Regional Seasonal Crop Yield Forecasts Through Hybrid Modeling and Remote Sensing Data Assimilation

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Outline

(1) Seasonal Crop Yield Predictions &

Hybrid Model Approaches & Data Assimilation

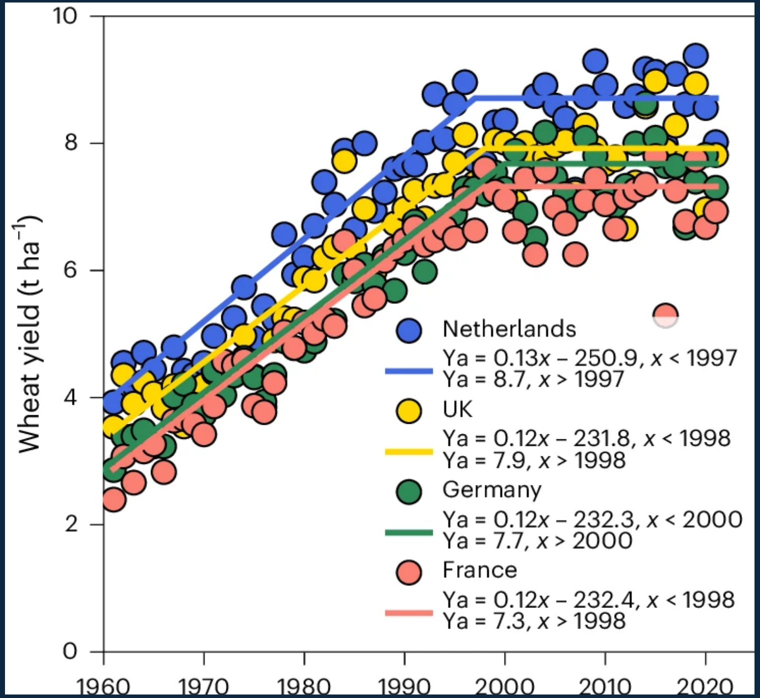
(2) Study Design & First Results

(3) Conclusions

(1) Seasonal Crop Yield Predictions & Hybrid Model Approaches & Data Assimilation

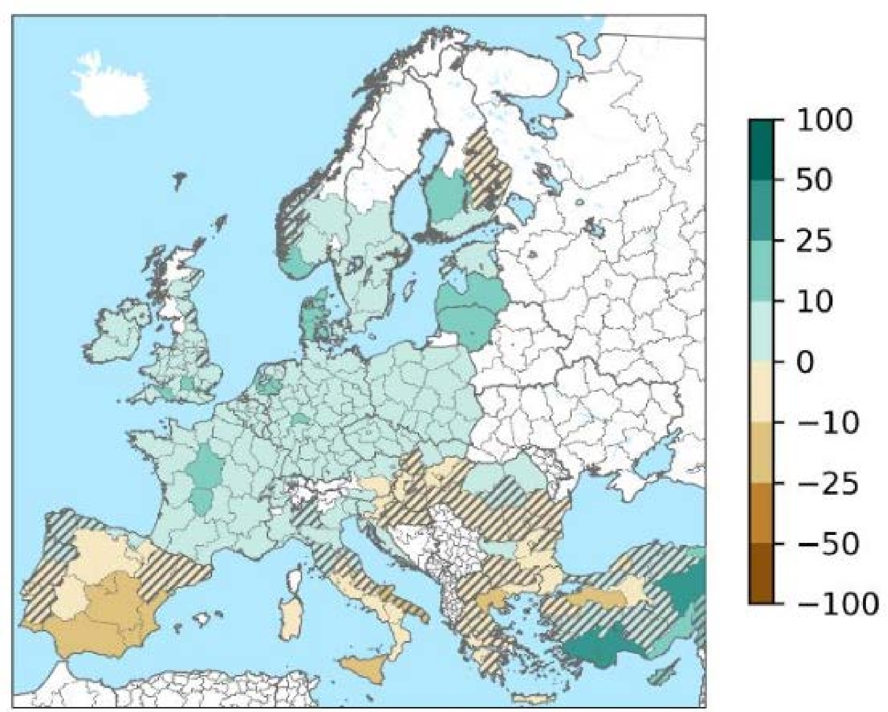
Why Seasonal Yield Forecasting is important

Northwest Europe Yield Increase and Plateau Since 2000 (FAOSTAT) with Spatial Variation Between Countries



Silva, J.V., Rijk, B., Berghuijs, H.N.C. et al. Agronomic management drives the wheat yield plateau in high-yielding environments of northwest Europe. Nat Food 7, 45–54 (2026). https://doi.org/10.1038/s43016-025-01286-w

Ensemble Mean Changes of Wheat Yield (% relative to the historical period) projected under the RCP85 for 1.5 °C warming conditions under rainfed conditions.



Hristov, J., Toreti, A., Pérez Domínguez, I., Dentener, F., Fellmann, T., Elleby C., Ceglar, A., Fumagalli, D., Niemeyer, S., Cerrani, I., Panarello, L., Bratu, M., Analysis of climate change impacts on EU agriculture by 2050, EUR 30078 EN, Publications Office of the European Union, Luxembourg, 2020, ISBN 978-92-76-10617-3, doi:10.2760/121115, JRC119632

What is Data Assimilation?

- paradigm: continuous integration of observations into a model
- reduce uncertainty of model state and variables
- methods:
  - State Updating / Parameter Forcing (e.g. FAPAR corrections)
  - Parameter Tuning
  - Ensemble Approaches (e.g. Ensemble Kalman Filter (EnKF), 4DEnVar)

- currently rarely operational in crop models at regional scale

What is Hybrid Modeling?

- paradigm: combine biophysics of process-based models with data-driven machine learning

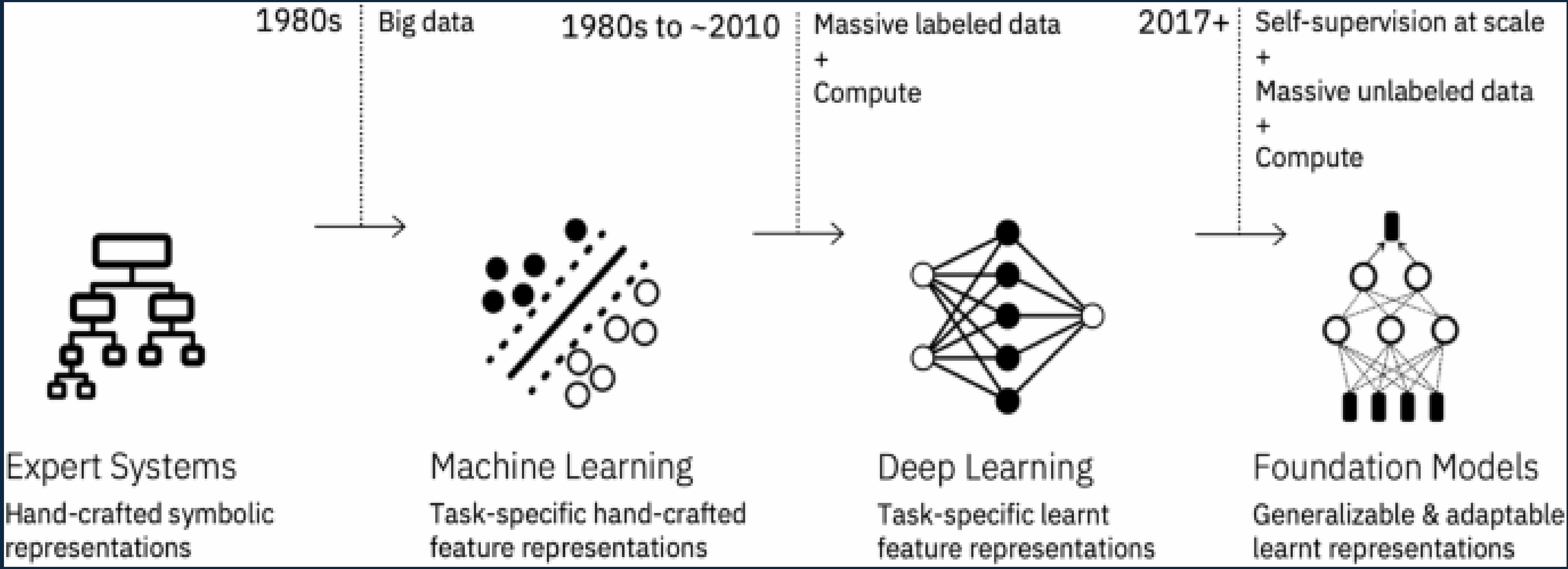
- ML learns e.g. residuals and non-linear relationships
- PM provides physical backbone
- PB is not replaced, but augmentation of process understanding

What we still do not know

- scalable EO model integration
- phenology timing and extreme event impacts
- transferability across regions

