Potsdam Institute for
Climate Impact Research

Identifying the meteorological drivers of yield variability in Europe

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PIK RD II Climate Resilience
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OBJECTIVE

Understanding the meteorological drivers of year-to-year yield variability is crucial for estimating future changes in the frequency of harvest loss events. The overall aim of this analysis is to derive a set of indicators that can explain a large part of yield variability and which can then be applied to climate simulations to estimate the frequency of yield-loss events in the future. Because such indicators can more easily be applied to a large set of climate simulations than process-based crop models, it provides a means to obtain robust estimates of changes in yield-loss events in the future.

METHODS

We analyse the simulated yields from the Gridded Global Crop Model Intercomparison (GGCMI) project (Fig. 1):

- four different crop models (LPJ-GUESS, LPJmL, pAPSIM, pDSSAT)
- three different crops (maize, soy, wheat)
- potential (N-unlimited) rainfed yields
- Princeton meteorological forcing (1948-2008)
- EURO-CORDEX region

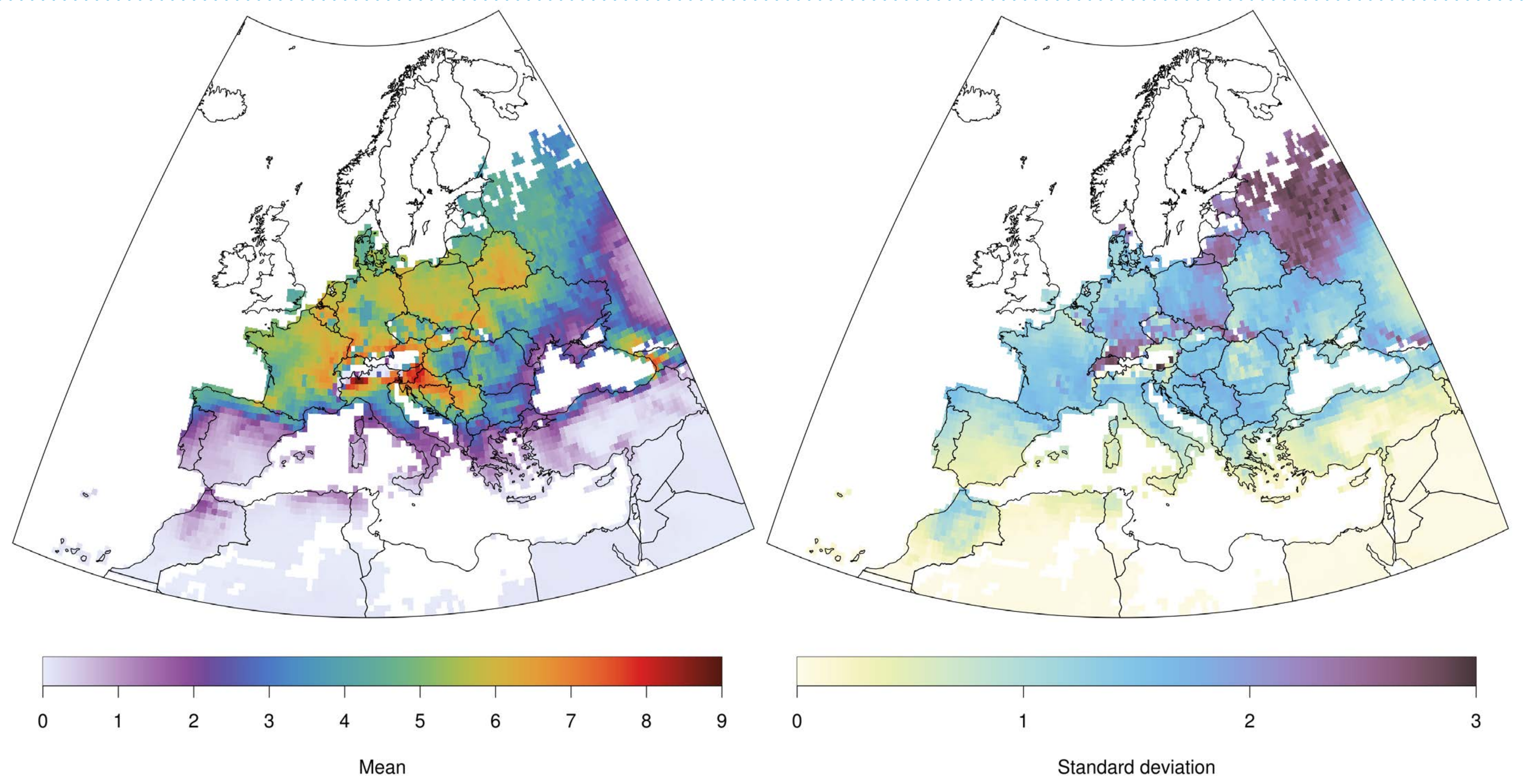

Figure 1. Mean and standard deviation for 61 years of simulated maize yield from LPJmL

Simulated yields can, in principle, be entirely explained by the model input. Meteorological conditions during the growing period for each harvest are extracted from the original Princeton data using the actual growing period as used in the simulation. In a first step, we calculate a set of climate indicators describing the average conditions during each growing period and the :

