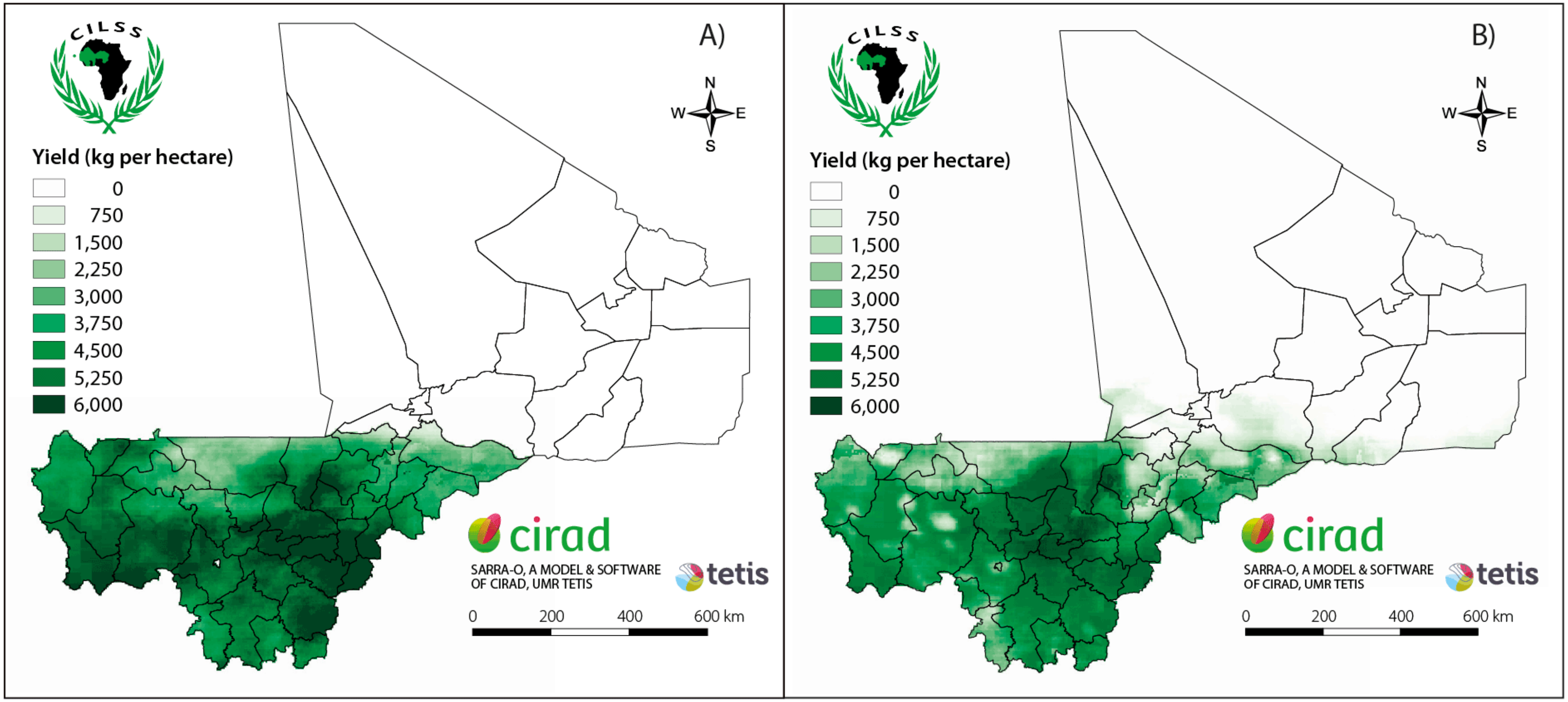
Remote sensing contributions to crop-yield simulation at national scale

## Sensitivity of SARRA-O crop model to RFE products




*Simulation of maize yield in optimum condition, Mali 2012, A) forced by TAMSAT rainfall estimation, B) forced by with TAMSAT corrected by SMOS satellite data.
* Both spatial variability and mean value of crop yield are affected

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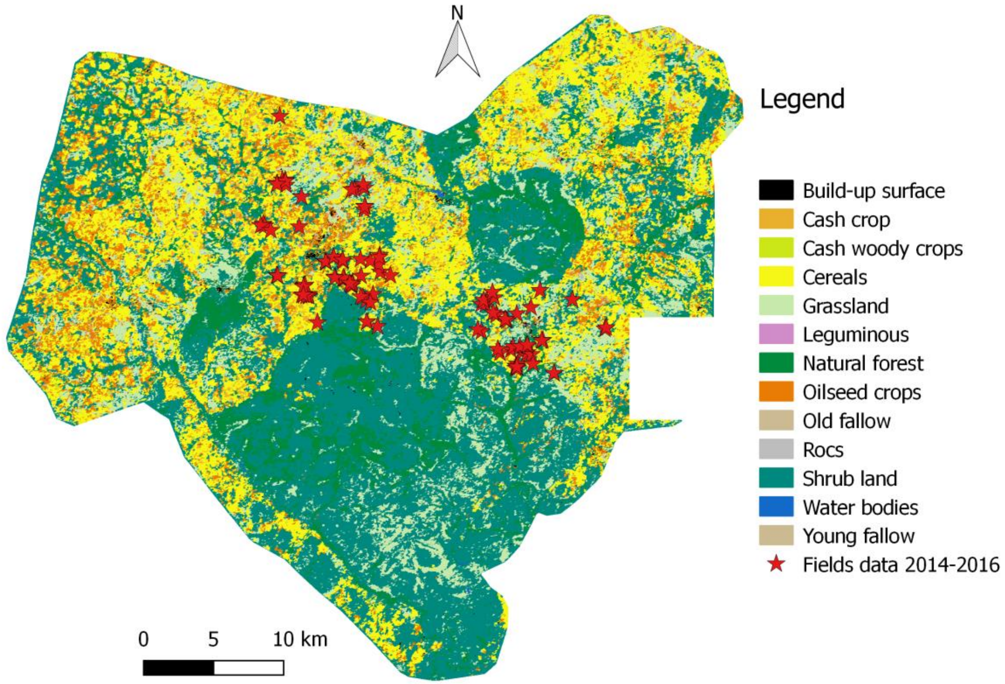
# Estimating grain yield in scarce field data-environment combining remote sensing and crop modelling

## 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]

**Crop model SARRA-O** : AGB at flowering, Cstr over flowering and maturing phases and final grain yield
**Remote sensing** : Vegetation indices and canopy temperature (MODIS), Surface Soil Moisture (SMOS)

## Study area : The cotton basin of Burkina Faso




Leroux et al., 2019, EJA

### CLIMATE

*Sudanian climate
*Rainy season : July to Oct.