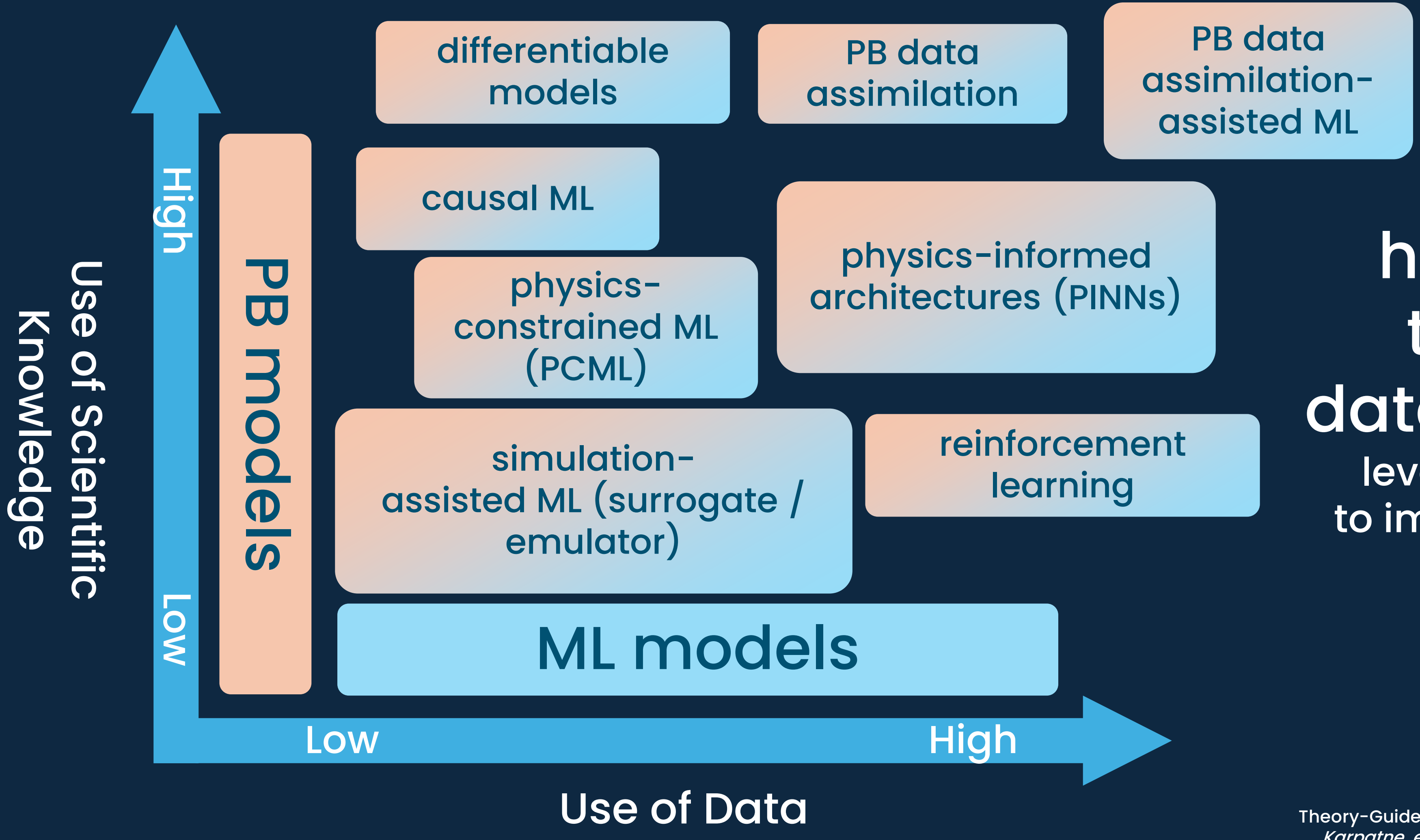
- approaches combining a process-based model data assimilation framework with machine learning models

From Expert Systems to Foundation Models



Pyzer-Knapp, E.O., Manica, M., Staar, P. et al. Foundation models for materials discovery – current state and future directions. npj Comput Mater 11, 61 (2025).

The modelling continuum



hybrid models = theory-guided data science models

leverage domain knowledge to improve model performance

Theory-Guided Data Science: A New Paradigm for Scientific Discovery from Data
Karpatne, et al.. (2017). IEEE Transactions on Knowledge and Data Engineering.
https://doi.org/10.1109/TKDE.2017.2720168

(2) Study Design & First Results

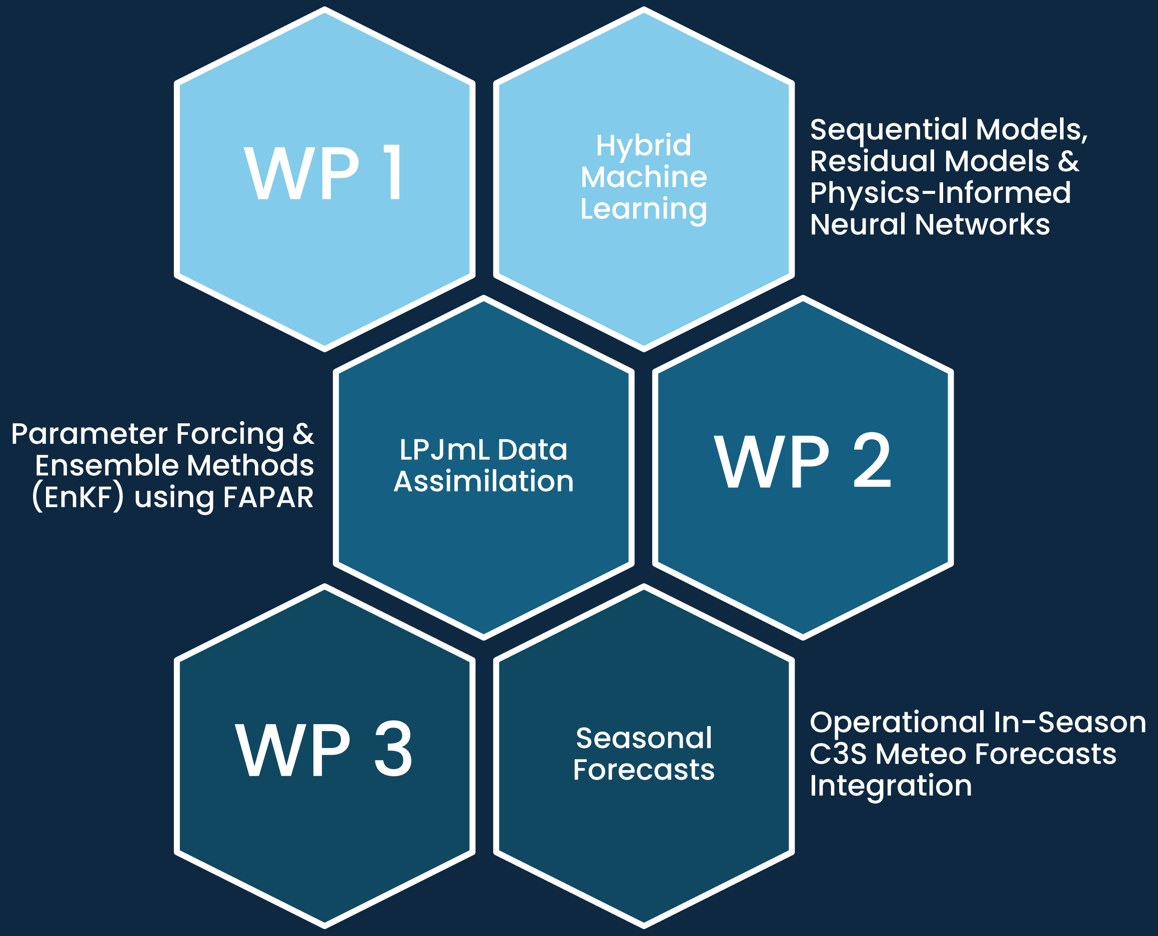
Project Design

Aim: Regional Early-Season Crop Yield Forecasts

Method: Hybrid ML Crop Modeling & Data Assimilation

Data: Remote Sensing Phenology Data

Project Plans & Work Packages



WP 1

Hybrid EO Model Framework for European Yield Predictions

WP 1

Hybrid Machine Learning

Data Collection

- ERA5-Land climate forcing
- LPJmL simulations
- yield statistics
- FAPAR canopy dynamics
- C3S seasonal forecasts

ERA5-Land Data

daily data on 10 km grid

temperature, precipitation & radiation

aggregation on NUTS-2/3 level

WP 1

Hybrid Machine Learning

Data Collection

- ERA5-Land climate forcing
- LPJmL simulations
- yield statistics
- FAPAR canopy dynamics
- C3S seasonal forecasts

