FAO EOSTAT Crop Yield Mapper: Forecasting Production by integrating geospatial data and crop simulation models

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Hannah Distinguished Professor

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The Global Food and Water Paradox

- Feeding more people with less water than we have now, in a **changing climate**
- Roughly one-third of food produced is wasted globally (1.3 Bil Ton/yr)
- 70% of global water withdrawals

Urbanization

Deforestation

Fires/Land Degradation

Soil Erosion

Water quality

Digital Twins

a bridge between the physical and digital world to promote innovation and performance

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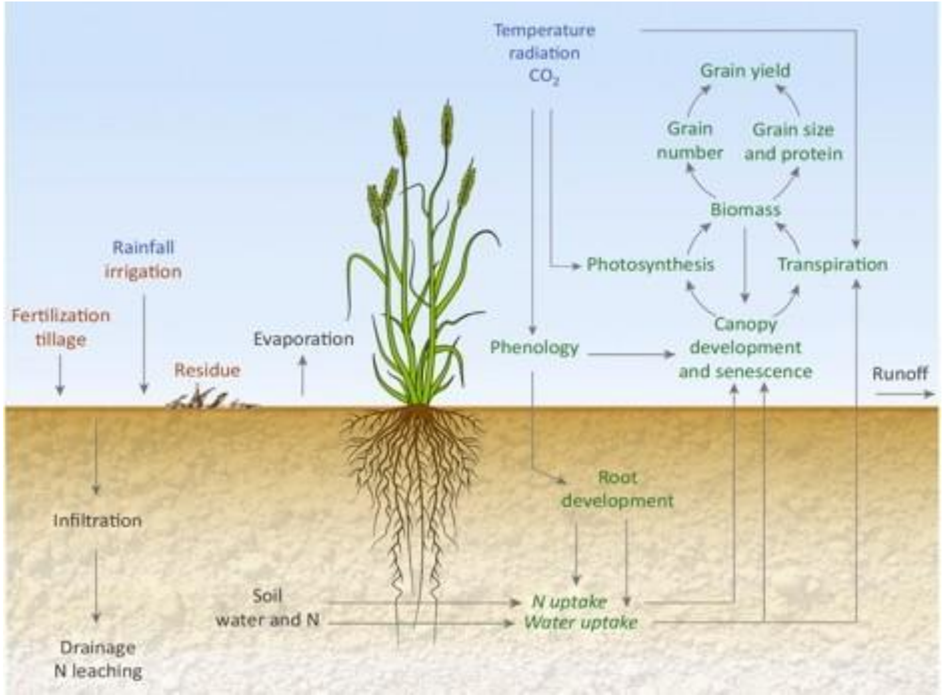
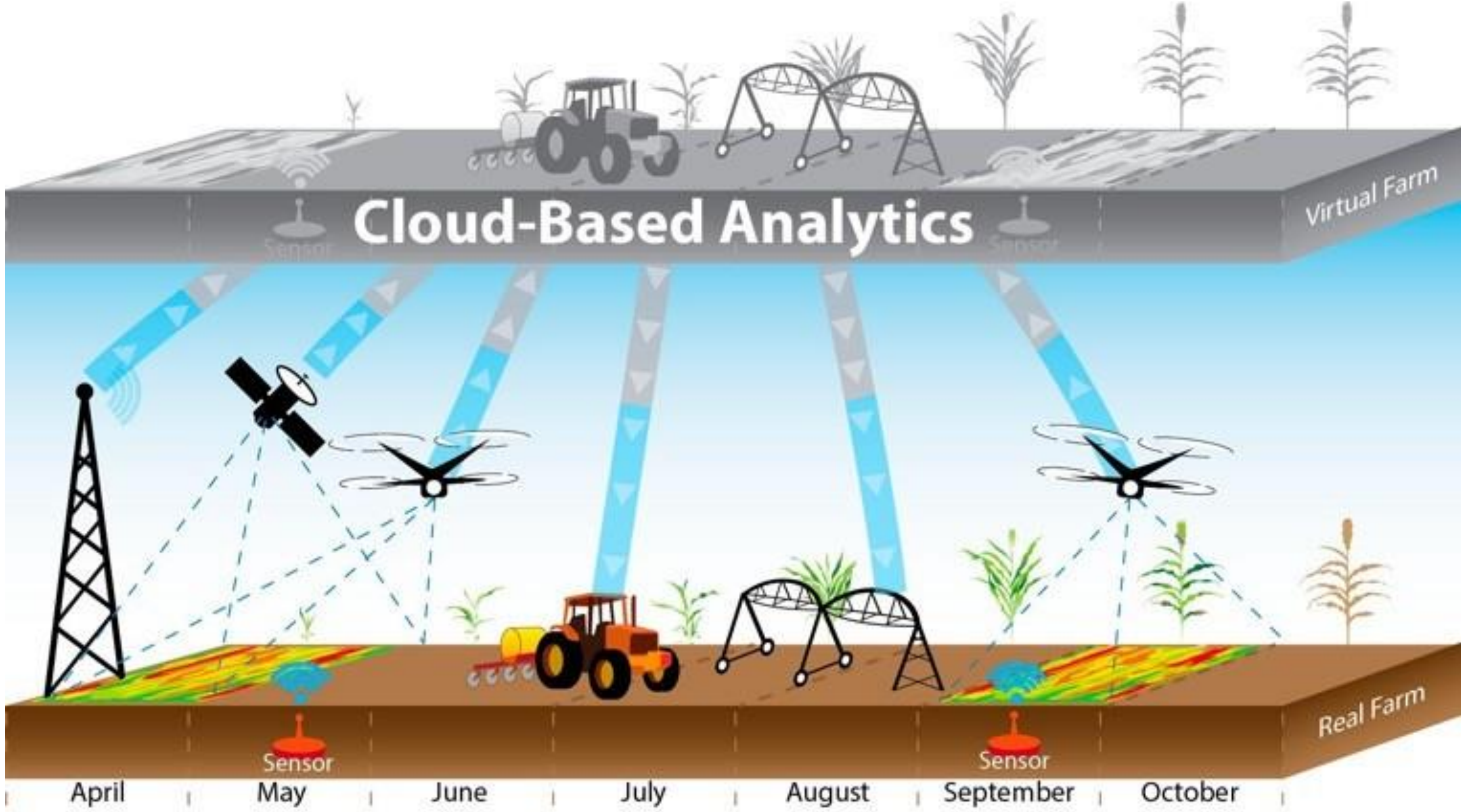
Digital twins can be used to evaluate the current condition of the asset, and more importantly, predict future behavior, refine the control, or optimize operation.





Seasonal crop yield forecast: Methods, applications, and accuracies

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Advances in Agronomy, Volume 154
ISSN 0065-2113
https://doi.org/10.1016/bs.agron.2018.11.002

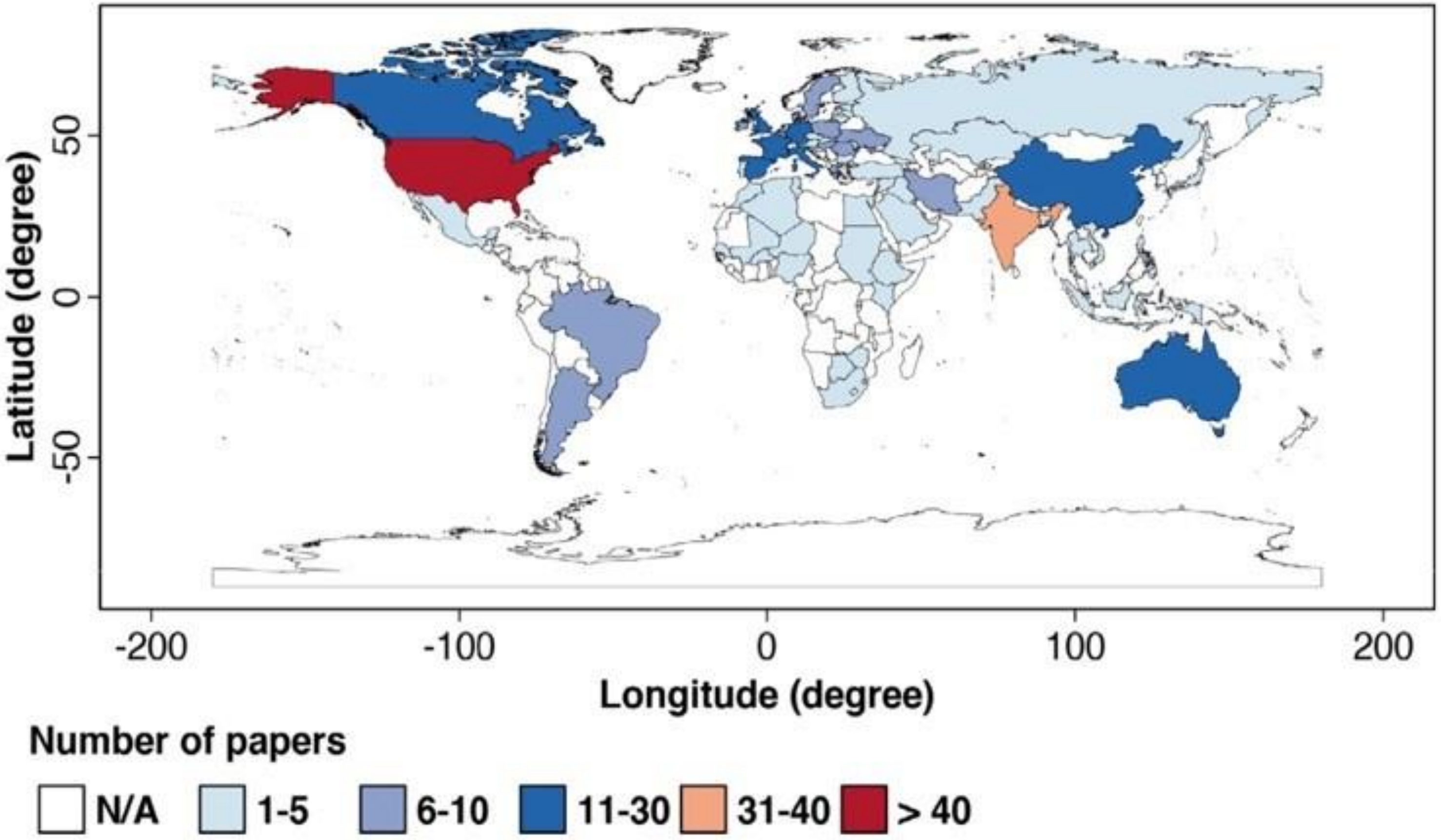
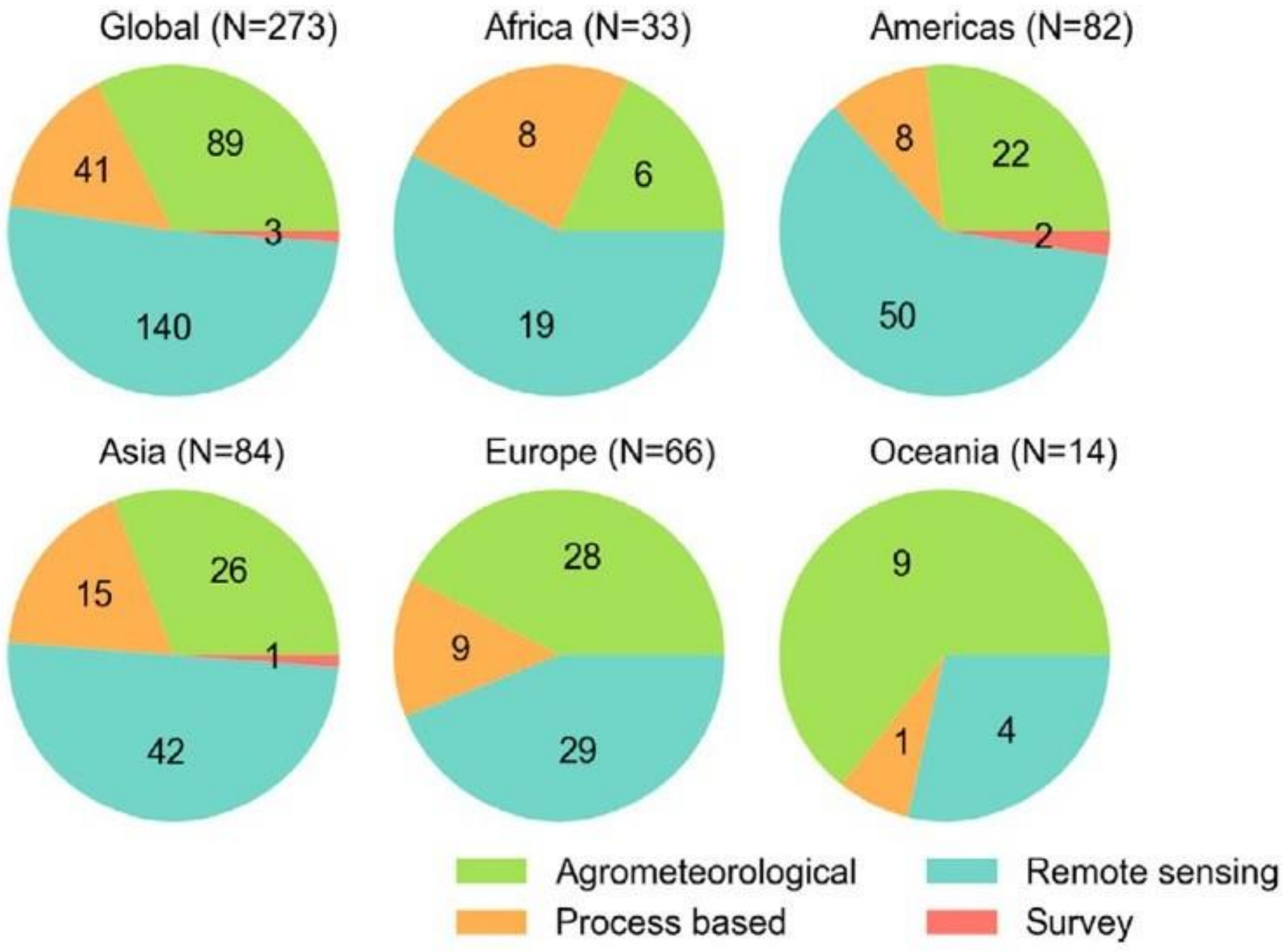
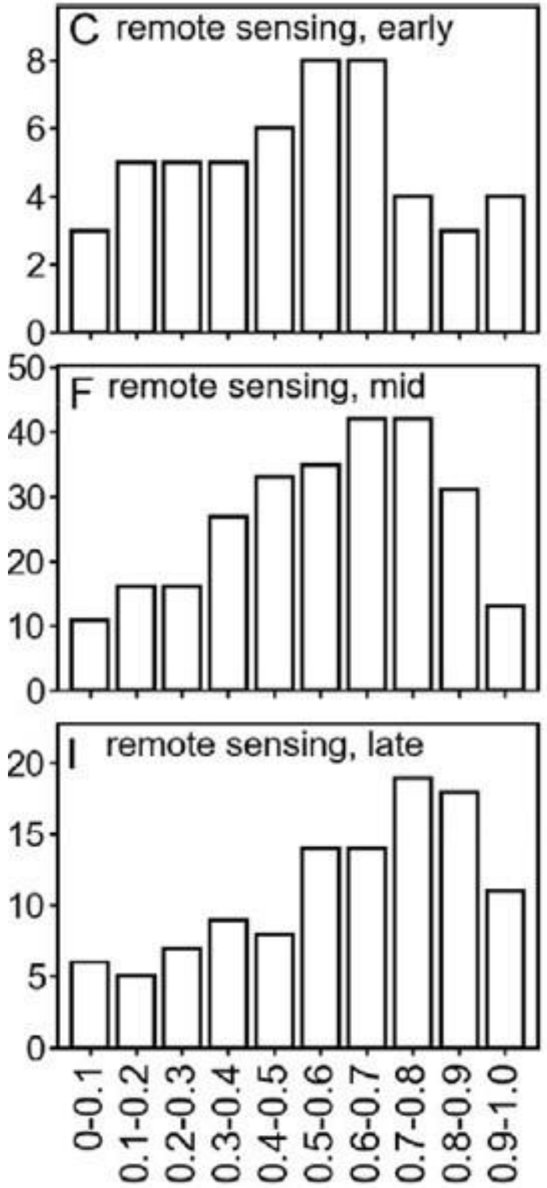


Fig. 1 Number of peer-reviewed papers in each country where the study sites or regions of the yield-forecasting papers were located.

Different methods have been used to forecast yield with different levels of granularity, accuracy and timing





Basso and Liu, 2019, Advances in Agronomy

SALUS: Systems Approach for Land Use Sustainability

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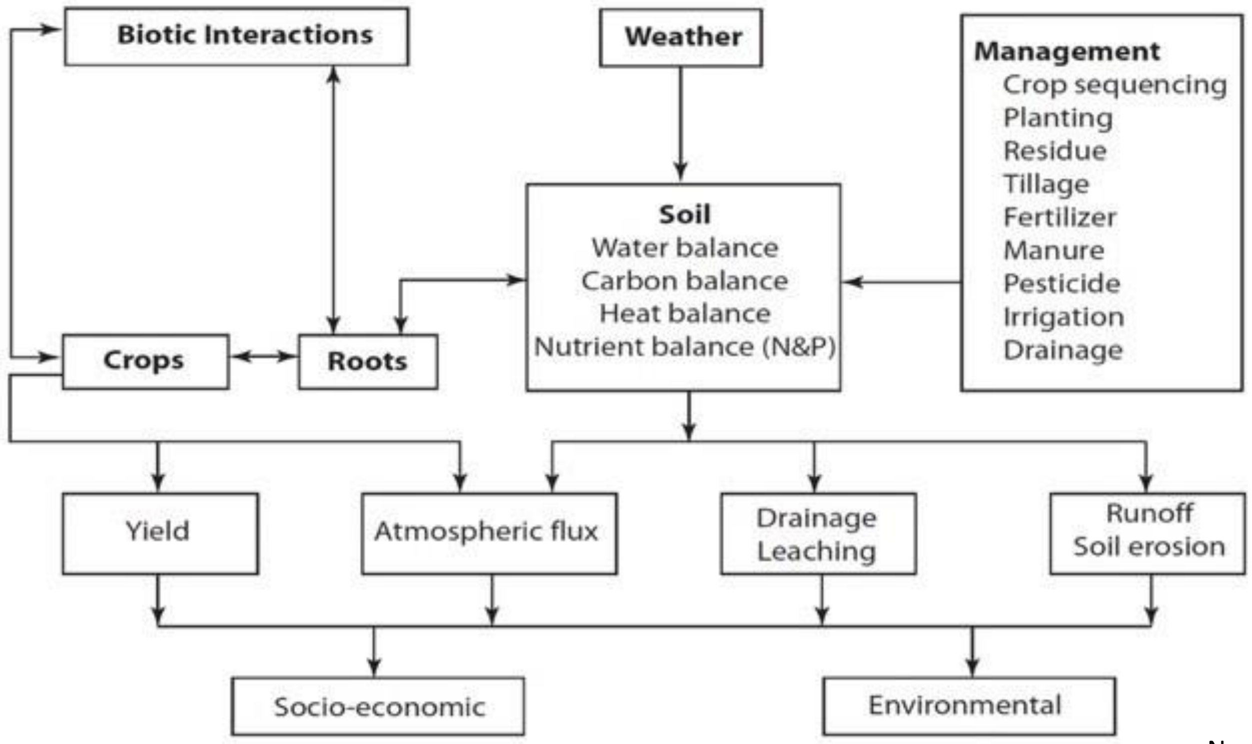
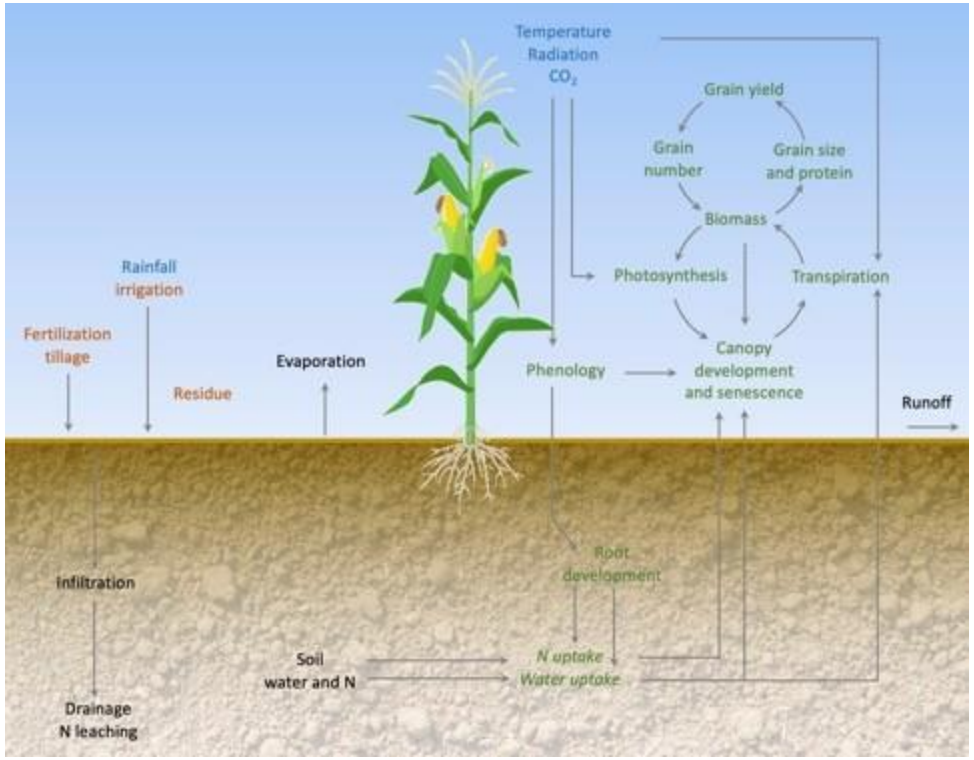
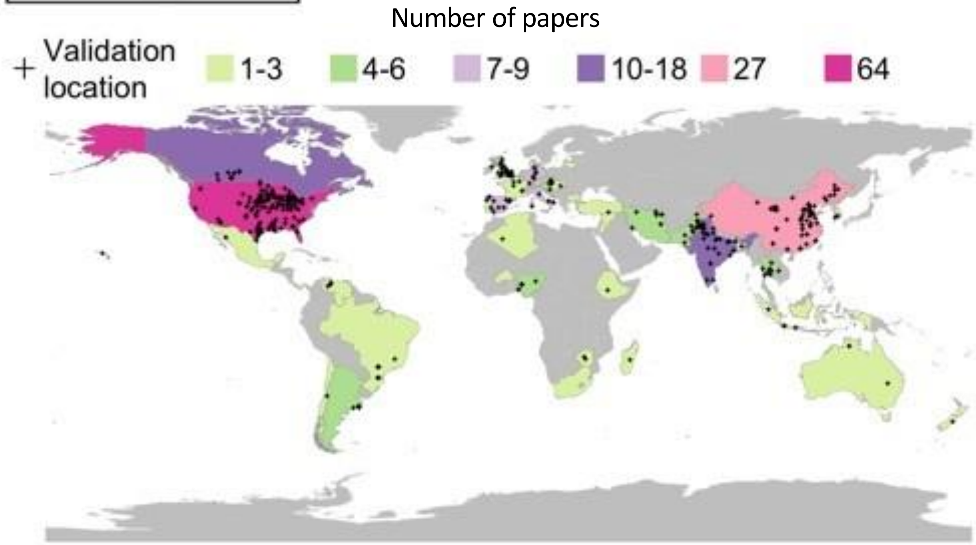
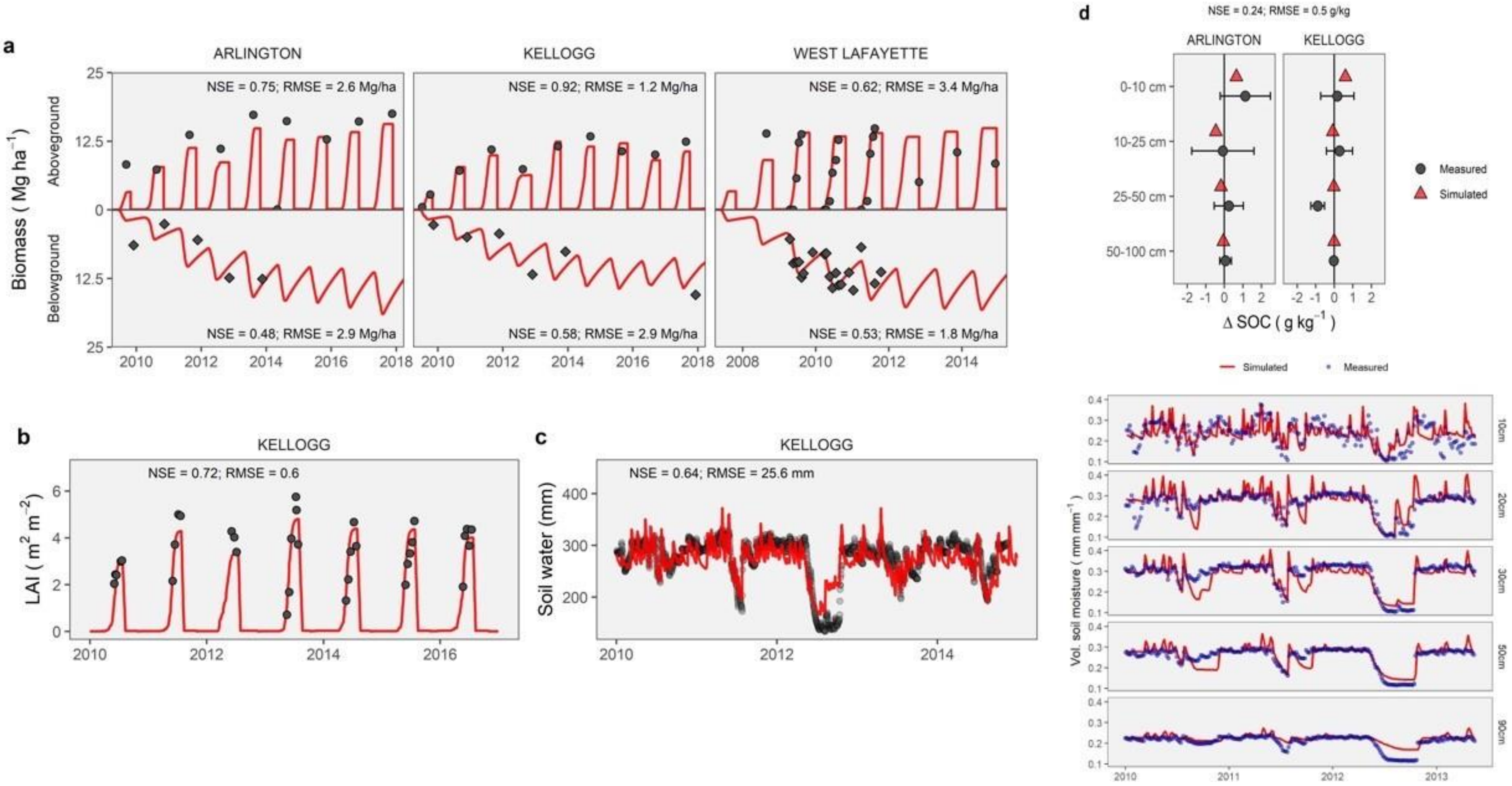






Basso, 2006; Basso and Ritchie, 2015, Basso et al., 2016

SALUS model validation



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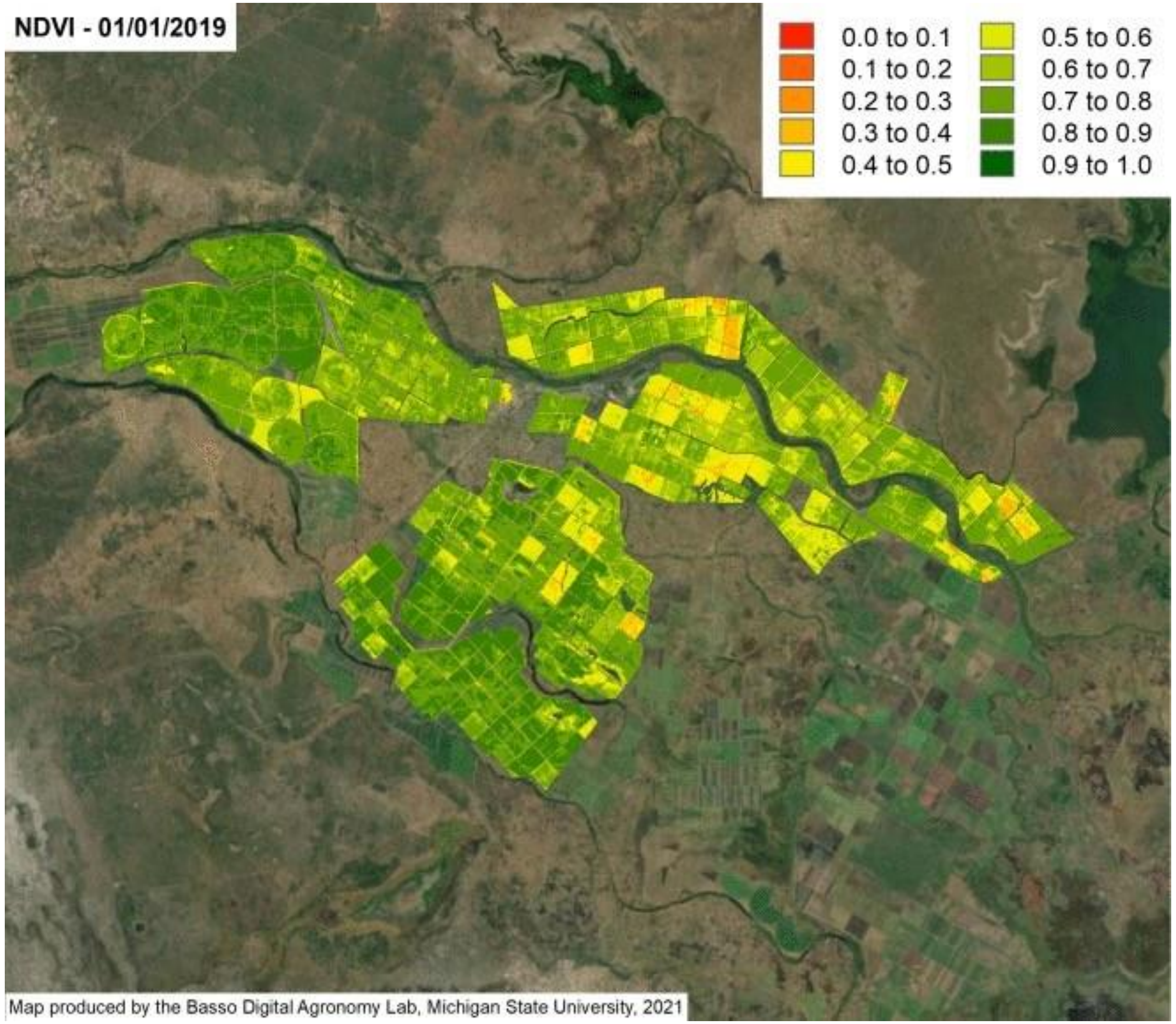
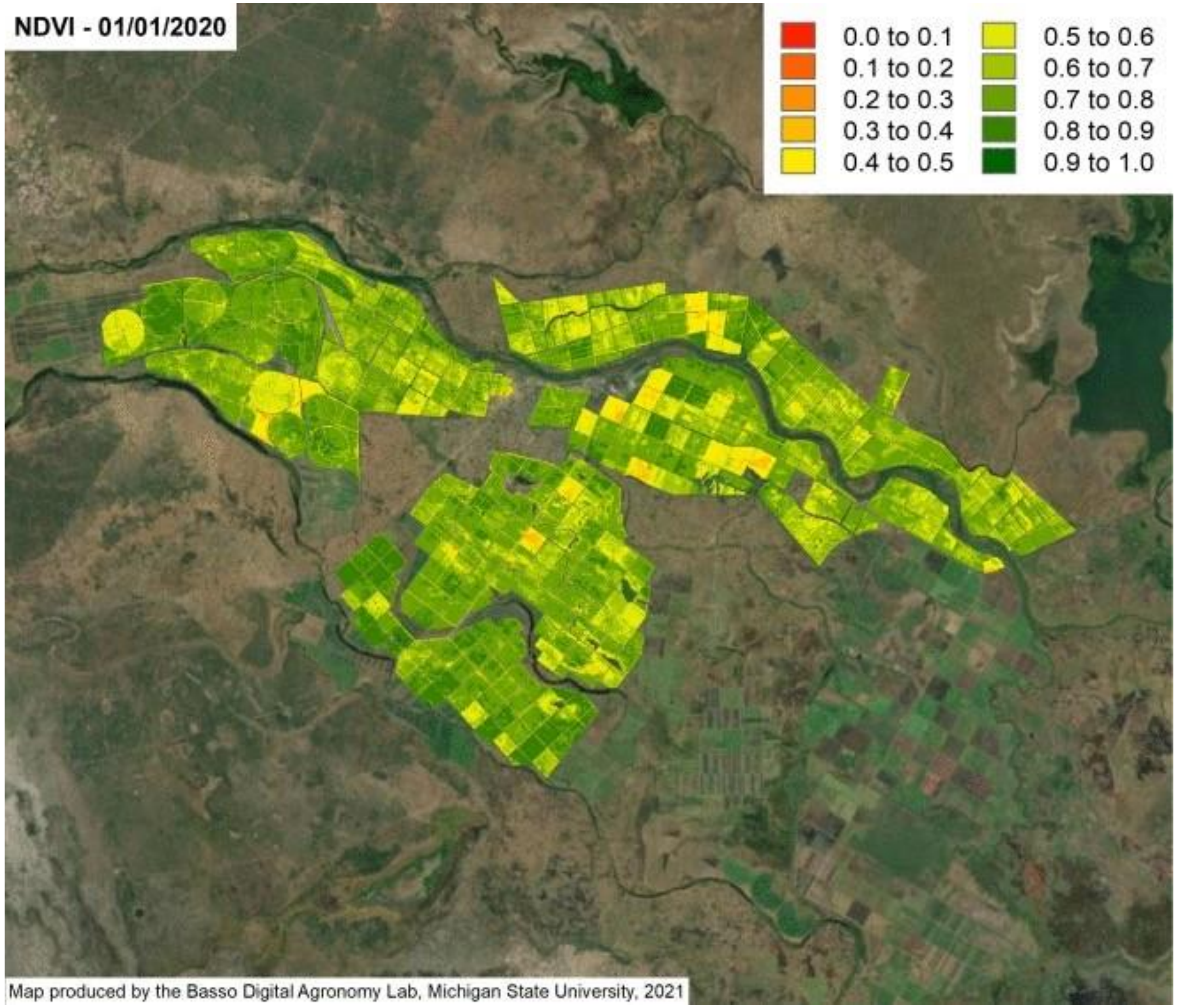
2019



