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Effects of diurnal temperature range and drought on wheat yield in Spain

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Abstract This study aims to provide new insight on the wheat yield historical response to climate processes throughout Spain by using statistical methods. Our data includes observed wheat yield, pseudo-observations E-OBS for the period 1979 to 2014, and outputs of general circulation models in Phase 5 of the Coupled Models Inter-comparison Project (CMIP5) for the period 1901 to 2099. In investigating the relationship between climate and wheat variability, we have applied the approach known as the Partial Least-Square regression, which captures the relevant climate drivers accounting for variations in wheat yield. We found that drought occurring in autumn and spring and the diurnal range of temperature experienced during the winter are major processes to characterize wheat yield variability in Spain. These observable climate processes are used for an empirical model that is utilized in assessing the wheat yield trends in Spain under different climate conditions. To isolate the trend within the wheat time series, we implemented

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the adaptive approach known as Ensemble Empirical Mode Decomposition. Wheat yields in the twenty-first-century are experiencing a downward trend that we claim is a consequence of widespread drought over the Iberian Peninsula and an increase in the diurnal range of temperature. These results are important to inform about wheat vulnerability in this region to coming changes and to develop adaptation strategies.

Keywords Climate Change impact · Empirical wheat yield model · Partial Least Square regression · Climate variability

1 Introduction

The IPCC (2014) report on impacts, adaptation, and vulnerability informs that rising temperatures and changes in rainfall may benefit agriculture in some countries but may damage in some other parts, as consequence of climate variability, weather extremes, and changes of the water cycle. The Joint Research Centre (JRC) denoted a reduction around 20% of agricultural production in Southern Europe by the end of the twenty-first century, in the PESETA II Project on impact studies in Europe (Ciscar et al, 2014). They also refer that technical adaptation can improve the yields all over Europe, however, modest effectiveness is expected in southern Spain due to excessive aridity. Particularly, in Spain there is currently a national concern about agricultural productions. Wheat is one of the world's most basic and necessary, its productivity is as large as olive, citrus and grape farming in Spain (FAO, 2014). Our study aims to address the following questions: what climate variables are essential to explaining wheat yield changes? What future trends will wheat production experience considering our findings regarding these variables?

Some of the motivations to perform this study are: diversity of results on climate change and crop impacts; variety in crop methodologies; and the need to evaluate the impacts of climate change on crops variability at the regional level. The methods to evaluate the impact of climate change on crop productions can be gather into process-based and statistical models. White et al (2011) reviewed methodologies for simulating impacts of climate change on crop productions using process-based crop models, which succeed locally. However, Palosuo et al (2011) noticed that process-based crop models for winter wheat simulation reproduce poorly the corresponding observations, since agricultural management input data are seldom available for larger areas. Otherwise, Angulo et al (2013) discussed the regionally applicability of process-based crop models. Rosenzweig et al (2013) indicated that wheat simulation is more sensitive to the crop model than to global climate model simulation and Carter (2013) recommended multi-model yield projections for impact studies. Some authors (Rotter and Hohn, 2015; Asseng et al, 2013) performed inter-comparisons of process-based crop models by analyzing the uncertainty of wheat simulation under climate change and considering differences in model structures. A meta-analyses from numerous studies indicated that projected response of crop to climate variability and change can vary according to the methodology (Challinor et al, 2014). However, process-based models are useful for determining the causes of yield variations while to reproduce historical yield variations statistical models are appropriated (Watson et al, 2015). Thus statistical approaches are attracting attention for assessing climate change impacts on crop production for larger areas (Lobell and Burke, 2010; Lobell, 2013).

Regarding wheat yield, Lobell et al (2011a) studied the impact of climate trend on global crop production and Moore and Lobell (2014) point out the benefits of adaptation to compensate the negative effect of rising temperature on the crops in Europe. The impacts of climate change on winter wheat are thought to be negative across Europe (Olesen et al, 2011). Trnka et al (2011b) calculated and projected agroclimate indices, reported decreases in potential productivity in the case of North and South Mediterranean zones due to increases in the proportion of dry days and increase in heat waves.

The majority of agro-climatic investigations focussed on analysing the relationships between crop yield, temperature, and precipitation; Challinor et al (2014) summarized the responses of various crops to changes in temperature, precipitation and effectiveness of adaptation. Currently, extreme indices of the apparent impacts upon ecosystems (Lobell, 2007; Lobell et al, 2011b; Ruiz-Ramos et al, 2011; Trnka et al, 2014; Eitzinger et al, 2013) have garnered much attention. Other studies develop analyses regarding the relationship between crop productions and teleconnections (Atkinson et al, 2005; Chen et al, 2015; Gonsamo and Chen, 2015; Hansen et al, 2001; Iizumi et al, 2014; Podesta et al, 2002; Royce et al, 2011; Bannayan et al, 2011; Dalla Marta et al, 2011; Jarlan et al, 2014; Tian et al, 2015).

In Spain, the effects of climate variations on wheat and barley yields in the Ebro valley have been estimated by Vicente-Serrano et al (2006) using drought indices and remote sensing data. Iglesias and Quiroga (2007) researched the risks entailed by climate variability for cereal production at five sites in Spain; Ruiz-Ramos et al (2011) projected the effects of maximum temperature on cereal yields by using regional climate models. Studies based on teleconnections and crop productions in Spain were conducted by Capa-Morocho et al (2014); Gimeno et al (2002); Rodriguez-Puebla et al (2007). However, the responses of regional crops to climate changes are very much uncertain, as indicated by Rotter (2014), hence multiple impact models should be considered for projecting future crop productivity (Challinor et al, 2014).

Most of the statistical studies are based on regression of the historical crop yield, precipitation and temperatures. We aim to identify relationships between wheat variability in Spain and climate processes such as drought and extreme temperature indices, updating previous work (Rodriguez-Puebla et al, 2007) and introducing new approaches: namely, the Partial Least-Squares (PLS) regression for ascertaining the modes of climate variables associated with wheat yield variability, Ensemble Empirical Mode Decomposition (EEMD) for identifying the trends and scales of wheat yield variability, and the Multivariate Regression model for empirically estimating wheat yield variability, considering the relative effects of different climate variables that affect soil moisture content as temperature and precipitation. Hence we have not considered changes in soil water storage capacity and CO_2 variations. The empirical statistical model of wheat yield variability in Spain is applied to estimate wheat productivity in the twentieth and twenty-first centuries, using the output data of twelve GCMs of CMIP5. We analysed the changes in wheat yields for individual models and the corresponding Multi-model for historical and representative concentration pathway 8.5 (RCP8.5) experiments (Taylor et al, 2012).

The paper is organized in the following way: the data and methods used are indicated in Section 2. Results regarding the analysis of climate impact upon wheat yield, the derived statistical model, and the identification of trends under different climate conditions are presented in Section 3. Discussion and main findings are summarized in Sections 4 and 5, respectively.

2 Data and Methods

2.1 Data and study area

Data regarding wheat production or yield over Spain is collected by the Spanish Agriculture, Food, and Environment Department (MAGRAMA, 2015). Wheat yield refers to the weight of production divided by the area of cultivation (T/ha). We used data from different provinces for the period 1979 to 2014. Regarding climate data in Spain (35-45N and 10W-5E), we used the daily pseudo-observations E-OBS (V11.0) dataset 0.25-degree resolution of precipitation (Pr), mean (Tmed), maximum (Tmax), and minimum (Tmin) temperatures (Haylock et al, 2008) for the period of September 1978 to August 2014. Although there are other datasets based on denser observational networks, Spain02 (Herrera et al, 2012), station density is not as relevant for purposes of this research as we are primarily interested in climate variations that affect the aggregated wheat yield in Spain. Furthermore, the Spain02 dataset was not available until 2014, while the E-OBS data are frequently updated and extensively used and tested. From the daily temperatures we derived the daily diurnal temperature range (DTR), then the monthly and seasonal DTR. From the daily precipitation we derived the accumulated monthly and seasonal precipitation, then we derived the Standardized Precipitation Index (SPI) (WMO, 2012; Vicente-Serrano et al, 2010) on a time scale of one month to reflect the response of wheat yield to rapid-onset drought events (Otkin et al, 2015) or agricultural drought (Lorenzo-Lacruz et al, 2013). The SPI consists of the transformation of precipitation into a standardized normal distribution, obtained with the script of Ncar Command Language (NCL) (UCAR/NCAR, 2015).

Our model indirectly takes into account the effect of soil moisture effect on crops, by considering both variables: precipitation, characterized with the SPI index, and temperature using the DTR index. A comparison of drought indices effect (Begueria et al, 2014) on wheat yield would be a challenge for further research since the choice of the formula to compute evapotranspiration is currently under debate (Dai, 2011; Trenberth et al, 2014).

We used a second dataset of climate variables of Pr, Tmed, Tmax and Tmin corresponding to the CMIP5 models (Taylor et al, 2012) indicated in the supplementary material (Table S1). In this study, we considered the historical experiment corresponding to the period of time from September 1901 to December 2005, forced by observed atmospheric composition changes, reflecting both anthropogenic and natural sources, and the future projection of the RCP8.5 experiment from January 2006 to August 2099, which corresponds to the pathway with the highest greenhouse gas emissions and a radiative forcing of 8.5 W/m^2 in 2100 (Riahi et al, 2011). One realization or ensemble run of the individual models is taken into account in order to give all models the same weight. The DTR and SPI modelled are derived as explained above in the case of pseudo-observations. For this comparison, we have re-gridded the data to the same resolution as E-OBS using the bilinear interpolation included in the Climate Data Operator (CDO) software (Schulzweida, 2015). The model performance of the GCMs selected has been evaluated through comparisons of some pattern statistics (Taylor, 2001) and climographs against the observations, included in the supplementary material.

2.2 Empirical Mode Decomposition

Much of the yield increase is likely due to improved crop management, according to results of Moore and Lobell (2015), since the contribution of the long-term temperature and precipitation trends to wheat yield trend is quite small during the observational period (Xiao and Tao, 2014). In addition, recent study (Asseng et al, 2013) indicate the controversial benefits from enhanced CO_2. Therefore, de-trending the wheat time series is recommended before exploring the relationships between climate variability and wheat yield. Ensemble Empirical Mode Decomposition (EEMD) is an adaptive approach to deconstructing a time series without linear or stationary assumptions (Chen et al, 2013; Huang et al, 1998; Moghtaderi et al, 2013; Wu et al, 2007). This approach acts as a high-pass filter and is used in decomposing wheat yield time series. EMD is a sifting process to decompose a time series x(t):

$$x(t) = \sum_{i=1}^{k} c_i(t) + r(t) \tag{1}$$

Here, $c_i(t)$ are intrinsic mode functions (IMFs) and $r(t)$ is the residual. IMFs depend on the signal and satisfy two conditions (Huang et al, 1998): the number of extreme and the number of zero crossing vary by at most one, and the local mean of each IMF is zero. The decomposition procedure is as follows: 1) locate all maxima and minima of the $x(t)$ and connect all maxima (minima) with a cubic spline; 2) compute the difference between the time series and the mean of upper and lower envelopes to yield a new time series $h(t)$; 3) for the time series h(t), repeat steps 1) and 2) until upper and lower envelopes are symmetric with respect to the zero mean under the specified criteria in order to obtain the IMF, $c_i(t)$; 4) subtract $c_i(t)$ from original time series

$x(t)$ to yield a residual $r(t)$ and treat $r(t)$ as the original time series and repeat steps 1-3 until the residual becomes a monotonic function or a function with only one extreme; this completes the sifting process (Chen et al, 2013). For better signal separation, a Monte Carlo approach recommended, in which zero-mean Gaussian white noise is added to each EMD process and the modified method is designed as Ensemble Empirical Mode Decomposition (EEMD) (Franzke, 2010; Wu et al, 2011).