LPJmL Simulations

0.5° grid / 10 km grid

World Cereal crop masks

ERA5-Land climate forcing

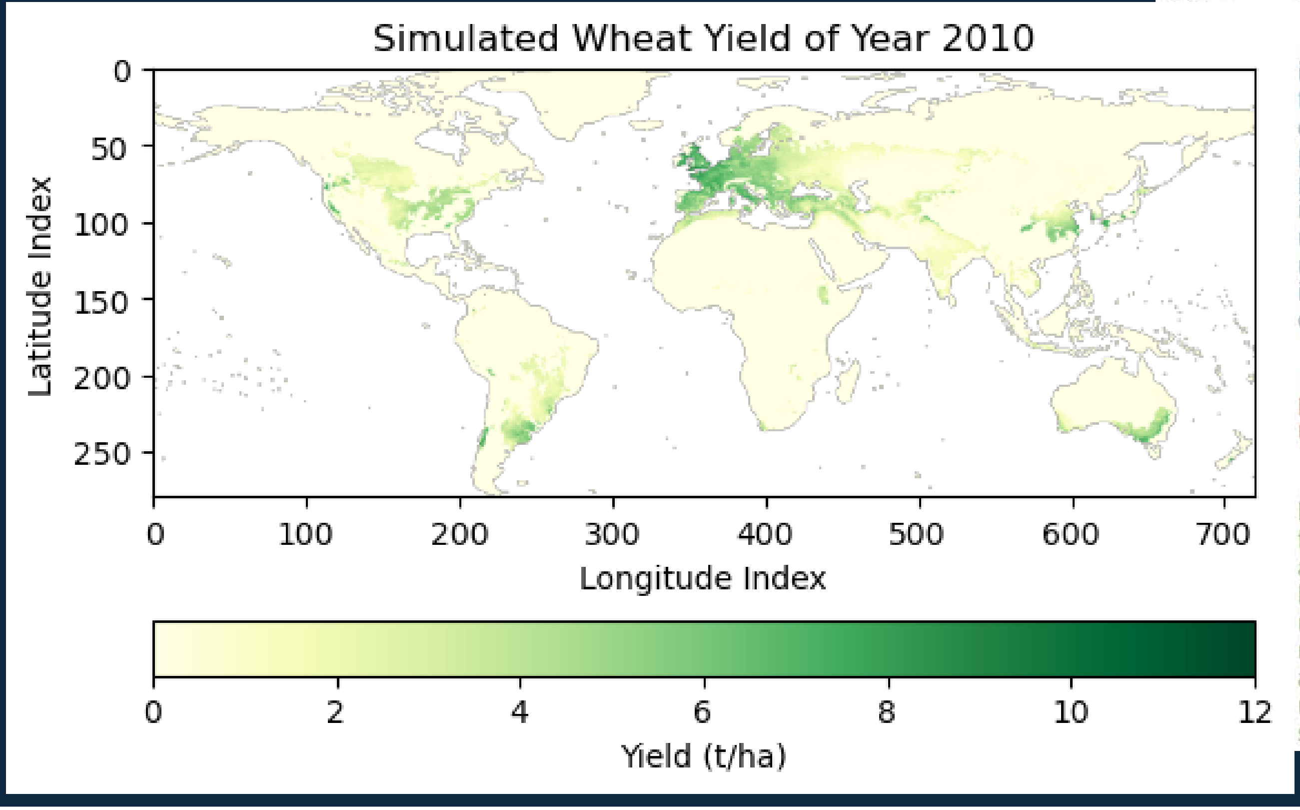
HWSD soil data

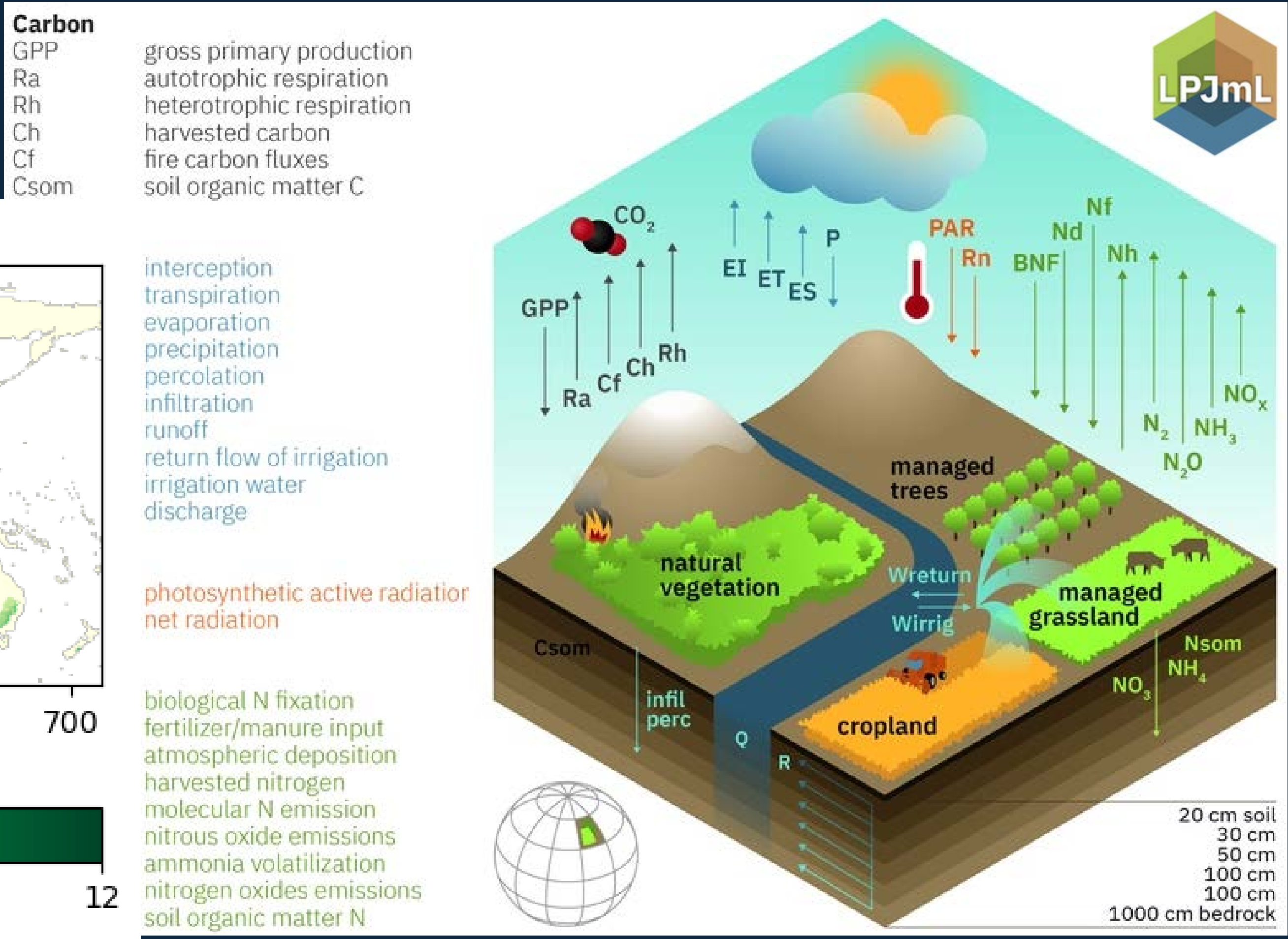
Data Collection | LPJmL

WP 1 Hybrid Machine Learning

LPJmL Dynamic Global Vegetation Model (DGVM)

LPJmL v.5.9 harvested carbon transformed to non-corrected yield in t/ha via crop specific harvest index





https://www.pik-potsdam.de/en/institute/departments/activities/biosphere-water-modelling/lpjml

Data Collection | LPJmL

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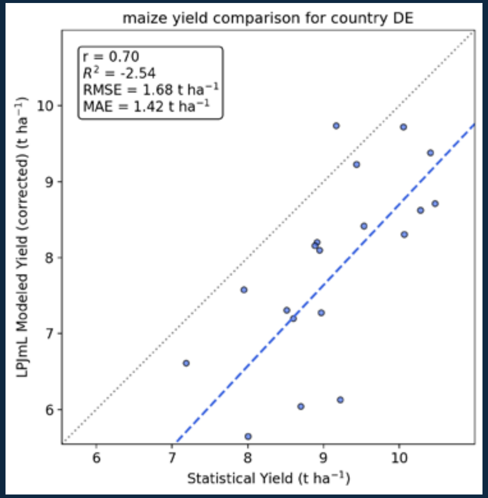
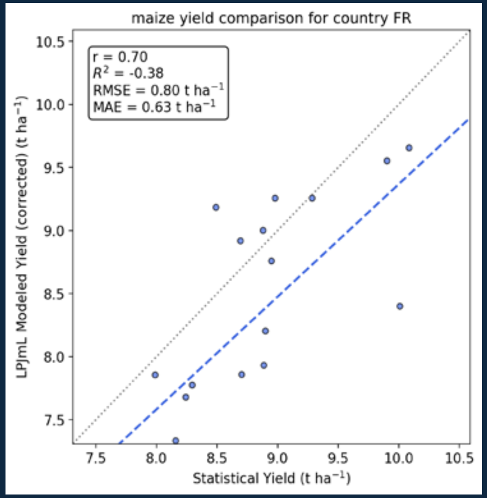
Hybrid Machine Learning

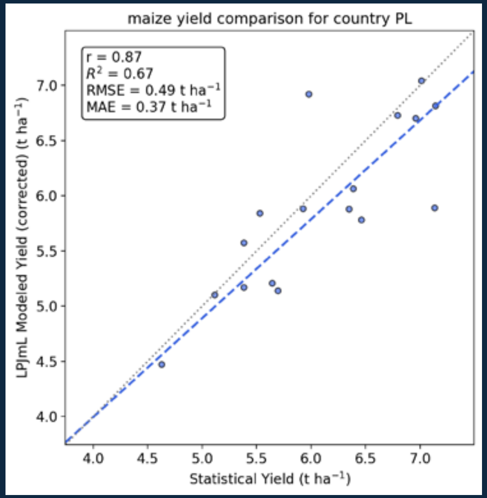
Maize



Germany (DE)

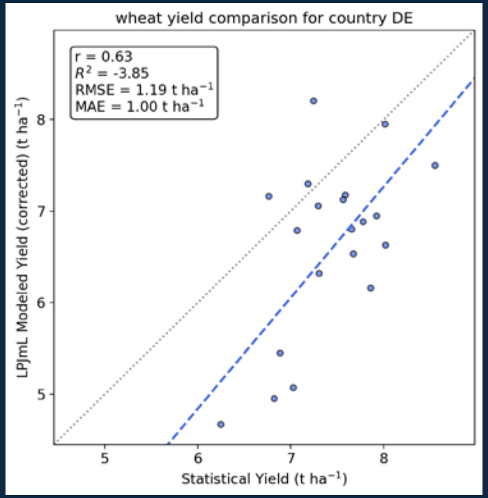


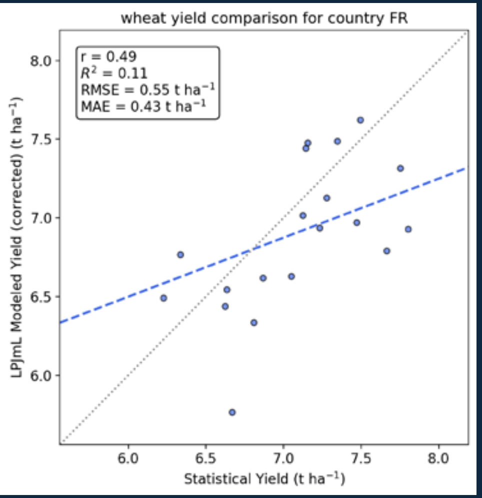
France (FR)

