StatEO

5–7 May 2026 | ESA–ESRIN | Frascati (Rome), Italy

EO and agrometeorological data-driven crop yield forecasting at national and sub-national scales

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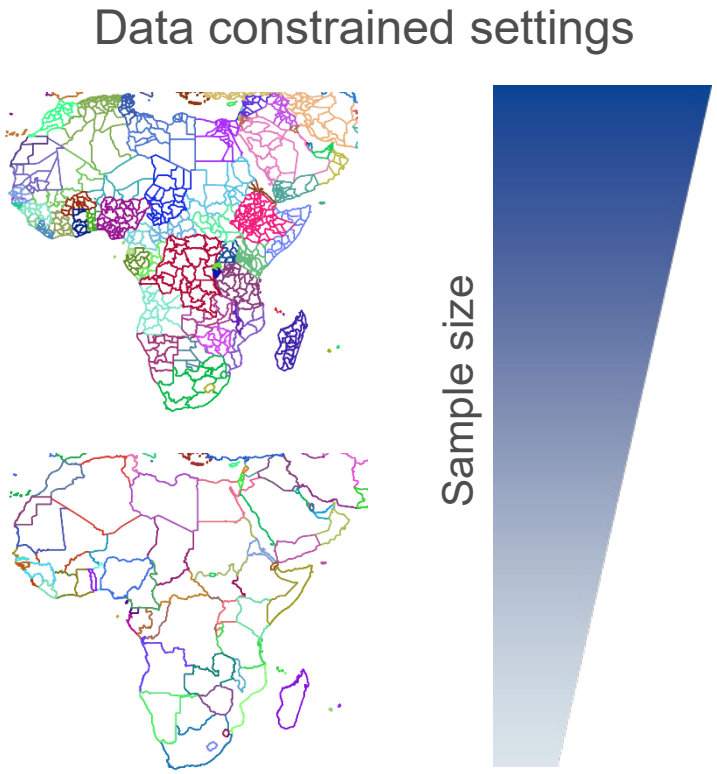
Crop yield forecasting in support to food security monitoring

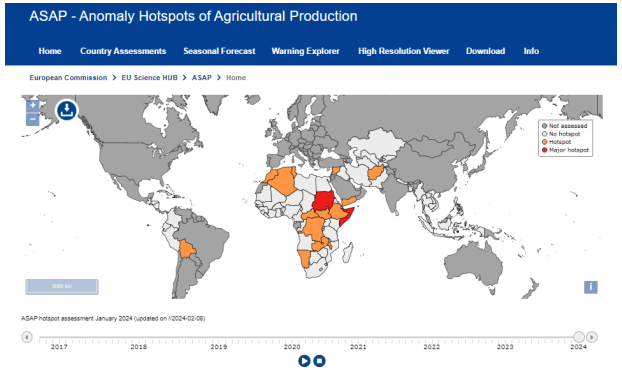
- **Sub-national yield forecasting for single countries**
  - Use of official yield statistics aggregated at admin level
  - Stakeholders: national authorities, food security initiatives (GEOGLAM)

- **National yield forecasting for 91 countries:**
  - Use of country reported statistics at national level (FAOSTAT)
  - Stakeholders: FAO-GIEWS, EC-JRC, GEOGLAM, IPC



Data for both systems are sourced from the JRC Anomaly hotSpot of Agricultural Production (ASAP) on-line Early Warning system

agricultural-production-hotspots.ec.europa.eu



Sub-national YF, data & methods

Predictors: JRC-ASAP (10 days time step)

Input type	Variable	From	Source
EO	FPAR	**2001**	MODIS/VIIRS
	Soil moisture	1978	C3S
Meteo	Precipitation	1984	CHIRPS
	Temperature	1984	ECMWF
	Solar radiation	1984	ECMWF

Auxiliary data:

- Cropland masks and crop specific masks
- Crop calendars

Statistics openly available on ASAP website: (https://agricultural-production-hotspots.ec.europa.eu/download.php)

ML workflow:

1. Automatic feature selection / data reduction
2. Identification of hyperparameters and evaluation of model accuracy through nested cross-validation
3. Explainability (SHAP)

Resource demanding process, tested the use of foundational model for tabular data to speed it up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Yield forecasting with machine learning and small data: What gains for grains?

