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Food security in a changing climate - how can Earth observation and machine learning help?

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Climate change is threatening food security. To ensure food security, we do not only have to safeguard agricultural production - crop yields also need to be optimally distributed. For that, decision-makers need reliable crop forecasts so that they can plan which regions are likely to experience crop yield losses and which regions will produce a surplus. Earth observation and machine learning are key tools to calculate such forecasts. However, extreme crop yield losses, for example caused by severe droughts, are often underestimated. To test this, we developed a machine learning-based crop yield anomaly forecasting system for the Pannonian Basin and examined its performance, with a focus on drought years. We trained the model (XGBoost) with crop yield data from 43 regions in southeastern Europe and predictors describing soil moisture, vegetation, and meteorological conditions. Maize and winter wheat yield anomalies were forecasted with different lead times (zero to three months) before the harvesting season. Our results show that the crop yield forecasts are significantly more reliable from 2 months before the harvest than before in both, drought and non-drought years. The models have their clear strength in forecasting interannual variabilities but struggle to forecast differences between regions within individual years. This is related to spatial autocorrelations and a lower spatial than temporal variability of crop yields. In years of severe droughts, the wheat yield losses remain underestimated, but the maize forecasts are fairly accurate. The feature importance analysis shows that in general wheat yield anomalies are controlled by temperature and maize by water availability during the last two months before harvest. In severe drought years, soil moisture is the most important predictor for the maize model and the seasonal temperature forecast becomes key for wheat forecasts two months before harvest.