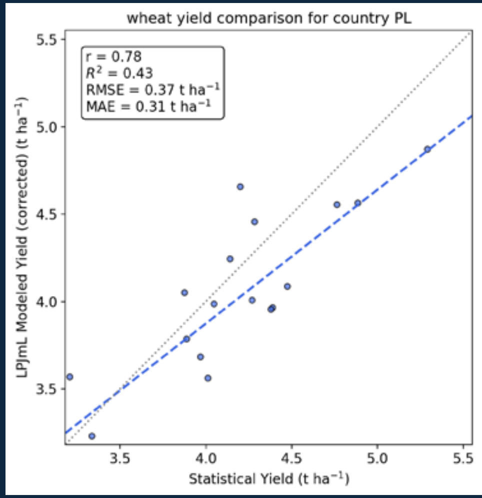


Poland (PL)

Wheat



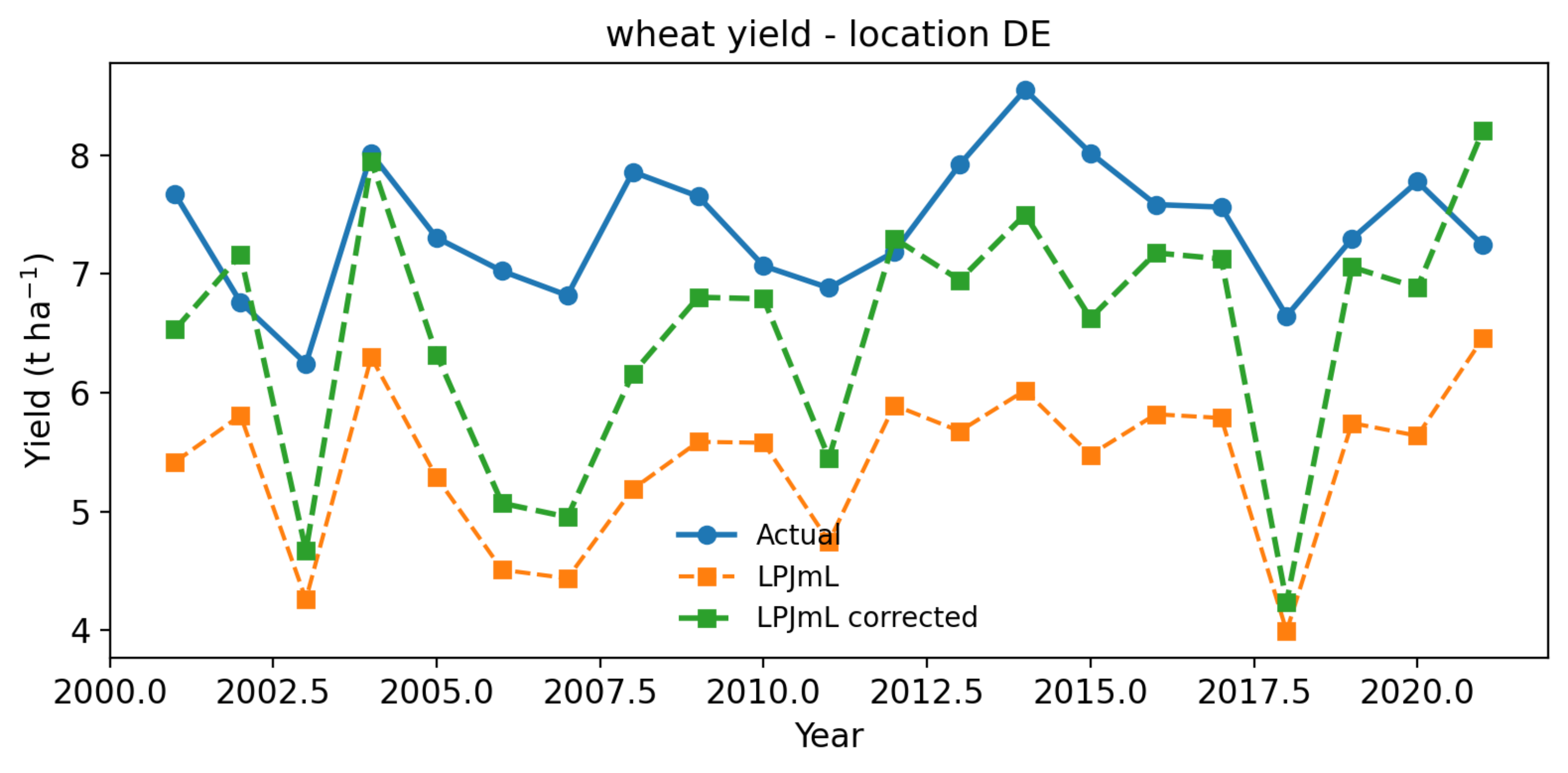




Data Collection | LPJmL

WP 1 | Hybrid Machine Learning

Validation against yield statistic



Comparison of (bias-corrected) LPJmL wheat yield simulations against EUROSTAT yield statistics for Germany.

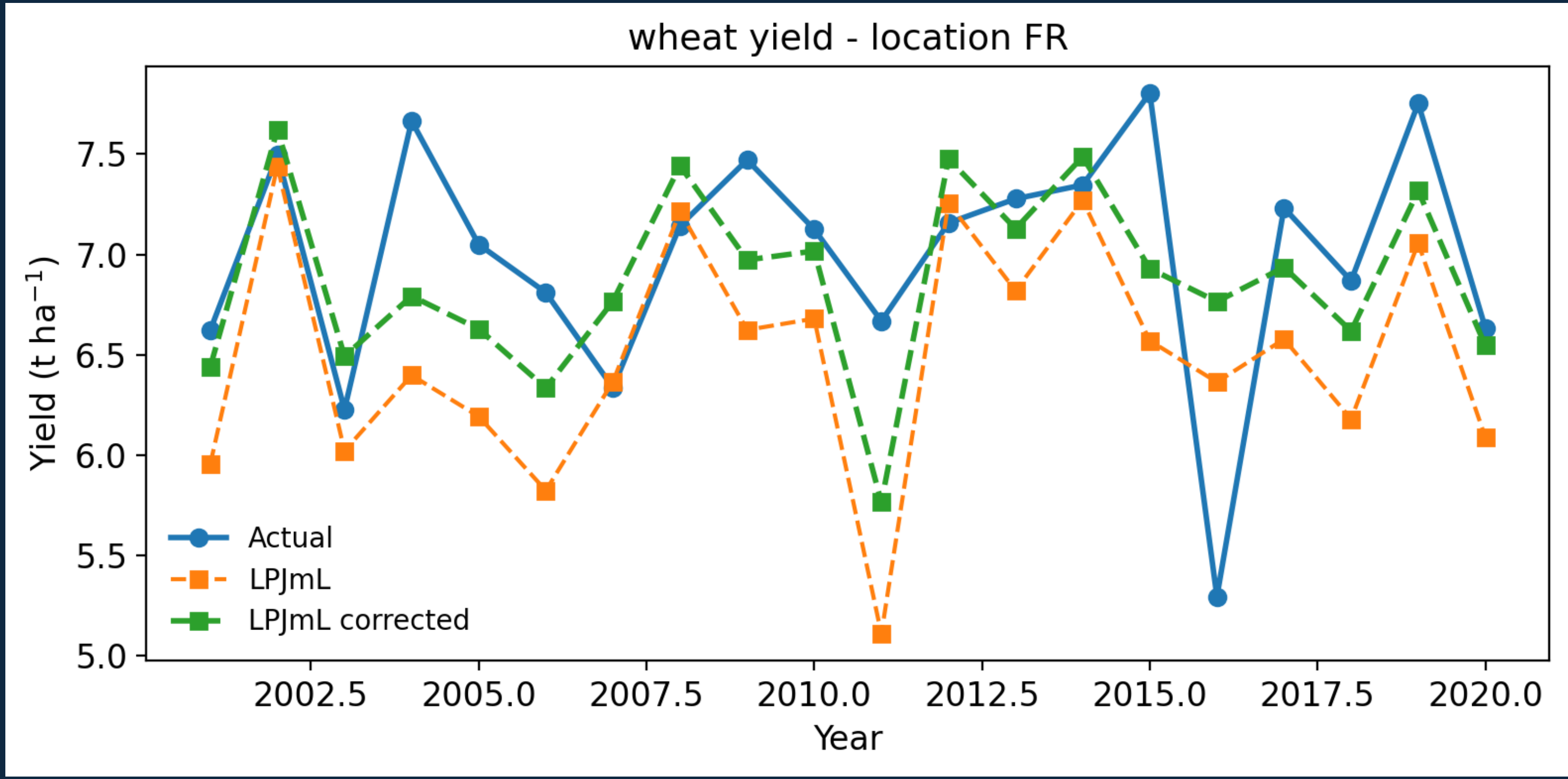
- bias-correction improves performance
- mapping of temporal pattern
- overall underestimation
- 2018 dry-year highly underestimated

Data Collection | LPJmL

WP 1

Hybrid Machine Learning

Validation against yield statistic



Comparison of (bias-corrected) LPJmL wheat yield simulations against EUROSTAT yield statistics for France.