The utility of the EEMD approach in separating the trend from natural variability in analyzing phenological responses to warming is demonstrated in the paper by Guan (2014).The robustness of EEMD has been applied in ascertaining surface air temperature trends (Capparelli et al, 2013; Ji et al, 2014), and trends in sea surface temperature (Feng et al, 2014). In our case, we use EEMD as a high-pass filter by retaining all the IMFs except the residual or trend component of the observed wheat time series; therefore, other improved techniques (Colominas et al, 2014) for analysing the intrinsic mode functions were not implemented. This method is also used to represent the trend component of the wheat yield simulation from CMIP5 models. The estimation utilized the Matlab EMD/EEMD package of Flandrin et al (2004).

2.3 Partial Least Squares Regression

The influence of climate variables on wheat production is investigated through use of the PLS regression. This procedure is a powerful method for describing covariance between variables by means of latent variables. This process entails dimension reduction and regression adjustment. The method was developed by Wold et al (2001) in order to solve the problem of co-linearity in linear regression. It has been applied with great success in chemometrics and is now being applied in climatology (Gonzalez-Reviriego et al, 2015; Smoliak et al, 2015, 2010; Wallace et al, 2012). PLS regression seeks to predict variables (Y) based on independent variables (X)

-that are correlated- by finding a few new uncorrelated variables, in addition to denominated latent variables. Imposing the constraint of orthogonality upon the latent variables serves to mitigate the problem of multi-linearity and reduces the number of independent variables needed to describe variations in the dependent data (Y); but PLS also chooses the optimum subset of predictors, which is not guaranteed when the Principal Regression Method is applied (Abdi, 2010). Therefore, PLS finds components from X that best predict Y.

In our study, PLS regression is applied in two different ways. The first step begins to assess the modes of a climate field in conjunction with the observed wheat yield variability corresponding to the observational period (1979-2014). The modes include spatial patterns and PLS components or time series congruent with the wheat time series. We obtained tailored time series of climate variation components that explain changes in wheat yield. In this case, the observed climate variables will be referred to as independent variables, or fields that vary in time and space dimensions $X(T,M)$, $(M = lat \times lon)$, and the detrended spatially averaged wheat yield in Spain is the dependent variable, which varies within the time dimension $Y(T)$. The outcomes include some orthogonal latent spatial vectors $Z(M)$ and temporal uncorrelated PLS components $B(T)$. Figure 1a shows a schematic diagram of the PLS approach. The procedure is applied to different climate fields such as Tmax, Tmin, Tmean, SPI, and DTR. The PLS component B, corresponding to different climate fields, will be considered in predicting the dependent variable Y by applying a forward and backward stepwise regression procedure (Wilks, 2006) that selects the climate indicators B to be included in the empirical agro-climate model. The uncertainty of the model was assessed through the use of cross-validation or by repeating the appropriate procedure upon data subsets to select robust variables and provide the confidence interval for the estimation. The quality of the model is given by the Pearson correlation coefficient with its error, which is obtained by repeating the correlation for many samples using a bootstrap re-

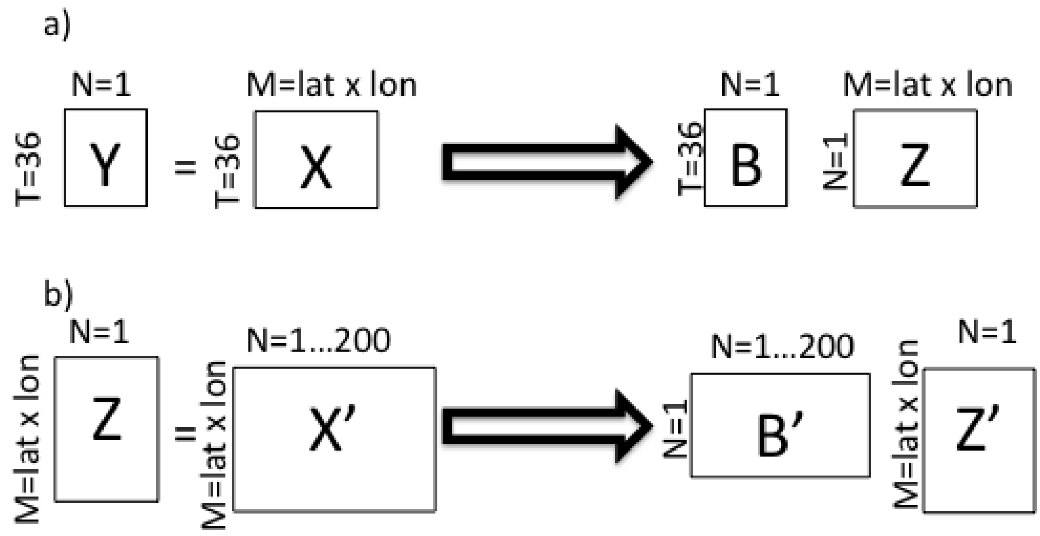

Fig. 1 Schematic diagram of the PLS regression in the temporal dimension (a) and the spatial dimension (b)

sampling with replacement. To construct the empirical model, we used the package stepwise linear regression model under Matlab statistical toolbox.

The second step of PLS application considers the spatial patterns of the climate variables associated with wheat yield variations, previously obtained through applying PLS to the observational period, and these patterns were analysed in conjunction with the CMIP5 data to find their common structure and associated time series (Gonzalez-Reviriego et al, 2015). In this case, the GCMs data are the independent variables $X^{'}(M,T)$ and the spatial patterns of the observed climate data are the dependent variables $Z(M)$. Consequently, PLS regression provides the time series $B^{'}(T)$ of the climate GCMs variables that will be used to project wheat yield variability. The procedure is applied to each individual model before being combined the B-values to derive the corresponding B-values for the Multimodel. Figure 1b shows a schematic diagram of this approach. The PLS computation is performed with the SIMPLS algorithm included in the Matlab statistical toolbox.

In addition, wheat yield changes were computed by means of the non-parametric Then-Sen estimator (Sen, 1968), given the trend significance with the Mann-Kendall Z test by taking the effect of serial correlation (Yue and Wang, 2004) into account.

3 Results

3.1 Analysis of historic wheat yields and filtering out the trend component

Figure 2a shows the mean wheat yield across different provinces in Spain indicated with the numbers in black (T/ha). The highest values corresponding to the northeast plateau. Wheat production time series for the period 1979 to 2014 spatially averaged over the entire country is shown in Figure 2b by a bar graph; the line represents the time series with a 6-term smoothing to illustrate the trend's progression. The representative nature of the spatially averaged wheat time series with respect to the time series in different provinces is evaluated by the Pearson correlation coefficient. These values, multiplied by 100, are indicated by the red numbers in Figure 2a. The spatially averaged yield correlated quite significantly with the time series at every province. Therefore, the averaged time series can be used to represent the year-to-year wheat yield variability in Spain in this impact study. Table 1 depicts some statistical metrics of the wheat time series: mean, standard deviation, skewness, kurtosis, trend change (computed using the Sen's estimator), and trend significance, obtained with the Mann-Kendall Z test. These statistical parameters indicated that the wheat time series behaves as a normal distribution and shows a trend of significant increases, probably due to agronomic managements as demonstrated by Xiao and Tao (2014).

We applied EEMD with the aim of decomposing the wheat time series into components or intrinsic mode functions (IMF) for the isolation of signals of specific timescales and a residual component or trend. Figure 3 (c, d and e) show the three intrinsic mode functions or scales of wheat yield variability, Figure 3a shows the initial data (black line) and the detrended time

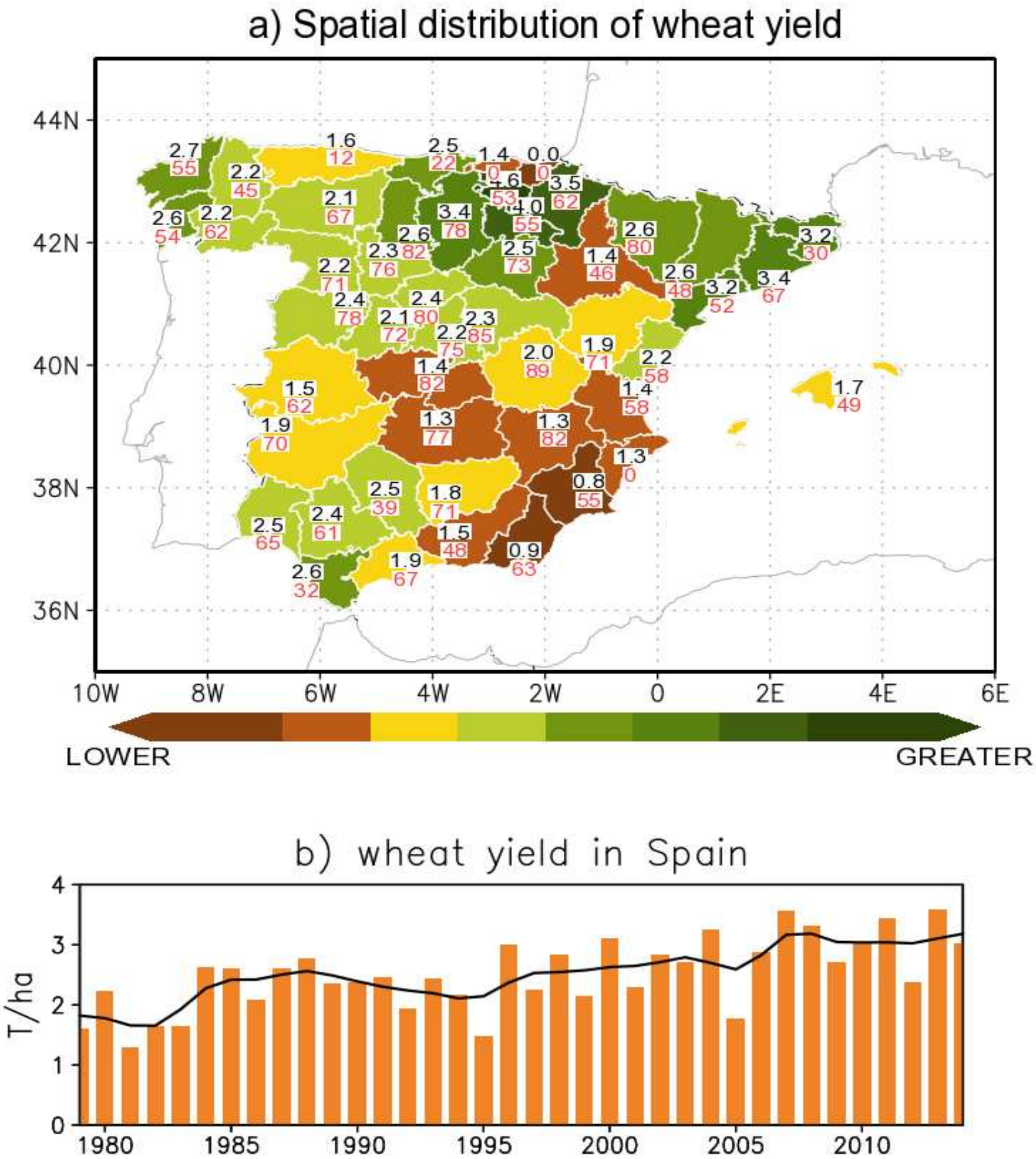

Fig. 2 a) Spatial distribution of wheat yield over Spain (in black) (T/ha) and correlation (in red) ($\times100$) between spatially averaged wheat yield over Spain and time series of individual provinces. b) Time series of spatially averaged wheat yield in Spain (bars) and running mean smoothing (line)

Table 1 Statistic metrics of wheat yield time series: mean (T/ha), standard deviation (STD in T/ha), skewness (SK), kurtosis (KT), trend changes (T/ha) in ten years (Sen's test) and trend significance Mann-Kendal Z test (MK-Z)

Mean	STD	SK	KT	Sen	MK-Z
2.5 ± 0.19	0.60 ± 0.11	-0.13 ± 0.47	-0.65 ± 0.71	0.36 ± 0.037	3.99

series (red line). The residual (Figure 3b) is the trend component accounting for 31% of the total wheat yield variability; the first, second, and third IMFs account for 33%, 14% and 22% of total variability, respectively. In our study, we retain the three IMFs, or de-trended wheat yields represented in Figure 3a, which will be analyzed in conjunction with climate variables. The variation of the trend component may depend on several factors, as technology improvements being among the most relevant. Atmospheric CO_2 increase can benefit wheat yield due to the fertilization effects, but the exact causes are still under debate. Therefore, this investigation only considers the effect of climate on wheat yield.