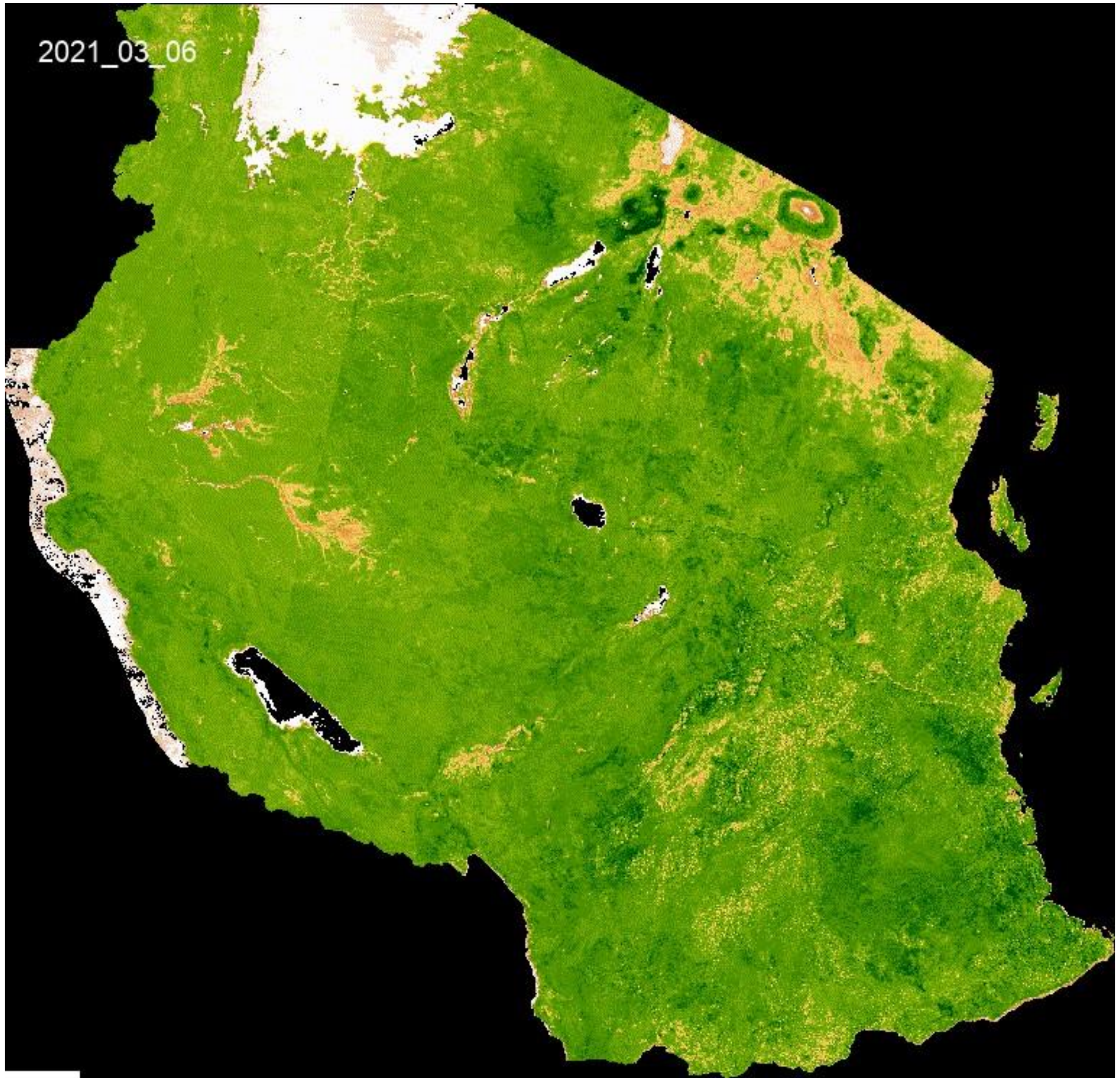
2020

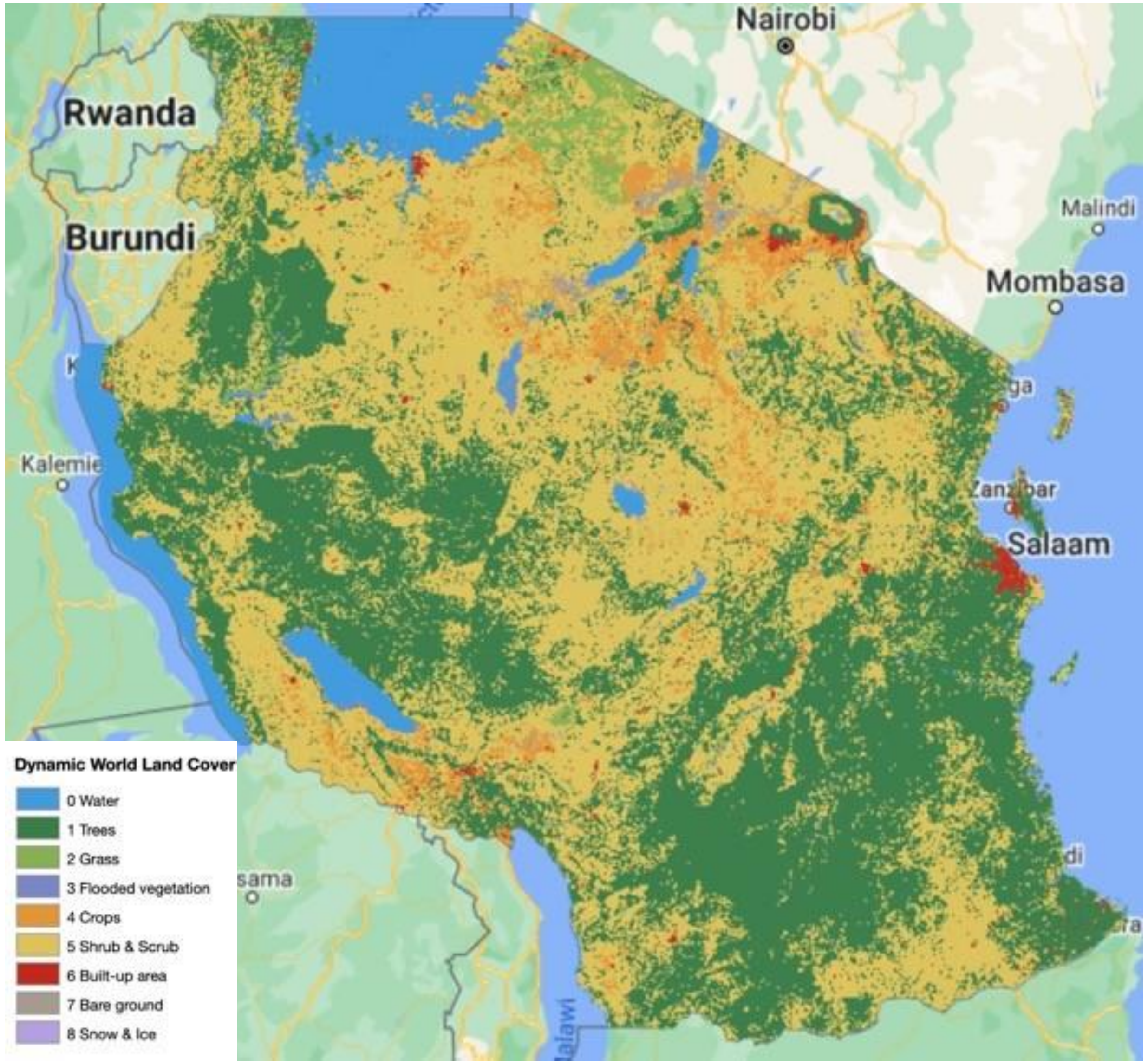


Daily changes of crop vigor and modeling yields in Mozambique sugarcane fields

Basso lab

Coupling remote sensing with crop models





EOSTAT Crop Yield Mapper

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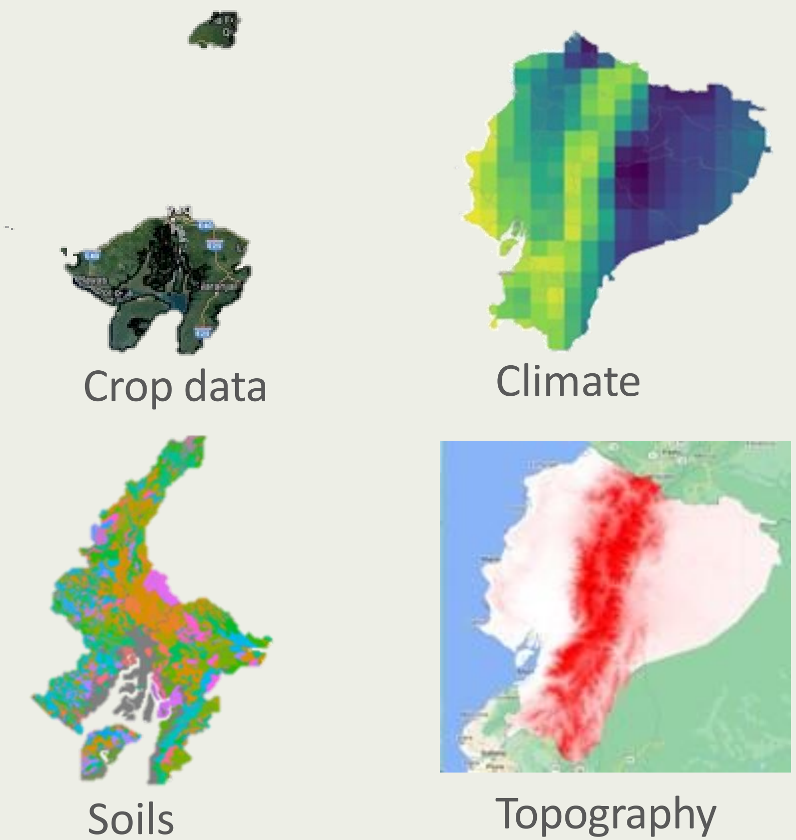
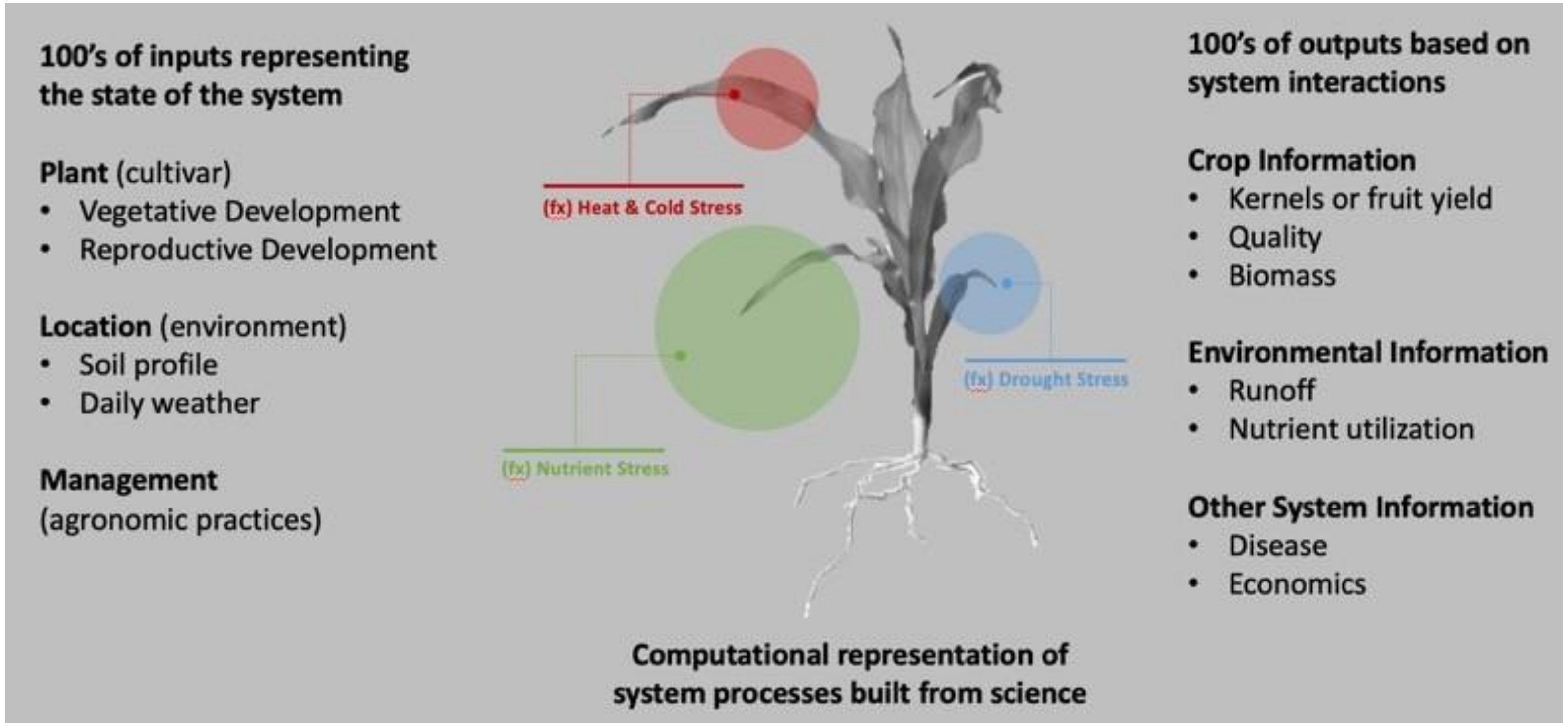
Earth Observation Data



The SALUS model



Design criteria:

- Built on Google Cloud system
- Can deal with low in country data requirements
- Rapid deployment and processing times
- Ground truth data collection is important for remote sensing and model validation and improvements

Platform structure

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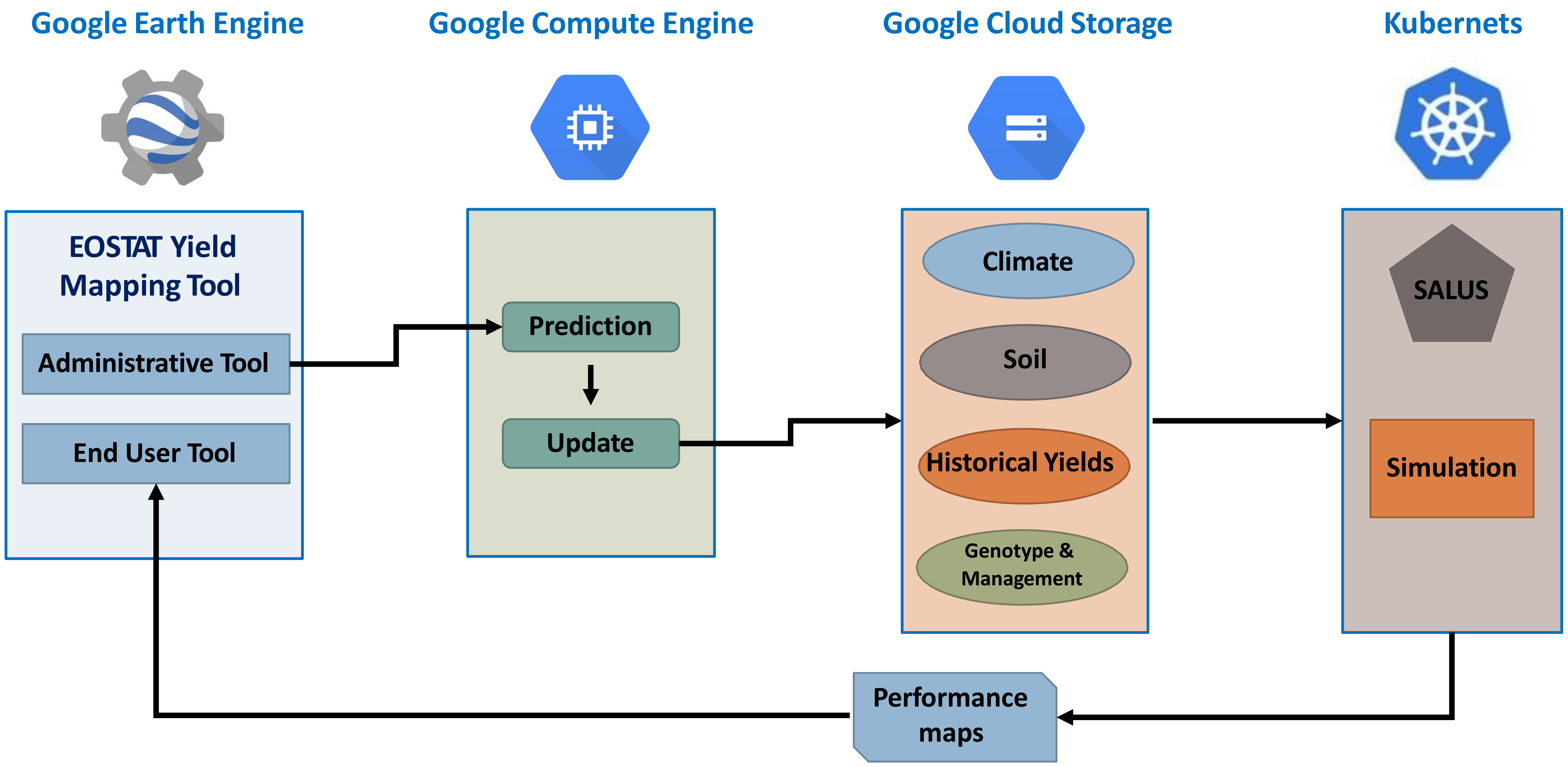
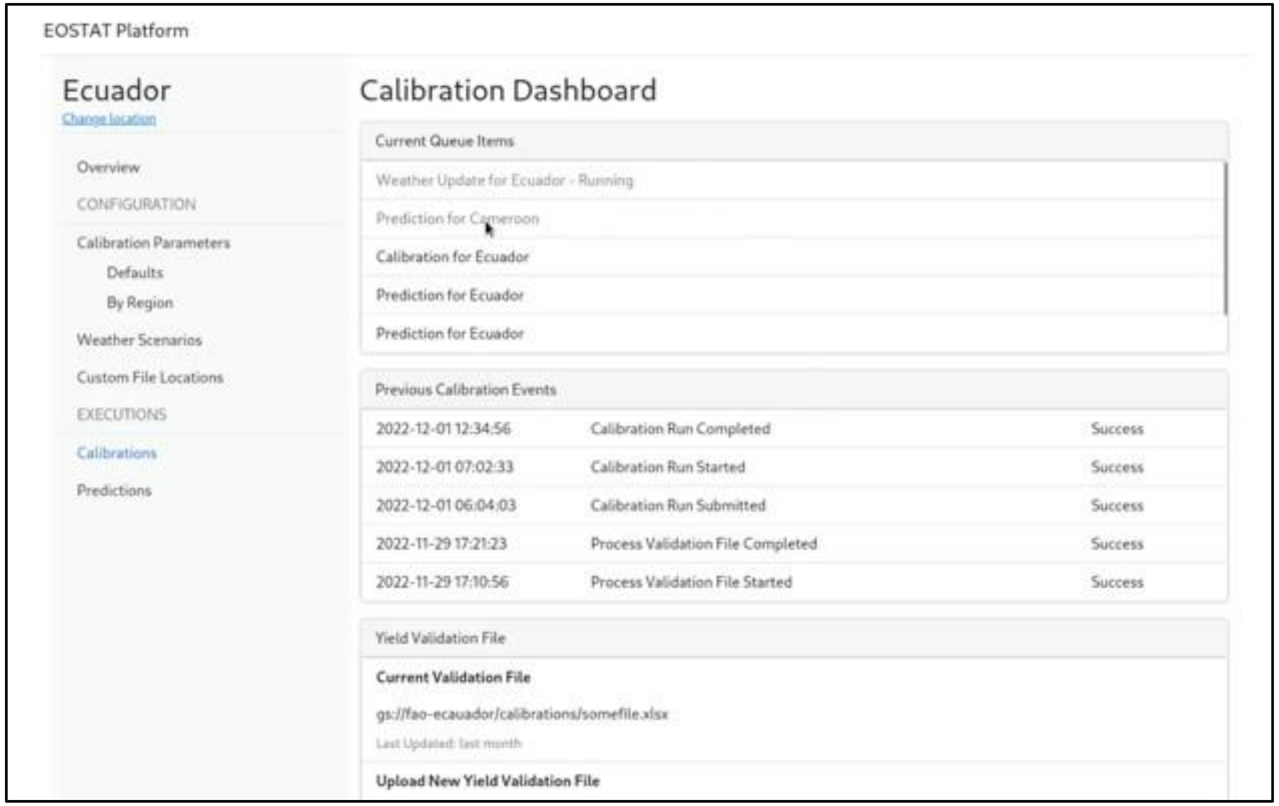
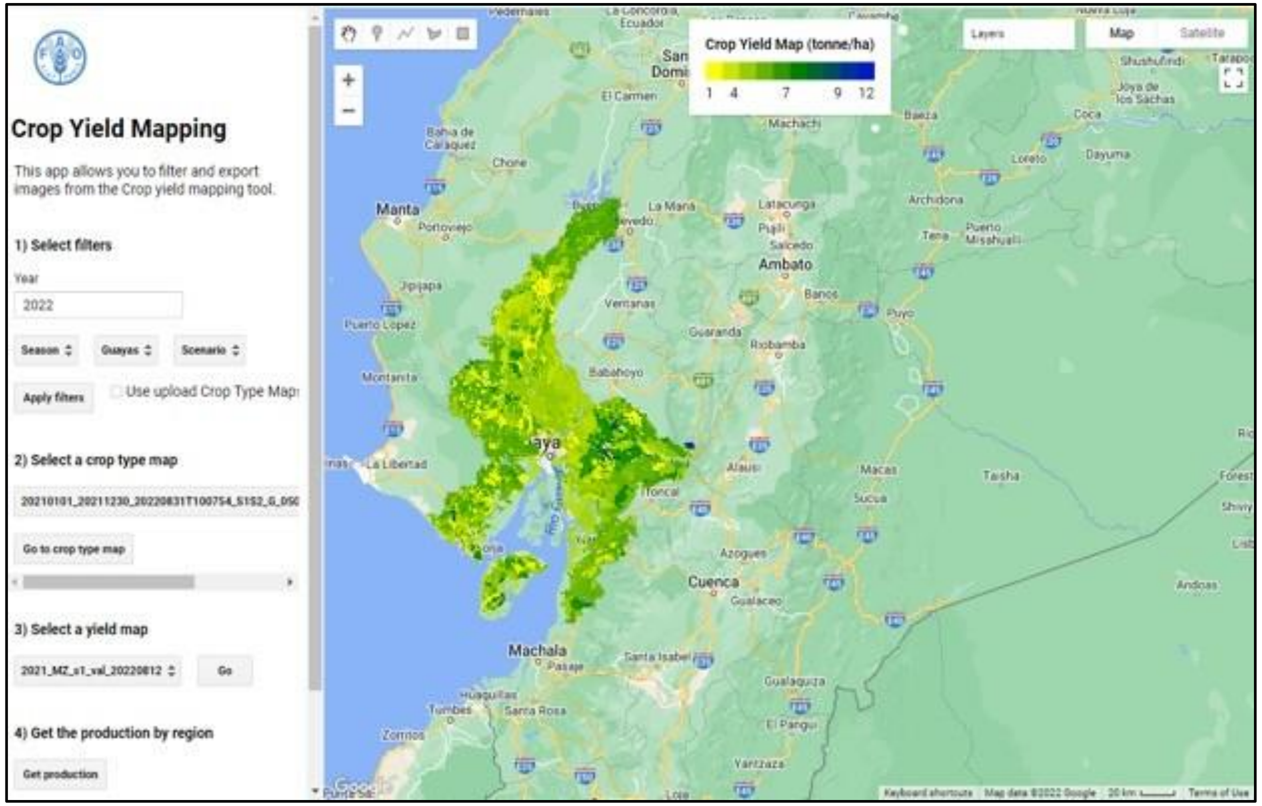


Friendly web application tools

Administrative Tool



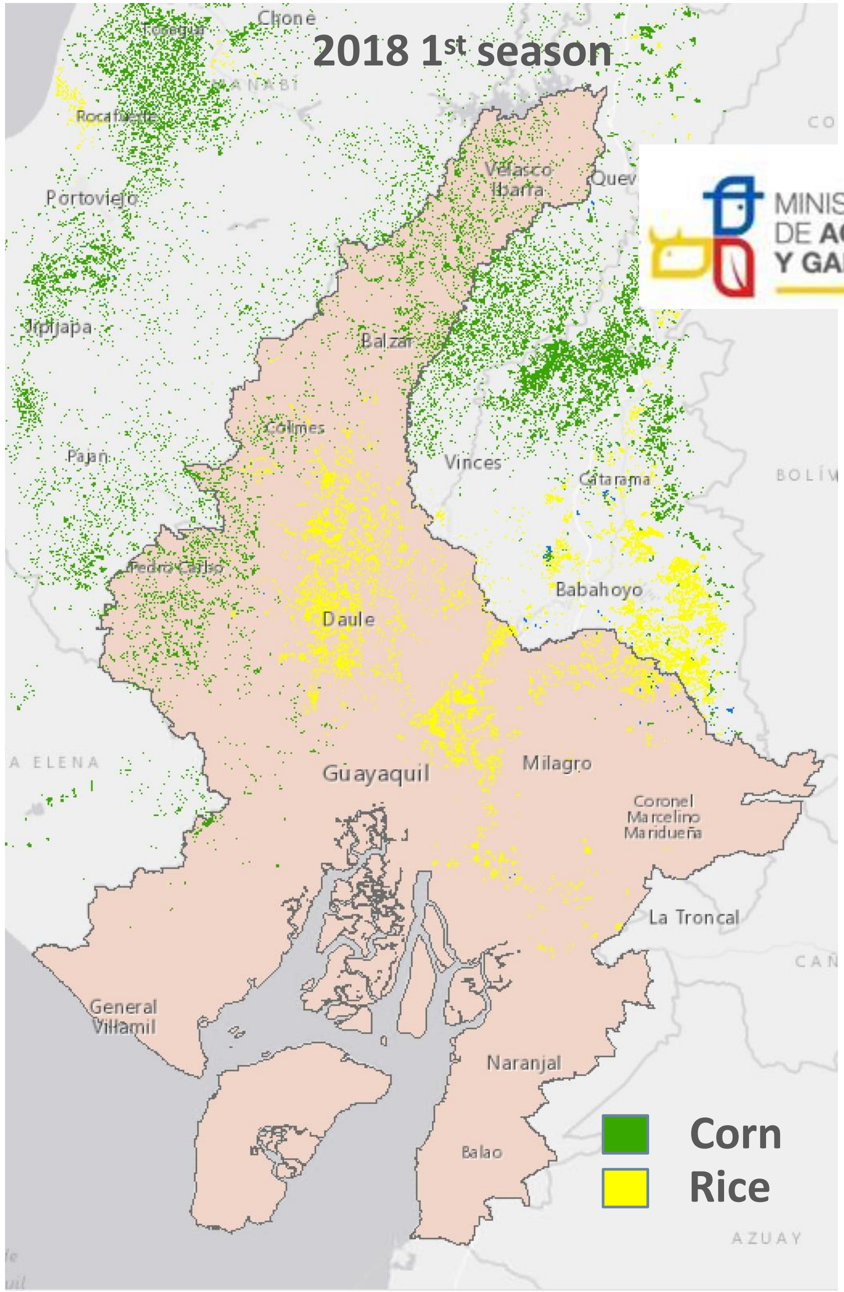
Visualization Tool



Crops

The country can upload its own data

The Crop Mapper can produce the type of crop using Sentinel 1 and 2



EOSTAT Crop Mapper: Ecuador

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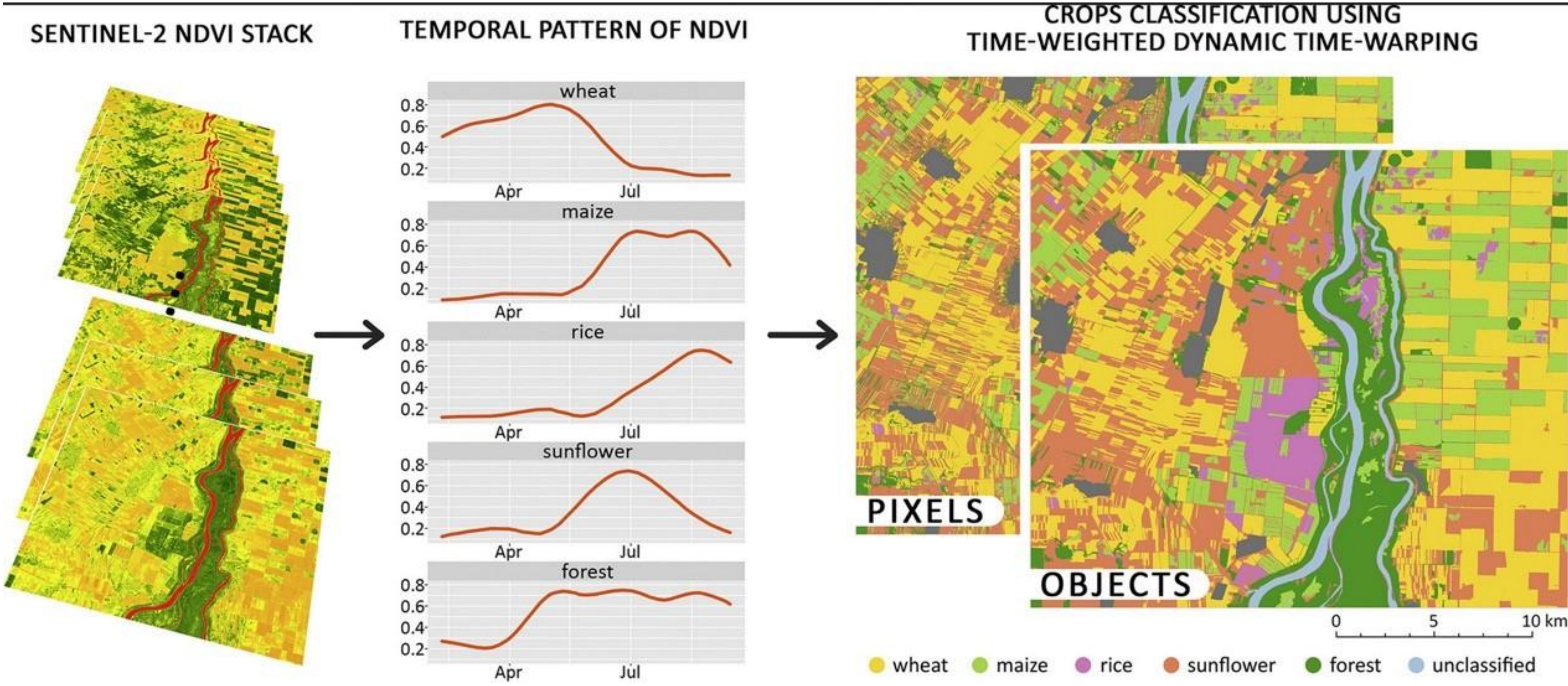
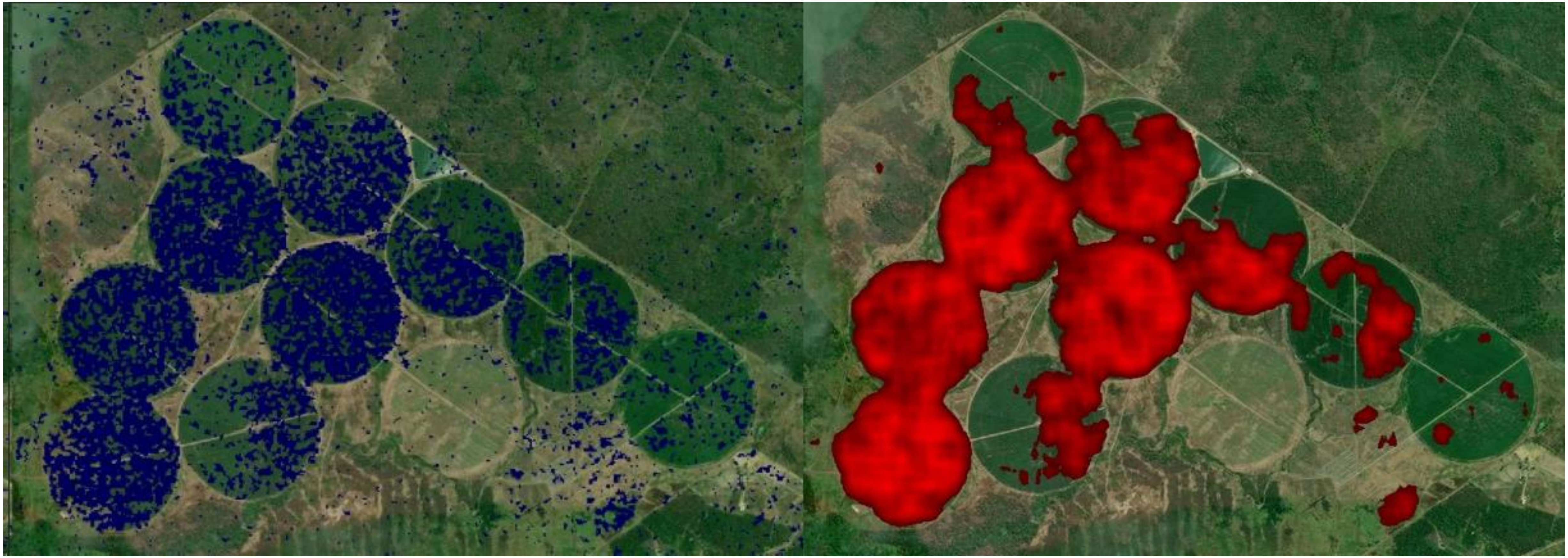


Belgiu and Csillik, 2018

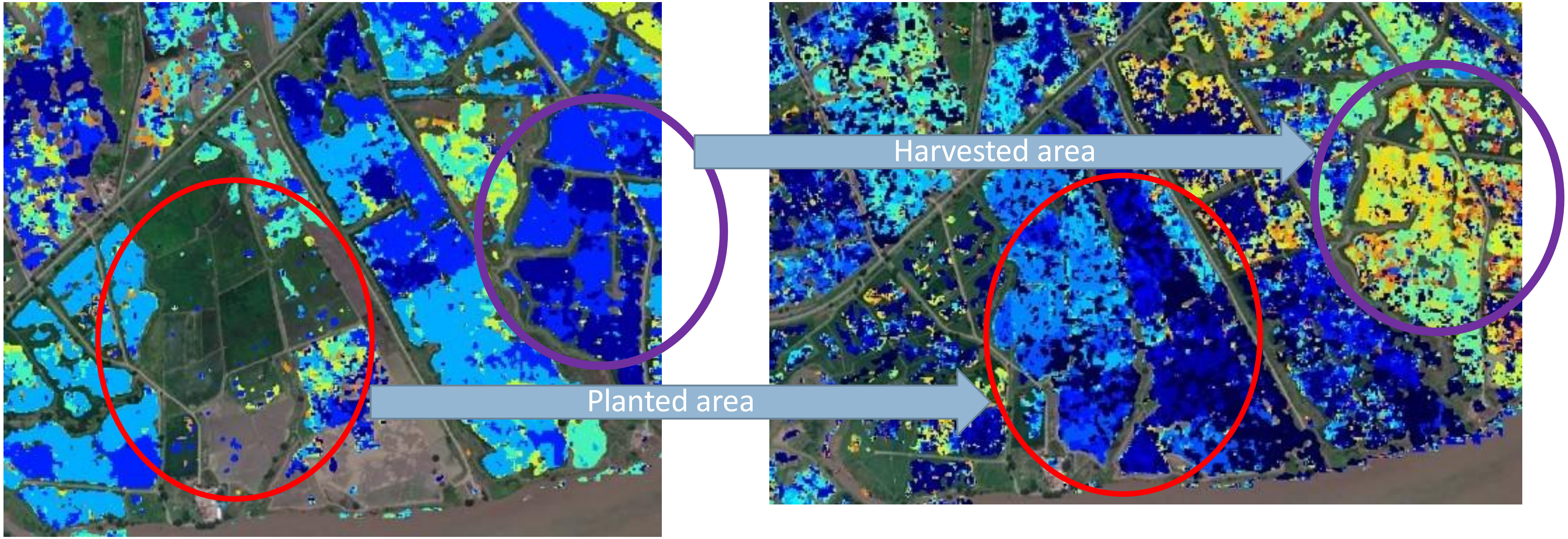
Example of short-term detection after harvest in irrigated Maize in Ecuador

- Using Sentinel-1



Rice land detection: Change between Dec 2020 to Jul 2021 using SAR (Radar)

