Combining a Process Based Model with Machine Learning for Potato Yield Prediction in Prince Edward Island, Canada

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Agriculture et Agroalimentaire Canada

Image source: https://atlantic.ctvnews.ca/prince-edward-island-farmers-destroy-136-million-kilos-of-spuds-1.5799465

Acknowledgments

The funding for this project was provided by Agriculture and Agri-Food Canada
René Morissette and Guillaume Jégo for their help and assistance with STICS
Kristen Murchison for climate data processing, gap filling and technical support

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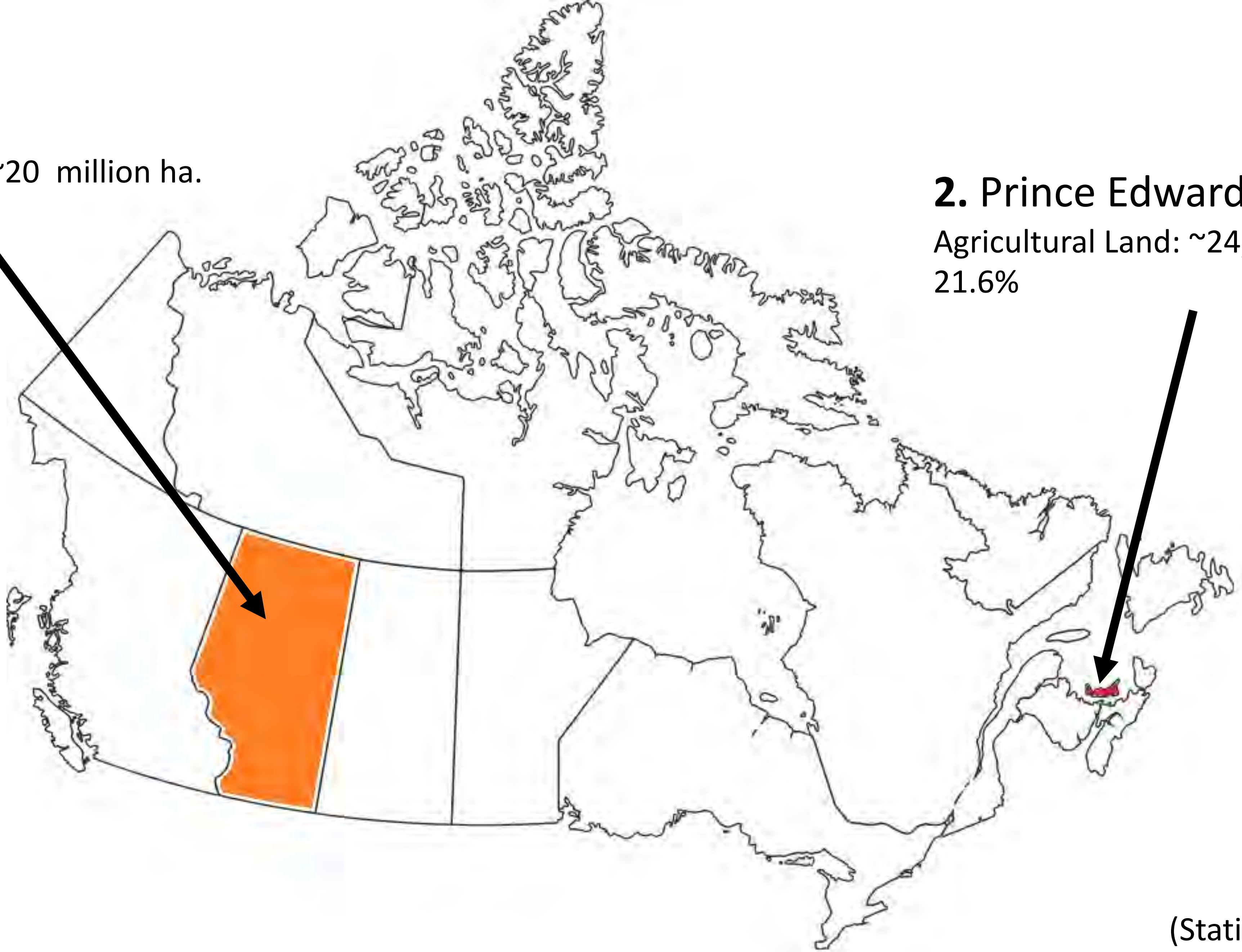
Canada



1. Alberta

Agricultural Land: ~20 million ha.
21.8%

2. Prince Edward Island

Agricultural Land: ~24,000 ha.
21.6%

(Statistics Canada, 2022)

Potato Production in Prince Edward Island

24.2%

of all land area

84%

of total exported agrifood products

10.8%

of the GDP

(Maqsood et al., 2020)


CFIA finds potato wart in 2 Prince Edward Island fields

Discovery has led to temporary suspension of seed potato expor

Nancy Russell · CBC News · Posted: Dec 02, 2020 5:00 PM AST | Last Updated: Dece


P.E.I. potato farmers worried excess n caused by Fiona may damage crops

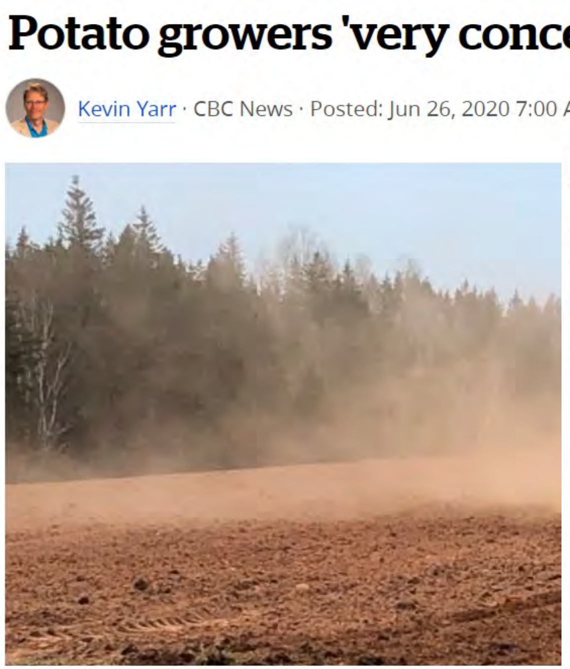
Potato Board says three warehouses lost entire roofs during st

Arturo Chang · CBC News · Posted: Sep 29, 2022 1:23 PM ADT | Last Updated: Sep


Record broken as P.E.I. enters 5th day of heat wave

Kevin Yarr · CBC News · Posted: Jul 25, 2022 7:53 AM ADT | Last Updated: July 25, 2022

https://www.cbc.ca/news/canada/prince-edward-island/pei-heat-wave-july-2022-1.6530900#:~:text=The%20temperature%20at%20Charlottetown%20Airport,about%207%20C%20above%20normal


Potato growers 'very concerned' by P.E.I. drought

Kevin Yarr · CBC News · Posted: Jun 26, 2020 7:00 AM ADT | Last Updated: June 26, 2020

https://www.cbc.ca/news/canada/prince-edward-


P.E.I. potato harvest yields fewer sp drought

Sara Fraser · CBC News · Posted: Oct 29, 2020 5:21 PM ADT | Last Updated: (

https://www.cbc.ca/news/canada/prince-edward-island/pei-potato-harvest-2020-1.5782193


Maritime farmers holding breath as record-dry spring wrings region

LUKE DYMENT

PUBLISHED MAY 23, 2023

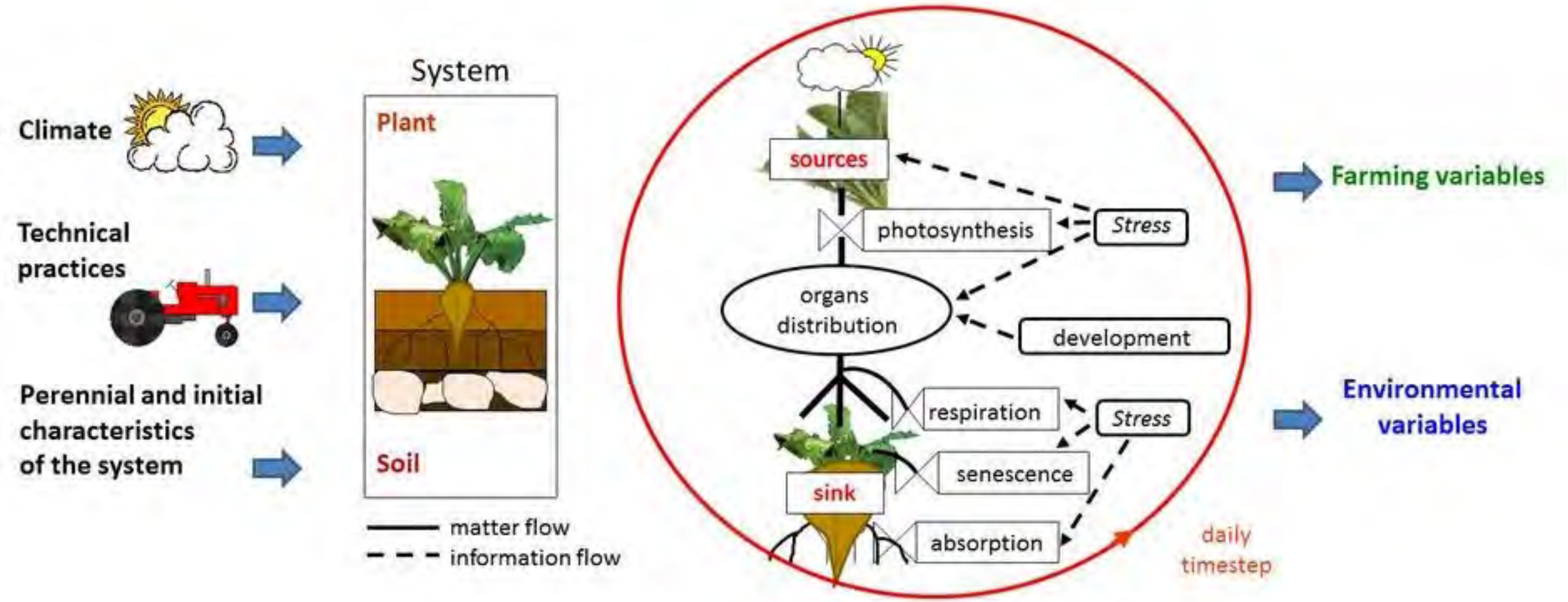
UPDATED MAY 24, 2023

https://www.theglobeandmail.com/business/article-maritime-farmers-holding-breath-as-record-dry-spring-wrings-region/

STICS

Simulateur mulTIdisciplinaire pour les Cultures Standard / Multidisciplinary Simulator for Standard Crops

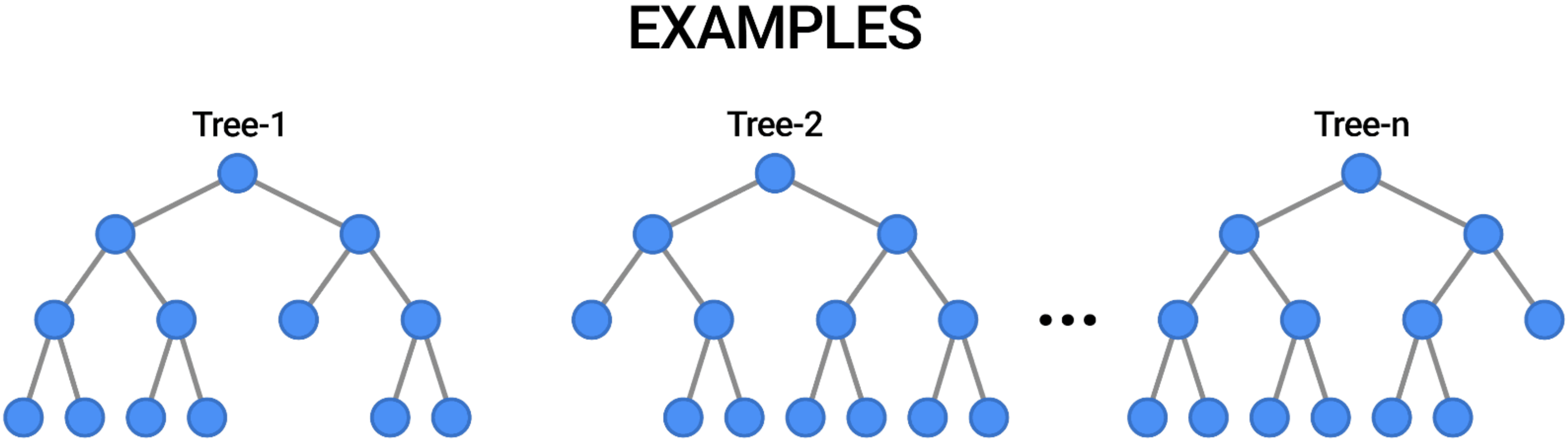
Inputs **System - process** **Outputs**



(Brisson et al., 2003)

Image source: https://www6.paca.inrae.fr/stics_eng/About-us/Stics-model-overview/Operating-principles

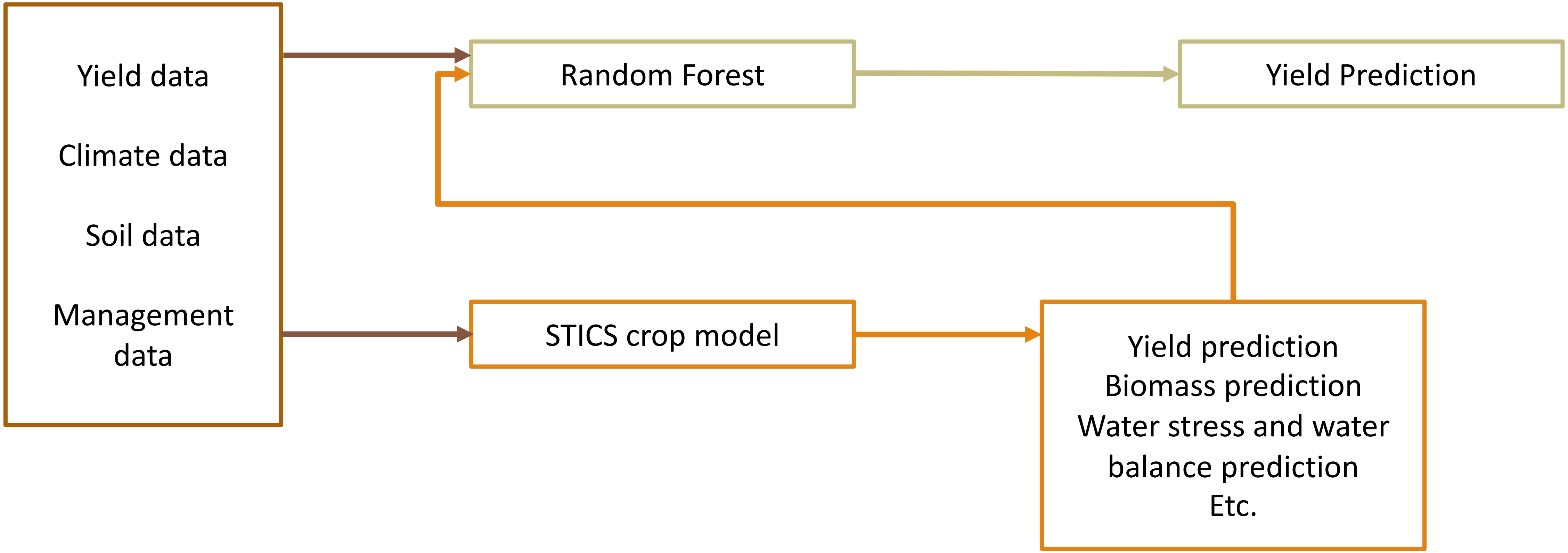
Random Forest (RF)



(Breiman, 2001)

Animation Source: https://blog.tensorflow.org/2021/05/introducing-tensorflow-decision-forests.html

Hybrid Approach


Yield data

Climate data

Soil data

Management data

Random Forest

Yield Prediction

STICS crop model

Yield prediction
Biomass prediction
Water stress and water balance prediction
Etc.

From Shahhosseini et al. (2021) Concept Framewor

Research Questions

Can a crop model calibrated on research farm data be used for industrial fields?

Can Random Forest predict the yield of unseen fields-years?

Will a hybrid approach improve model performance?

Industrial Farm Data

Provided by Matt Ramsay
Oyster Cove Farms, Prince County, PEI
46°29’N, 63°42’ W
2015-2021, excluding 2018

Source: Esri, Maxar, Earthstar Geographics, and the GIS User Community

STICS Calibrated Model

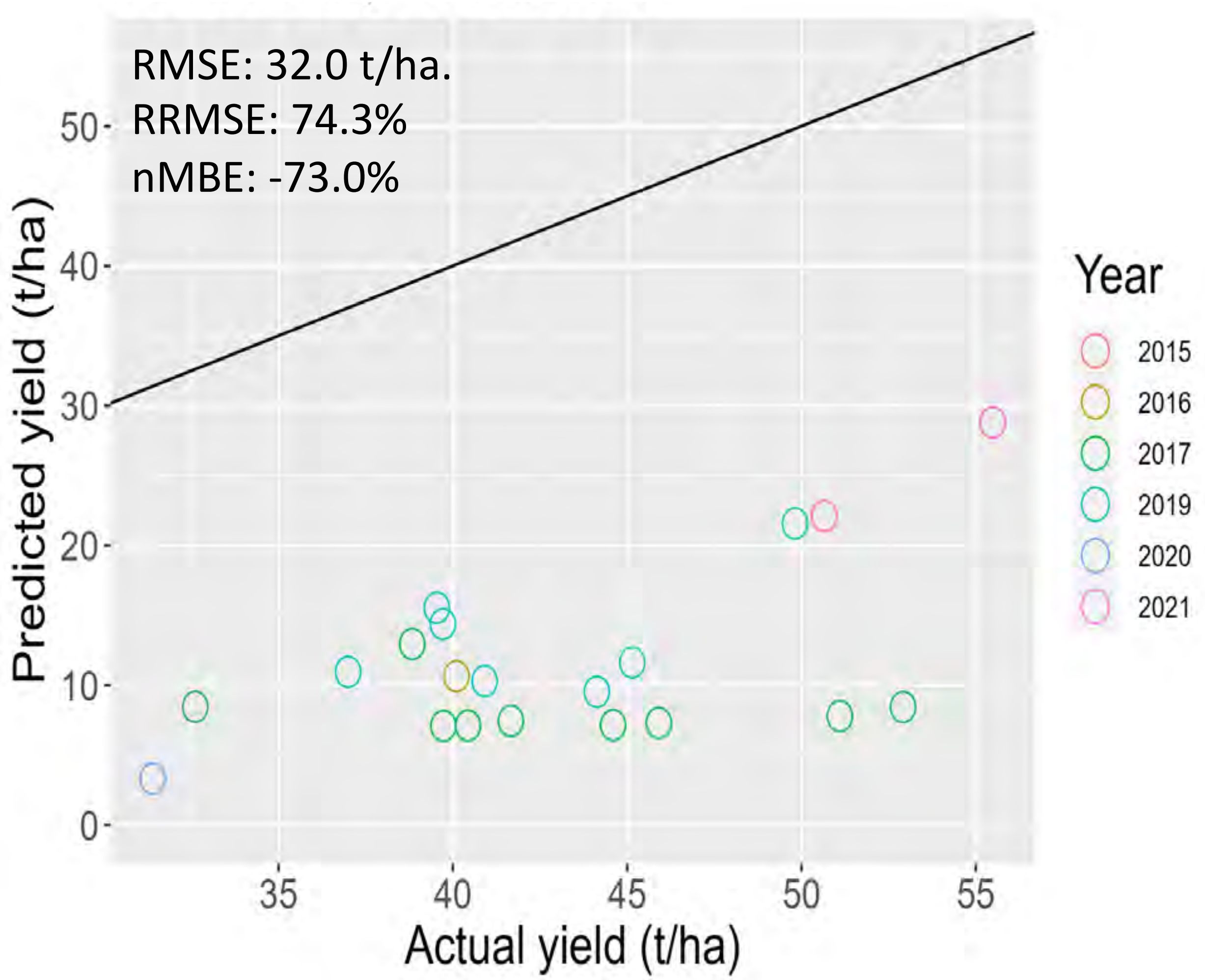
- Morisette et al., 2016
- Calibrated and evaluated on research fields
- Russet Burbank
- Ste. Foy, Quebec and Fredericton, New Brunswick
- 2012-2013
- Crop Coefficient

Two Options for Water Balance Calculation:

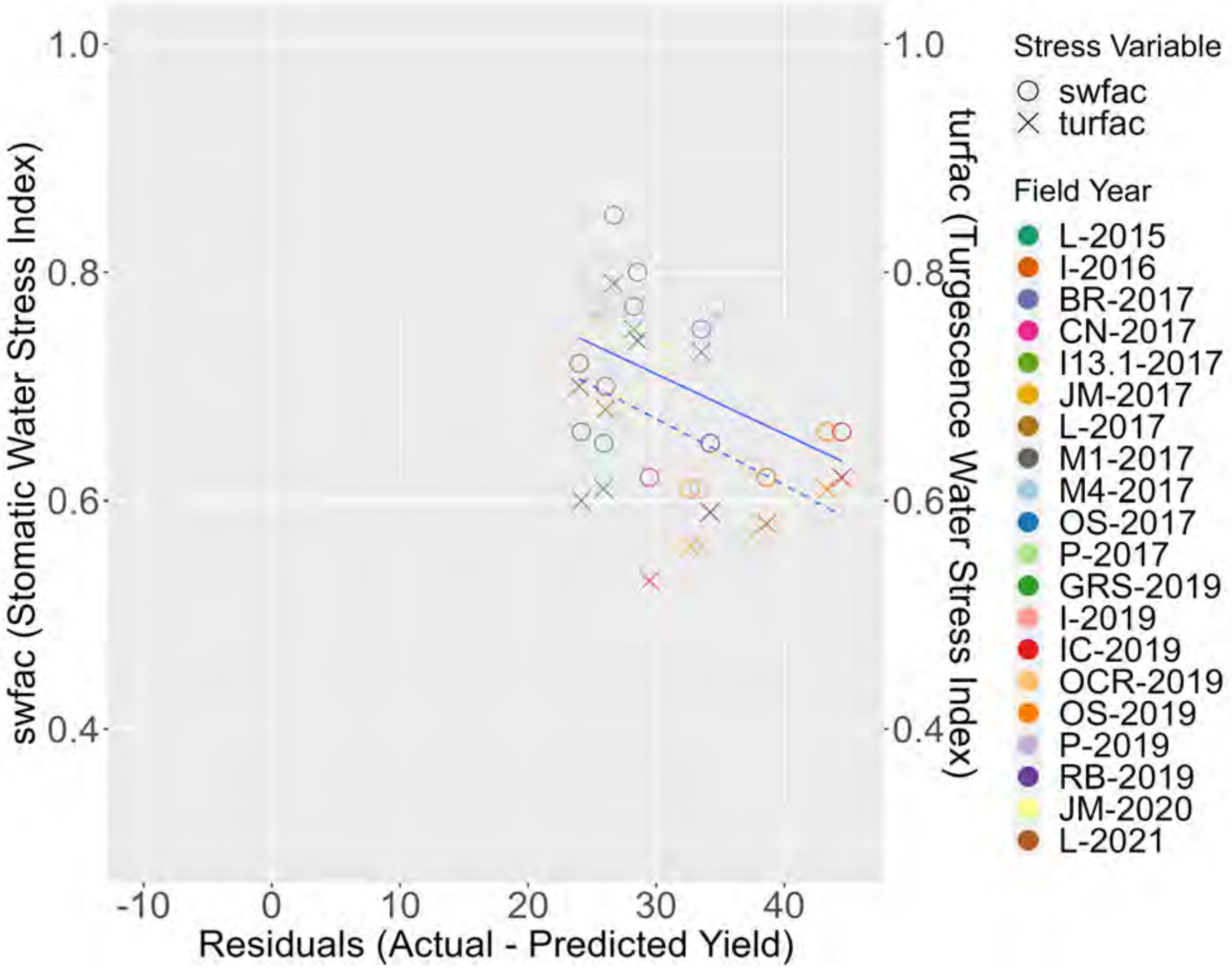
1. Crop Coefficient
   - Simplified
   - Reference crop evapotranspiration x Crop Coefficient

2. Resistance Approach
   - More sophisticated
   - Based on energy balance
   - Soil evaporation and crop water requirement calculated separately