- average precipitation (pr)
- average surface air temperature (tas)
- average shortwave downward radiation (rsds)
- average vapour pressure deficit (vpd)
- sowing date (sdate)
- length of growing period (lgp)

Using random forest (RF) regression, we estimate the fraction of yield variance explained by each variable alone as well as their cumulative explanatory power by stepwise addition to a combined model. In a second step, we test by how much the combined RF model can be further improved by adding variables characterizing to variability within the growing season or extreme weather events:

- standard deviation of daily precipitation (pr_sdev)
- standard deviation of daily mean surface air temperature (tas_sdev)
- standard deviation of daily shortwave downward radiation (rsds_sdev)
- standard deviation of daily vapour pressure deficit (vpd_sdev)
- maximum number of consecutive dry days (cdd_max)
- minimum of cumulative climatic water balance (wb_min)
- number of frost days < 0° C (ndays_frost)
- sum of frost degree days < 0° C (fdd_sum)
- number of heat days > 30° C (ndays_heat)
- sum of frost degree days > 30° C (hdd_sum)

RESULTS

The fraction of explained yield variance that can be explained by each variable alone varies by crop model as well by crop type (Fig. 2, bar length). For LPJmL and pAPSIM, average precipitation has the highest explanatory power among all variables. The combined RF model using only average growing conditions as well as growing season start and length can explain 90 % to 96 % of yield variance for LPJ-GUESS and LPJmL. but only 72 % to 90 % for pAPSIM and pDSSAT. pAPSIM and pDSSAT are dedicated crop models, wheeas LPJ-GUESS and LPJmL are extensions of dynamic global vegetation models.