- December 2020
- July 2021



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Daily Climate data

Climate

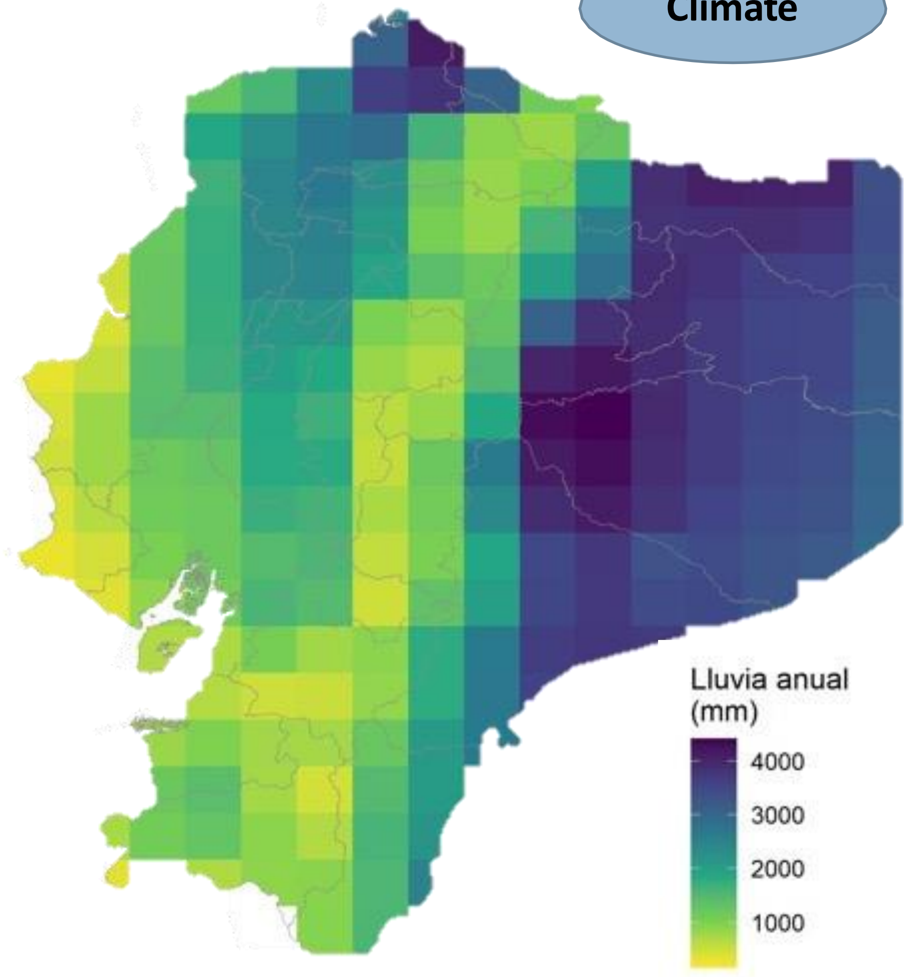
Climate Forecast System Version 2 (CFSv2)

- Temperature, Solar radiation
- Resolution ~22km

Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS)

- Rain
- Resolution ~5,5 km

Scenarios for forecasting yield : Wet, Dry, Normal



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Soil Data

Soil

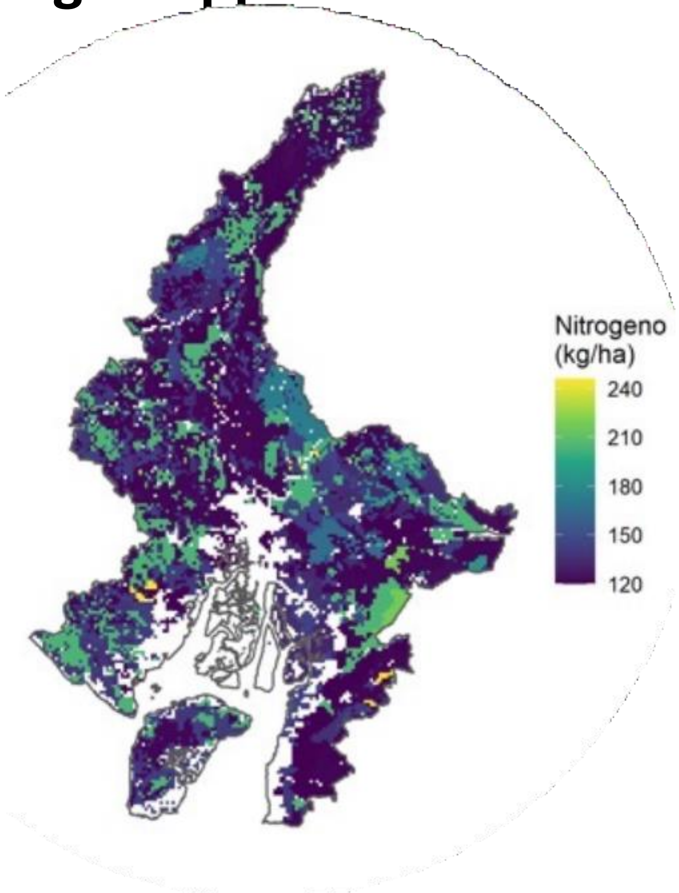
- **The country can provide National data or use a global product.**

- **This Case study uses Ecuador's national soil dataset.**

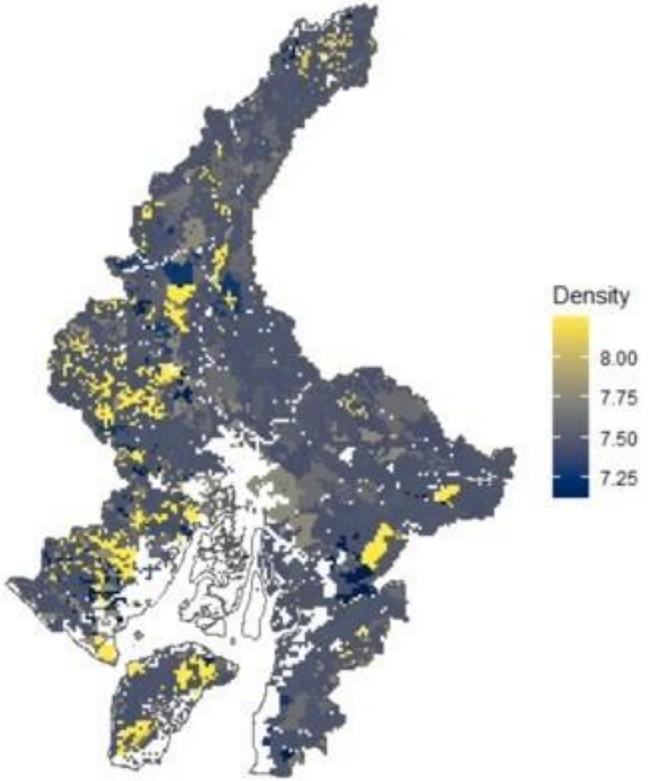
MINISTERIO DE AGRICULTURA Y GANADERÍA

Inferred management: Maize

Nitrogen Application

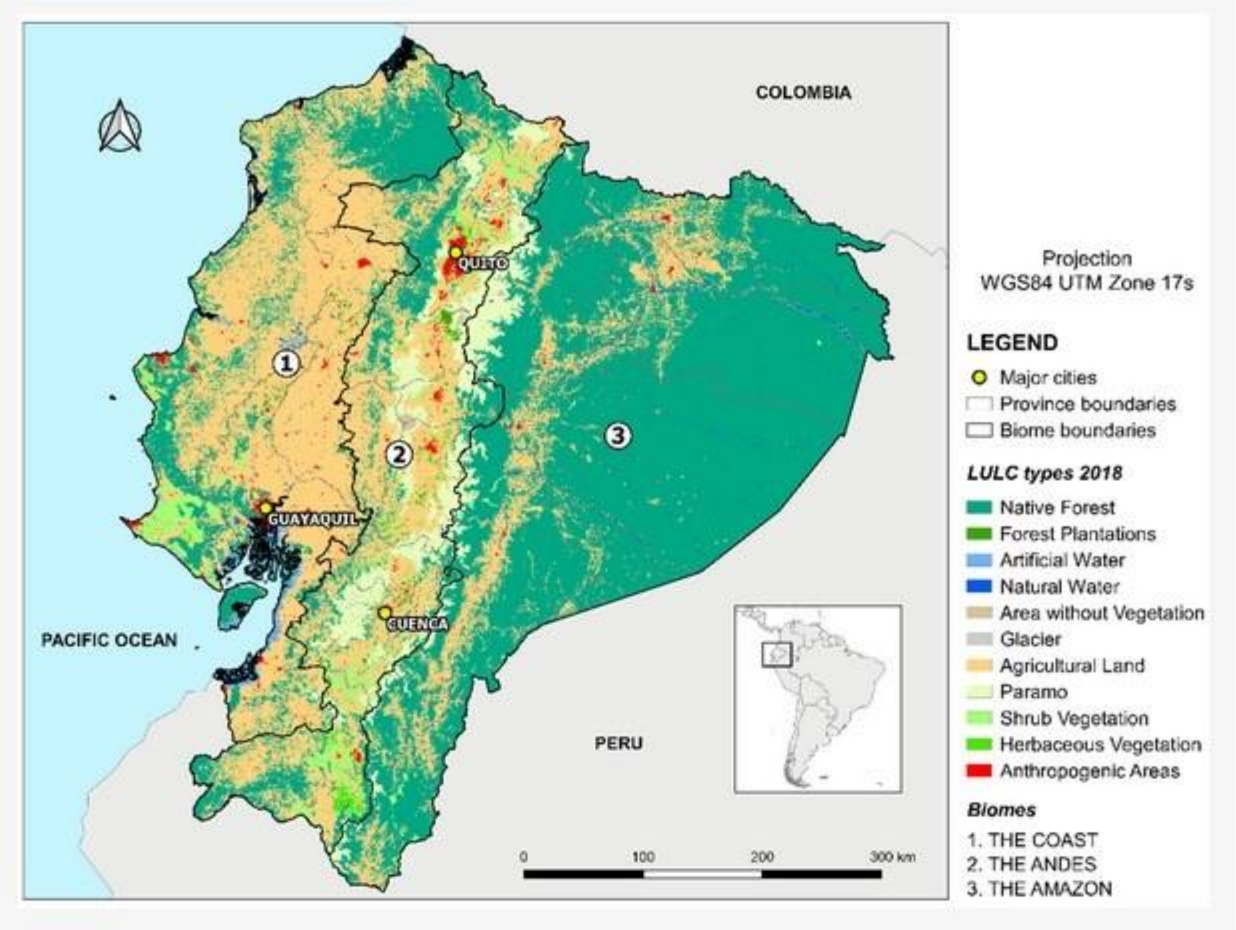


Planting density



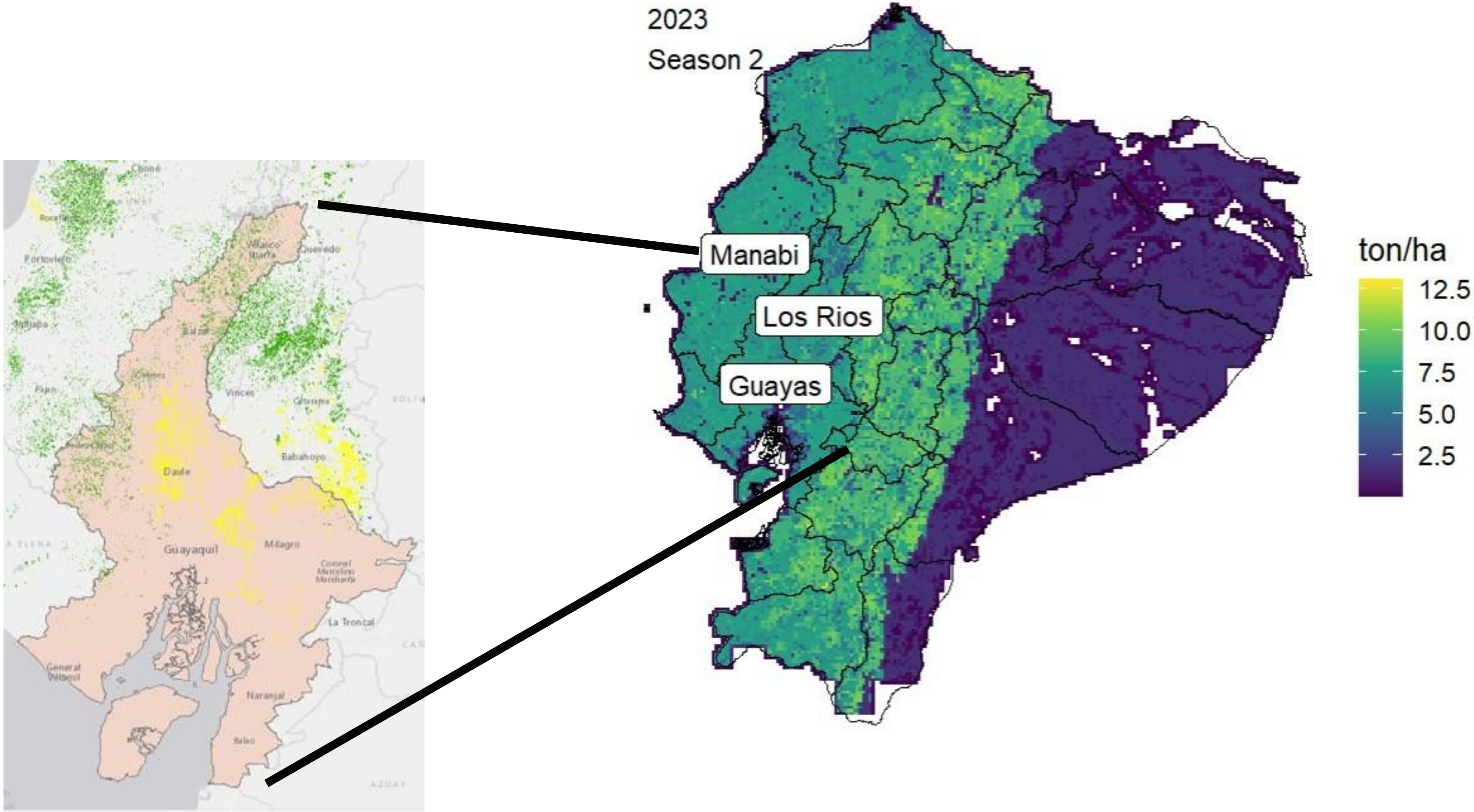
Ecuador:
Model parameterization and calibration

- Using only local soil dataset and global climate data.
- In-country calendar planting.
- Commercial crop production occurs in the coast area.



Kleemann et al., 2022

Crop yields: Maize



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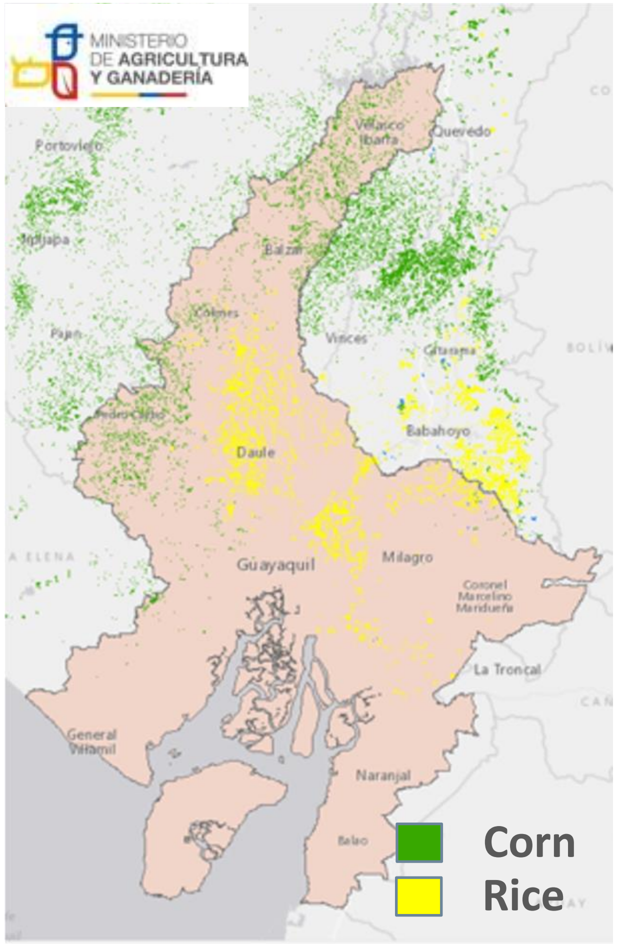
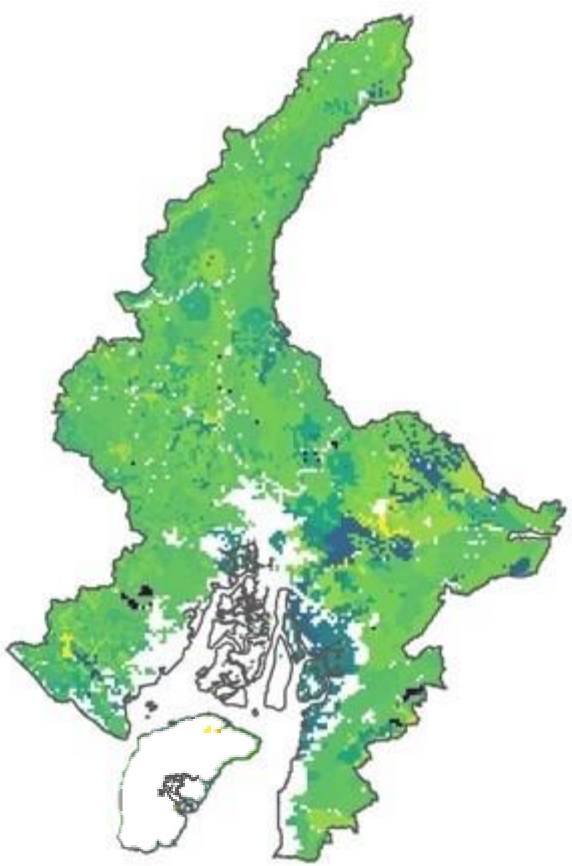
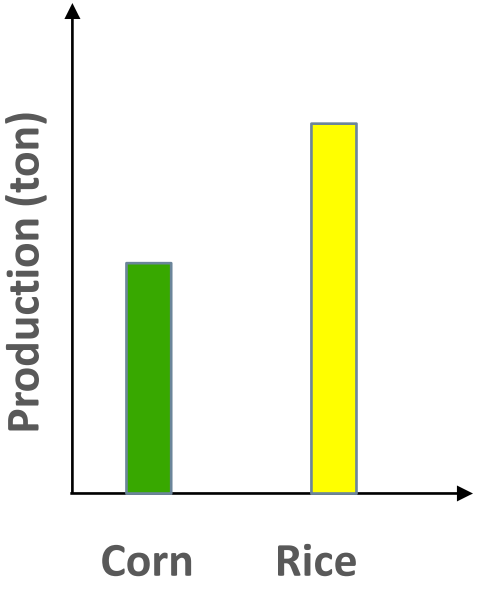
Total production



Crop area



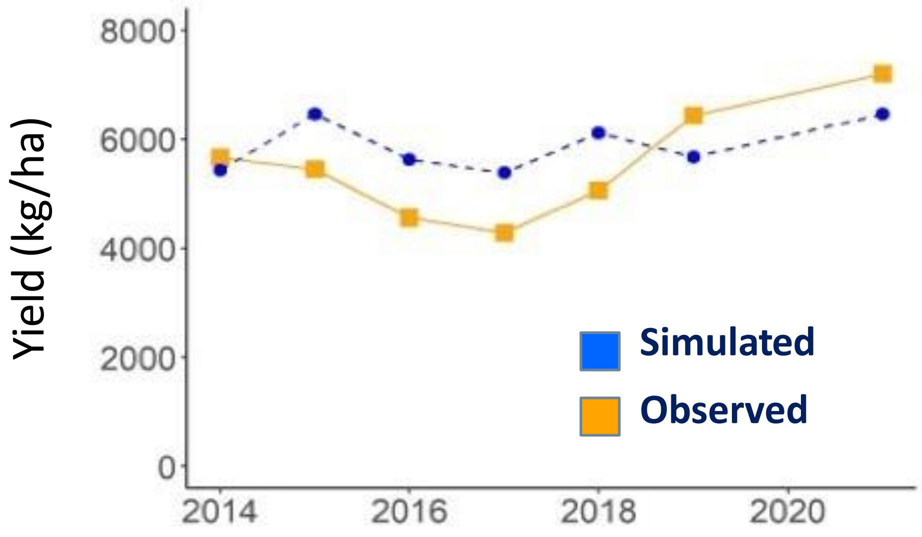
Yield (ton/ha)

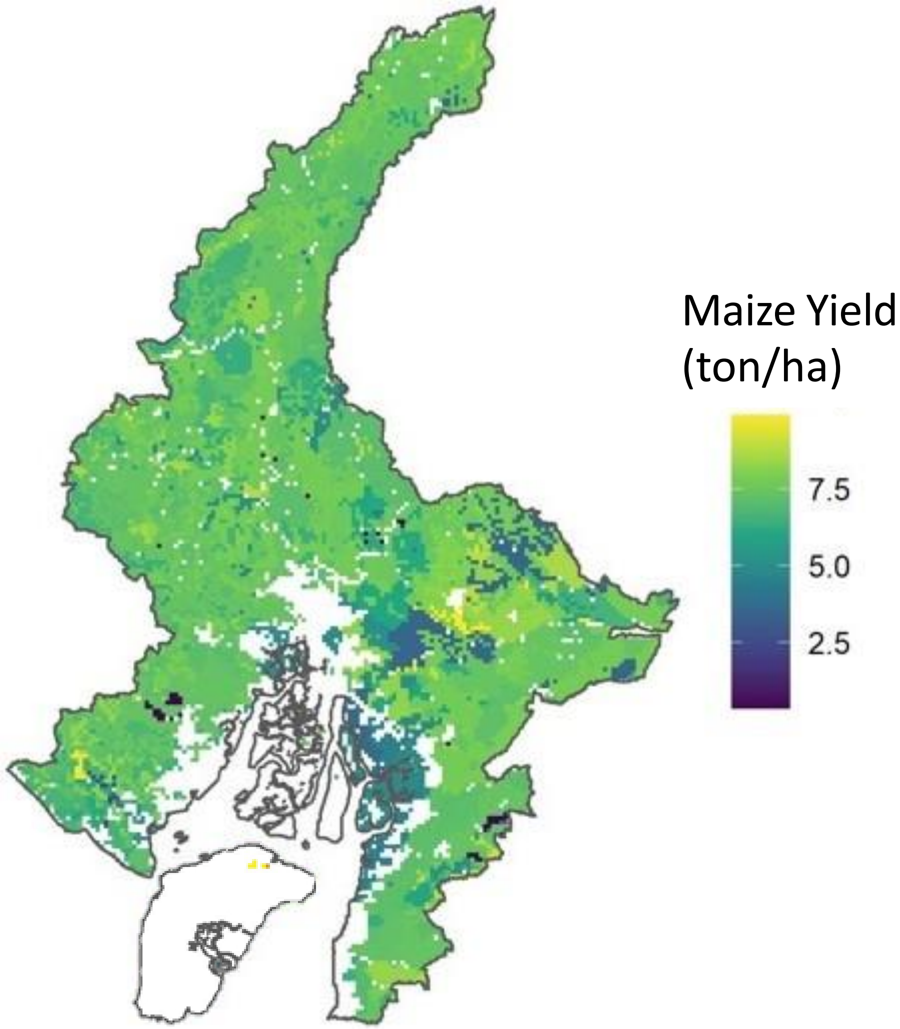


Production

Crop yields

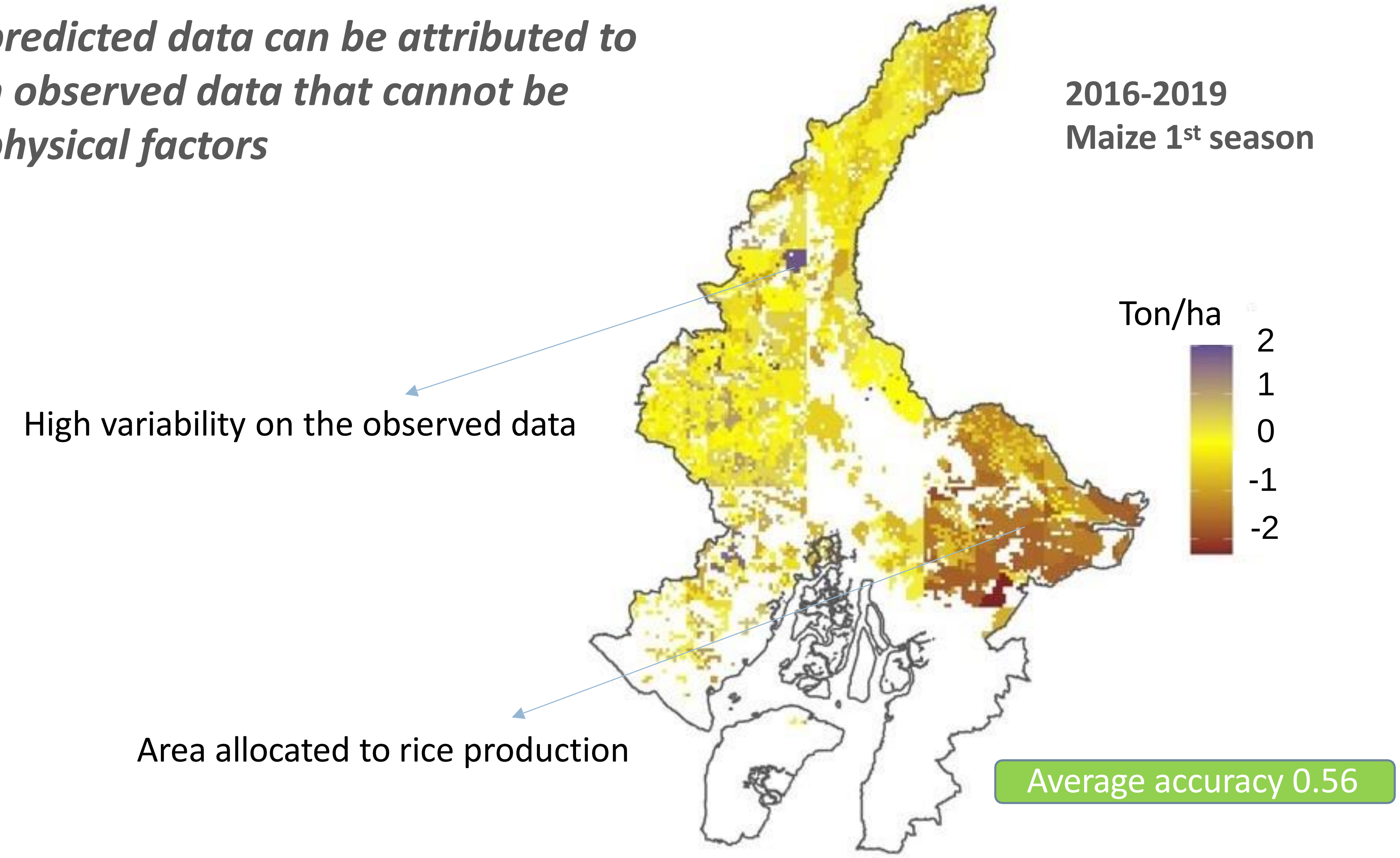
- Simulation of historical and forecasted yields
- Focused on the main food crops
  (i.e. maize, wheat, soy, rice)





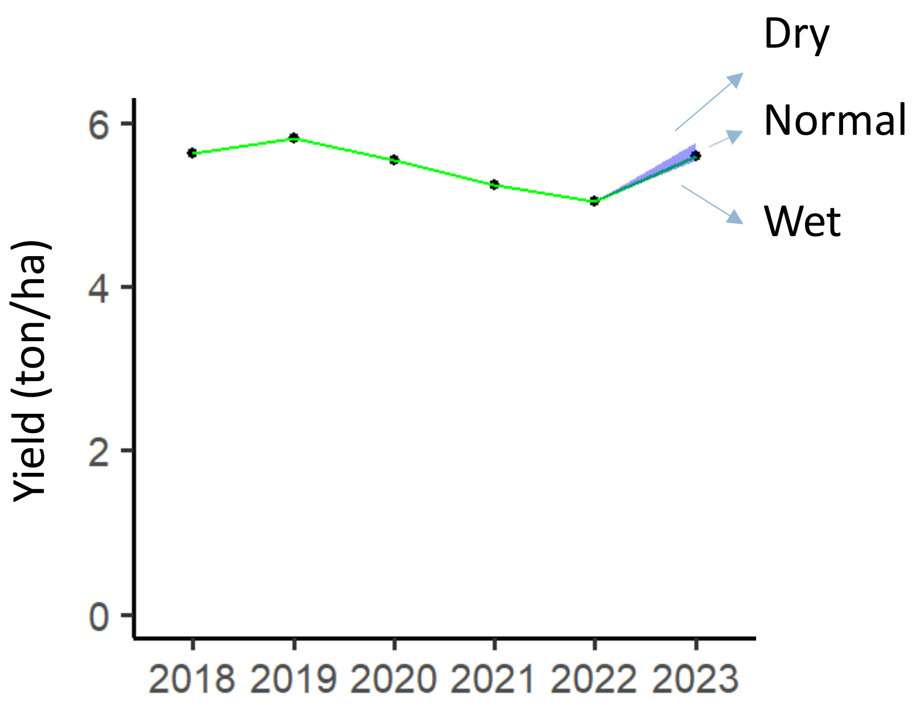
Calibration and uncertainties

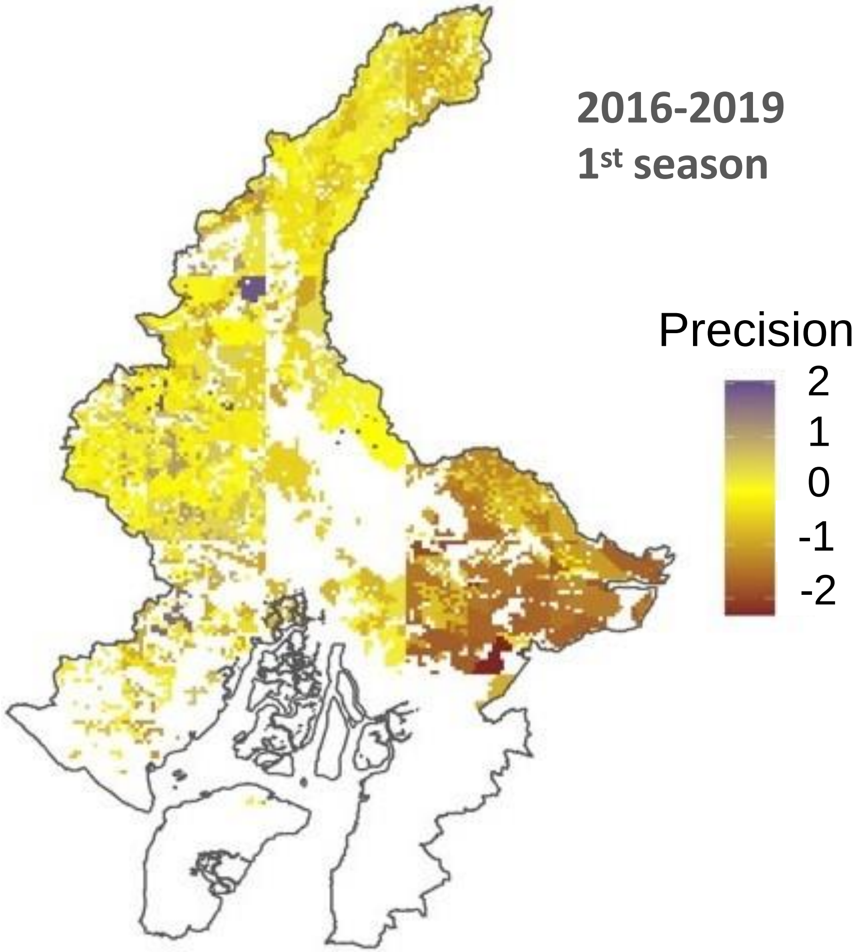
- ***Low accuracy in predicted data can be attributed to high variability in observed data that cannot be explained by biophysical factors***



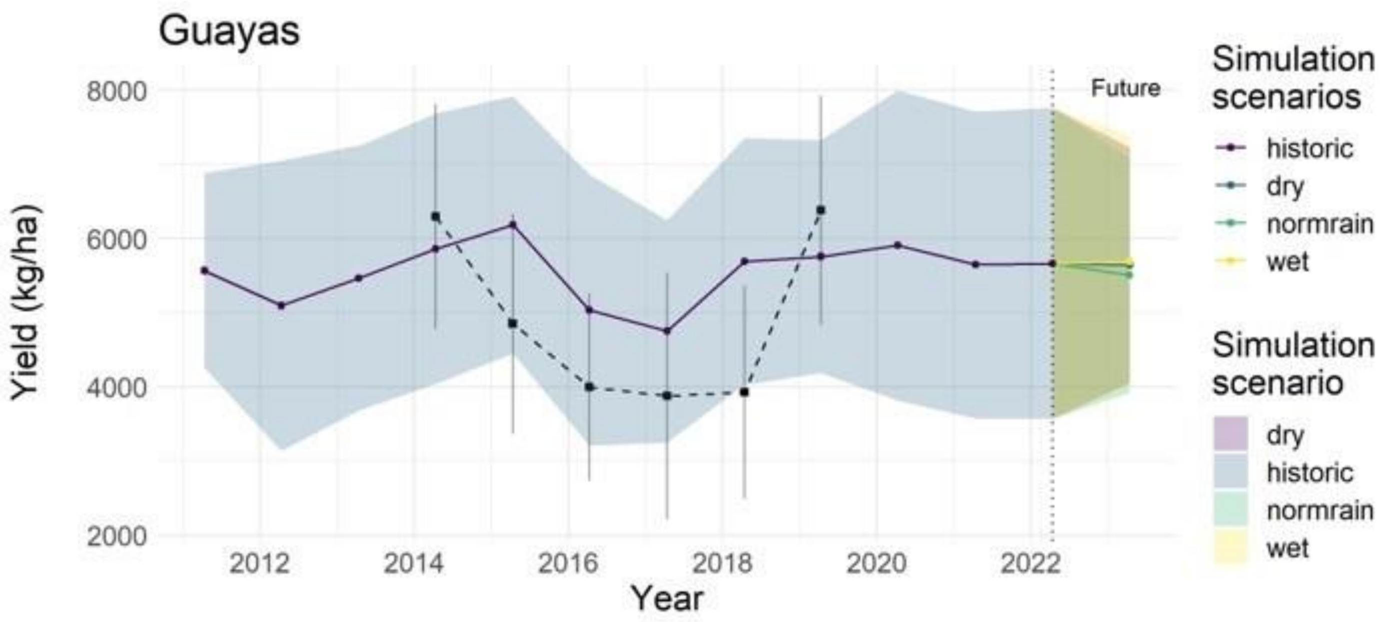
Calibration and uncertainties

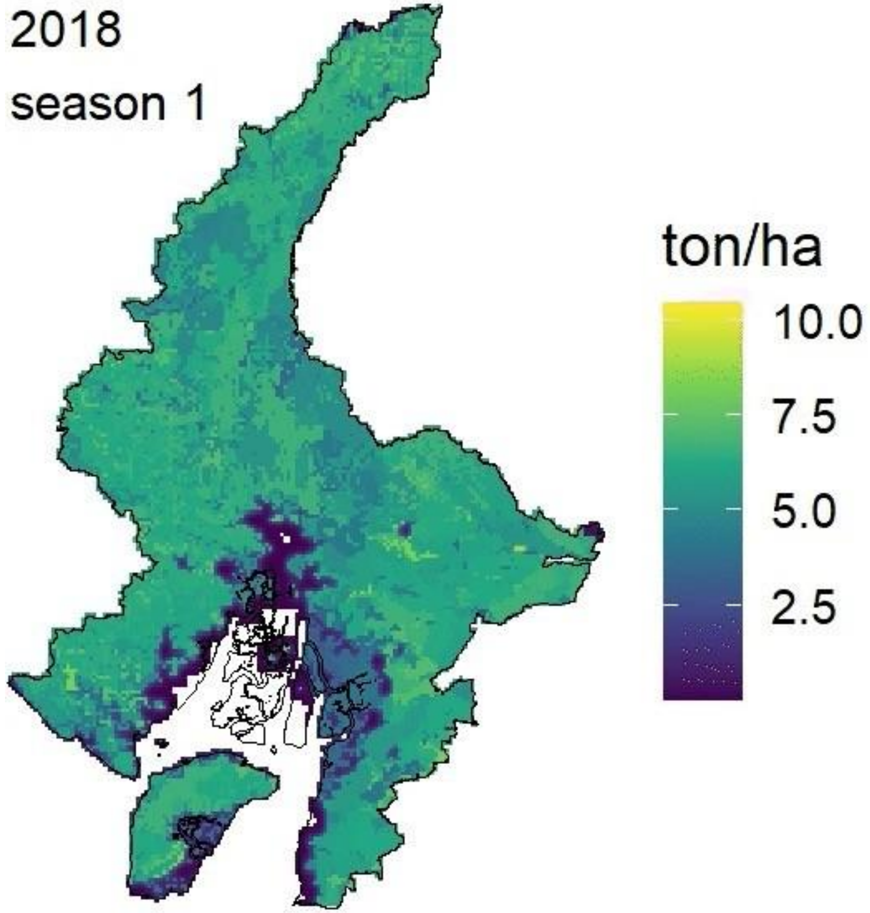
- **Future climate for wetter, drier and normal conditions**



