





living planet symposium BONN 23-27 May 2022

TAKING THE PULSE OF OUR PLANET FROM SPACE

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Improving predictions of crop yield loss in years of severe droughts by integrating Earth observation and climate data in a machine learning framework. A case study for the Pannonian basin

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Motivation

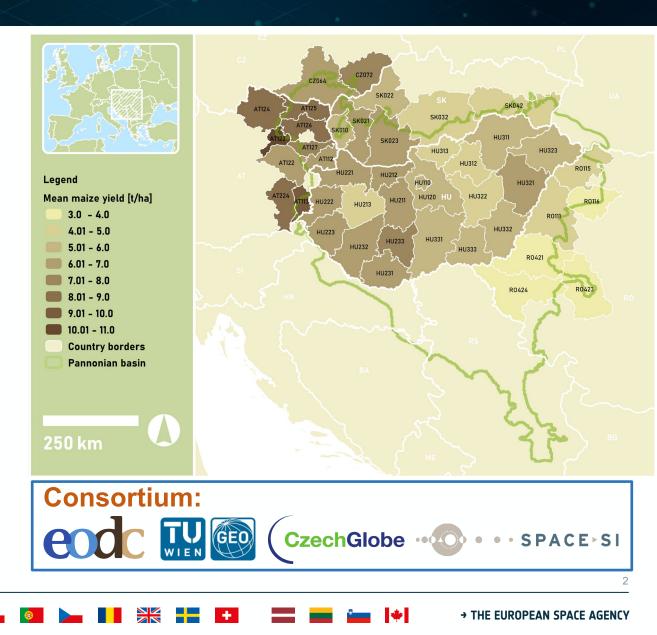
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Pannonian basin

- Sheltered with relatively low levels of precipitation (< 600 mm/year)
- High dependency of population on agriculture: 10-20% of population; >70% of area
- Several drought episodes in the last decades caused significant crop yield losses
- Further exacerbated by climate change





Introduction





Many crop yield models have been applied

process based and machine learning

Application over large areas possible using EO data, reanalysis and interpolated datasets

Extreme weather events complicate accurate crop yield forecasts

The ARYA crop yield forecasting algorithm: Application to the main wheat exporting countries

B. Franch ^{a, b,*}, E. Vermote ^c, S. Skakun ^{b,c}, A. Santamaria-Artigas ^{b,c}, N. Kalecinski ^{b,c}, J.-C. Roger ^{b,c}, I. Becker-Reshef ^b, B. Barker ^b, C. Justice ^b, J.A. Sobrino ^a

Towards regional grain yield forecasting with 1 km-resolution EO biophysical products: Strengths and limitations at pan-European level

Raúl López-Lozano^{a,*}, Gregory Duveiller^{a,b}, Lorenzo Seguini^a, Michele Meroni^a, Sara García-Condado^a, Josh Hooker^a, Olivier Leo^a, Bettina Baruth^a

Statistical modelling of crop yield in Central Europe using climate data and remote sensing vegetation indices

Anikó Kern^a, Zoltán Barcza^{b,c,d,*}, Hrvoje Marjanović^e, Tamás Árendás^f, Nándor Fodor^f, Péter Bónis^f, Péter Bognár^a, János Lichtenberger^{a,g}

In-season performance of European Union wheat forecasts during extreme impacts

Seasonal weather forecasts for crop yield modelling in Europe

glar, S. Garcia Condado, S. Karetsos, R. Lecerf,) & M. van den Berg

Pierre Cantelaube & Jean Statistical modelling of drought-related yield losses using soil moisturevegetation remote sensing and multiscalar indices in the south-eastern Europe

Vera Potopová^{a,*}, Miroslav Trnka^{b,c}, Pavel Hamouz^a, Josef Soukup^a, Tudor Castraveț^d

Yield estimation and forecasting for winter wheat in Hungary using time series of MODIS data

Péter Bognár^a, Anikó Kern^a, Szilárd Pásztor^a, János Lichtenberger^b, Dávid Koronczay^a and Csaba Ferencz^a







Apply a random forest based crop yield forecasting system and thoroughly assess its forecasting skill in normal years and severe drought years

Assessment of the contribution of the different explanatory variables to the model skill at different times during the growing season