STICS with Crop Coefficient on Industrial Farm Data



RMSE: 32.0 t/ha.
RRMSE: 74.3%
nMBE: -73.0%

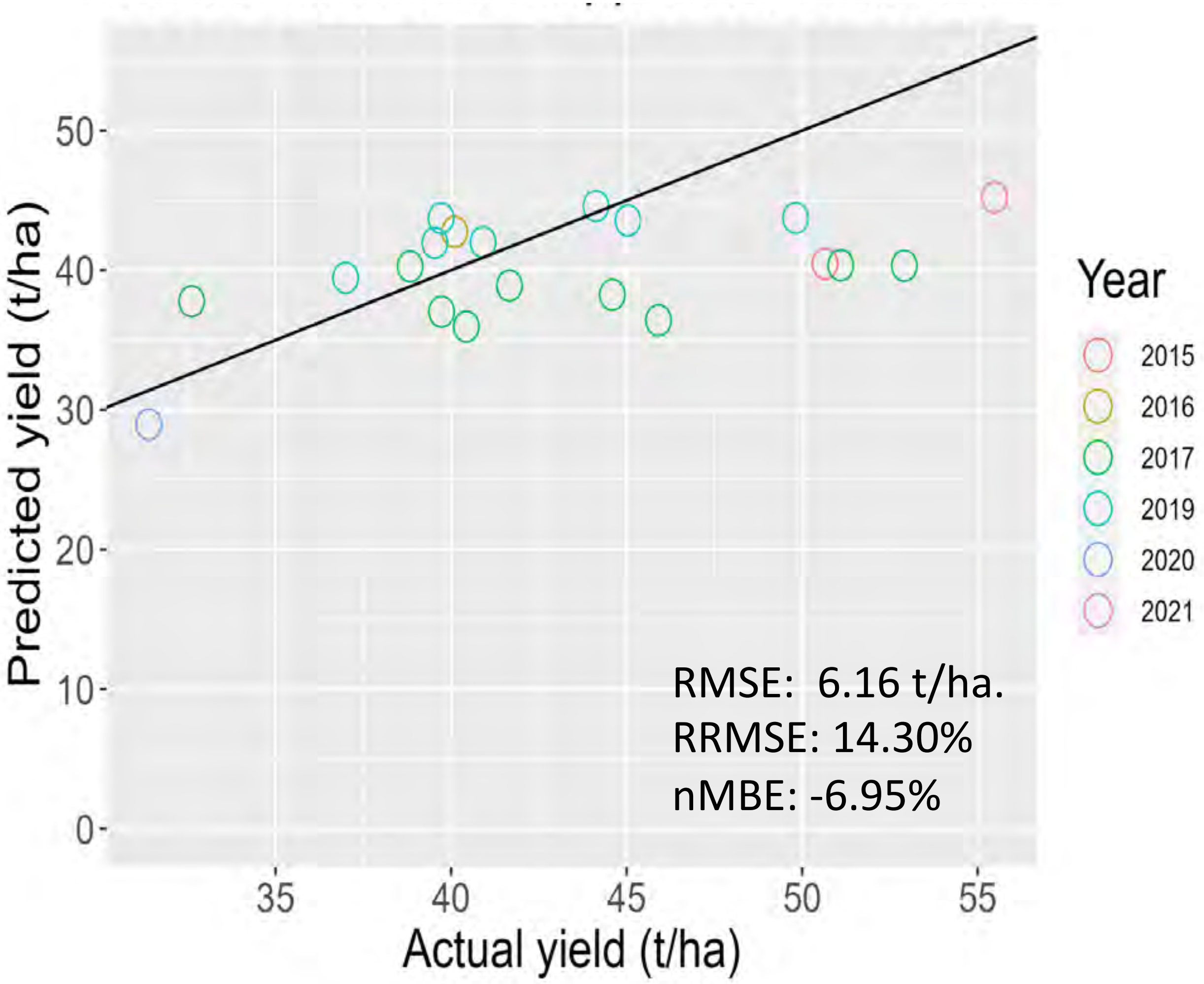


STICS Water Stress Parameters

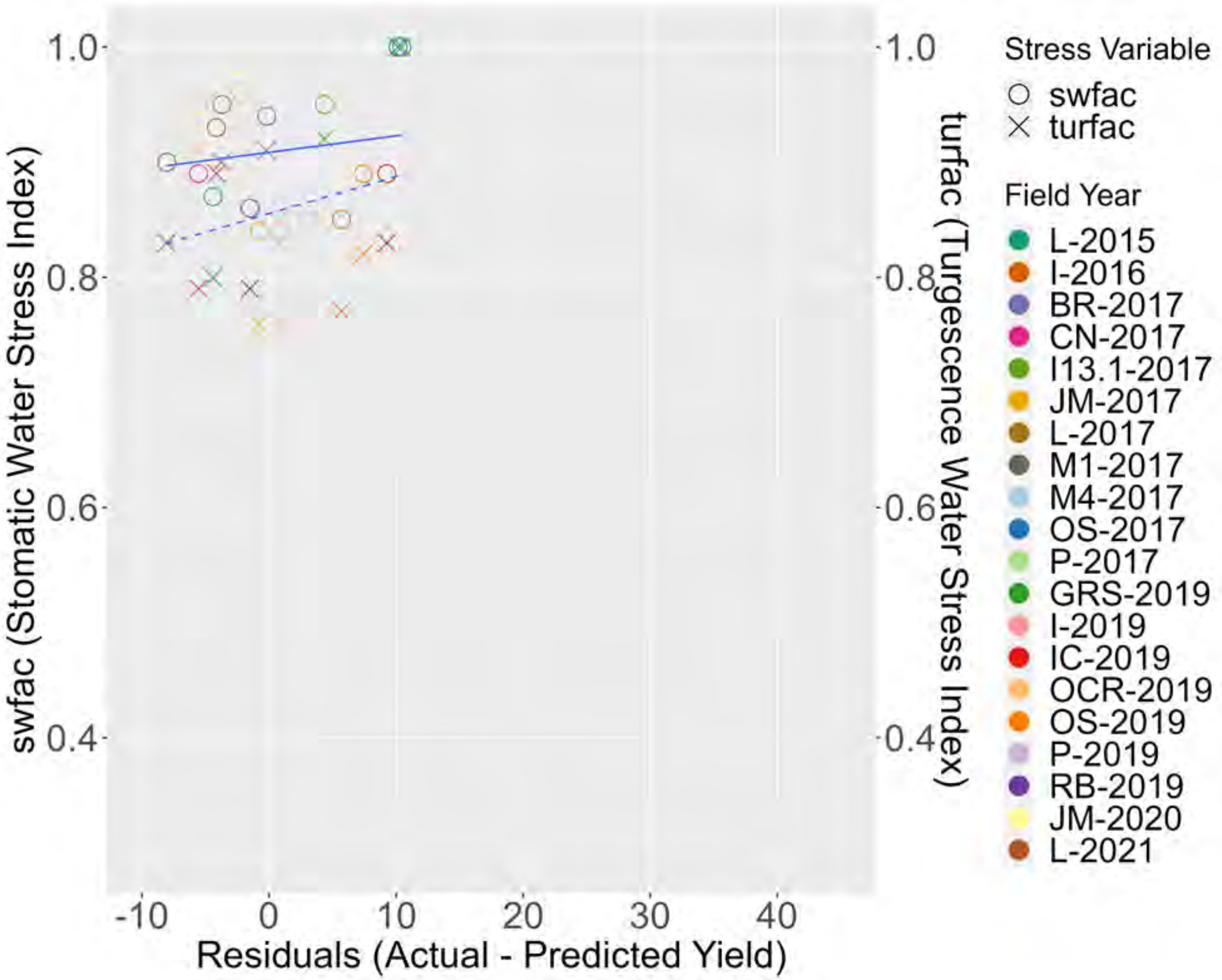
Parameter	Description	Unit	Default	Adjusted
aclim	Climatic component for calculation of actual soil evaporation	mm	20	4
rsmin	Minimal stomatal resistance of leaves	$s\ m^{-1}$	10	167

(Stark, 1987)

STICS with Calibrated Resistance Approach



RMSE: 6.16 t/ha.
RRMSE: 14.30%
nMBE: -6.95%



Random Forest Alone

Top 10 from of 43 Total Features:

1. Cumulative GDD (base 5) to Harvest Date
2. Cumulative growing season GDD (base 5)
3. Total September Precipitation (mm)
4. Julian Harvest Date
5. Cumulative Growing Season Radiation (MJ m^{-2})
6. DEM Slope
7. Julian Sowing Date
8. % Clay (Top 20 cm)
9. Soil pH (Top 20 cm)
10. % Organic Matter (Top 20 cm)

Train/Test Split:

Test on specific field-year, train on the rest

Number of Features Sampled at Each Node Split:

6

Number of Trees:

300

Hybrid Approach

Top 18 from 68 Total Features (25 from STICS):

1. Cumulative growing season GDD (base 5)
2. Total September precipitation (mm)
3. Stomatic water stress index (**swfac**) (0-1)
4. Plant N uptake (kg h^{-1})
5. Julian start date of plant physiological maturity
6. DEM Slope
7. Cumulative crop cycle transpiration (mm)
8. Cumulative crop cycle evapotranspiration (mm)
9. Soil pH (Top 20 cm)
10. Average denitrification rate (kg h^{-1} d^{-1})
11. Ratio of water content in top 30cm soil layer to field capacity (mm)
12. Above ground fresh matter (t ha^{-1})
13. Cumulative growing season radiation (MJ m^{-2})
14. % clay in soil (top 20cm)
15. Max depth of root system (cm)
16. % Organic matter in soil (top 20cm)
17. Cumulative NO_3-N leached over crop cycle (kg h^{-1})
18. Amount of N in harvest organs (kg h^{-1})

Train/Test Split:

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10

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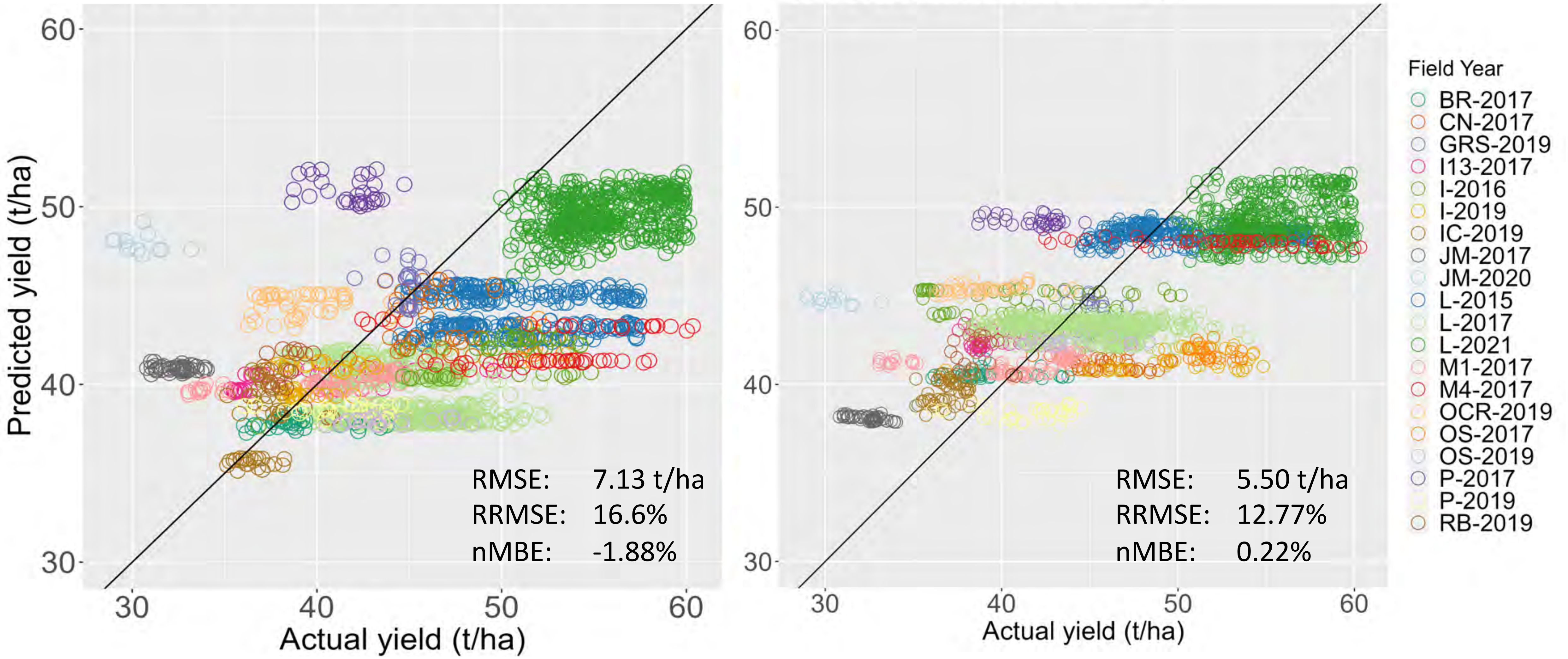
Random Forests for Unseen Field-Years



Random Forest Alone

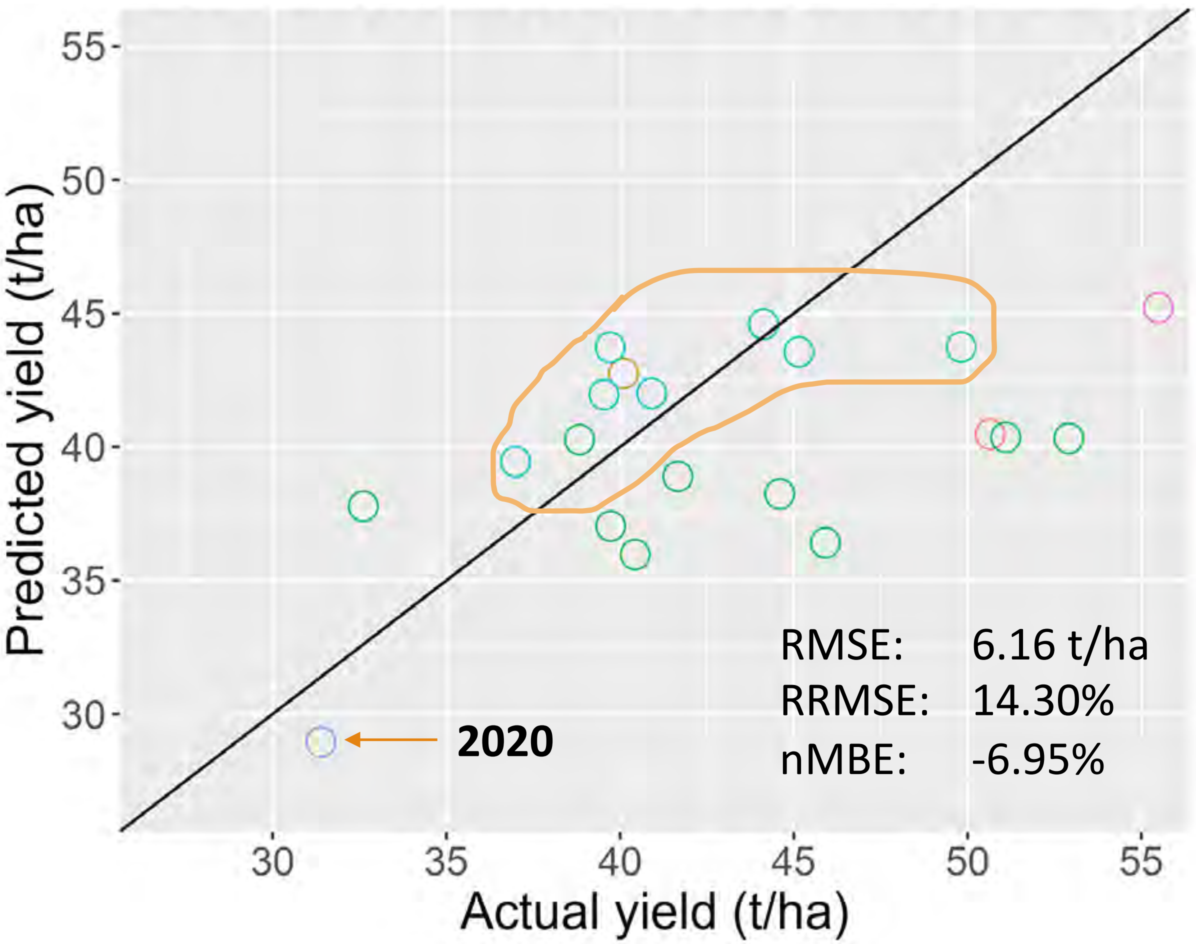
RMSE: 7.13 t/ha
RRMSE: 16.6%
nMBE: -1.88%

Hybrid

RMSE: 5.50 t/ha
RRMSE: 12.77%
nMBE: 0.22%

Performance on Field-Years

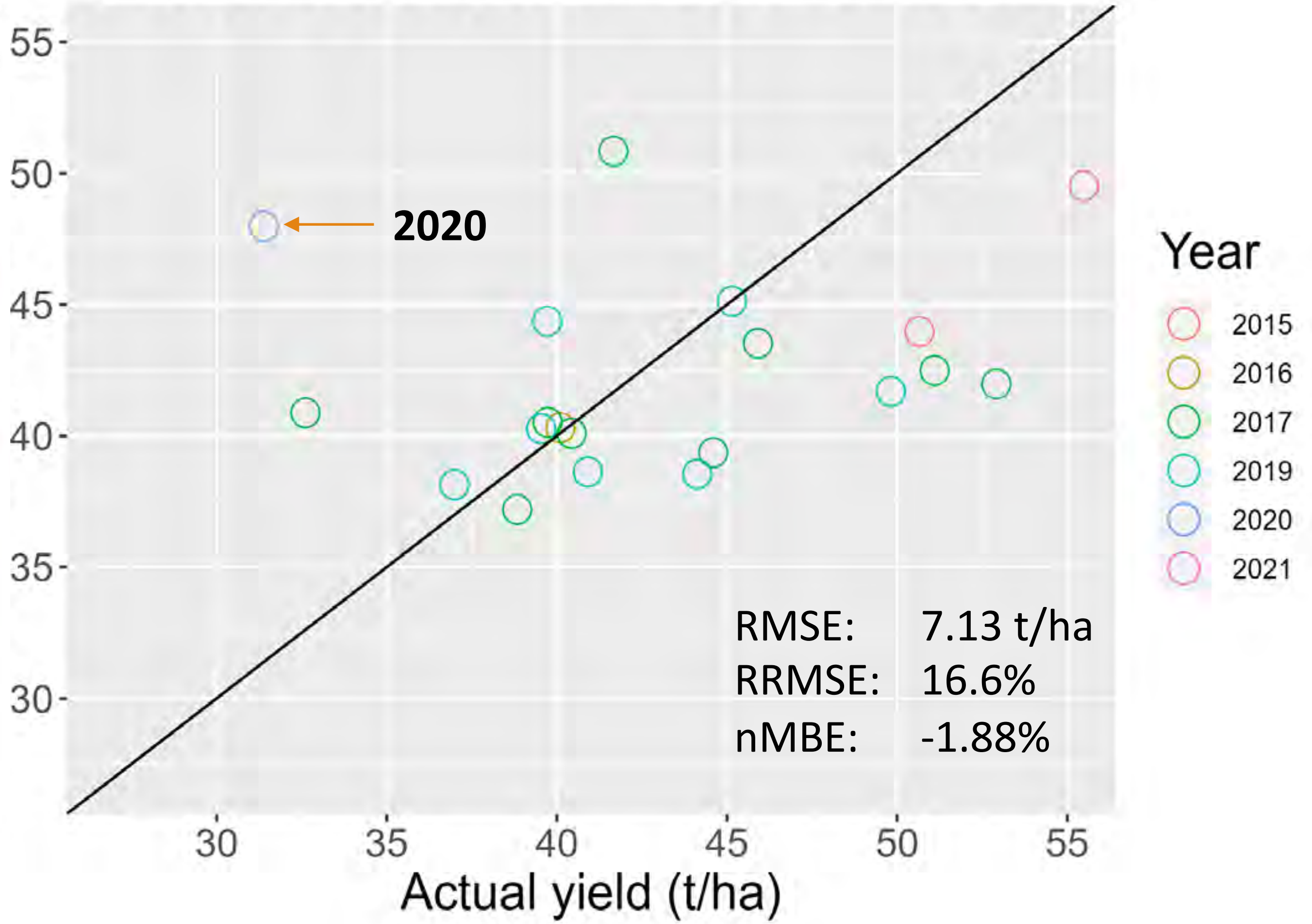
STICS



2020

RMSE: 6.16 t/ha
RRMSE: 14.30%
nMBE: -6.95%

Random Forest



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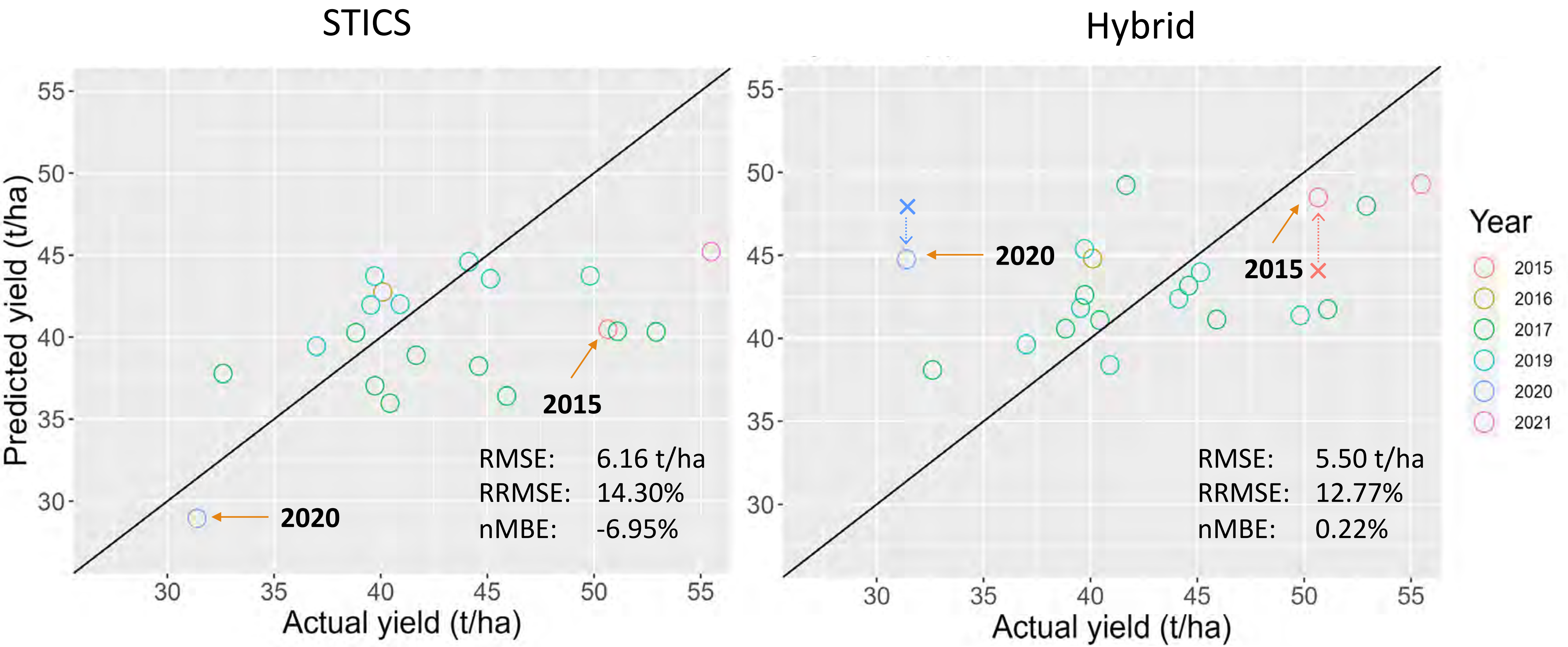
Performance on Field-Years



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Hybrid

RMSE: 5.50 t/ha
RRMSE: 12.77%
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Conclusion

- All models had good performance overall
- Crop models calibrated using crop coefficient should be recalibrated for resistance approach
- STICS predicted drought year well
  - Did not predict higher yielding field-years well
- Random Forest produced good predictions at the field scale
  - Poor performance for extreme year
- The hybrid approach improved predictions of both crop model and random forest alone

Next Steps

- Increase dataset size including CANSIS (Canadian Soil Information Service) data
- Apply a blocked sequential procedure cross validation