Figure 2b allow us to identify low yields in the years 1981, 1995, 2005, and 2012, which coincide with drier years (Vicente-Serrano et al, 2014), while high yields were observed for the years 2013, 2007, 1996, and 1988. Some of these features are reported in the JRC bulletins Centre (2014). For example: excellent positive conditions for wheat yield in Spain were noticed in 2013 with precipitation above-average and temperature below-average in May, what permitted the maintenance of sufficient soil moisture; the low wheat productivity in 2012 as consequence of above-average temperature and dry conditions in May and June.

To better understand the effects of monthly precipitation and temperature upon the overall yield, Figure 4 compares the annual cycle of the variables Pr, Tmax, Tmin, and DTR for the years of high (low) wheat yield with respect the annual cycle for the entire period 1979 to 2014. The precipitation curve is above (below) the corresponding mean cycle for years with high (low) wheat yield, indicating the positive (negative) effect of precipitation upon the yield

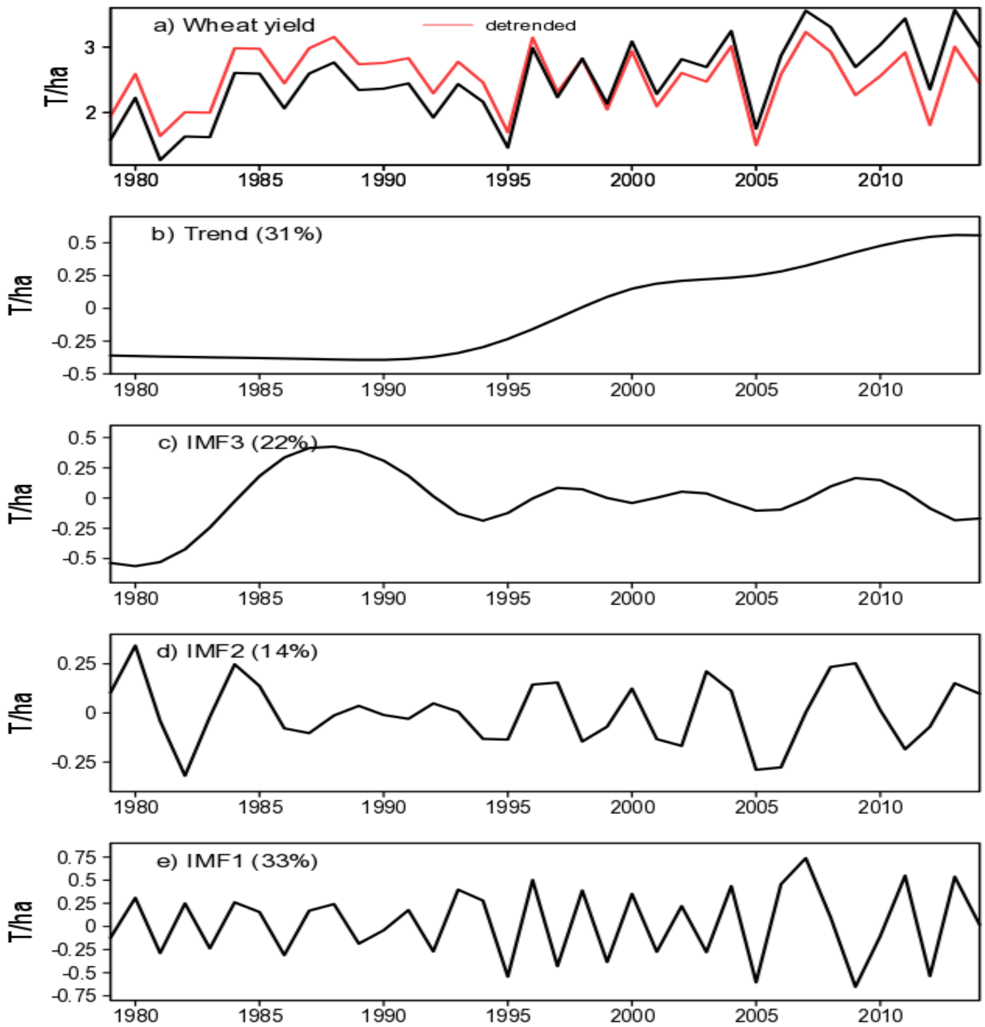

Fig. 3 a) Time series of: wheat yield (black) and detrended component (red); b) trend component; (c to e) Intrinsic Mode Functions, amplitude against years, noting the percentage of accounted variance

for every month (Figure 4a). However, regarding the influence of monthly temperatures, we can see how high maximum and minimum temperatures in spring may damage the yield and how high minimum temperature in winter provides favorable condition for the yield (Figures 4c and d). It is interesting to note the negative effect of DTR on wheat yield for every month (Figure 4b). Physiological processes of the plants depend on the sensible and latent heat. Sensible heat is related to solar radiation and Tmax during hours of sunshine, while at night is associated to the heat lost into space as infrared radiation and Tmin (Bristow and Campbell, 1984). Our results indicate greater influence of DTR than Tmax, and Tmin independently. DTR includes the effects of solar and terrestrial radiation, accounting for sensible heat across the day and representing both the frost risk in winter and heat stress in spring.

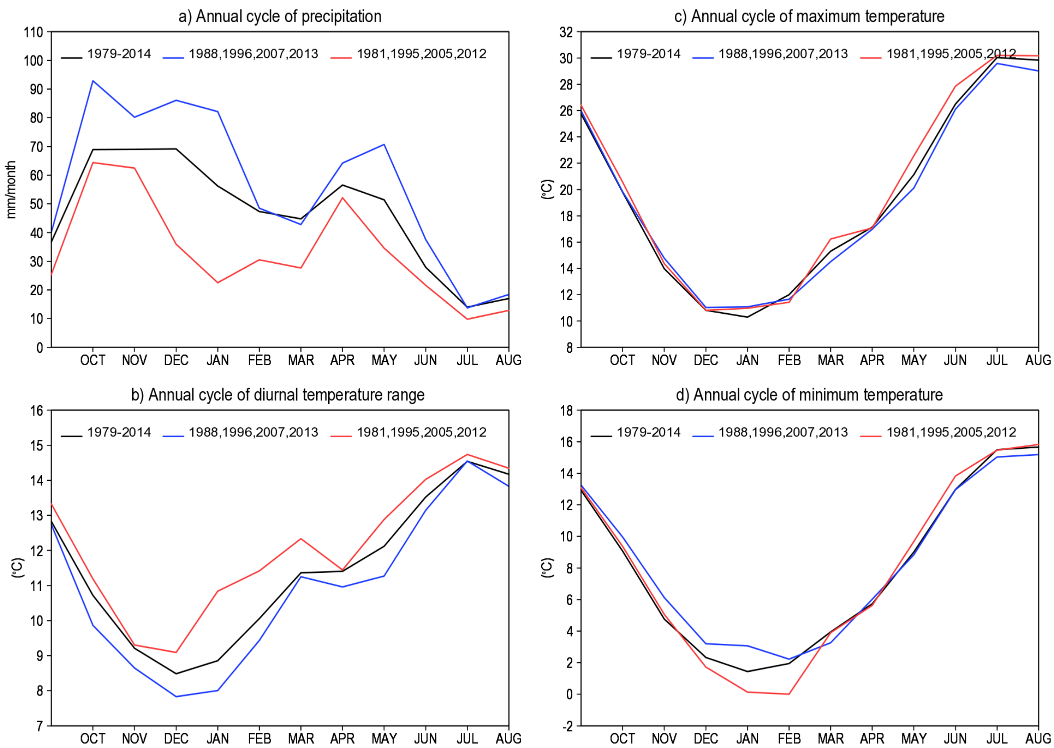

Fig. 4 a) Seasonal cycle of precipitation (Pr); b) Diurnal temperature range (DTR); c) Maximum temperature (Tmax); d) Minimum temperature (Tmin). For the period 1979-2014 (black line), years of high wheat yield (blue) and years of low wheat yield (red)

3.2 Effects of observed climate variables on wheat yield

As climate variables can affect wheat yield differently, depending on the season, we assessed the relationships between wheat yields and climate variables in different seasons autumn (SON), winter (DJF), and spring (MAM) covering the wheat crop from sowing to harvest. The first estimation for linking wheat yield to climate variation is deduced through the use of correlation maps between wheat time series and climate fields over Spain. Positive correlations were found in autumn and spring for standardized precipitation index (SPI_ SON and SPI_ MAM) (Figures 5a and b), and in winter for minimum temperature (Tmin_ DJF) (Figure 5e); negative correlation was found in spring for maximum temperature (Tmax_ MAM) (Figure 5d) and in winter for diurnal range of temperature (DTR_ DJF) (Figure 5c). The hatched areas in the correlation maps figures indicate when the correlation is higher than $|\ 0.50|$.

Wheat yield is represented against the anomalies of spatially averaged climate time series of SPI, DTR, Tmax and Tmin across Spain to assess the sensitivity of wheat yield to these climate variables, as the scatter plots of Figure 5 show. SPI in MAM and in SON cause an increase in wheat yield, with greater sensitivity in MAM. Our empirical finding shows the damage of frost in winter and of heat in spring. These results are in agreement with previous studies (Rodriguez-Puebla et al, 2007) and with Gouache et al (2015), which reported the importance of drought and heat stress in French yields during grain filling; Wu et al (2014) also indicated the importance of rainfall in the spring. Frost and heat are reducing factors for crop yield. These processes are incorporated in some processed-based crop models (Challinor et al, 2005), however their effects are not always well capturated (Barlow et al, 2015). From our results crop models could consider functions depending on DTR, accounting for frost and heat risk.