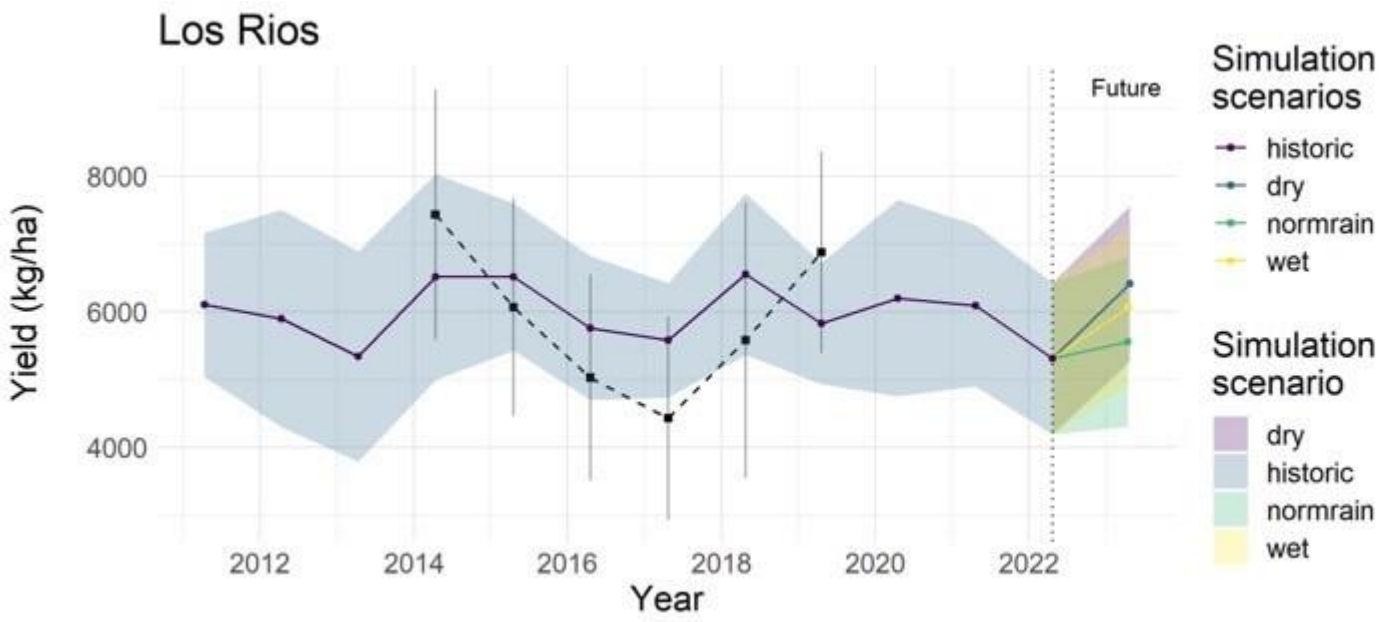


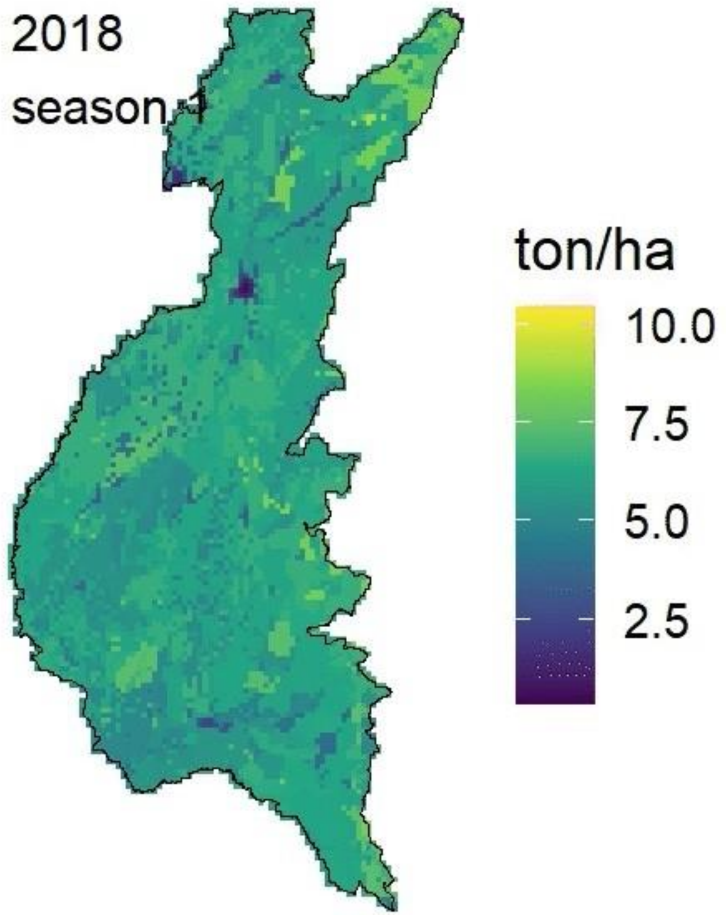
Crop yields: Maize Season 1





Crop yields: Maize season 2

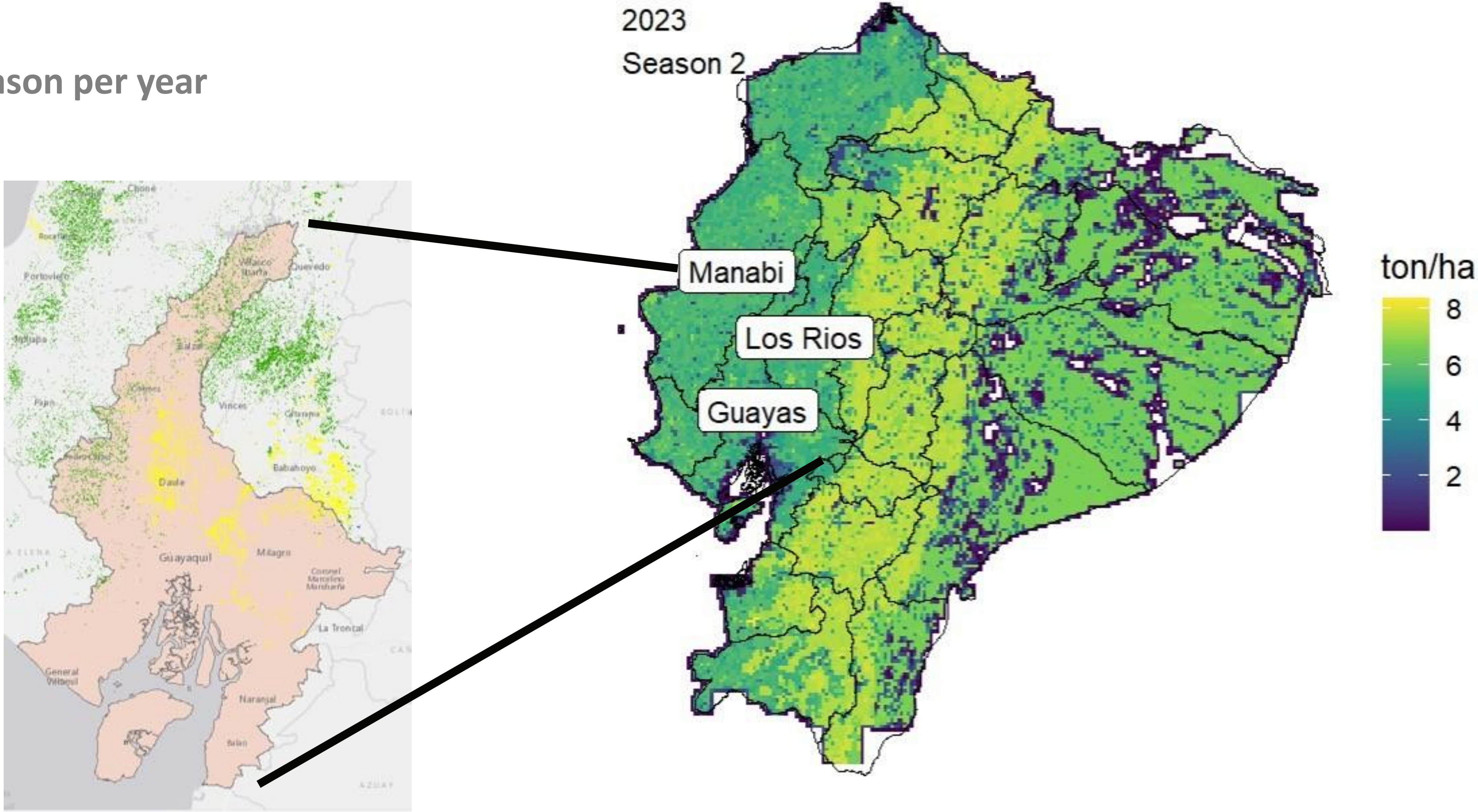




Crop yields: Rice

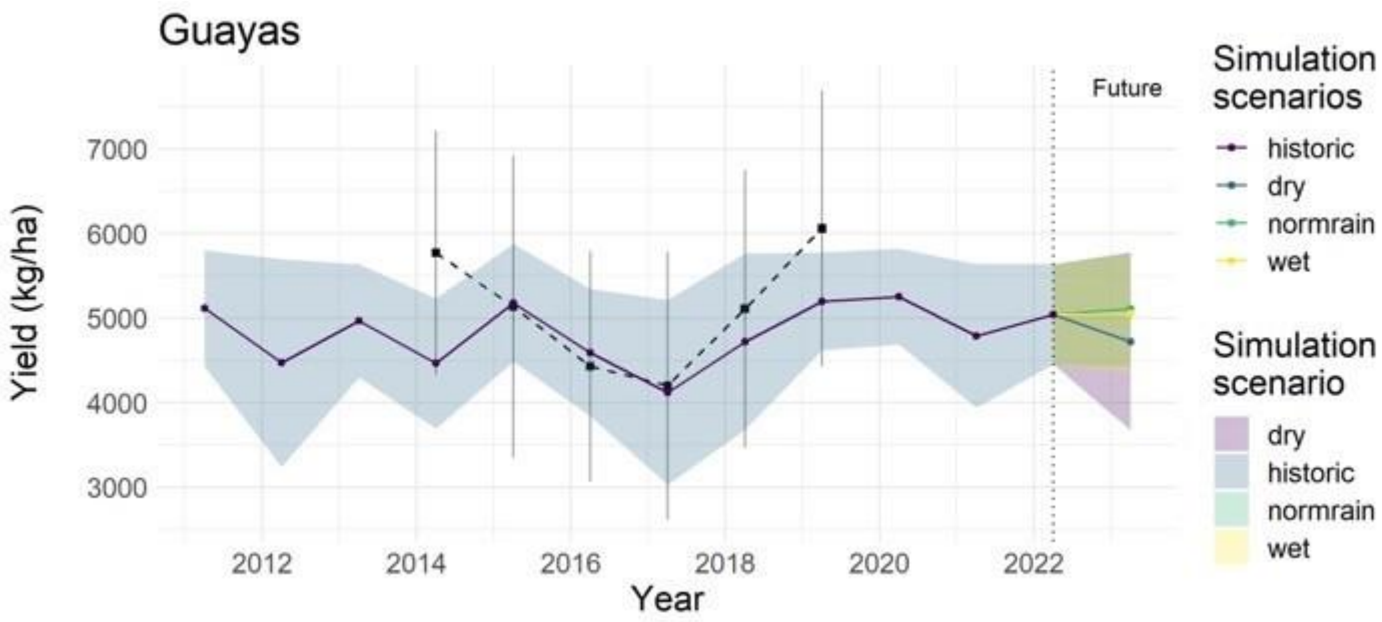
- Three season per year

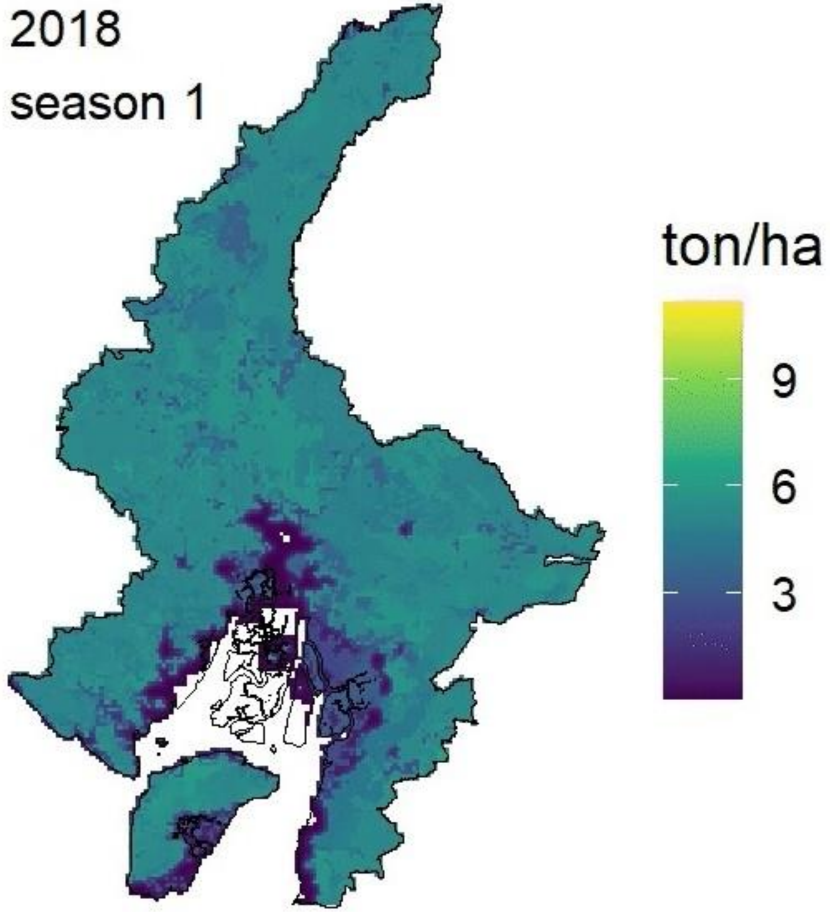
Areas on production



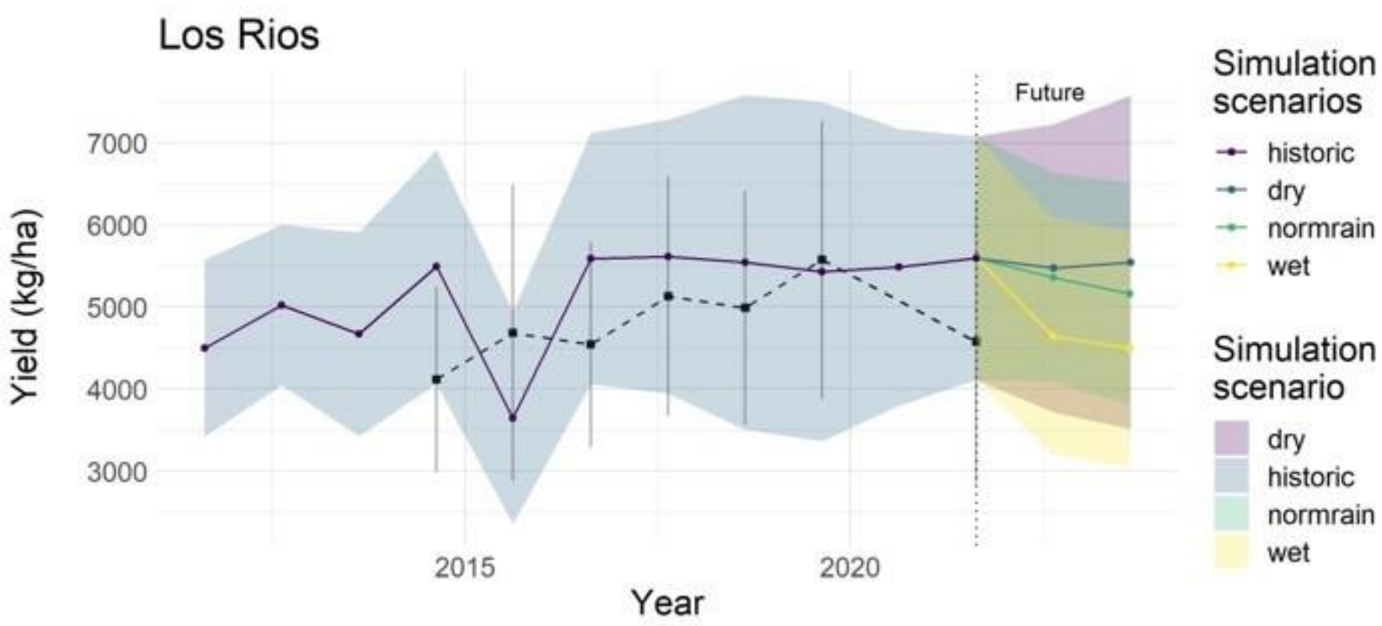
Maize
Rice

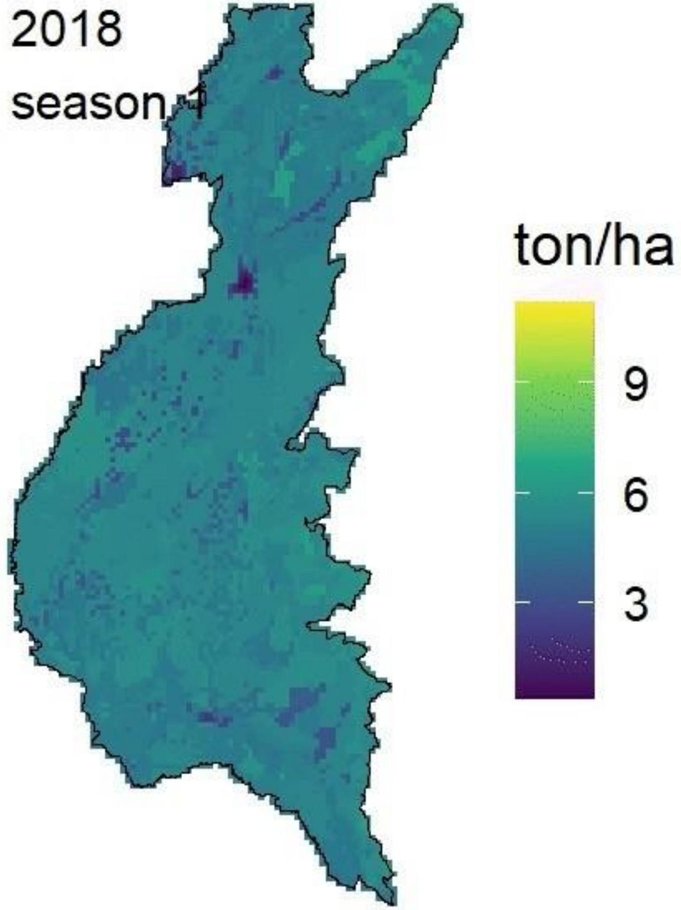
Crop yields: Rice season 1



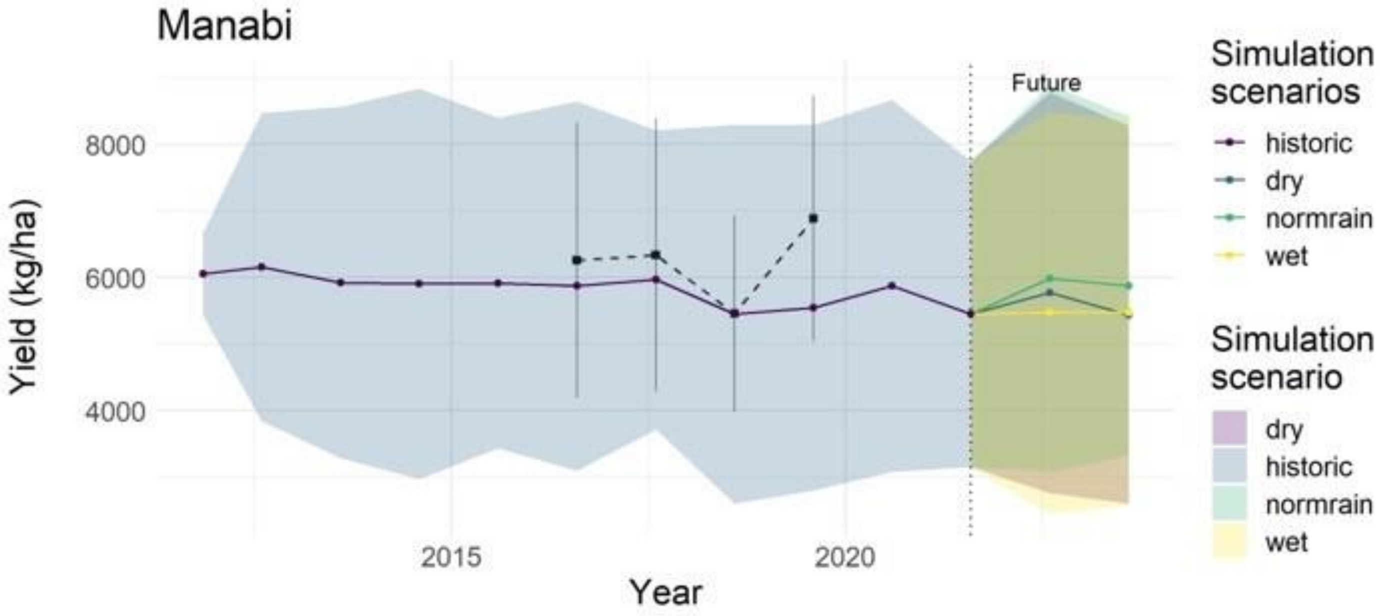


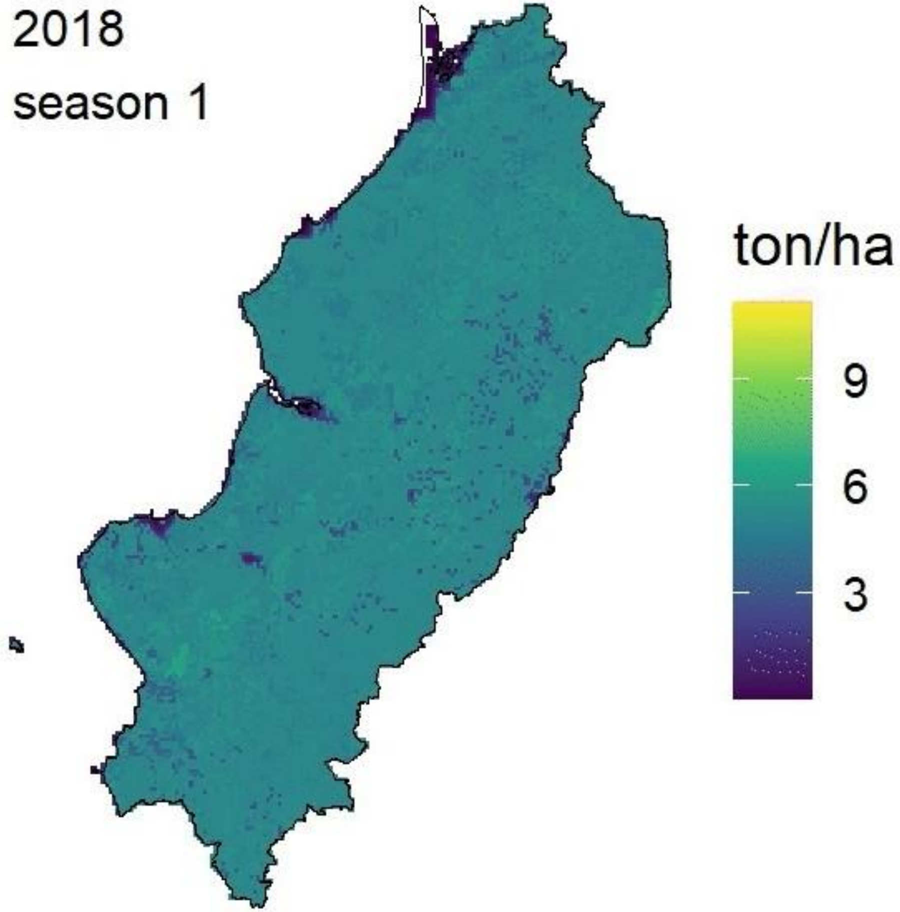
Crop yields: Rice season 2





Crop yields: Rice season 3





Rice 2021

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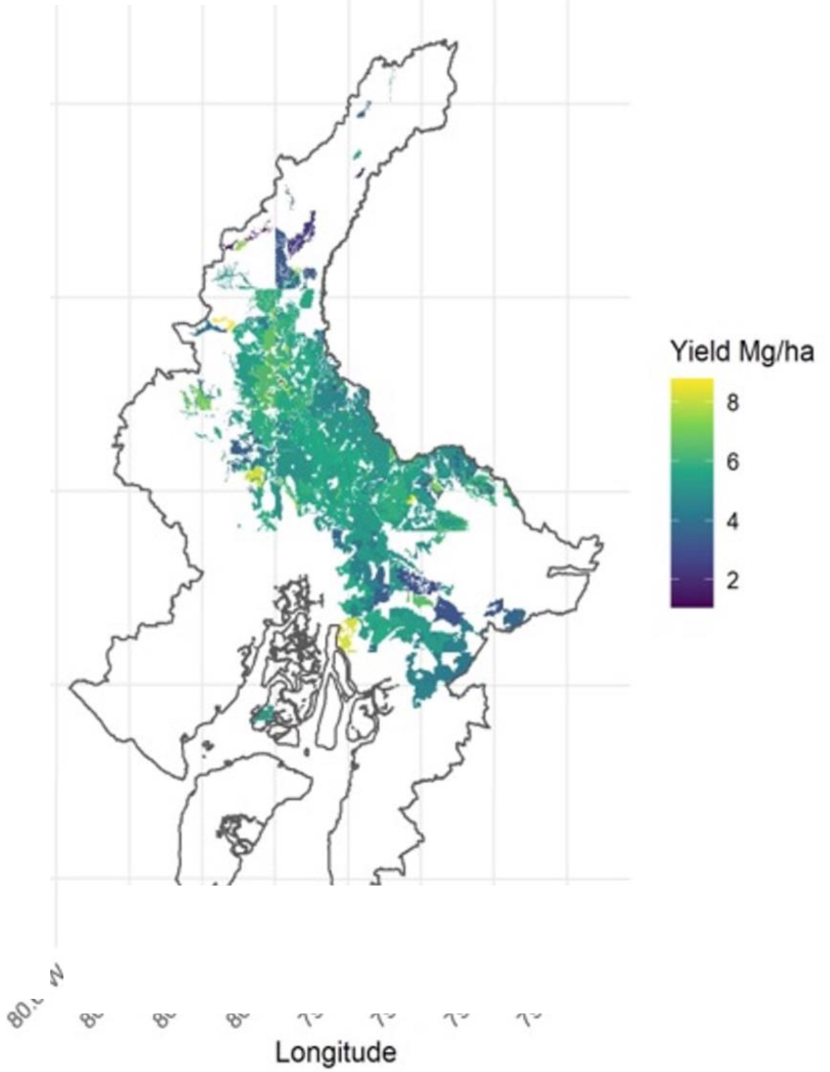
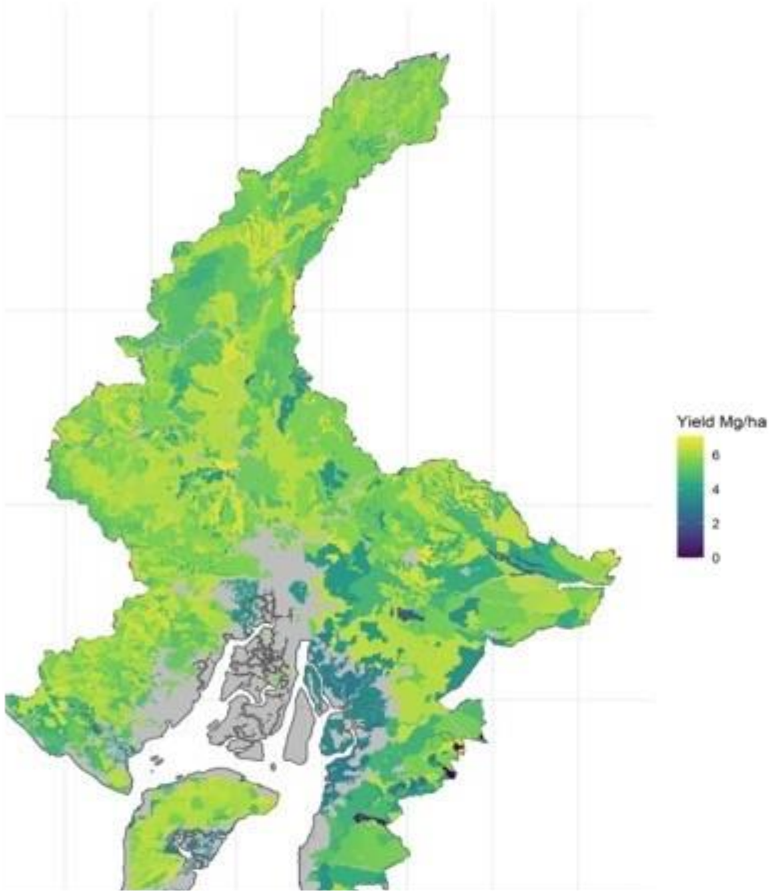
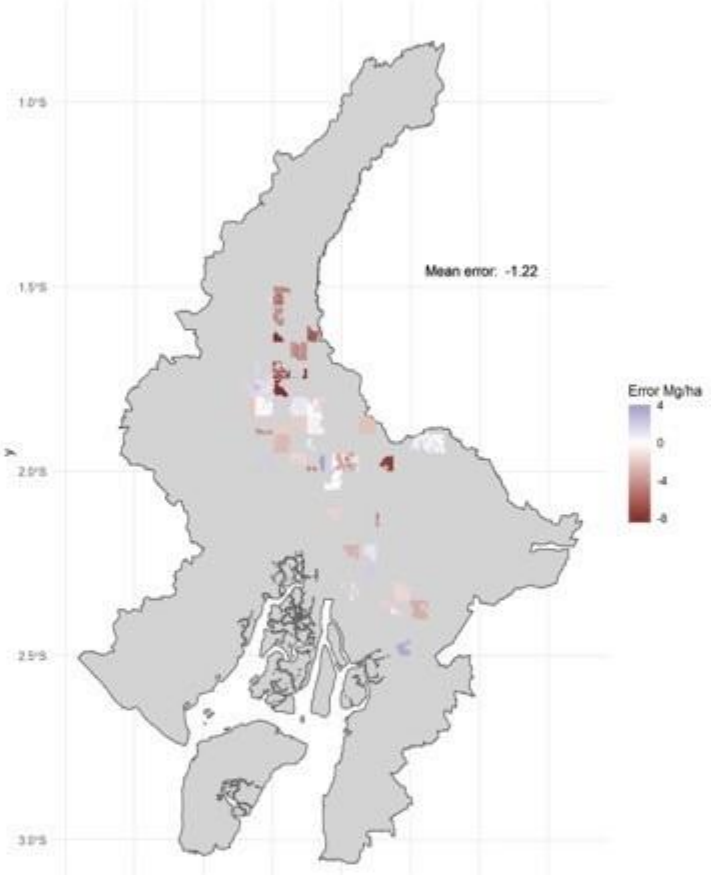
Obs: 2016-2020



Sim: 2021



Eval: 2021



Mean Error: -1.22

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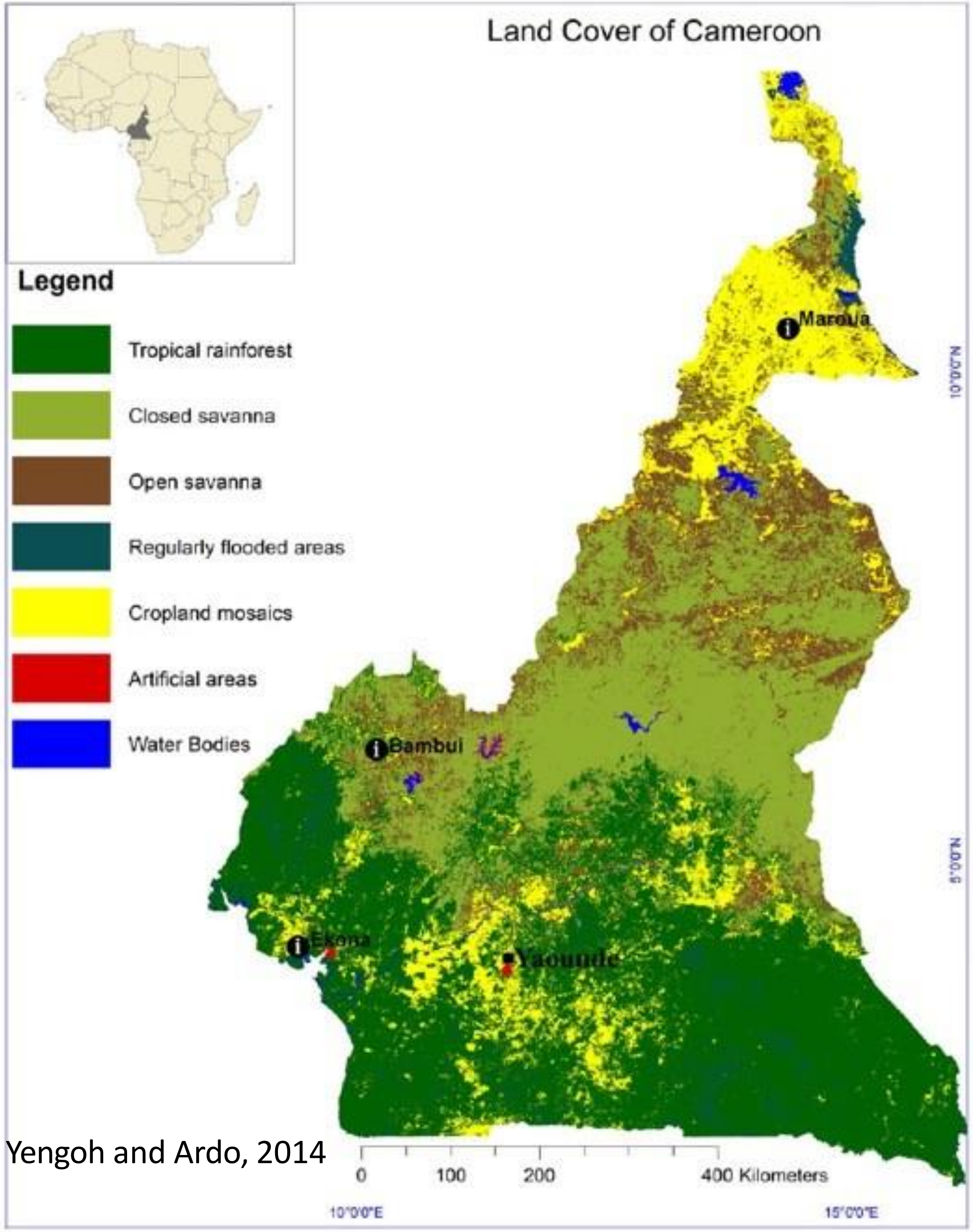
Cameroon:

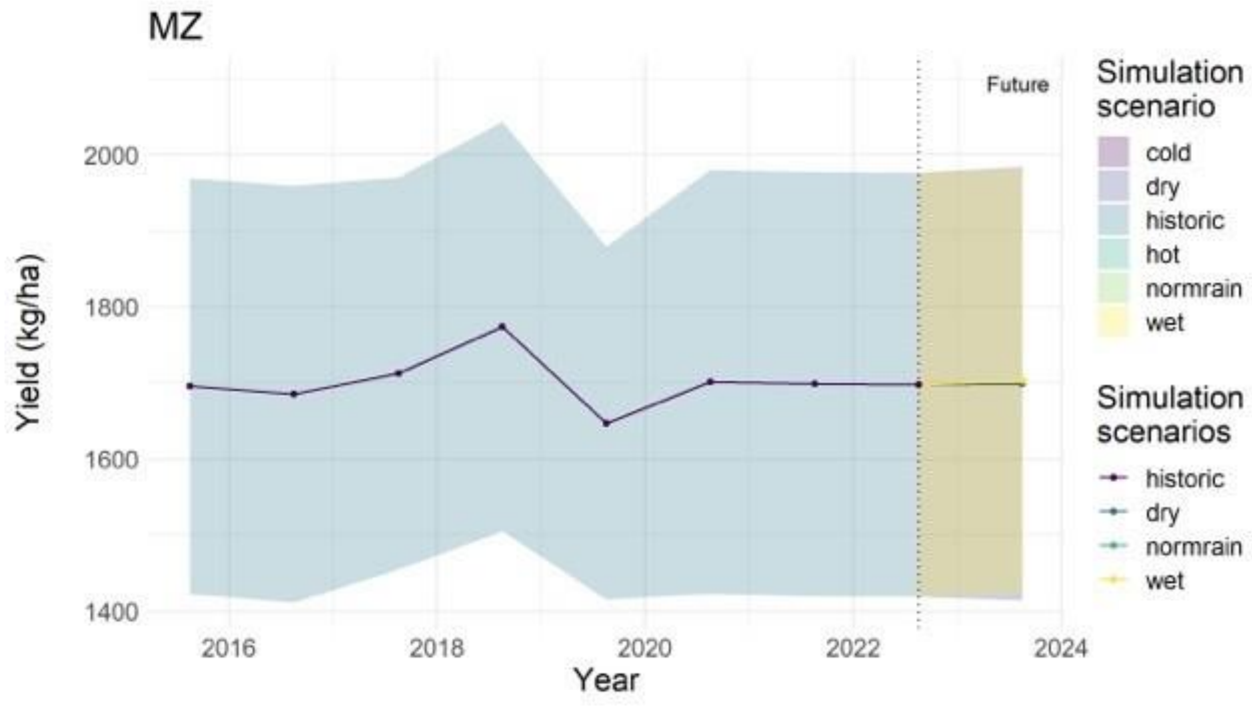
Model parameterization and calibration

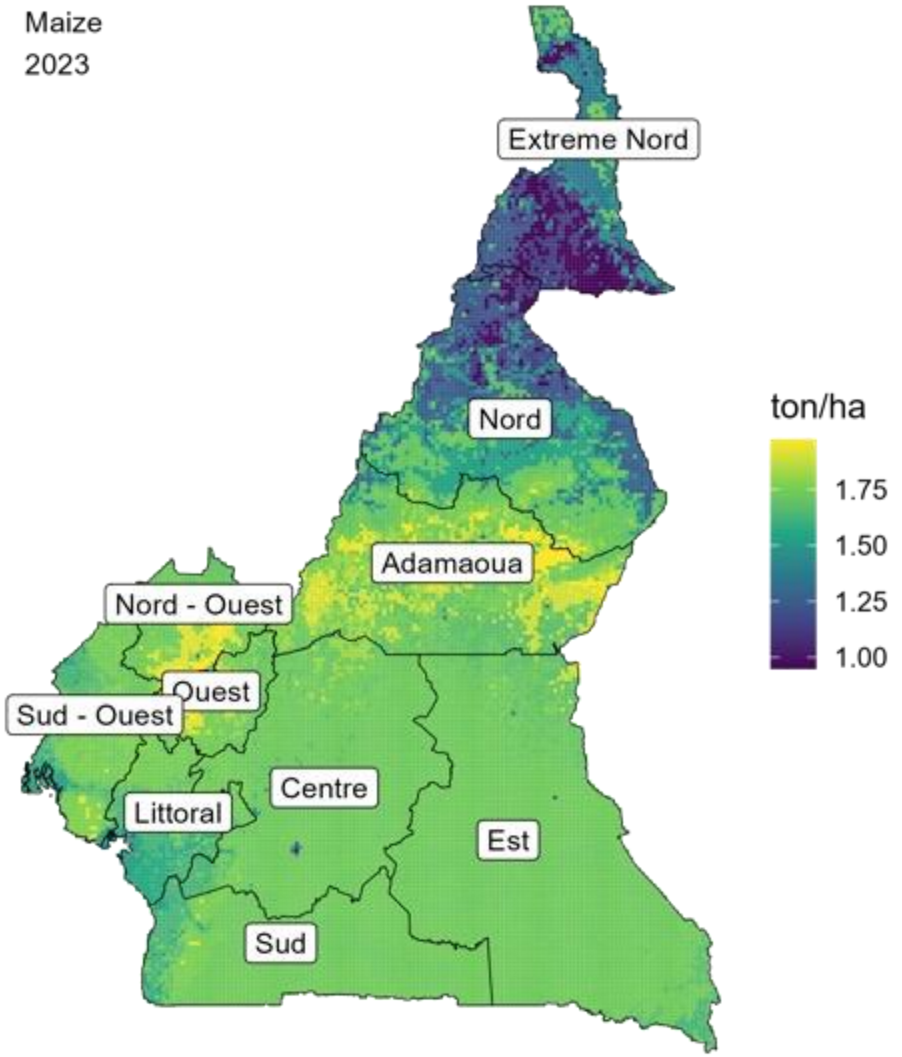
- Using only global soil and climate data
- FAO crop calendar and country wide yield data
- We simulated potential yields for all regions



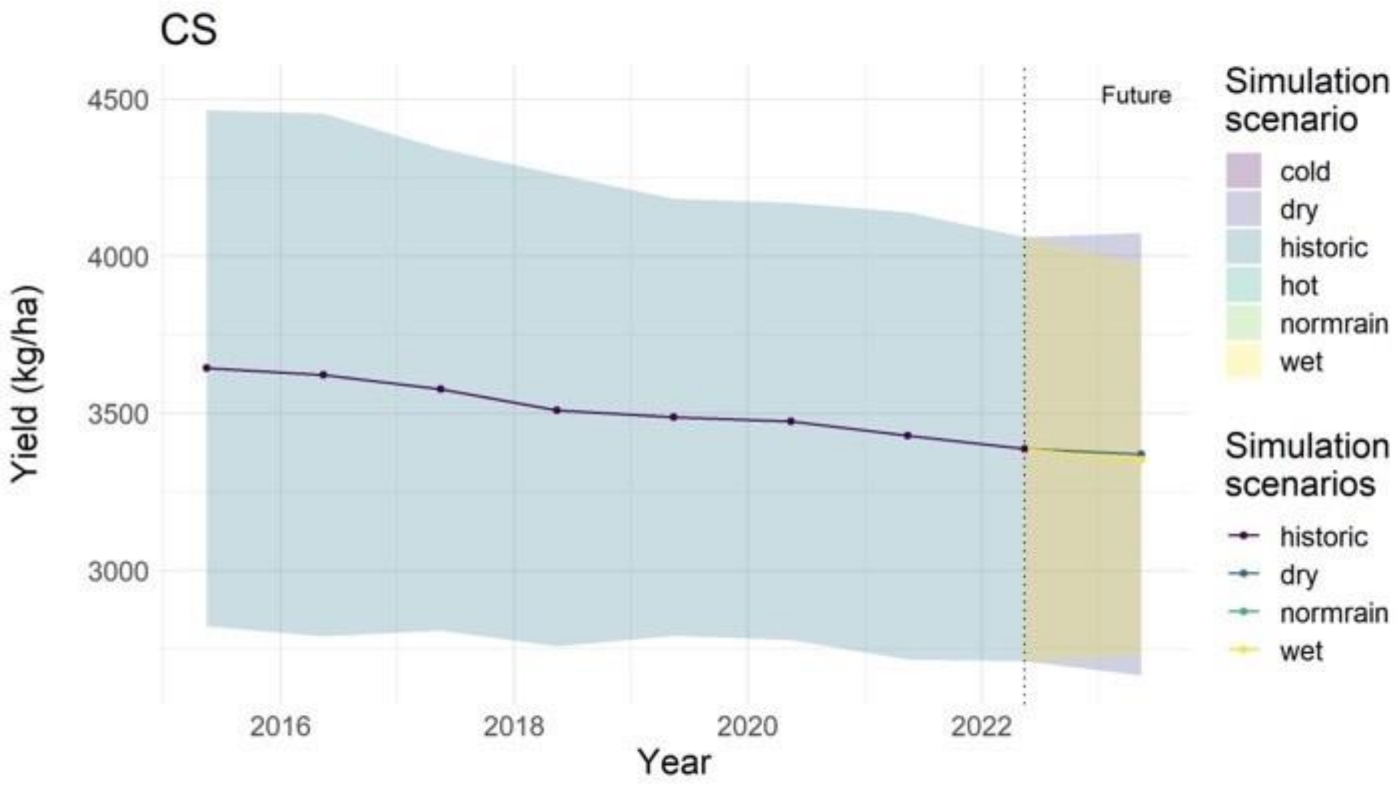
Yengoh and Ardo, 2014

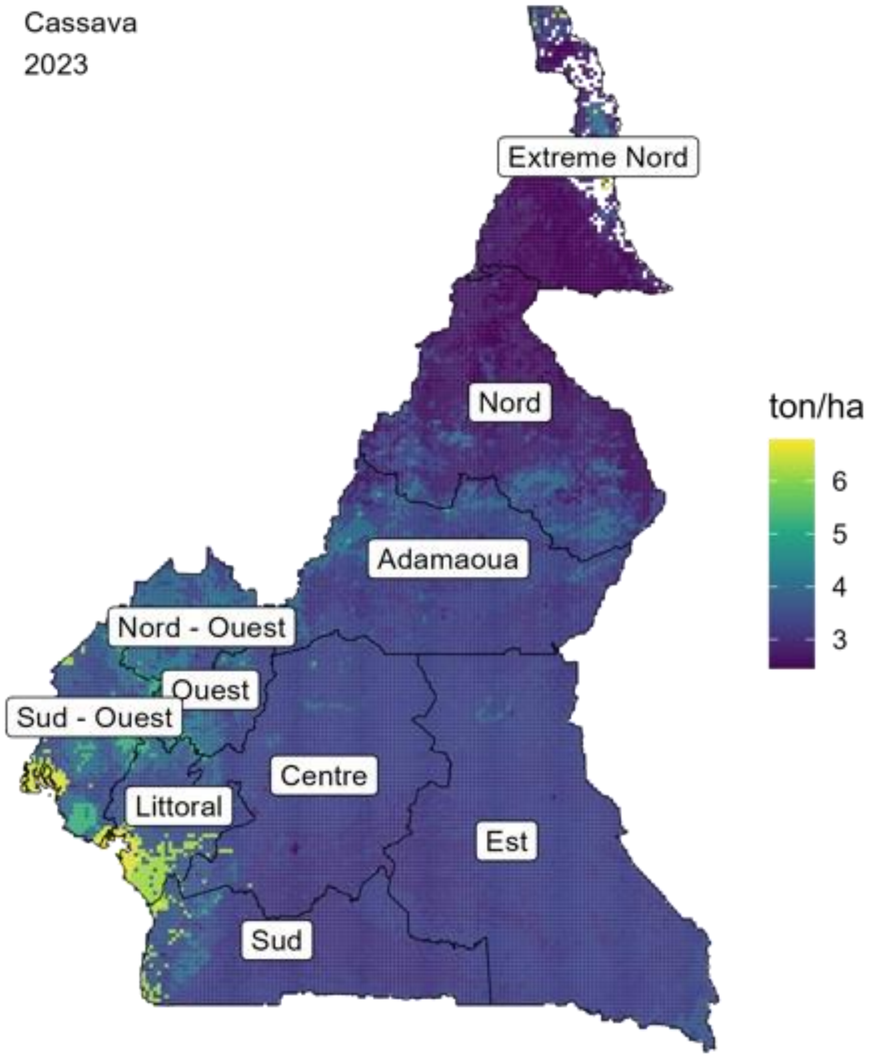
Crop yields: Maize



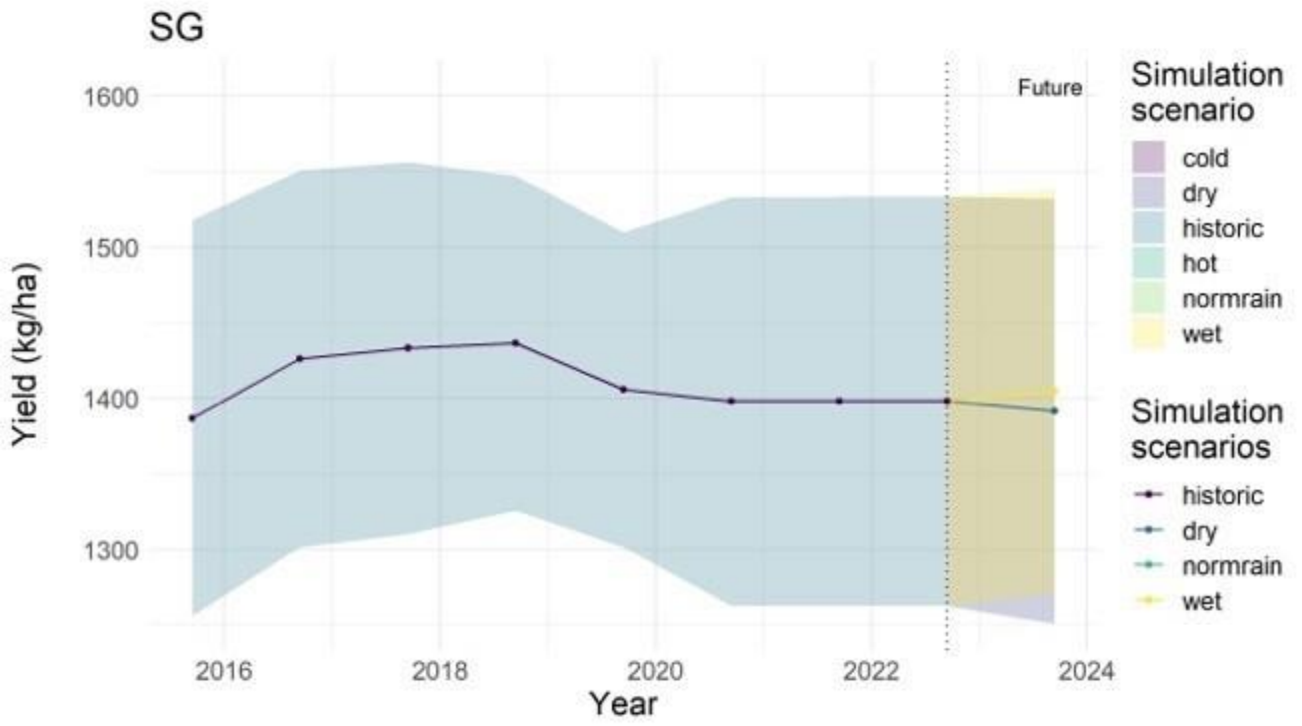


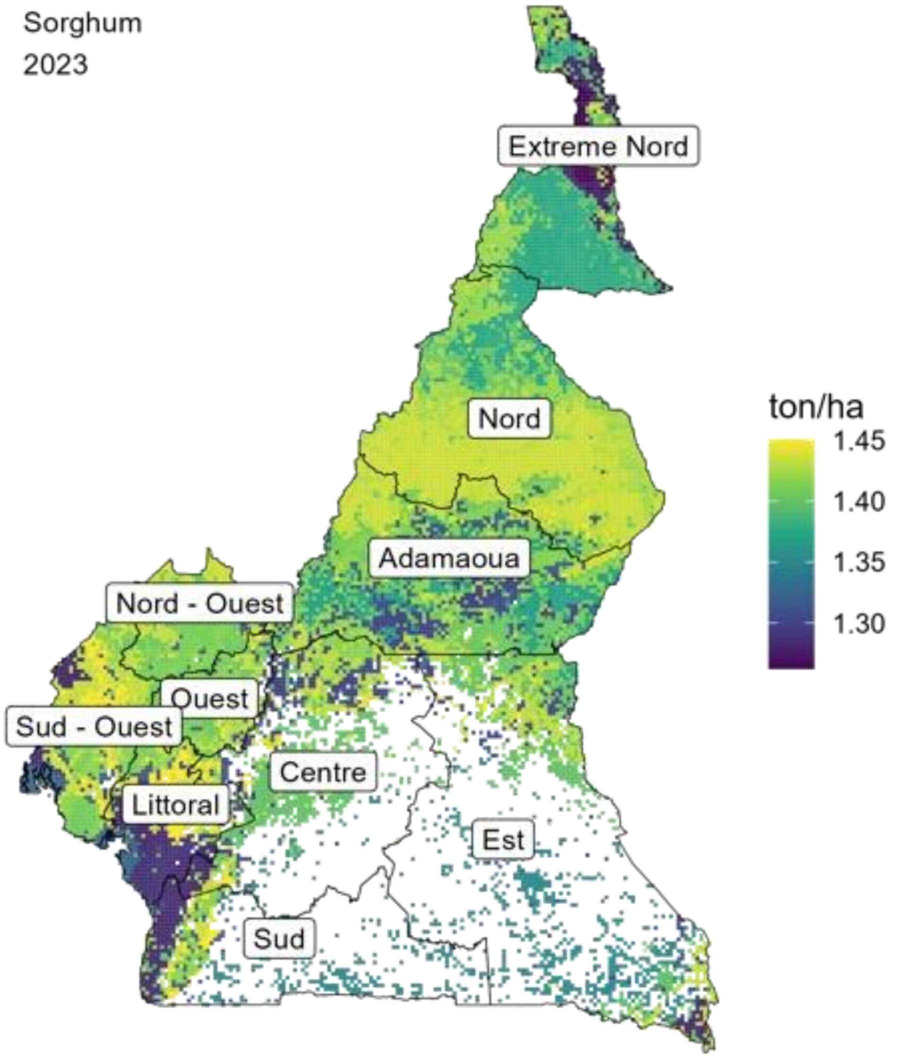
Crop yields: Cassava



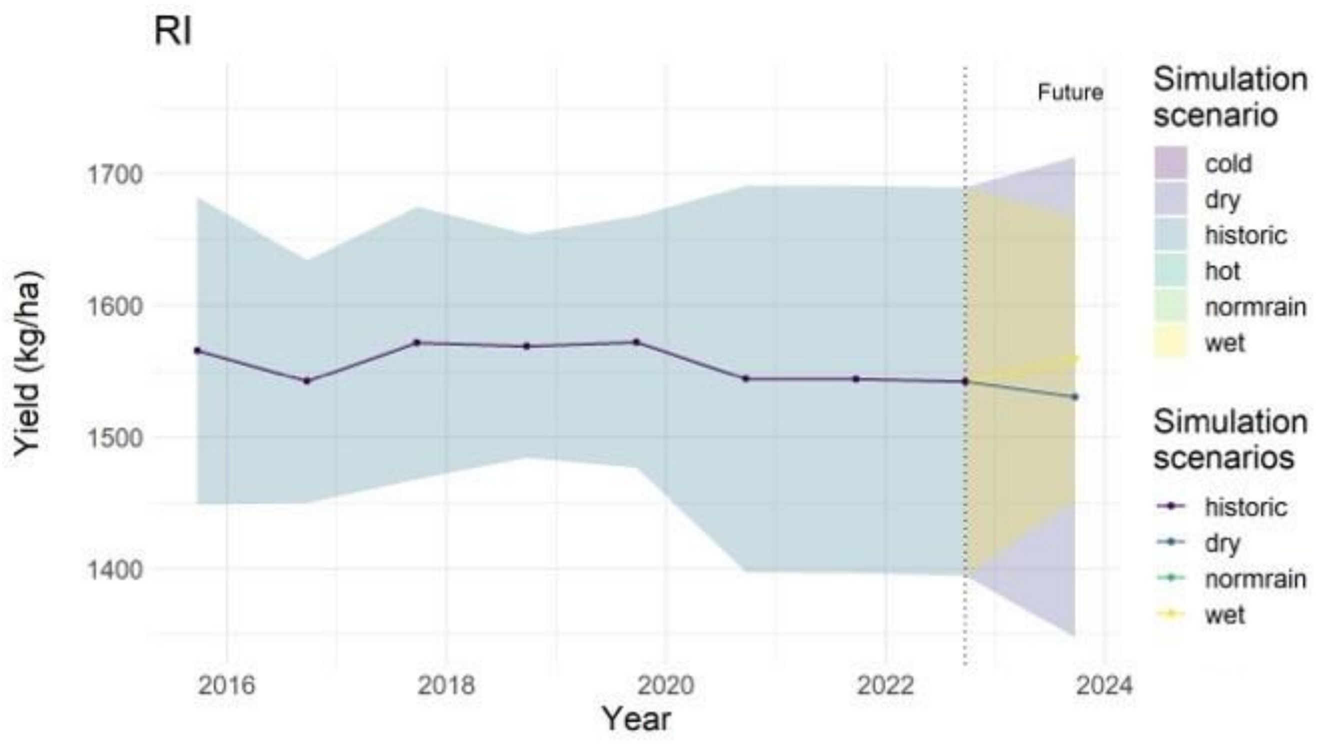


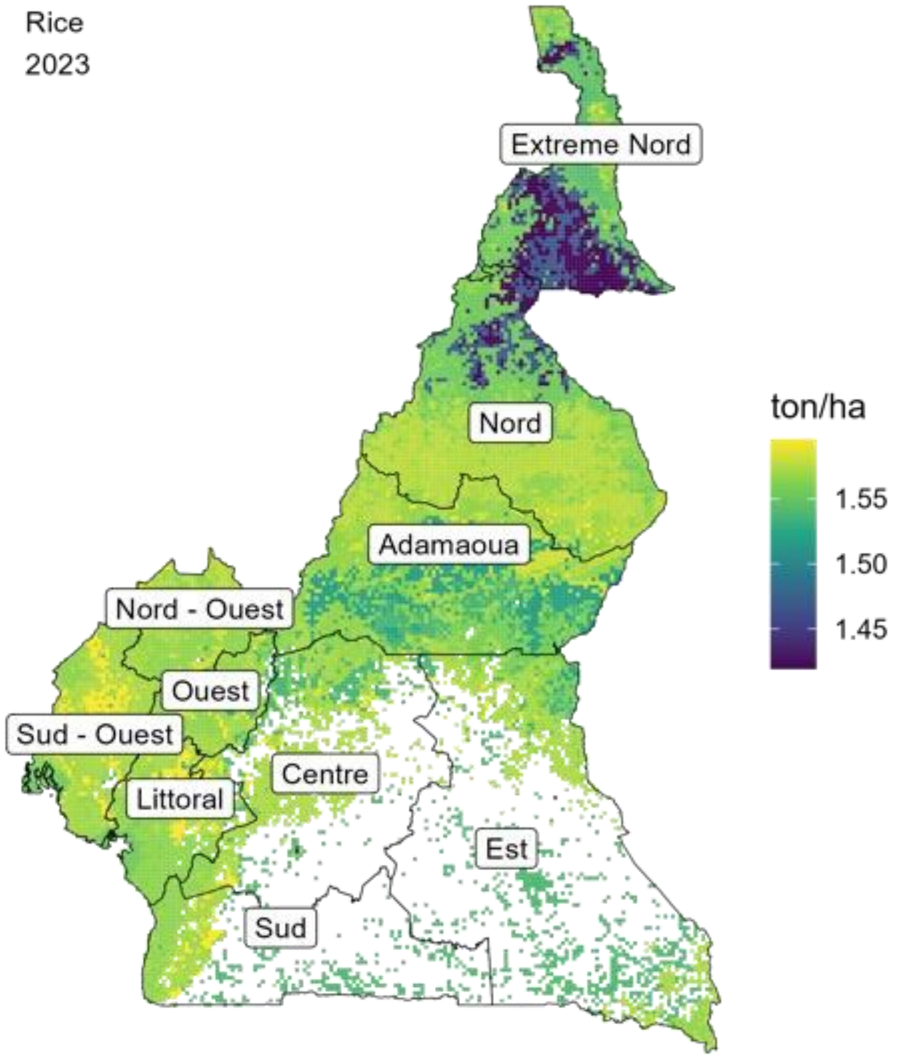
Crop yields: Sorghum



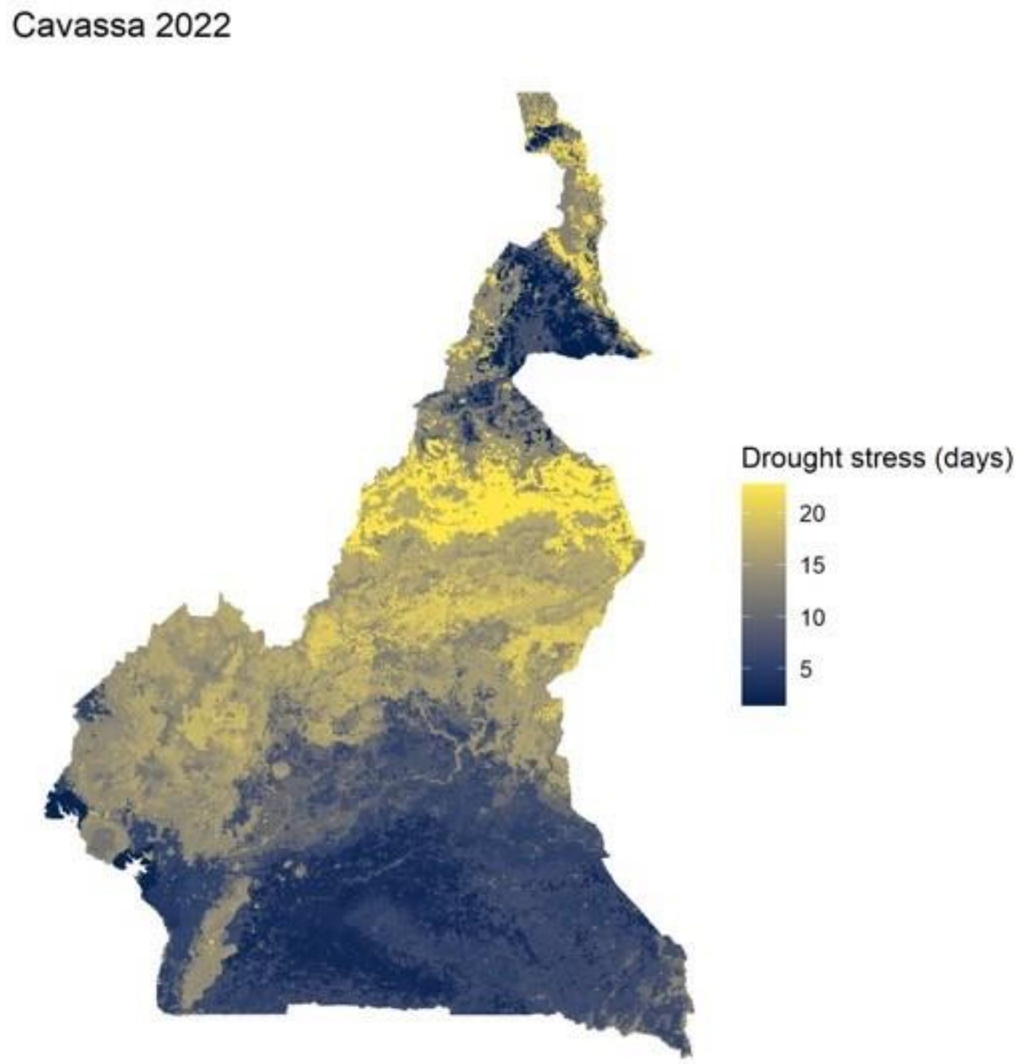


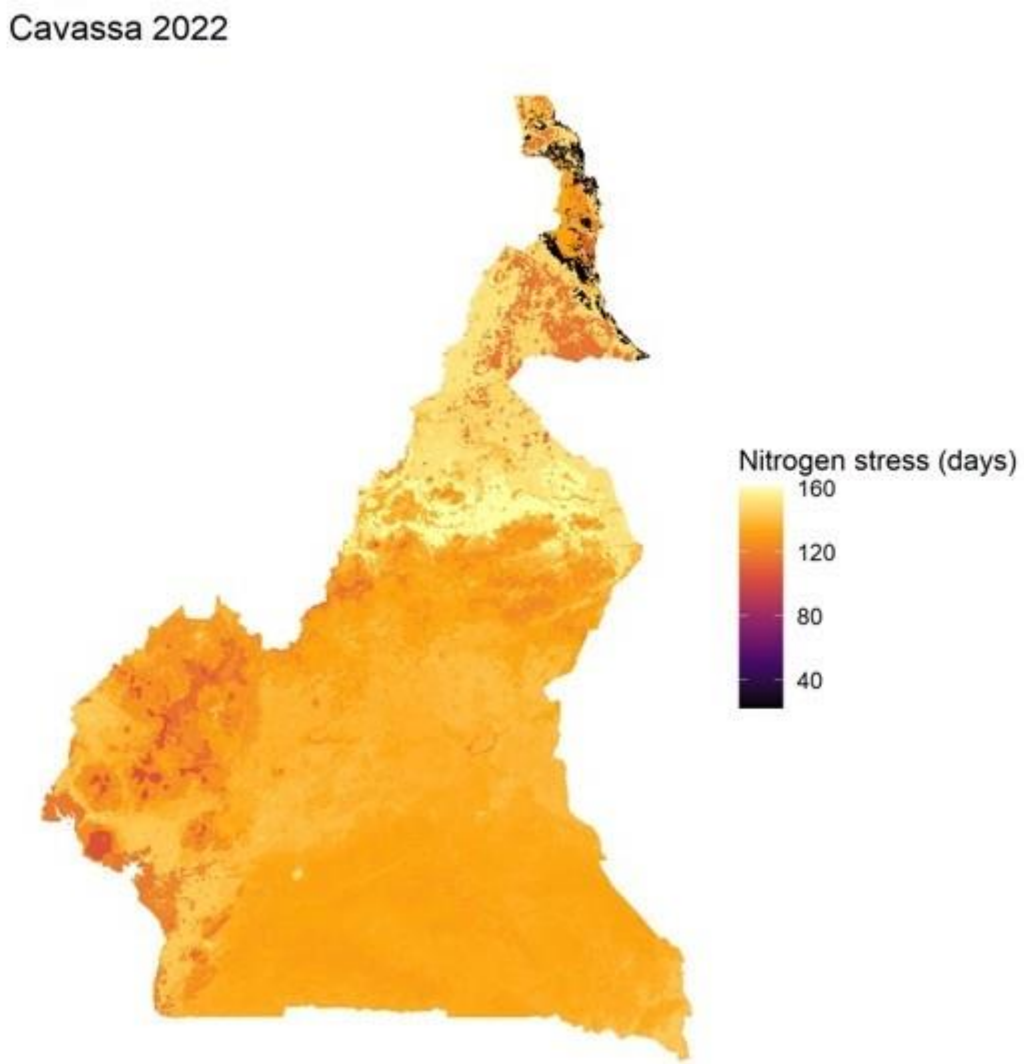
Crop yields: Rice





Using models to improve management: Simulated nitrogen and drought stress





Crop Yield Forecasting System in Tanzania

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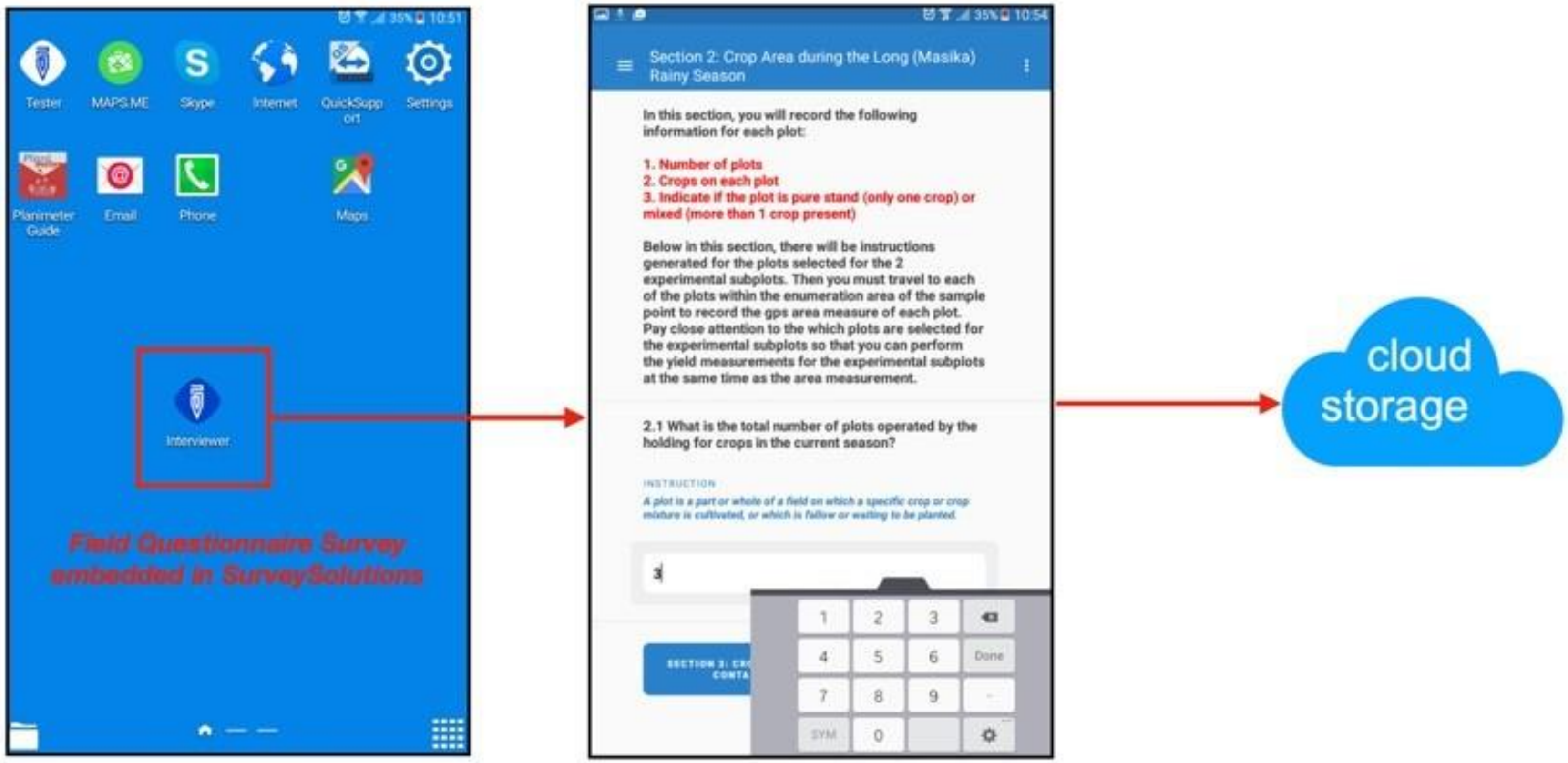
Food Security (2020) 12:537–548
https://doi.org/10.1007/s12571-020-01020-3