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Thank you

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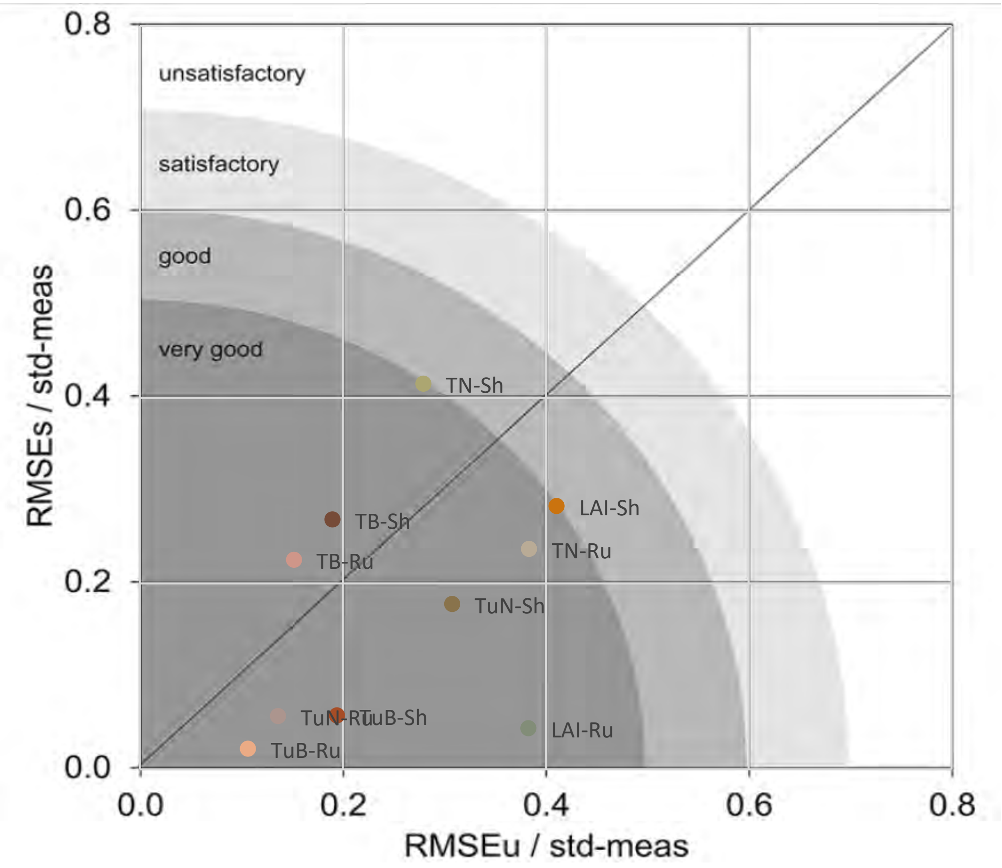
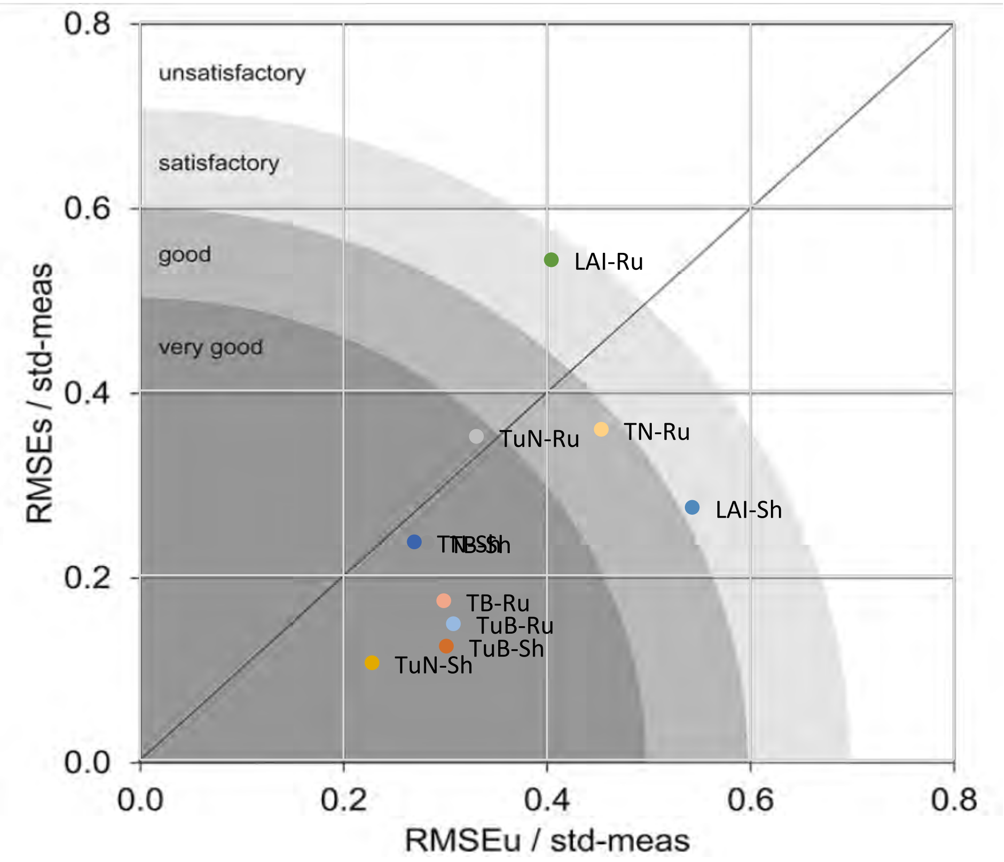
Morissette et. al (2016) Original Calibration and Evaluation

Calibration

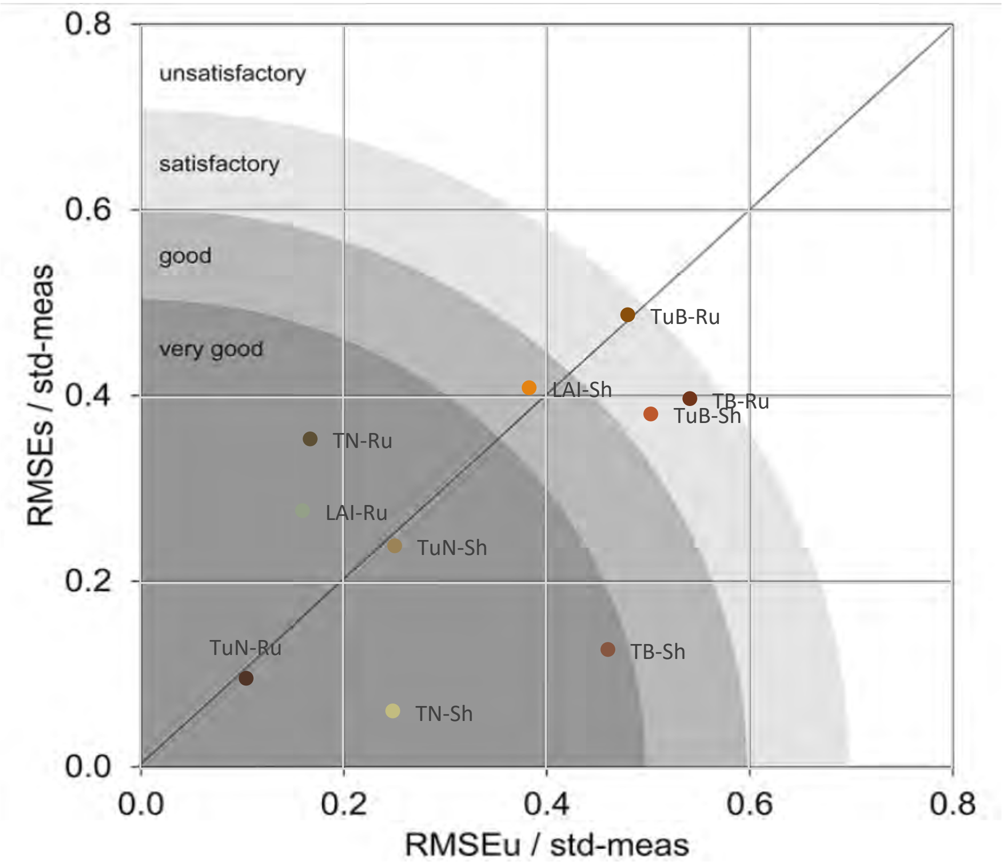


Evaluation

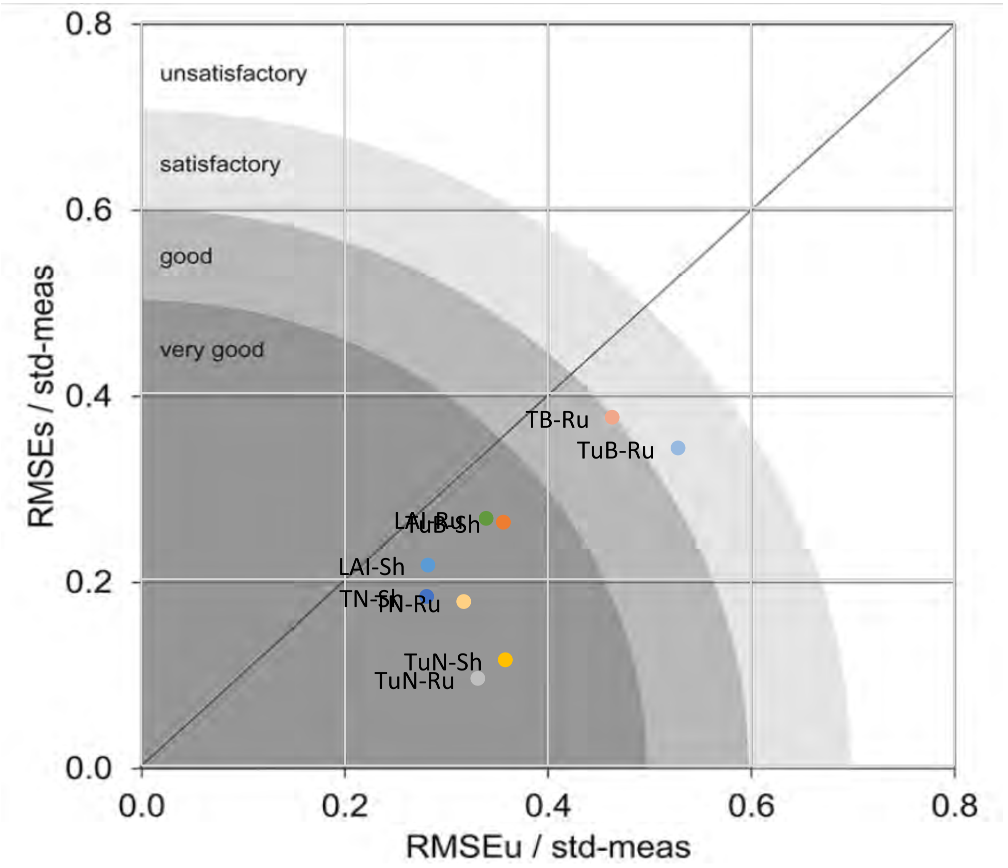


Morissette et. al (2016) Calibration and Evaluation after Resistance Approach Adjustments

Calibration



Evaluation



Model Performance

Model	RMSE	RRMSE	nMBE
STICS	6.16 t h^{-1}	14.30%	-6.95%
Random Forest	7.13 t h^{-1}	16.55%	-1.88%
Hybrid	5.50 t h^{-1}	12.77%	0.22%

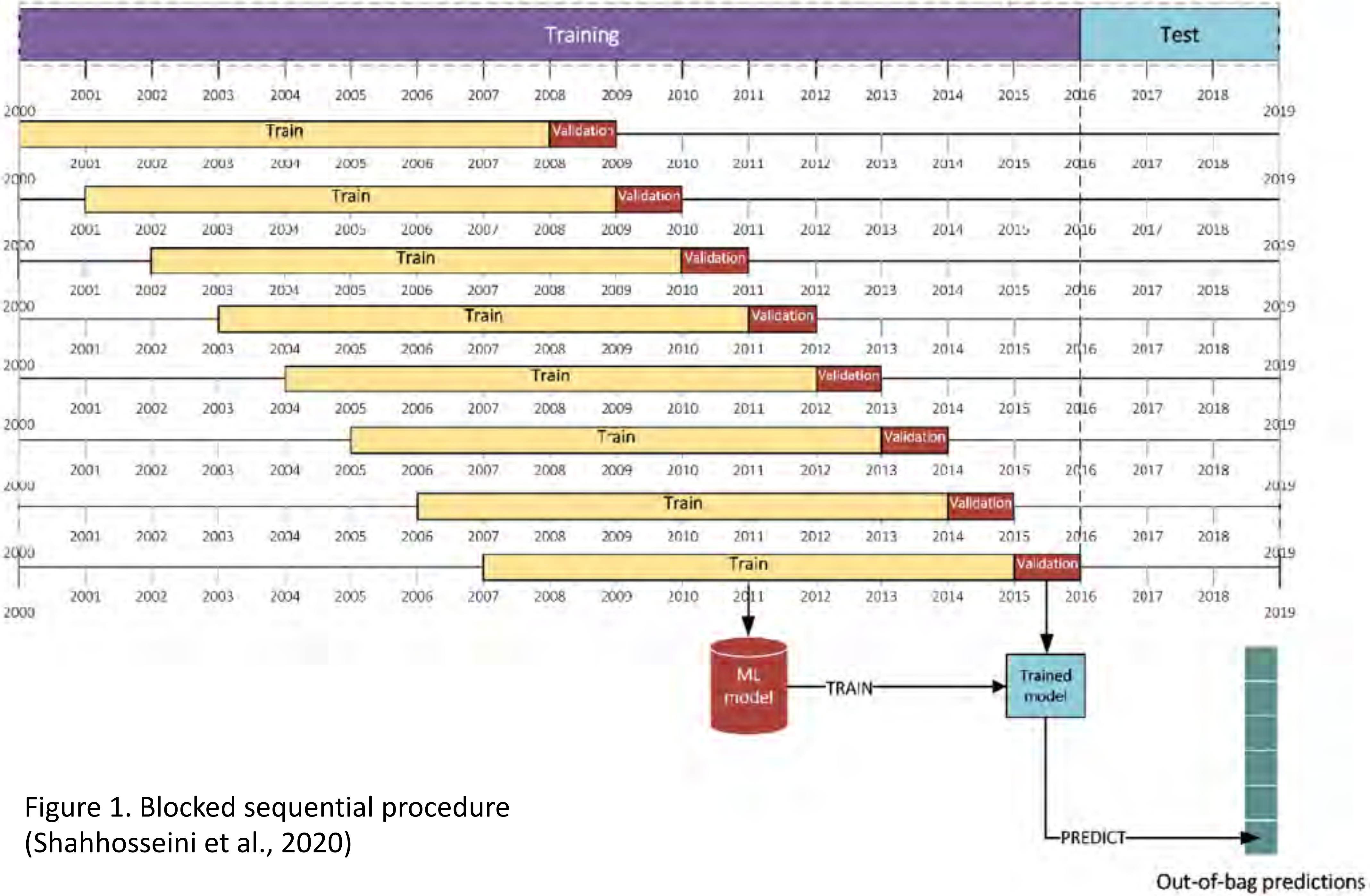
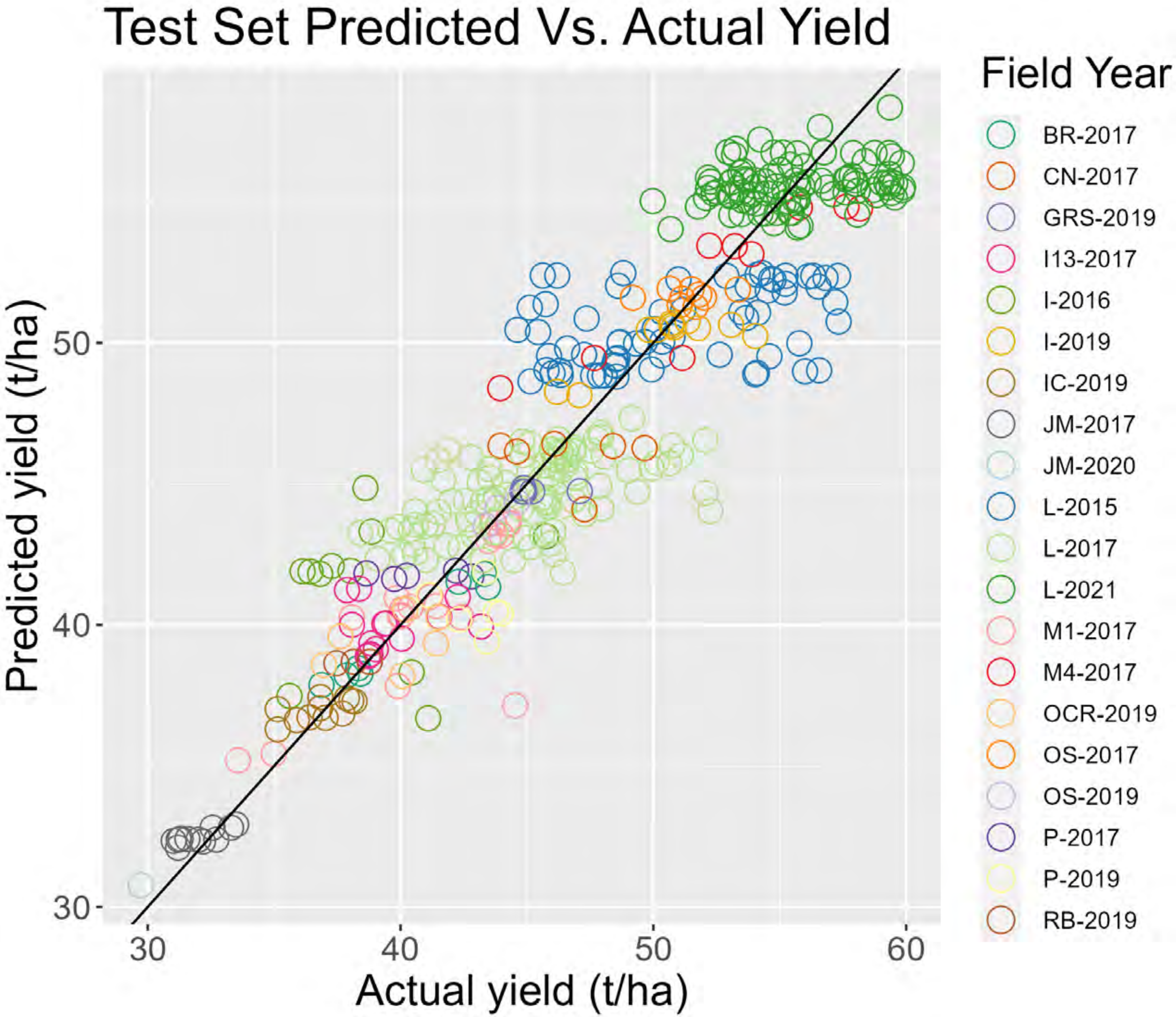


Figure 1. Blocked sequential procedure (Shahhosseini et al., 2020)



Random Forest Fine-Tuning

RMSE

2.54 t/ha

RRMSE

5.35%

Bias(%)

0.28%

Test Sets for Random Forests for Individual Field Years

Field Year	Number of Datapoints	Field Year	Number of Datapoints
L-2015	347	P-2017	32
I-2016	57	GRS-2019	28
BR-2017	38	I-2019	54
CN-2017	40	IC-2019	56
I13-2017	47	OCR-2019	47
JM-2017	45	OS-2019	25
L-2017	518	P-2019	32
M1-2017	77	RB-2019	17
M4-2017	55	JM-2020	12
OS-2017	25	L-2021	516

Assessing the performance of crop forecasts for in-season nitrogen management of winter wheat

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AgMIP9 Modeling the Future of Food, June 26th-30th
Columbia University, New York, NY

Outline

- Introduction
- Crop Forecasts
    - Development
    - Generation
    - Performance and skill
    - Operational potential
- Conclusion

Introduction

- **Increasing climate variability – decreasing frequency of average growing conditions** (IPCC 2022)

- Crop management commonly relies on **empirical approaches** representing **average seasons**
  - Fertilization recommendations and practices do not consider **inter-seasonal variation in crop growth and demand for nutrients** (BMLFUW 2017)
- Low nutrient use efficiency – economic and ecological consequences

- Continuous **improvement of seasonal ensemble weather forecasting** methods (Johnson et al. 2019)

Objective

Develop and evaluate a **forecasting tool for site- and season-specific crop management – case study nitrogen (N)**

Crop Forecasts – Development

Field experiments

Winter wheat grown in three seasons (2017-2020) in Tulln, Austria
4 N fertilization levels (0-210 kgN ha^{-1})
4 cultivars (Arnold, Aurelius, Bernstein, Emilio)

N range

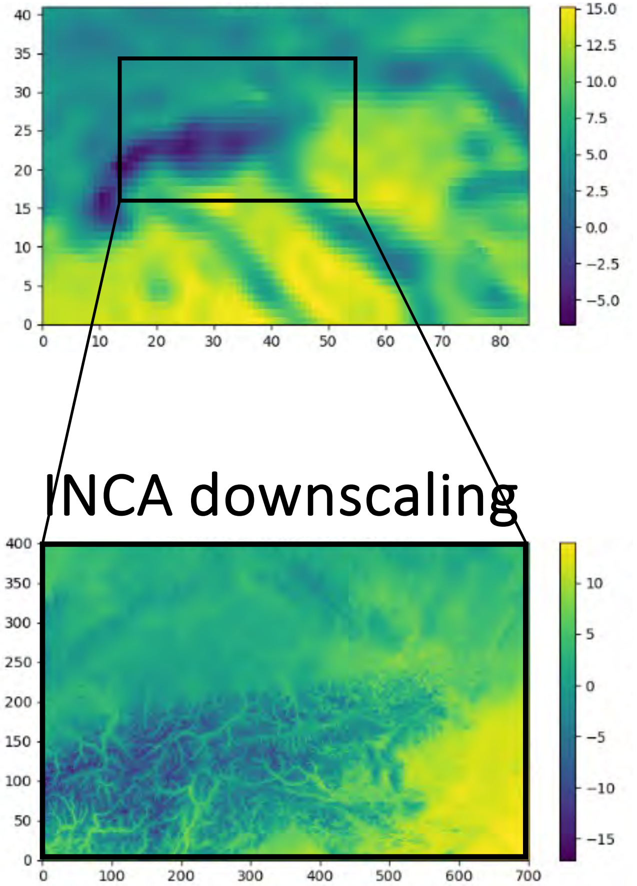
Spectral

Destructive

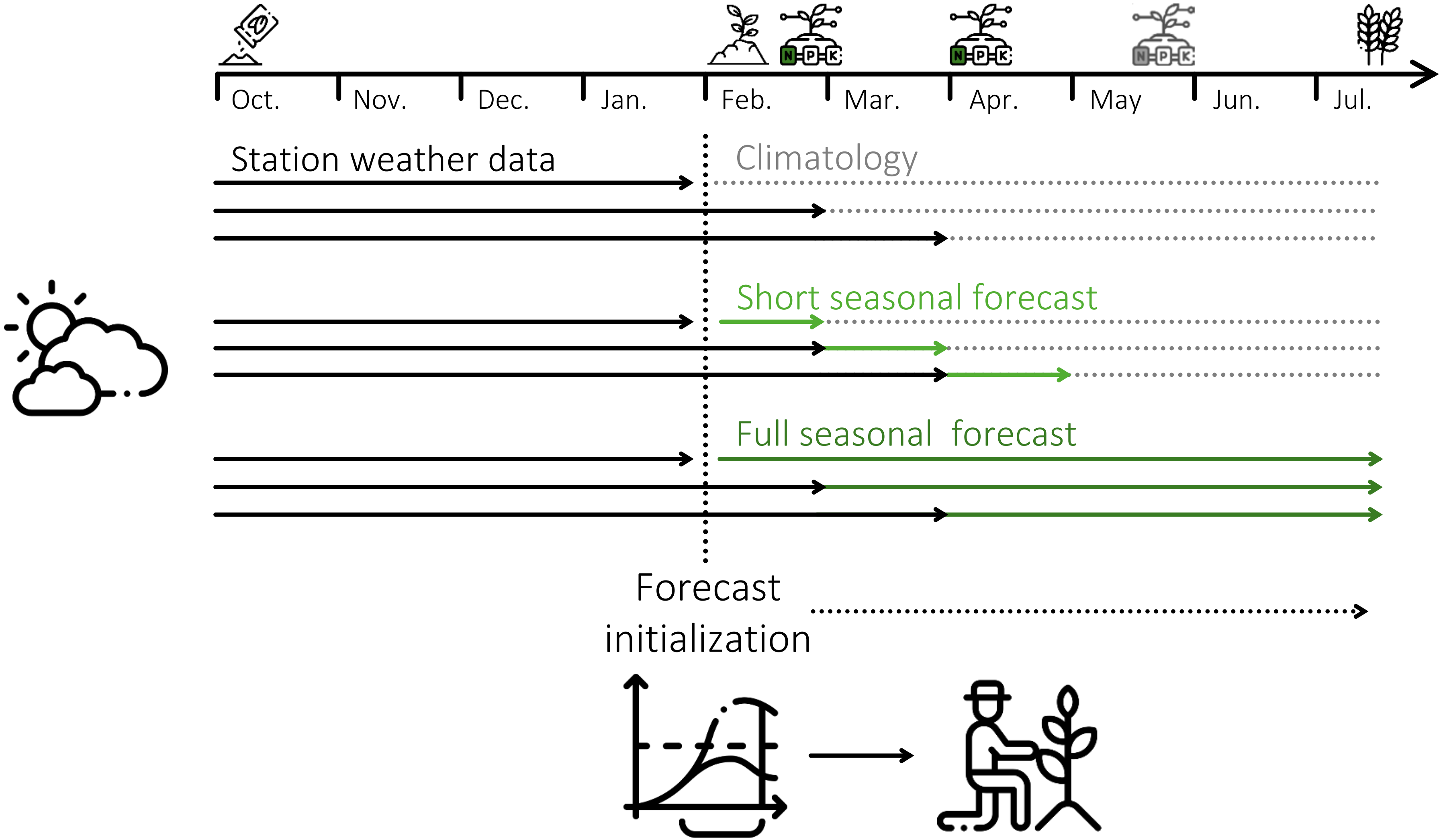
Manschadi et al. (2021)
Palka et al. (2021)
Manschadi et al. (2022)

SEAS5

INCA downscaling



Crop Forecasts – Generation



Oct. Nov. Dec. Jan. Feb. Mar. Apr. May Jun. Jul.