### FARMING SYSTEM

* Agriculture dominated by:
-**Maize** (on-farm consumption)
-**Cotton** (cash crop)
-Livestock

### FIELD DATA

*114 farmers maize fields
*2014,2015,2016
*Agricultural practices and vegetation parameters

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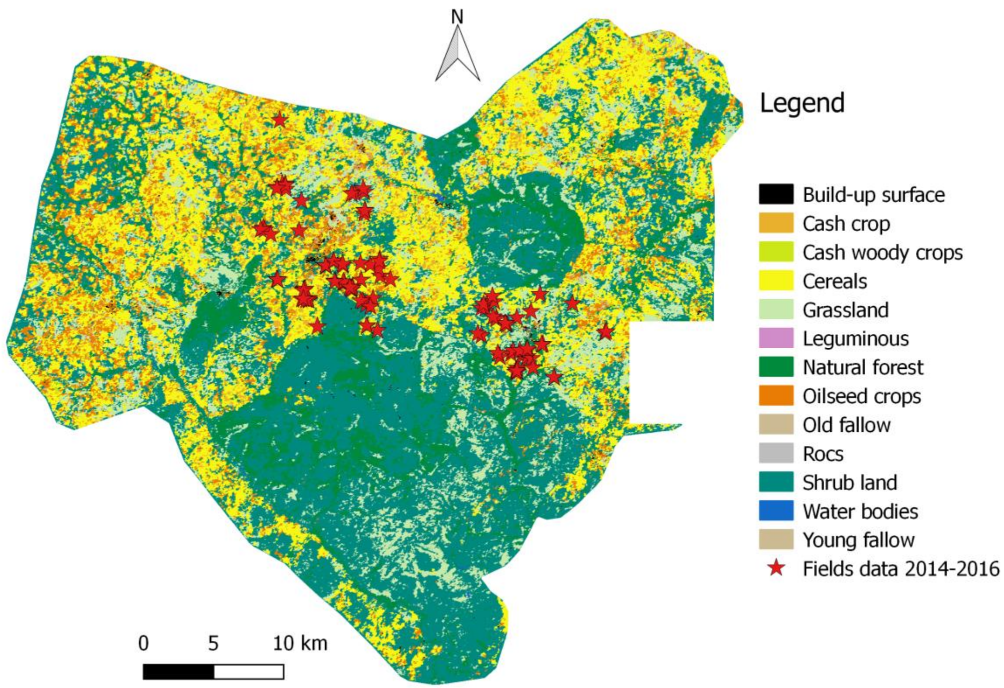


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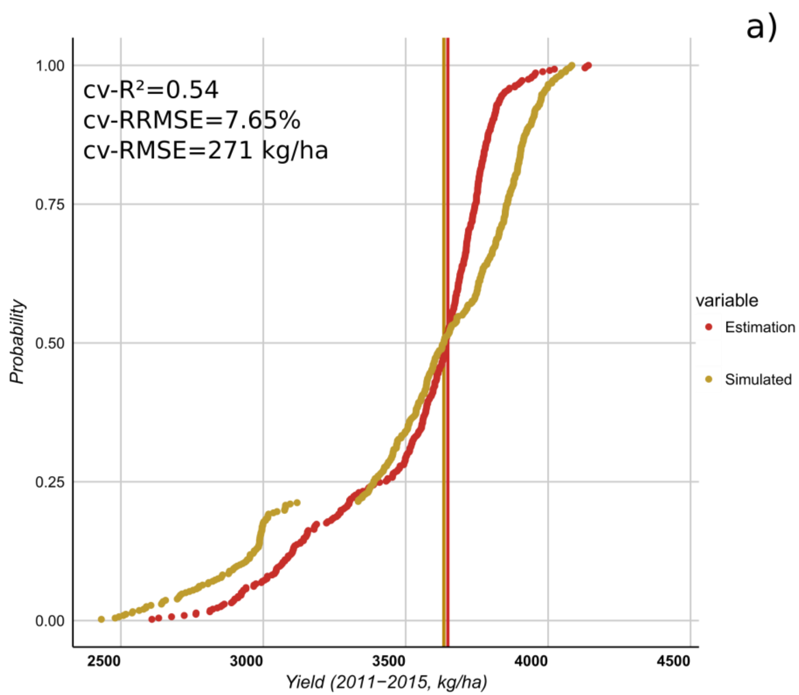
INDEPENDENT DATASET TO TEST THE ROBUSTNESS OF THE APPROACH

# Estimating grain yield in scarce field data-environment combining remote sensing and crop modelling

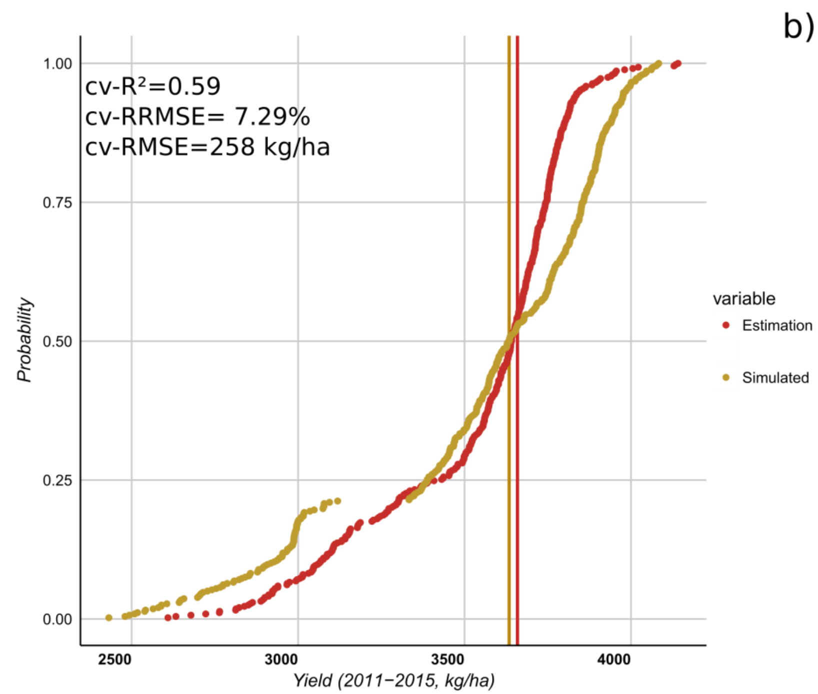
## Evaluation of maize yield estimation at the end of the Season

Comparison linear and non-linear model to account for non-linear ecophyisiological process in agroecosystems functionning

MLR




RF




*$\text{Yield} = f(\text{AGB} - \text{F}, \text{Cstr Phase } 4 - 5 \text{ estimated})$

*Good potential for maize yield estimation (RMSE<300 kg/ha)

*Surface soil moisture (SSM) information, as a proxy for soil water available for plant growth, helped to improve the RF maize yield model

Leroux et al., 2019, EJA

# Estimating grain yield in scarce field data-environment combining remote sensing and crop modelling

## Evaluation of maize yield estimation before the end of the Season

Comparison linear and non-linear model to account for non-linear ecophyisiological process in agroecosystems functionning

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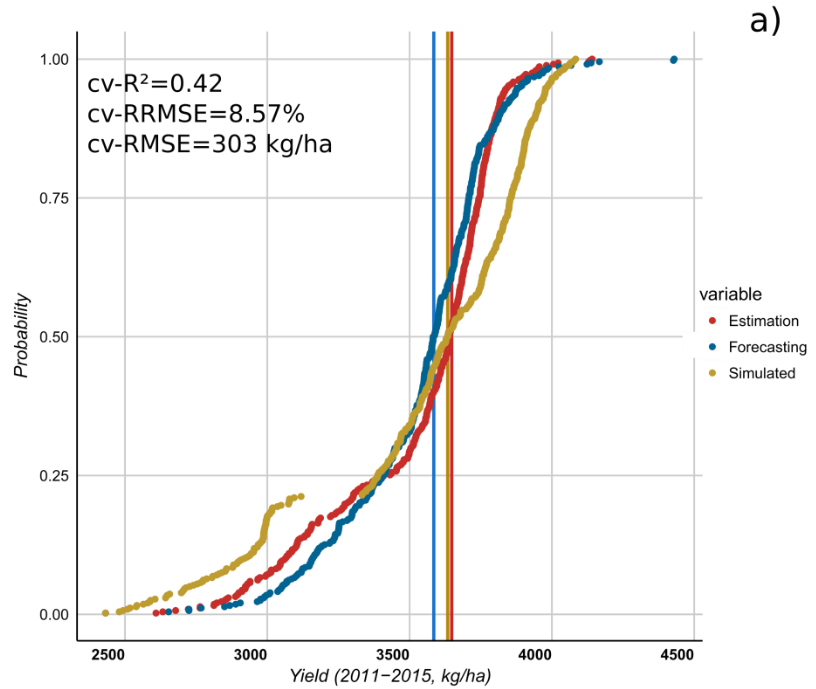