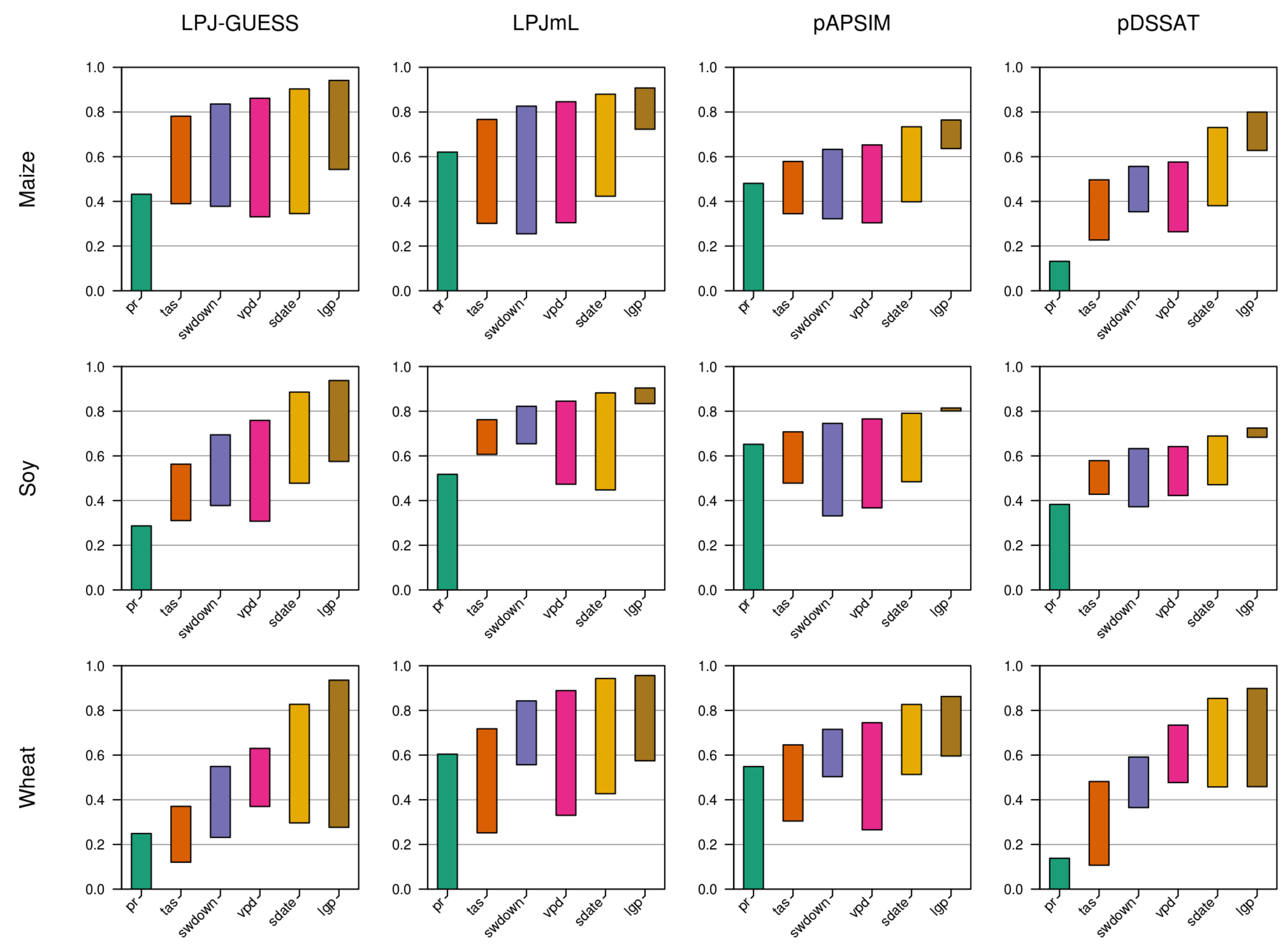

Figure 2. Fraction of explained yield variance (R^2) per variable (length of bars) and cumulative effect by stepwise addition to a combined RF model (top of bars).

Adding variables characterizing weather variability or extreme events to the combine RF model increases the explained yield variance by up to 3 percentage points. Improvements are larger for the the dedicated crop models (pAPSIM and pDSSAT), and for variables related to heat extremes (ndays_heat and hdd_sum). Variables describing rainfall variability or drought conditions lead to no or only very small improvements for all crops and crop models. Further promising candidates for inclusion in the combined model are standard deviation daily mean surface air temperature (tas_sdev) and vapour pressure deficit (vpd).