41 NUTS3 regions; 2002-2016

Wheat and maize (harvested approx. in July and September)

Different datasets representing:

Temperature and water availability as key drivers of wheat and maize growth State of the plants: VOD, NDVI, LAI Drought indices SPEI and ESI for specific drought information Seasonal forecast show conditions for

remaining growing season

Dataset	Source	Spatial Resolution	Temporal Resolution
Yield data	DriDanube	NUTS3 level	yearly
Earth Observation			
Soil Moisture	ESA CCI	0.25°	daily
Soil Water Index	ESA CCI	0.25°	daily
VOD Ku-Band	VODCA	0.25°	daily
NDVI	CGLS	0.01°	10-daily
LAI	CGLS	0.01°	10-daily
Reanalysis			
Diurnal Temperatures	ERA5-Land	0.1°	daily
Growing Degree Days	ERA5-Land	0.1°	monthly
SPEI (1 month)	Based on ERA5	0.25°	monthly
SPEI (3 months)	Based on ERA5	0.25°	monthly
ESI (1 month)	Based on MODIS	0.05°	weekly
ESI (3 months)	Based on MODIS	0.05°	weekly
Seasonal forecasts			
Precipitation	ECMWF	1°	monthly
Temperature	ECMWF	1°	monthly
In situ data			
Temperature	E-OBS	0.25°	daily
Precipitation	E-OBS	0.25°	daily
Fraction of wet days	E-OBS	0.25°	monthly

Methods

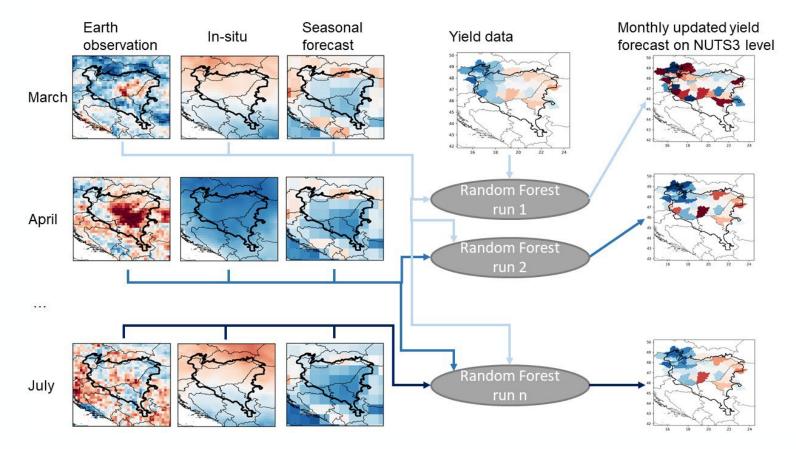




Crop yield forecasts with lead times up to 4 months before harvest

Random forest to combine input datasets Feature importance to assess impact of predictors

Monthly updated with latest data



Methods

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Cross-validation leaving 3 years out

Full timeseries 2002-2016 with test data for 41 regions

Validation for different skills of model:

Regional performance (A)

Validation per NUTS3 region

Pannonian basin mean yield forecast (B)

Mean forecasted NUTS3 regions vs. mean observed yield

Yearly performance

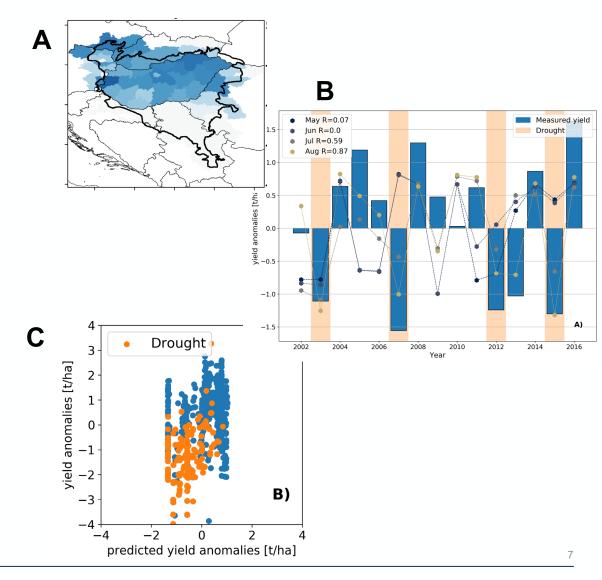
Validation forecast of all NUTS3 region within individual year