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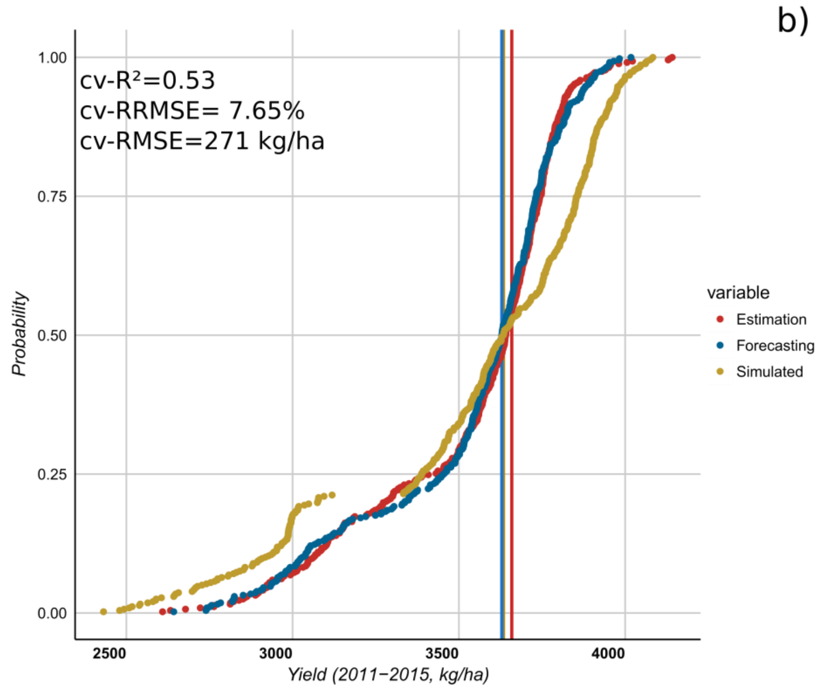
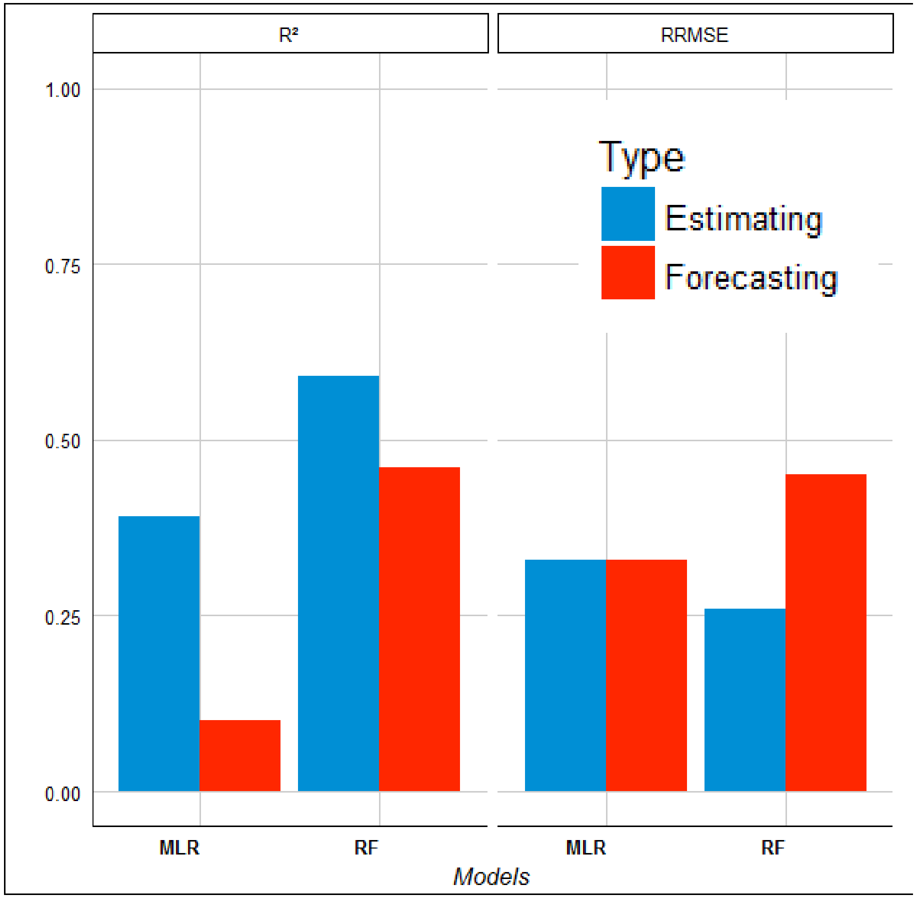



*Yield = f(Remote Sensing Indices − Vegetative period)
*Good potential for maize yield estimation (RMSE<300 kg/ha)
*~50% of maize yield variability can be explained ~2 months before harvest

Leroux et al., 2019, EJA

## Validation of maize yield estimation with ground data

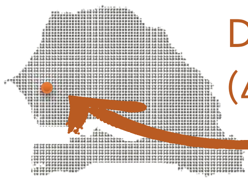
*Independant data set




*Non linear model outperforms the linear models
*Overestimation in forecasting

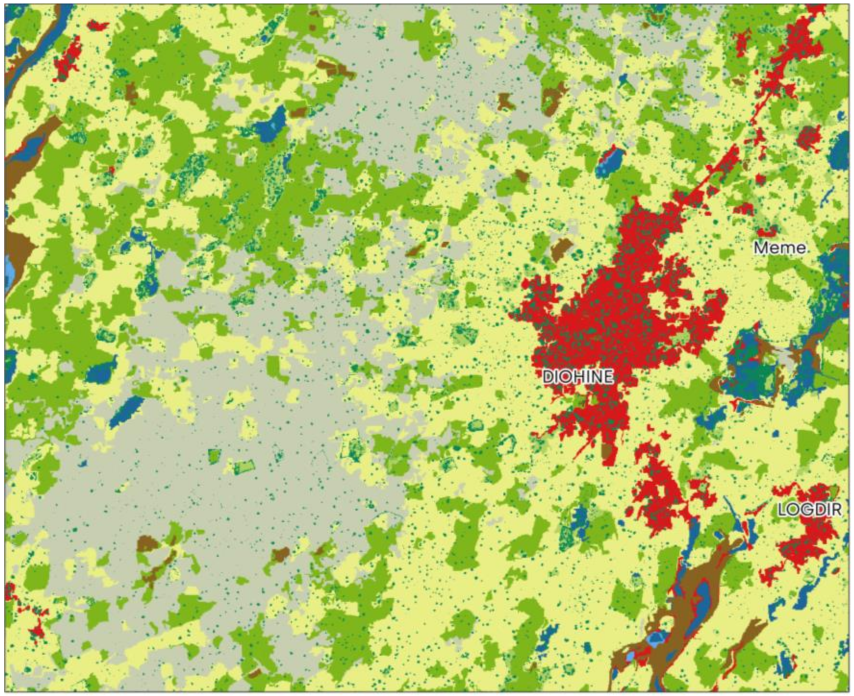
Leroux et al., 2019, EJA

## The « old » peanut basin : the Senegalese breadbasket



Diohine site
(4km x 3 km)

### A agricultural landscape dominated by rainfed crops …



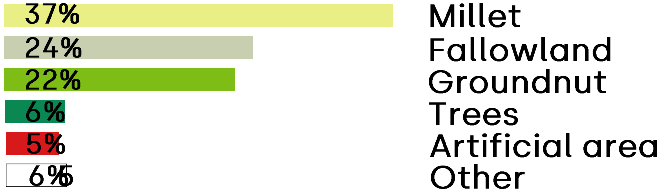

Ndao et al., 2019

#### Climate

*Sudanian climate
*Annual rainfall : **500-650 mm**
*Rainy season : July to Oct.