- better overall performance
- extremes not properly mapped
- 2016 heavy rainfall highly overestimated

Data Collection

WP 1 | Hybrid Machine Learning

- ERA5-Land climate forcing
- LPJmL simulations
- yield statistics
- FAPAR canopy dynamics
- C3S seasonal forecasts

Yield Statistics

- official EUROSTAT statistics
- NUTS-2/3 level
- 2000-2024 validation data
- CY-Bench dataset used

WP 1

Hybrid Machine Learning

Data Collection

- ERA5-Land climate forcing
- LPJmL simulations
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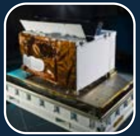
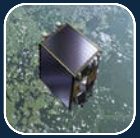
- **FAPAR canopy dynamics**
- C3S seasonal forecasts

FAPAR Observations


Sentinel-3


MODIS


VIIRS


PROBA-V

FAPAR Processing


5 km resampling


2018-2024 monthly data


European NUTS-2/3 aggregation

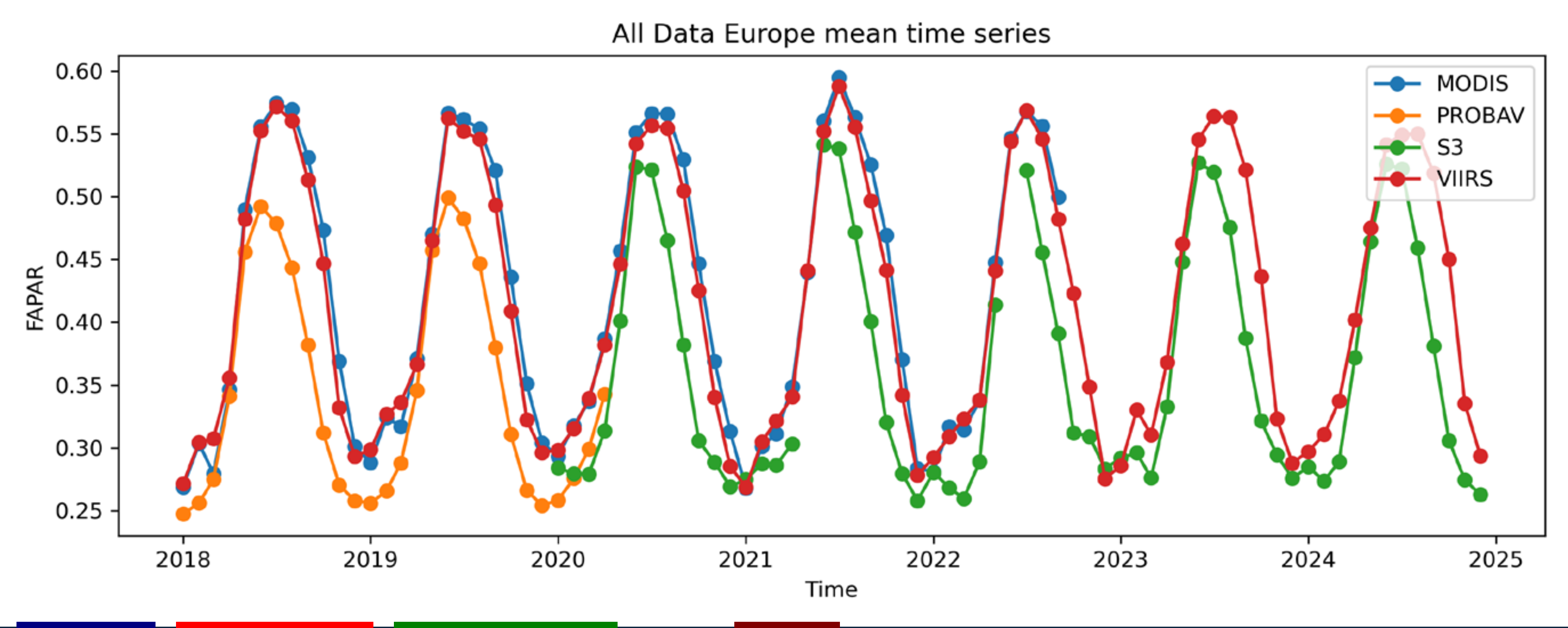

weighting by arable land

Data Collection | FAPAR

WP 1

Hybrid Machine Learning

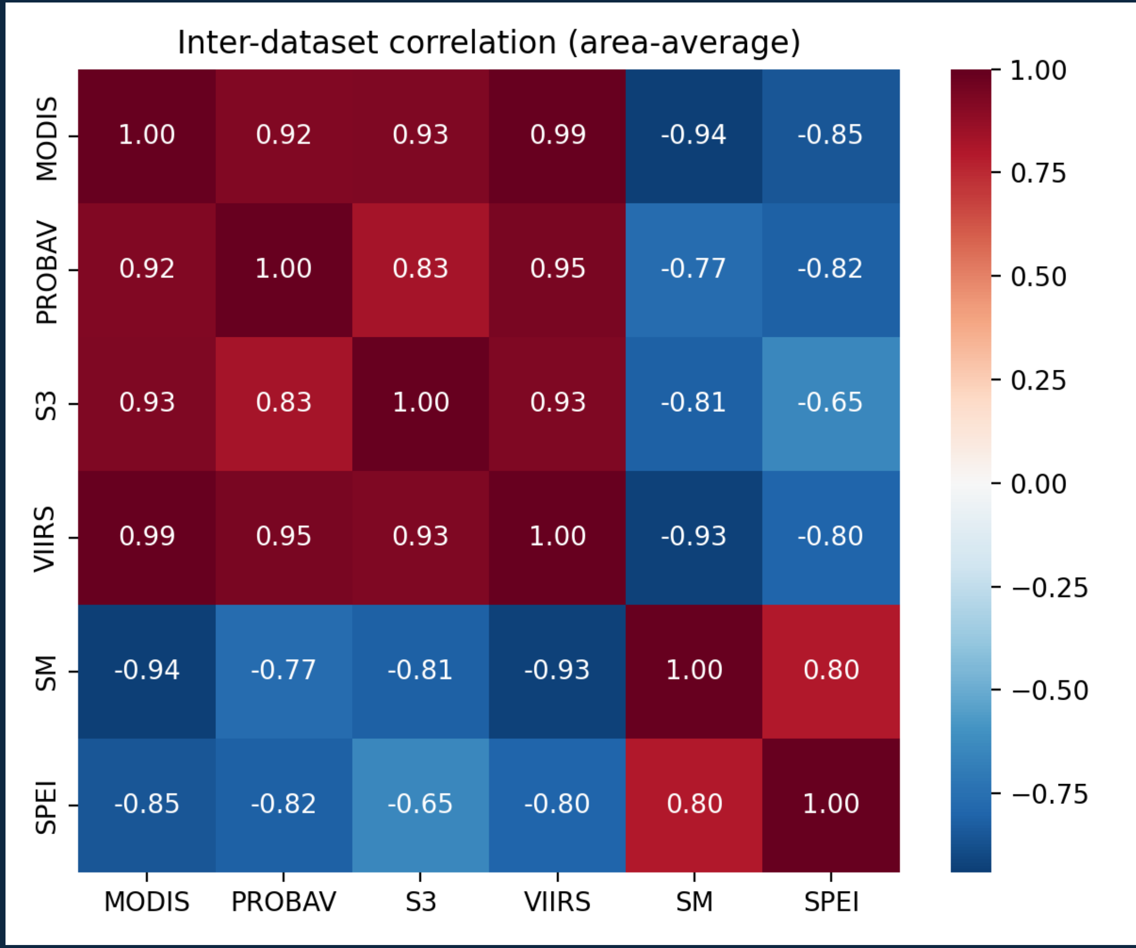
- FAPAR provides phenological timings of green-up, peak, and senescence phases
- indirect signal for vegetation stress and canopy density dynamics
- constraints timing and magnitude of vegetation development



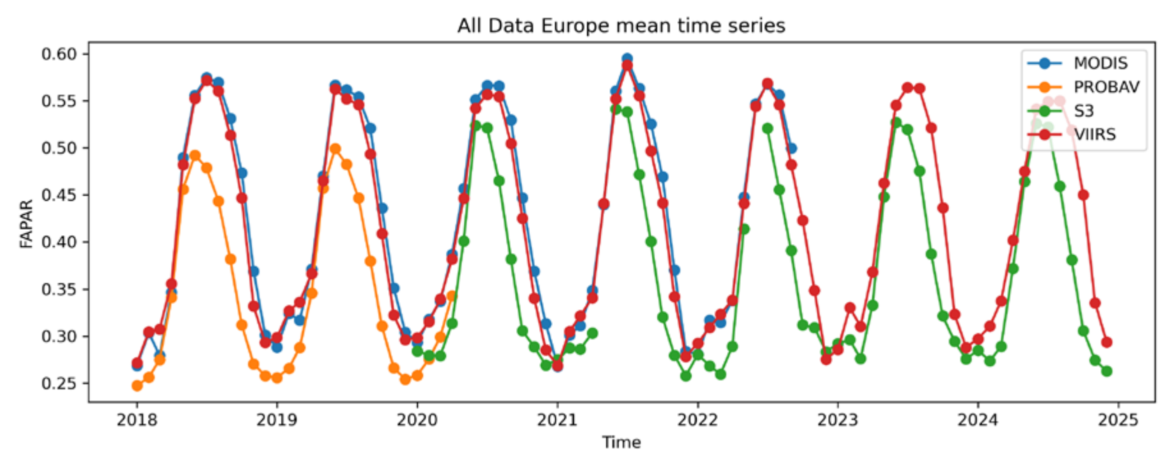
Comparison of MODIS, PROBA-V, Sentinel-3, and VIIRS monthly European FAPAR composites mean.