Overall performance (C)

All forecasted NUTS3 yields of all years vs. Observed yields

Drought year performance (C)

As overall but only for drought years



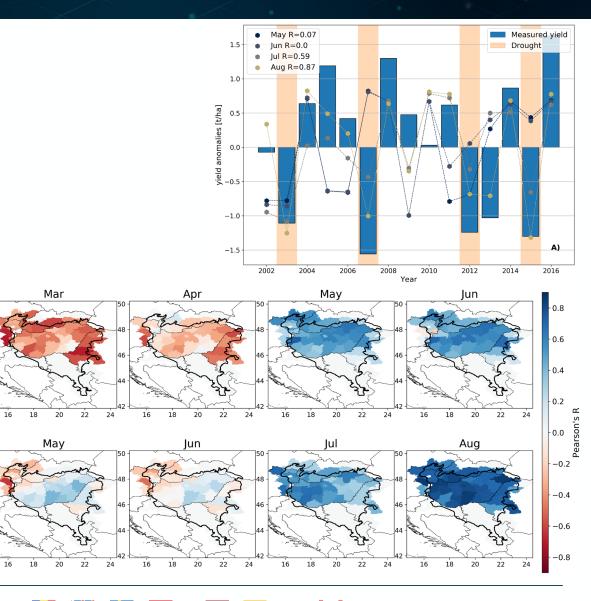
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What **can** be forecasted by the model?

All regions have high correlations to observed yields 2 months before harvest (Regional performance and Pannonian basin mean)

Highest correlations to predict Pannonian basin mean maize yield the month before harvest (R=0.87)

Model early detects negative anomalies in drought years



Wheat

Maize

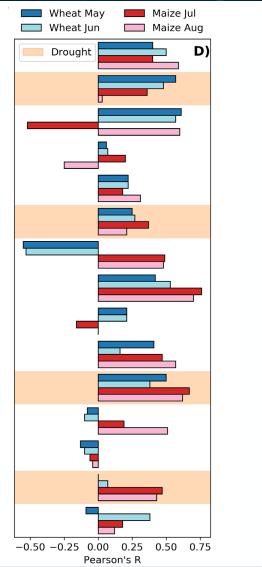
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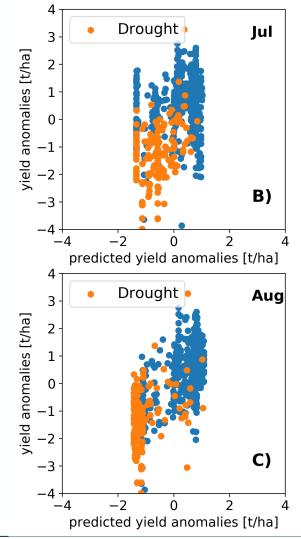


What **cannot** be forecasted by the model?

- Model does not do well to distinguish the crop yields between different NUTS3 regions
 - ->Low yearly performance
 - High spatial autocorrelations of yields and predictors Coarse resolution of predictors
 - -> Impacts overall performance and drought year performance

	Overall (R)	Drought (R)
Maize Jul	0.51	0.36
Maize Aug	0.67	0.33
Wheat May	0.41	0.47
Wheat Jun	0.47	0.44





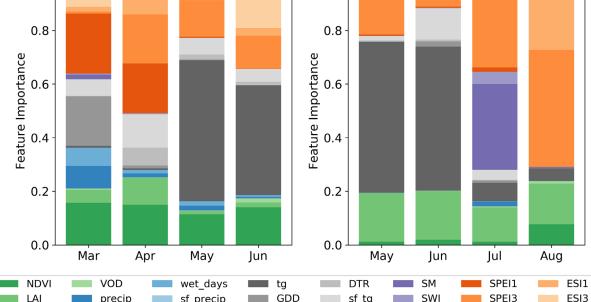
Large changes of the feature importance from first to last two months

> Wheat Maize 1.0 1.0 0.8 0.8 Feature Importance 0 9 9 Feature Importance 0.2 0.2 0.0 0.0 Mar Apr May Jun May Jun Jul Aug ESI1 NDV VOD wet davs tg SM SPEI: ESI3 GDD precip sf precip sf tg SWI SPE13

