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

Bruno Basso, PhD Hannah Distinguished Professor

Team: Fidel Maureira, Ames Fowler, Brian Baer, Christopher Villalobos, Juliana Hanle, Ryan Jane, Jac Stelly



Department of Earth and Environmental Sciences Michigan State University

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

Deforestation

Urbanization



Fires/Land Degradation

Soil Erosion

Water quality

Digital Twins

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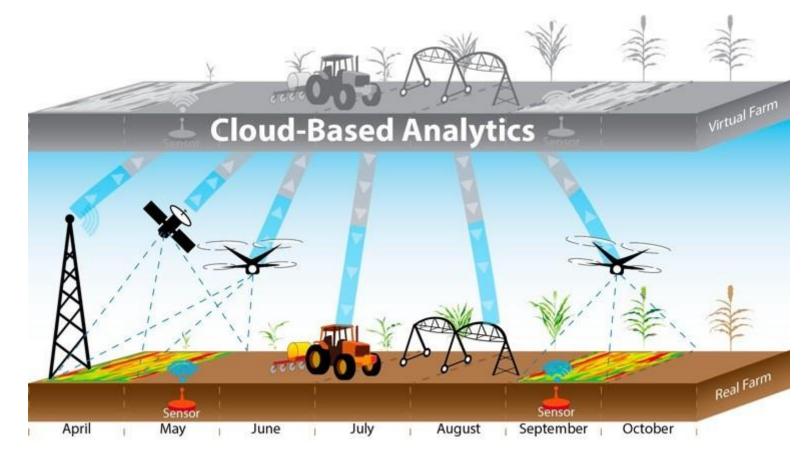
a bridge between the physical and digital world to promote innovation and performance



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radiation Grain vield Grain size Rainfal Photosynthesis Transpiration irrigation Fertilization Evaporation tillage Phenology Residue Runoff development Infiltration water and N Drainage N leaching

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

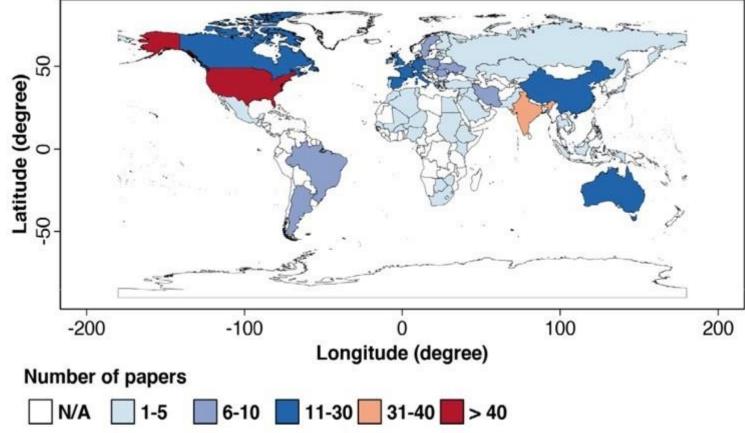
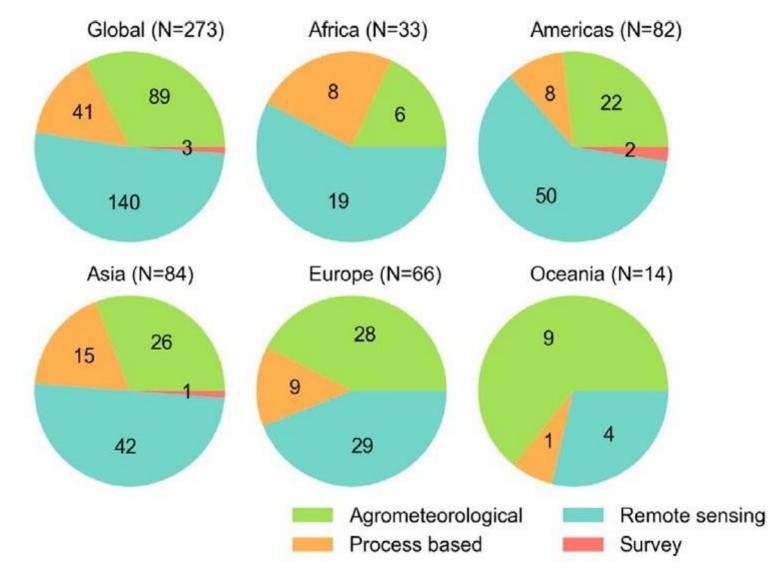
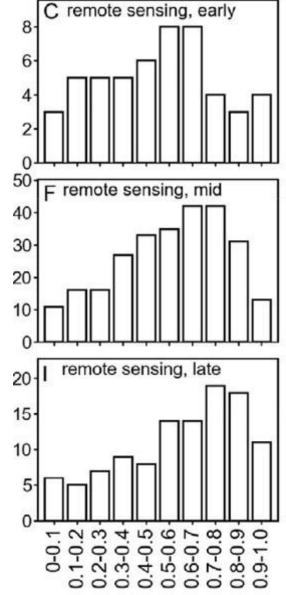


Fig. 1 Number of peer-reviewed papers in each country where the study sites or regions of the yield-forecasting papers were located.

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

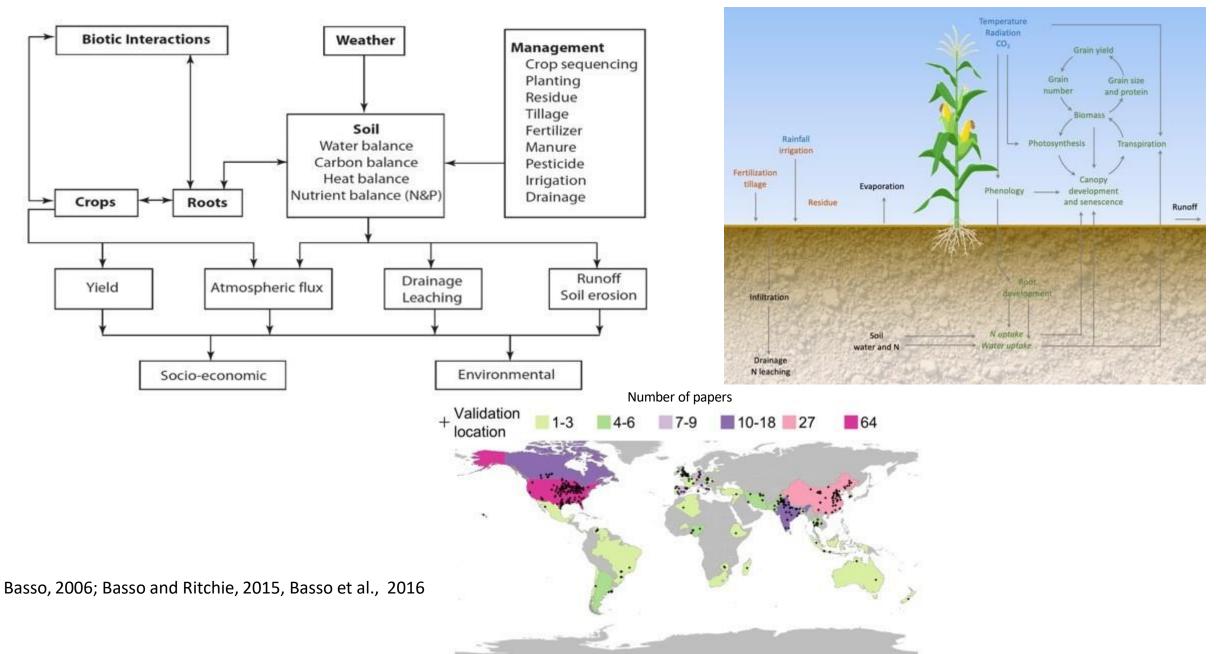




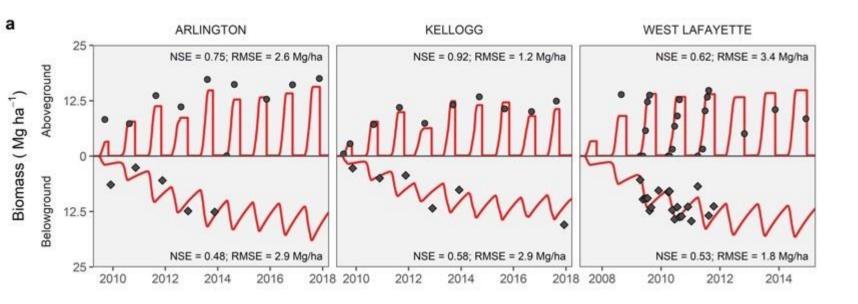
Basso and Liu, 2019, Advances in Agronomy

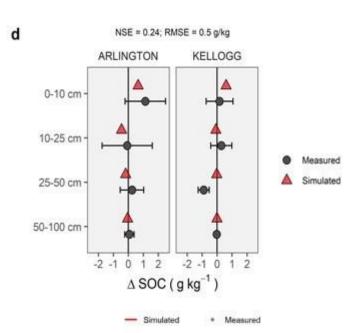
SALUS: Systems Approach for Land Use Sustainability

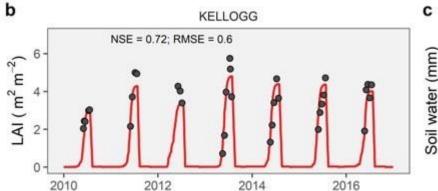
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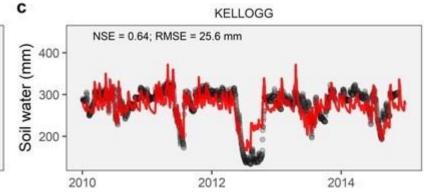


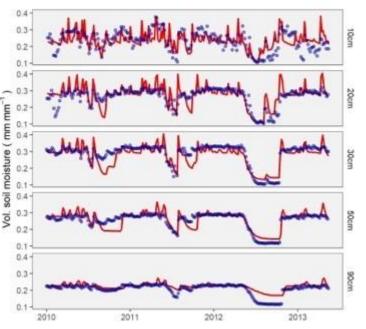
SALUS model validation













NDVI - 01/01/2019 NDVI - 01/01/2020 0.5 to 0.6 0.0 to 0.1 0.0 to 0.1 0.5 to 0.6 0.1 to 0.2 0.6 to 0.7 0.1 to 0.2 0.6 to 0.7 0.7 to 0.8 0.2 to 0.3 0.2 to 0.3 0.7 to 0.8 0.8 to 0.9 0.3 to 0.4 0.3 to 0.4 0.8 to 0.9 0.4 to 0.5 0.9 to 1.0 0.4 to 0.5 0.9 to 1.0 Map produced by the Basso Digital Agronomy Lab, Michigan State University, 2021

Map produced by the Basso Digital Agronomy Lab, Michigan State University, 2021

2020

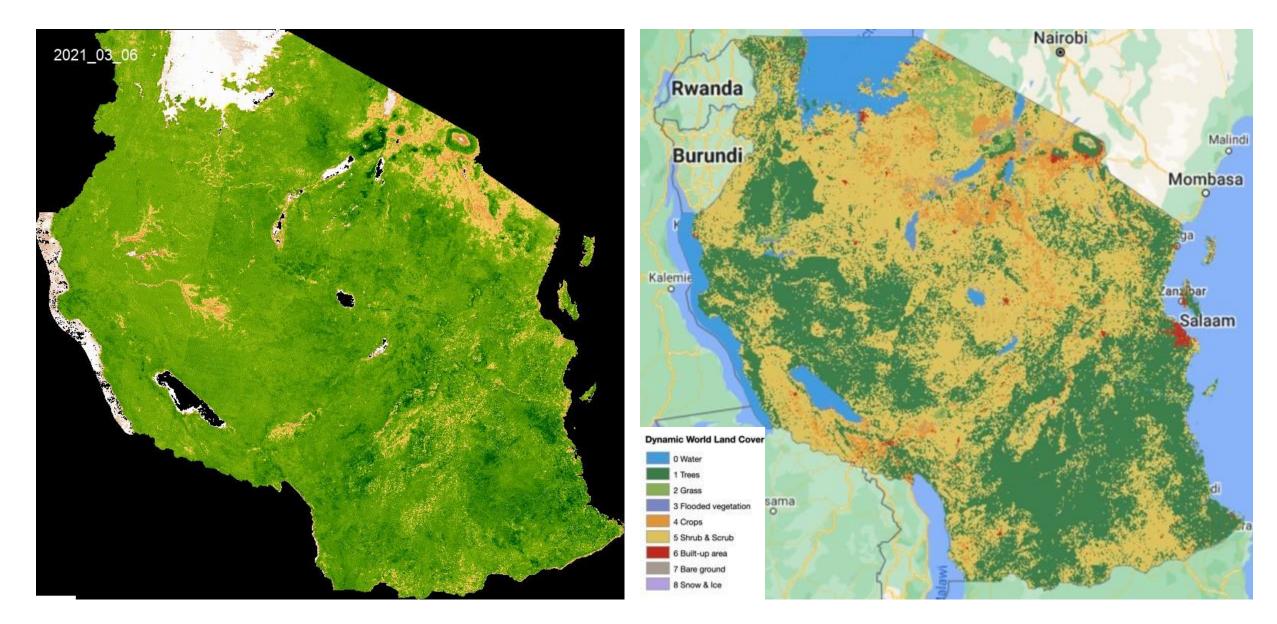
Daily changes of crop vigor and modeling yields in Mozambique sugarcane fields

Basso lab

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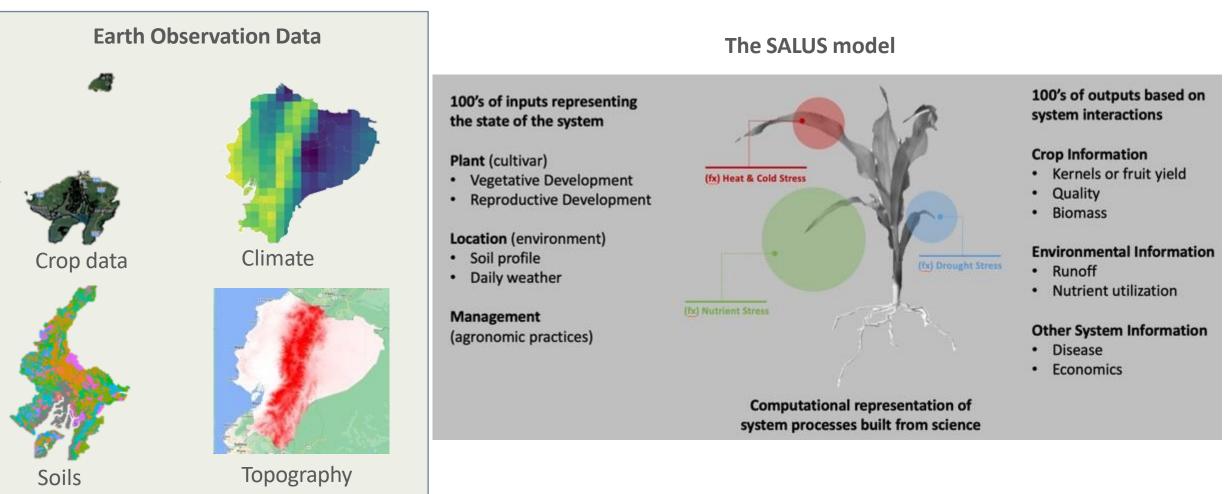
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Coupling remote sensing with crop models