Data Collection | FAPAR

WP 1 Hybrid Machine Learning



- very good agreement between MODIS and VIIRS (`r=0.99`)
- smaller peaks for PROBA-V and Sentinel-3 (monthly aggregation scheme)
- lowest correlation (`r=0.83`) between PROBA-V and Sentinel-3



Data Collection

WP 1

Hybrid Machine Learning

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C3S Seasonal Forecasts

0.5° grid / 10 km grid

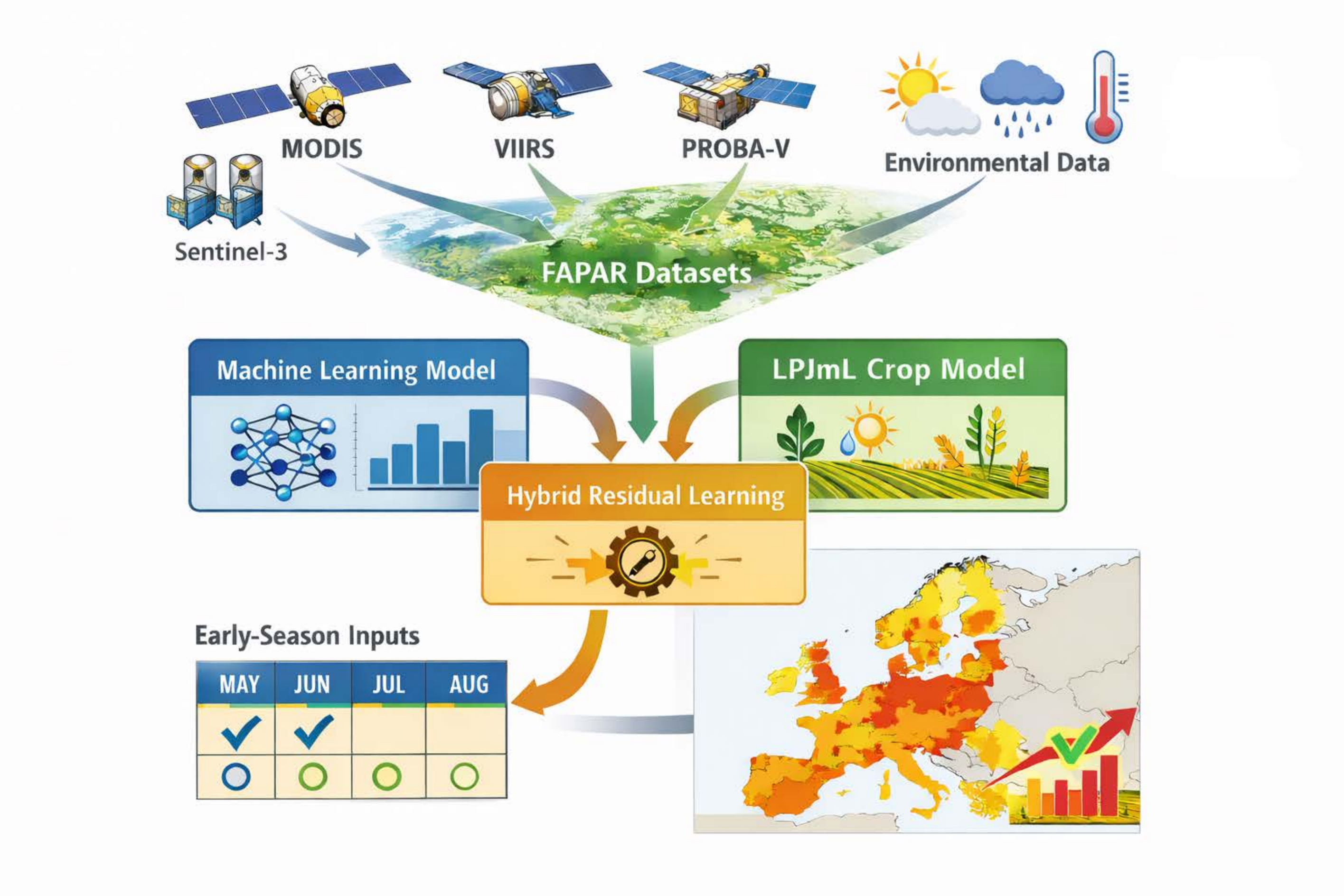
temperature, precipitation & radiation for next 6 months

fill gap between EOF and EOY with daily representative climatology

sensitivity experiments with different ensemble members

Hybrid Model Framework

WP 1
Hybrid Machine Learning



Maize & Wheat Yield Prediction

spatial domain: European NUTS regions

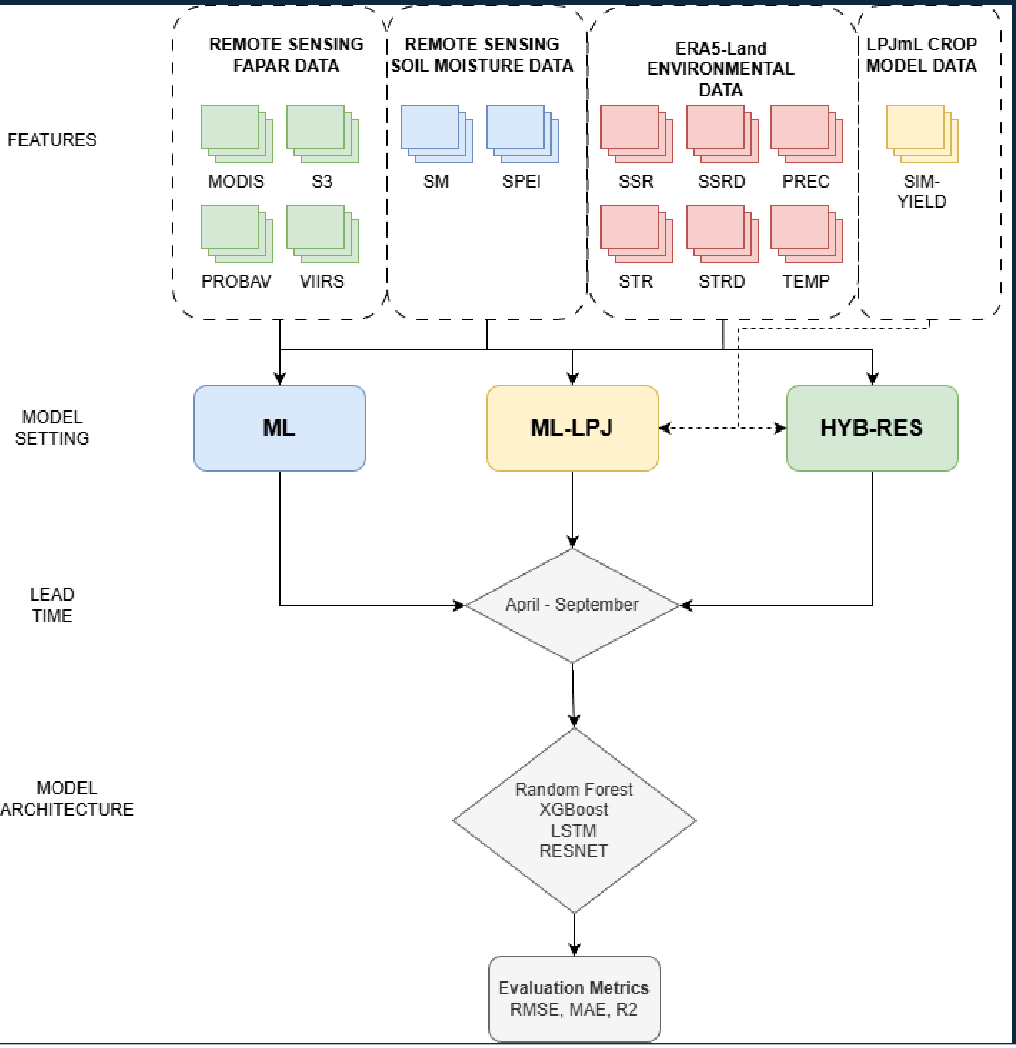
challenges: heterogeneity and crop diversity & climate gradients

Random Forest & XGBoost

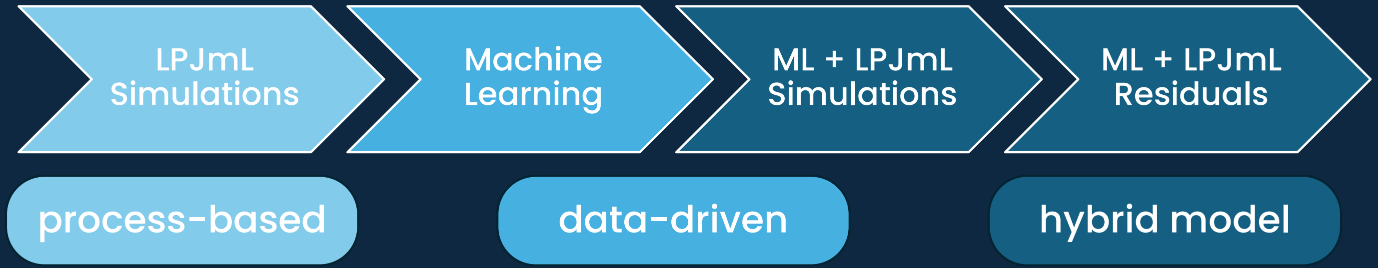
LSTM & RESNET

Hybrid Model Framework

WP 1 | Hybrid Machine Learning



- Features: monthly time series of different feature combinations
- Settings:



- Train: 2018-2021 years
- Test: 2021-2024 years
- Lead Time: Oct-April, …, Oct-Sept
- Models: RF, XGB, LSTM, RESNET