#### Farming system

* Agriculture dominated by:
-**Millet** (on-farm consumption)
-**Groundnut** (cash crop)
-Livestock
* **Agroforestry parkland** (F.albida)
* **Low input**



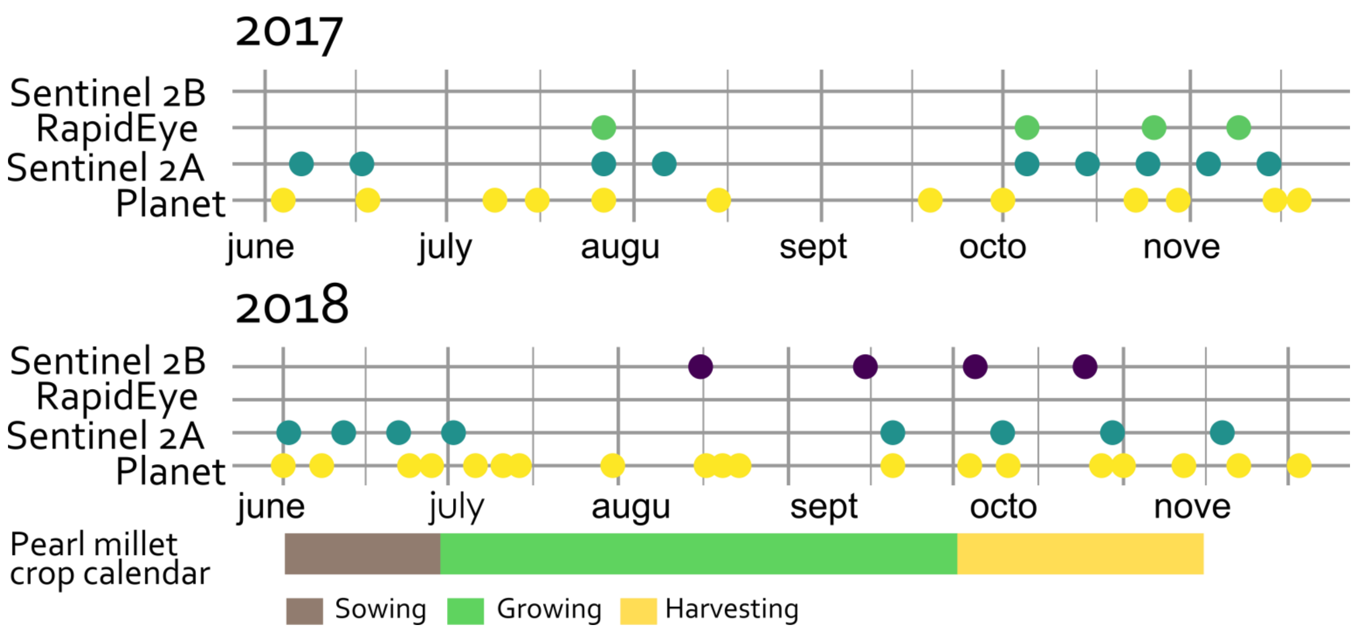

Leroux et al., 2019, in prep for Agr,Eco&Envi

# At the nexus of remote sensing, landscape ecology and statistical modelling

## Ground data: Agronomical survey

- **50 pearl millet** farmers' fields
- **2 cropping seasons**: 2017 (n=35) – 2018 (n=46)
- Agricultural practices, tree inventory and **yield components**

## Remote sensing observation: multisources optical time series




Leroux et al., 2019, in pr

Sentinel = 10-m ; RapidEye = 5-m ; Planet = 3-m

# Using satellite data to identify drivers of yield heterogeneity : local scale

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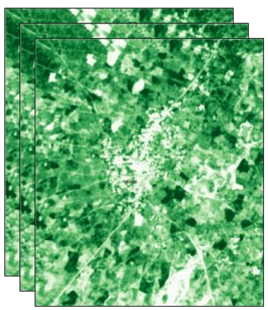
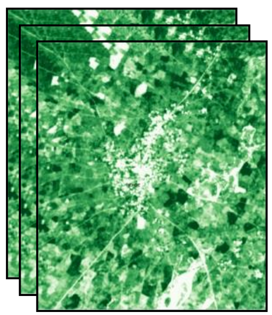
Vegetation productivity

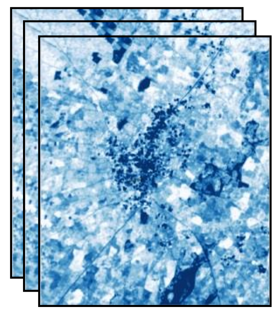


NDVI



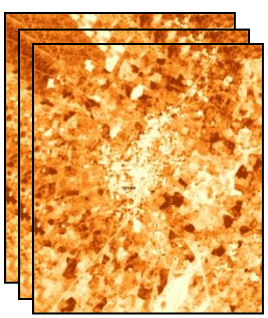
MSAVI2

Water stress

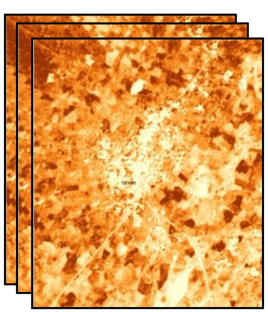


NDWI

Nutrient stress

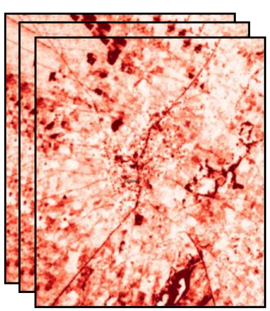


CiGreen



GDVI

Senescence



PSRINIR

**1.Parkland structuring proxies**

*Nbs of trees
*Woody cover
*Tree density

**2.Vegetation productivity proxies**

*Phenological metrics
*Vegetation indices cumulated

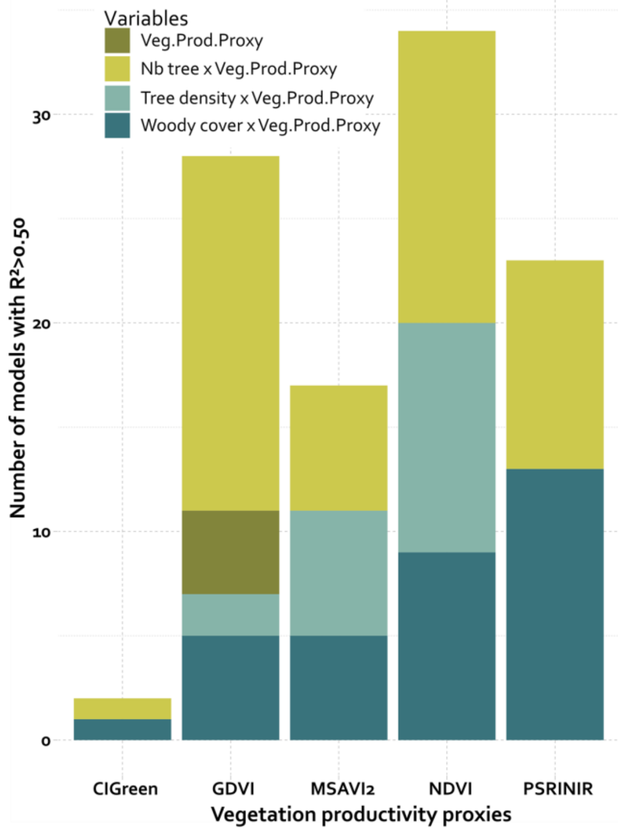
+

**3.Soil information**

*Texture
*Soil Org Carbon/Soil Org Nitrogen/Soil Phosphorus

# From satellite information to yield estimates accounting for tree effects

## 1~Sensitivity to vegetation productivity proxy and tree information




***Integrating parklands structuring information improves millet yield model**
***Best model : GDVI x Nb of trees ($R^2$ 0.70 & RRMSE = 0.28)**