Station weather data

Climatology

Short seasonal forecast

Full seasonal forecast

Forecast initialization

Crop Forecasts – Performance and Skill

- **High performance of crop forecasts** over a wide range of simulated crop and soil variables (Reference: simulation dataset using observed weather data)

- **Significantly higher skill** of crop forecasts generated using **seasonal ensemble weather forecasts**, if:
    - Growing conditions **deviate from long-term averages**
    - **Initial soil conditions** at sowing are **unfavorable**

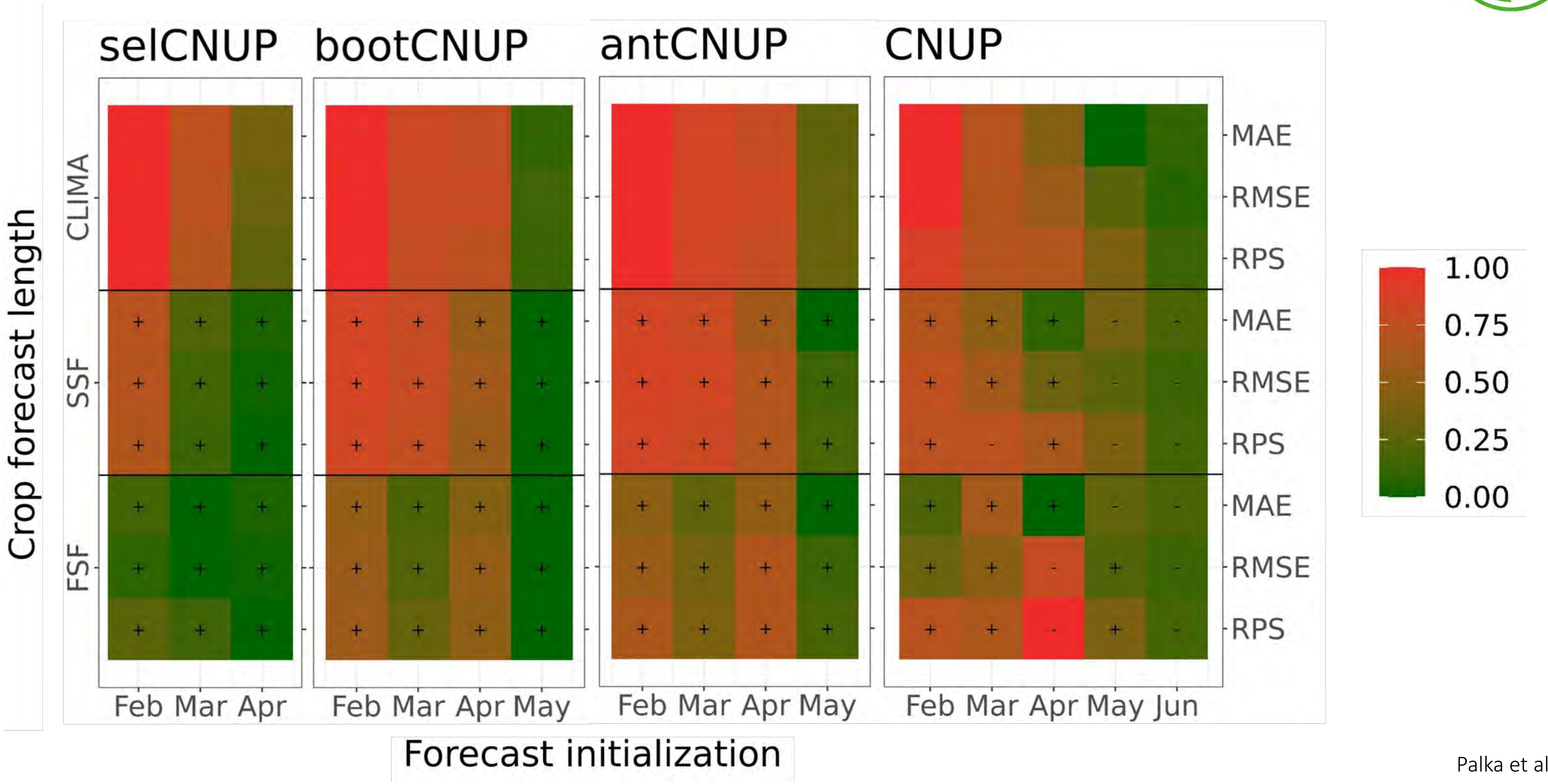
- Performance and skill **improve with decreasing lead time**

Variable	RMSE	rel. RMSE (%)
Phenology	5 DAS	2.49
Crop biomass	71.53 g m^{-2}	9.15
Yield	62.70 g m^{-2}	10.97
Total crop N-uptake	1.08 g m^{-2}	8.99
Plant-available soil water content	39.55 mm	20.45

Table 1: Root mean squared error (RMSE) and relative RMSE (rel. RMSE) of important crop and soil variables, forecasted over three experimental seasons at different phenological stages, and compared to a simulation dataset using observed weather data.

Palka et al. (under review)

Crop Forecasts – Performance and Skill



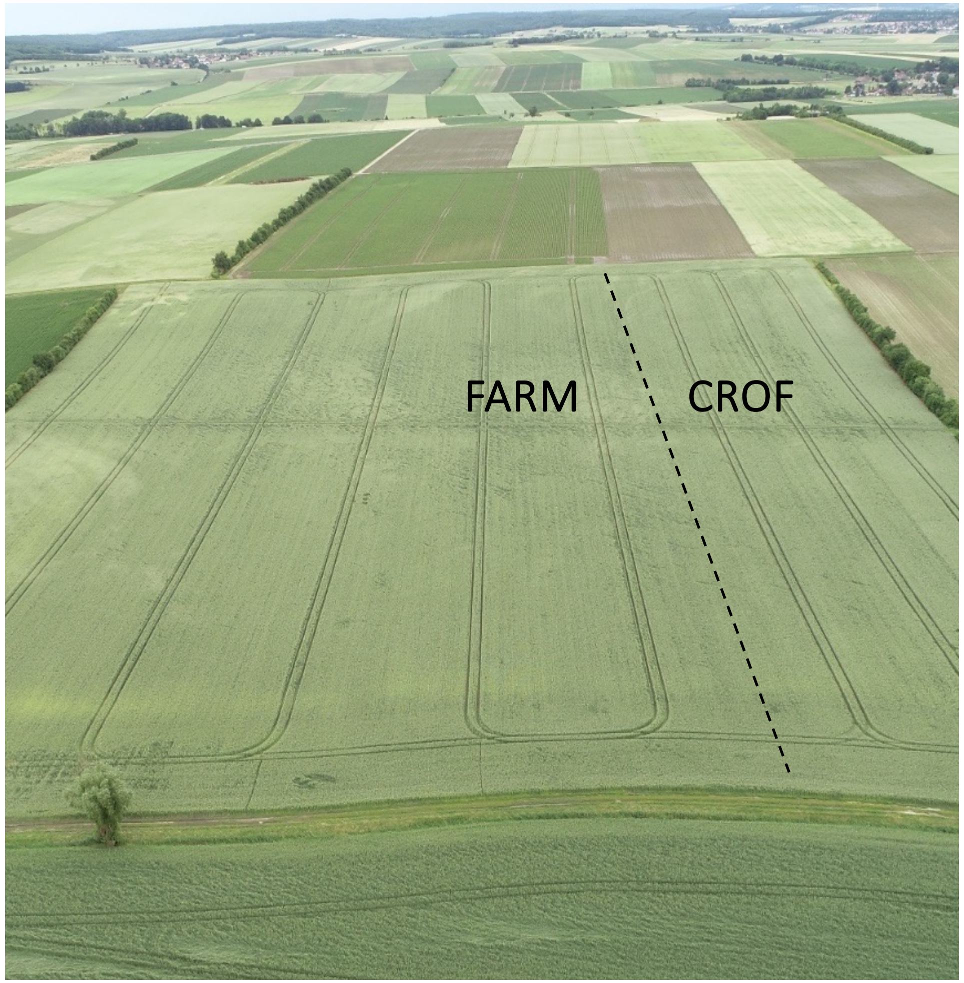
Palka et al. (under review)

Crop Forecasts – Operational Potential

- **On-farm testing in cooperation with local farmers in Eastern Austria**
- **2 locations and 2 seasons** (2020-2022)
- **Two N-fertilization treatments:**
  - FARM: N applied according to common farm practice
  - **CROF: N applied according to** site-specific ensemble **crop forecasts**
- Mean **economic return to N** (ERN):

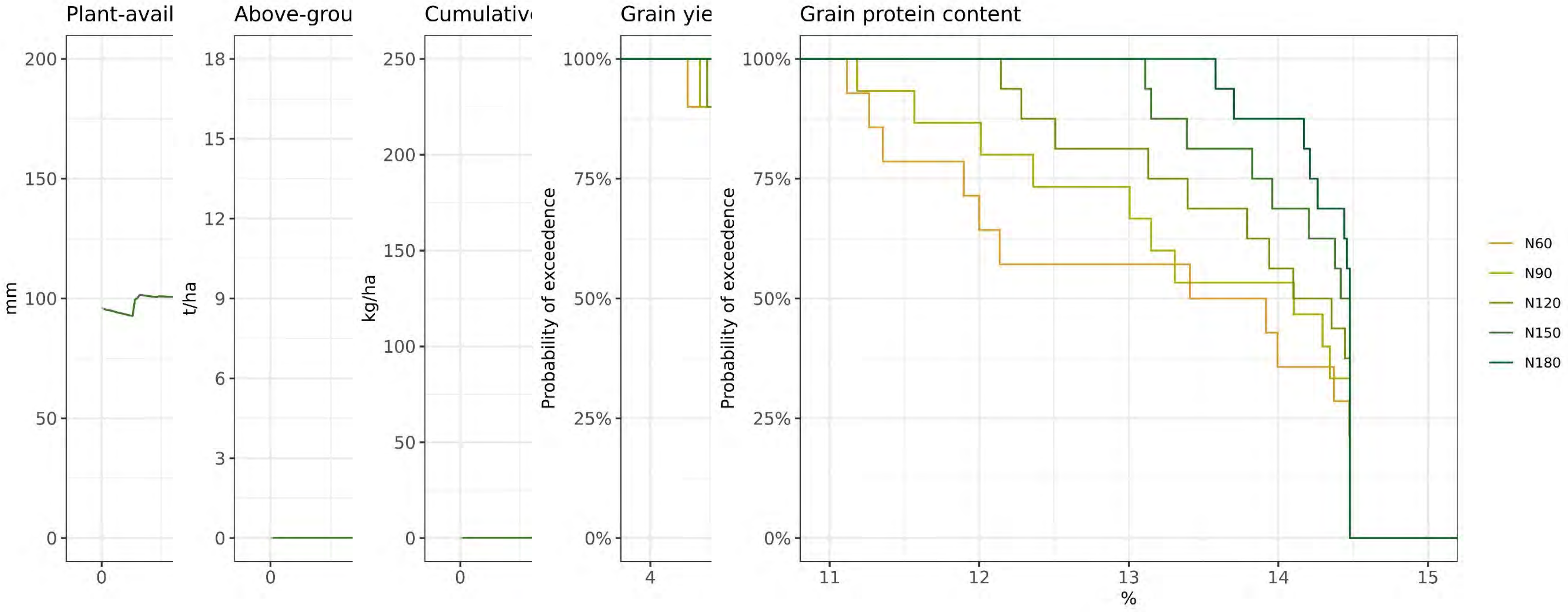
$$ERN = \frac{Revenue}{N_{applied}}$$

- **Significant increase in ERN** of CROF compared to FARM (+30.2 %), through **reducing $N_{applied}$** (-23.4 %) while **maintaining revenue** (1320.2 € ha^{-1})



Palka et al. (in preparation)

Crop Forecasts – Operational Potential



Conclusion

- **Generation and application** of crop forecasts: **well-parameterized** crop model and **downscaled** seasonal ensemble weather forecasts required

- **“non-average” seasons and/or unfavorable initial soil conditions**:
    - **Significantly higher skill** of crop forecasts using **seasonal ensemble weather forecasts**

- Significant **reduction in N fertilization** without sacrificing economic revenue

Outlook:

- Extending crop forecast-based management approach to other crops and measures (e.g., irrigation)
- Inclusion of remote sensing and AI for regional application

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Thank you! Questions/Feedback?

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IMPLICATIONS OF WHEAT SUPPLY DISRUPTIONS FOR GLOBAL FOOD SECURITY

ROGÉRIO DE S. NÓIA JÚNIOR, JEAN-CHARLES DESWARTE, JEAN-PIERRE COHAN, PIERRE MARTRE, MARIJN VAN DER VELDE, REMI LECERF, HEIDI WEBBER, FRANK EWERT, ALEX C. RUANE, GUSTAVO A. SLAFER, SENTHOLD ASSENG

CAUSES OF WHEAT PRODUCTION FAILURES

- WARS AND CONFLICTS
- EXTREME WEATHER EVENTS
- LOW COMMODITY PRICES
- COMBINATION OF THESE FACTORS

CAUSES OF WHEAT PRODUCTION FAILURES

WARS AND CONFLICTS

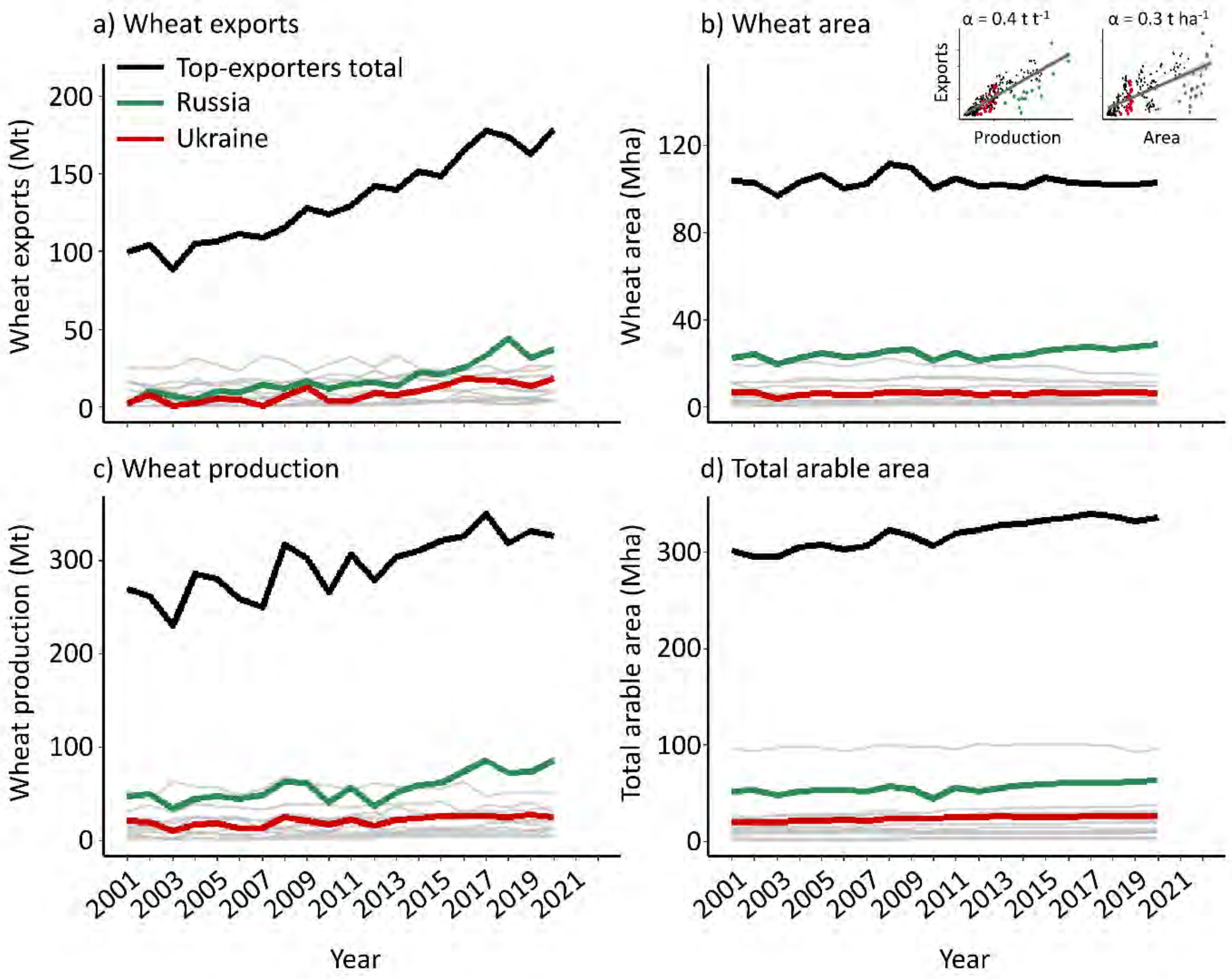
EXTREME WEATHER EVENTS

LOW COMMODITY PRICES

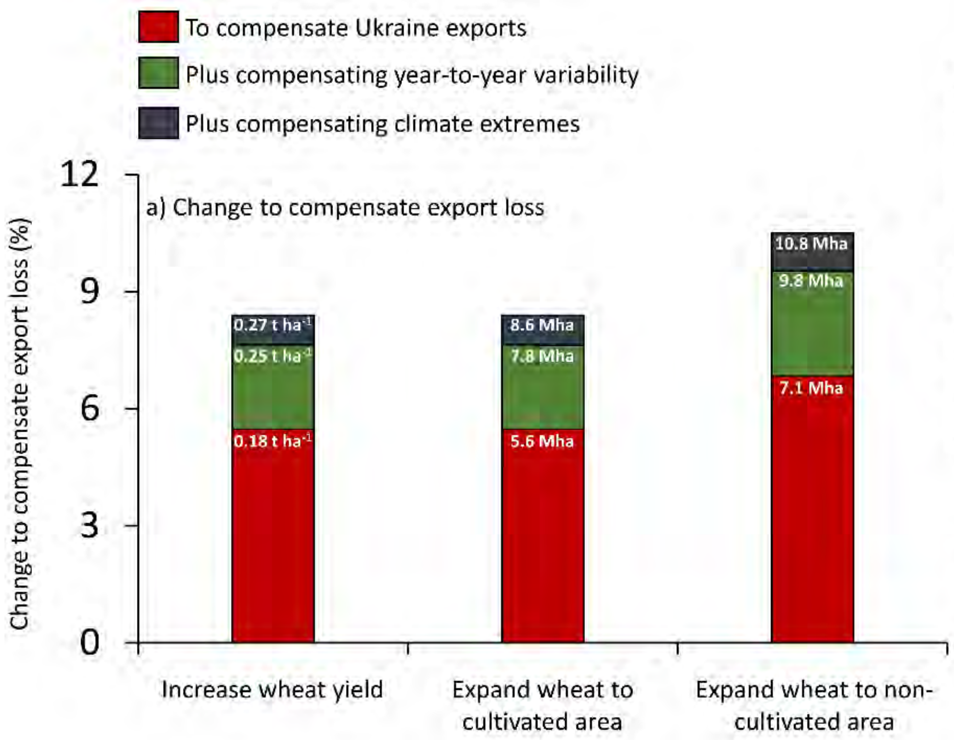
COMBINATION OF THESE FACTORS

Wars disrupt wheat production and trade, limiting availability and impacting the global market. (Example: Ukraine conflict)

UKRAINE'S SIGNIFICANCE IN GLOBAL WHEAT PRODUCTION



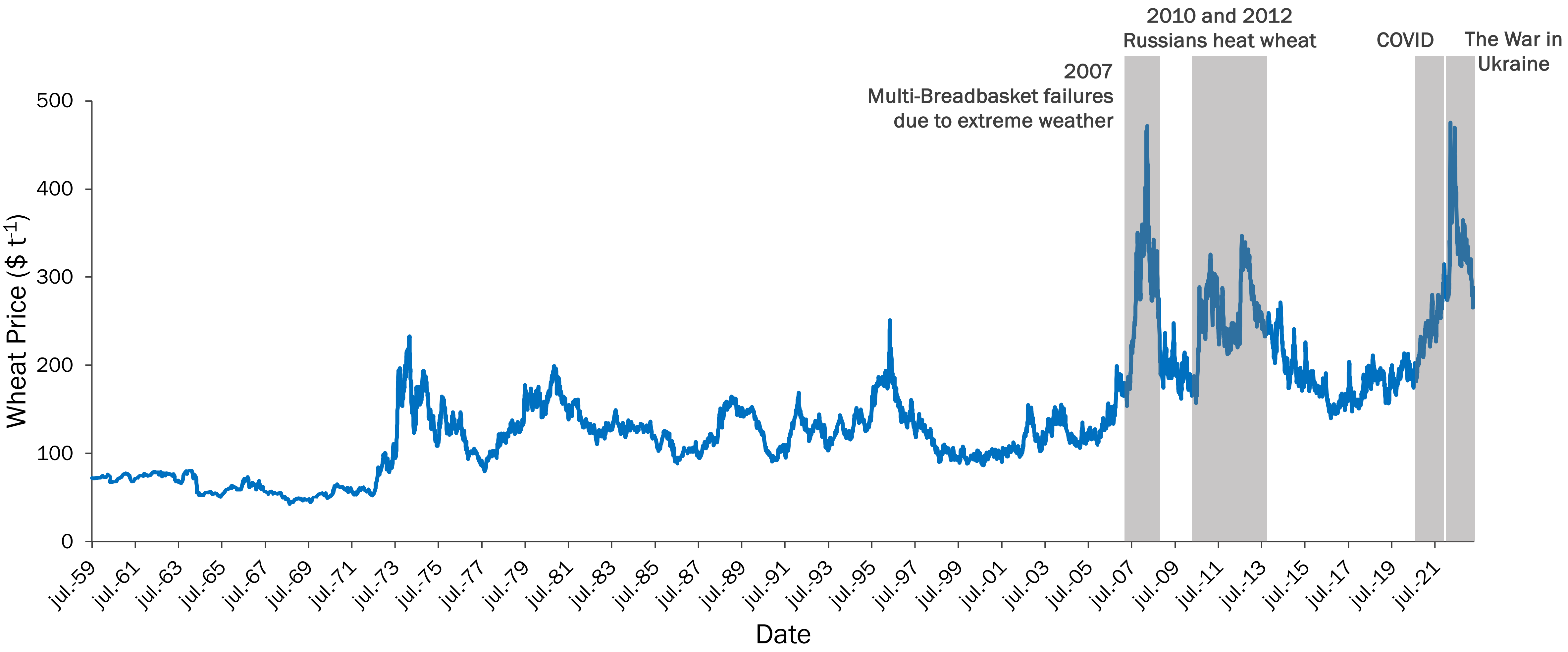
In 2020, Ukraine produced 26 million tons (Mt) of which they exported 72%, which was valued at more than 3.5 billion dollars



GLOBAL WHEAT MANAGEMENT IN RESPONSE TO UKRAINE WAR

- Expand cropping or improve yields by 8% in top exporters.
- Production increase requires extra half a million tons of nitrogen fertilizer.
- Climate change and variability may reduce exports by 5-7 million tons.