ORIGINAL PAPER

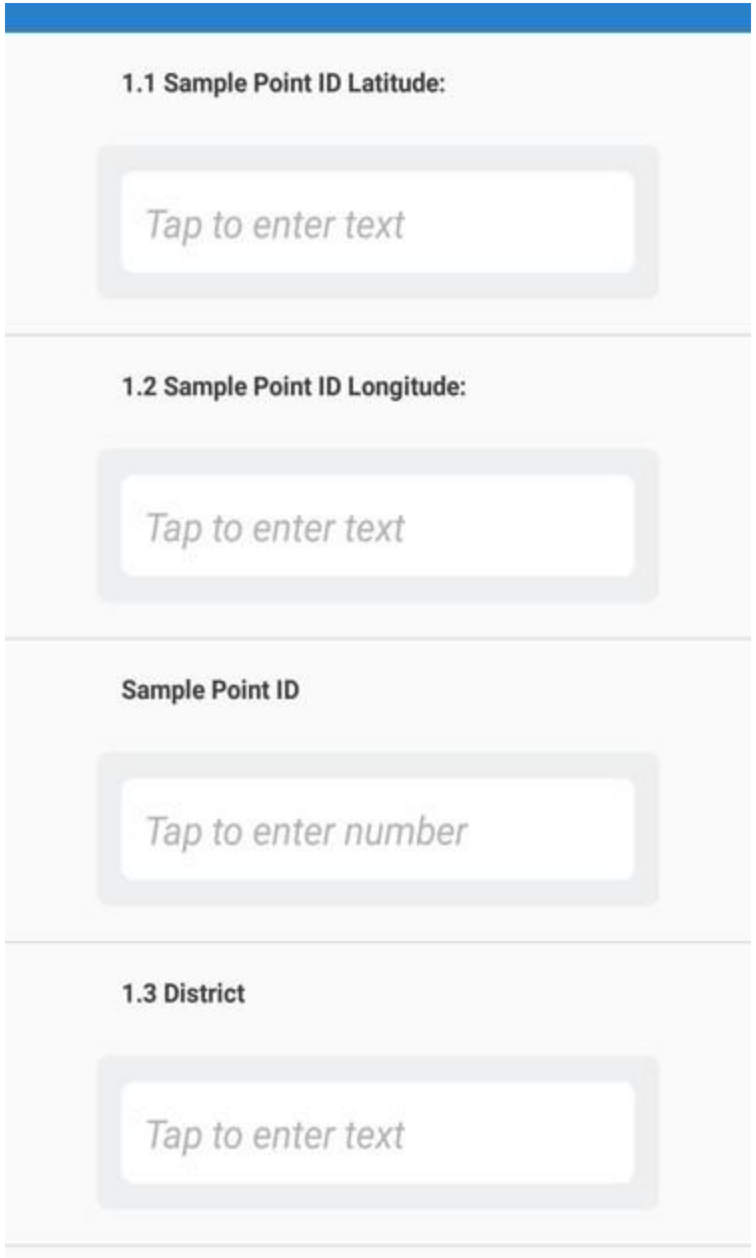
Linking field survey with crop modeling to forecast maize yield in smallholder farmers' fields in Tanzania

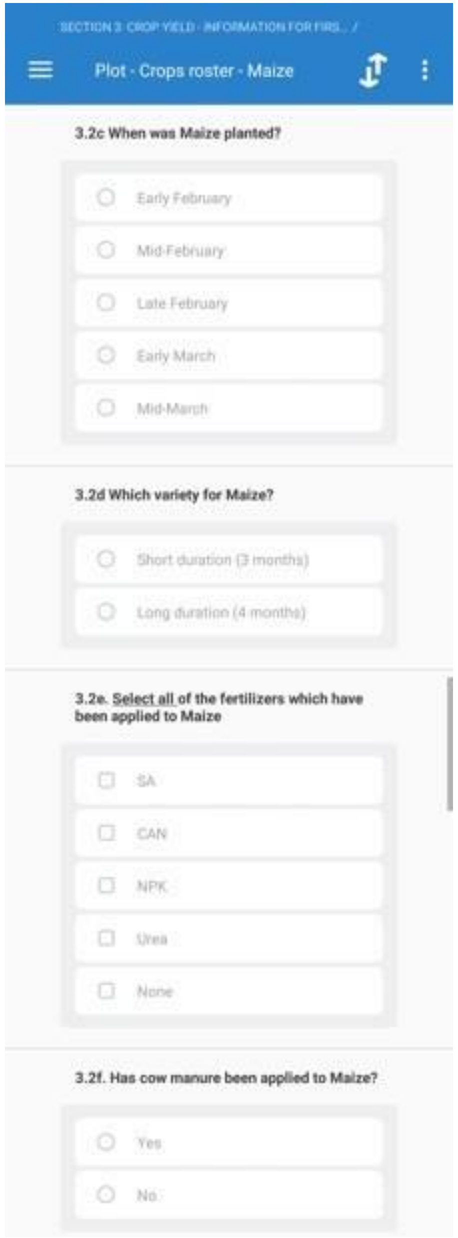
Lin Liu[1] · Bruno Basso[1,2]

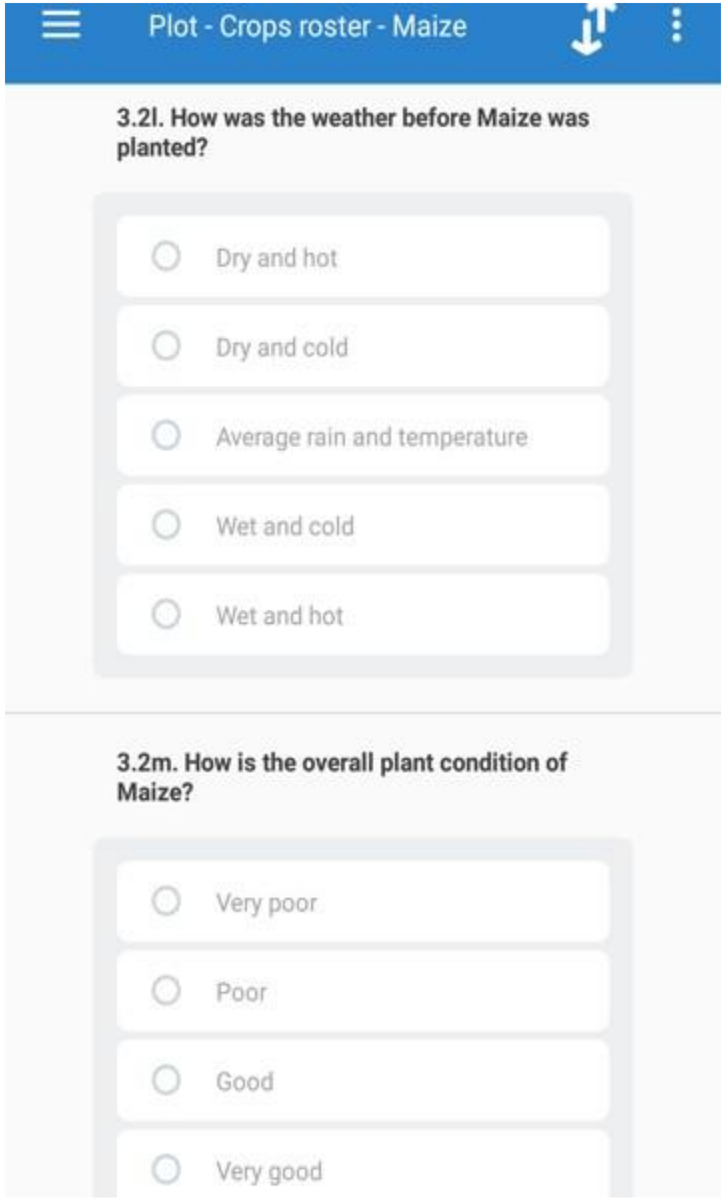
Received: 1 May 2019 / Accepted: 20 February 2020 / Published online: 5 March 2020



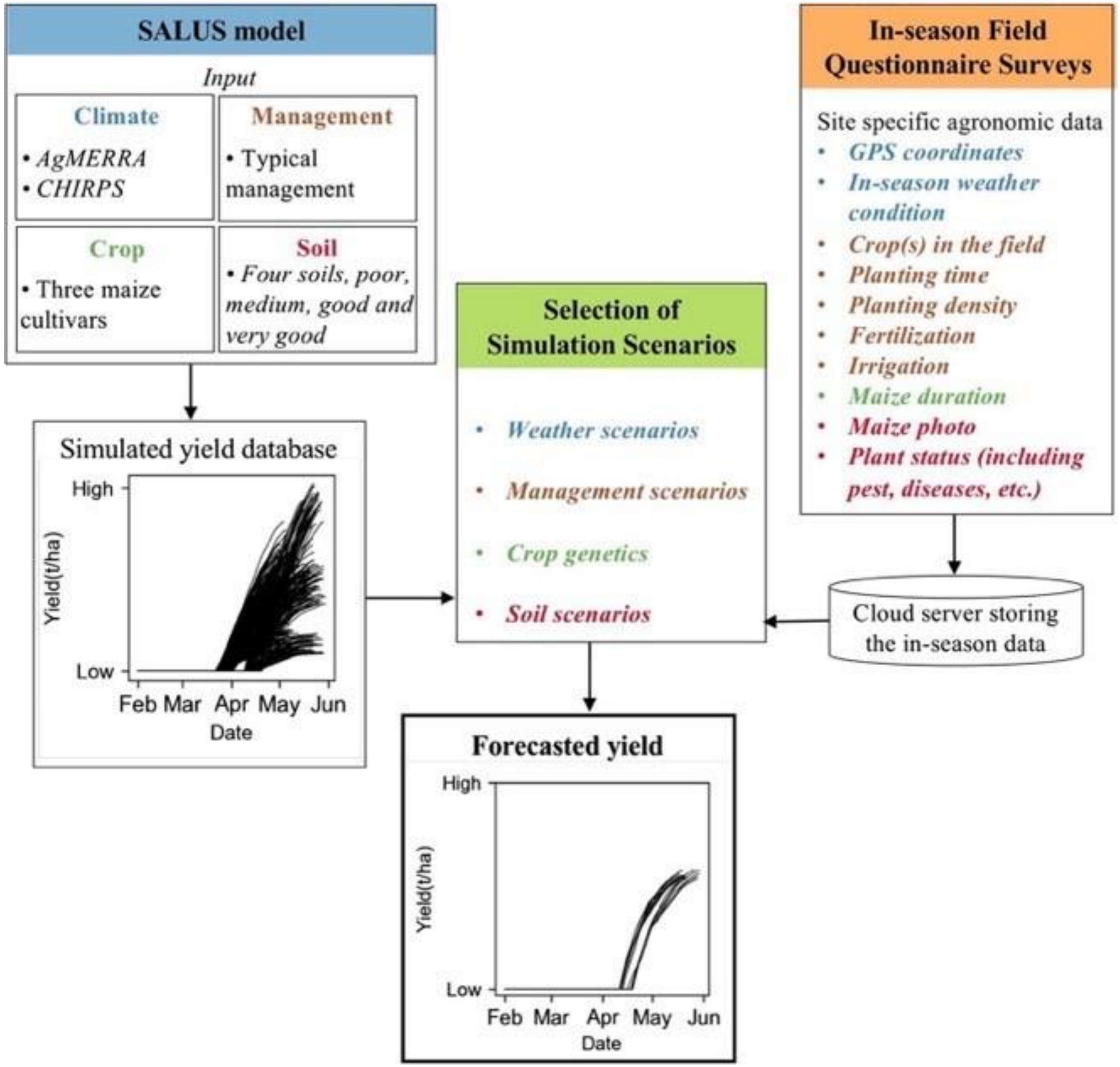
Example of field survey

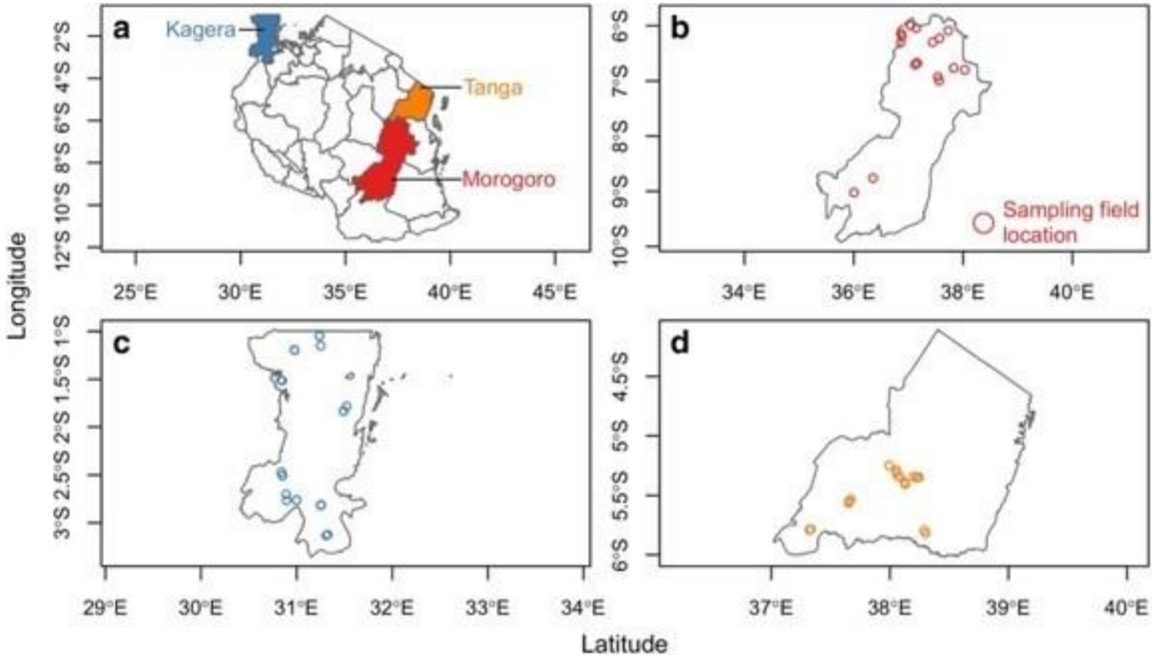






Crop Yield Forecasting System





Field Survey

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Field questionnaire survey

Field sampling

Forecasting date (1st visit)

- Randomly established 1 or 2 sampling subplots per field
- Coordinate, plant density, plant status & maize photo

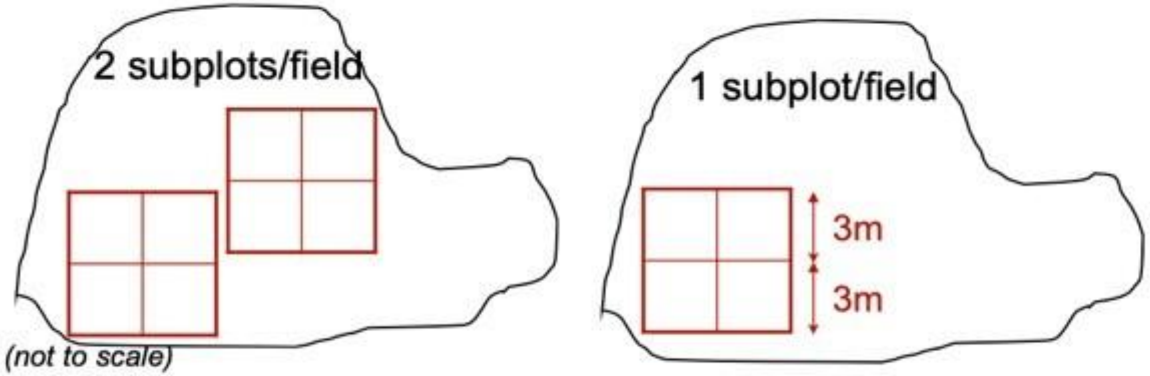
Validation of the methodology (2nd visit)

- Final yield information

Interviews with farm owner/manager *(1 visit)*

- Within-season agronomic information
- Within-season climatic information

Illustration of quadrant experiment design for field sampling



In-season Field Questionnaire Surveys

Site specific agronomic data

- *GPS coordinates*
- *In-season weather condition*
- *Crop(s) in the field*
- *Planting time*
- *Planting density*
- *Fertilization*
- *Irrigation*
- *Maize duration*
- *Plant status & maize photo*
- *Insects, diseases, weeds*

Liu and Basso, 2020 Food Security

Results from field survey

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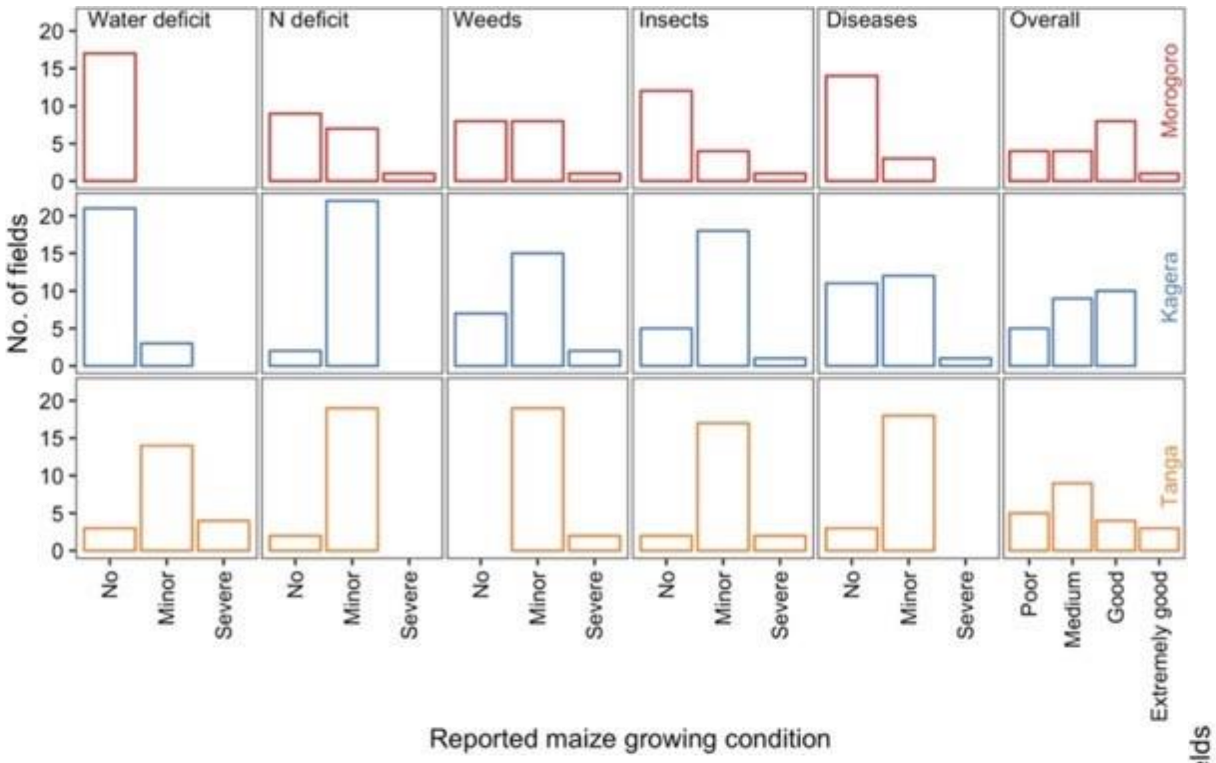
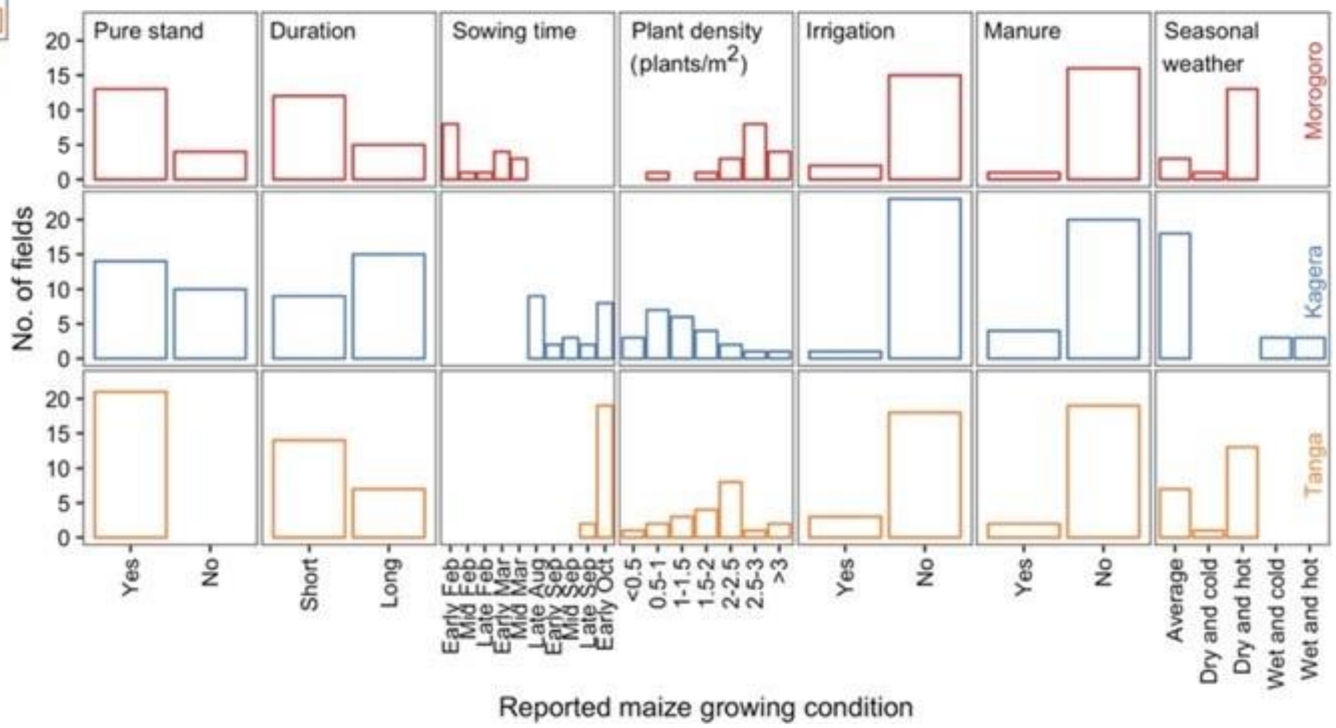
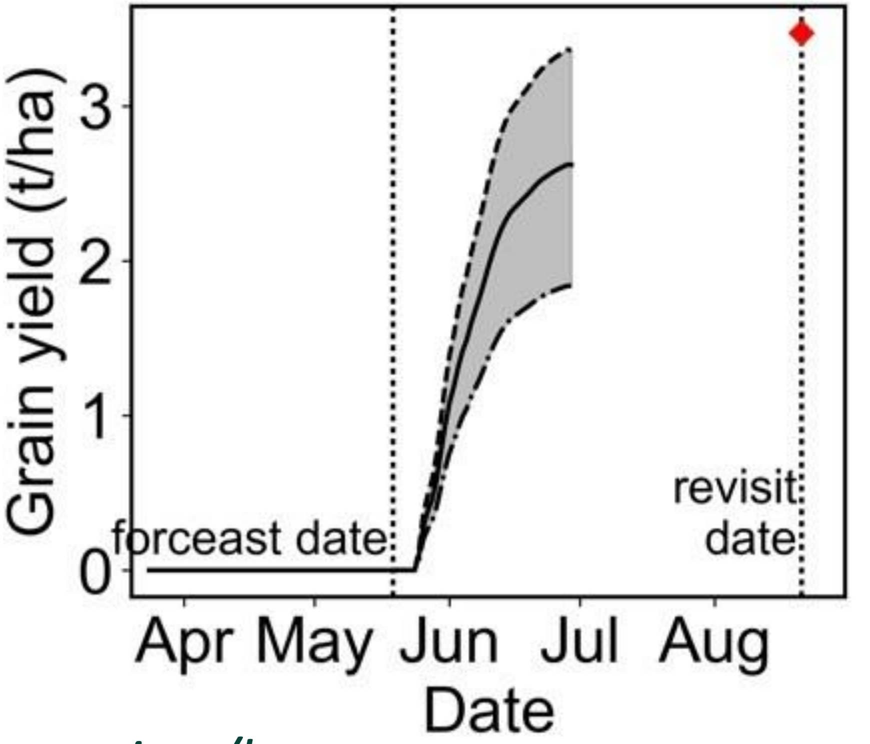


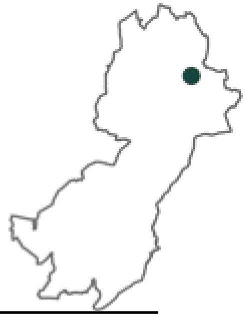


Liu and Basso, 2020 Food Security

In-season crop yield forecast

Sampling location ID: 182





unit: t/ha

Forecasted yield	**Reported yield**
1.84- 3.36 (avg: 2.62)	3.45

In-season crop yield forecast

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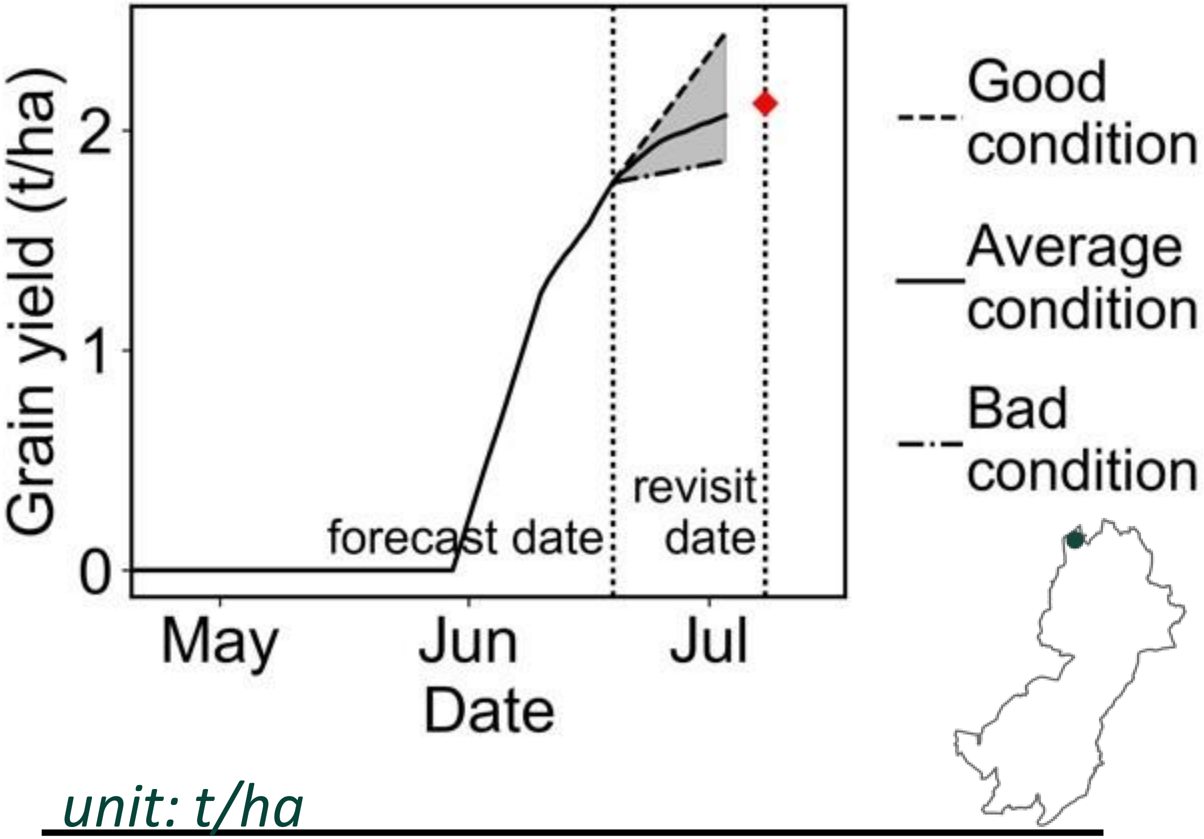
Sampling location ID: 282