3.3 Variable selection and statistical model

We applied the PLS regression to identify the modes of climate variables that covariate with wheat yields. Conceptually, PLS determines the spatio-temporal modes of the climate variables that account for the maximum covariance between wheat yields and climate data. This method provides a dynamical adjustment for wheat yields using different climate variables. Figure 6

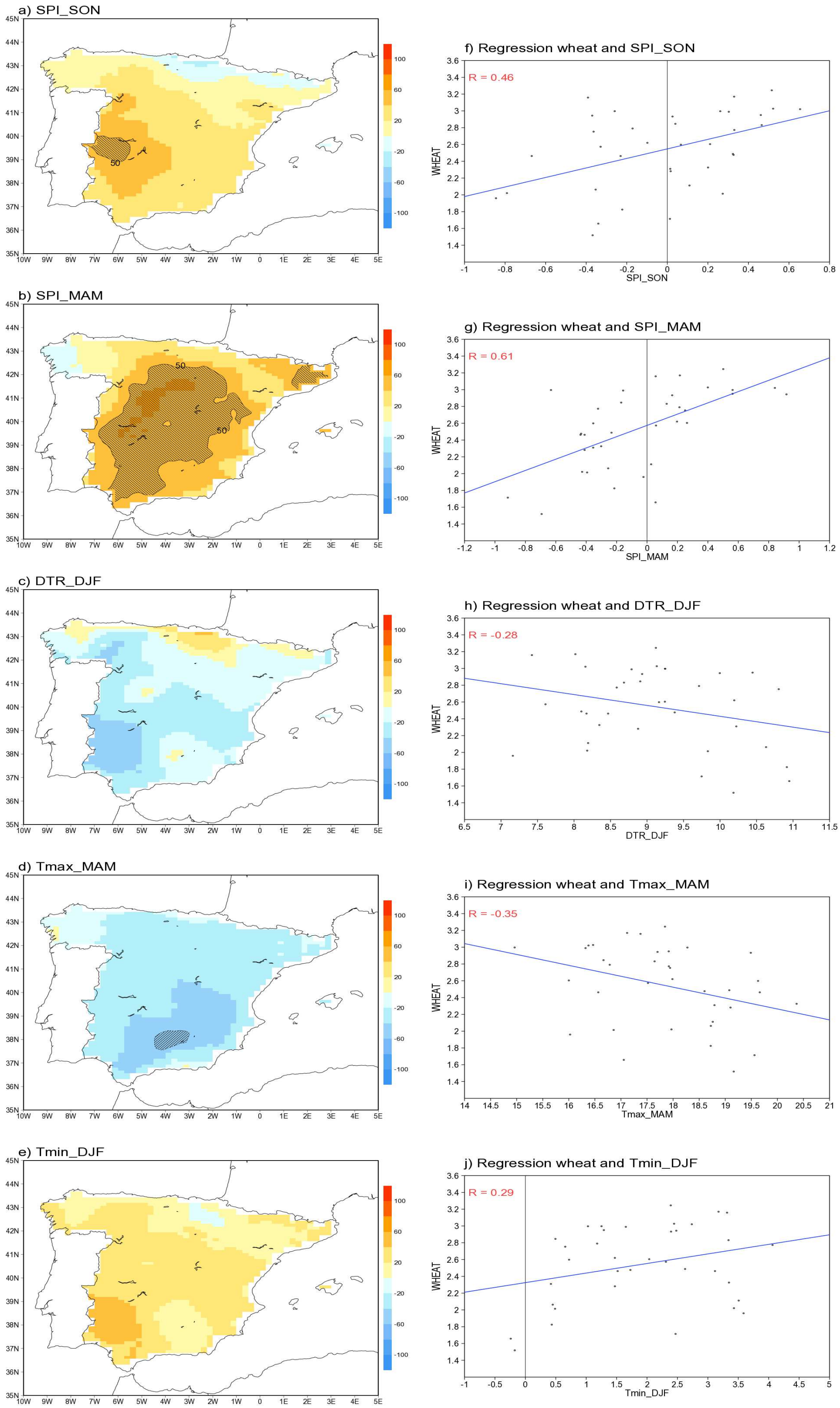

Fig. 5 Correlation between the detrended wheat yield and climate variables, hatched areas when correlation is greater than |50%|; a) SPI in autumn; b) SPI in spring; c) DTR in winter; d) Tmax in spring; e) Tmin in winter. Scatter plots of Wheat yield versus: f) SPI averaged in autumn and g) in spring ; h) DTR averaged in winter; i) Tmax in spring; j) Tmin in winter. R is the correlation of the regression equation

shows the spatial structures or patterns of the variables that are selected when the statistical model is applied; these include SPI in SON and MAM, and DTR in DJF. The spatial patterns are characterized by correlating the component time series (B) with the corresponding climate fields (X), multiplied by 100. The hatched areas indicate when the correlation is higher than $|0.50|$ and associated statistical significance p test lower than 0.01. Figures 6a and 6b suggest the following interpretation: major yield is obtained when fewer drought events (SPI) occur in SON and MAM; the pattern accounts for 39% and 65% of SPI variability respectively. Figure 6c indicates that lower values of DTR correlate with increases in wheat productivity in DJF; this mode accounts for 51% of DTR variability. The derived adjustments from these climate variables are represented and quantified by the Pearson correlation coefficients, these are depicted in Figures 6d, e and f ($R = 0.82 \pm 0.06$), which show the sensitivity of detrended wheat yields in comparison with the representative indices or components (B) of the climate fields SPI in SON and MAM, and DTR in DJF. A comparison of Figures 5 and 6 demonstrates the utility of the PLS method in characterizing climate effects on wheat yields since the PLS components of the different variables better represent the adjustment than the time series of the spatially averaged climate variables over Spain.

Initially, the potential predictors that have influence on wheat time series were SPI in SON and MAM, DTR in DJF and MAM, Tmin in DJF, and Tmax in MAM. By using the stepwise regression approach, the function identifies at each step terms to add to or remove, considering the criterion of minimizing the square error. Therefore, the variables selected were: SPI in SON and MAM, and DTR in DJF. However, those climatic factors influencing wheat yield are often correlated with each other. The effect of Tmax in MAM is included by SPI, and the effect of Tmin is included by DTR in DJF. The model results are represented by Figure 7; the adjustment describes the observed wheat yield fluctuations reasonably well, accounting for almost 63% of wheat yield variability. Yield is underestimated before 1985 and overestimated between 1985

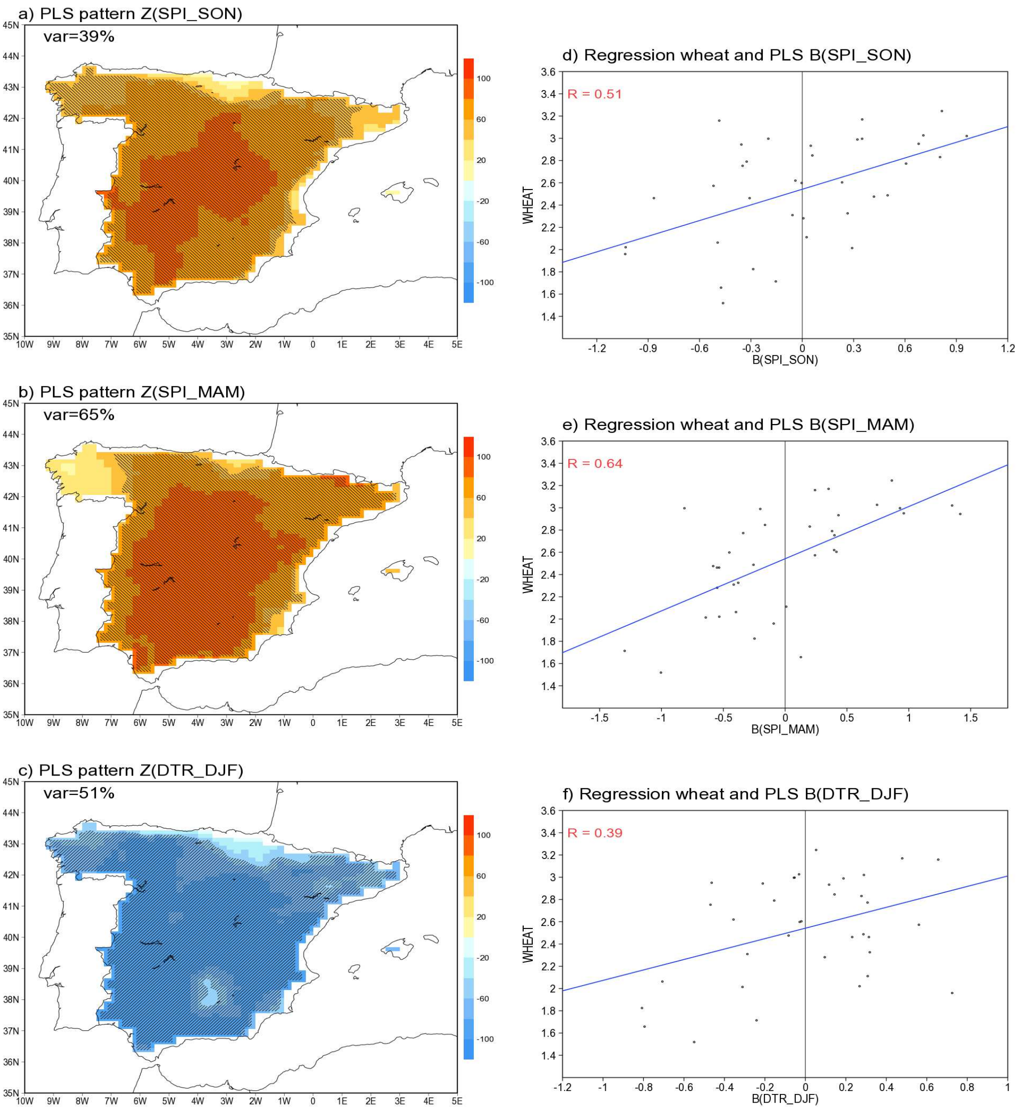

Fig. 6 Patterns of the Partial Least Square regression derived between wheat time series and the climate fields; hatched areas when correlation is greater than |50|%: a) SPI in autumn; b) SPI in spring; c) DTR in winter. Scatter plots of Wheat yield versus the representative indices of: d) SPI in autumn; e) SPI in spring; f) DTR in winter

and 1995. These results may be due to the fact that the model does not capture well the inter-decadal oscillation represented in figure 3c. The shaded areas represent the confidence interval of the results, indicating the uncertainty of the outputs. The error of the statistical model is

323 quantified by the interval of the correlation coefficient, obtained using the bootstrap approach
324 with 500 realizations. The statistical model is defined:

$$Y = 0.96 \cdot B(SPI\_SON) + 0.94 \cdot B(DTR\_DJF) + 1.44 \cdot B(SPI\_MAM) \quad (2)$$

325 Where Y represents wheat yield; $B(SPI\_SON)$, $B(SPI\_MAM)$ are the representative indices
326 of the variables SPI in autumn and spring; and $B(DTR\_DJF)$ is the representative index of DTR
327 in winter.

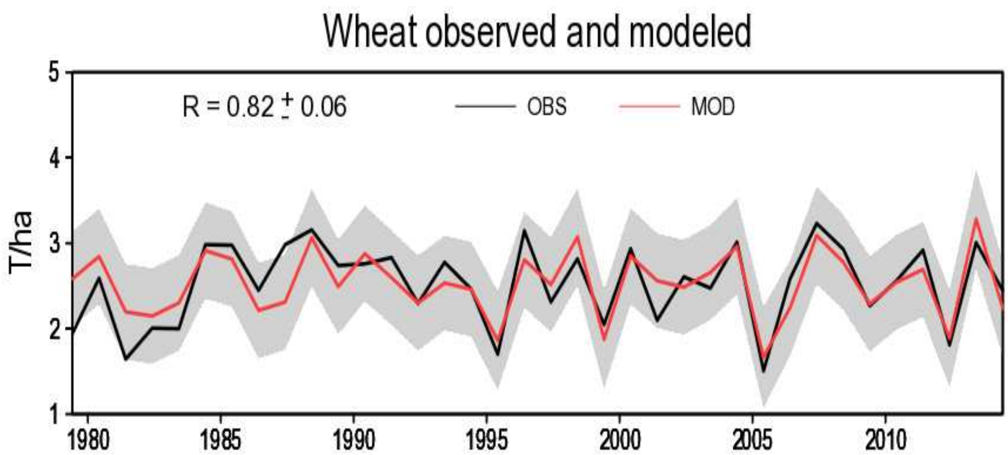

Fig. 7 Time series of observed wheat yield (black) and results of empirical model (red); grey shading indicates the confidence interval. The correlation coefficient between both time series is 0.82 ± 0.06

328 We obtained different drought effects according to the phases of the wheat's growth, being
329 higher during the maturity phases than at earlier stages. Some authors investigated the causes of
330 production variation by their relationships to changes in phenology (Xiao et al, 2013; Tao et al,
331 2012; Li et al, 2015; Yu et al, 2014), in particular Oteros et al (2015) studied the influence of
332 rainfall on change in wheat phenology in Spain and pointed out the more marked changes in
333 spring, what justify our findings.