Michele Meroni [*,1], François Waldner [1], Lorenzo Seguini, Hervé Kerdiles, Felix Rembold

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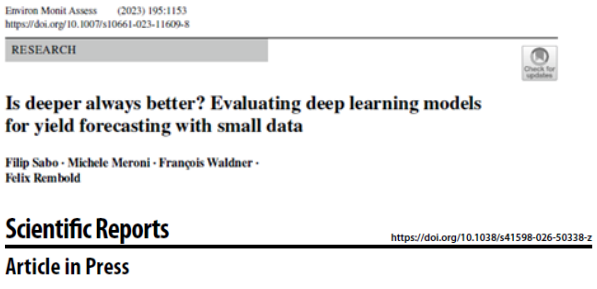
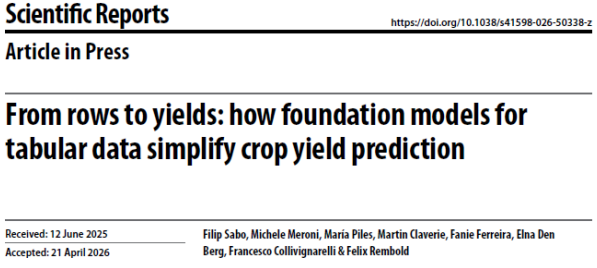

Environ Monit Assess (2023) 195:1153
https://doi.org/10.1007/s10661-023-11609-8

RESEARCH

Is deeper always better? Evaluating deep learning models for yield forecasting with small data

Filip Sabo · Michele Meroni · François Waldner · Felix Rembold


Scientific Reports

https://doi.org/10.1038/s41598-026-50338-z

Article in Press

From rows to yields: how foundation models for tabular data simplify crop yield prediction

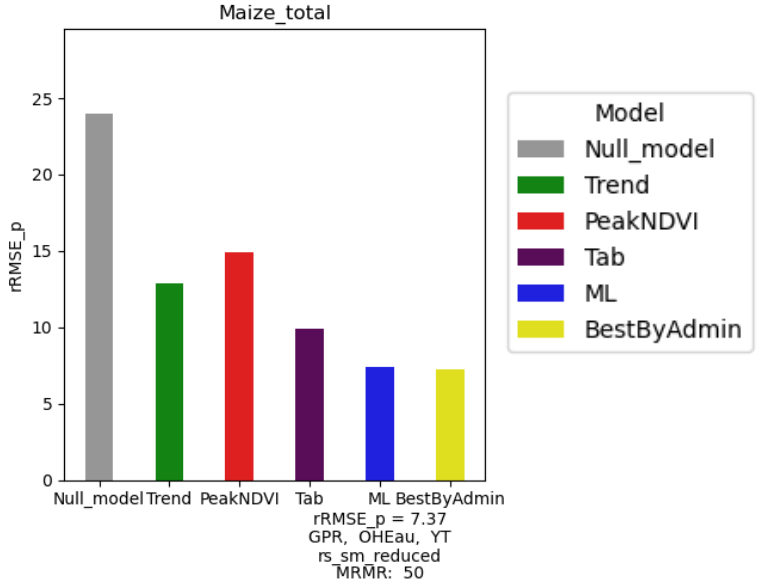
Received: 12 June 2025
Accepted: 21 April 2026