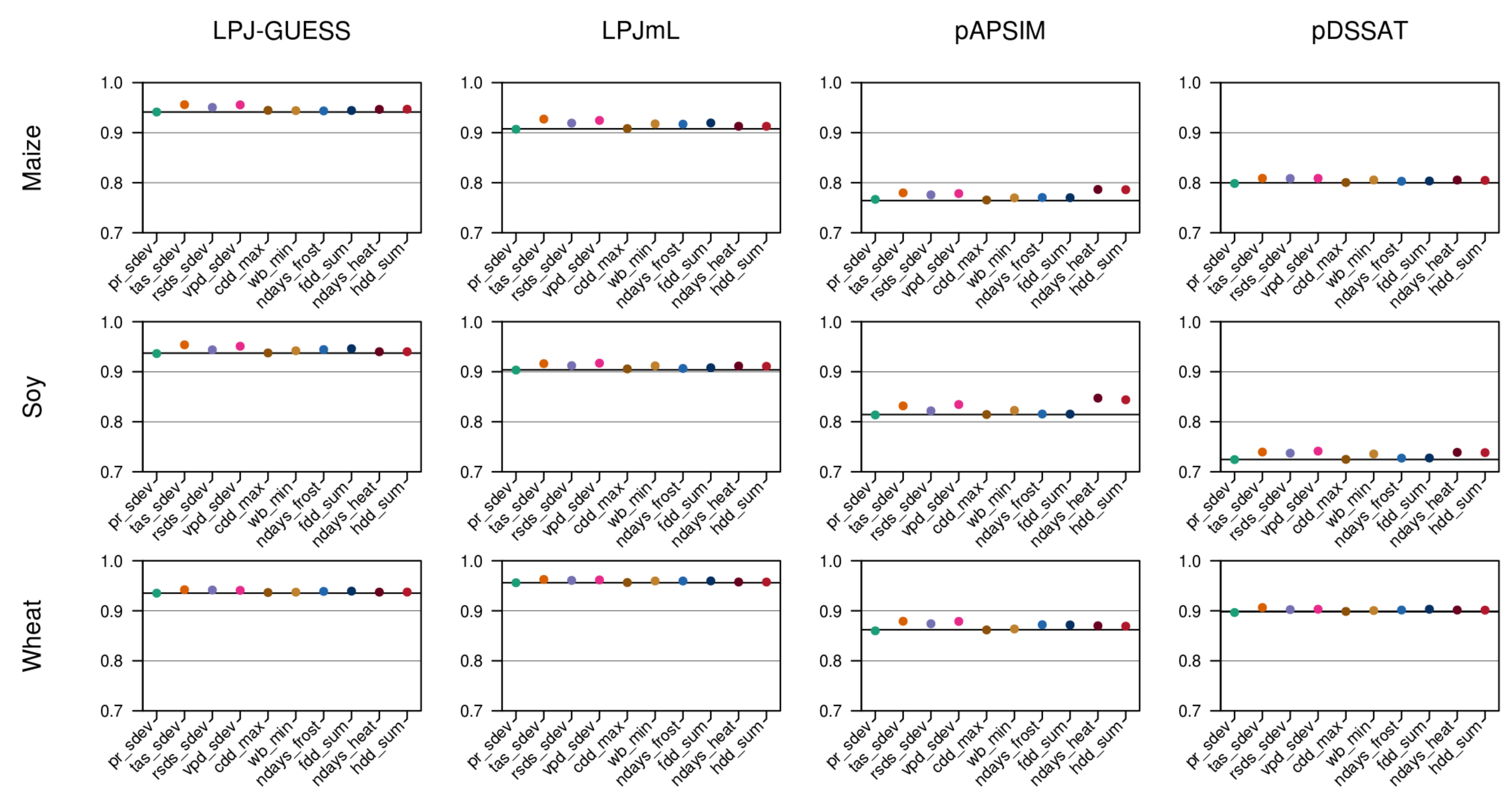

Figure 3. Increase in explained yield variance by adding variables related for variability or extremes to the combined RF model.

Next steps:

- reformulate RF models to predict annual yield anomalies (derivation from long-term mean) per grid cell rather than absolute yields
- include other input used by the models models (e.g. soil type) in RF models
- develop refined indicators to capture variability, extremes, and compound or cascading events that lead to yield losses

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