The increase of DTR in winter causes a reduction of wheat yield in Spain. In addition, we obtained positive influence of the increase of Tmin in winter. Thereafter, this finding can justify the opposite relationships between DTR and wheat yield. However, in spring the causes of the negative relationships between DTR and wheat yield are due to the higher increase of Tmax than Tmin. Tmax is responsible of heat stress. Althought DTR is associated negatively with wheat yield in spring, it was not included in our model because its effect are represented by SPI.

3.4 Retrospective and Future wheat yield using CMIP5 models

Previous findings address the question regarding the impacts of climate change on wheat yields. To determine the projections of climate conditions and wheat yield in Spain, we examined the wheat yield results obtained by using GCMs outputs of CMIP5 models, in particular the variables specified in the agro-climate model, taking into account their relative importance (Equation 2).

When we implement the PLS regression in projecting wheat yields under climate change, the adjustment requires the consideration of spatial configurations or climate patterns associated with wheat yield, represented as dependent variable $Z(M)$, which were previously identified when the PLS regression was applied to the observations as it is explained in subsection 3. The CMIP5 data of the same variable constitute the independent variables $X^{'}(M,T)$. That is why, the PLS regression is applied to the spatial dimension instead of the temporal dimension, as was the case for the study with observations. The idea is to identify and capture structures from the CMIP5 data, that resemble the ones found in the observed climate variables associated with wheat yield. This approach provides not only the structures but also the components of the PLS regression, which represents how these structures evolve over time. Therefore, to project wheat yield in different climate conditions, we suggest the use of the derived components ($B^{'}$) or the time series to build the statistical model.

The PLS regression is applied to the variables SPI in SON and MAM, and DTR in DJF in each individual model. The derived time series are multiplied by the coefficients of the multivariate empirical agro-climate models, which estimated wheat yield for the observational period. We combined the wheat yield simulated by each model to compute the simulation of the Multi-model. Here, we focus on the trend component of the individual models and the Multi-model, which is isolated through the EEMD approach. Figure 8 shows the trend time series of different models, including the Multi-model. Most of the models display a tendency towards wheat yield reduction; this trend is even more pronounced in the case of the Multi-model for the entire period (1901-2099). However, the trend is not stationary, even showing an increase in some periods. Therefore, in Figure 9, we compare trends throughout the twentieth and twenty-first centuries, quantifying variations (T/ha in 100 years) through Sen's estimator and gauging their significance with the Mann-Kendall Z test. For the twentieth century, the model CMCC-CESM displays a trend toward significant increase (when Z tests higher than $|2|$). Trends featuring a more dramatic decrease correspond to the model MIROC5 (Z=-3.8). For the twenty-first century, the most significant decreasing trend corresponds to the model CanESM2, in accordance with the results showed by Figure 8. In the case of the Multi-model, our results indicate a decrease in wheat yield of 0.4 T/ha for the period 1901 to 2000, which constitutes approximately 16% of reduction. For the period from 2001 to 2099, a decrease of 0.8 T/ha or about a 32% reduction was observed.

In support of these results, we provided an estimation of the probability distribution in wheat yield with a box-and-whisker representation in Figure 10, which compares observed wheat yields for individual models and the Multi-model between periods of observation (1979-2014) and the corresponding future projection period (2070-2099). The dot represents the position of

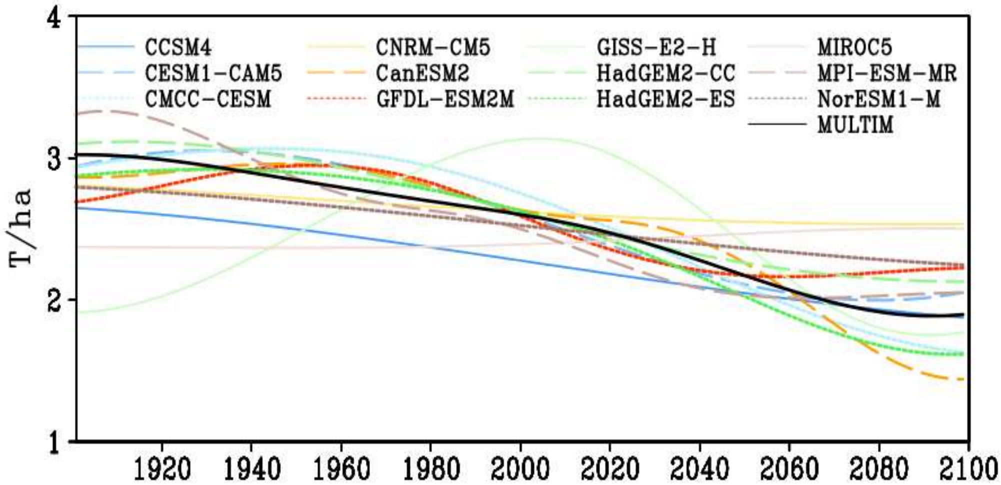

Fig. 8 Trend time series of individual models and the Multimodel

the median, the upper and lower lines of the box correspond to the 75th and 25th percentiles, and the topmost and bottommost lines correspond to the extremes values (Negative values are changed to 0). The models that exhibit a greater reduction in the median are CanESM2, HadGEM2-CC, HadGEM2-ES, and NorESM1-M. However, the MIRO5 model indicates an increase in wheat yields at the end of twenty-first century. The Multi-model predicts a decrease in the median, but similar variability in far future climate, compared to the observational period.

The mechanisms behind the projected changes in wheat yield are likely due to the evolution of the variables incorporated in the agro-climate model, such as SPI in SON, MAM, and DTR in DJF. Observations and model projections provide information about a trend towards a drier climate (IPCC, 2013), and an increase of DTR in Spain (Franzke, 2015), which may cause a reduction in wheat yields. Figure 11 depicts the evolution of SPI and DTR variables according to data obtained through the Multi-model. We note a decreasing trend for SPI in SON and MAM,

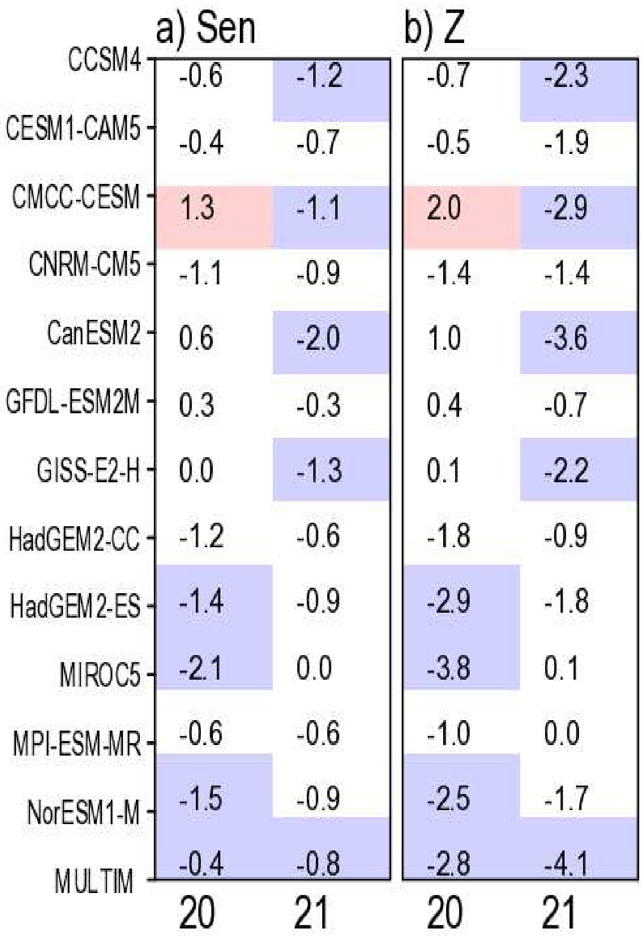

Fig. 9 a) Wheat yield changes in the twentieth and twenty-first centuries assessed using Sen's estimator; b) Significance of the trend in the twentieth and twenty-first centuries as determined by using the Mann-Kendall Z test. Negative (positive) trend in blue (red) shading

and an increasing trend for DTR in DJF, which support the observed decreased wheat yields due to the influence of SPI and DTR upon wheat growth.

4 Discussion

One of the main difficulties in obtaining the impact of climate change on crops in each region is to identify the driver variables due to their inter-relationships. In model inter-comparison Rotter

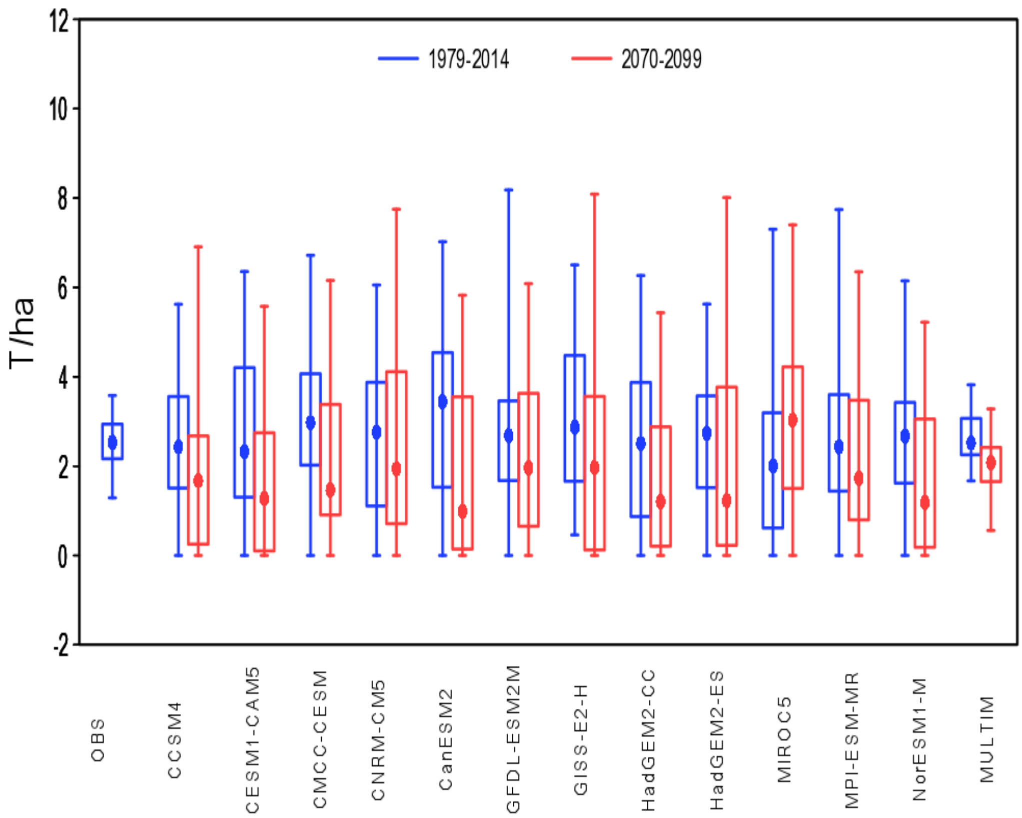

Fig. 10 Box-and-whisker representation compares probability distribution of wheat yield for the periods 1979-2014 and 2070-2099. The dot indicates the position of the median, the upper and lower lines of the box correspond to the 75th and 25th percentiles, and the topmost and bottommost lines correspond to the extreme values. Negative values are changed to 0

et al (2011) reported deficiencies in descriptions related to extreme temperatures and drought. Our analysis selects as relevant variables SPI and DTR, which are indirectly representing the effects of drought, heat and frost risk on wheat variability. Drought in spring is the climate process most influential for wheat yield variability in Spain. The positive effect of precipitation on global wheat yields has been found by different authors (Challinor et al, 2014; Luo and Wen, 2015). However, too much rainfall may affect negatively wheat (Rotter et al, 2013), and in some areas such as Scotland drier summers indicated a positive influence (Brown, 2013).