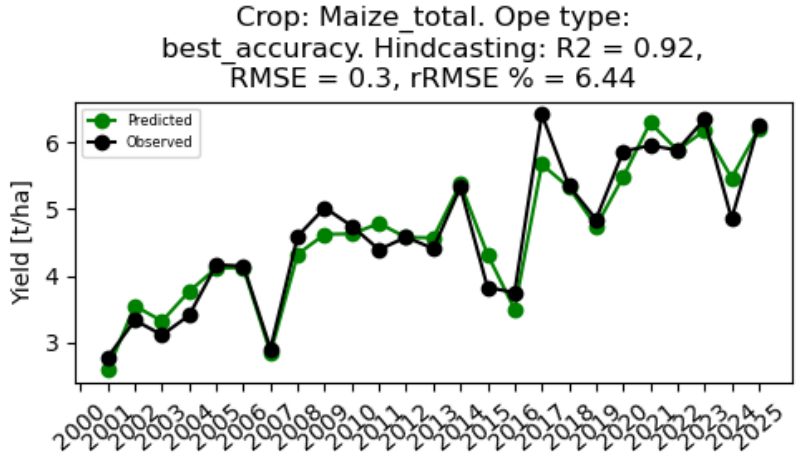
Filip Sabo, Michele Meroni, Maria Piles, Martin Claverie, Fanie Ferreira, Elna Den Berg, Francesco Collivignarelli & Felix Rembold

Sub-national YF, example results

South Africa, Summer crops (Maize, Soybeans, Sunflower), Time of forecast: early April (75 % of season)

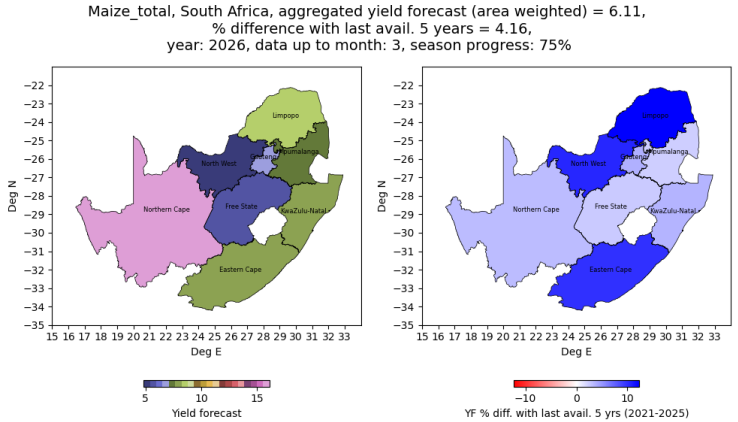
Hindcasting performances

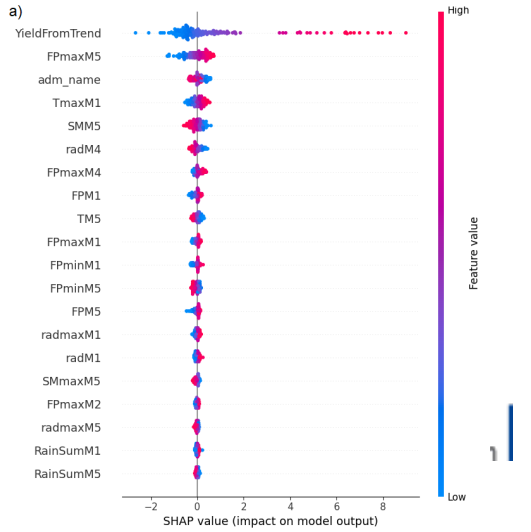




- ML models outperform benchmarks
- TabPFN provides comparable performances

April 2026 Forecasts





National YF, data & methods

- Collaboration between JRC, FAO-GIEWS, and UVEG
- Started in 2024

Food and Agriculture Organization of the United Nations

Universitat de València

European Commission

Objective: Set up of an operational system covering 91 food security relevant countries serving JRC-Food Security Unit and FAO-GIEWS

Predictors:

- JRC-ASAP EO and agromet
- Conflicts (UCDP)
- GDP (WB)

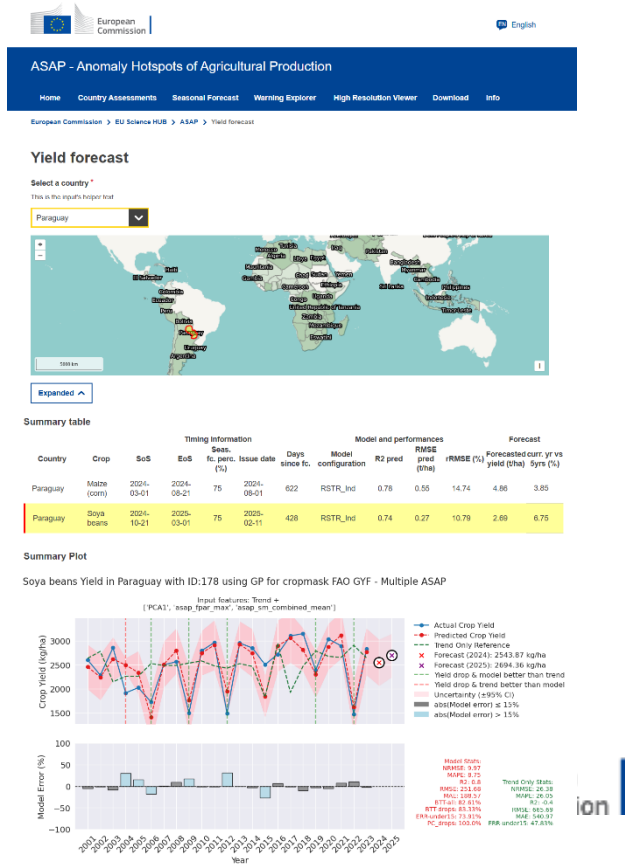
Auxiliary data:

- Cropland masks and crop specific masks
- Crop calendars

ML workflow:

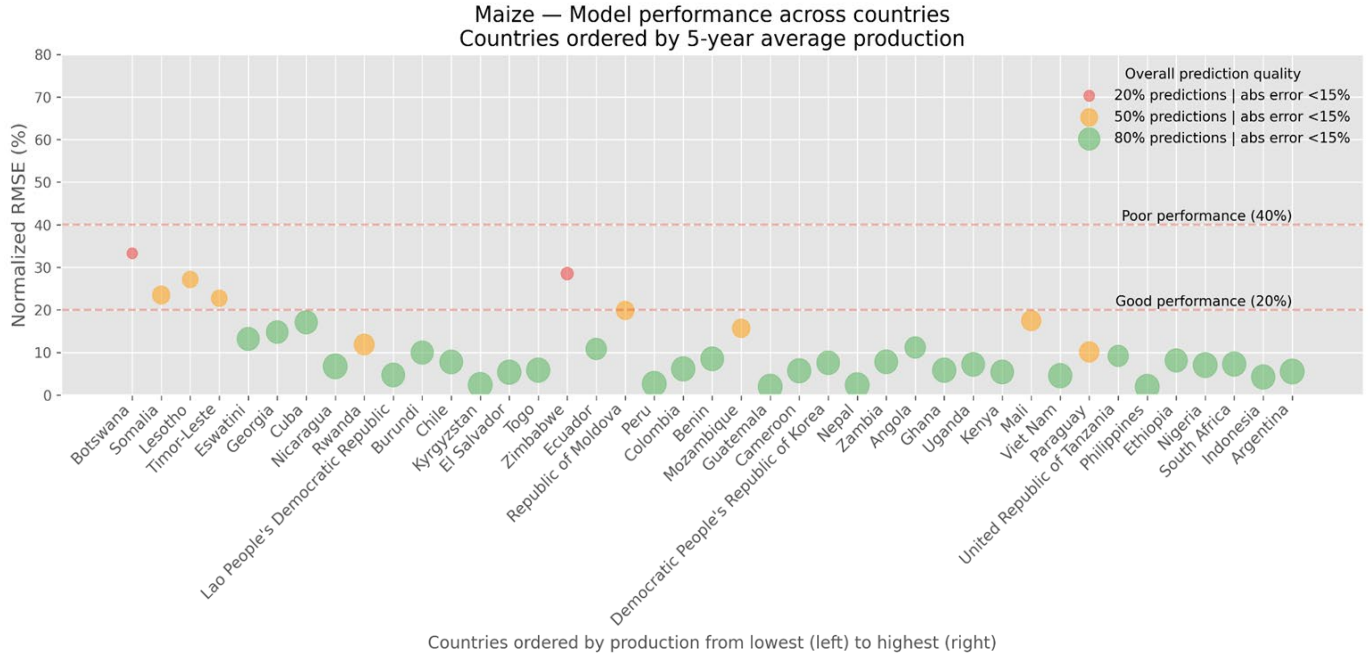
1. Aggregate predictors over the season
2. Parsimonious ML model selection in CV
3. Error metrics and explainability (SHAP)