EOSTAT Crop Yield Mapper

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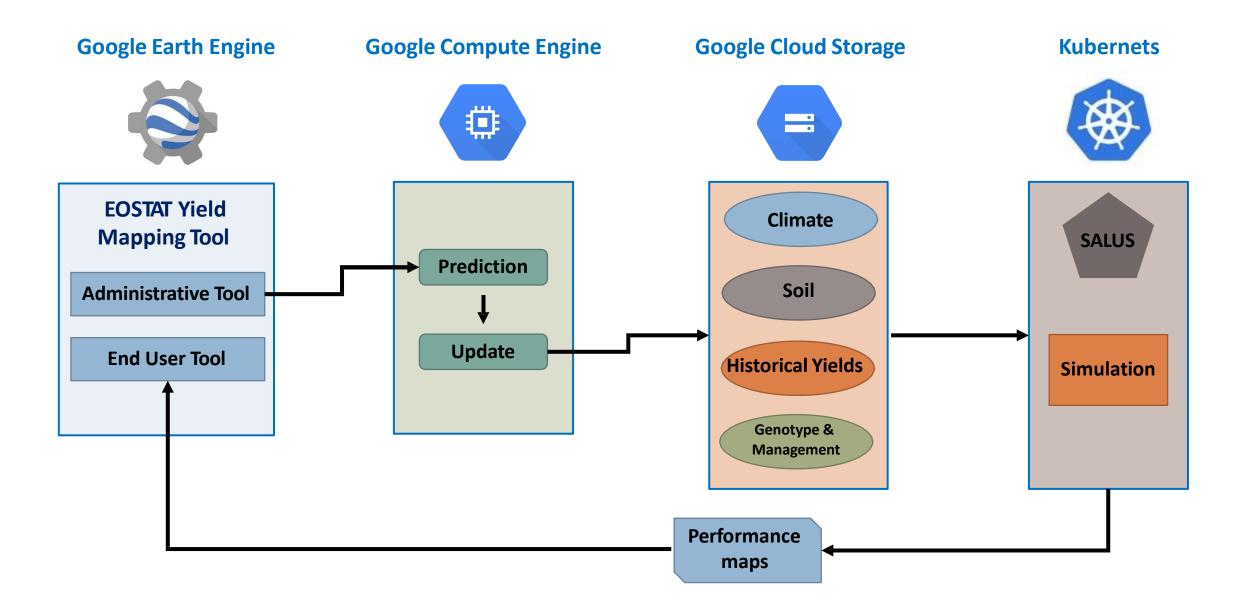


Design criteria:

- 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

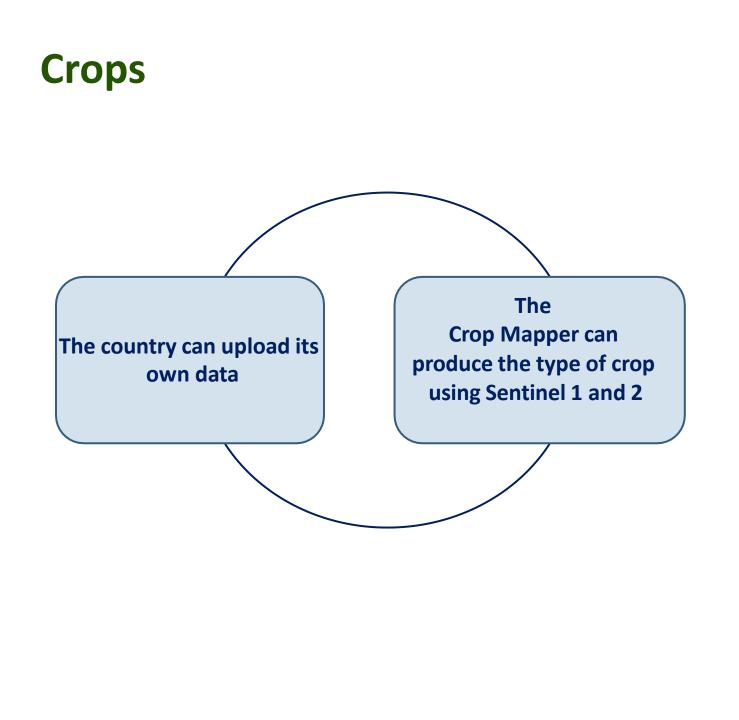
Platform structure

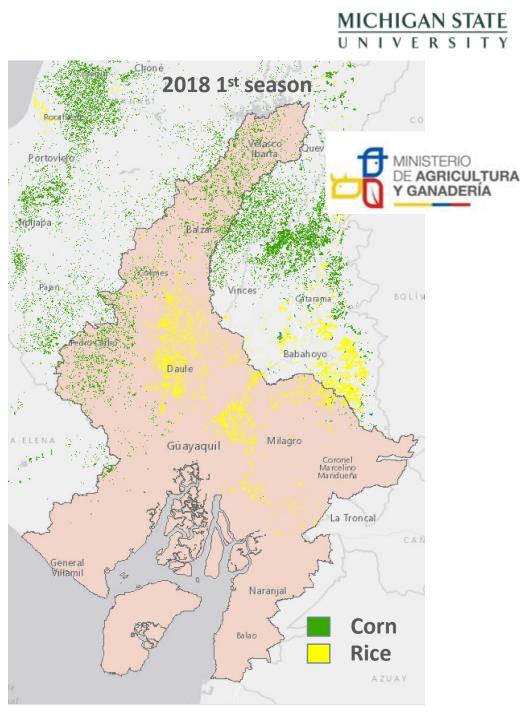
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Friendly web application tools

Administ	rative Tool		Visualization	ΤοοΙ		
EOSTAT Platform			(A)	0 9 ~ > =	Crop Yield Map (tonne/ha)	Leyers Map Satella
Ecuador	Calibration Dashboard			1	Domi El Carmen 1 4 7 9 12	Shashufindi Joya de Teo Sachas
Change location	Current Queue Items		Crop Yield Mapping	Bahia de Calisquez	Machachi	10
Overview	Weather Update for Ecuador - Running		This app allows you to filter and export images from the Crop yield mapping tool.	Chore	Par - les - ma	
CONFIGURATION	Prediction for Comercon			Manta	Base La Mana Latecurga evedo, 10 Piati	Archalona Terre Puerto Terre Missihueli
Calibration Parameters Defaults	Calibration for Ecuador		1) Select filters		Sacedo Ambato	Aller Misshult
By Region	Prediction for Ecuador		2022	etel de	Venanas De Banos	1
Weather Scenarios	Prediction for Ecuador		Season © Guayas © Scenario ©	Puerto Lopez	Guaranda Robamba	
Custom File Locations	Previous Calibration Events		Apply filters Use upload Crop Type Map	Montanta	Labohoyo 🐨 👘	
EXECUTIONS	2022-12-01 12:34:56 Calibration Run Completed	Success		10 10 10	aya 👘 👘	
Calibrations	2022-12-01 07:02:33 Calibration Run Started	Success	2) Select a crop type map	mit caliborat	Alaur Mac	at Tasha Fore
Predictions	2022-12-01 06:04:03 Calibration Run Submitted	Success	20210101_20211230_30220831T100754_5152_6_090	A Start	Succes	shu
	2022-11-29 17:21:23 Process Validation File Completed	Success	Go to crop type map	and a second	Azogues TO	
	2022-11-29 17:10:56 Process Validation File Started	Success	•	87	Cuenca To	Andran
	Yield Validation File		3) Select a yield map	Mac	A 117 7	e
	Current Validation File		2021_MZ_s1_vsl_20220812 0 60	a second li	Pasage Garta tabel () Gualagouta	
	gs://fao-ecauador/calibrations/somefile.xlsx Last Updated: last month		4) Get the production by region	Tumbes Sarra Zornios	ElParqui	
	Upload New Yield Validation File		Get production	Gasto S		Keyboard shortouts Map data \$2022 Google : 20 km





EOSTAT Crop Mapper: Ecuador

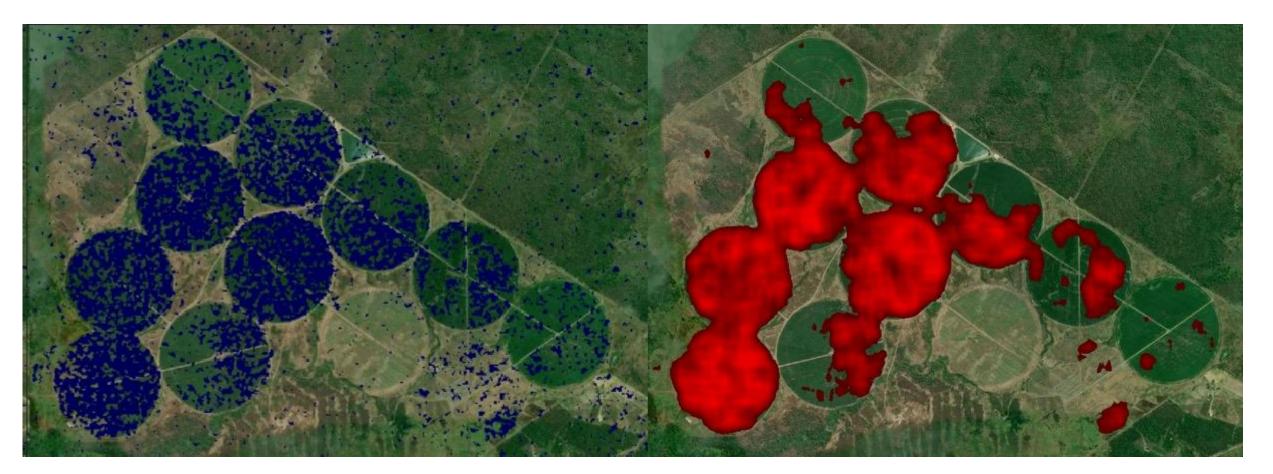
CROPS CLASSIFICATION USING **TEMPORAL PATTERN OF NDVI** SENTINEL-2 NDVI STACK TIME-WEIGHTED DYNAMIC TIME-WARPING wheat 0.8 0.6 0.4 0.2 Apr Júl maize 0.8 0.6 0.4 0.2 Apr Júl rice 0.8-0.6 0.4 0.2 Apr Jul sunflower 0.8 0.6 PIXELS 0.4 0.2 Apr Jůl forest **OBJECTS** 0.8 0.6 10 km 0.4 0.2 sunflower unclassified wheat rice maize forest 0 Apr Júl

Belgiu and Csillik, 2018



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

• Using Sentinel-1

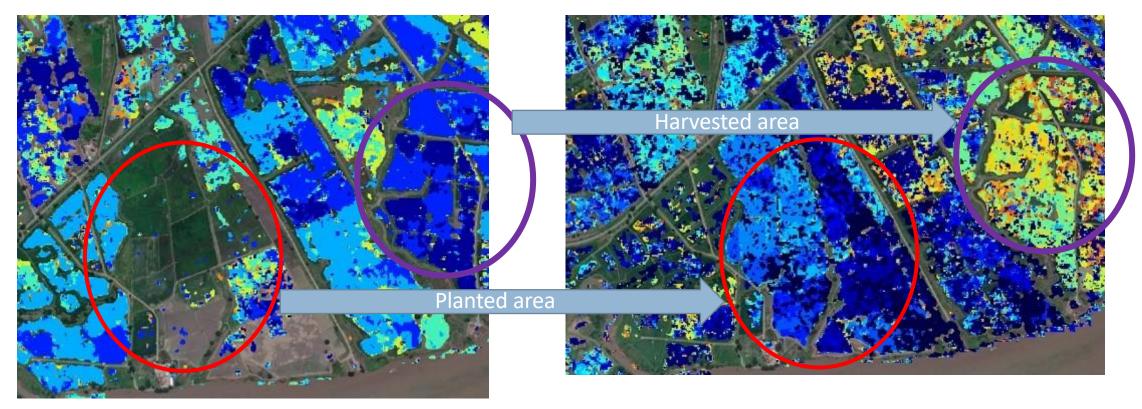




Rice land detection: Change between Dec 2020 to Jul 2021 using SAR (Radar)

• December 2020

• July 2021





Daily Climate data

Climate Forecast System Version 2 (CFSv2)

- Temperature, Solar radiation
- Resolution ~22km



Hazards

Center

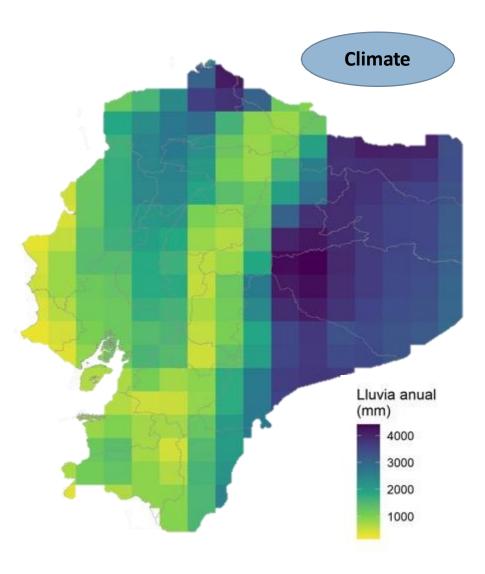
Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS)

- Rain
- Resolution ~5,5 km

Scenarios for forecasting yield : Wet, Dry, Normal



USAID



Soil Data





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

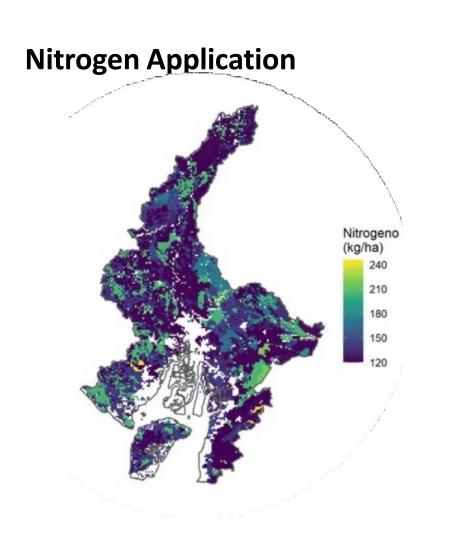


• This Case study uses Ecuador's national soil dataset.