GLOBAL WHEAT PRICE



CAUSES OF WHEAT PRODUCTION FAILURES

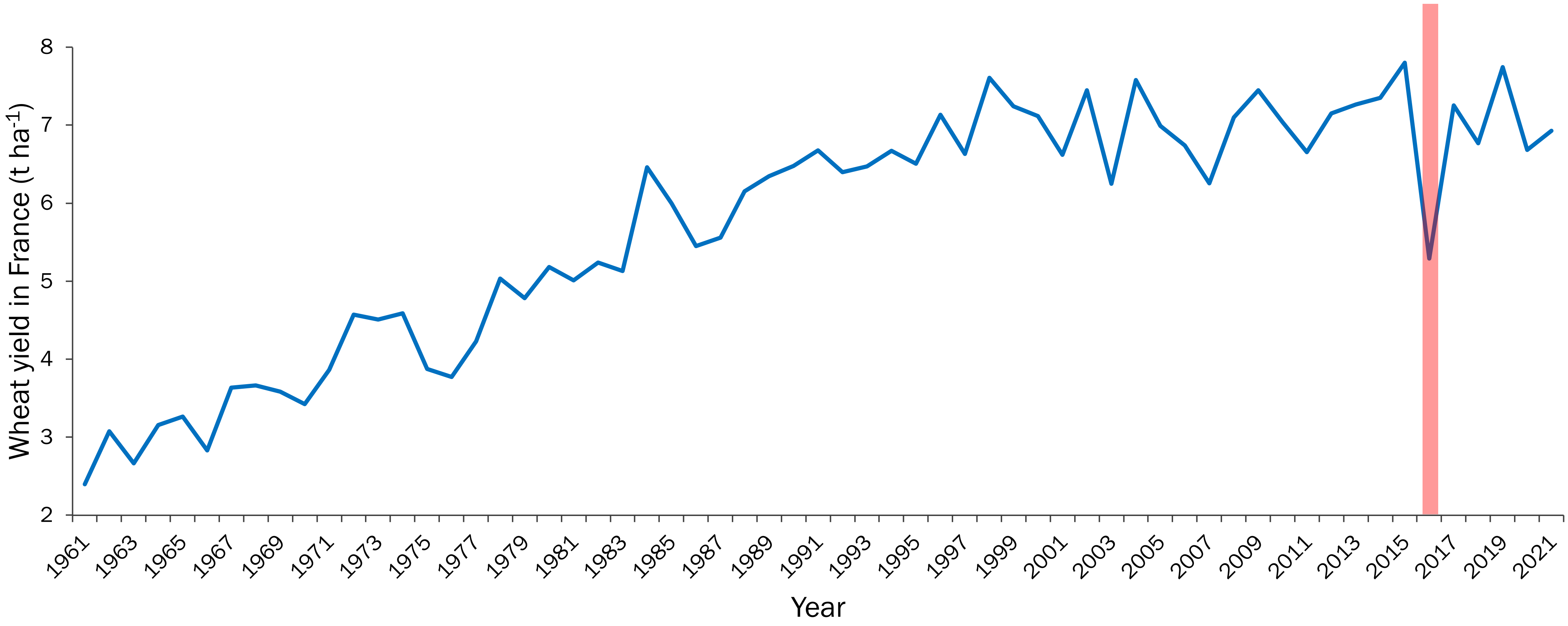
WARS AND CONFLICTS

EXTREME WEATHER EVENTS

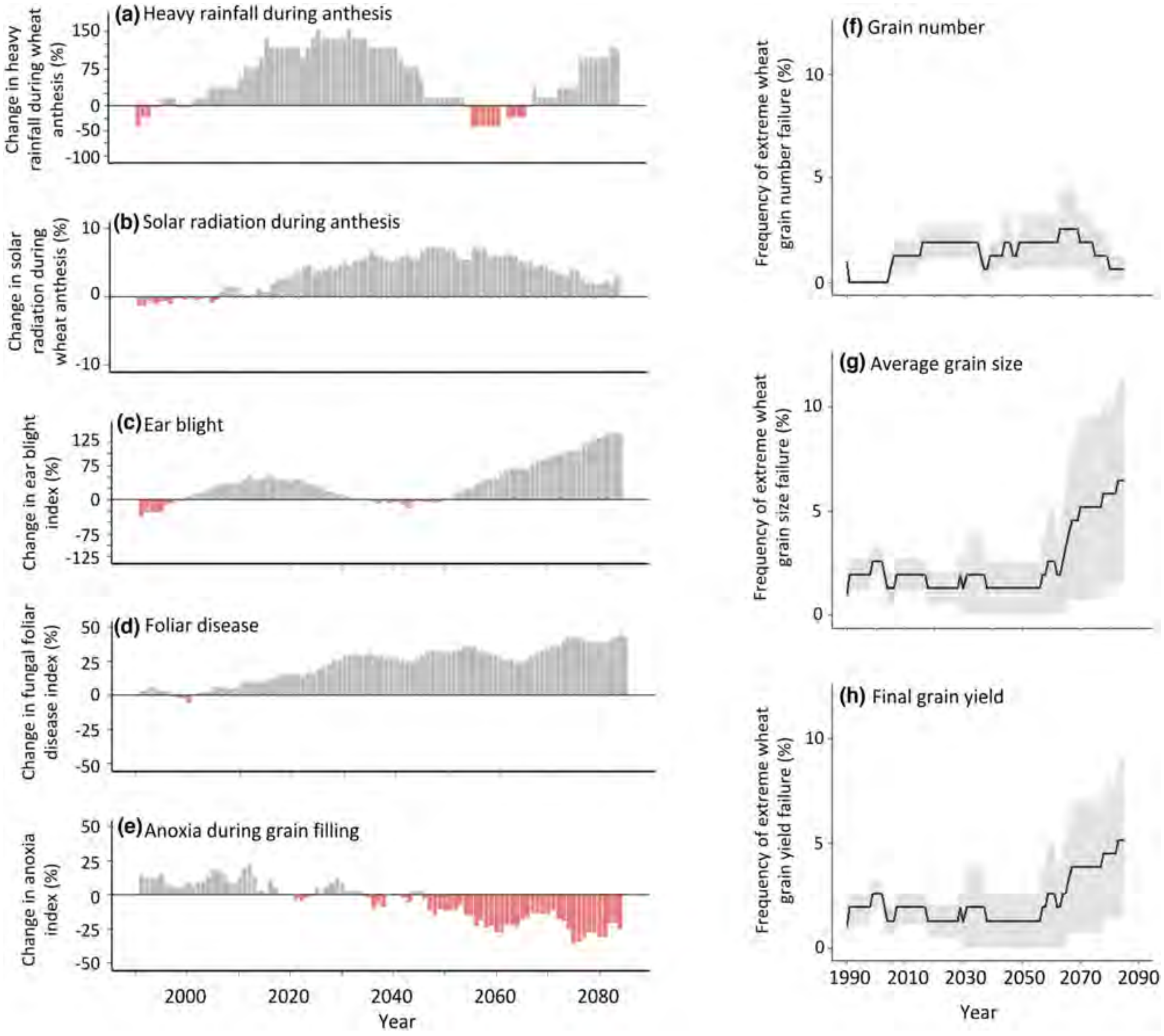
LOW COMMODITY PRICES

COMBINATION OF THESE FACTORS

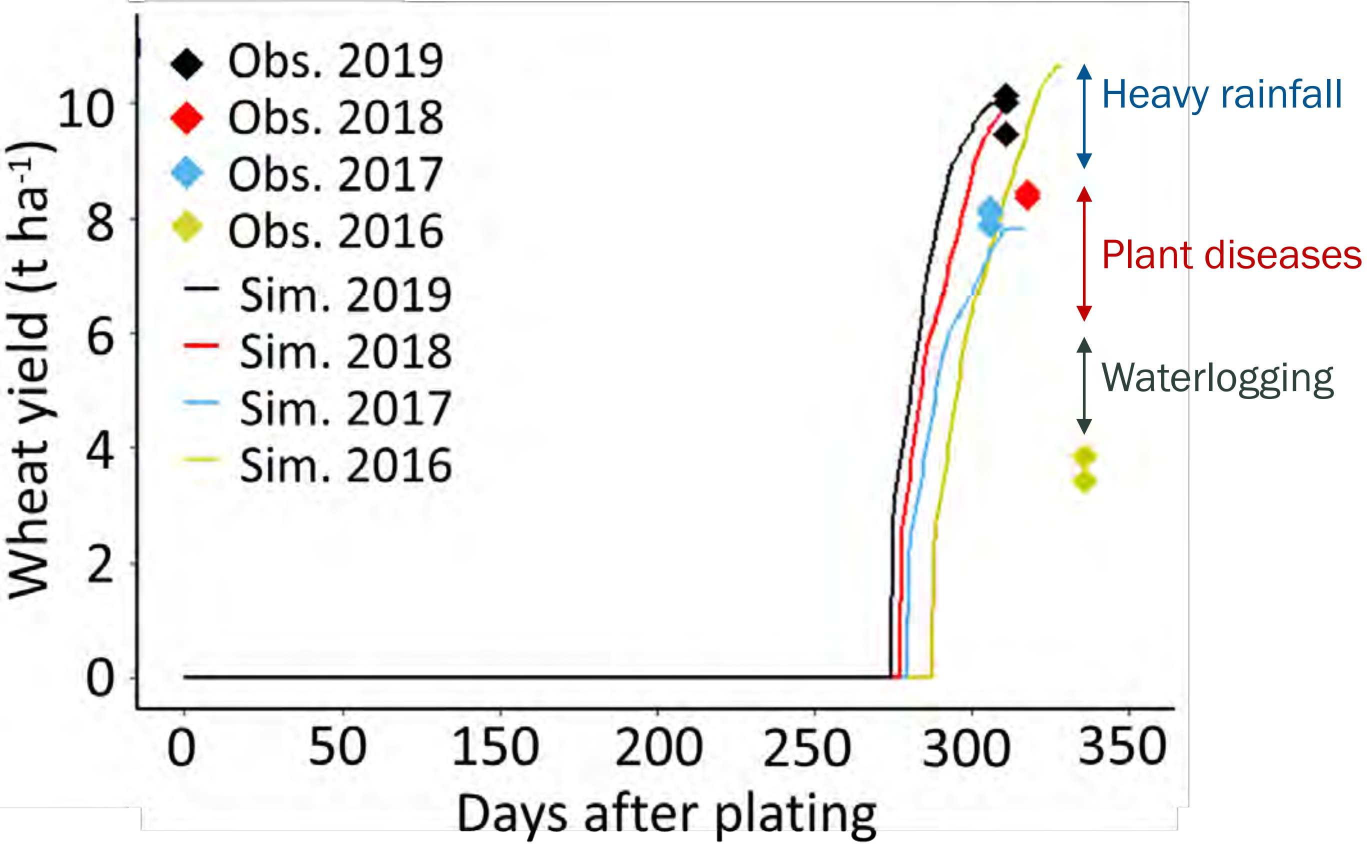
IN 2016, FRANCE EXPERIENCED ITS MOST SEVERE YIELD LOSS IN OVER 50 YEARS



WE ASSESSED THE CAUSES BEHIND FRANCE'S EXTREME WHEAT YIELD DECLINE IN 2016 AND PROJECTED THEIR FUTURE FREQUENCY.



CURRENT CROP MODELING APPROACHES OFTEN OVERLOOK NUMEROUS CLIMATE-RELATED EVENTS DURING CROP GROWTH AND DEVELOPMENT.



Heavy rainfall

Plant diseases

Waterlogging

The 2016 event indicates that the projected impacts of climate change on agriculture may be underestimated.

CAUSES OF WHEAT PRODUCTION FAILURES

WARS AND CONFLICTS

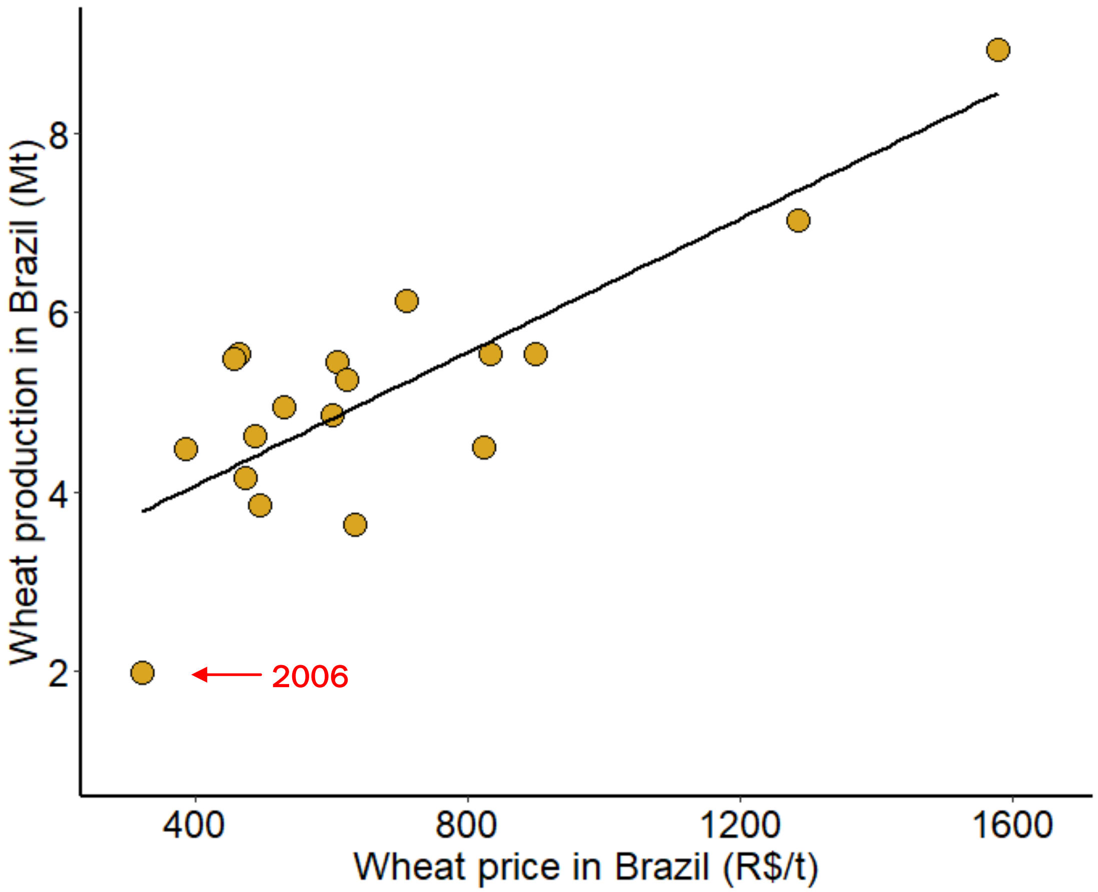
EXTREME WEATHER EVENTS

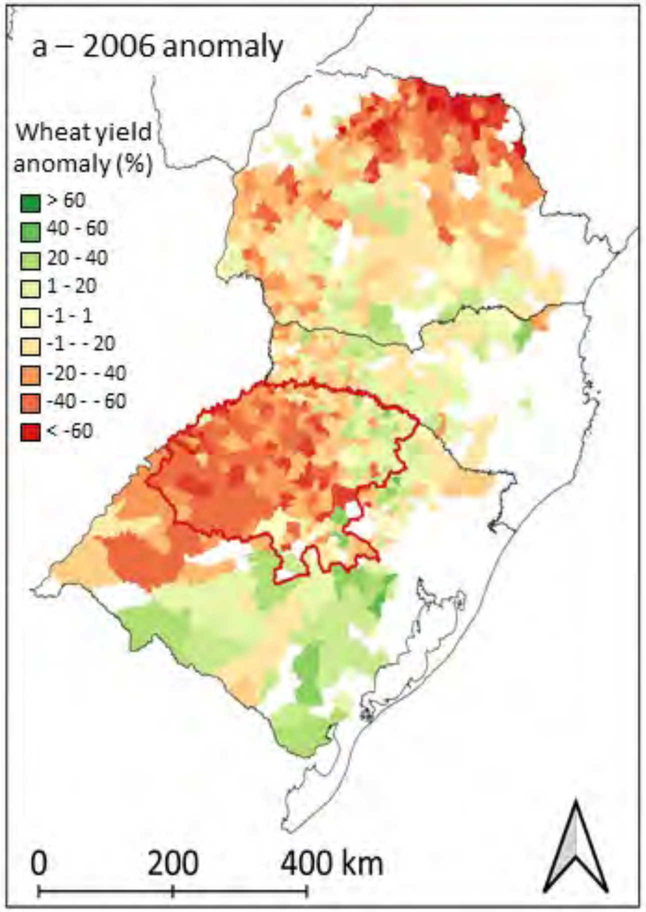
LOW COMMODITY PRICES

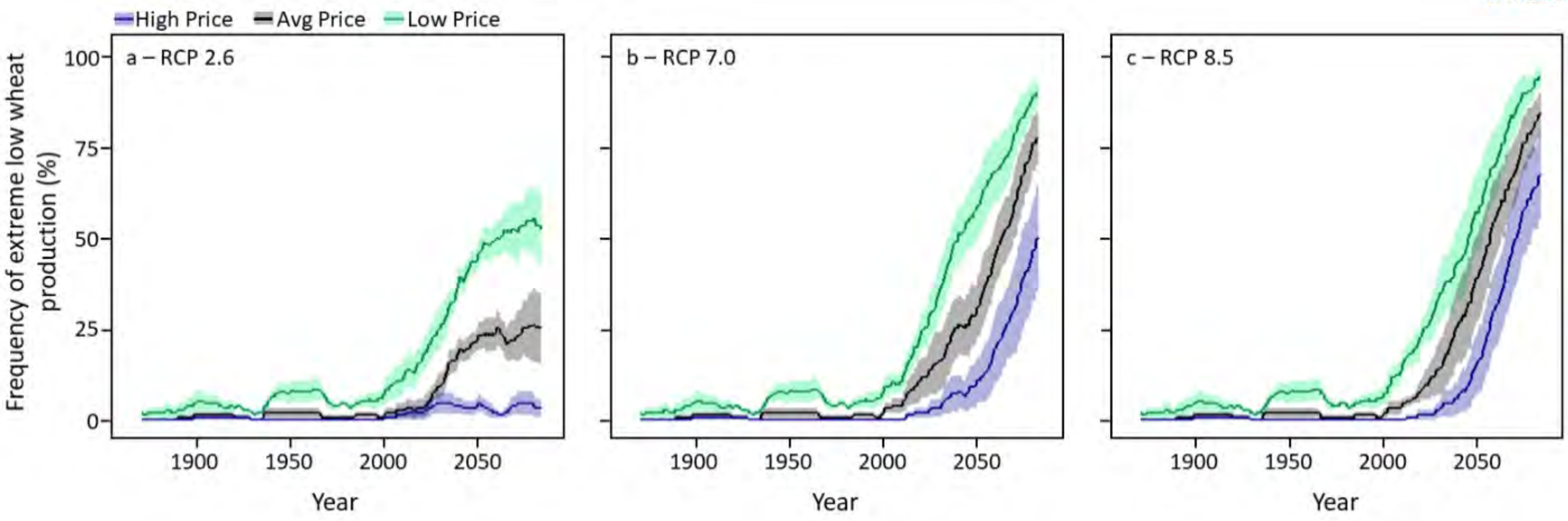
COMBINATION OF THESE FACTORS

Low prices discourage investments for wheat cultivation, further impacting production.

WHEAT PLANTING AREA IN BRAZIL IS HIGHLY RESPONSIVE TO CHANGES IN WHEAT PRICES.

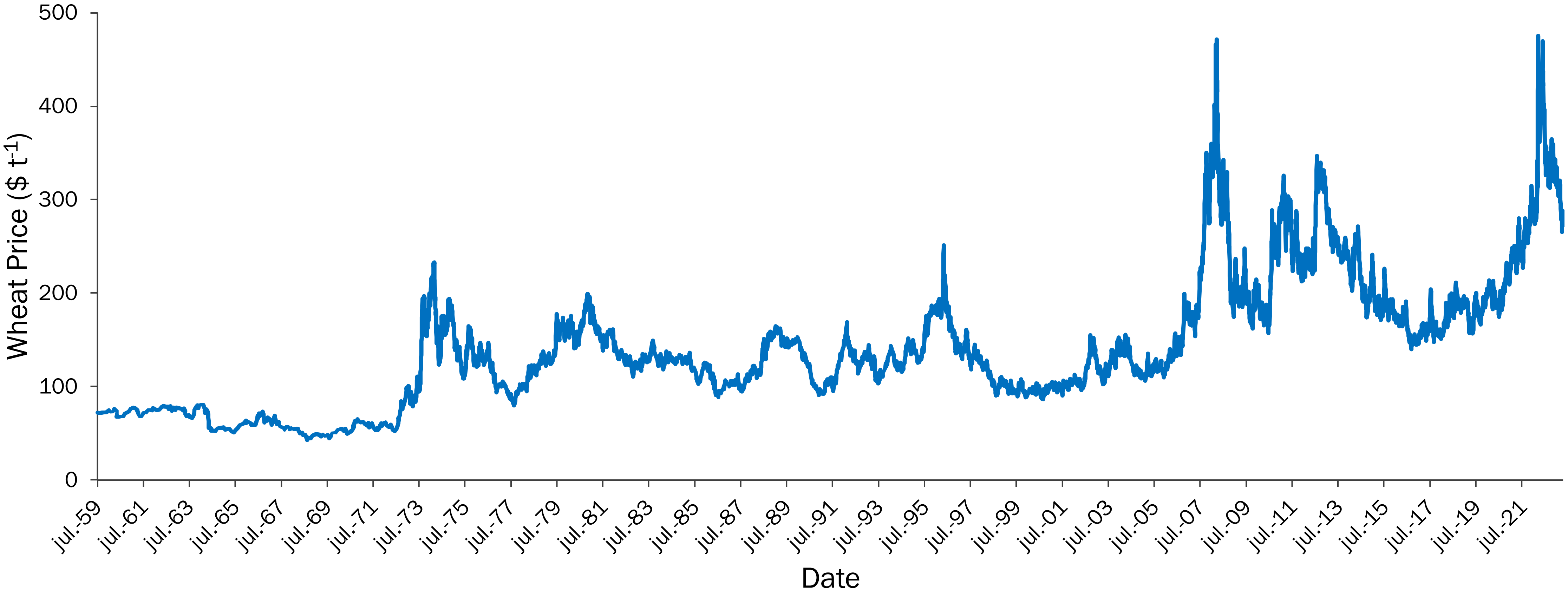






CMIP6 CLIMATE CHANGE MODELS SUGGEST INCREASED FREQUENCY OF LOW WHEAT PRODUCTION EVENTS, AMPLIFIED BY WHEAT PRICE.