Leroux et al., 2019, in prep for Agr,Eco&Envi

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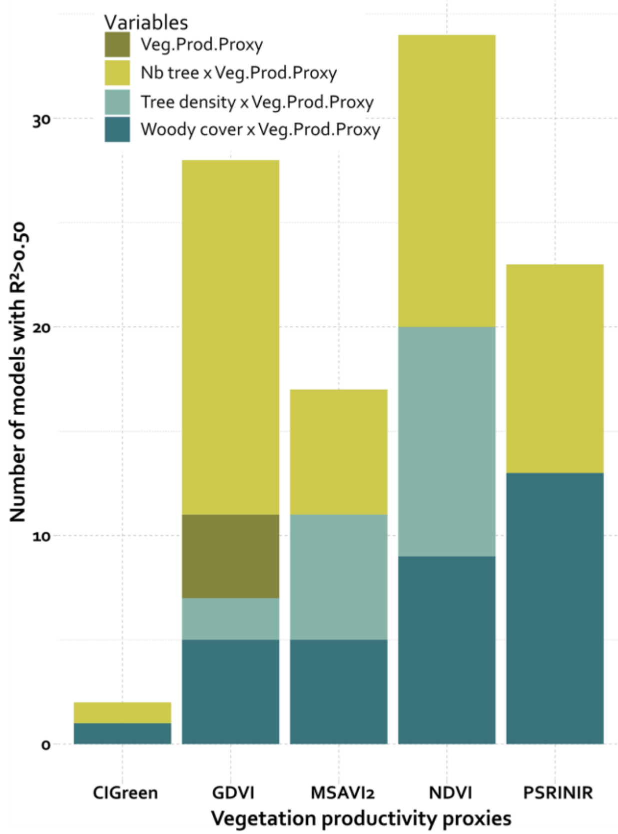
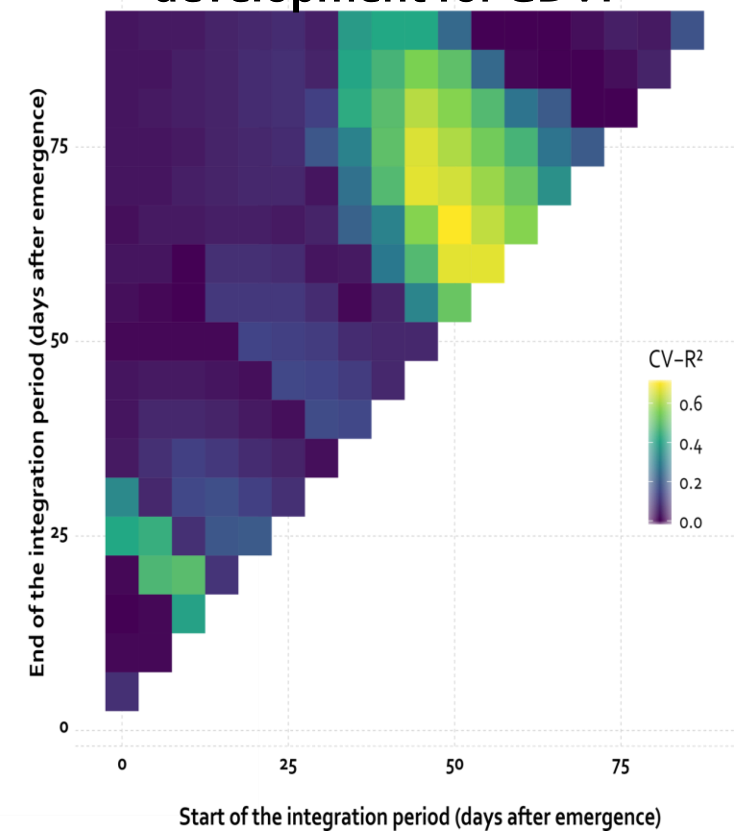



## 2~Sensitivity to phenological development for GDVI




***Integrating parklands structuring information improves millet yield model**
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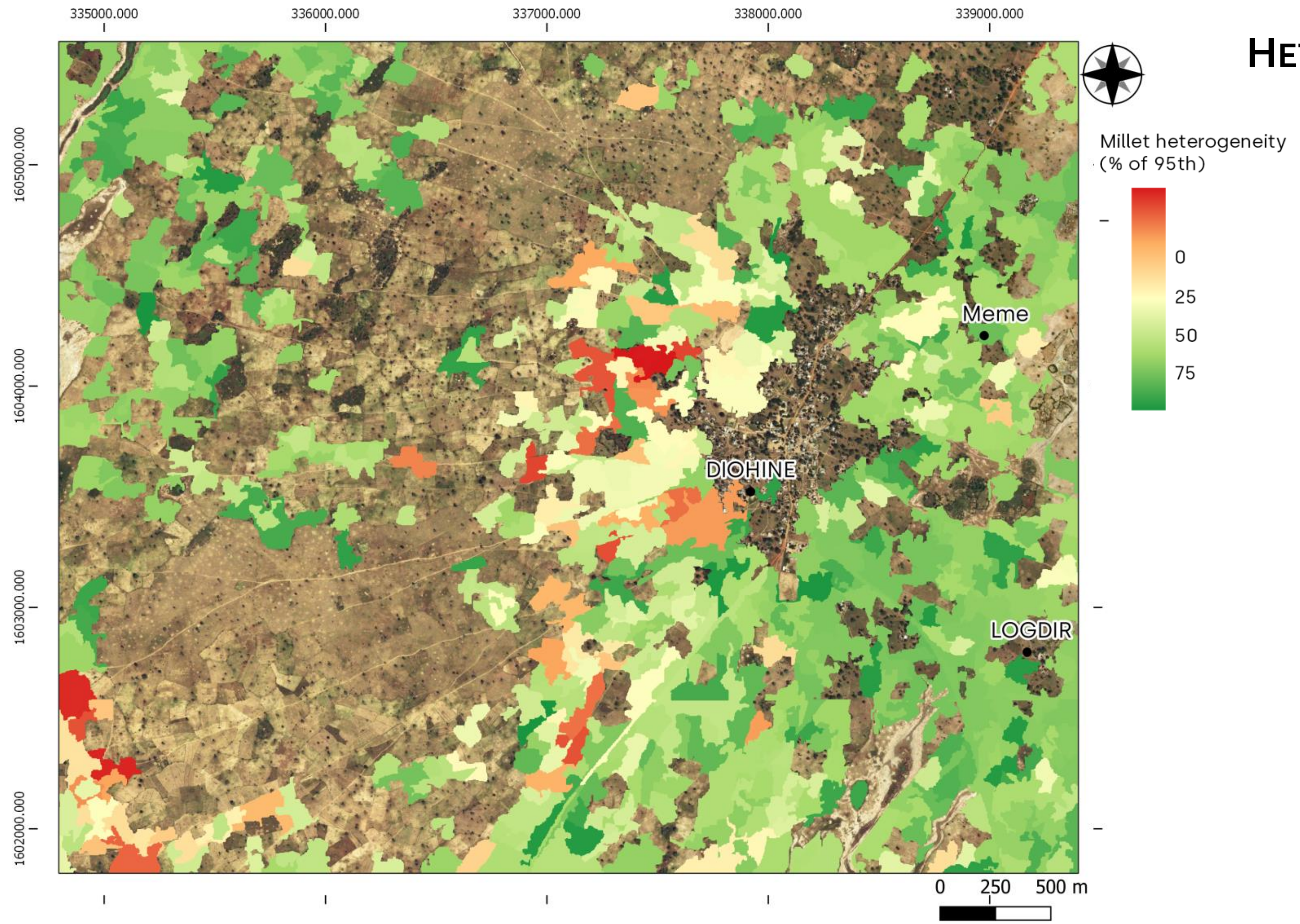
*** Panicle initiation phase to mid of the grain filling phase are more sensitive period**