Results | Wheat Yield Forecast

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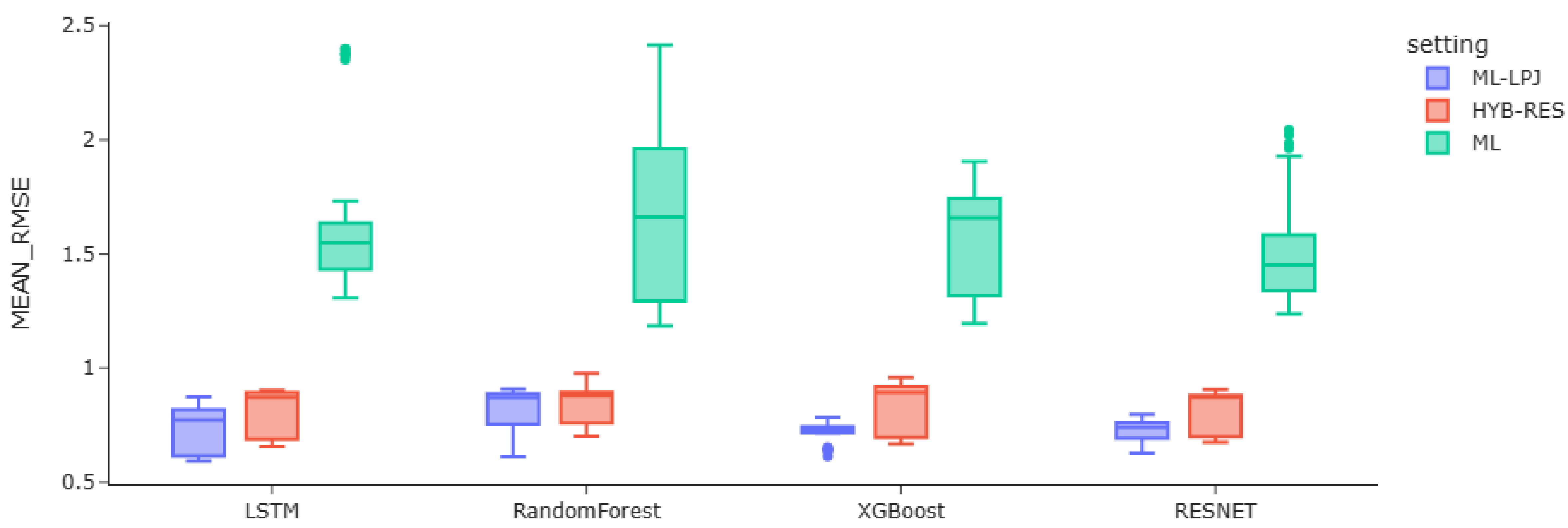
Hybrid Machine Learning

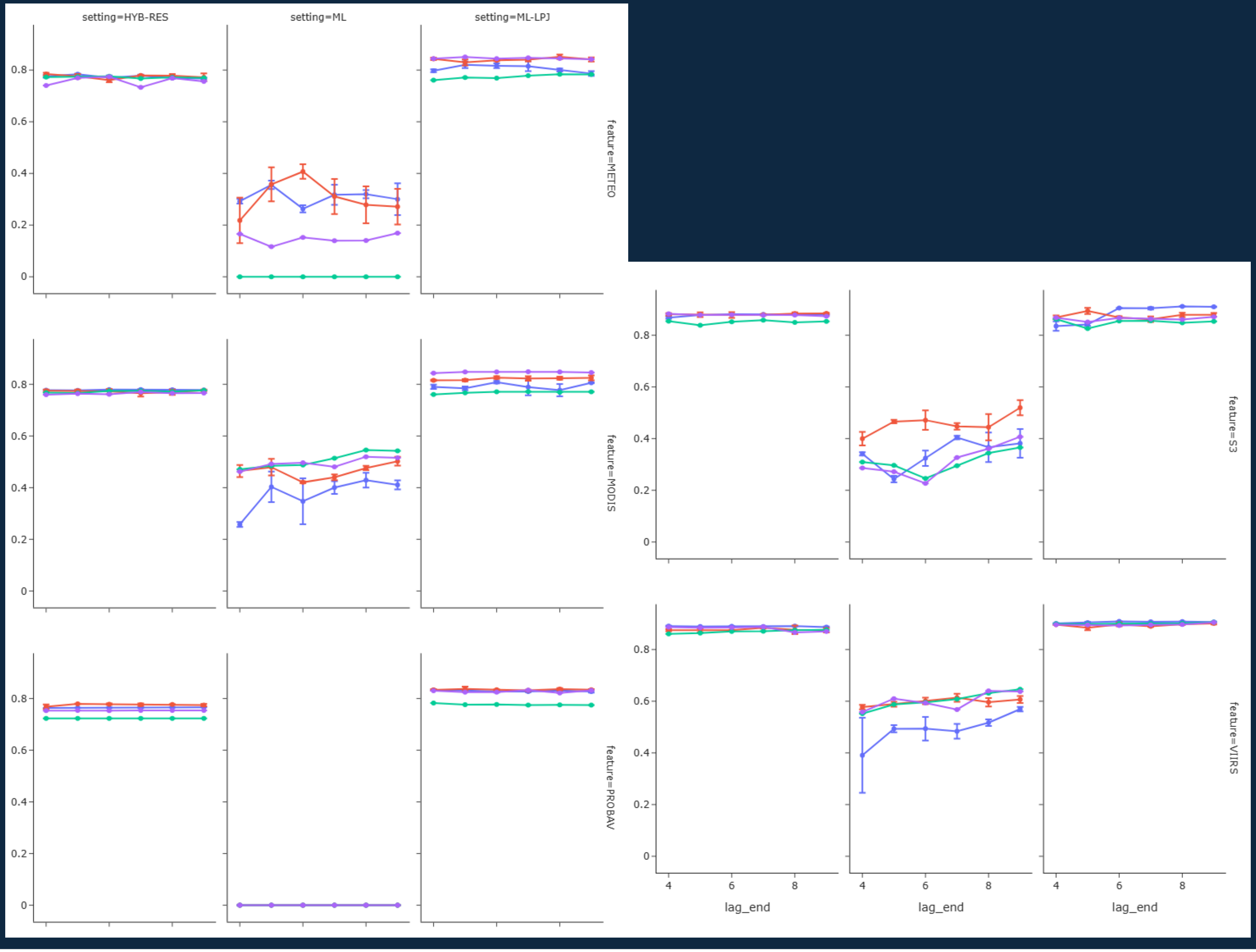


ML+LPJmL shows lowest RMSE

Results | Wheat Yield Forecast

WP 1

Hybrid Machine Learning

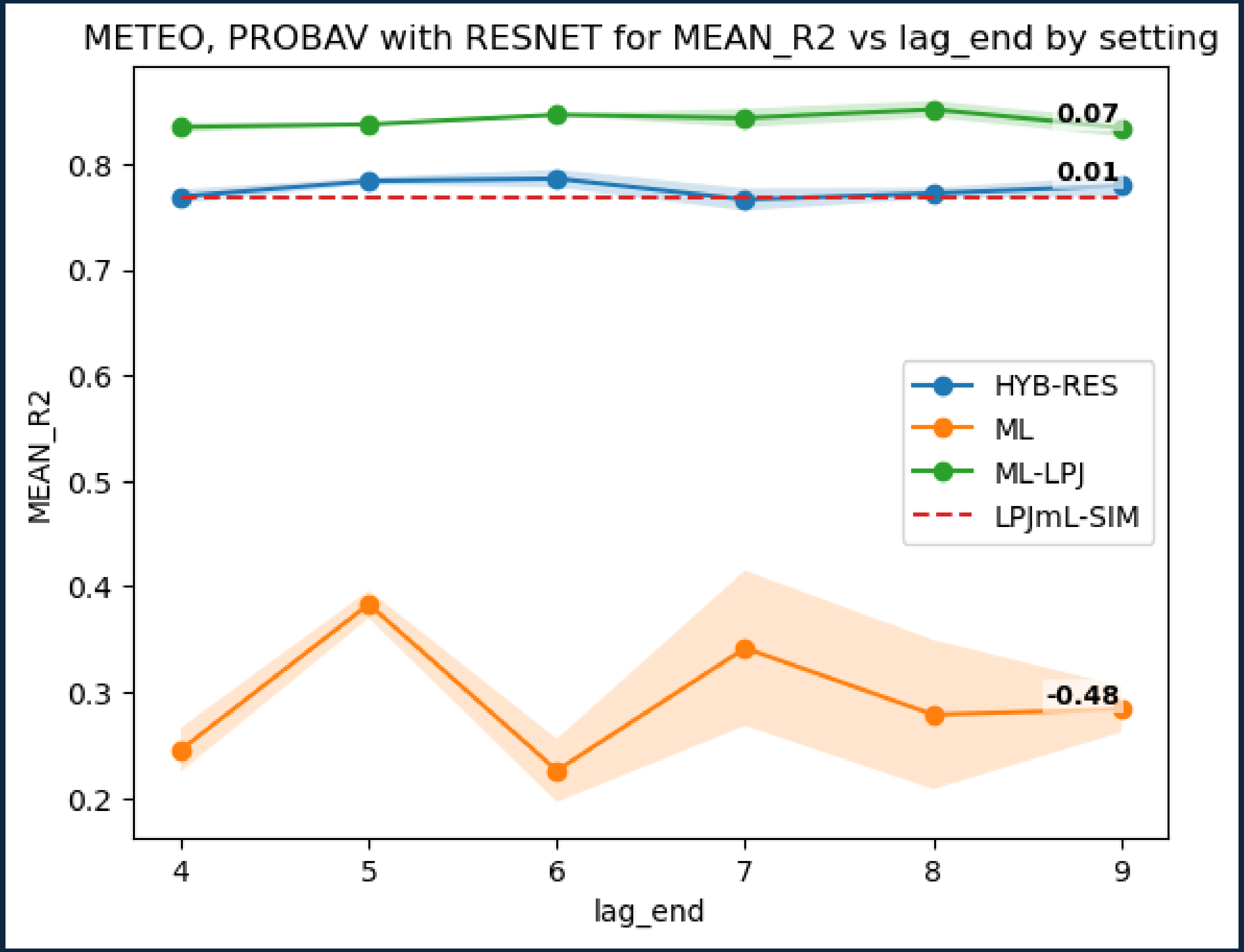


- performance ML+LPJmL > Residual > ML only for all feature combinations
- ML only performance increases until harvest
- FAPAR reduces ML model variability compared to METEO

