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Linking crop yield anomalies to large-scale atmospheric circulation in Europe

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ABSTRACT

Understanding the effects of climate variability and extremes on crop growth and development represents a necessary step to assess the resilience of agricultural systems to changing climate conditions. This study investigates the links between the large-scale atmospheric circulation and crop yields in Europe, providing the basis to develop seasonal crop yield forecasting and thus enabling a more effective and dynamic adaptation to climate variability and change. Four dominant modes of large-scale atmospheric variability have been used: North Atlantic Oscillation, Eastern Atlantic, Scandinavian and Eastern Atlantic-Western Russia patterns. Large-scale atmospheric circulation explains on average 43% of inter-annual winter wheat yield variability, ranging between 20% and 70% across countries. As for grain maize, the average explained variability is 38%, ranging between 20% and 58%. Spatially, the skill of the developed statistical models strongly depends on the large-scale atmospheric variability impact on weather at the regional level, especially during the most sensitive growth stages of flowering and grain filling. Our results also suggest that preceding atmospheric conditions might provide an important source of predictability especially for maize yields in south-eastern Europe. Since the seasonal predictability of large-scale atmospheric patterns is generally higher than the one of surface weather variables (e.g. precipitation) in Europe, seasonal crop yield prediction could benefit from the integration of derived statistical models exploiting the dynamical seasonal forecast of large-scale atmospheric circulation.

1. Introduction

Climate variability and extremes have a profound influence on agricultural systems (Deryng et al., 2014; Siebert and Ewert, 2014; Challinor et al., 2014). Understanding their effects represents a necessary step to assess the resilience of agricultural systems to changing climate conditions as well as to develop adequate adaptation measures (Moore and Lobell, 2014). Numerous studies have investigated the link between climate and crop yields in Europe (e.g. Ceglar et al., 2016; Moore and Lobell, 2015; Hawkins et al., 2013) providing the basis to develop a seasonal crop yield forecasting system and thus enabling a more effective and dynamic adaptation to climate variability and change. Indeed, early and reliable predictions of severe weather events and/or conditions can significantly contribute to the mitigation of adverse effects on crops and alleviate their negative impacts (e.g. Träger-Chatterjee et al., 2014).

Seasonal climate forecasts have been increasingly used across a range of sectors, e.g. energy, water resources, insurance, natural hazards (Marcos et al., 2016, 2015; Soares and Dessai, 2015; Doblas-Reyes et al., 2013). It has been shown that seasonal forecasts can represent a valuable source of information also for the agricultural management process (e.g. Hansen, 2005; Challinor et al., 2003). However, seasonal crop yield forecasting in Europe poses a great challenge due to the poor seasonal climate forecast skill of some relevant local surface climate variables (e.g. precipitation), showing acceptable skill at mid-latitude regions only for particular seasons (Frías et al., 2010; Shongwe et al., 2007). Predicting extreme events (such as the 2003 heat wave) remains challenging (Weisheimer et al., 2011) in the extra-tropical regions. However, new emerging findings show the potential for a better understanding of the spatio-temporal features of these climatic events, along with associated precursors (Prodhomme et al., 2016, 2015; Pepler et al., 2015; Quesada et al., 2012).

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Recent works have demonstrated that key aspects of European and North American winter climate and the North Atlantic Oscillation (*NAO*) are predictable months ahead (Dunstone et al., 2016; Scaife et al., 2014). Since seasonal forecasts only show modest level of skill in predicting surface climate in Europe, it is therefore important to explore different ways to use selected variables of seasonal forecasts where better skill can be observed, such as in the large-scale atmospheric circulation. Indeed, large-scale climate patterns can produce synchronous variations of local surface variables (e.g. temperature) over large areas and can be generally forecast more accurately (Doblas-Reyes et al., 2003).

The relationship between large-scale teleconnection patterns and crop yields has been widely studied in the past. ENSO-induced variability and its influence on crop yields have been investigated globally (Iizumi et al., 2014) as well as for several different regions of the world: USA (Hansen et al., 1999), southern America (Ferreyra et al., 2001), Australia (Meinke and Hochman, 2000) and Zimbabwe (Phillips et al., 1998). Several local/regional studies in Europe support the existence of a relationship between crop yields and large-scale atmospheric patterns (Irannezhad and Klöve, 2015; Brown, 2013; Sepp and Saue, 2012; Persson et al., 2012; Kettlewell et al., 2003; Gimeno et al., 2002). However, these studies are limited to small spatial domains.