Leroux et al., 2019, in prep for Agr,Eco&Envi

# Millet yield heterogeneity analysis at landscape scale




## Heterogenity in 2018

* Comparison with the 95th percentile
* 95th.p > 1912 kg/ha

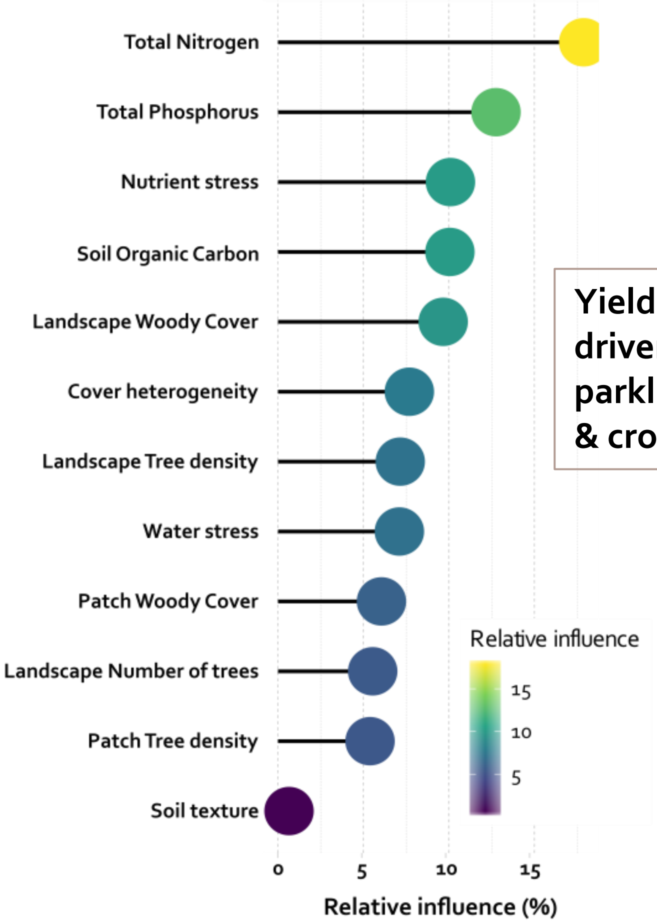
***Median millet yield estimates = 730 kg/ha with high variability (coef.var = 61%)**
***High spatial heterogeneity, with a clear spatial pattern**

Leroux et al., 2019, in prep for Agr,Eco&Envi

## What are drivers of spatial heterogeneity pattern?

### VARIABLE IMPORTANCE FOR THE GRADIENT BOOSTING TREE

$R^2=0.82^{***}$




Yield heterogeneity drivers : soil fertility, parklands structuring & crop health

***Parkland structuring information and soil fertility as drivers of spatial heterogeneity**

Leroux et al., 2019, in prep for Agr,Eco&Envi

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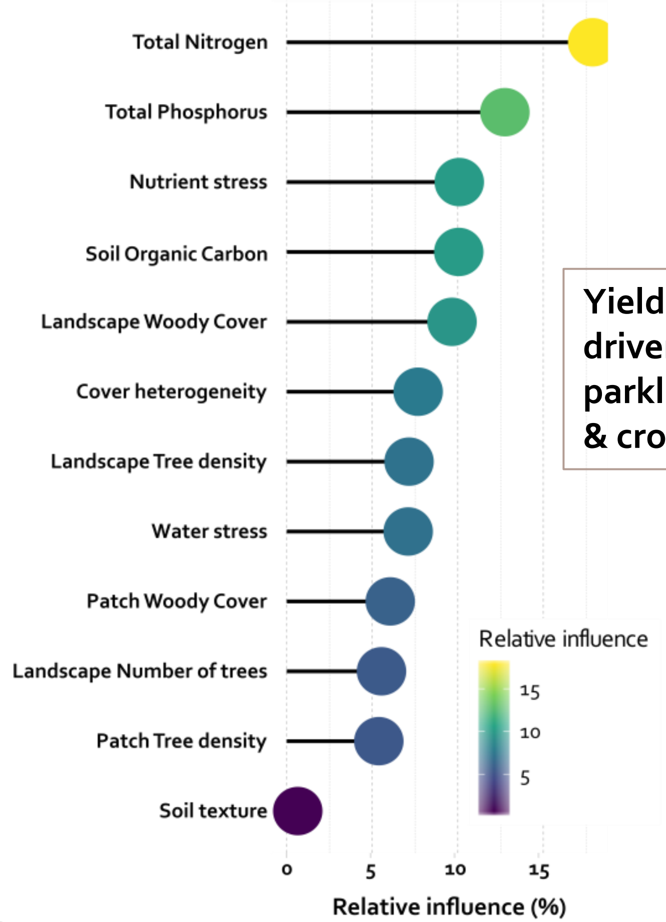
### Variable importance for the Gradient boosting tree

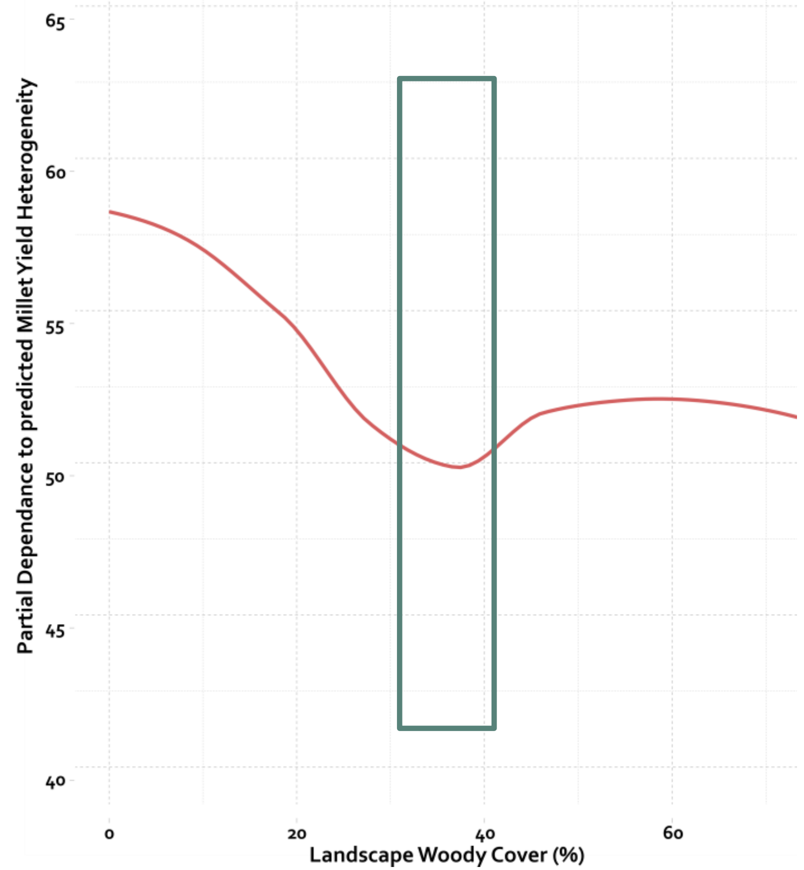
R²=0.82***




Yield heterogeneity drivers : soil fertility, parklands structuring & crop health