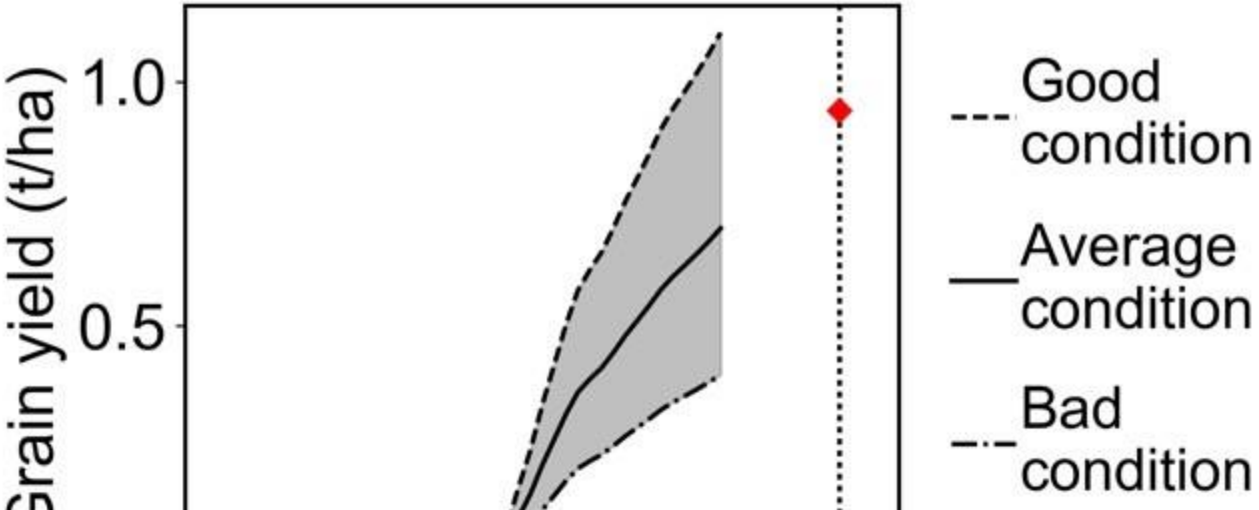


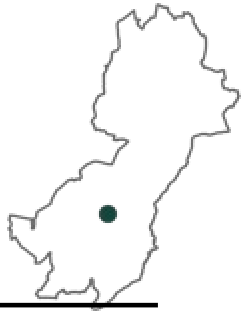
unit: t/ha

Forecasted yield	Reported yield
1.86 – 2.44 (avg: 2.09)	2.12

In-season crop yield forecast

Sampling location ID: 203



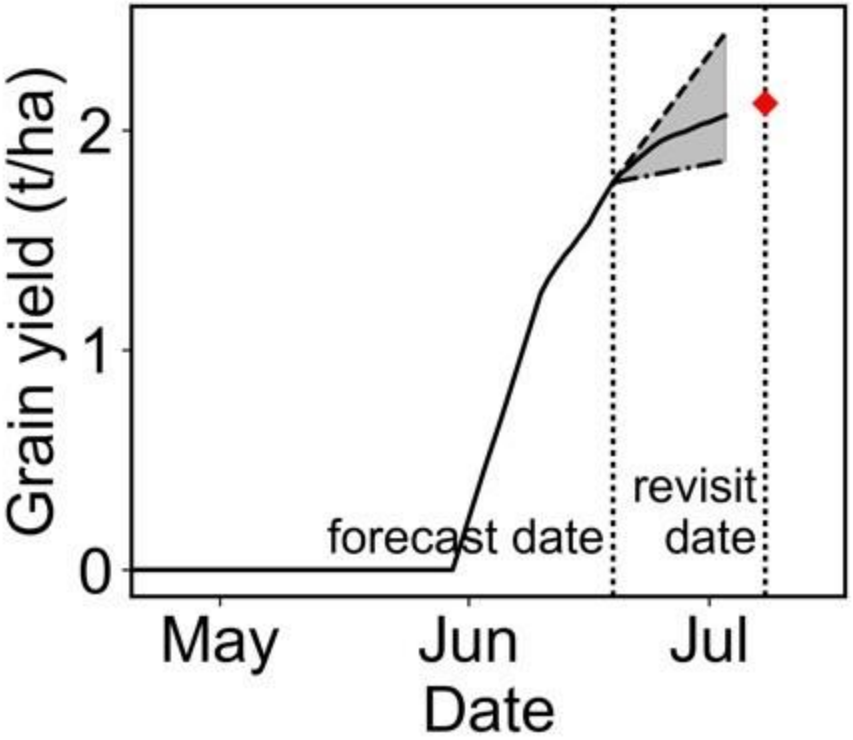


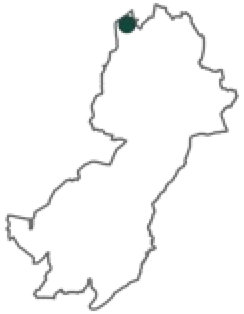
unit: t/ha

Forecasted yield	Reported yield
0.41 – 1.14 (avg: 0.66)	0.94

In-season crop yield forecast

Sampling location ID: 282



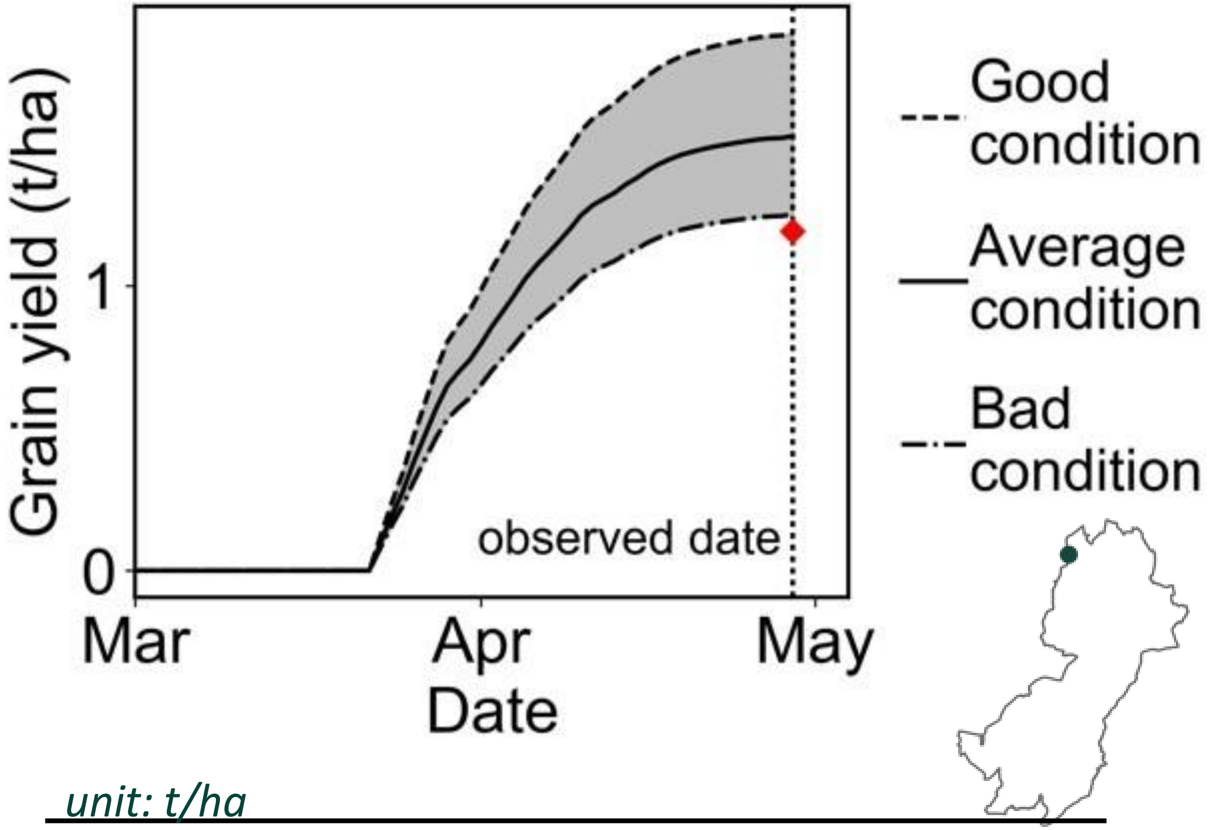


unit: t/ha

Forecasted yield	Reported yield
1.86 – 2.44 (avg: 2.09)	2.12

In-season crop yield forecast

Sampling location ID: 300

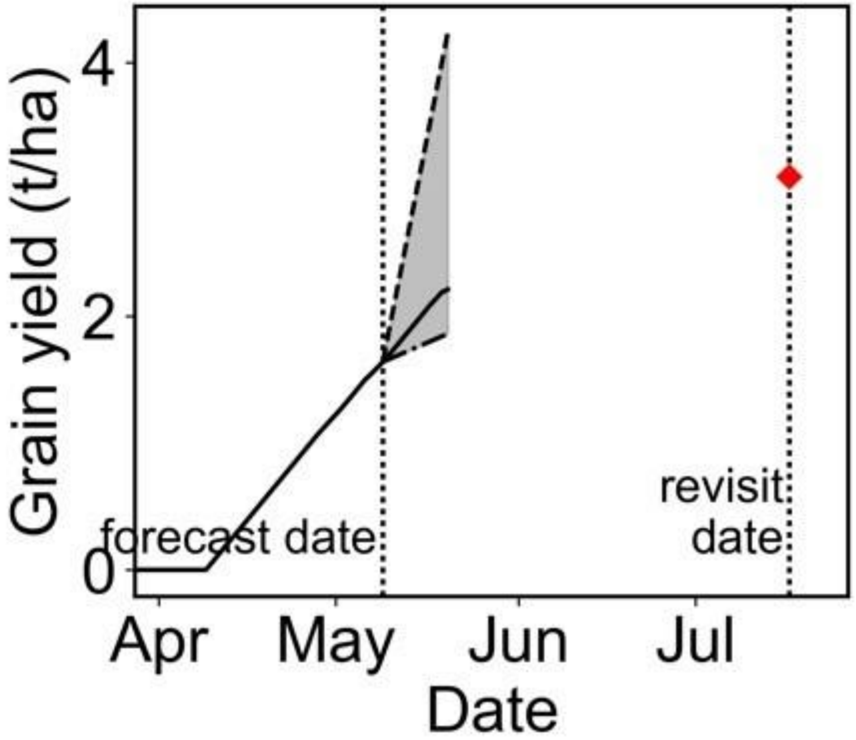


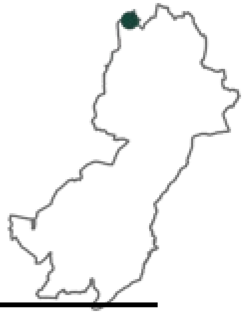
unit: t/ha

Forecasted yield	Reported yield
1.25 – 1.89 (avg: 1.53)	1.19

In-season crop yield forecast

Sampling location ID: 333



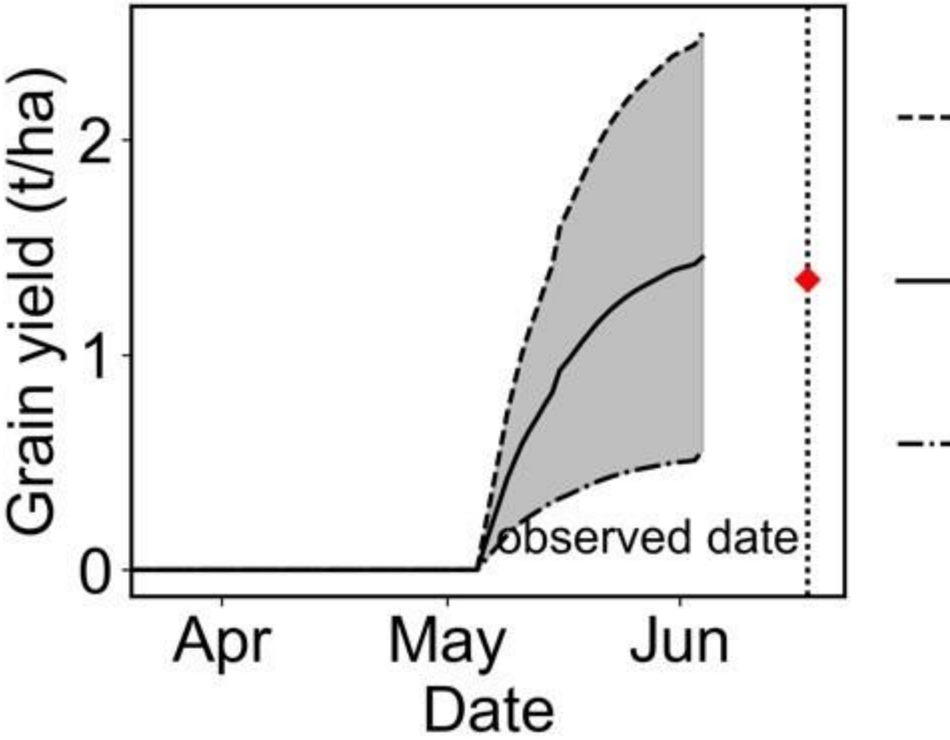


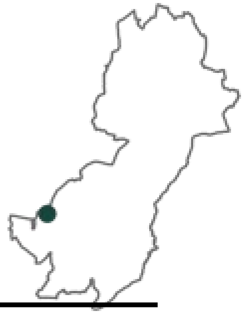
unit: t/ha

Forecasted yield	Reported yield
1.86 – 4.23 (avg: 2.21)	3.10

In-season crop yield forecast

Sampling location ID: 373



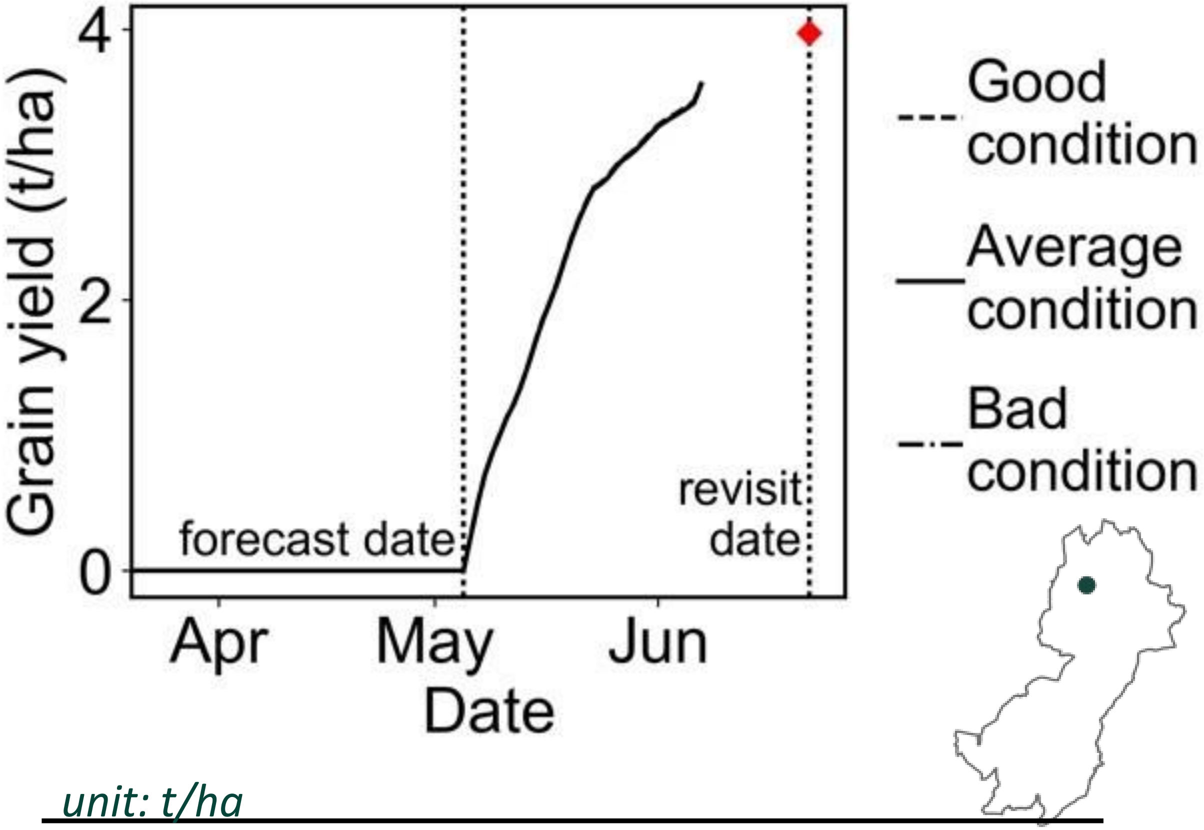


unit: t/ha

Forecasted yield	Reported yield
0.56 – 2.49 (1.45)	1.35

In-season crop yield forecast

Sampling location ID: 387

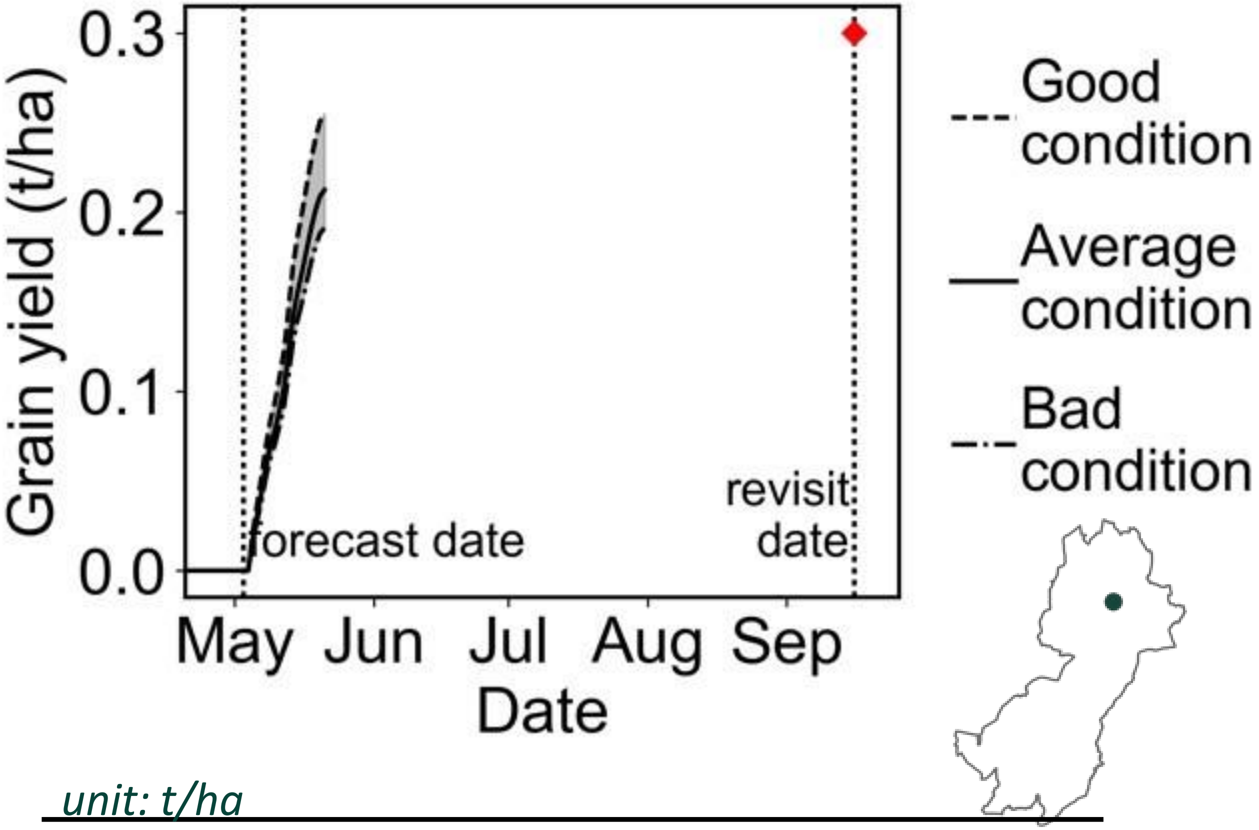


unit: t/ha

Forecasted yield	Reported yield
3.59 – 3.60 (avg: 3.59)	3.87

In-season crop yield forecast

Sampling location ID: 438

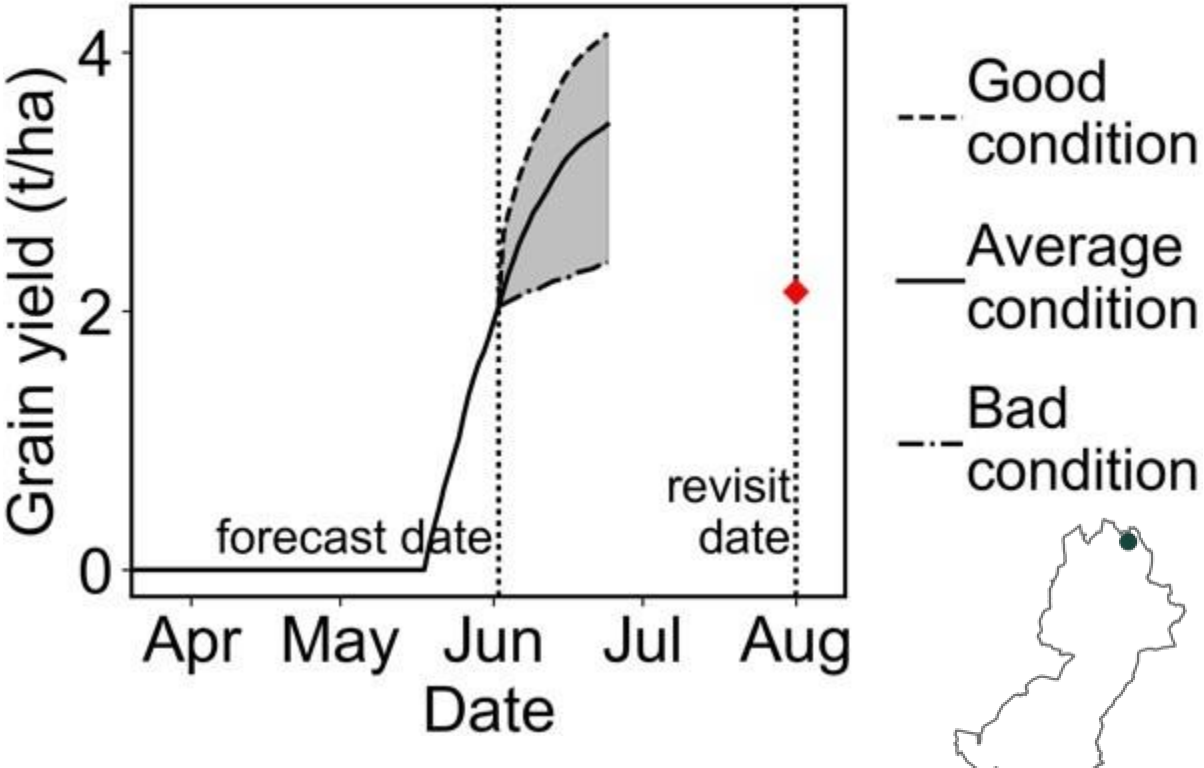


unit: t/ha

Forecasted yield	Reported yield
0.19 – 0.25 (avg: 0.21)	0.30

In-season crop yield forecast

Sampling location ID: 457

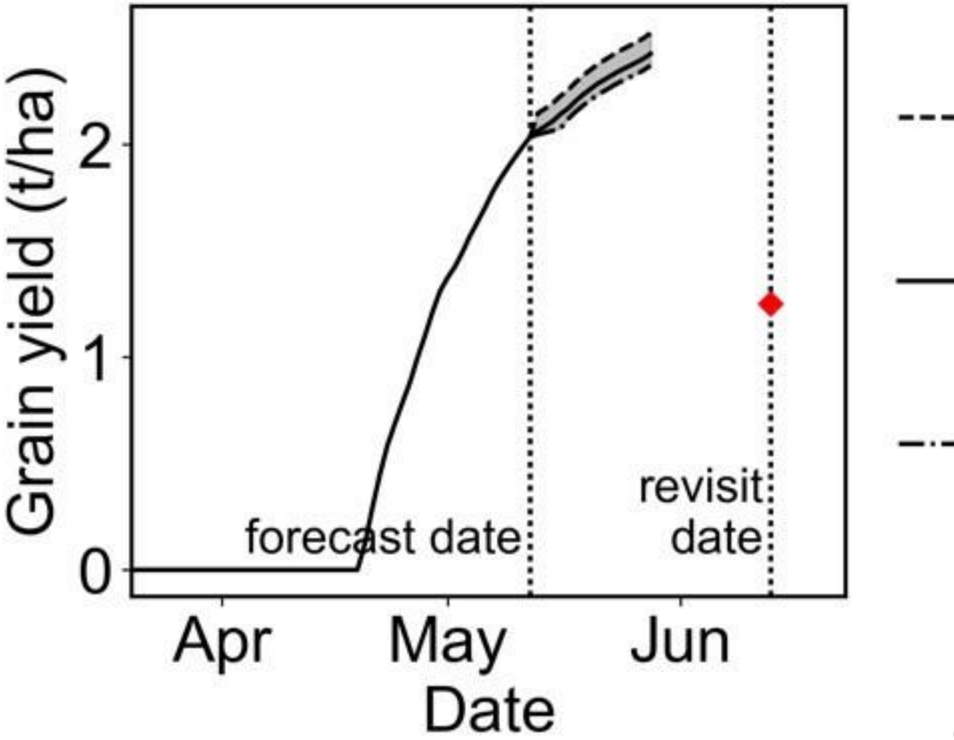


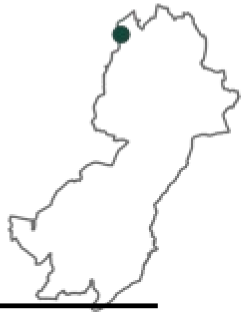
unit: t/ha

Forecasted yield	Reported yield
2.50 - 4.15 (avg: 3.44)	2.15

In-season crop yield forecast

Sampling location ID: 503





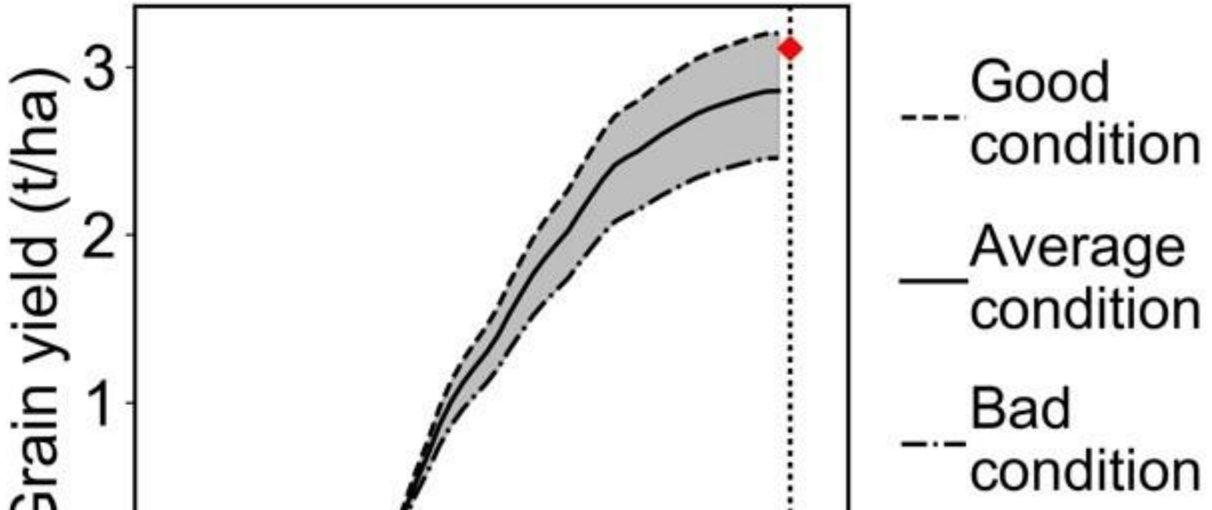
unit: t/ha

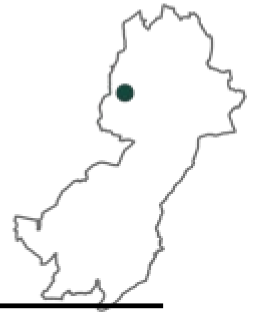
Forecasted yield	Reported yield
2.37 – 2.52 (avg: 2.43)	1.25