The Euro-Atlantic region is mainly dominated by four large-scale atmospheric modes of variability: North Atlantic Oscillation (*NAO*), Eastern Atlantic (*EA*), Scandinavian (*SCAND*) and Eastern Atlantic-Western Russia (*EAWR*) patterns (Casanueva et al., 2014; Casado et al., 2009). Cantelaube et al. (2004) have shown the existence of a relationship between leading winter atmospheric modes of variability and winter wheat yields in Europe. However, the link between teleconnection patterns and climate anomalies over Europe exists also in other seasons (e.g. Casanueva et al., 2014; Krichak et al., 2014; Bladé et al., 2012; Toreti et al., 2010; Yiou and Nogaj, 2004). In addition, combining observed climate information within the growing season (e.g. large-scale atmospheric modes responsible for precipitation, temperature and accumulated soil moisture) with seasonal forecasts for the rest of the crop growth period (e.g. anthesis and harvesting stages) could significantly contribute to an increase of the crop yield predictability.

Thus, the main objective of this study is to further explore and deepen our understanding of the dynamical sources of crop yield predictability in Europe originating from large-scale atmospheric circulation during the growing season for both winter wheat (October–July) and grain maize (March–September). Understanding of dynamic precursors leading to seasonal climate anomalies can significantly contribute to extending the long-range predictability of crop yields. To this aim, a statistical approach is here developed to build climate-crop yield models based on large-scale atmospheric circulation patterns that can be used to set up a seasonal forecast system.

2. Data

Winter wheat and grain maize yields at the national level were obtained from national statistical institutes in Europe (Eurostat, 2016). Fig. S1 shows the national yield time series of both crops aggregated at the national levels. The study period spans from 1980 to 2015; time series having at least 25 years of data were included in this study, as a tradeoff between having long enough time series of crop yields for statistical analysis and largest possible number of countries included in the analysis.

Leading modes of large-scale atmospheric variability in the Euro-Atlantic region were obtained from the National Oceanic and Atmospheric Administration. These indices are based on a rotated principal component analysis of monthly standardized geopotential anomalies at 500 hPa (Barnston and Livezey, 1987). Specifically, four leading modes of large-scale atmospheric variability over the Euro-Atlantic region have been used: *NAO*, *EA*, *EAWR* and *SCAND*.

Daily precipitation and daily mean temperature data were obtained from the MARS Crop Yield Forecasting System (MCYFS) database, established and maintained by the Joint Research Centre of the European Commission for the purpose of crop growth monitoring and forecasting (Biavetti et al., 2014). These data are available on a regular 25 km × 25 km grid covering Europe and neighboring countries.

3. Methods

Crop yield time series can be modelled by using two main components: a decadal trend (induced by the combined effects of changes in agro-management practices, environmental and socio-economic factors and climatic changes) and a weather-related component (driving the crop yield variability). A proper estimation of the decadal trend is important, as the influence of slowly changing factors needs to be minimized in order to more accurately capture the effect of the inter-annual climate variability. Three different methods have therefore been compared for this purpose here: polynomial (with linear and quadratic term on both *yield* and *log*(*yield*)) and LOESS (Cleveland, 1979). Then, de-trended yields have been correlated with large-scale circulation indices on monthly to seasonal time scales. As the differences in correlations based on different de-trending methods are only minor (not shown), the polynomial method has been applied on *log*(*yield*) to obtain yield anomalies for the subsequent analysis. Yield anomalies Y_t are derived as follows:

$$Y_t = \log(Z_t) - \hat{\beta}_0 - \hat{\beta}_1 \cdot t - \hat{\beta}_2 \cdot t^2 \qquad (1)$$

where Z_t denotes the original yield data at year t and with $\hat{\beta}_0$, $\hat{\beta}_1$ and $\hat{\beta}_2$ being estimated by ordinary least squares. Logarithmic transformation has been selected to reduce problems with heteroscedasticity caused by large differences in yields between countries (Lobell, 2013) and to normalize positively skewed crop yield distribution.

The main statistical model used in this study is:

$$Y_t = \gamma_0 + \sum_i \gamma_i \cdot X_{i,t} + \epsilon_t \qquad (2)$$

where $X_{i,t}$ represents the predictor i in year t and ϵ_t are the residuals. $X_{i,t}$ can represent any potential predictor (*NAO*, *SCAND*, *EA* and *EAWR*) in any of the averaging periods (one, two or three months; see the next sub-section) during the crop growing season. The growing period between October and July is considered for winter wheat, while the period between March and September is considered for grain maize (MCYFS – MARS Crop Yield Forecasting System, 2016). As crop yields and predictor variables are standardized, γ_0 is equal to zero. The standardization makes the regression results for the different regions comparable with each other. The model residuals ϵ_t should be normally distributed, independent and homoscedastic; therefore, these assumptions are tested by using Shapiro, Durbin–Watson and *F* tests (Wilks, 2006).

3.1. Selection of relevant predictors

The relevant predictors have been selected for each country separately. The potentially relevant modes of atmospheric variability (i.e. the predictors) are constructed for different time aggregation periods, from one to three months. Different aggregation periods are considered due to the varying sensitivity of crop growth to climate anomalies during different growing stages, allowing for