### Partial variable dependance plot

**Influence of woody cover in surroundig landscape**

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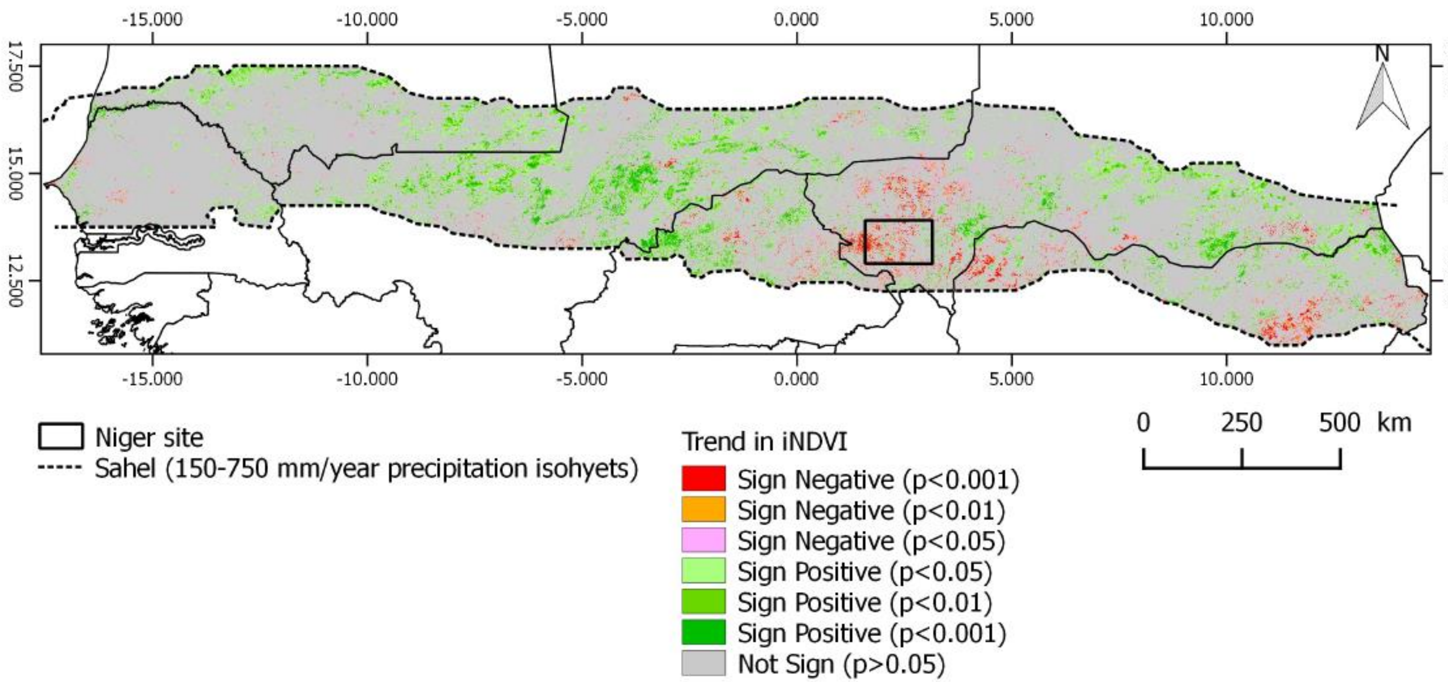
## What are drivers of temporal heterogeneity pattern in crop vegetation productivity dynamics?

Leroux et al., 2017, RSE

# What are drivers of temporal heterogeneity pattern in crop vegetation productivity dynamics?

## NDVI TRENDS OVER THE CROPPING SEASON – 2000-2015



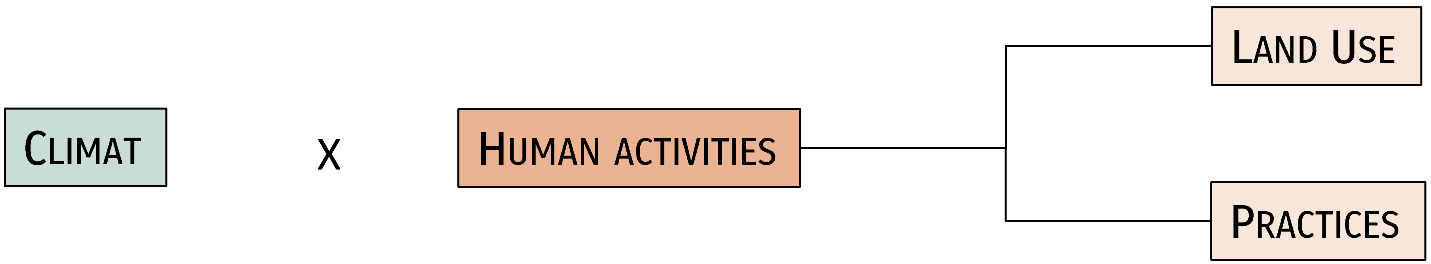

***Changes are spatially heterogeneous, with an West/East Gradient**

Leroux et al., 2017, RSE

# Using satellite data to identify drivers of yield heterogeneity : regional scale

## What are drivers of temporal heterogeneity pattern in crop vegetation productivity dynamics?

### Mapping the drivers of NDVI changes – 2000-2015

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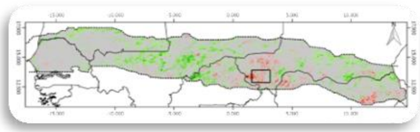
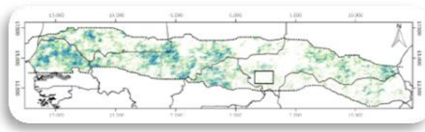
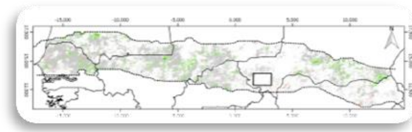
NDVI trend