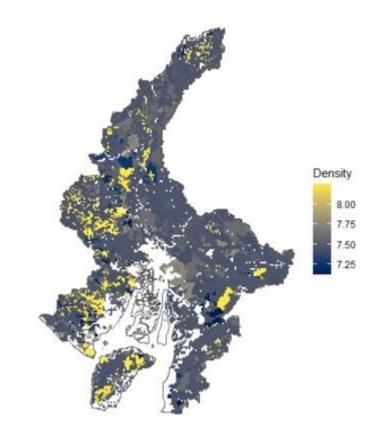




Inferred management: Maize



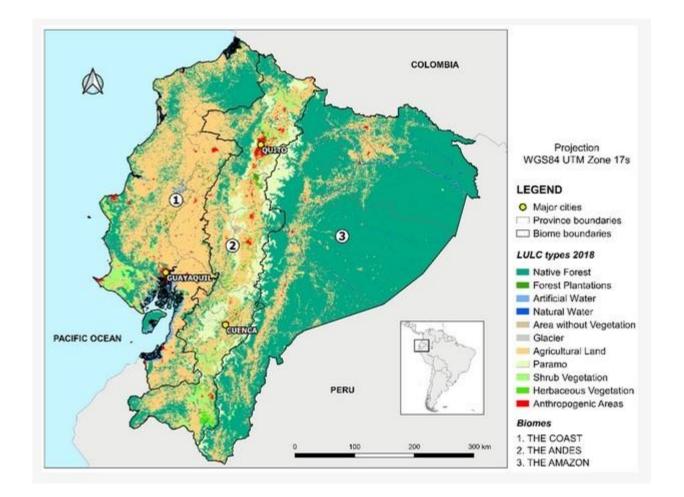
Planting density



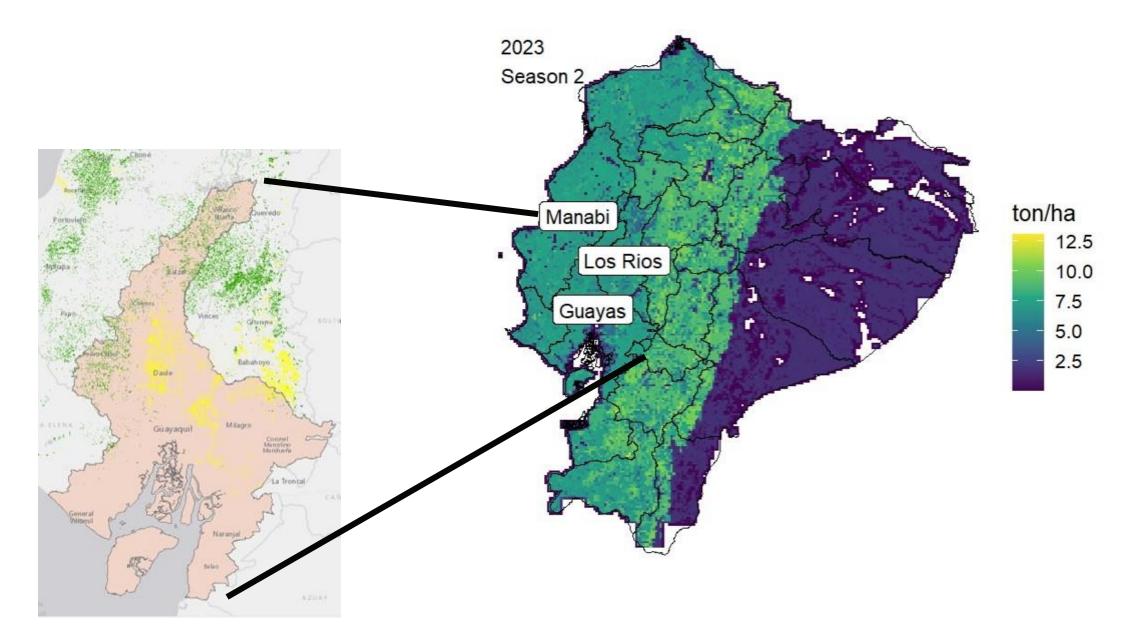
Ecuador:

Model parameterization and calibration

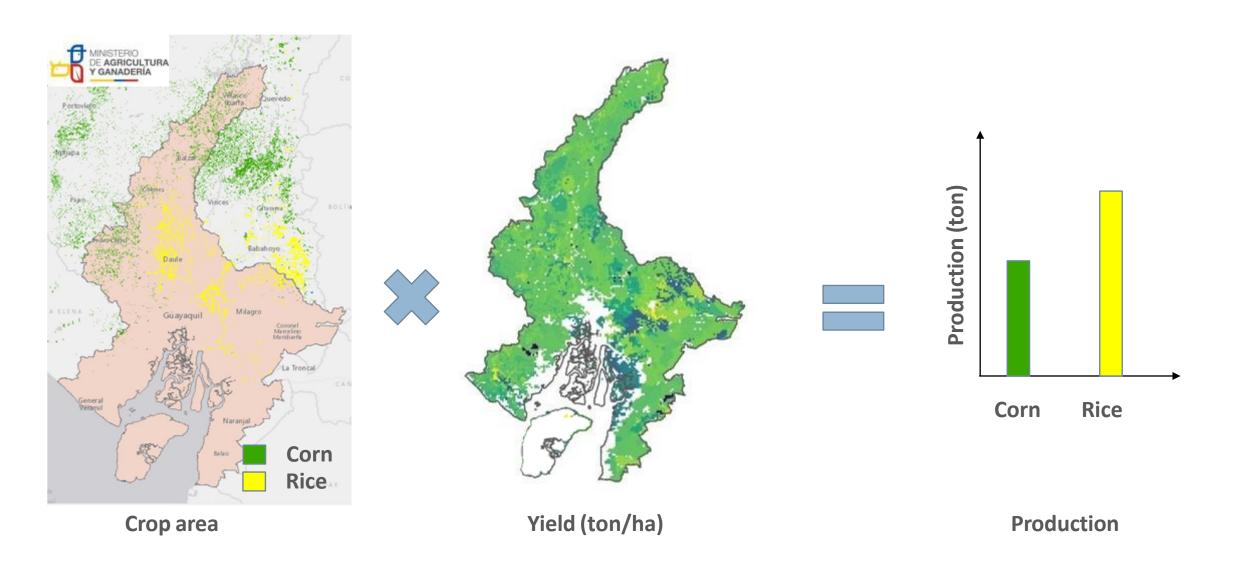
- Using only local soil dataset and global climate data.
- In-country calendar planting.
- Commercial crop production occurs in the coast area.



Crop yields: Maize



Total production

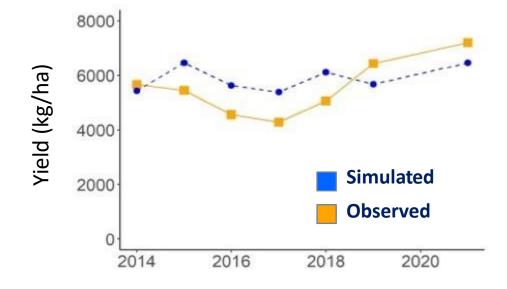


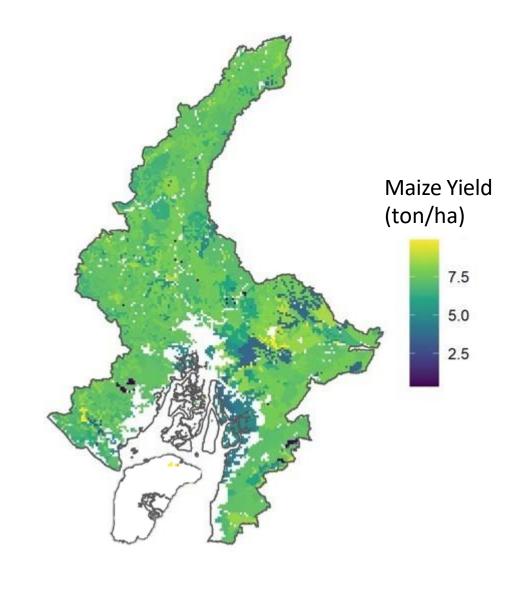
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Crop yields

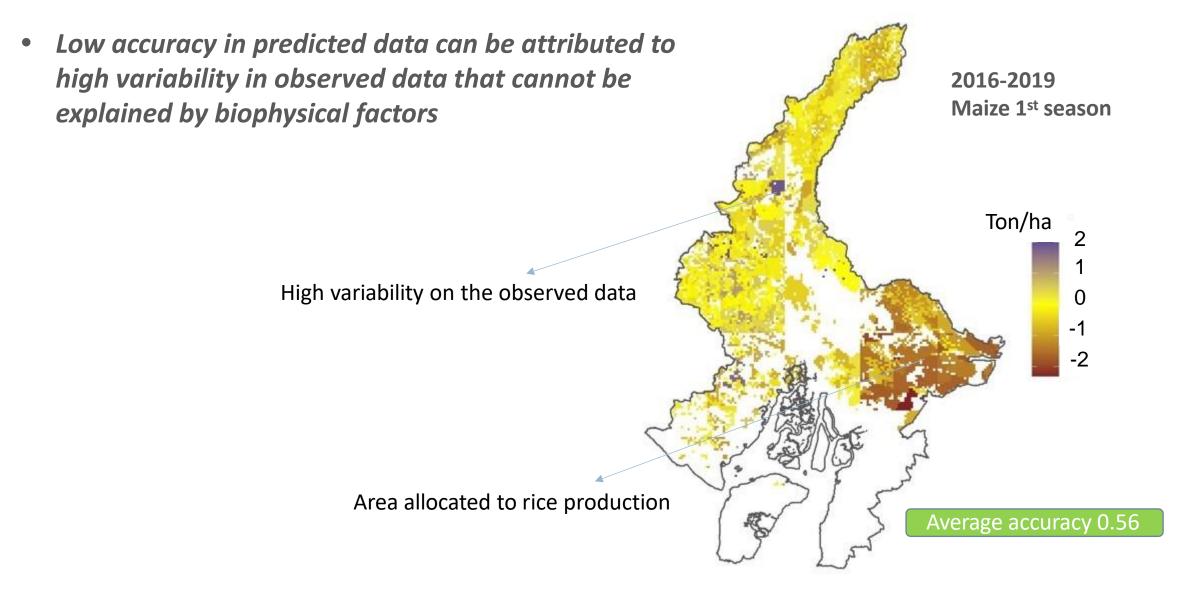
- Simulation of historical and forecasted yields
- Focused on the main food crops (i.e. maize, wheat, soy, rice)







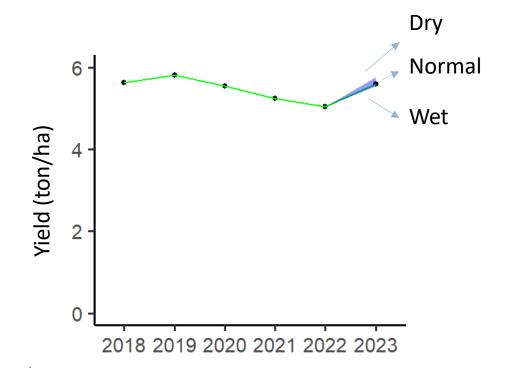
Calibration and uncertainties

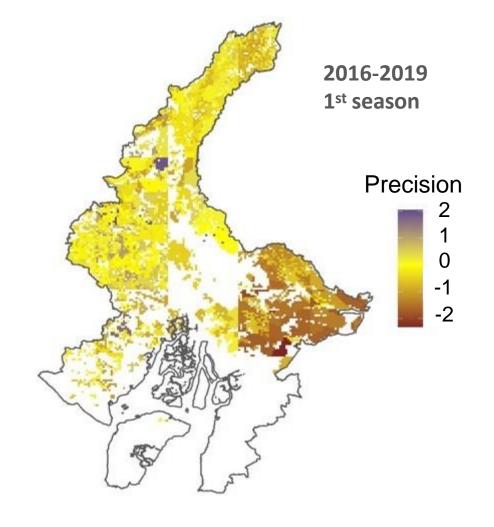




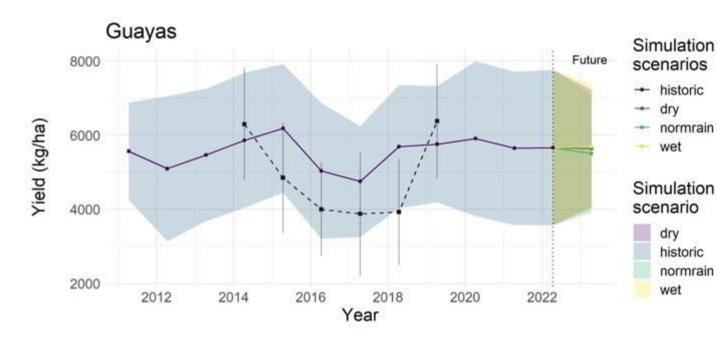
Calibration and uncertainties

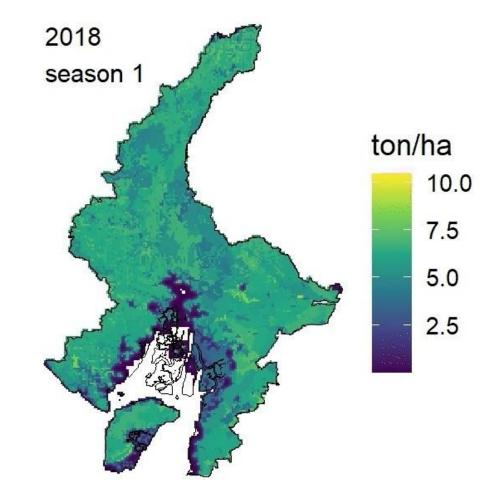
• Future climate for wetter, drier and normal conditions