GLOBAL WHEAT PRICE – CONSEQUENCES IN BRAZIL



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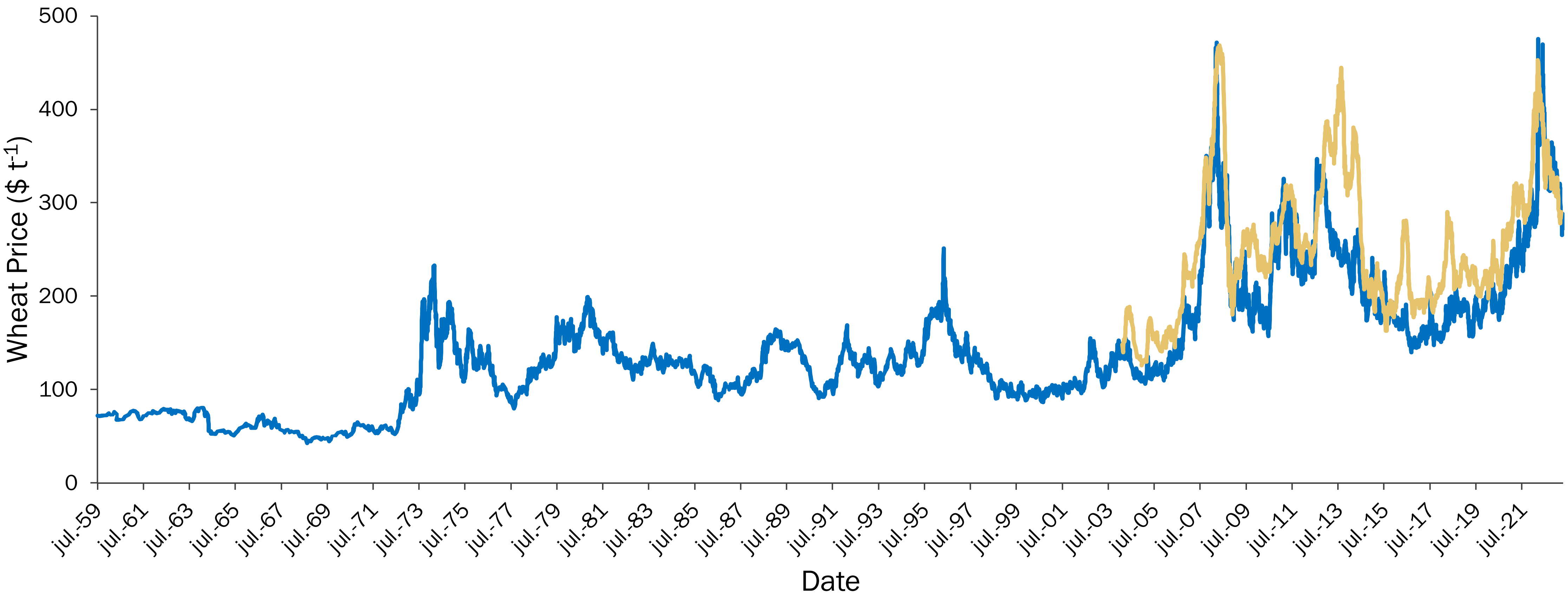
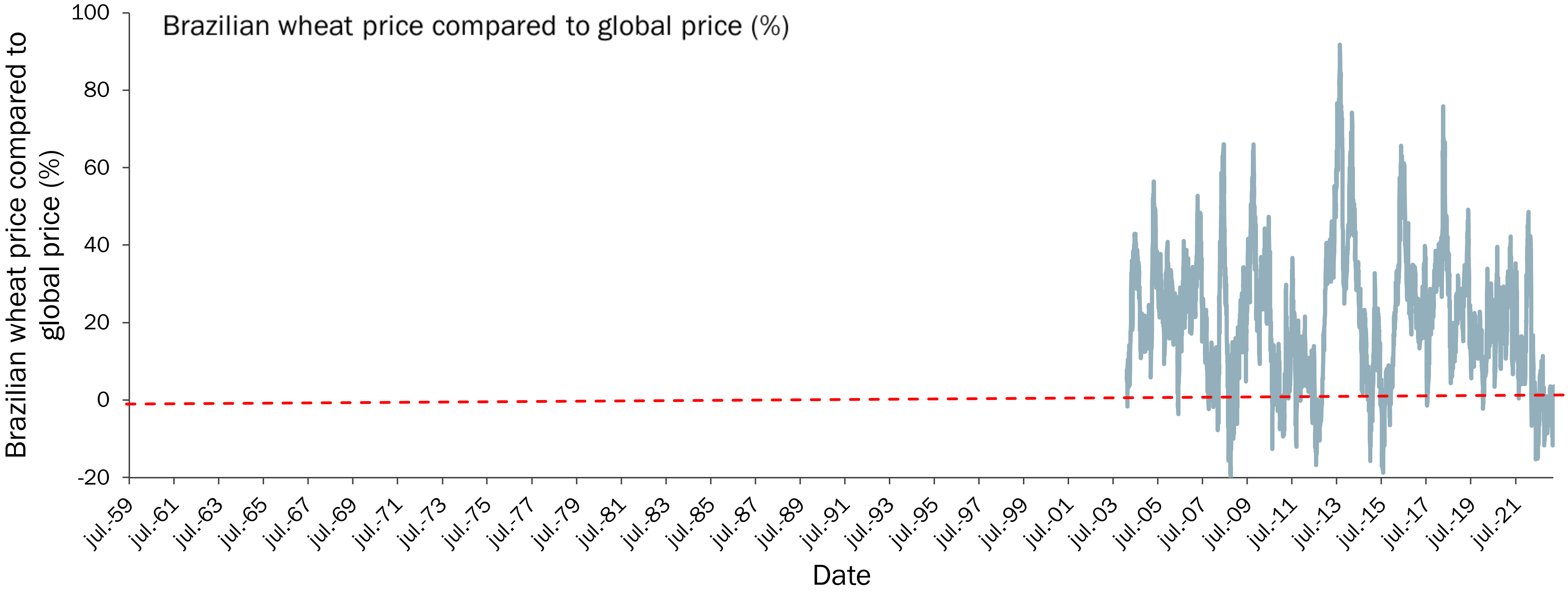
University
of Munich

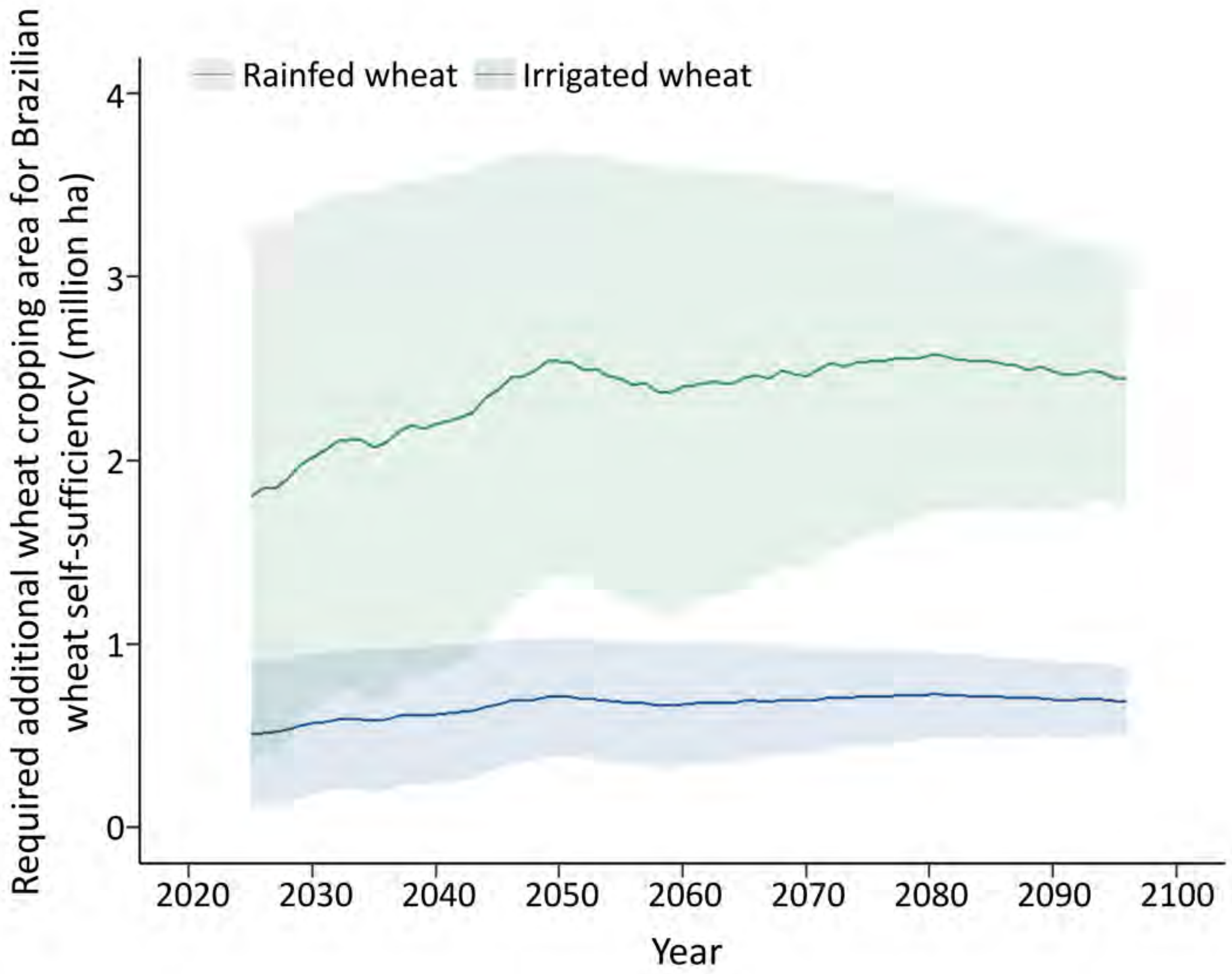
GLOBAL WHEAT PRICE – CONSEQUENCES IN BRAZIL



GLOBAL WHEAT PRICE – CONSEQUENCES IN BRAZIL



BRAZIL SEEKS WHEAT SELF-SUFFICIENCY THROUGH EXPANDED PLANTING.



Tomorrow in **Session 1B** titled "Improving Crop Models to Capture Extreme Climate Responses."

Thank you

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Economic Research Service
U.S. DEPARTMENT OF AGRICULTURE

Multi-Breadbasket Failures and Shocks to Food Systems: AgMIP Simulations

Ron Sands, USDA Economic Research Service
Tim Sulser and Keith Wiebe, International Food Policy Research Institute
Jonas Jägermeyr, Columbia University
Alex Ruane, NASA Goddard Institute for Space Studies

AgMIP9 Workshop on Modeling the Future of Food
June 27-29, 2023
Columbia University

Economic Research Service
www.ers.usda.gov

Multi-Breadbasket Failures

Research Questions

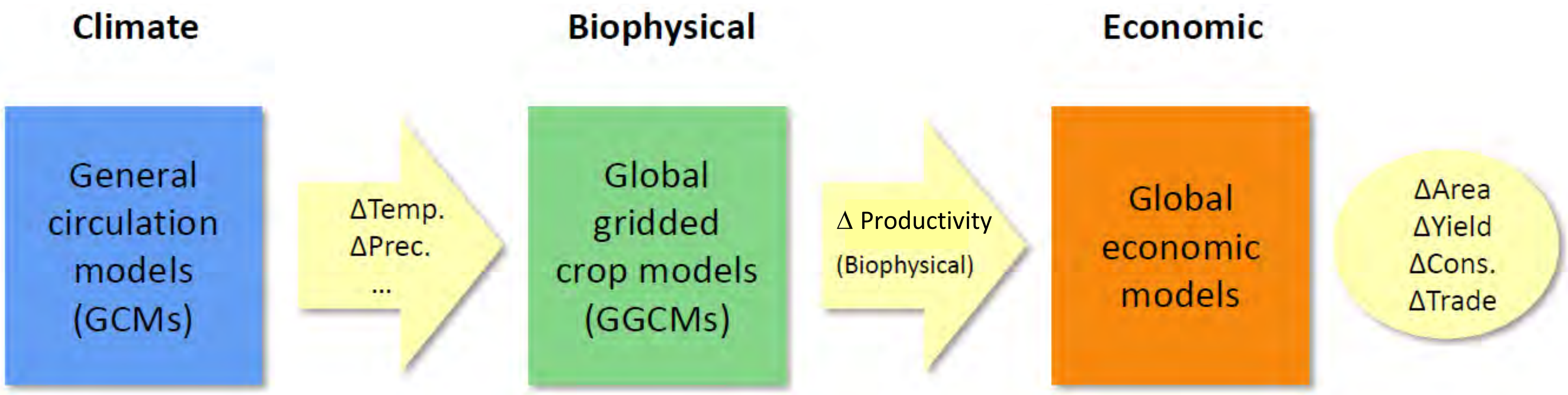
1. What is the potential for food shocks caused by simultaneous breadbasket failures in multiple locations across the globe to overwhelm food systems?
2. What are the economic and food system responses to multi-breadbasket failures?

This project was motivated by a 2019 Aspen Global Change Institute workshop on modeling food shocks.

Approach

- Economic responses to biophysical shocks assessed with two global agri-economic models:
  - International Model for Policy Analysis of Agricultural Commodities and Trade (IMPACT)
  - Future Agricultural Resources Model (FARM)
- Food shock scenarios:
  - Uniform global productivity deficits of 5%, 10%, and 15% for three major field crops
  - Vary distribution of global productivity shocks to be concentrated in major breadbaskets

The climate modeling chain: From biophysical to socioeconomic



Climate

General circulation models (GCMs)

ΔTemp.
ΔPrec.
…

Biophysical

Global gridded crop models (GGCMs)

Δ Productivity
(Biophysical)

Economic

Global economic models

ΔArea
ΔYield
ΔCons.
ΔTrade

Economic responses to a decline in agricultural productivity due to climate change in 2050

Climate change effects on agriculture: Economic responses to biophysical shocks

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Edited by Hans Joachim Schellnhuber, Potsdam Institute for Climate Impact Research, Potsdam, Germany, and approved August 31, 2013 (received for review January 31, 2013)

Agricultural production is sensitive to weather and thus directly affected by climate change. Plausible estimates of these climate change impacts require combined use of climate, crop, and economic models. Results from previous studies vary substantially due to differences in models, scenarios, and data. This paper is part of a collective effort to systematically integrate these three types of models. We focus on the economic component of the assessment, investigating how nine global economic models of agriculture represent endogenous responses to seven standardized climate change scenarios produced by two climate and five crop models. These responses include adjustments in yields, area, consumption, and international trade. We apply biophysical shocks derived from the Intergovernmental Panel on Climate Change's representative concentration pathway with end-of-century radiative forcing of 8.5 W/m^2. The mean biophysical yield effect with no incremental CO_2 fertilization is a 17% reduction globally by 2050 relative to a scenario with unchanging climate. Endogenous economic responses reduce yield loss to 11%, increase area of major crops by 11%, and reduce consumption by 3%. Agricultural production, cropland area, trade, and prices show the greatest degree of variability in response to climate change, and consumption the lowest. The sources of these differences include model structure and specification; in particular, model assumptions about ease of land use conversion, intensification, and trade. This study identifies where models disagree on the relative responses to climate shocks and highlights research activities needed to improve the representation of agricultural adaptation responses to climate change.

climate change adaptation | model intercomparison | integrated assessment | agricultural productivity

Climate change alters weather conditions and thus has direct, biophysical effects on agricultural production. Assessing the ultimate consequences of these effects after producers and consumers respond requires detailed assessments at every step in the impact chain from climate through to crop and economic modeling.

Comparisons of results from global studies that have attempted such model integration in the past show substantial differences in effects on key economic variables. Studies in the early 1990s found that climate change would have limited agricultural impacts globally, but with varying effects across regions (1–3). Adaptation and carbon dioxide (CO_2) fertilization effects were the two largest sources of variation in the results. New simulation approaches emerged in the mid-2000s, with gridded representation of yield impacts and more comprehensive coverage of variability in climate model projections (4, 5). However, these studies still relied on a single crop model and a single economic model. The number of economic models used for these types of analysis has remained relatively limited, and there has been no attempt to compare their behavior systematically. The Fourth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC) (6) renewed the call to "enhance crop model intercomparison" and noted that "economic, trade and technological assumptions used in many of the integrated assessment models to project food security under climate change were poorly tested against observed data" (ref. 6, p. 285).

This paper is part of a collective effort (7) to make progress in this direction by systematically integrating results from the three types of models—climate, crop, and economic—to assess how agriculture responds to climate change. The modeling chain is portrayed in Fig. 1. General circulation models (GCMs) use a

Significance

Plausible estimates of climate change impacts on agriculture require integrated use of climate, crop, and economic models. We investigate the contribution of economic models to uncertainty in this impact chain. In the nine economic models included, the direction of management intensity, area, consumption, and international trade responses to harmonized crop yield shocks from climate change are similar. However, the magnitudes differ significantly. The differences depend on model structure, in particular the specification of endogenous yield effects, land use change, and propensity to trade. These results highlight where future research on modeling climate change impacts on agriculture should focus.

Author contributions: G.C.N., H.V., R.D.S., M.V.L., H.L.-C., H.v.M., D.v.d.M., and C.M. designed research; G.C.N., H.V., R.D.S., P.H., H.A., D.D., J.E., S.F., T.H., E.H., P.K., M.V.L., H.L.-C., D.M.d., H.v.M., D.v.d.M., C.M., A.P., R.R., S.R., E.S., C.S., A.T., and D.W. performed research; G.C.N., H.V., R.D.S., P.H., H.A., D.D., J.E., S.F., T.H., E.H., P.K., M.V.L., H.L.-C., D.M.d., D.v.d.M., C.M., A.P., R.R., S.R., E.S., C.S., A.T., and D.W. analyzed data; and G.C.N. and H.V. wrote the paper.

The authors declare no conflict of interest.

This article is a PNAS Direct Submission.

Data deposition: A data file, a metadata file, and R code to generate the graphs are stored and made available on the Agricultural Model Intercomparison and Improvement Project Web site, www.agmip.org, and the Inter-Sectoral Impact Model Intercomparison Project Web site, www.isi-mip.org. They are also available as Datasets S1, S2, and S3.

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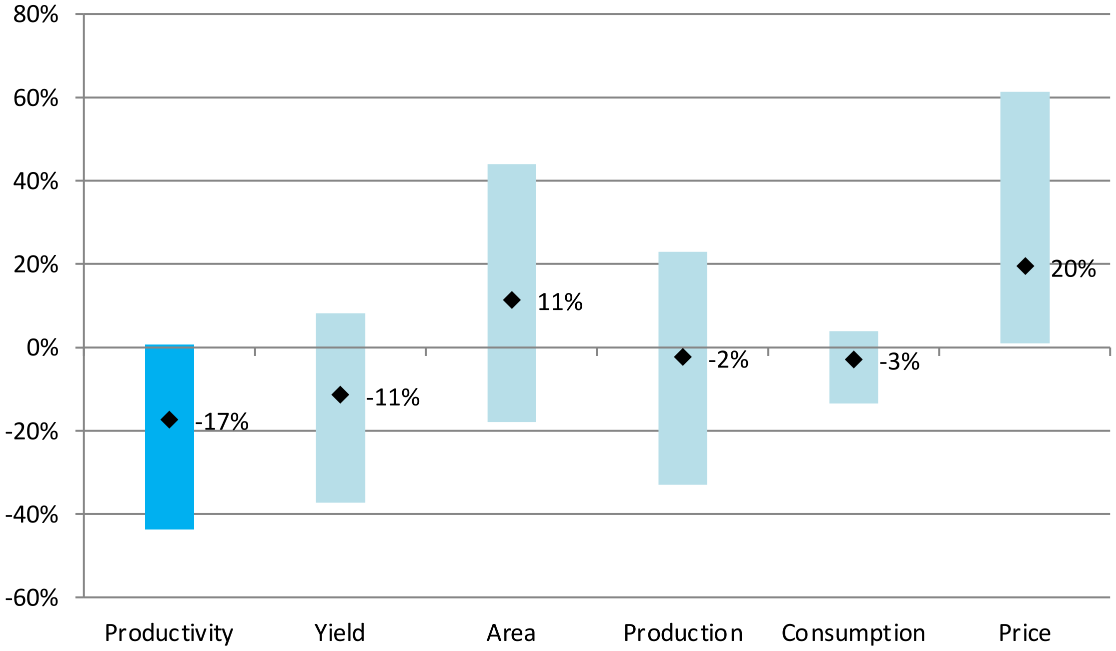
www.pnas.org/cgi/doi/10.1073/pnas.1222465110

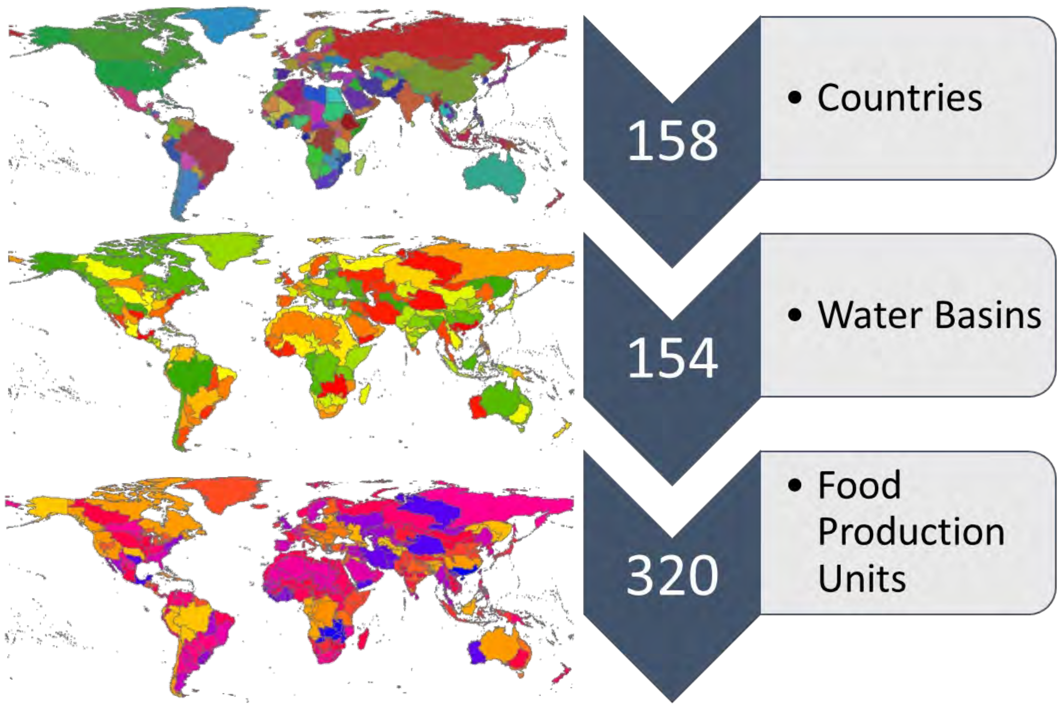


Change in Productivity is the exogenous shock. All other changes are endogenous responses relative to baseline. The black diamond is the average (mean) percent change with climate change compared to no climate change in year 2050; the height of a column is the range across climate models, crop models, and nine economic models. Results are a world average across major field crops: wheat, rice, coarse grains, and oil seeds.

Source: Nelson et al. (2014) "Climate change effects on agriculture: Economic responses to biophysical shocks," *Proceedings of the National Academy of Sciences*, Vol. 111(9): 3274-3279.

The IMPACT modeling framework

- Highly disaggregated regionally and by commodity
  => 320 geographic units, 60+ commodities, irrigated/rainfed agriculture



158
- Countries

154
- Water Basins

320
- Food Production Units

Cattle	Barley	Bananas
Dairy	Maize	Plantains
Eggs	Millet	Sub-tropical fruits
Pigs	Rice	Temperate fruits
Poultry	Sorghum	Vegetables
Sheep/goat	Wheat	
Groundnuts	Cocoa	Beans
Oil palm	Coffee	Chickpeas
Rapeseed	Cotton	Cowpeas
Soybeans	Tea	Lentils
Sunflower		Pigeonpeas
Cassava	Sugarbeet	Others…
Potato	Sugarcane	
Sweet potatoes	Refined sugar	
Yams		

Future Agricultural Resources Model (FARM)

Global computable general equilibrium (CGE) model with 13 world regions, 38 production sectors, and five-year time steps from 2011 through 2101.