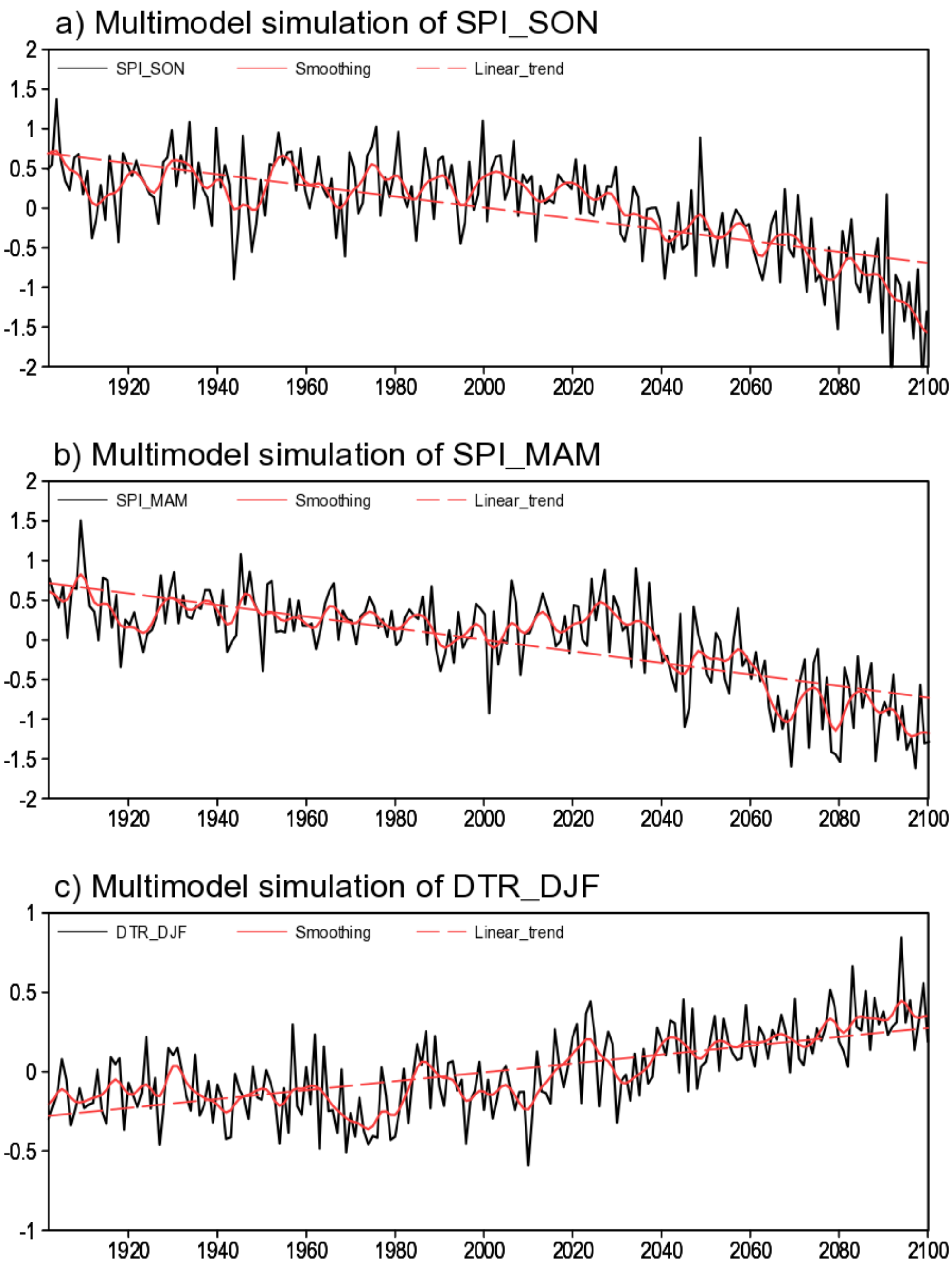

Fig. 11 Multimodel simulation of the spatially averaged time series across Spain of: a) SPI in SON, b) SPI in MAM, and c) DTR in DJF. Black line represents the simulated; the solid red line represents the 15-years smoothing, and the dashed red line indicates the linear trend

DTR is a good indicator of climate change impact on wheat yield, since can characterize the frost and heat risk in Spain. However, these interpretations may vary for other latitudes such as in northern Europe, where an increased temperatures can prolong the vegetation period and reduce frost risk (Trnka et al, 2011a). Nevertheless, Chen et al (2015) in China and Lobell (2007) in Australia and Canada obtained opposite relationships between DTR and crops. The negative response of Australian wheat yield to increase DTR was also reported by Nicholls (1997).

Wheat yield trends reveal a decrease in the twenty-first century in Spain if CO_2 effect is not taken into account. These findings are in accordance with other studies that project wheat yields using different approaches. Moore and Lobell (2014) reported a negative impact upon wheat yields throughout Europe as a result of future warming using empirical models. Process-based wheat models used by Pirttioja et al (2011), showed decreases in wheat yields over Europe assuming current CO_2 levels, with higher temperatures and decreased precipitation. These reductions may be due to the vulnerability of crops to extreme weather events, such as heat waves and drought (Coumou and Rahmstorf, 2012; IPCC, 2012; Trenberth, 2012; Trnka et al, 2014; WMO, 2013). Fertilization effects could be expected to rise from CO_2 increase. However, there is uncertainty in wheat yield simulated impacts with CO_2: Supit et al (2012) inform of wheat yield increase while Asseng et al (2013) and Deryng et al (2014) reported negative impact upon wheat yields throughout Europe under future warming. Lobell and Gourdji (2012) also reported uncertainty about the interactions between elevated CO_2 and high temperature and the effect of CO_2 on the reduction of water stress. Since the relationships between wheat yield and climate may be non-stationary due to CO_2 effect on factors such as water-use efficiently, our model may be limited, as it does not take into account that the relationships between wheat and climate in present climate may change in future conditions. Otherwise, wheat projections may not be reliable because model data are uncertain (Knutti and Sedlacek, 2013). Regarding the uncertainty of the models considered in this work, we first evaluated the precipitation and temperature against observations for the same period represented in the Taylor diagram. This indicates how closely the model and observation patterns correlate, which is also accomplished by comparing the climographs showing the monthly averages of precipitation and temperature.

Figures S1 in the supplementary material include the Taylor diagram (Taylor, 2001), for precipitation in SON and MAM, and maximum and minimum temperature in DJF, since these are the primary variables for deriving the SPI and DTR indices. Among the metrics used in the diagram are spatial correlation, standard deviation, and root-mean-square difference. For precipitation in SON, the models that closely agree with observation are CCSM4, CESM1-CAM5, HadGEM2-CC, and the Multi-model; for MAM, CCSM4, CESM1-CAM5, and the Multi-model correlate most closely. For maximum temperature in DJF, better agreement is observed in the models CNRM-CM5, GISS-E2-H, and the Multi-model; minimum temperature in DJF shows better agreement for the models CCSM4, CNRM-CM5, and the Multi-model.

Additionally, Figure S2 in the supplementary material shows the climographs of the recorded observations and individual models, corresponding to the area of Spain for the period 1979 to 2014. These climographs consider the agro-climate year, which begins in September and concludes in August. It was found that most models predict more precipitation than what is observed, with the exception of CMCC-CESM and CanESM2. The models that best represent the precipitation cycle are CESM1-CAM5, CCSM4, and HadGEM2-ES. The Multi-model largely succeeds in representing the temperature progression but predict bias to higher levels of precipitation, mainly in summer. Despite the deficiencies of model data, we may have some confidence in the trend projections offered by the Multi-model.

5 Conclusions

In this study, we have quantified the potential impacts of temperature extremes and precipitation deficit on overall wheat yield in Spain. In the interest of this goal, we applied different novel approaches, such as the Partial Least Square regression and Empirical Mode Decomposition. We obtained that precipitation deficit is more influential in autumn and spring, and DTR (sensible heat) is more influential in winter. The variability of both processes have been considered in our study to justify the variability of wheat yield by means of an empirical agro-climate model.

The performance of the model is measured in terms of the correlation coefficient obtained by regression between model results and the observed wheat yield. We found that climatic warming will cause a decrease in precipitation in spring and autumn and an increased diurnal range of temperature in winter for the twenty-first century throughout Spain. These changes will lead to a decrease in wheat yield, which is demonstrated through simulations of wheat yields using CMIP5 data. Here we have analyzed climate effects on wheat yield, the individual models and the Multi-model predict a decrease in wheat production in the twenty-first century at about a 32% decline. These results are a simplification of the reality because this is a projection which does not take into account a potential CO_2 effect on crops. The future challenge entails ascertaining the effects of drought indices and large-scale patterns onto wheat yield variability by applying the PLS regression approach, which allows for progress in interpreting the relationships between climate processes and crop production variability.

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References

Abdi H (2010) Partial least squares regression and projection on latent structure regression (pls regression). WIREs Computational Statistics pp 1–10, DOI DOI: 10.1002/wics.051

Angulo C, Rotter R, Lock R, Enders A, Fronzek S, Ewert F (2013) Implication of crop model calibration strategies for assessing regional impacts of climate change in europe. Agricultural and Forest Meteorology 170:32–46, DOI 10.1016/j.agrformet.2012.11.017

Asseng S, Ewert F, Rosenzweig C, Jones JW, Hatfield JL, Ruane AC, Boote KJ, Thorburn PJ, Rotter RP, Cammarano D, Brisson N, Basso B, Martre P, Aggarwal PK, Angulo C, Bertuzzi P, Biernath C, Challinor AJ, Doltra J, Gayler S, Goldberg R, Grant R, Heng L, Hooker J, Hunt LA, Ingwersen J, Izaurralde RC, Kersebaum KC, Muller C, Kumar SN, Nendel C, O'Leary G, Olesen JE, Osborne TM, Palosuo T, Priesack E, Ripoche D, Semenov MA, Shcherbak I, Steduto P, Stockle C, Stratonovitch P, Streck T, Supit I, Tao F, Travasso M, Waha K, Wallach D, White JW, Williams JR, Wolf J (2013) Uncertainty in simulating wheat yields under climate change. Nature Climate Change 3(9):827–832, DOI 10.1038/nclimate1916

Atkinson MD, Kettlewell PS, Hollins PD, Stephenson DB, Hardwick NV (2005) Summer climate mediates uk wheat quality response to winter north atlantic oscillation. Agricultural and Forest Meteorology 130(1-2):27–37, DOI 10.1016/j.agrformet.2005.02.002

Bannayan M, Lotfabadi SS, Sanjani S, Mohamadian A, Aghaalikhani M (2011) Effects of precipitation and temperature on crop production variability in northeast iran. International Journal of Biometeorology 55(3):387–401, DOI 10.1007/s00484-010-0348-7

Barlow KM, Christy BP, O'Leary GJ, Riffkin PA, Nuttall JG (2015) Simulating the impact of extreme heat and frost events on wheat crop production: A review. Field Crops Research 171:109–119, DOI 10.1016/j.fcr.2014.11.010