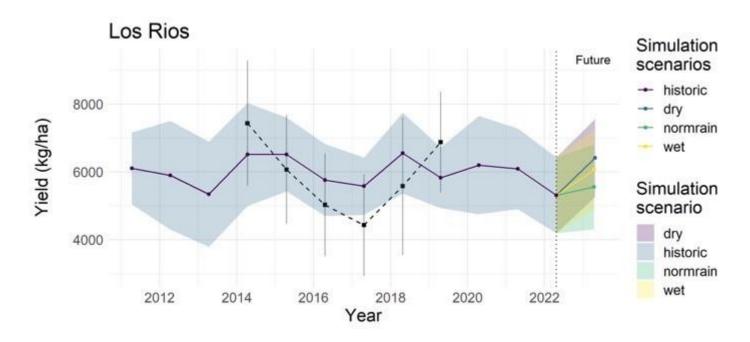


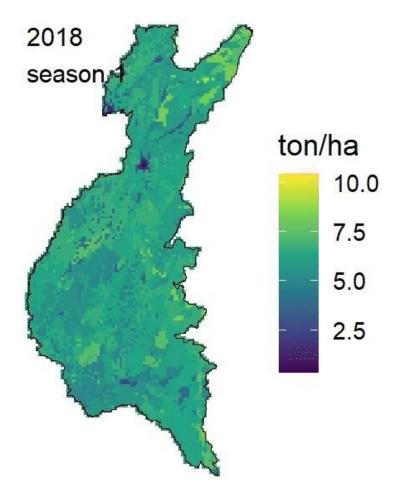
Crop yields: Maize Season 1





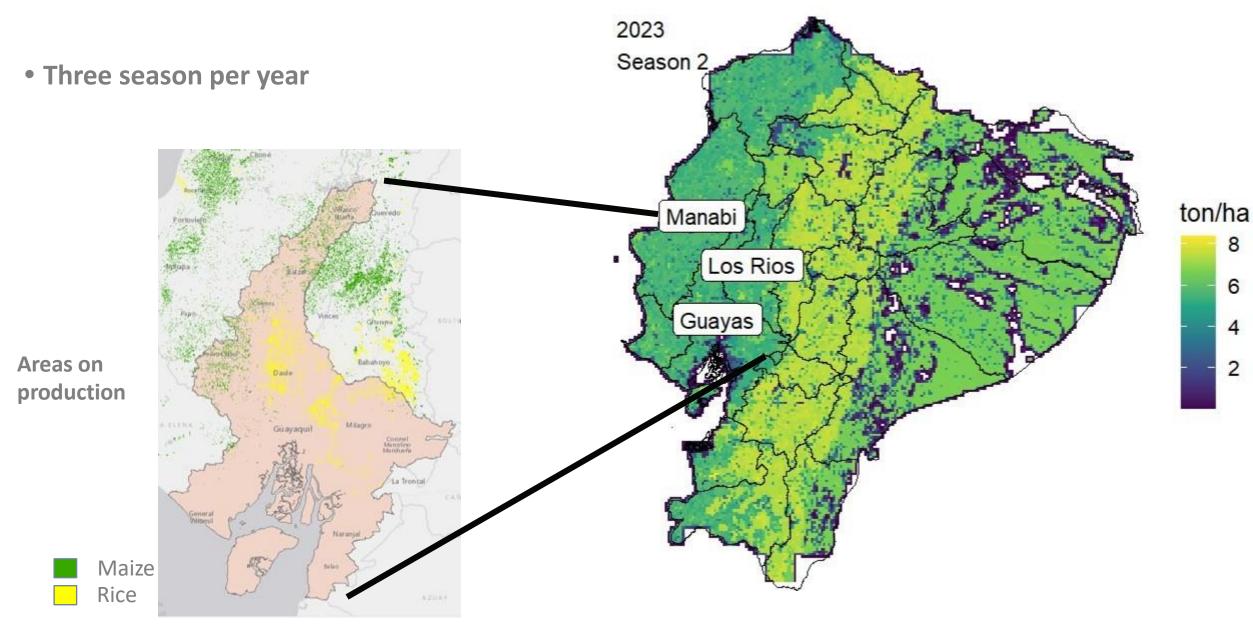
Crop yields: Maize season 2



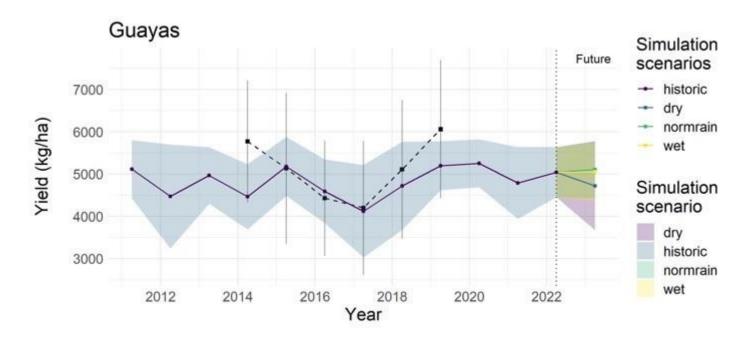


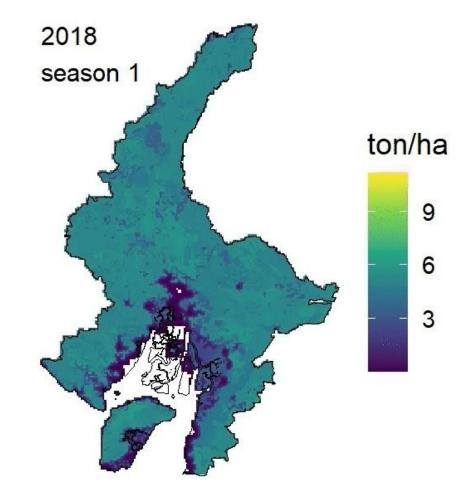


Crop yields: Rice

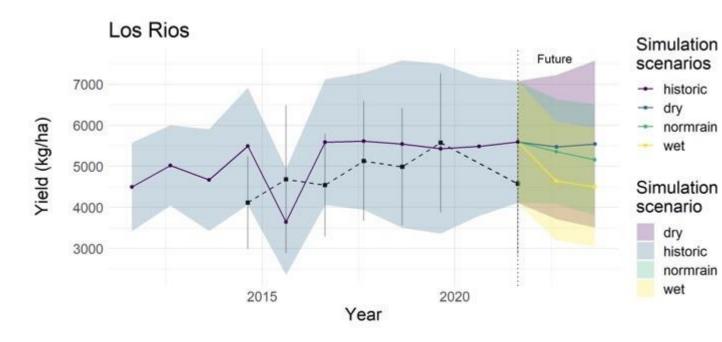


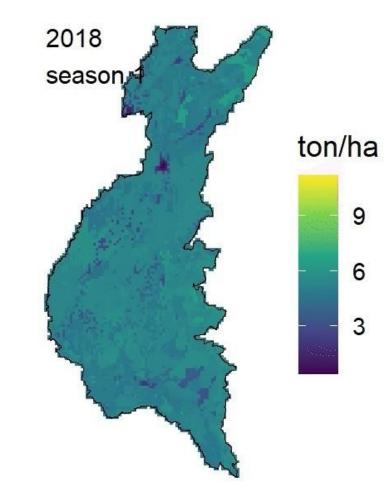
Crop yields: Rice season 1



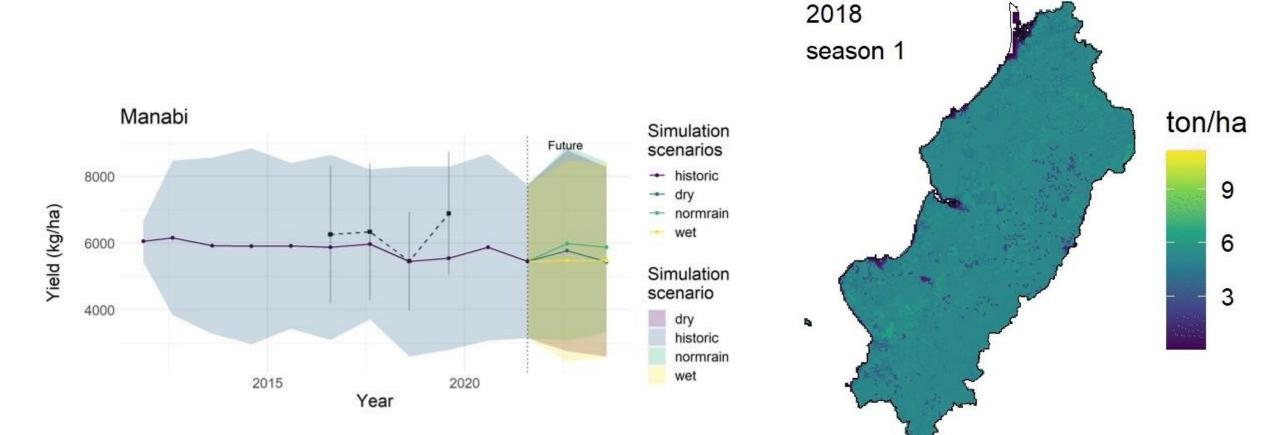


Crop yields: Rice season 2



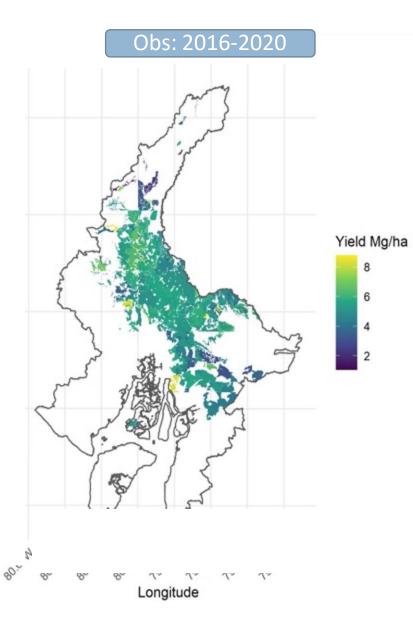


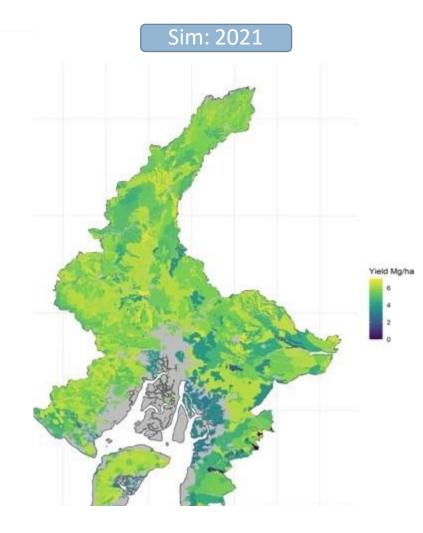
Crop yields: Rice season 3

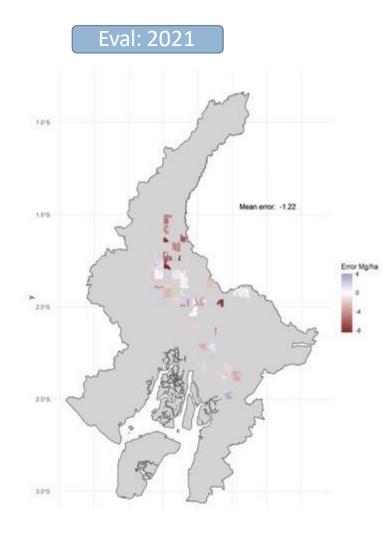


Rice 2021

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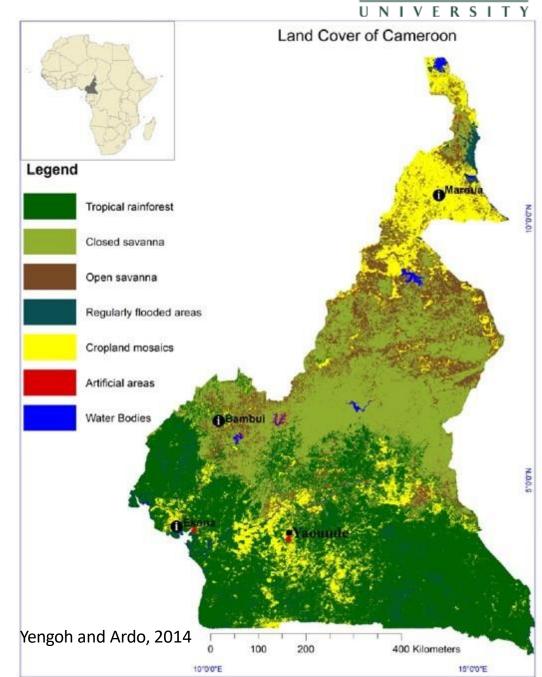


Mean Error: -1.22

Cameroon:

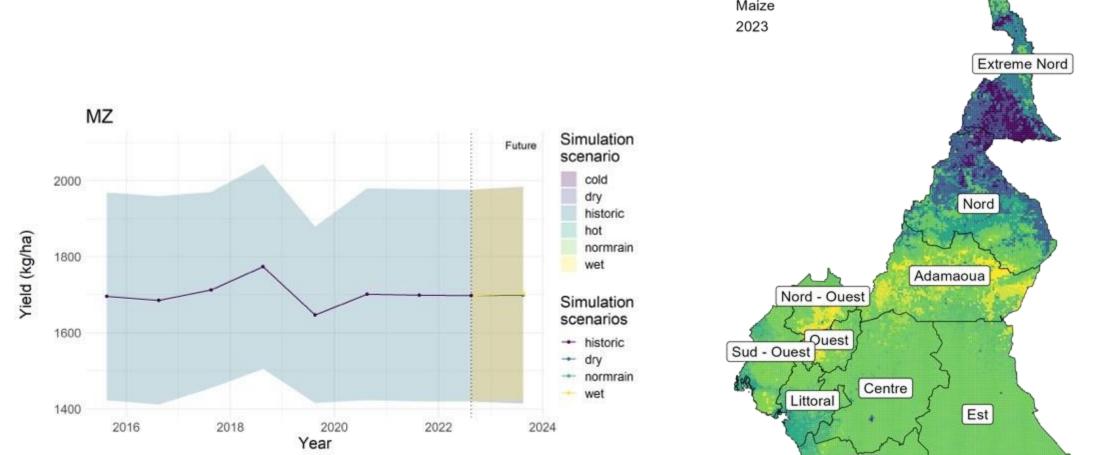
Model parameterization and calibration

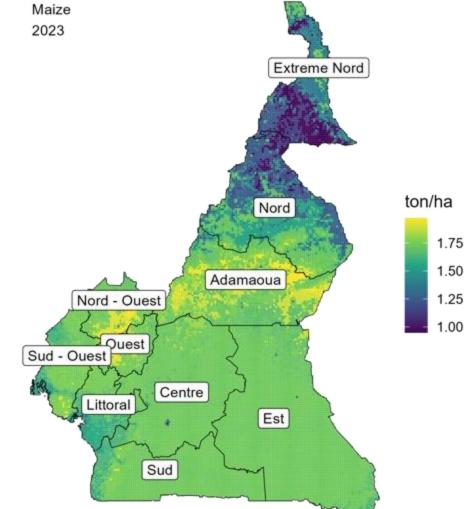
- Using only global soil and climate data
- FAO crop calendar and country wide yield data
- We simulated potential yields for all regions



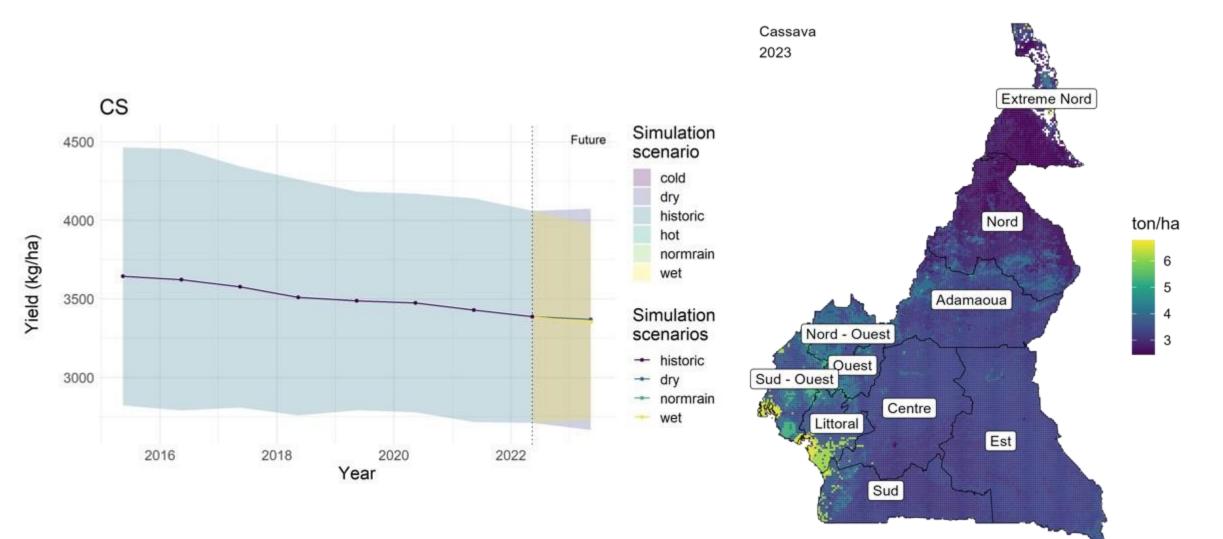
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Crop yields: Maize