In-season crop yield forecast

Sampling location ID: 513

No photo was taken



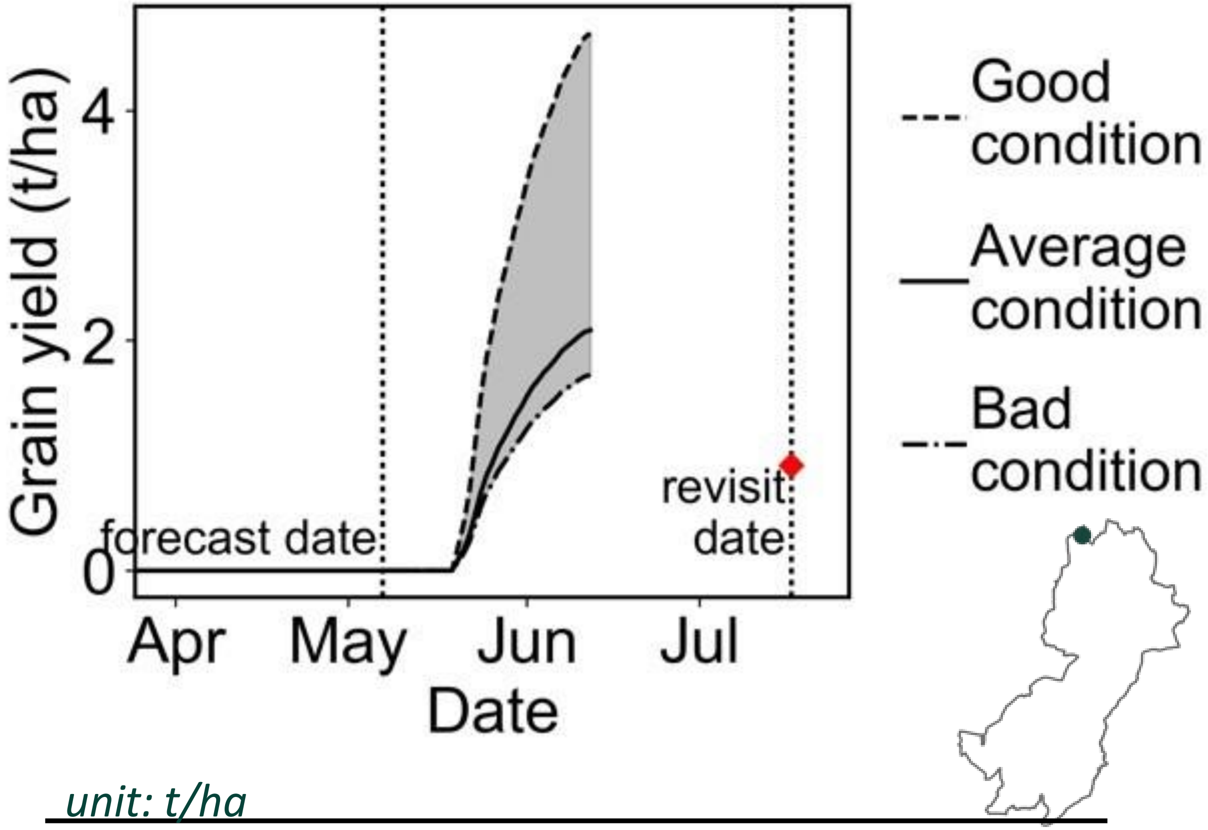


unit: t/ha

Forecasted yield	Reported yield
2.46 – 3.20 (avg: 2.86)	3.11

In-season crop yield forecast

Sampling location ID: 571

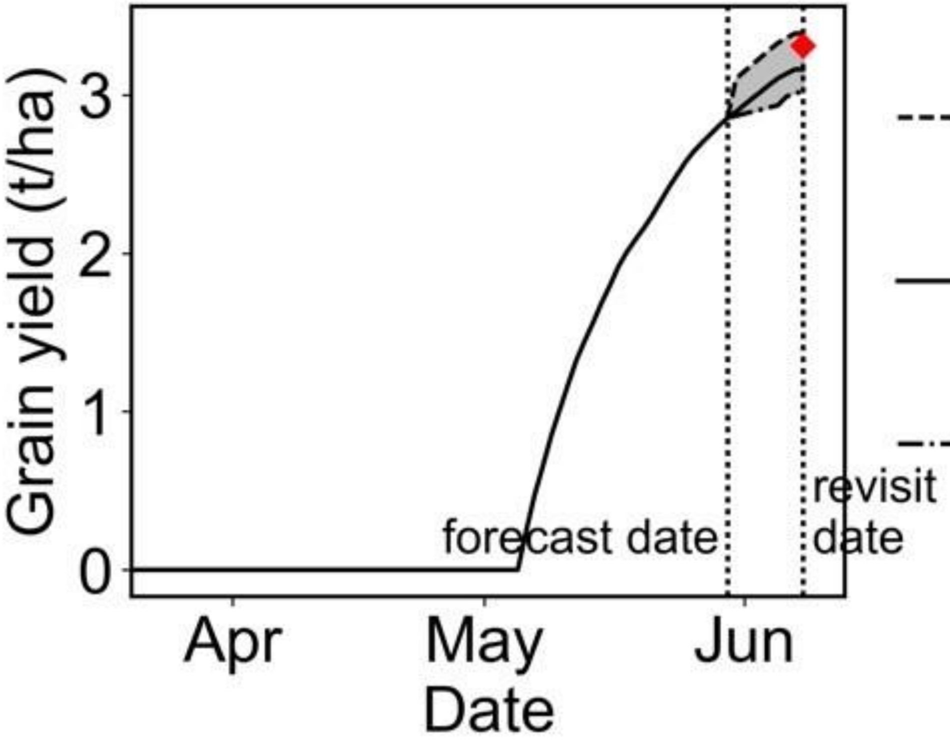


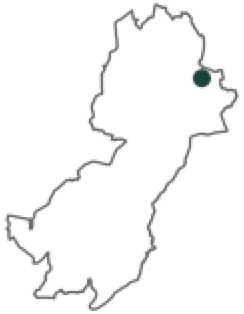
unit: t/ha

Forecasted yield	Reported yield
1.70 – 4.67 (avg: 2.09)	0.91

In-season crop yield forecast

Sampling location ID: 578



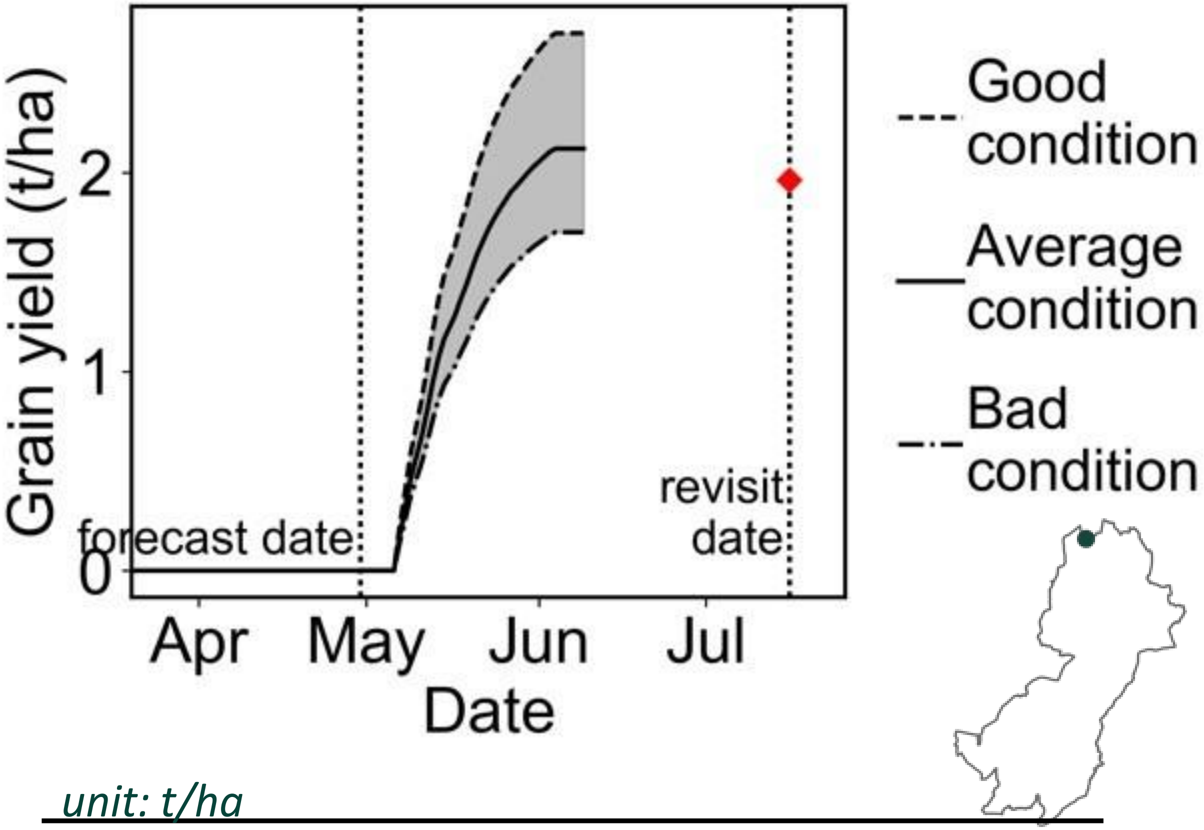


unit: t/ha

Forecasted yield	Reported yield
3.02 – 3.39 (avg: 3.16)	3.31

In-season crop yield forecast

Sampling location ID: 702

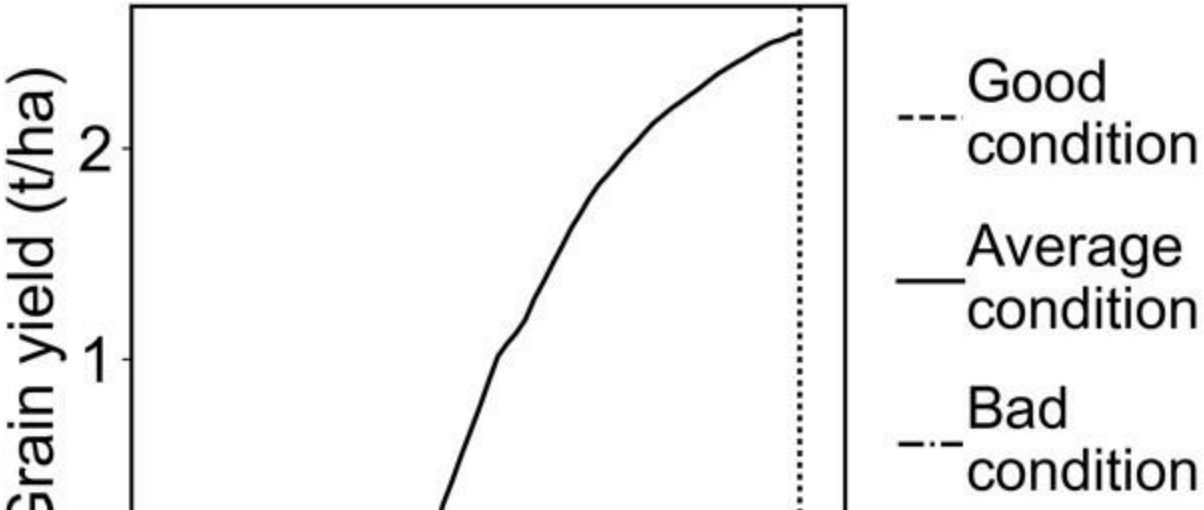


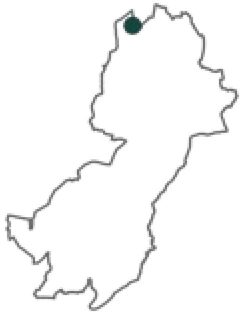
unit: t/ha

Forecasted yield	Reported yield
1.70 – 2.70 (avg: 2.12)	1.96

In-season crop yield forecast

Sampling location ID: 728

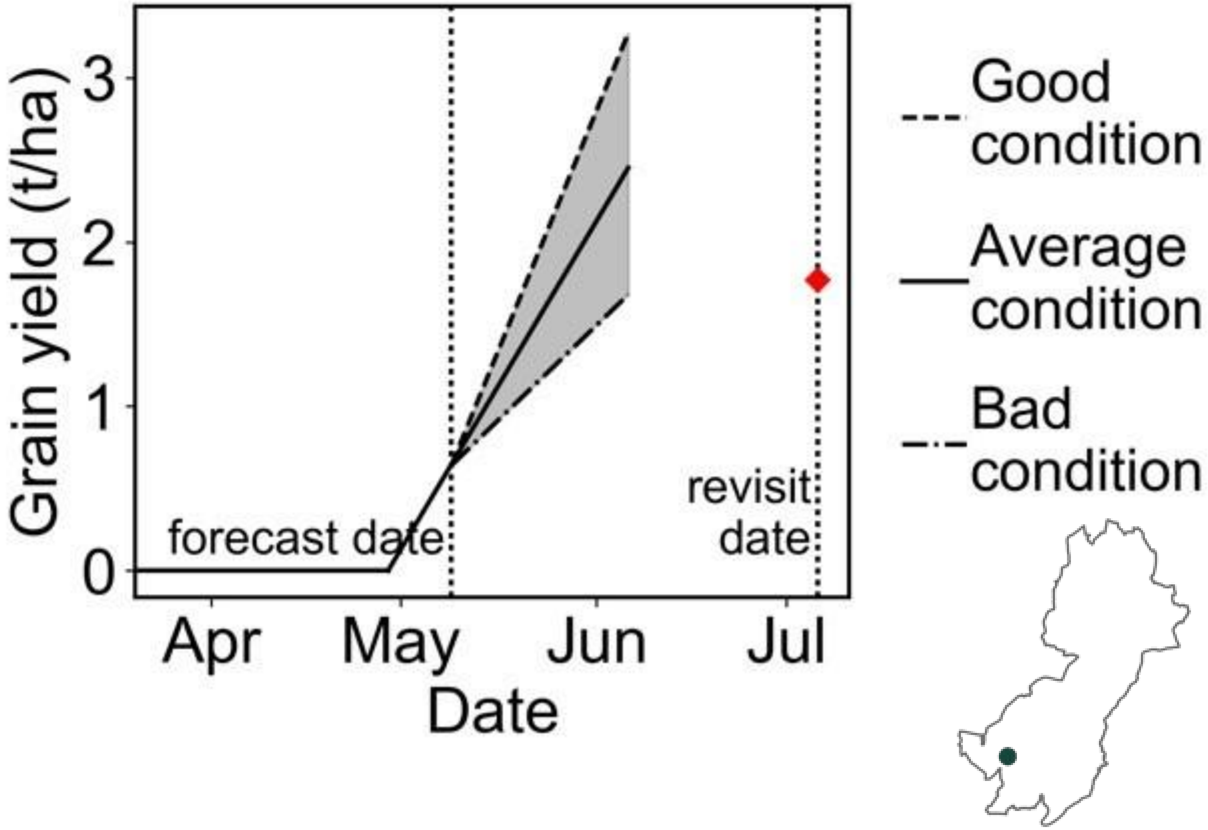




Forecasted yield	Reported yield
2.28 – 2.70 (avg: 2.54)	*Waiting for results*

In-season crop yield forecast

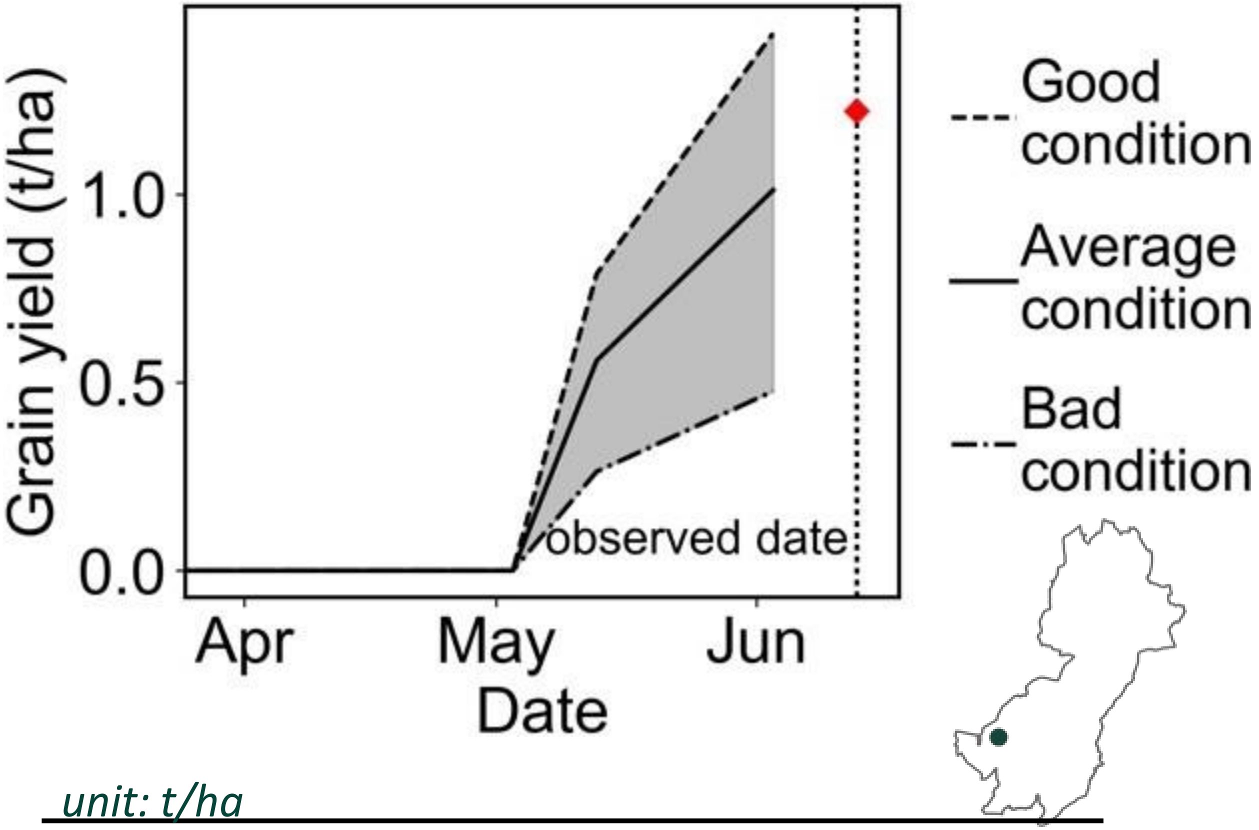
Sampling location ID: 754



Forecasted yield	Reported yield
1.68 – 3.27 (avg: 2.45)	1.77

In-season crop yield forecast

Sampling location ID: 763



unit: t/ha

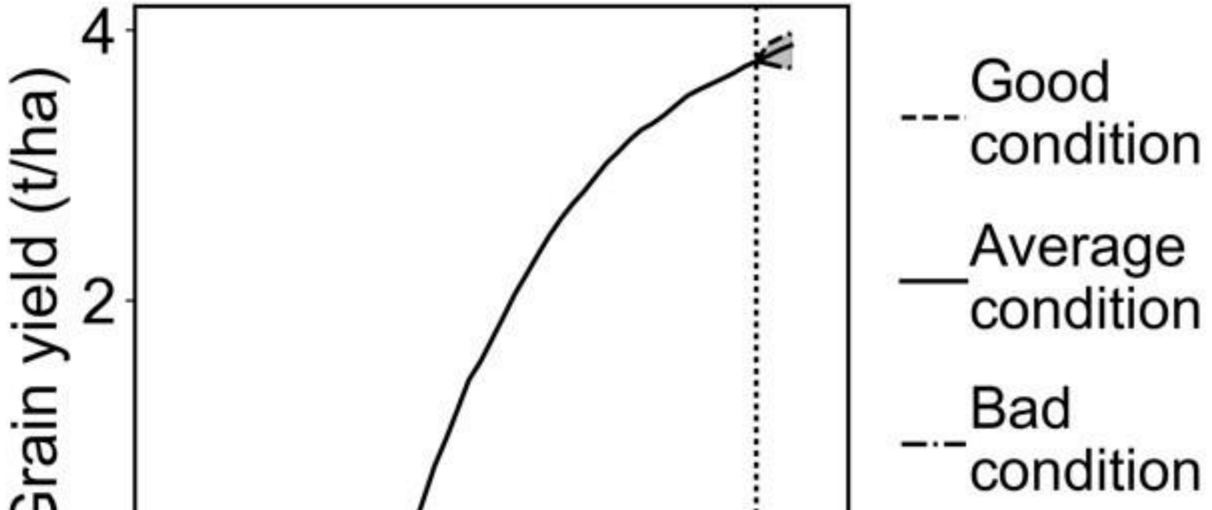
Forecasted yield	Reported yield
0.50 – 1.49 (avg: 1.05)	1.24

In-season crop yield forecast

Sampling location ID: 800

No photo was taken

(rejected by supervisor)

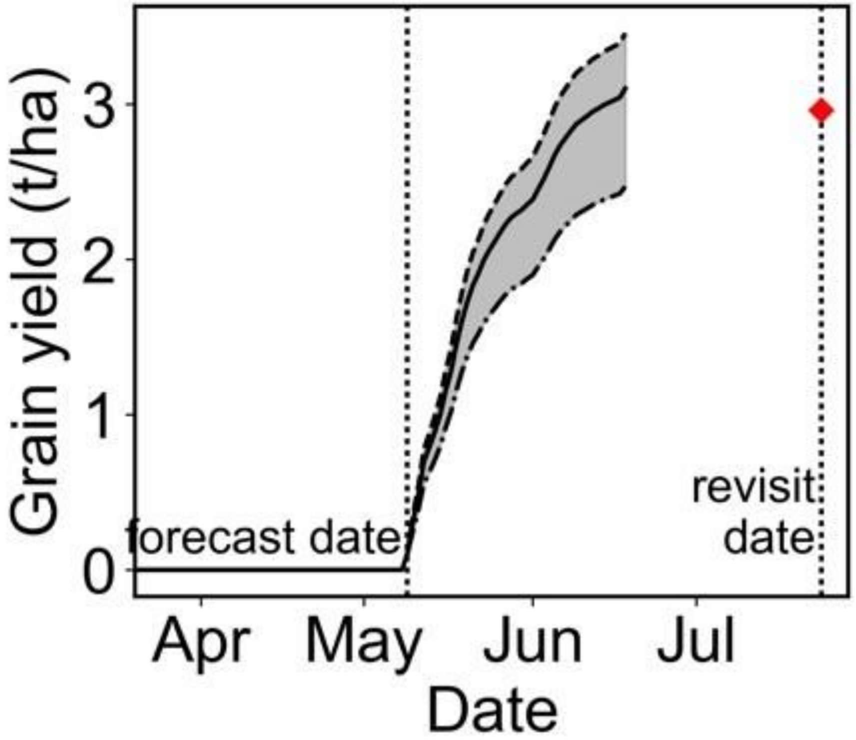


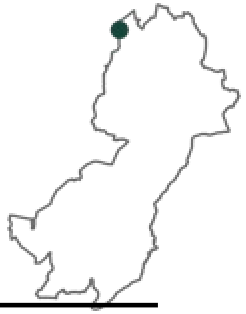
unit: t/ha

Forecasted yield	Reported yield
3.72 – 3.98 (avg: 3.89)	*Waiting for results*

In-season crop yield forecast

Sampling location ID: 807



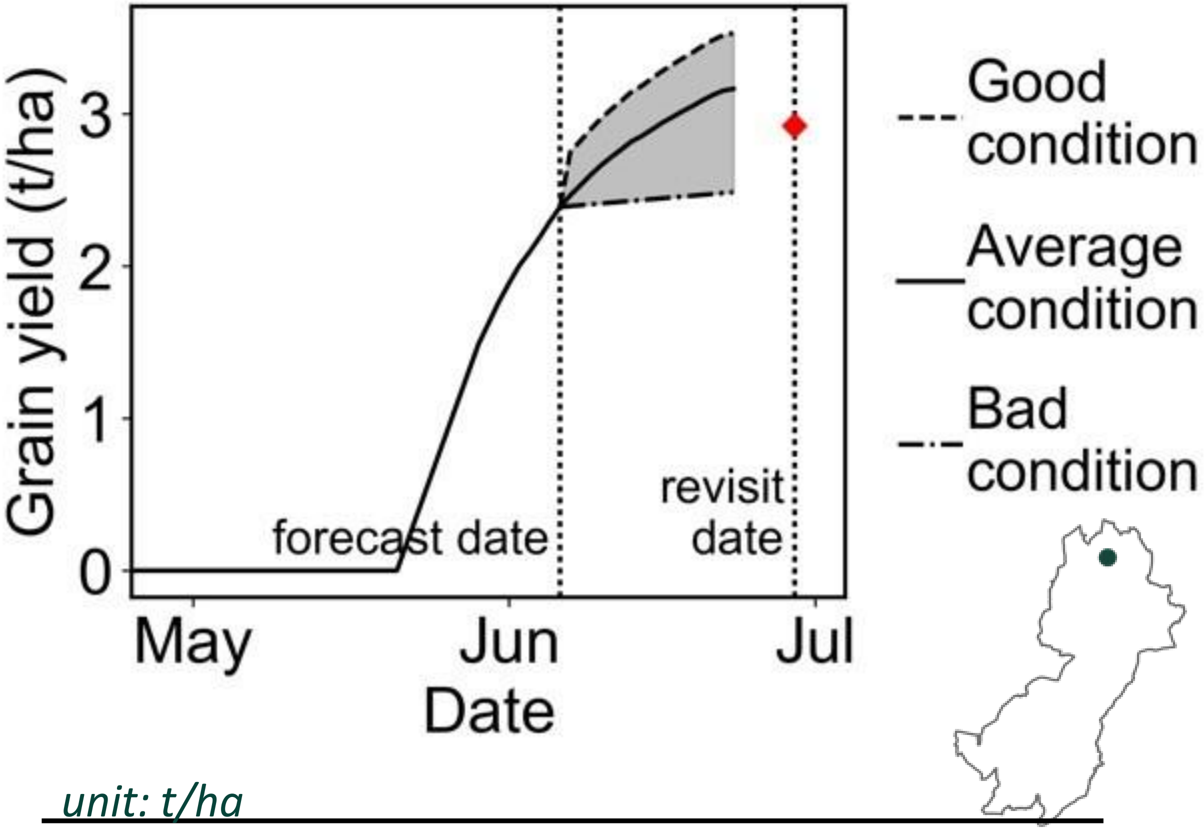


unit: t/ha

Forecasted yield	Reported yield
2.47 – 3.46 (avg: 3.10)	2.96

In-season crop yield forecast

Sampling location ID: 811



unit: t/ha

Forecasted yield	Reported yield
2.49 – 3.53 (avg: 3.16)	2.92

Results of crop yield forecast for three districts in Tanzania

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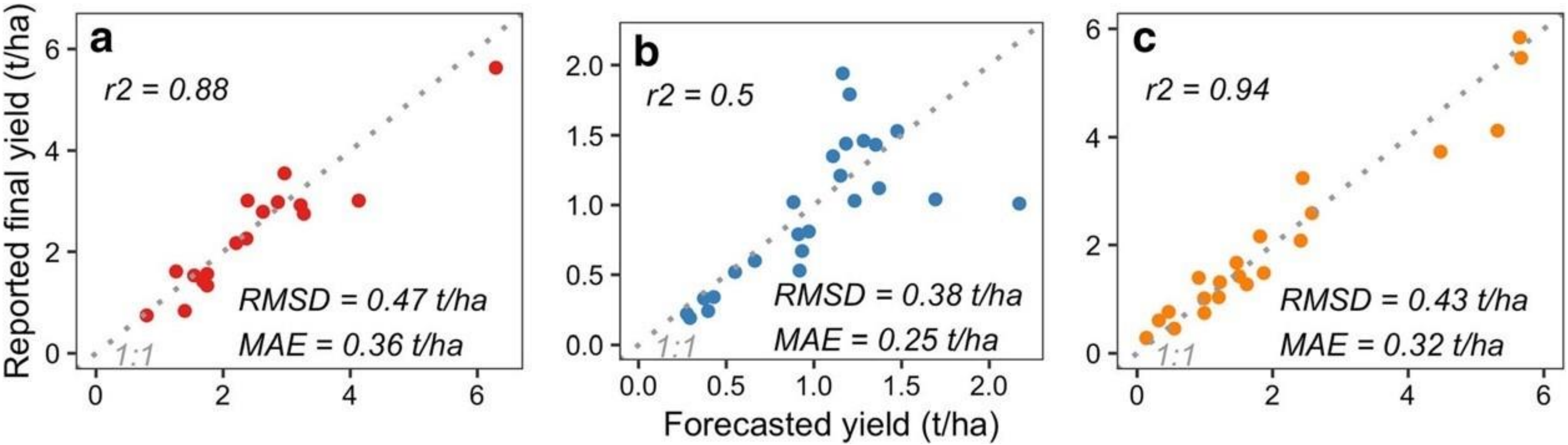
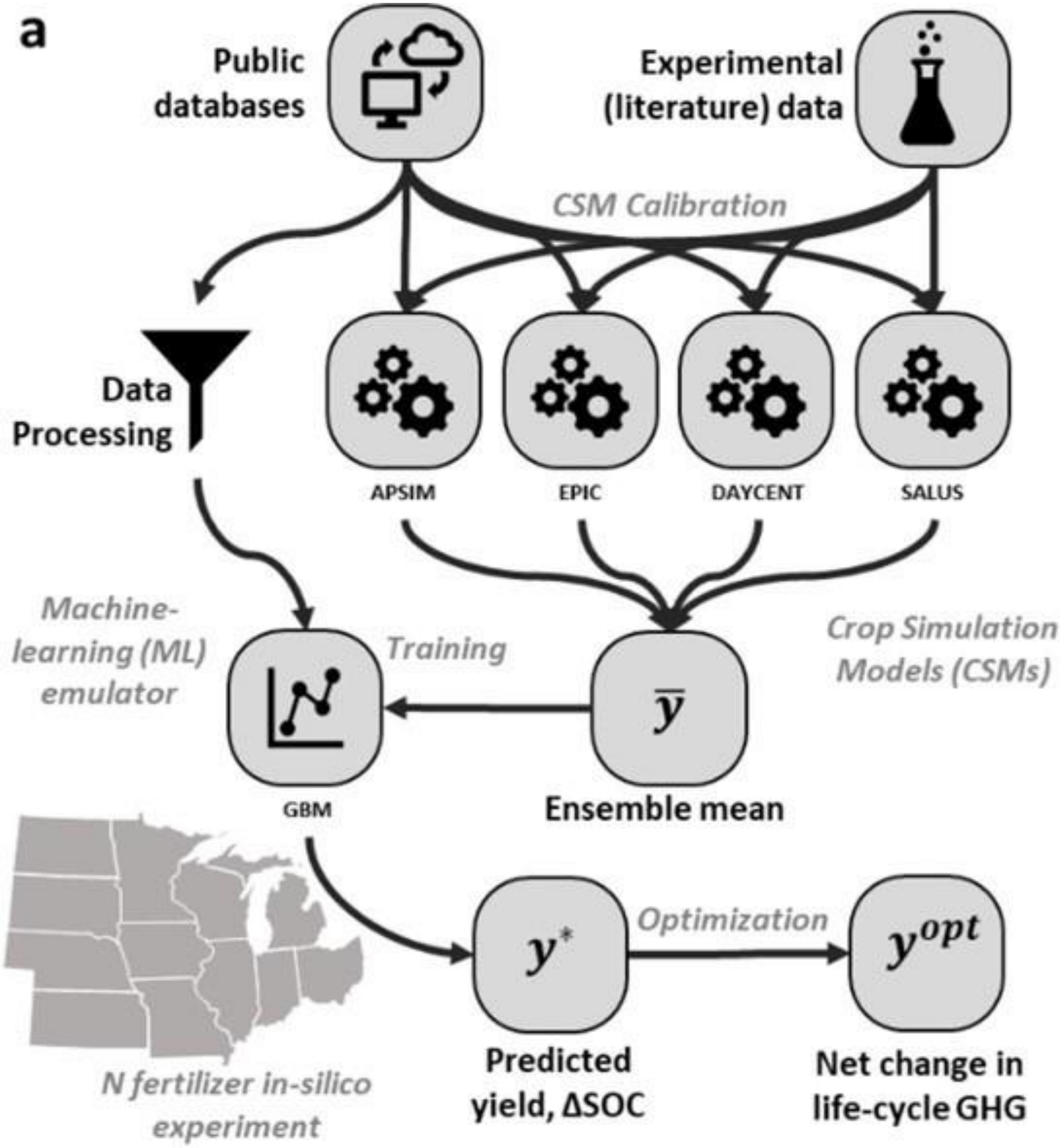
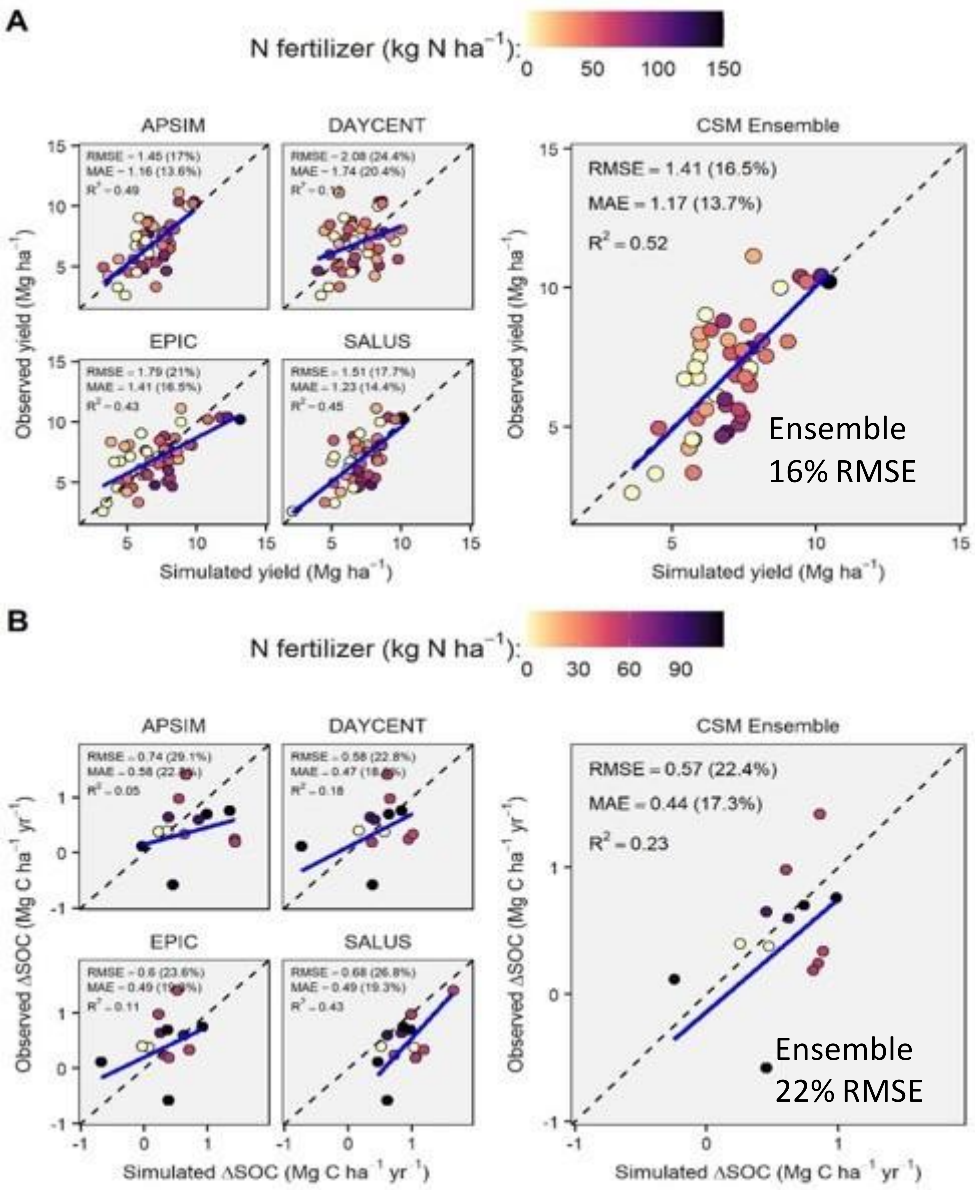


Multi model ensemble and Machine Learning emulators





Martinez-Feria, Basso, Kim, ERL 2021

Emulator: A statistical model that ‘learns’ the behavior of a more complex model (A.K.A Surrogate model or metamodel)

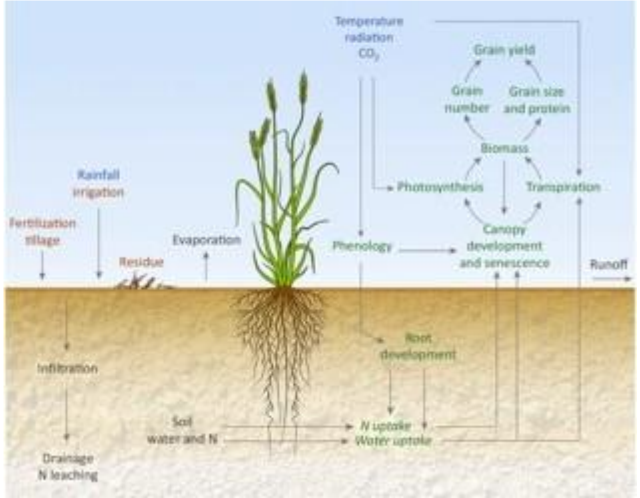
The Pros:

Fast and easy to run
Less computationally expensive

The Cons:

Potential loss of predictive power (propagated errors)

Crop models



The Pros:

Multiple outputs (explanation)
Can deal with new/unseen environments
Good for hypothesis testing

The Cons:

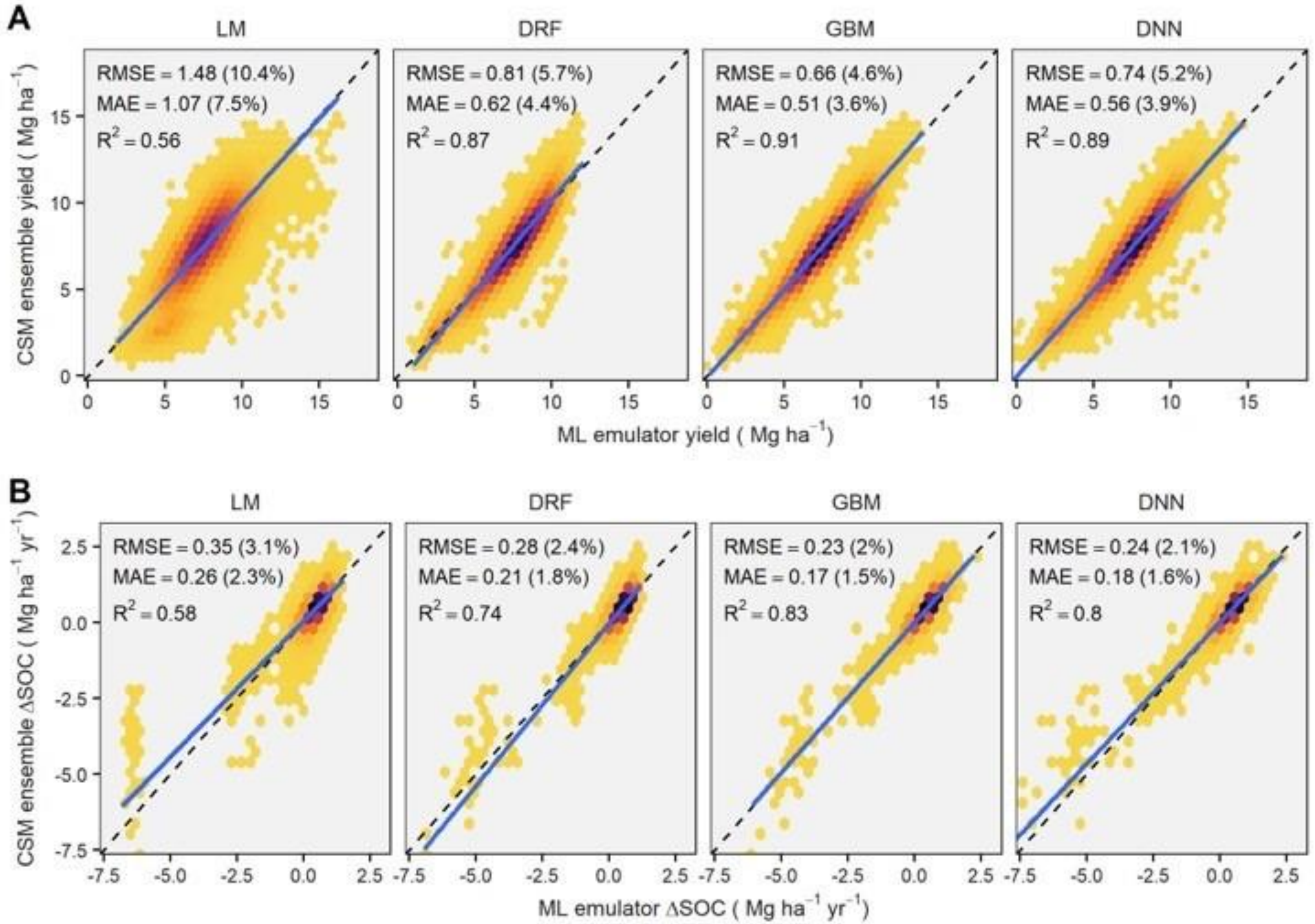
Steep learning curve
Difficult to set up and (re)calibrate
Idiosyncratic (bias, model structure)
Computationally expensive (complex, slow to run on large scales)

Better performance when predicting the ensemble rather than single-models

ML models

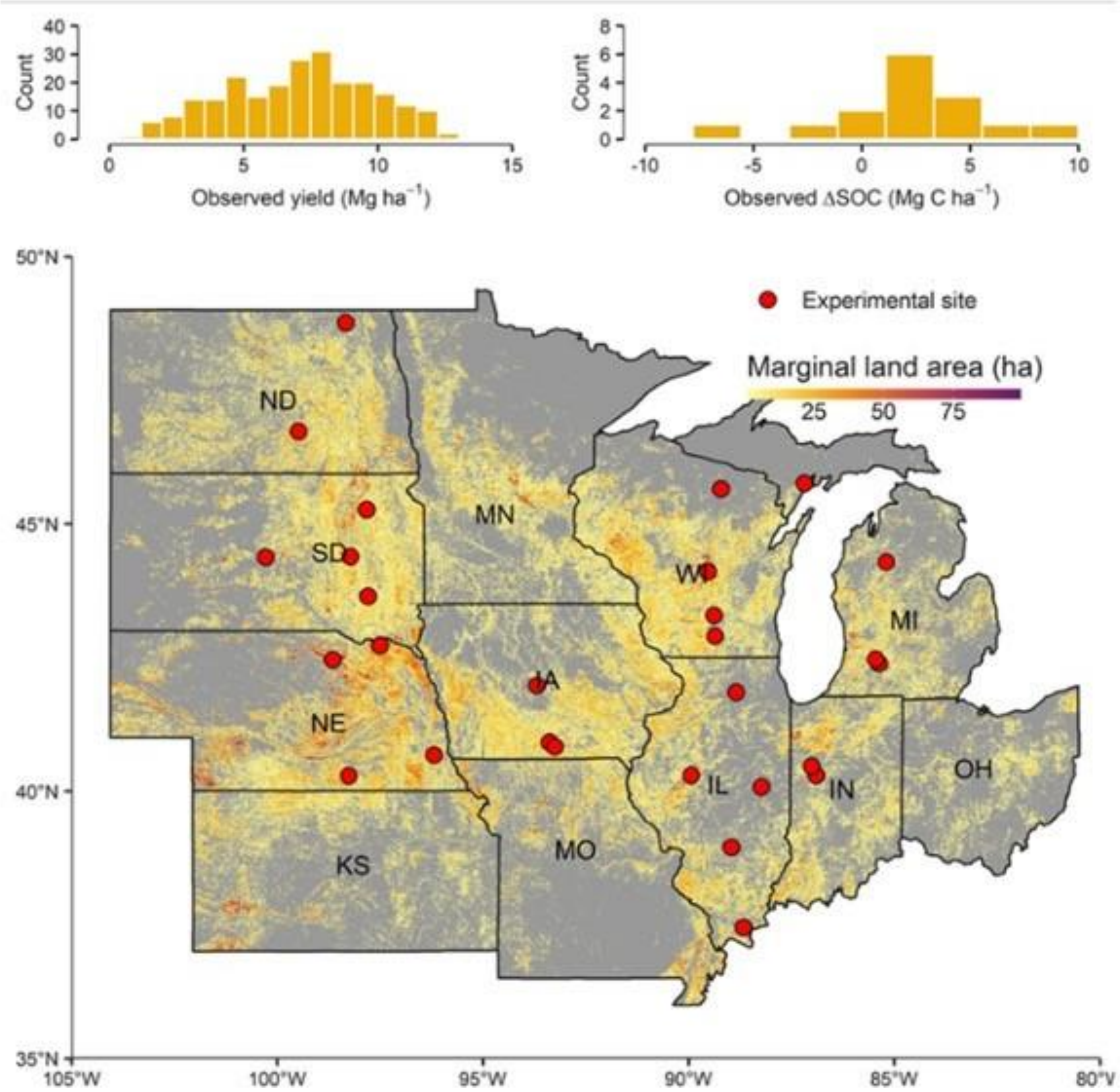
Generalized Linear Model (LM)
Distributed Random Forest (DRF)
Gradient Boosted Machines (GBM)
Deep neural network (DNN)

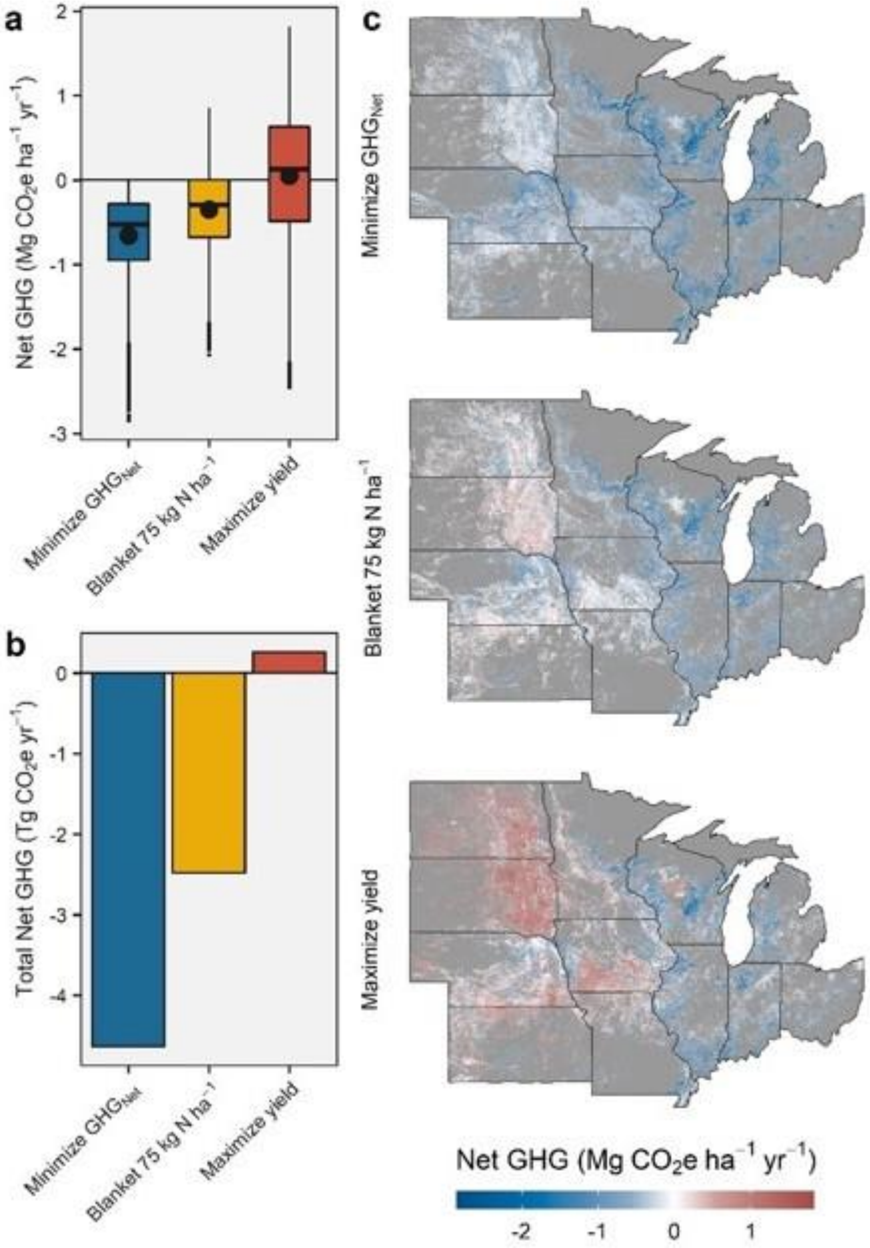
40 predictive features for each simulation (Yearly bioclimate, soil characteristics, management)



Multi-model response to N rates

Switchgrass





Take away

- The integration of process-based crop models and with Earth Observation data improves crop statistics and forecasts yields
- Global partnerships and data sharing are essential to achieving maximum impact
- Ground-truth data collection should be standardized and harmonized to validate image analysis and model results
- The platform we presented has great potential to quantify risk with tangible data and information for stakeholders to make more informed decisions and policy

Basso Computational Agronomy and Environmental Sustainability Lab

Department of Earth and Environmental Sciences
MICHIGAN STATE UNIVERSITY

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National Institute of Food and Agriculture

NSF

USDA Natural Resources Conservation Service
United States Department of Agriculture

Food and Agriculture Organization of the United Nations

NASA

USAID
UNITED STATES AGENCY INTERNATIONAL DEVELOPMENT

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