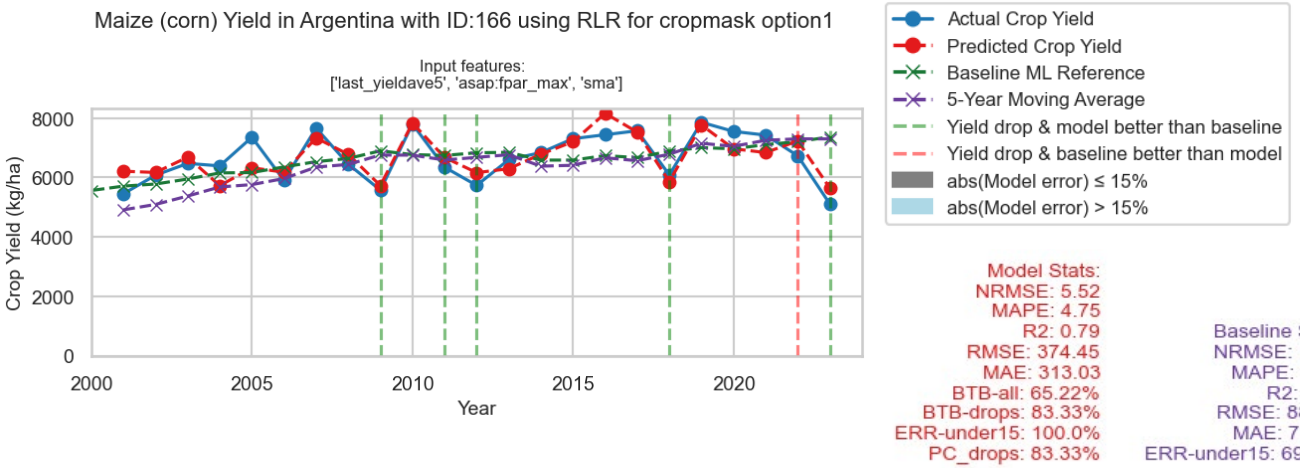
Test version on the ASAP system

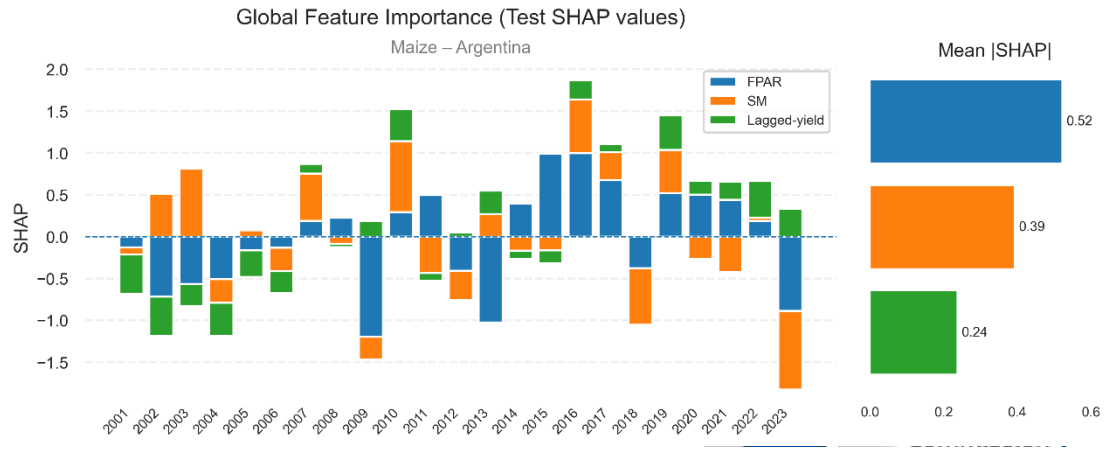


National YF, example results

- Example for Maize (50 countries)