Wheat model mainly dependent on temperature

Maize on water availability (SPEI3 and soil moisture)

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Conclusions





- Crop yield forecasts show reasonable performance from around two months before harvest for interannual variabilities
- High spatial autocorrelations within individual years leads to poorer performance to compare regions
- Crop yield losses in years of severe droughts underestimated negative anomalies are correctly early detected
- Wheat is mainly dependent on the temperature maize on water availability

Next steps:

- Improving spatial and temporal resolutions to improve regional model performance; toward field-scale prediction
- Using novel EO datasets to better capture key variables like temperature and water availability
 - Sentinel-1 soil moisture, LSTM temperature





Thank you for your attention!

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Results



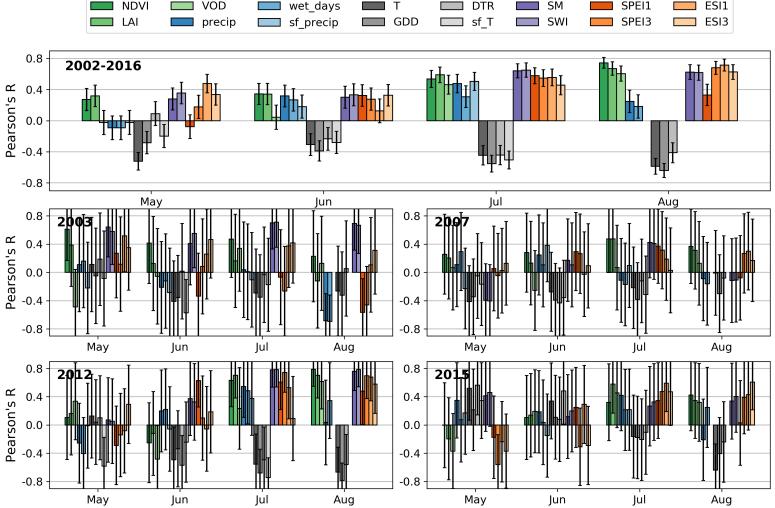


Correlation analysis of input parameters and final wheat yields: Clear pattern for all years Increasing closer to harvest Temperature-related negativ, rest positive EO and temperature highest correlations Barely significant in individual years

Maize yields:

Higher than for wheat EO and SPEI highest correlations

Barely significant in individual years



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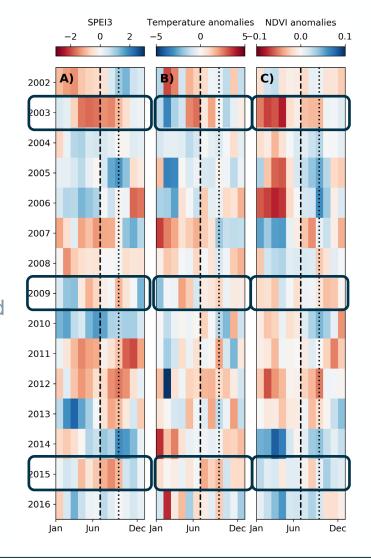
Model can mostly be explained by variability of the three main input parameters:

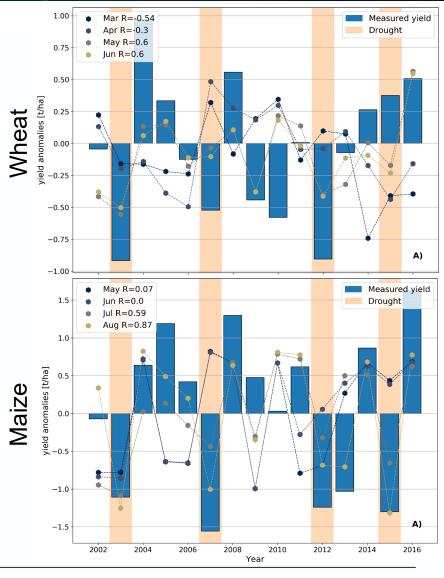
2003: long-lasting severe drought starting from around March

2009: High fluctations over the months, lead to unreliable (long-term) forecasts

2015: Wheat not yet impacted much by drought, but maize

Crop yield of maize and wheat are highly dependent on the conditions in the last two months before the harvest





Appendix



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