Region name	Notes
Sub-Saharan Africa	
India	
Other Asia (south)	
Brazil	
Other South America	Including Central America, Caribbean, and Mexico
Middle East and North Africa	Including Turkey
Economies in Transition	Russia, Belarus, Ukraine, Kazakhstan, Kyrgyzstan, Armenia, Azerbaijan, Georgia, Tajikistan, Turkmenistan, and Uzbekistan
China	
Southeast and East Asia	Including Japan
United States	
Canada	
Europe	Including Estonia, Latvia, and Lithuania
Australia and New Zealand	Including Oceania

Group	Subgroup	Production Sector
Primary agriculture	Crops	Wheat
		Paddy rice
		Other grains
		Oilseeds
		Sugar (cane and beet)
		Vegetables and fruits
		Plant fibers
		Other crops
	Animal products	Cattle and other ruminants
		Raw milk
		Wool
		Other animal products
	Fisheries	Fish
	Forestry	Forestry
Food processing		Vegetable oils
		Processed rice
		Sugar
		Beverages and tobacco products
		Other food
		Meat from cattle and other ruminants
		Dairy products
		Other meat products
Energy	Production	Coal
		Crude oil
		Natural gas
	Transformation	Refined coal and petroleum products
		Electricity
Energy-intensive industries		Wood products
		Paper and pulp
		Chemicals, rubber, and plastic
		Nonmetallic minerals
		Iron and steel
		Nonferrous metals
Other industry		Other industry
Transportation		Land transportation
		Water transportation
		Air transportation
Services		Services

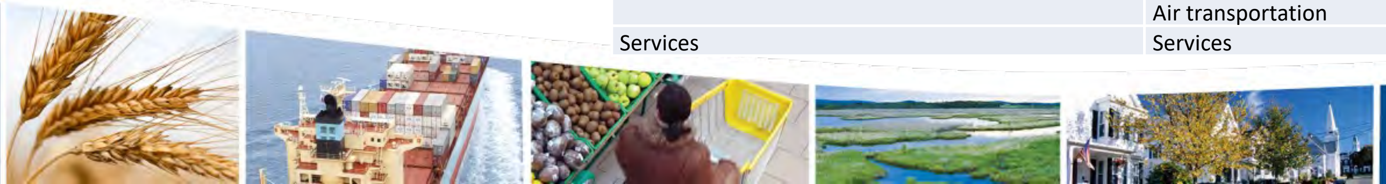


Table of Scenarios

Magnitude of production deficit	1A	IMPACT	FARM	Uniform global negative yield shocks to maize, rice, wheat of 5% with immediate rebound
	1B	IMPACT	FARM	Uniform global negative yield shocks to maize, rice, wheat of 10% with immediate rebound
	1C	IMPACT	FARM	Uniform global negative yield shocks to maize, rice, wheat of 15% with immediate rebound
Distribution of production deficit	2A		FARM	10% productivity deficit from losses in United States
	2B		FARM	10% productivity deficit from losses in 3 major breadbaskets (United States, Russia, Ukraine and other Economies in transition)
	2C		FARM	10% productivity deficit from losses in many minor breadbaskets (countries other than scenario 2B)
Sequential effects	3A			10% global productivity deficit in 1st year; 2nd year normal
	3B	IMPACT		Uniform global negative yield shocks to maize, rice, wheat of 10% WITHOUT immediate rebound (persistence of yield shock for 3 years)
Buffers	4A			10% global reduction from 2 major breadbaskets, but good year elsewhere mean only 5% global production deficit
	4B	IMPACT		Uniform global negative yield shocks to maize of 10% and positive yield shock to wheat of 5% with immediate rebound
	4C	IMPACT		Uniform global negative yield shocks to maize of 10% and positive yield shock to rice of 5% with immediate rebound
Alternative futures	5A			10% global productivity deficit with severe climate change impacts
	5B			10% global productivity deficit with bioenergy competition

Selected results from the IMPACT model (World)

Yield index (REF = 1.0) with shock in 2015

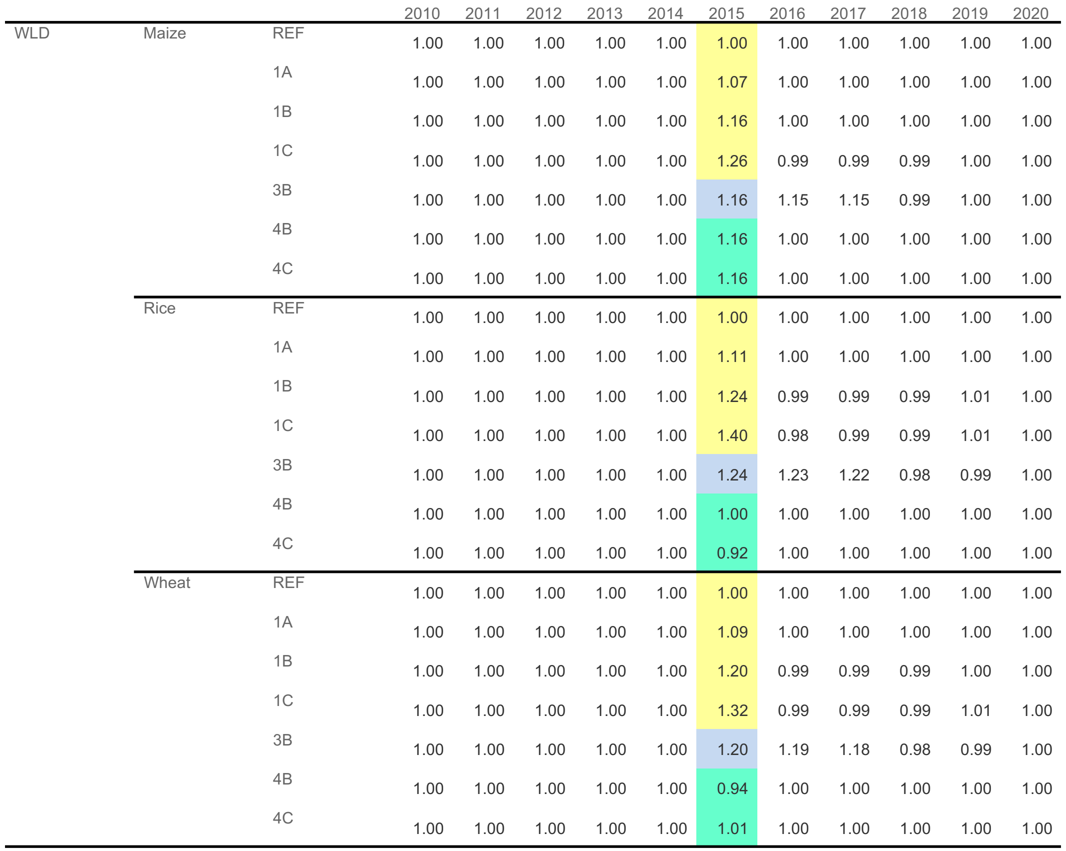
			2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
WLD	Maize	REF	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		1A	1.00	1.00	1.00	1.00	1.00	0.95	1.00	1.00	1.00	1.00	1.00
		1B	1.00	1.00	1.00	1.00	1.00	0.90	1.00	1.00	1.00	1.00	1.00
		1C	1.00	1.00	1.00	1.00	1.00	0.85	1.00	1.00	1.00	1.00	1.00
		3B	1.00	1.00	1.00	1.00	1.00	0.90	0.90	0.90	1.00	1.00	1.00
		4B	1.00	1.00	1.00	1.00	1.00	0.90	1.00	1.00	1.00	1.00	1.00
		4C	1.00	1.00	1.00	1.00	1.00	0.90	1.00	1.00	1.00	1.00	1.00
	Rice	REF	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		1A	1.00	1.00	1.00	1.00	1.00	0.95	1.00	1.00	1.00	1.00	1.00
		1B	1.00	1.00	1.00	1.00	1.00	0.90	1.00	1.00	1.00	1.00	1.00
		1C	1.00	1.00	1.00	1.00	1.00	0.85	1.00	1.00	1.00	1.00	1.00
		3B	1.00	1.00	1.00	1.00	1.00	0.90	0.90	0.90	1.00	1.00	1.00
		4B	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		4C	1.00	1.00	1.00	1.00	1.00	1.05	1.00	1.00	1.00	1.00	1.00
	Wheat	REF	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		1A	1.00	1.00	1.00	1.00	1.00	0.95	1.00	1.00	1.00	1.00	1.00
		1B	1.00	1.00	1.00	1.00	1.00	0.90	1.00	1.00	1.00	1.00	1.00
		1C	1.00	1.00	1.00	1.00	1.00	0.85	1.00	1.00	1.00	1.00	1.00
		3B	1.00	1.00	1.00	1.00	1.00	0.90	0.90	0.90	1.00	1.00	1.00
		4B	1.00	1.00	1.00	1.00	1.00	1.05	1.00	1.00	1.00	1.00	1.00
		4C	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

Production index (REF = 1.0) with shock in 2015

			2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
WLD	Maize	REF	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		1A	1.00	1.00	1.00	1.00	1.00	0.96	1.00	1.00	1.00	1.00	1.00
		1B	1.00	1.00	1.00	1.00	1.00	0.92	1.01	1.01	1.00	1.00	1.00
		1C	1.00	1.00	1.00	1.00	1.00	0.89	1.01	1.01	1.01	0.99	1.00
		3B	1.00	1.00	1.00	1.00	1.00	0.92	0.93	0.94	1.02	1.01	1.00
		4B	1.00	1.00	1.00	1.00	1.00	0.96	1.00	1.00	1.00	1.00	1.00
		4C	1.00	1.00	1.00	1.00	1.00	0.95	1.00	1.00	1.00	1.00	1.00
	Rice	REF	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		1A	1.00	1.00	1.00	1.00	1.00	0.97	1.00	1.00	1.00	1.00	1.00
		1B	1.00	1.00	1.00	1.00	1.00	0.95	1.00	1.00	1.00	1.00	1.00
		1C	1.00	1.00	1.00	1.00	1.00	0.92	1.00	1.00	1.00	1.00	1.00
		3B	1.00	1.00	1.00	1.00	1.00	0.95	0.95	0.95	1.01	1.00	1.00
		4B	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		4C	1.00	1.00	1.00	1.00	1.00	1.02	1.00	1.00	1.00	1.00	1.00
	Wheat	REF	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		1A	1.00	1.00	1.00	1.00	1.00	0.97	1.00	1.00	1.00	1.00	1.00
		1B	1.00	1.00	1.00	1.00	1.00	0.94	1.00	1.00	1.00	1.00	1.00
		1C	1.00	1.00	1.00	1.00	1.00	0.91	1.01	1.00	1.00	1.00	1.00
		3B	1.00	1.00	1.00	1.00	1.00	0.94	0.94	0.95	1.01	1.00	1.00
		4B	1.00	1.00	1.00	1.00	1.00	1.02	1.00	1.00	1.00	1.00	1.00
		4C	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00

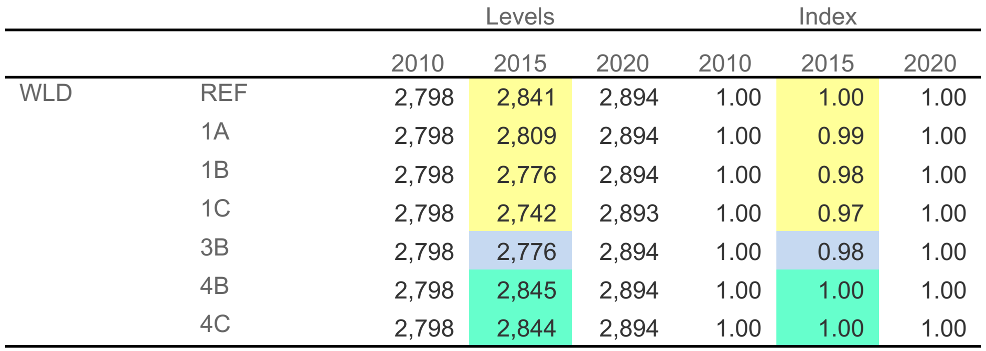
Additional results from the IMPACT model

Price index (REF = 1.0) with shock in 2015



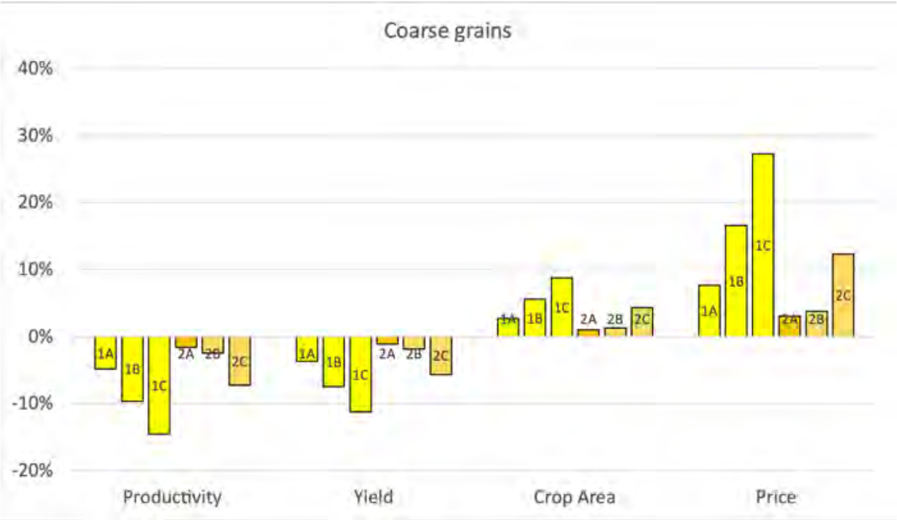
			2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
WLD	Maize	REF	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		1A	1.00	1.00	1.00	1.00	1.00	1.07	1.00	1.00	1.00	1.00	1.00
		1B	1.00	1.00	1.00	1.00	1.00	1.16	1.00	1.00	1.00	1.00	1.00
		1C	1.00	1.00	1.00	1.00	1.00	1.26	0.99	0.99	0.99	1.00	1.00
		3B	1.00	1.00	1.00	1.00	1.00	1.16	1.15	1.15	0.99	1.00	1.00
		4B	1.00	1.00	1.00	1.00	1.00	1.16	1.00	1.00	1.00	1.00	1.00
		4C	1.00	1.00	1.00	1.00	1.00	1.16	1.00	1.00	1.00	1.00	1.00
	Rice	REF	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		1A	1.00	1.00	1.00	1.00	1.00	1.11	1.00	1.00	1.00	1.00	1.00
		1B	1.00	1.00	1.00	1.00	1.00	1.24	0.99	0.99	0.99	1.01	1.00
		1C	1.00	1.00	1.00	1.00	1.00	1.40	0.98	0.99	0.99	1.01	1.00
		3B	1.00	1.00	1.00	1.00	1.00	1.24	1.23	1.22	0.98	0.99	1.00
		4B	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		4C	1.00	1.00	1.00	1.00	1.00	0.92	1.00	1.00	1.00	1.00	1.00
	Wheat	REF	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
		1A	1.00	1.00	1.00	1.00	1.00	1.09	1.00	1.00	1.00	1.00	1.00
		1B	1.00	1.00	1.00	1.00	1.00	1.20	0.99	0.99	0.99	1.00	1.00
		1C	1.00	1.00	1.00	1.00	1.00	1.32	0.99	0.99	0.99	1.01	1.00
		3B	1.00	1.00	1.00	1.00	1.00	1.20	1.19	1.18	0.98	0.99	1.00
		4B	1.00	1.00	1.00	1.00	1.00	0.94	1.00	1.00	1.00	1.00	1.00
		4C	1.00	1.00	1.00	1.00	1.00	1.01	1.00	1.00	1.00	1.00	1.00

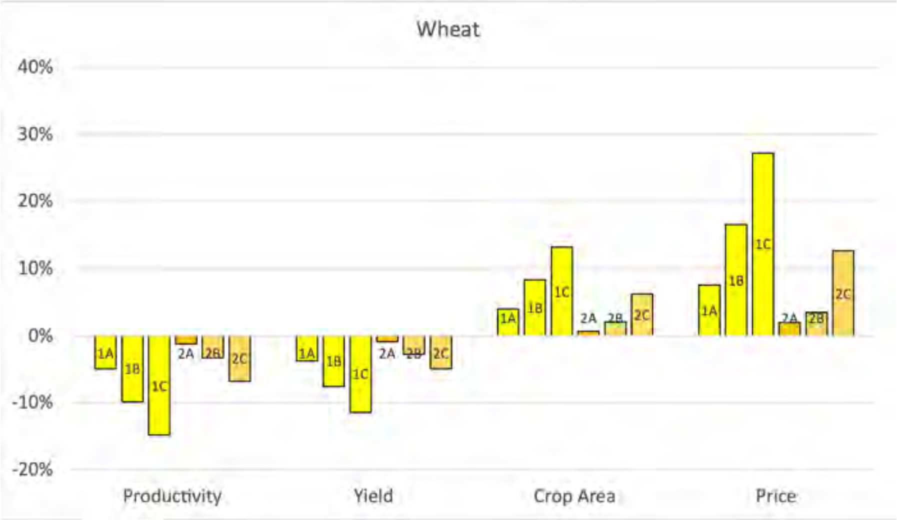
Per capita calorie (kcal) availability levels and index

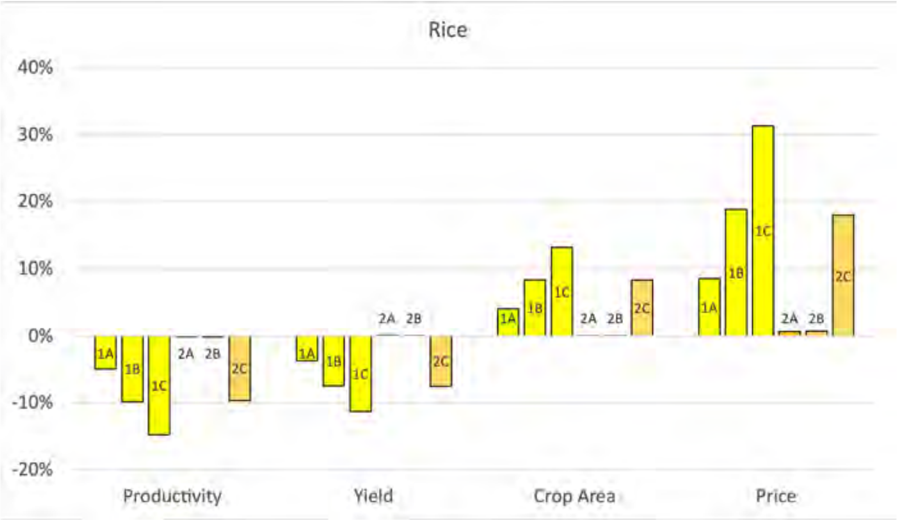


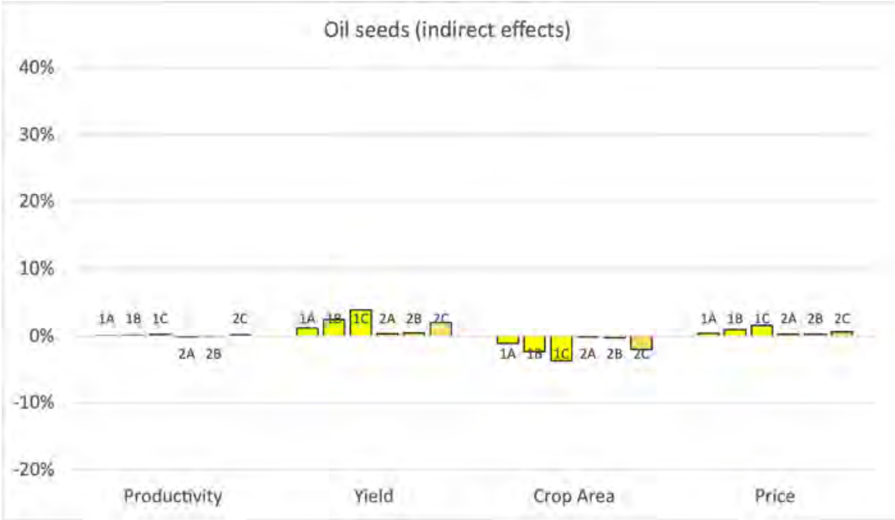
		Levels			Index		
		2010	2015	2020	2010	2015	2020
WLD	REF	2,798	2,841	2,894	1.00	1.00	1.00
	1A	2,798	2,809	2,894	1.00	0.99	1.00
	1B	2,798	2,776	2,894	1.00	0.98	1.00
	1C	2,798	2,742	2,893	1.00	0.97	1.00
	3B	2,798	2,776	2,894	1.00	0.98	1.00
	4B	2,798	2,845	2,894	1.00	1.00	1.00
	4C	2,798	2,844	2,894	1.00	1.00	1.00

Selected results from the FARM model (World)

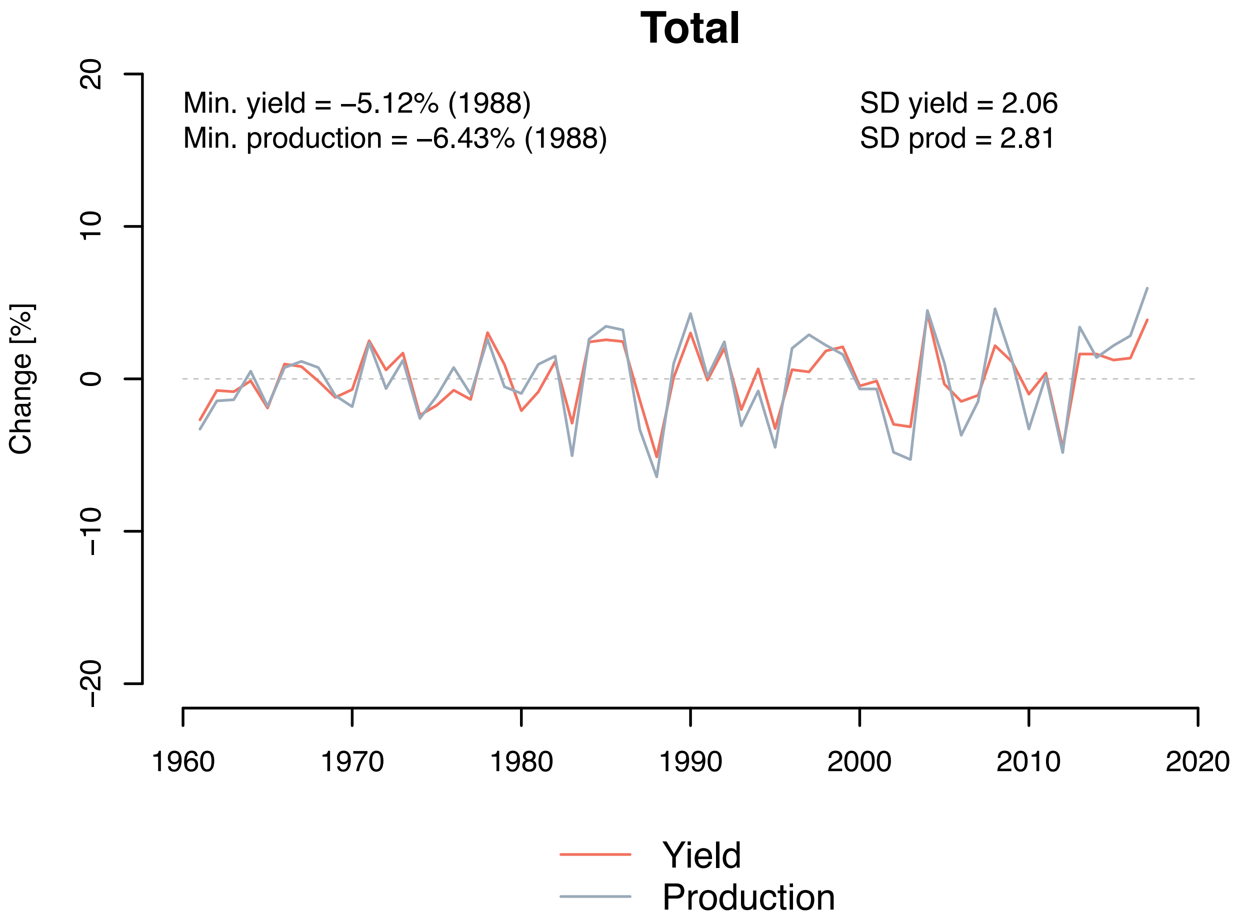




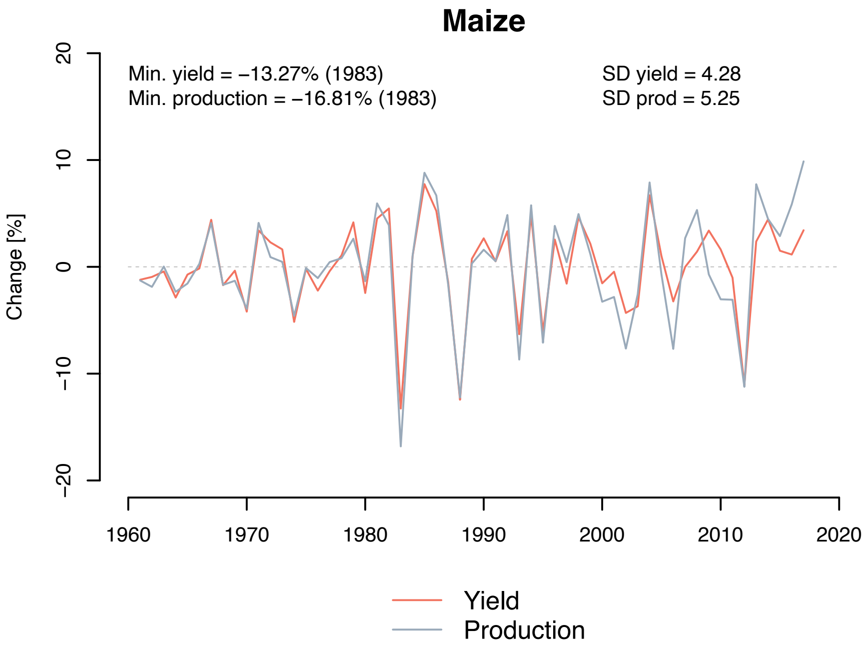


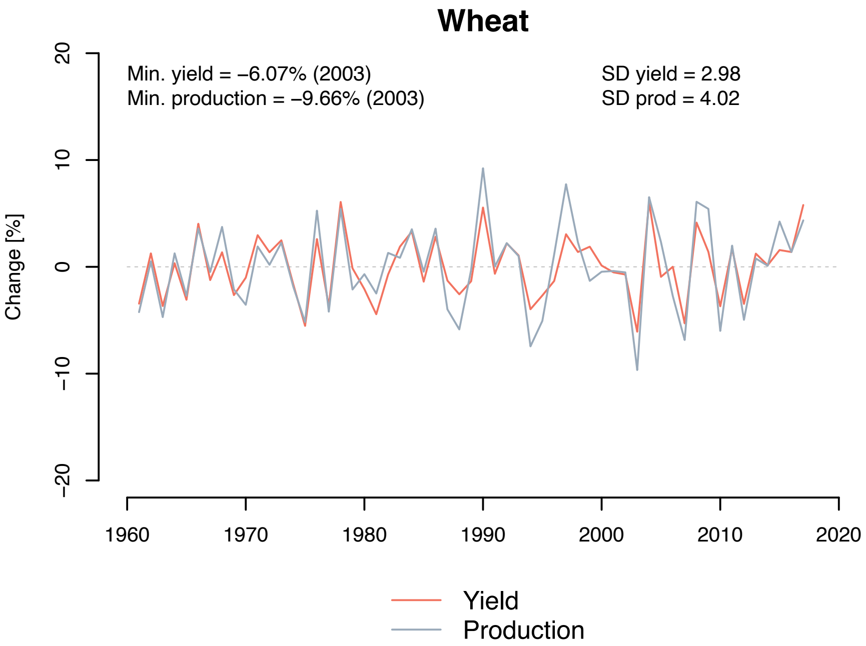


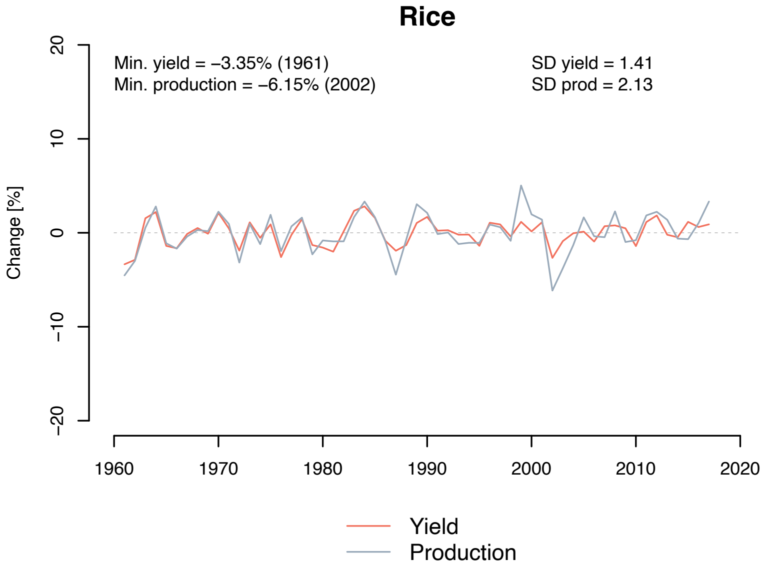
Scenario 1A – Historical global production deficit in maize, wheat, rice