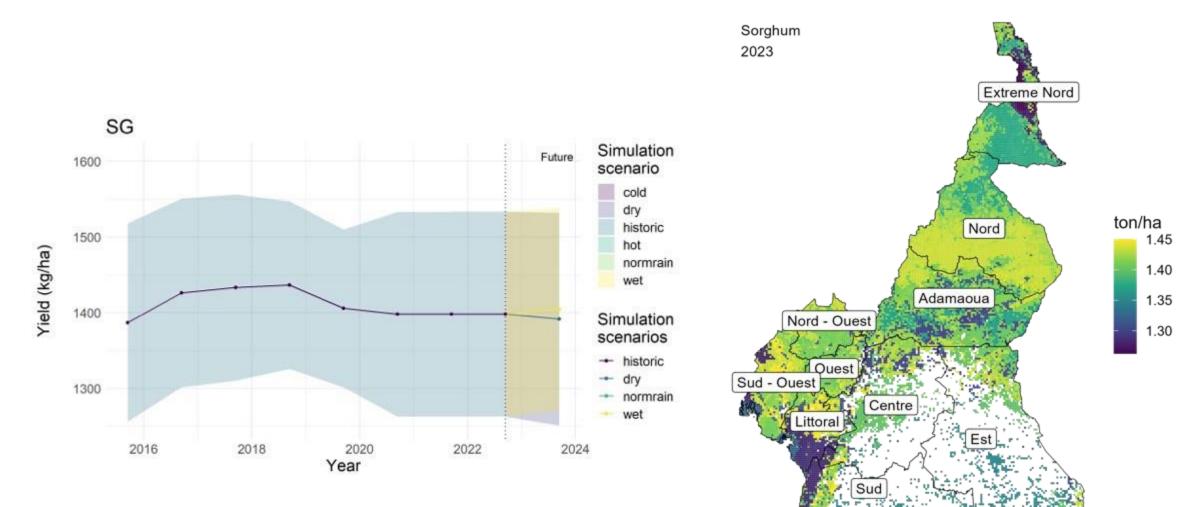




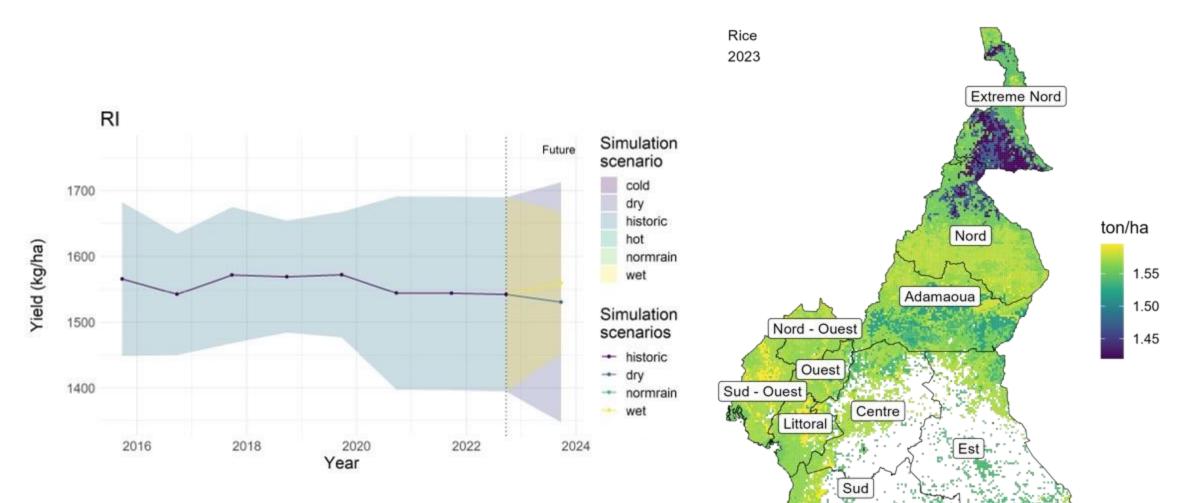
Crop yields: Cassava



Crop yields: Sorghum



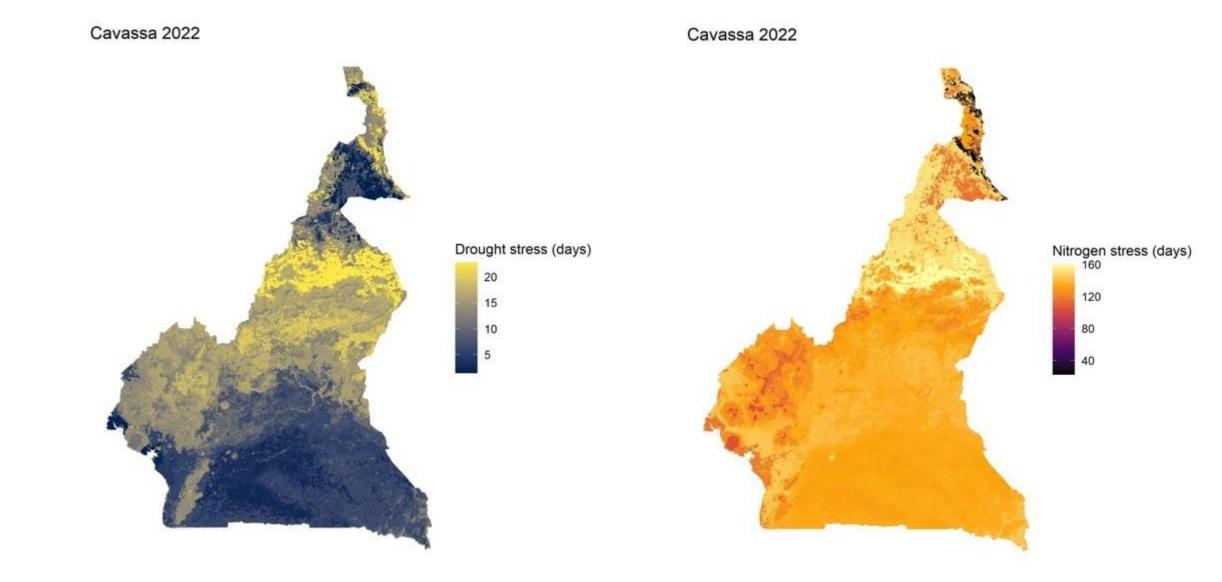
Crop yields: Rice



Using models to improve management: Simulated nitrogen and drought stress

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Crop Yield Forecasting System in Tanzania

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

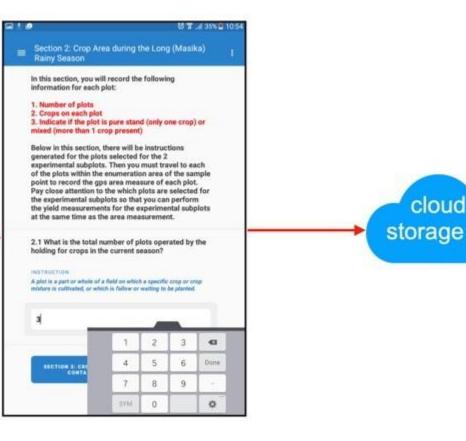
ORIGINAL PAPER

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

Lin Liu¹ • Bruno Basso^{1,2}

Received: 1 May 2019 / Accepted: 20 February 2020 / Published online: 5 March 2020 © The Author(s) 2020





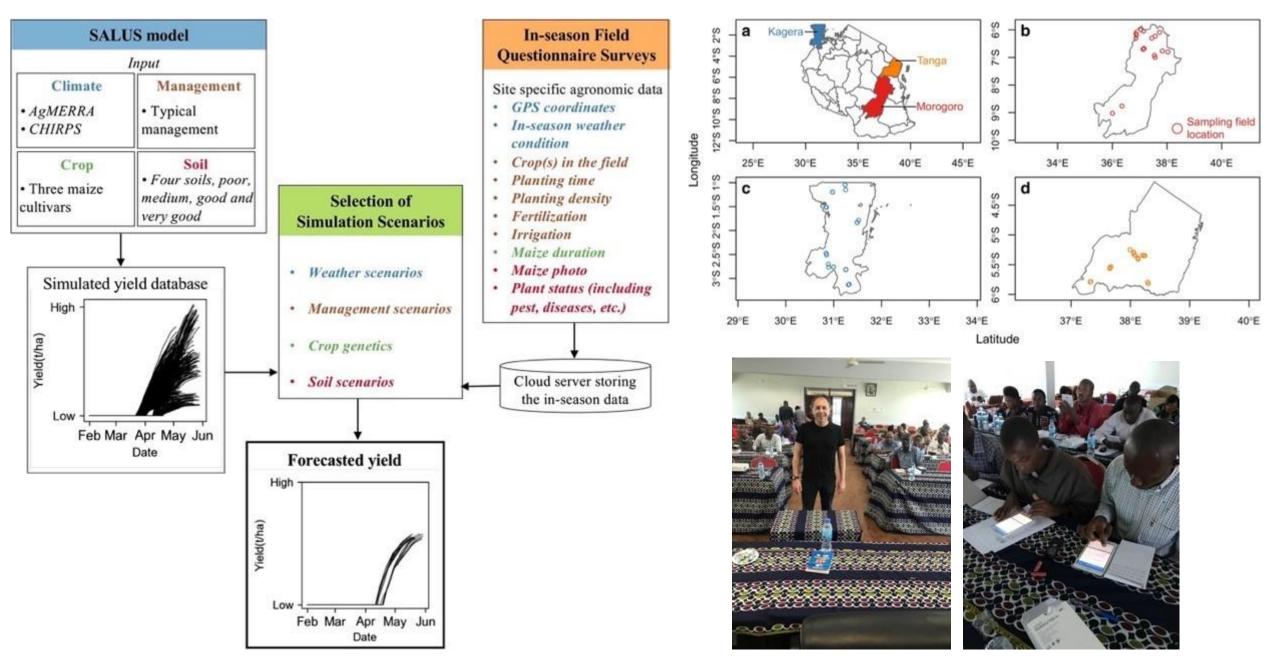


Example of field survey

	SECTION 3: CROP YIELD - INFORMATION FOR FIRE, 7	Plot - Crops roster - Maize
Sample Point ID Latitude:	= Plot - Crops roster - Maize 🥂 :	3.2I. How was the weather before Maize was
	3.2c When was Maize planted?	planted?
Tap to enter text	C Early February	
	Mid-February	O Dry and hot
	C Late February	
1.2 Sample Point ID Longitude:	C Early March	O Dry and cold
	O Mid-Margh	 Average rain and temperature
Tap to enter text	3.2d Which variety for Maize?	0
	 Short duration (3 months) 	O Wet and cold
	C Long duration (4 months)	O Wet and hot
	3.2e. Select all of the fertilizers which have been applied to Maize	
	I SA	3.2m. How is the overall plant condition of Maize?
Tap to enter number	C CAN	maize:
	D NPK	O Very poor
	C Stren	O Very poor
	None	O Poor
Tap to enter text	3.2f. Has cow manure been applied to Malze?	O Good
	O Yes	
	O No	 Very good

Crop Yield Forecasting System





Field Survey

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

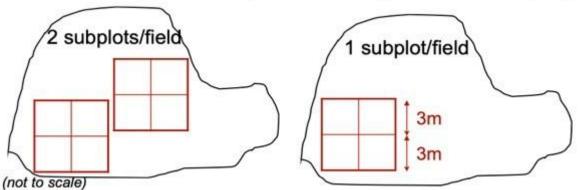
Validation of the methodology (2nd visit)

• 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

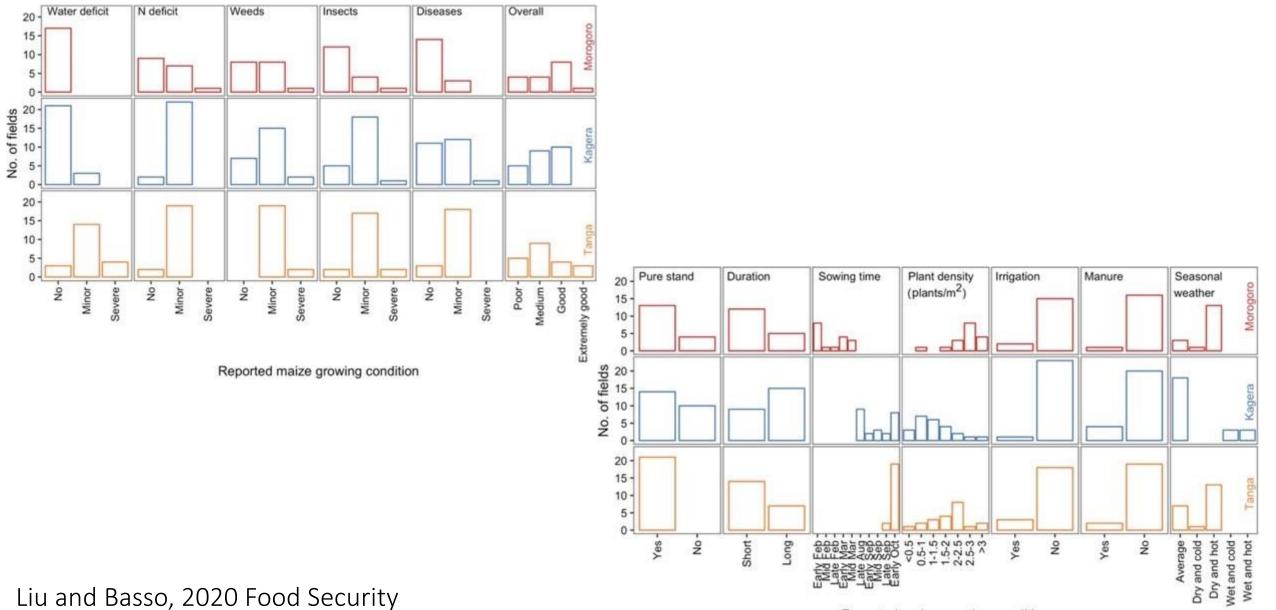


In-season Field Questionnaire Surveys Site specific agronomic data **GPS** coordinates . In-season weather condition Crop(s) in the field **Planting time Planting density** Fertilization ٠ Irrigation . Maize duration Plant status & maize ٠ photo Insects, diseases, weeds .