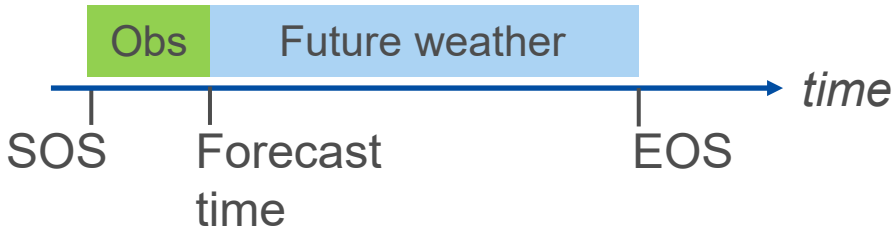






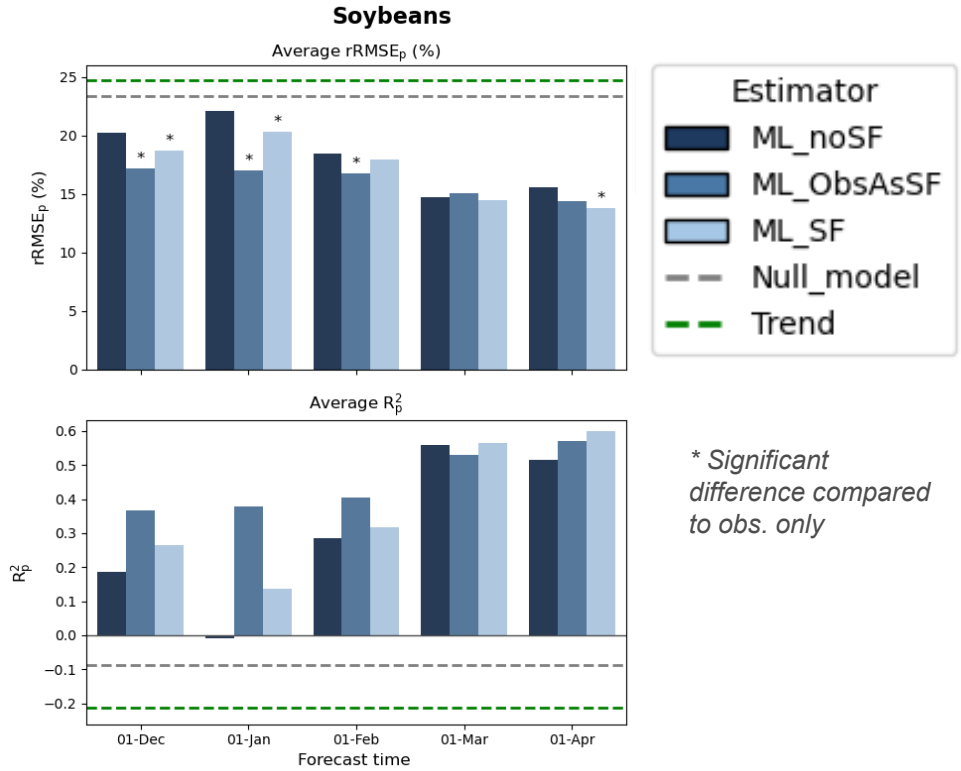
Anticipating yield forecast with seasonal climate forecasts