Begueria S, Vicente-Serrano SM, Reig F, Latorre B (2014) Standardized precipitation evapotranspiration index (spei) revisited: parameter fitting, evapotranspiration models, tools, datasets and drought monitoring. International Journal of Climatology 34(10):3001–3023, DOI 10.1002/joc.3887

Bristow KL, Campbell GS (1984) On the relationship between incoming solar-radiation and daily maximum and minimum temperature. Agricultural and Forest Meteorology 31(2):159–166, DOI 10.1016/0168-1923(84)90017-0

Brown I (2013) Influence of seasonal weather and climate variability on crop yields in scotland. International Journal of Biometeorology 57(4):605–614, DOI 10.1007/s00484-012-0588-9

Capa-Morocho M, Rodriguez-Fonseca B, Ruiz-Ramos M (2014) Crop yield as a bioclimatic index of el nino impact in europe: Crop forecast implications. Agricultural and Forest Meteorology 198:42–52, DOI 10.1016/j.agrformet.2014.07.012

Capparelli V, Franzke C, Vecchio A, Freeman MP, Watkins NW, Carbone V (2013) A spatiotemporal analysis of us station temperature trends over the last century. Journal of Geophysical Research-Atmospheres 118(14):7427–7434, DOI 10.1002/jgrd.50551

Carter TR (2013) Agricultural impacts multi-model yield projections. Nature Climate Change 3(9):784–786

Centre JR (2014) Mars bulletin vol.21. no6, 2013 and vol.20 n06, 2012. crop monitoring in europe. URL http://mars.jrc.ec.europa.eu/mars/Bulletins-Publications

Challinor AJ, Wheeler TR, Craufurd PQ, Slingo JM (2005) Simulation of the impact of high temperature stress on annual crop yields. Agricultural and Forest Meteorology 135(1-4):180–189

Challinor AJ, Watson J, Lobell DB, Howden SM, Smith DR, Chhetri N (2014) A meta-analysis of crop yield under climate change and adaptation. Nature Climate Change 4(4):287–291, DOI 10.1038/nclimate2153

Chen C, Zhou GS, Pang YM (2015) Impacts of climate change on maize and winter wheat yields in china from 1961 to 2010 based on provincial data. Journal of Agricultural Science 153(5):825–836, DOI 10.1017/s0021859614001154

Chen X, Wang M, Zhang Y, Feng Y, Wu Z, Huang NE (2013) Detecting signals from data with noise: Theory and applications. Journal of the Atmospheric Sciences 70(5):1489–1504, DOI 10.1175/jas-d-12-0213.1

Ciscar J, Soria A, Lavalle C, Raes F, Perry M, Nemry F, Demirel H, Rozsai M, Dosio A, Donatelli M, Srivastava A, Fumagalli D, Niemeyer S, Shrestha S, Ciaian P, Himics M, VanDoorslaer B, Barrios S, Ibanez N, Bianchi A, Dowling P, Camia A, Liberta G, San Miguel J, de Rigo D, Caudullo G, Barredo J, Paci

D, Pycroft J, Saveyn B, VanRegemorter D, Revesz T, Vandyck T, Vrontisi Z, Baranzelli C, Vandecasteele I, BatistaSilva F, Ibarreta D (2014) Climate impacts in europe. the jrc peseta ii project. Report, URL http://www.jrc.ec.europa.eu

Colominas MA, Schlotthauer G, Torres ME (2014) Improved complete ensemble emd: A suitable tool for biomedical signal processing. Biomedical Signal Processing and Control 14:19–29, DOI 10.1016/j.bspc.2014.06.009

Coumou D, Rahmstorf S (2012) A decade of weather extremes. Nature Climate Change 2(7):491–496, DOI 10.1038/nclimate1452

Dai A (2011) Drought under global warming: a review. Wiley Interdisciplinary Reviews-Climate Change 2(1):45–65, DOI 10.1002/wcc.81

Dalla Marta A, Grifoni D, Mancini M, Zipoli G, Orlandini S (2011) The influence of climate on durum wheat quality in tuscany, central italy. International Journal of Biometeorology 55(1):87–96, DOI 10.1007/s00484-010-0310-8

Deryng D, Conway D, Ramankutty N, Price J, Warren R (2014) Global crop yield response to extreme heat stress under multiple climate change futures. Environmental Research Letters 9(3), DOI 10.1088/1748-9326/9/3/034011

Eitzinger J, Thaler S, Schmid E, Strauss F, Ferrise R, Moriondo M, Bindi M, Palosuo T, Rotter R, Kersebaum KC, Olesen JE, Patil RH, Saylan L, Caldag B, Caylak O (2013) Sensitivities of crop models to extreme weather conditions during flowering period demonstrated for maize and winter wheat in austria. Journal of Agricultural Science 151(6):813–835, DOI 10.1017/s0021859612000779

FAO (2014) Food agriculture organization of the united nations (fao). URL http://faostat3.fao.org/compare/E

Feng J, Wu Z, Liu G (2014) Fast multidimensional ensemble empirical mode decomposition using a data compression technique. Journal of Climate 27(10):3492–3504, DOI 10.1175/jcli-d-13-00746.1

Flandrin P, Rilling G, Goncalves P (2004) Empirical mode decomposition as a filter bank. Ieee Signal Processing Letters 11(2):112–114, DOI 10.1109/lsp.2003.821662

Franzke C (2010) Long-range dependence and climate noise characteristics of antarctic temperature data. Journal of Climate 23(22):6074–6081, DOI 10.1175/2010jcli3654.1

Franzke C (2015) Local trend disparities of european minimum and maximum temperature extremes. Geophysical Research Letters (in press), DOI 10.1002/

Gimeno L, Ribera P, Iglesias R, de la Torre L, Garcia R, Hernandez E (2002) Identification of empirical relationships between indices of enso and nao and agricultural yields in spain. Climate Research 21(2):165–172, DOI 10.3354/cr021165

Gonsamo A, Chen JM (2015) Winter teleconnections can predict the ensuing summer european crop productivity. Proceedings of the National Academy of Sciences of the United States of America 112(18):E2265–E2266, DOI 10.1073/pnas.1503450112

Gonzalez-Reviriego N, Rodriguez-Puebla C, Rodriguez-Fonseca B (2015) Evaluation of observed and simulated teleconnections over the euro-atlantic region on the basis of partial least squares regression. Climate Dynamics 44(11-12):2989–3014, DOI 10.1007/s00382-014-2367-2

Gouache D, Bouchon AS, Jouanneau E, Le Bris X (2015) Agrometeorological analysis and prediction of wheat yield at the departmental level in france. Agricultural and Forest Meteorology 209:1–10, DOI 10.1016/j.agrformet.2015.04.027

Guan BT (2014) Ensemble empirical mode decomposition for analyzing phenological responses to warming. Agricultural and Forest Meteorology 194:1–7, DOI 0.1016/j.agrformet.2014.03.010

Hansen JW, Jones JW, Irmak A, Royce F (2001) El Nino-Southern Oscillation impacts on crop production in the southeast United States, pp 55–76. Asa Special Publication

Haylock MR, Hofstra N, Tank A, Klok EJ, Jones PD, New M (2008) A european daily high-resolution gridded data set of surface temperature and precipitation for 1950-2006. Journal of Geophysical Research-Atmospheres 113(D20):55–76, DOI D20119 10.1029/2008jd010201

Herrera S, Gutierrez JM, Ancell R, Pons MR, Frias MD, Fernandez J (2012) Development and analysis of a 50-year high-resolution daily gridded precipitation dataset over spain (spain02). International Journal of Climatology 32(1):74–85, DOI 10.1002/joc.2256

Huang NE, Shen Z, Long SR, Wu MLC, Shih HH, Zheng QN, Yen NC, Tung CC, Liu HH (1998) The empirical mode decomposition and the hilbert spectrum for nonlinear and non-stationary time series analysis. Proceedings of the Royal Society of London Series a-Mathematical Physical and Engineering Sciences 454(1971):903–995

Iglesias A, Quiroga S (2007) Measuring the risk of climate variability to cereal production at five sites in spain. Climate Research 34(1):47–57

Iizumi T, Luo JJ, Challinor AJ, Sakurai G, Yokozawa M, Sakuma H, Brown ME, Yamagata T (2014) Impacts of el nino southern oscillation on the global yields of major crops. Nature Communications 5, DOI 10.1038/ncomms4712

IPCC (2012) Ipcc, 2012: Managing the risks of extreme events and disasters to advance climate change adaptation. a special report of working groups i and ii of the intergovernmental panel on climate change [field, c.b., v. barros, t.f. stocker,d. qin, d.j. dokken, k.l. ebi, m.d. mastrandrea, k.j. mach, g.-k. plattner, s.k. allen, m. tignor, and p.m. midgley (eds.)]. Report, IPCC

IPCC (2013) Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, S.K. Allen, J. Boschung, A. Nauels, Y. Xia, V. Bex and P.M. Midgley (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA,

IPCC (2014) Climate Change 2014: Impacts, Adaptation, and Vulnerability. Part A: Global and Sectoral Aspects. Contribution of Working Group II to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. [Field, C.B., V.R. Barros, D.J. Dokken, K.J. Mach, M.D. Mastrandrea, T.E. Bilir, M. Chatterjee, K.L. Ebi, Y.O. Estrada, R.C. Genova, B. Girma, E.S. Kissel, A.N. Levy, S. MacCracken, P.R. Mastrandrea, and L.L. White (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA,

Jarlan L, Abaoui J, Duchemin B, Ouldbba A, Tourre YM, Khabba S, Le Page M, Balaghi R, Mokssit A, Chehbouni G (2014) Linkages between common wheat yields and climate in morocco (1982-2008). International Journal of Biometeorology 58(7):1489–1502, DOI 10.1007/s00484-013-0753-9

Ji F, Wu Z, Huang J, Chassignet EP (2014) Evolution of land surface air temperature trend. Nature Climate Change 4(6):462–466, DOI 10.1038/nclimate2223

Knutti R, Sedlacek J (2013) Robustness and uncertainties in the new cmip5 climate model projections. Nature Climate Change 3(4):369–373, DOI 10.1038/nclimate1716

Li K, Yang X, Tian H, Pan S, Liu Z, Lu S (2015) Effects of changing climate and cultivar on the phenology and yield of winter wheat in the north china plain. Int J Biometeorol (in press), DOI 10.1007/s00484-015-1002-1

Lobell DB (2007) Changes in diurnal temperature range and national cereal yields. Agricultural and Forest Meteorology 145(3-4):229–238, DOI 10.1016/j.agrformet.2007.05.002

Lobell DB (2013) Errors in climate datasets and their effects on statistical crop models. Agricultural and Forest Meteorology 170:58–66, DOI 10.1016/j.agrformet.2012.05.013

Lobell DB, Burke MB (2010) On the use of statistical models to predict crop yield responses to climate change. Agricultural and Forest Meteorology 150(11):1443–1452, DOI 10.1016/j.agrformet.2010.07.008

Lobell DB, Gourdji SM (2012) The influence of climate change on global crop productivity. Plant Physiology 160(4):1686–1697, DOI 10.1104/pp.112.208298

Lobell DB, Schlenker W, Costa-Roberts J (2011a) Climate trends and global crop production since 1980. Science 333(6042):616–620, DOI 10.1126/science.1204531

Lobell DB, Torney A, Field CB (2011b) Climate extremes in california agriculture. Climatic Change 109:355–363, DOI 10.1007/s10584-011-0304-5