Liu and Basso, 2020 Food Security

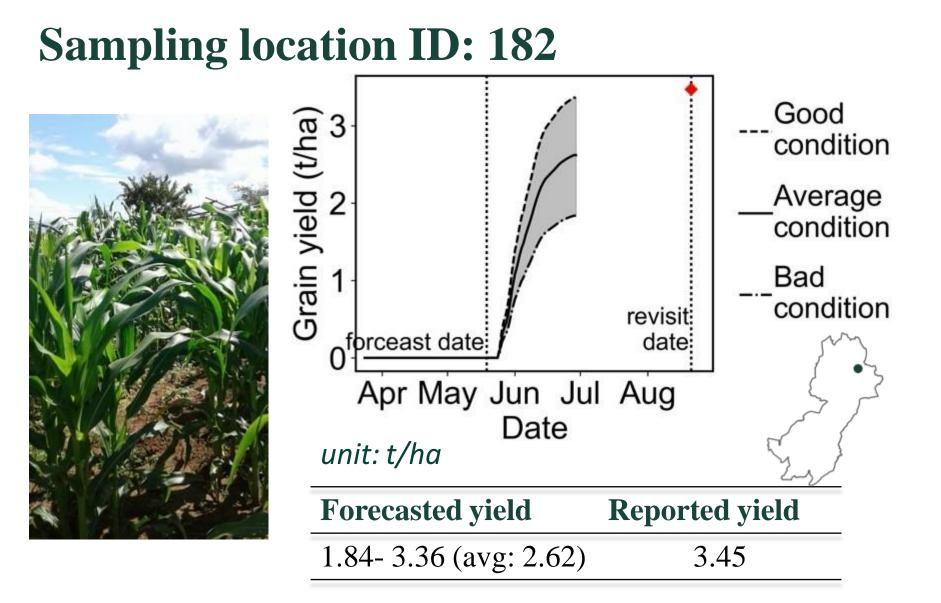
Results from field survey



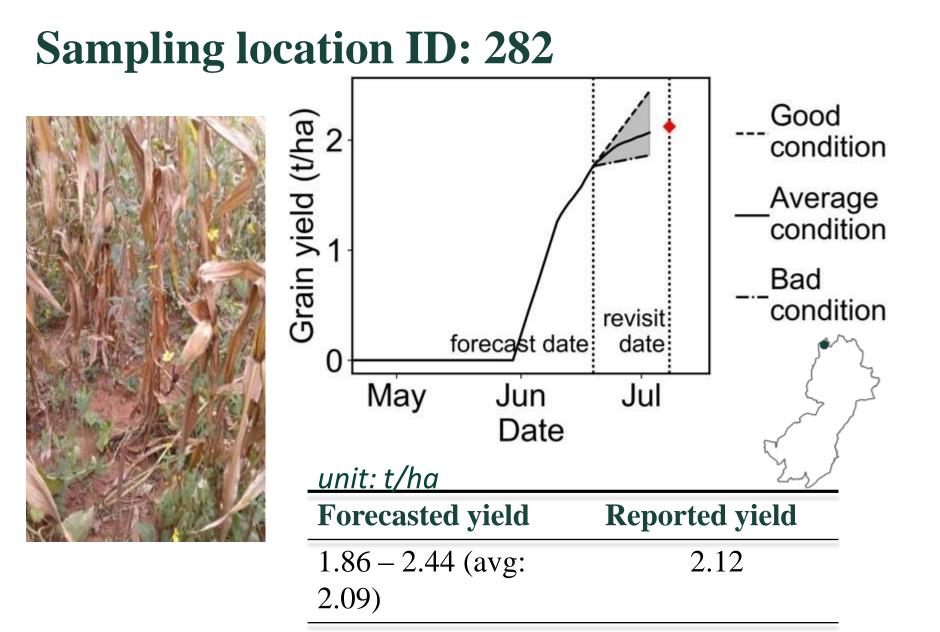


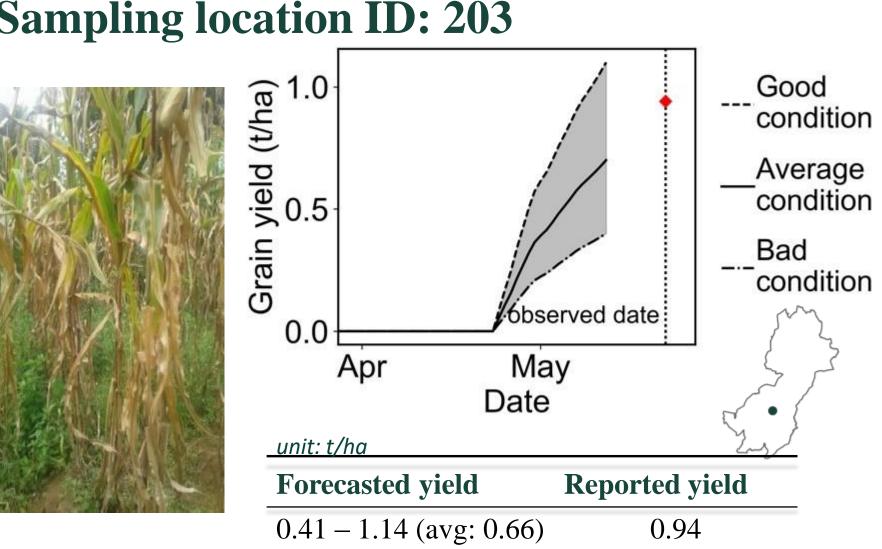
Reported maize growing condition

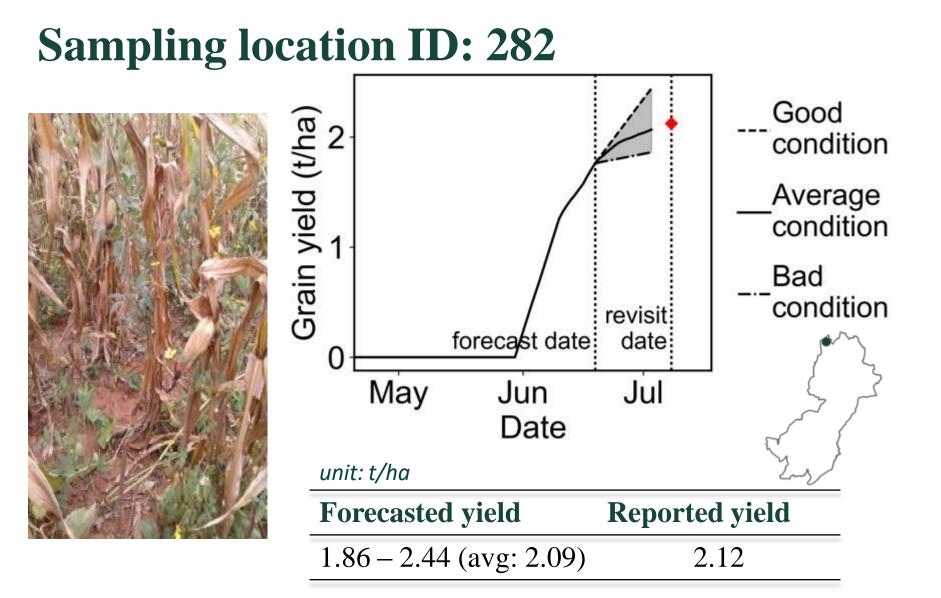


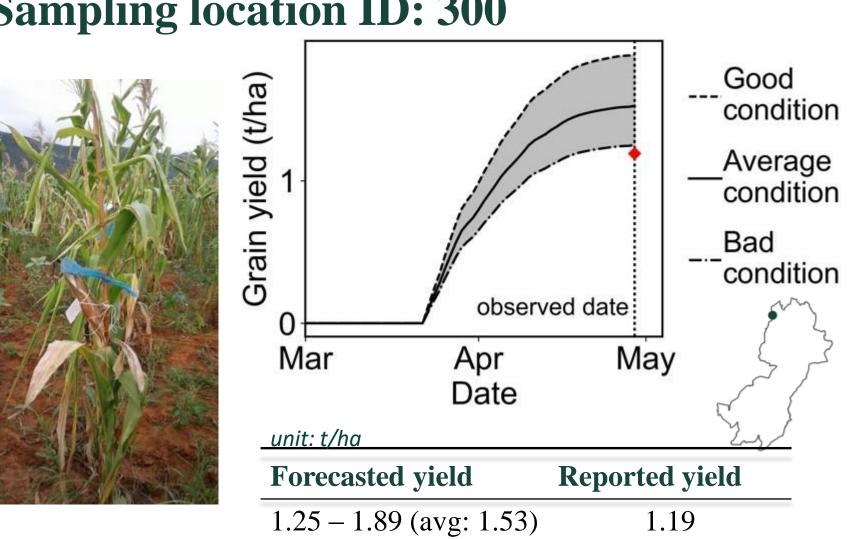


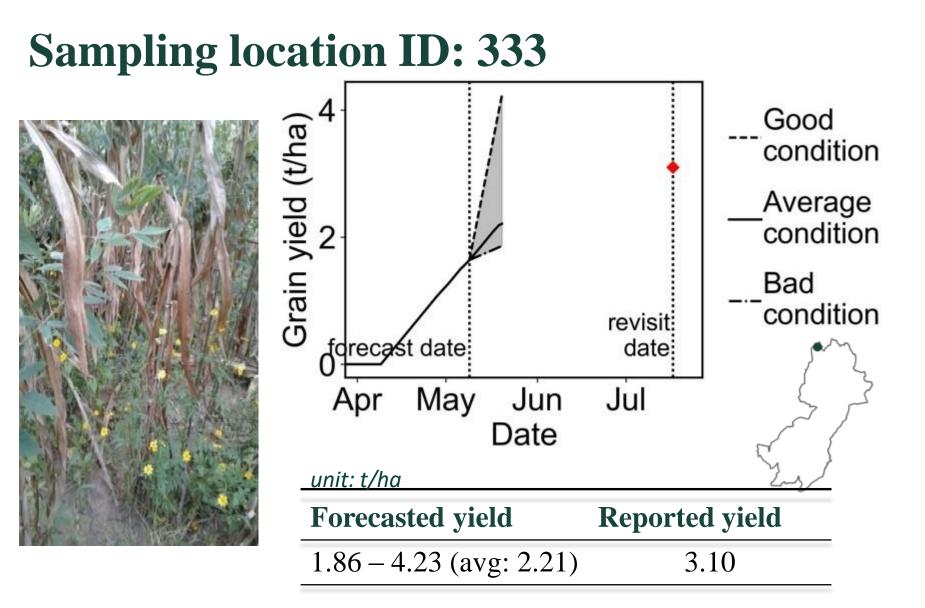


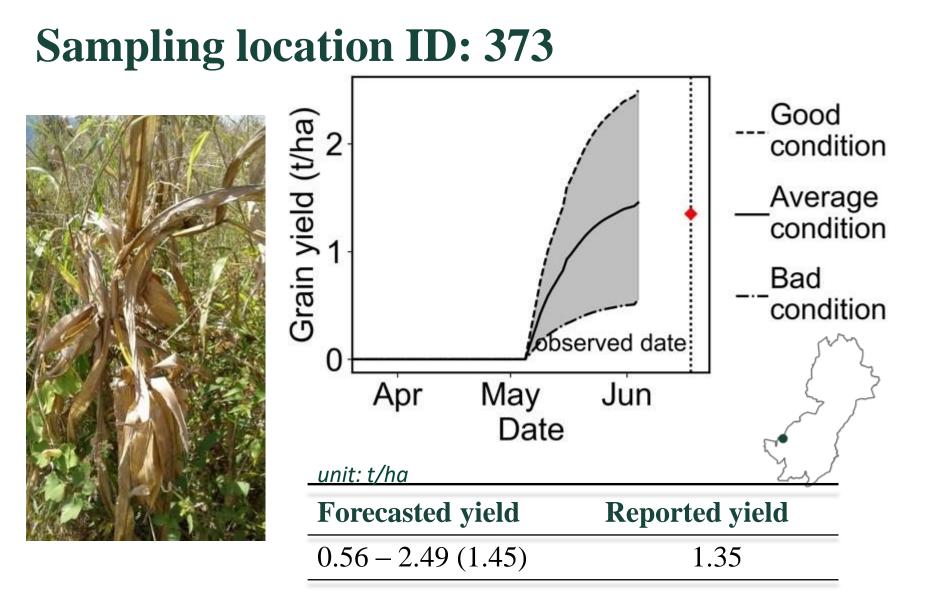


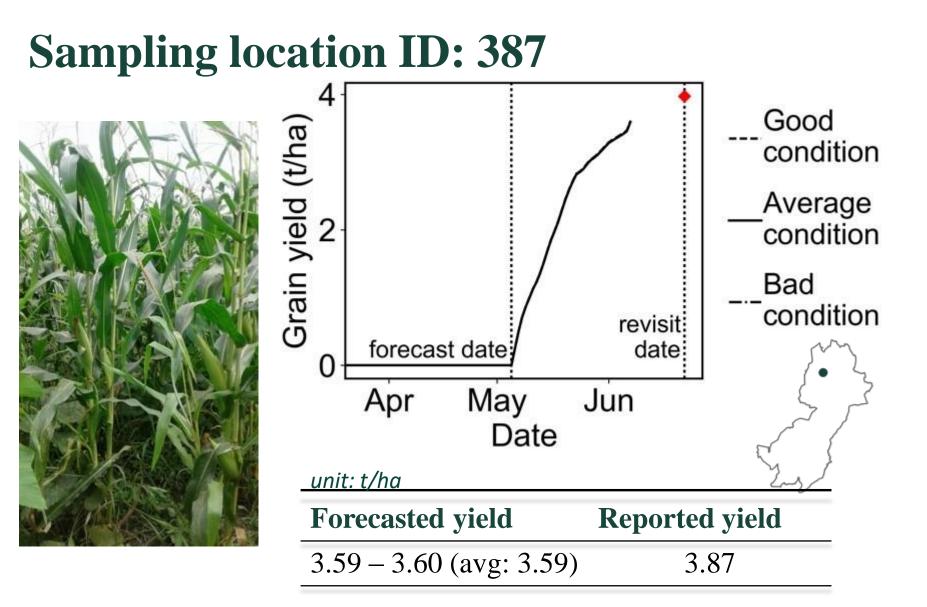


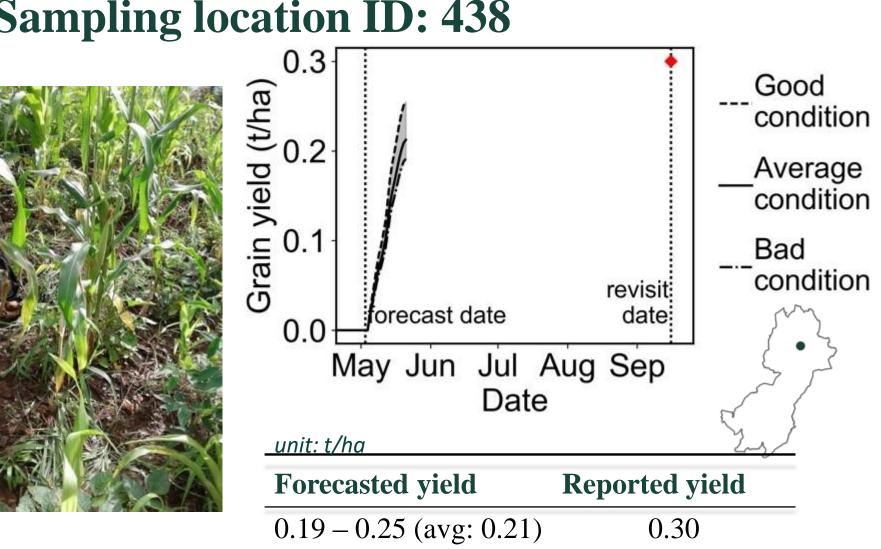


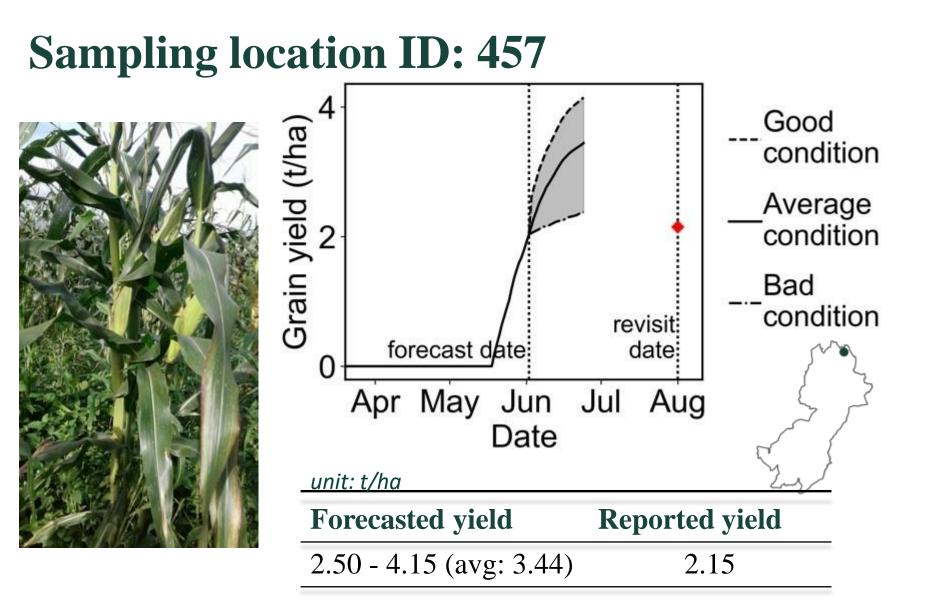


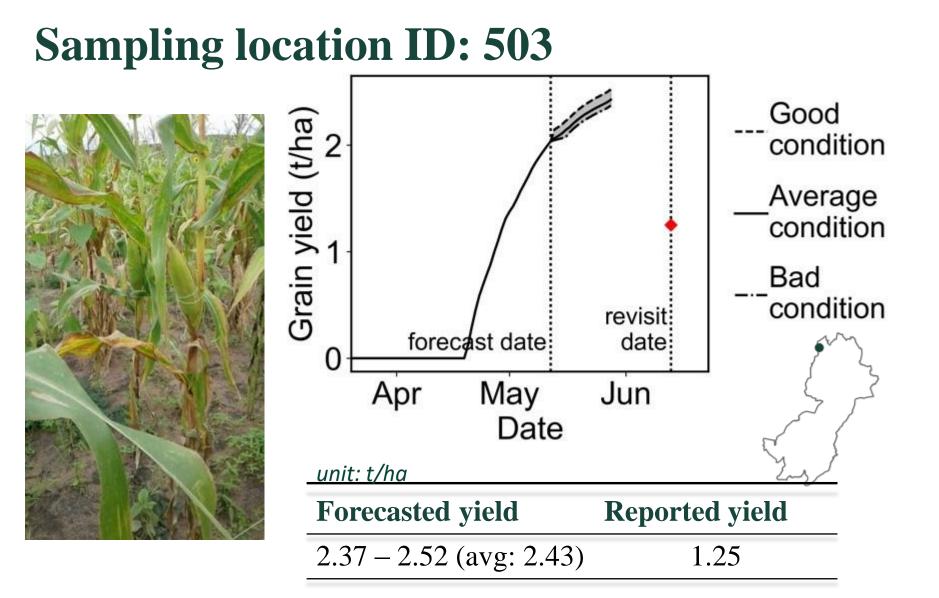


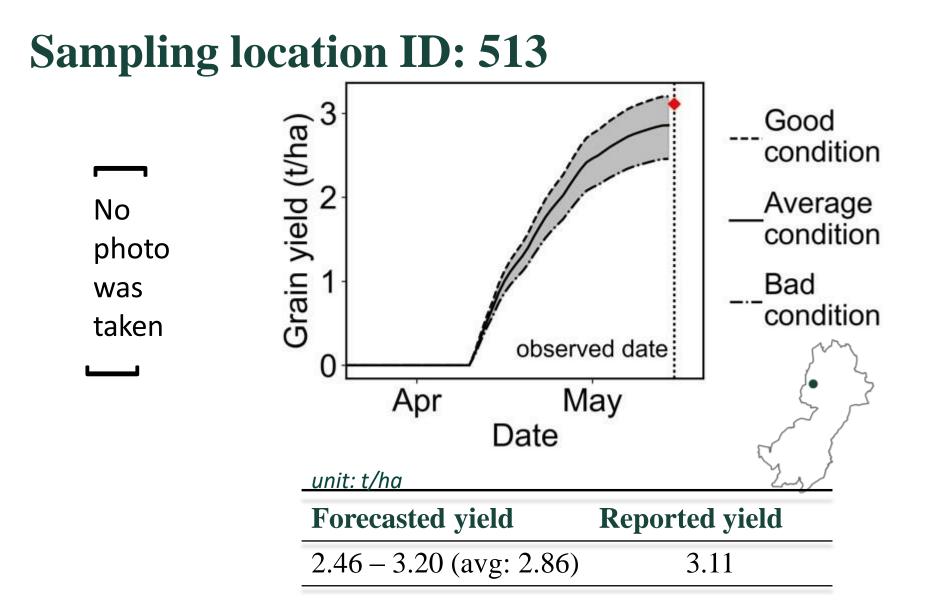


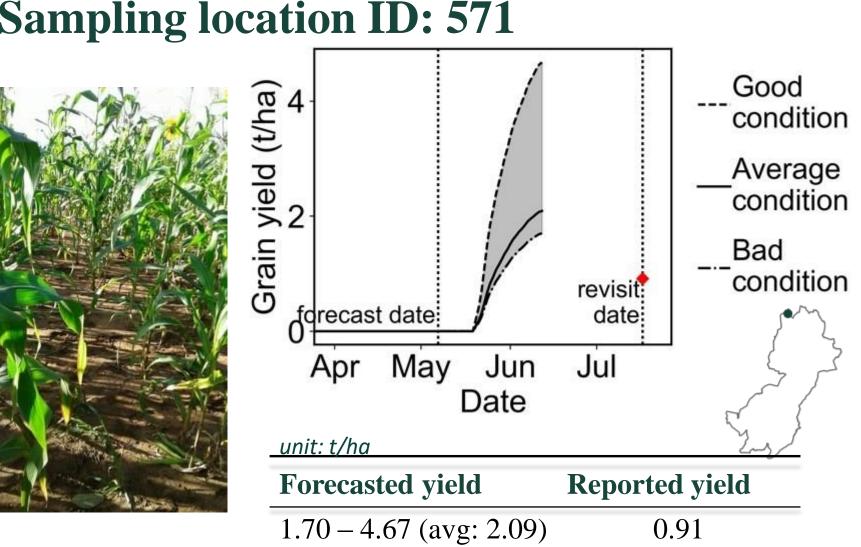


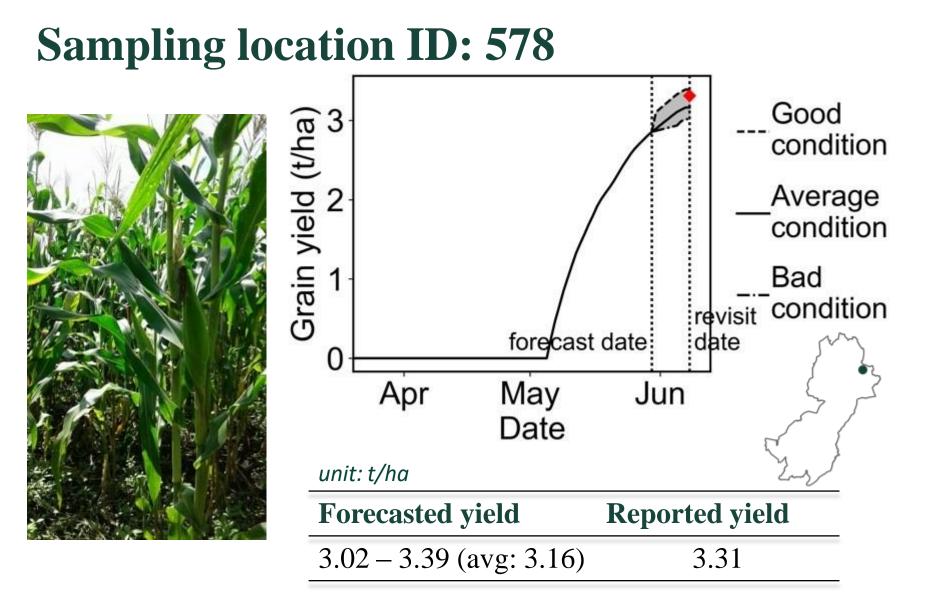