Forecast data: ECMWF SEAS5 precipitation and temperature seasonal forecasts (7 months horizon, 36 km resolution)



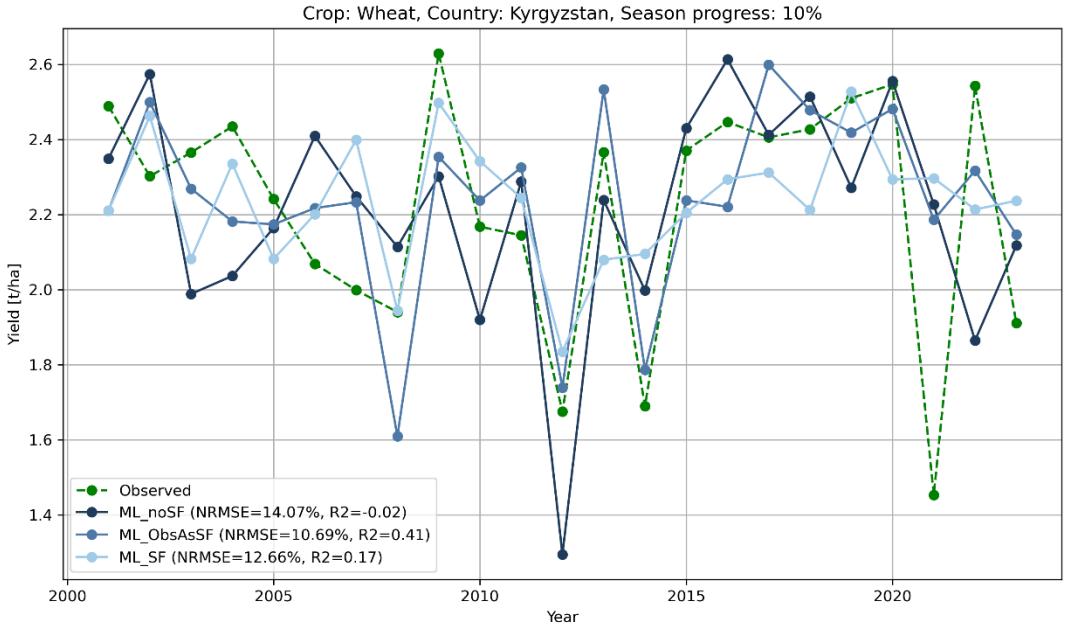
- Use of observation ASAP data up to the time of forecast + **future weather** for the remaining part of the season
- Use of **observational data as forecast** to understand utility of future weather
- Use **actual SF** to evaluate operational performances

Sub-national YF, South Africa



** Significant difference compared to obs. only*

National YF, Kyrgyzstan (10% of season)



Conclusions

Subnational YF

- Running on selected countries
- Joining NASA-Harvest operational model intercomparison initiative

National YF

- Running on 91 countries
- Public operational implementation to be deployed (Q3 2026)

- Tabular foundational model (TabPFN) achieves similar performances but does not outperform ML. However, it simplifies and speed up to workflow, making it suitable for application in regional institutions with limited ML expertise.
- Seasonal Forecasts provide improvements for early forecasts.
- Despite good hindcasting accuracy, in-season forecasts may be poor in specific real-world conditions (e.g. unobserved driver coming into play). Model outputs should be reviewed by analysts.

Thank you!

European Commission