Results | Wheat Yield Forecast

WP 1

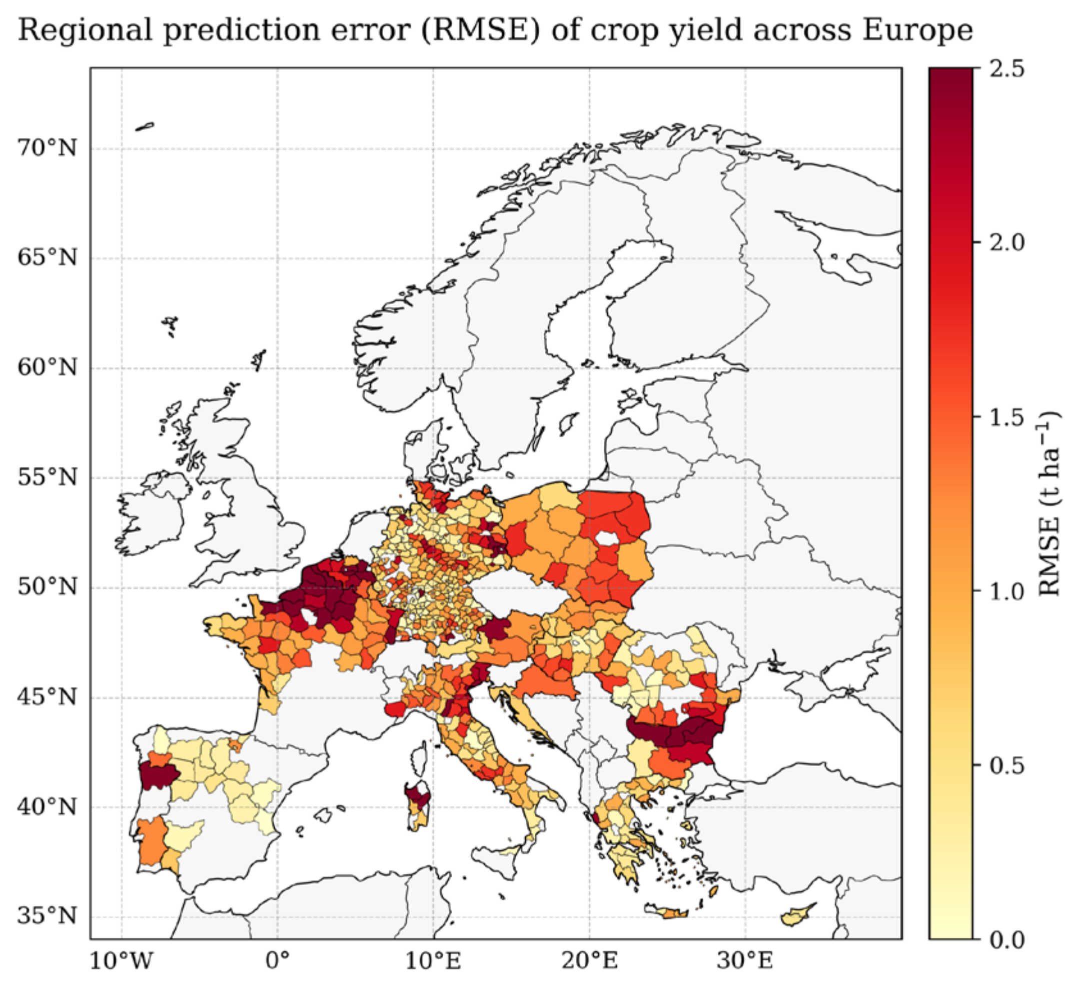
Hybrid Machine Learning



- combining meteorological and PROBA-V FAPAR data with RESNET model leads to +7% R^2 for ML+LPJmL and +1% R^2 for hybrid residual model on average across Europe
- LPJmL simulation shows R^2 of 0.77 for test years

Results | Wheat Yield Forecast

WP 1 Hybrid Machine Learning



Spatial Distribution of RMSE

- Model: RESNET
- Features: Meteo + MODIS FAPAR
- Setting: Hybrid Model (ML + LPJmL)

- high RMSE in coastal areas
- high RMSE in northern Italy
- rest randomly distributed

(3) Conclusions

Discussion & Limitations

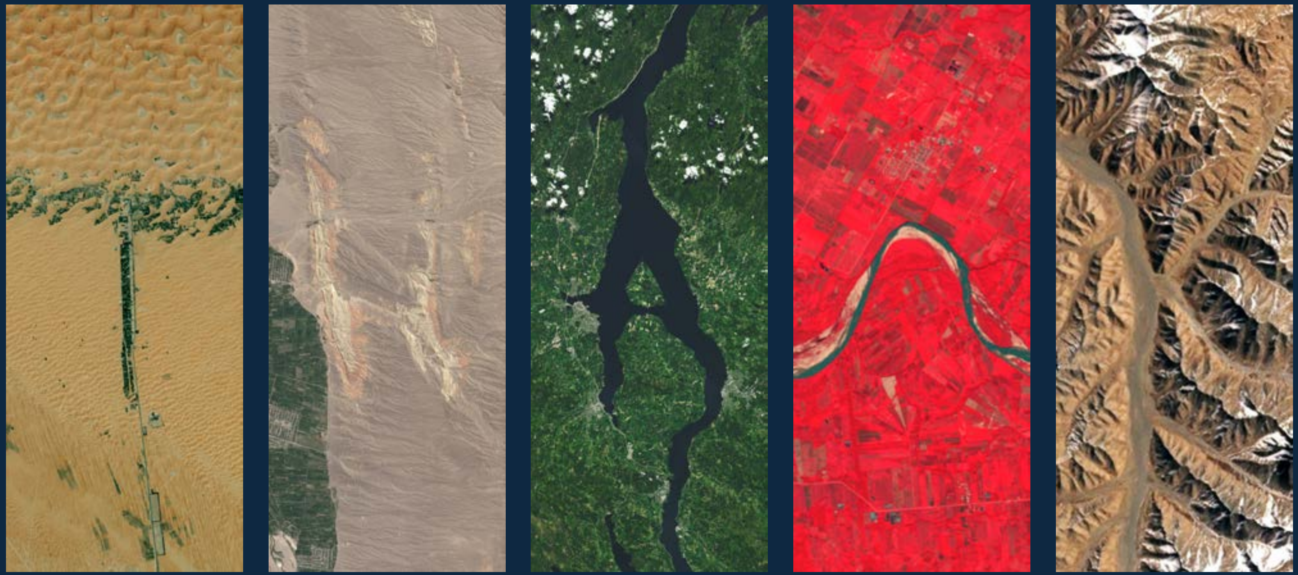
WP 1
Hybrid Machine Learning

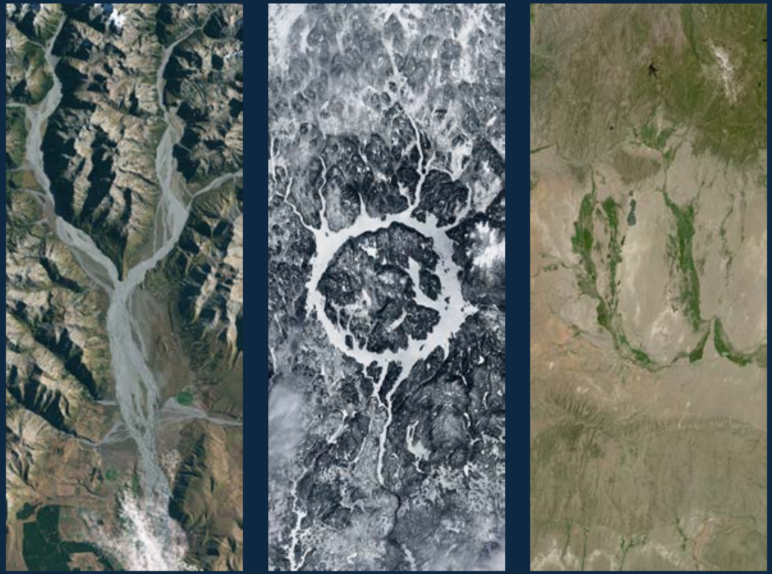
- FAPAR retrieval uncertainties
  - sensitive to sensor choice
  - PROBA-V showed highest increase of +7% R^2
- LPJmL structural constraints (e.g., harvest date)
- ML (generalization) limits
  - DL (LSTM, RESNET) better than tree-based (RF, XGB)
  - hybrid ML+LPJmL feature better than hybrid residual approach
- scale mismatches – 500m to NUTS-level
- scarce yield validation data

General Conclusions & Outlook

- hybrid modeling improves seasonal yield forecasts
- EO can constraints PB phenology
- ML might capture non-linear stress factors
- strong benefits for European food security

- next:
  - extent to other crops (maize)
  - design PINN architecture
  - integrate assimilation methods (parameter forcing, EnKF)
  - build operational forecasting system including C3S (WP 3)





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