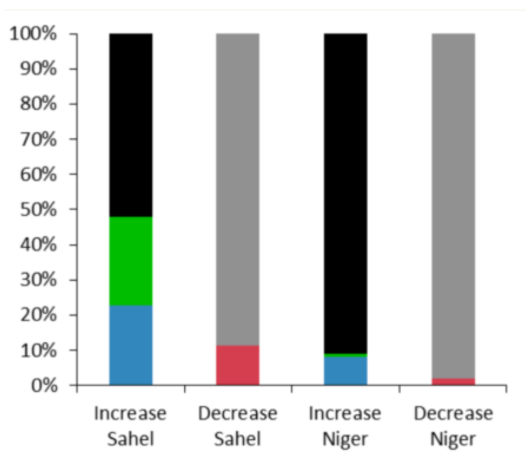
NDVI-Rain correlation

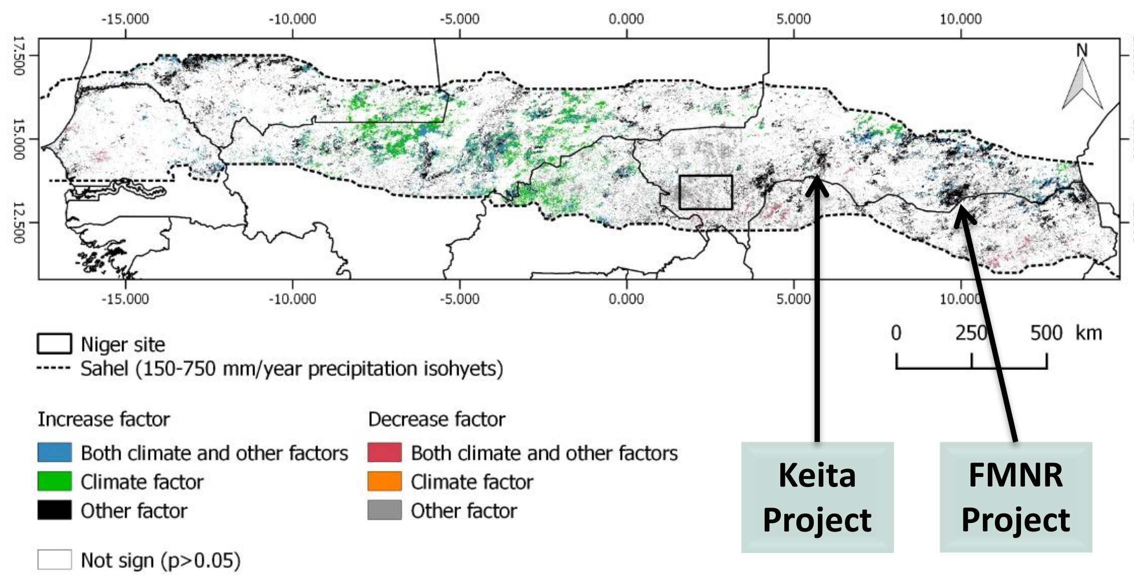


Residuals trend



Spatial distribution of the main drivers of NDVI changes




***Increase** : Rain is not the only important driver (~50%)

***Decrease** : Almost entirely explained by other drivers than rainfall (>80%)

# Perspectives for ACCWA

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LONG-TERM CHANGES IN THE WATER AVAILIBILITY-VEGETATION PRODUCTIVITY RELATIONSHIP:

- Analysis of changes in Land Surface Phenology
- Impact of changes in water availibility (rainfall and soil moisture): SM, RZSM, Vege?
- 1 Master student in **2020**
- 1 month of secondement : IsardSAT / IRTA (?)

# Perspectives for ACCWA

## Long-term changes in the water availibility-vegetation productivity relationship:

- Analysis of changes in Land Surface Phenology
- Impact of changes in water availibility (rainfall and soil moisture): SM, RZSM, Vege?
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## Short-term crop yield monitoring at local scale

- To estimates yields rainfed crops using output of ACCWA (SM, RZSM, Vege and ET)
- Senegal (Millet), Burkina (Maize), Other sites (Niger?, Tunisia?)
- Collaboration with IsardSAT / Agrhymet

## Short-term crop yield monitoring at regional scale?

- Activity mainly conducted by Aghrymet
- Assimilate EO-RZSM and EO-ET within SARRA-O
- Comparison with yield simulated with SARRA-O+tamsat only

# THANKS FOR YOUR ATTENTION

QUESTIONS-REMARKS : louise.leroux@cirad.fr - https://louise.leroux.igeo.fr/





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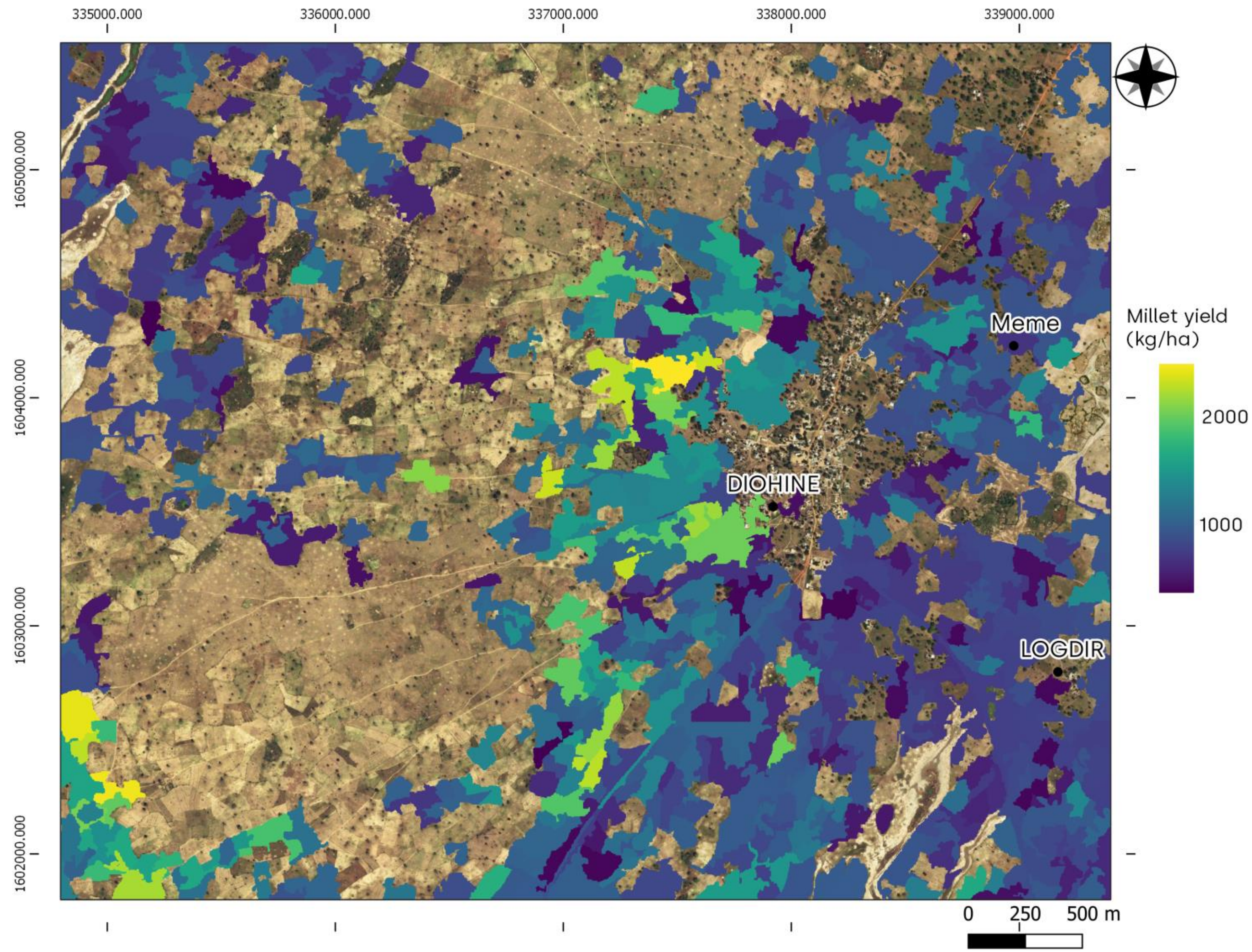
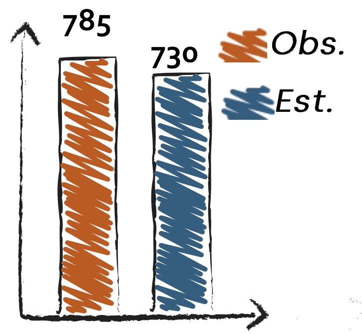
# Results ~ from a landscape perspective

## Millet yield heterogeneity analysis at landscape scale




### MEDIAN YIELD IN 2018




*Median estimated millet yield for 2018 = 730 kg/ha with high variability (coef.var = 61%)