- Largest FAO-observed historical production loss was 6.4%, a 10% and 15% global shock would be 55% and 133% larger than the observed extreme
- Losses >4% occurred in 1983, 1988, 1995, 2002, 2003, 2012
- Yield variability (Standard Deviation) smaller than production variability, changes in harvested area exacerbate production fluctuations







- Individual crops have larger inter-annual variation than total production
- Different crops have worst losses in different years
- **Maize** had global losses >10% in 3 years (1983, 1988, 2012) and >5% in 7 years (1983, 1988, 1993, 1995, 2002, 2006, 2012)
- **Wheat** had losses >5% in 7 years (1975, 1988, 1994, 1995, 2003, 2007, 2010)
- **Rice** had losses >5% in 1 year (2002) and losses >3% in 5 years (1961, 1972, 1987, 2002, 2003)
- Maize variability highest among the three crops, more than twice the rice variability

Takeaways

Results

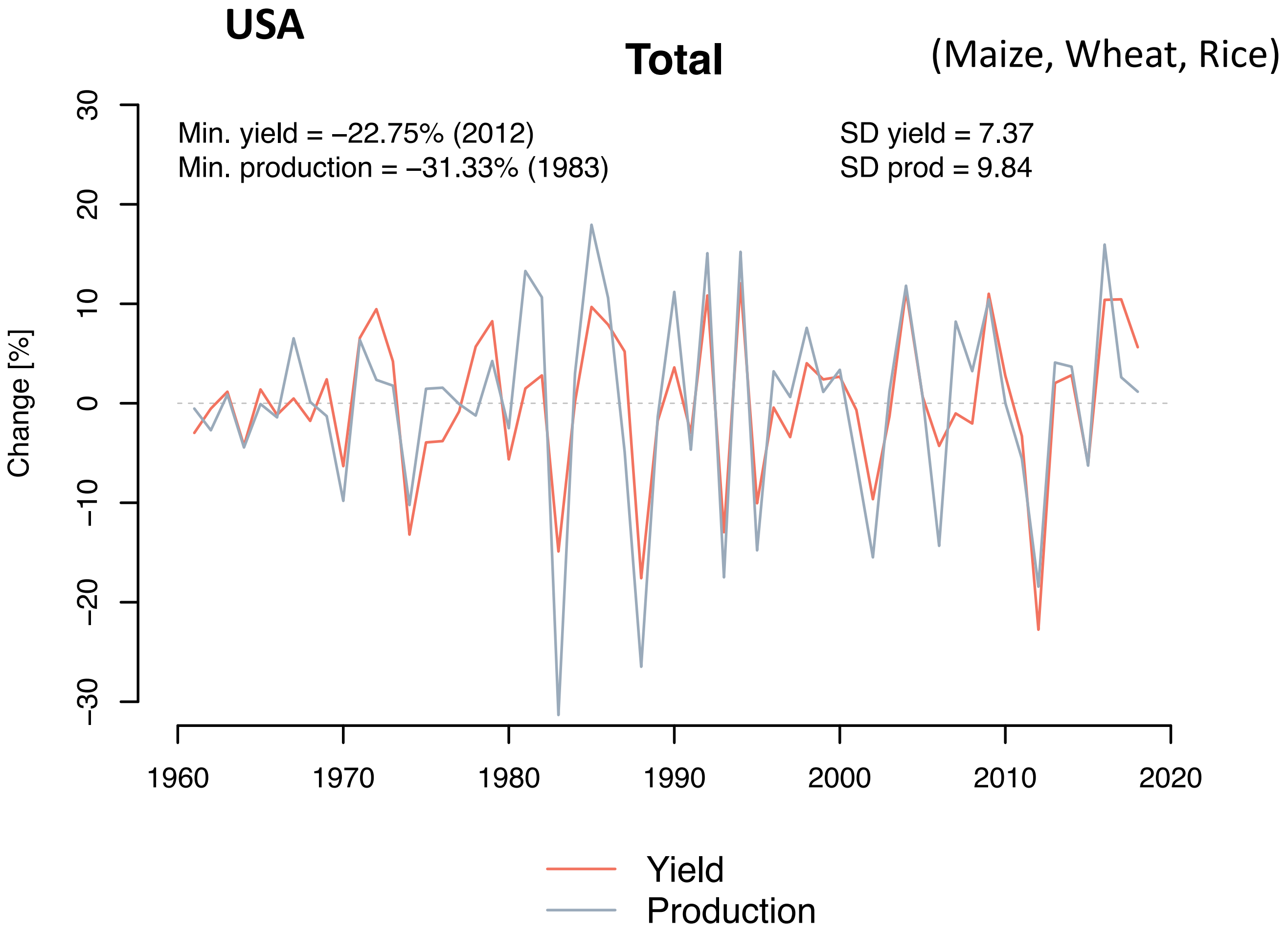
- Decline in consumption is much less than decline in productivity or yield
- Food price increases bring more non-land inputs into production and increase area harvested
- Changes in yield and area depend on flexibility of production structure
- Increase in area of crops affected by food shock is partly offset by a decline in area of other crops

Modeling Challenges

- How should productivity changes from crop models be interpreted in economic production functions?
- Dynamics and drawdown of food stocks
- Results depend on whether the shock is known in advance or is a surprise after planting

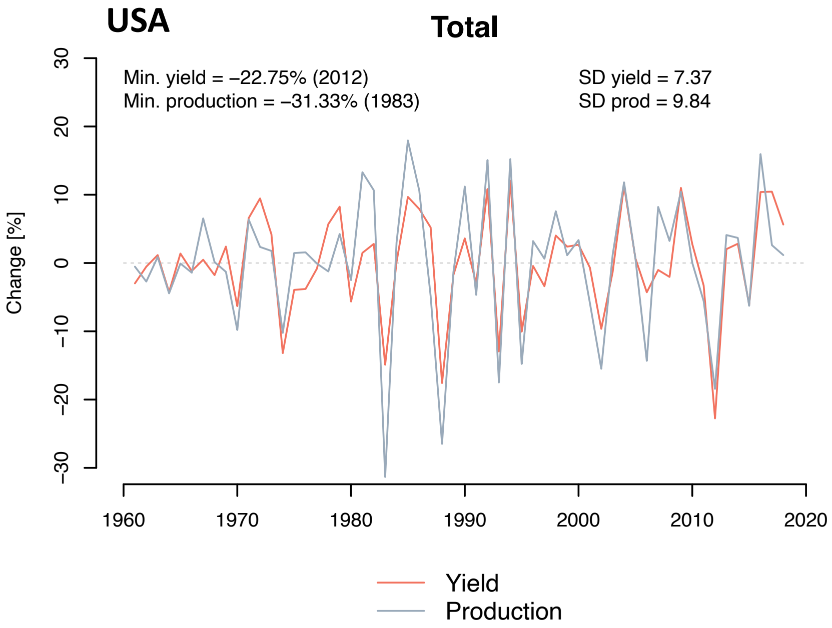
Extra Slides

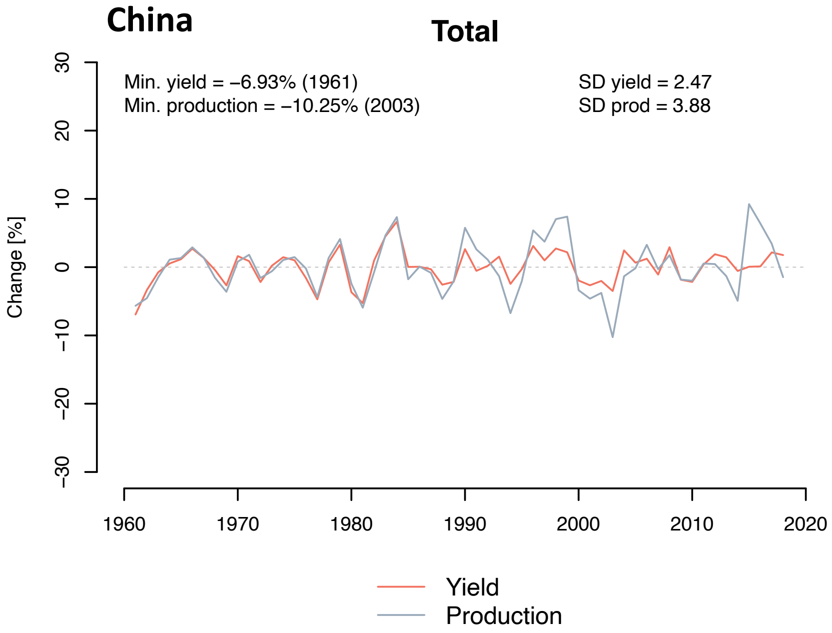
Scenario 2A – 10% global production deficit from losses in USA

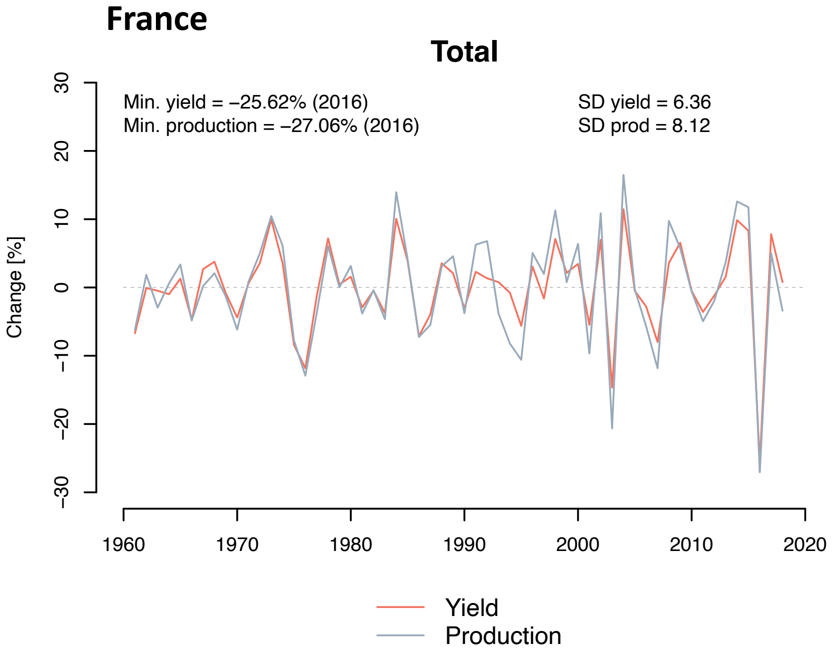


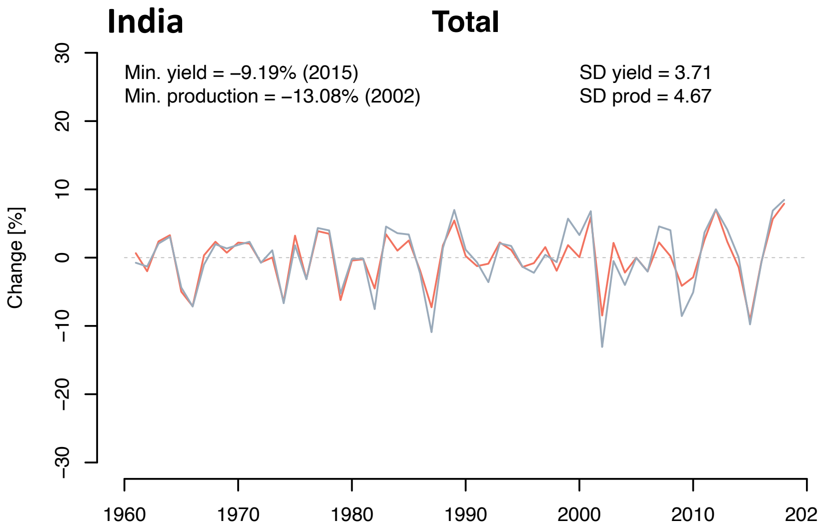
- US production had largest deficit in 1983 with -31%
- Largest yield losses occurred in 2012 (-23%)
- Dust bowl had yield losses up to 32% in 1933 (before FAO observations start)
- US contribution to global production of maize, wheat, and rice is 17% (past 10 years)
- To generate a global loss of 10%, US production would need to fall by 59% (down to 41% of average level in past 10 years)
- Largest historical production losses (1983) caused a global production deficit of 5.8%, today the same shock would cause a global deficit of 5.3%

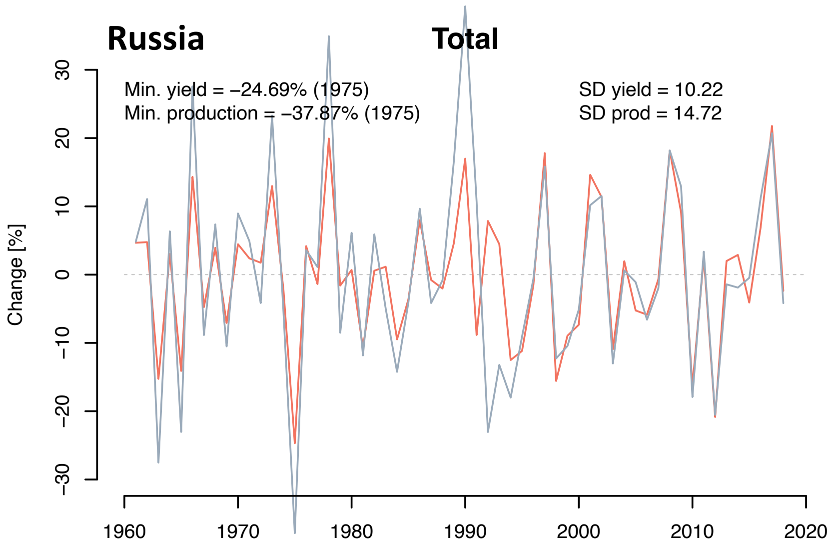
Scenario 2B – 10% global production deficit from losses in various breadbaskets











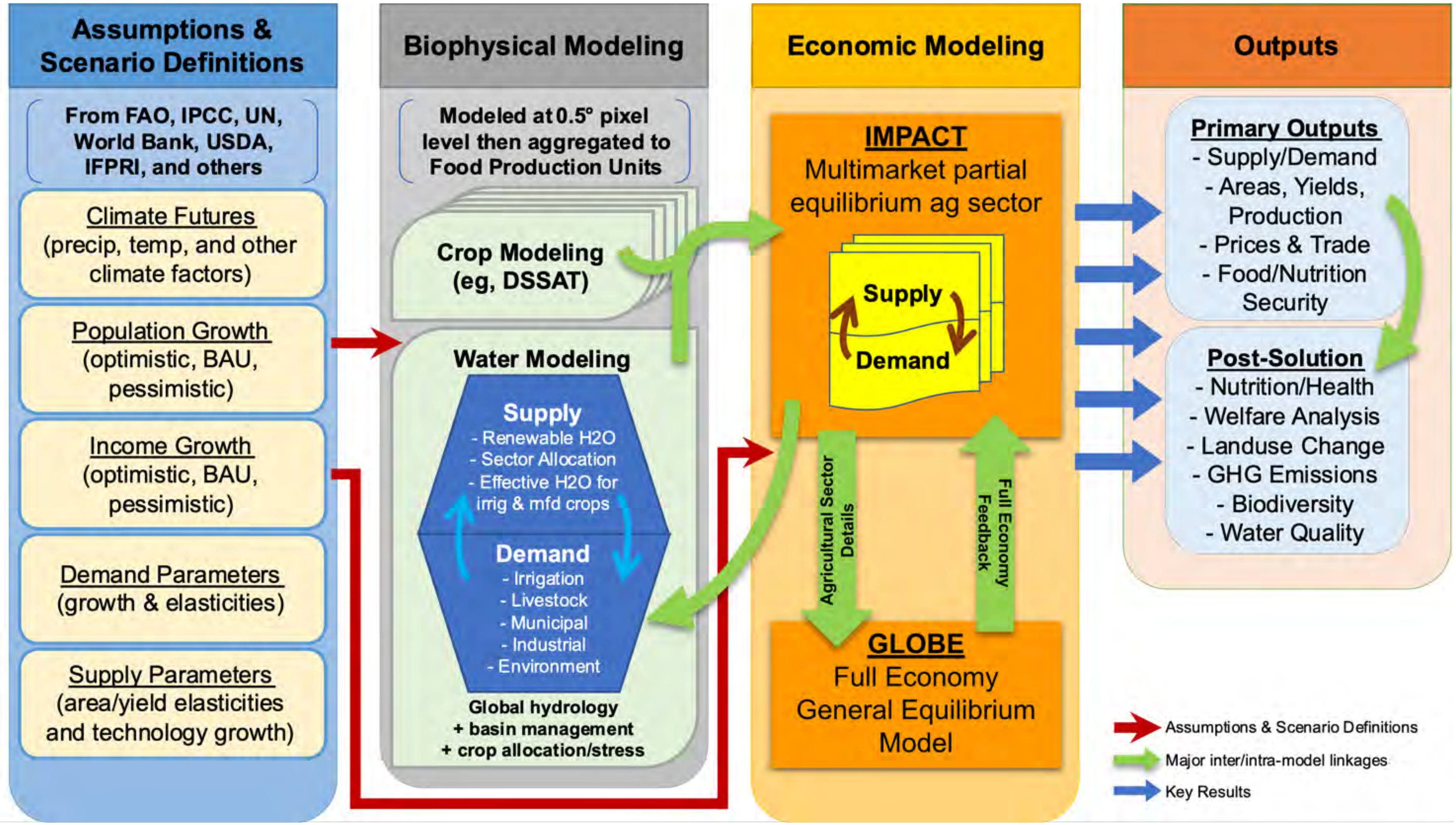
- US largest production losses 31% (1983)
- China largest production losses 10% (2003)
- France largest production losses 27% (2016)

- Contribution to global production (past 10 years) of maize, wheat, and rice is 39.6% (USA + CHN), 41.74% (USA + CHN + FRA), 56% (USA + CHN + FRA + IND + RUS)

- If the largest losses occurred in the same year, the global deficit would be
  - 7.6% USA + China
  - 8.2% USA + China + France
  - 10.1% USA + China + France + India + Russia

The IMPACT modeling framework

- International Model for Policy Analysis of Agricultural Commodities and Trade
- Advanced, interconnected framework of different types of models (micro to macro)



Assumptions & Scenario Definitions

From FAO, IPCC, UN, World Bank, USDA, IFPRI, and others

Climate Futures (precip, temp, and other climate factors)

Population Growth (optimistic, BAU, pessimistic)

Income Growth (optimistic, BAU, pessimistic)

Demand Parameters (growth & elasticities)

Supply Parameters (area/yield elasticities and technology growth)

Biophysical Modeling

Modeled at 0.5° pixel level then aggregated to Food Production Units

Crop Modeling (eg, DSSAT)

Water Modeling

Supply
- Renewable H2O
- Sector Allocation
- Effective H2O for irrig & mfd crops

Demand
- Irrigation
- Livestock
- Municipal
- Industrial
- Environment

Global hydrology + basin management + crop allocation/stress

Economic Modeling

IMPACT
Multimarket partial equilibrium ag sector

Supply
Demand

Agricultural Sector Details

Full Economy Feedback

GLOBE
Full Economy General Equilibrium Model

Outputs

Primary Outputs
- Supply/Demand
- Areas, Yields, Production
- Prices & Trade
- Food/Nutrition Security

Post-Solution
- Nutrition/Health
- Welfare Analysis
- Landuse Change
- GHG Emissions
- Biodiversity
- Water Quality

Assumptions & Scenario Definitions
Major inter/intra-model linkages
Key Results

more info at https://www.ifpri.org/project/ifpri-impact-model

Future Agricultural Resources Model (FARM)

- The FARM model simulates six major drivers of global change into the future
  - population (U.N. World Population Prospects)
  - per capita income growth
  - agricultural productivity
  - dietary preference
  - climate change effects on agriculture
  - large-scale demand for bioenergy as part of a climate change mitigation strategy
- Time dimension
  - Five-year time steps starting in 2011
  - Time horizon of 2050 or 2100 depending on application
- Shared Socio-economic Pathways (SSPs)
  - GDP projections
  - Narratives for productivity growth, per-capita food consumption, international trade flexibility
- Computable general equilibrium (written in GAMS)
- Spatial dimension
  - 13, 15, or 20 world regions
  - Up to 18 agro-ecological zones (AEZs) in each world region
- Data sources
  - Global Trade Analysis Project (GTAP) for base-year social accounts and land use by AEZ
  - International Energy Agency (IEA) for energy balances
  - Food and Agricultural Organization (FAO) of the United Nations for production statistics and food balance sheets
- Productivity and efficiency assumptions
  - Labor-augmenting parameter adjusted to roughly match SSP GDP projections
  - Land-augmenting parameter adjusted to match external sources on changes in crop yield
- Production sectors
  - Start with 38 production sectors from GTAP
  - Eight crop types (plus a stylized switchgrass crop) compete for land with ruminant livestock and forests
  - Ten electricity generation technologies including two bio-electricity technologies (switchgrass and forest residue)
  - Carbon dioxide capture and storage (CCS) can be either on or off for fossil-electricity and bio-electricity