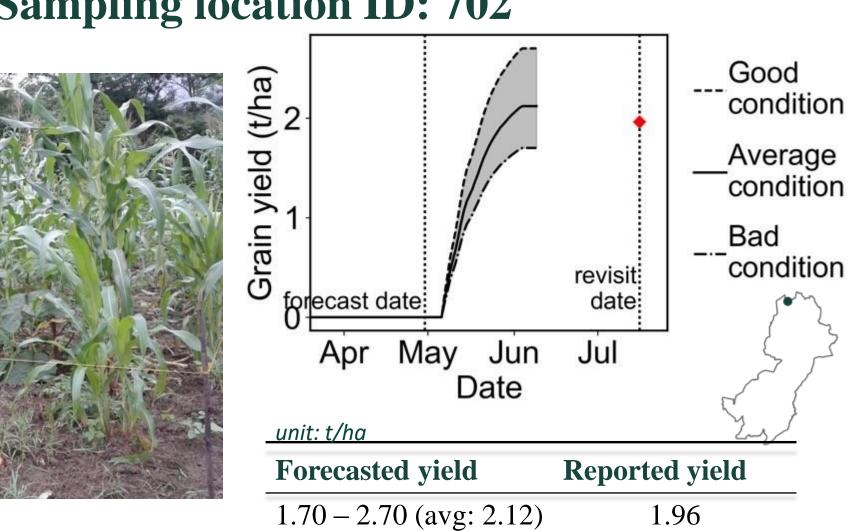


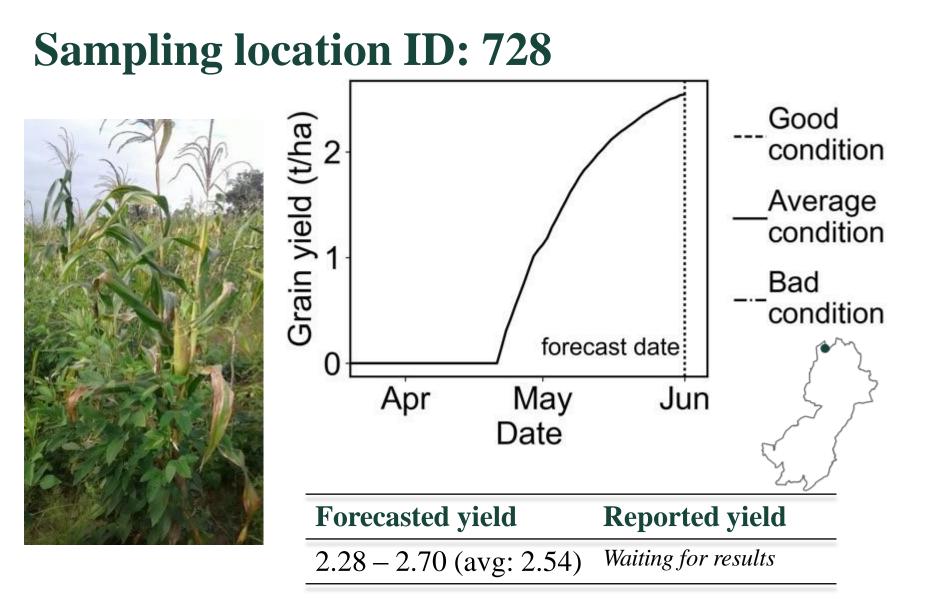


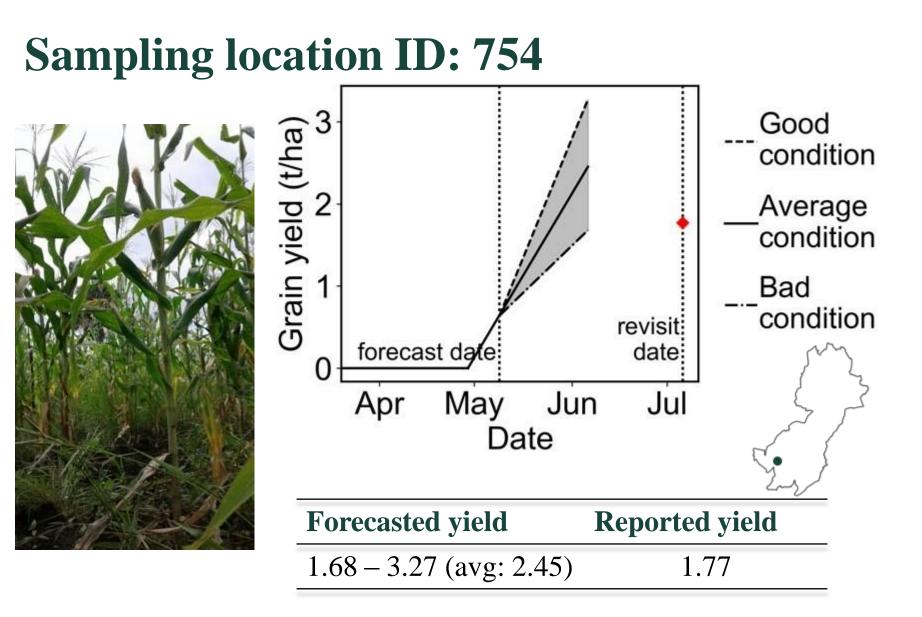


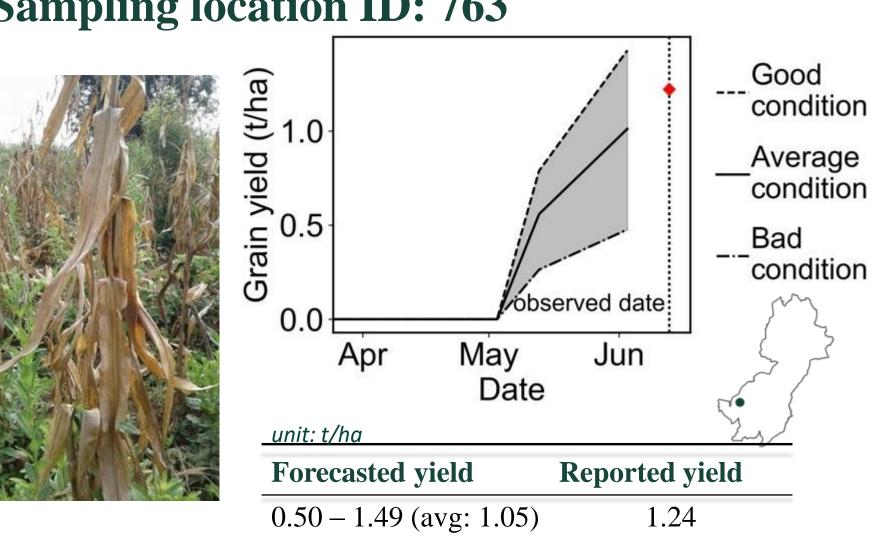


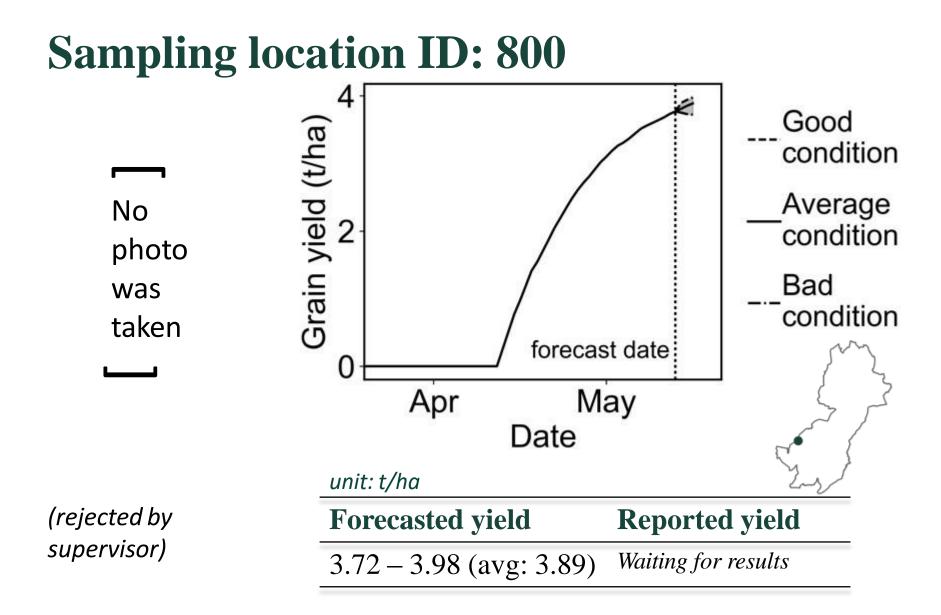


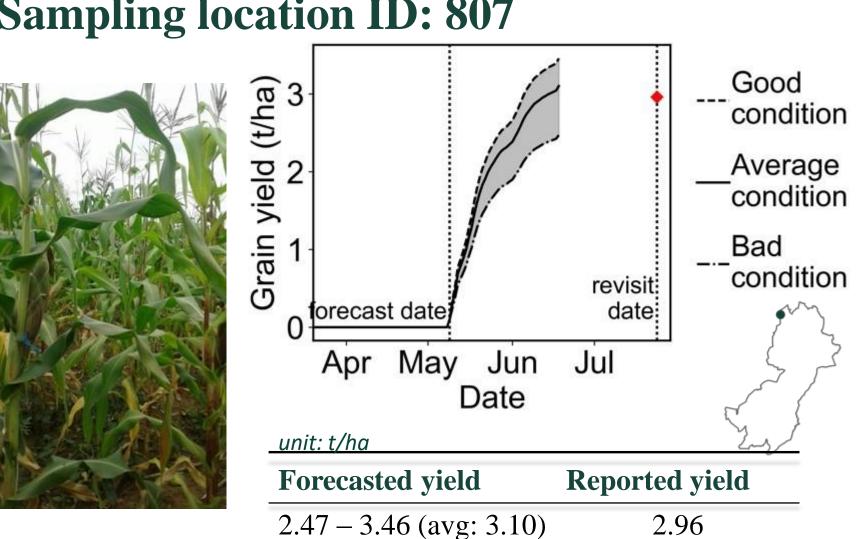


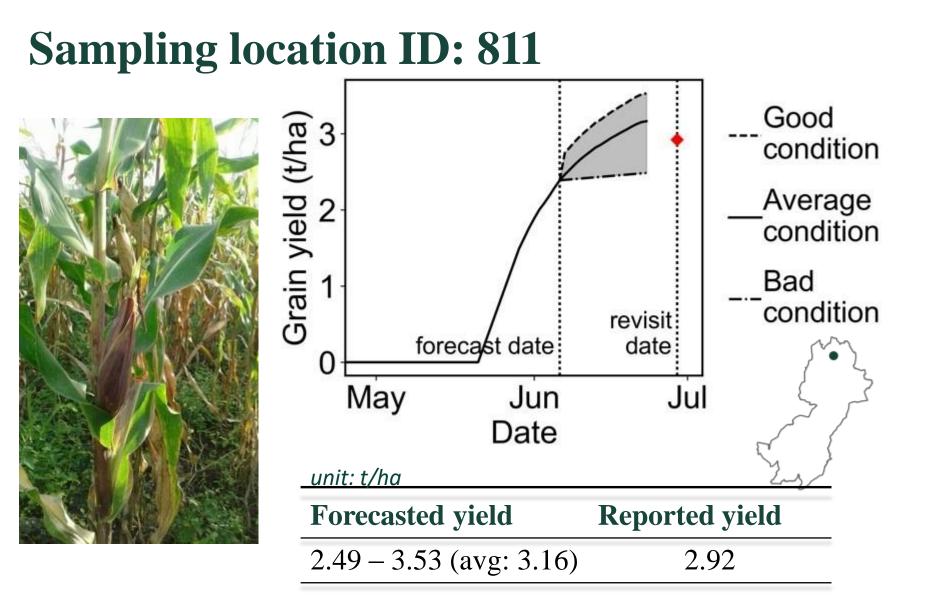




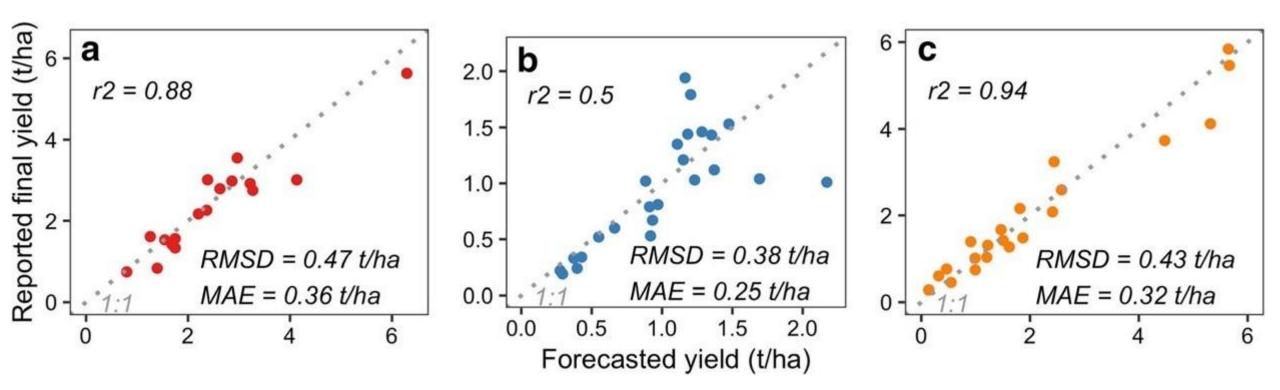






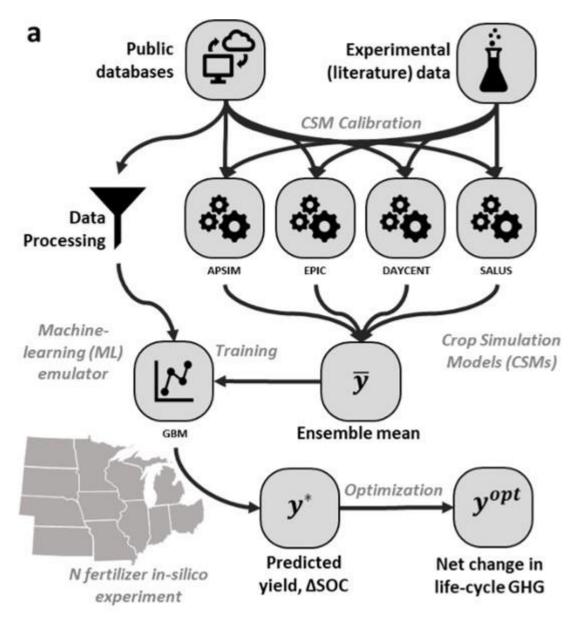


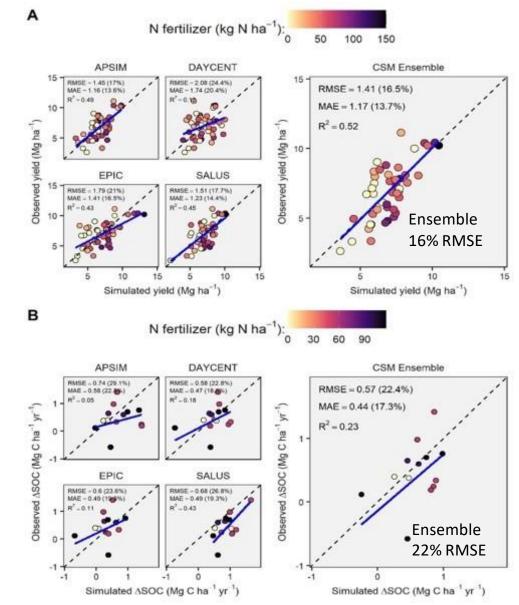
Results of crop yield forecast for three districts in Tanzania



MICHIGAN STATE

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)



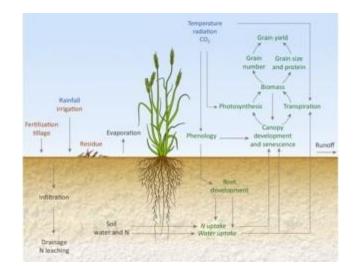
The Pros:

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:

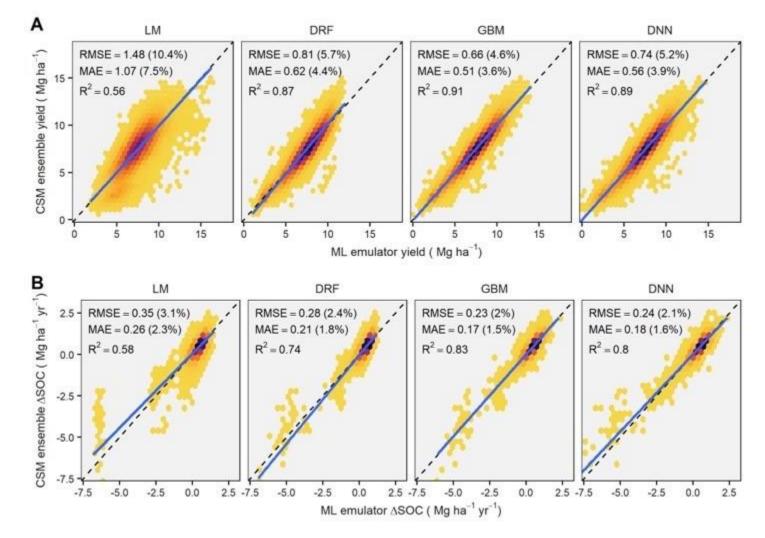
Steep learning curve Difficult to set up and (re)calibrate Idiosyncratic (bias, model structure) Computationally expensive (complex, slow to run on large scales)

Better performance when predicting the ensemble rather than single-models

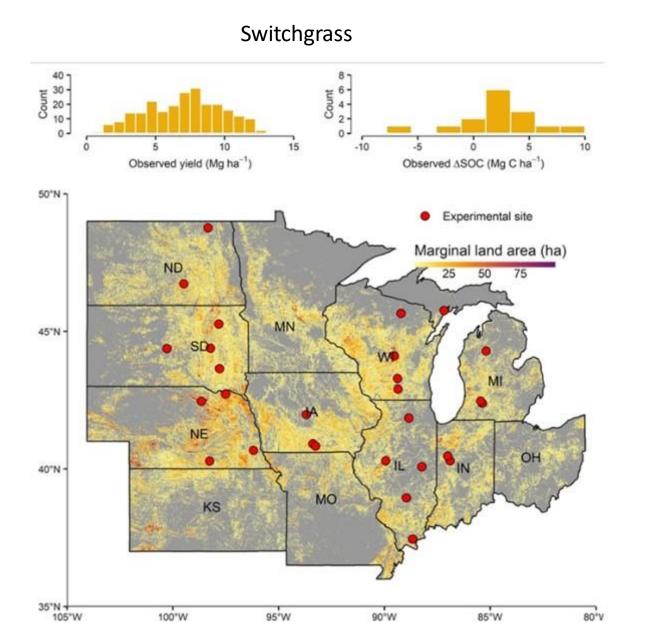
ML models

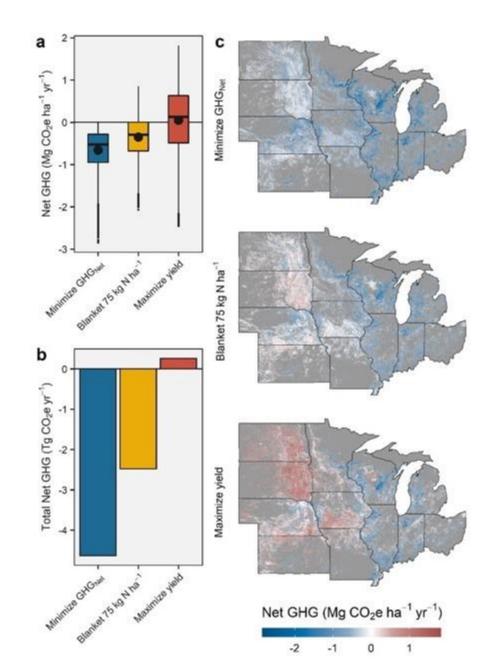
Generalized Linear Model (LM) Distributed Random Forest (DRF) Gradient Boosted Machines (GBM) Deep neural network (DNN)

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



Multi-model response to N rates





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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CLIMATE TRACE