Lorenzo-Lacruz J, Vicente-Serrano SM, Gonzalez-Hidalgo JC, Lopez-Moreno JI, Cortesi N (2013) Hydrological drought response to meteorological drought in the iberian peninsula. Climate Research 58(2):117–131, DOI 10.3354/cr01177

Luo Q, Wen L (2015) The role of climatic variables in winter cereal yields: a retrospective analysis. International Journal of Biometeorology 59(2):181–192, DOI 10.1007/s00484-014-0834-4

MAGRAMA (2015) Spanish agriculture, food and environment department. URL http://www.magrama.gob.es/es/estadistica/temas/estadisticas-agrarias/agricultura/avances-superficies-producciones-agricolas/

Moghtaderi A, Flandrin P, Borgnat P (2013) Trend filtering via empirical mode decompositions. Computational Statistics and Data Analysis 58:114–126, DOI 10.1016/j.csda.2011.05.015

Moore FC, Lobell DB (2014) Adaptation potential of european agriculture in response to climate change. Nature Climate Change 4(7):610–614, DOI 10.1038/nclimate2228

Moore FC, Lobell DB (2015) The fingerprint of climate trends on european crop yields. Proceedings of the National Academy of Sciences of the United States of America 112(9):2670–2675, DOI 10.1073/pnas.1409606112

Nicholls N (1997) Increased australian wheat yield due to recent climate trends. Nature 387(6632):484–485

Olesen JE, Trnka M, Kersebaum KC, Skjelvag AO, Seguin B, Peltonen-Sainio P, Rossi F, Kozyra J, Micale F (2011) Impacts and adaptation of european crop production systems to climate change. European Journal of Agronomy 34(2):96–112, DOI 10.1016/j.eja.2010.11.003

Oteros J, Garcia-Mozo H, Botey R, Mestre A, Galan C (2015) Variations in cereal crop phenology in spain over the last twenty-six years (1986-2012). Climatic Change 130(4):545–558, DOI 10.1007/s10584-015-1363-9

Otkin J, Mark Shafer M, Svoboda M, Wardlow B, Anderson M, Hain C, Basara J (2015) Facilitating the use of drought early warning information through interactions with agricultural stakeholders. Bulletin of the American Meteorological Society 7:1073–1078, DOI 10.1175/BAMS-D-14-00219.1

Palosuo T, Kersebaum KC, Angulo C, Hlavinka P, Moriondo M, Olesen JE, Patil RH, Ruget F, Rumbaur C, Takac J, Trnka M, Bindi M, Caldag B, Ewert F, Ferrise R, Mirschel W, Saylan L, Siska B, Rotter R (2011) Simulation of winter wheat yield and its variability in different climates of europe: A comparison of eight crop growth models. European Journal of Agronomy 35(3):103–114, DOI 10.1016/j.eja.2011.05.001

Pirttioja N, Carter TR, Fronzek S, Bindi M, Hoffmann H, Palosuo T, Ruiz-Ramos MR, Tao F, Trnka M, Acutis M, Asseng S, Baranowski P, Basso B, Bodin P, Buis S, Cammarano D, Deligios P, Destain M, Dumont B, Ewert F, Ferrise R, Franois L, Gaiser T, Hlavinka P, Jacquemin I, Kersebaum KC, Kollas C, Krzyszczak J, Lorite IJ, Minet J, Minguez M M Iand Montesino, Moriondo M, Mller C Cand Nendel, I O, Perego A, Rodrguez A, Ruane AC, Ruget F, Sanna M, Semenov MA, Slawinski C, Stratonovitch P, Supit I, Waha K, Wang E, Wu L, Zhao Z, P RR (2011) Temperature and precipitation effects on wheat yield across a european transect: a crop model ensemble analysis using impact response surfaces. Climate Research 65:87105, DOI 10.3354/cr01322

Podesta G, Letson D, Messina C, Royce F, Ferreyra RA, Jones J, Hansen J, Liovet I, Grondona M, O'Brien JJ (2002) Use of enso-related climate information in agricultural decision making in argentina: a pilot experience. Agricultural Systems 74(3):371–392, DOI 10.1016/s0308-521x(02)00046-x

Riahi K, Rao S, Krey V, Cho C, Chirkov V, Fischer G, Kindermann G, Nakicenovic N, Rafaj P (2011) Rcp 8.5-a scenario of comparatively high greenhouse gas emissions. Climatic Change 109(1-2):33–57, DOI 10.1007/s10584-011-0149-y

Rodriguez-Puebla C, Ayuso SM, Frias MD, Garcia-Casado LA (2007) Effects of climate variation on winter cereal production in spain. Climate Research 34(3):223–232

Rosenzweig C, Jones JW, Hatfield JL, Ruane AC, Boote KJ, Thorburne P, Antle JM, Nelson GC, Porter C, Janssen S, Asseng S, Basso B, Ewert F, Wallach D, Baigorria G, Winter JM (2013) The agricultural model intercomparison and improvement project (agmip): Protocols and pilot studies. Agricultural and Forest Meteorology 170:166–182, DOI 10.1016/j.agrformet.2012.09.011

Rotter R, Hohn J (2015) Chapter 4: An overview of climate change impact on crop production and its variability in Europe, related uncertainties and research challenges, Food Agriculture Organization of the United Nations (FAO), Rome, 201, Rome

Rotter R, Ewert F, Palosuo T, Bindi M, Kersebaum K, Olesen J, Trnka M, van Ittersum M, Janssen S, Rivington M, Semenov M, Wallach D, Porter J, Stewart D, Verhagen J, Angulo C, Gaiser T, Nendel C, Martre P, de Wit A (2013) Challenges for agro-ecosystem modelling in climate change risk assessment for major european crops and farming systems. In: Impacts World 2013 Conference Proceedings, pp 555–564, DOI 10.2312/pik.2013.001

Rotter RP (2014) Agricultural impacts robust uncertainty. Nature Climate Change 4(4):251–252

Rotter RP, Carter TR, Olesen JE, Porter JR (2011) Crop-climate models need an overhaul. Nature Climate Change 1(4):175–177

Royce FS, Fraisse CW, Baigorria GA (2011) Enso classification indices and summer crop yields in the southeastern usa. Agricultural and Forest Meteorology 151(7):817–826, DOI 10.1016/j.agrformet.2011.01.017

Ruiz-Ramos M, Sanchez E, Gallardo C, Minguez MI (2011) Impacts of projected maximum temperature extremes for c21 by an ensemble of regional climate models on cereal cropping systems in the iberian peninsula. Natural Hazards and Earth System Sciences 11(12):3275–3291, DOI 10.5194/nhess-11-3275-2011

Schulzweida U (2015) Cdo climate data operators, users guide. URL https://code.zmaw.de/projects/cdo

Sen PK (1968) Estimates of regression coefficient based on kendalls tau. Journal of the American Statistical Association 63(324):1379–1389

Smoliak BV, Wallace JM, Stoelinga MT, Mitchell TP (2010) Application of partial least squares regression to the diagnosis of year-to-year variations in pacific northwest snowpack and atlantic hurricanes. Geophysical Research Letters 37, DOI L03801 10.1029/2009gl041478

Smoliak BV, Wallace JM, Lin P, Fu Q (2015) Dynamical adjustment of the northern hemisphere surface air temperature field: Methodology and application to observations. Journal of Climate 28(4):1613–1629, DOI 10.1175/jcli-d-14-00111.1

Supit I, van Diepen CA, de Wit AJW, Wolf J, Kabat P, Baruth B, Ludwig F (2012) Assessing climate change effects on european crop yields using the crop growth monitoring system and a weather generator. Agricultural and Forest Meteorology 164:96–111, DOI 10.1016/j.agrformet.2012.05.005

Tao F, Zhang S, Zhang Z (2012) Spatiotemporal changes of wheat phenology in china under the effects of temperature, day length and cultivar thermal characteristics. Europ J Agronomy 43:201–212

Taylor KE (2001) Summarizing multiple aspects of model performance in a single diagram. Journal of Geophysical Research-Atmospheres 106(D7):7183–7192

Taylor KE, Stouffer RJ, Meehl GA (2012) An overview of cmip5 and the experiment design. Bulletin of the American Meteorological Society 93(4):485–498, DOI 10.1175/bams-d-11-00094.1

Tian D, Asseng S, Martinez CJ, Misra V, Cammarano D, Ortiz BV (2015) Does decadal climate variation influence wheat and maize production in the southeast usa? Agricultural and Forest Meteorology 204:1–9, DOI 10.1016/j.agrformet.2015.01.013

Trenberth KE (2012) Framing the way to relate climate extremes to climate change. Climatic Change 115(2):283–290, DOI 10.1007/s10584-012-0441-5

Trenberth KE, Dai AG, van der Schrier G, Jones PD, Barichivich J, Briffa KR, Sheffield J (2014) Global warming and changes in drought. Nature Climate Change 4(1):17–22, DOI 10.1038/nclimate2067

Trnka M, Eitzinger J, Semeradova D, Hlavinka P, Balek J, Dubrovsky M, Kubu G, Stepanek P, Thaler S, Mozny M, Zalud Z (2011a) Expected changes in agroclimatic conditions in central europe. Climatic Change 108(1-2):261–289, DOI 10.1007/s10584-011-0025-9

Trnka M, Olesen JE, Kersebaum KC, Skjelvag AO, Eitzinger J, Seguin B, Peltonen-Sainio P, Rotter R, Iglesias A, Orlandini S, Dubrovsky M, Hlavinka P, Balek J, Eckersten H, Cloppet E, Calanca P, Gobin A, Vucetic V, Nejedlik P, Kumar S, Lalic B, Mestre A, Rossi F, Kozyra J, Alexandrov V, Semeradova D, Zalud Z (2011b) Agroclimatic conditions in europe under climate change. Global Change Biology 17(7):2298–2318, DOI 10.1111/j.1365-2486.2011.02396.x

Trnka M, Roetter RP, Ruiz-Ramos M, Kersebaum KC, Olesen JE, Zalud Z, Semenov MA (2014) Adverse weather conditions for european wheat production will become more frequent with climate change. Nature Climate Change 4(7):637–643, DOI 10.1038/nclimate2242

UCAR/NCAR (2015) The ncar command language (software,version 6.3.0). URL http://dx.doi.org/10.5065/D6WD3XH5

Vicente-Serrano SM, Cuadrat-Prats JM, Romo A (2006) Early prediction of crop production using drought indices at different time-scales and remote sensing data: application in the ebro valley (north-east spain). International Journal of Remote Sensing 27(3):511–518

Vicente-Serrano SM, Begueria S, Lopez-Moreno JI (2010) A multiscalar drought index sensitive to global warming: The standardized precipitation evapotranspiration index. Journal of Climate 23(7):1696–1718, DOI 10.1175/2009jcli2909.1

Vicente-Serrano SM, Lopez-Moreno JI, Begueria S, Lorenzo-Lacruz J, Sanchez-Lorenzo A, Garcia-Ruiz JM, Azorin-Molina C, Moran-Tejeda E, Revuelto J, Trigo R, Coelho F, Espejo F (2014) Evidence of increasing drought severity caused by temperature rise in southern europe. Environmental Research Letters 9(4):9, DOI 10.1088/1748-9326/9/4/044001

Wallace JM, Fu Q, Smoliak BV, Lin P, Johanson CM (2012) Simulated versus observed patterns of warming over the extratropical northern hemisphere continents during the cold season. Proceedings of the National Academy of Sciences of the United States of America 109(36):14,337–14,342, DOI 10.1073/pnas.1204875109

Watson J, Challinor AJ, Fricker TE, Ferro CAT (2015) Comparing the effects of calibration and climate errors on a statistical crop model and a process-based crop model. Climatic Change 132(1):93–109, DOI 10.1007/s10584-014-1264-3

White JW, Hoogenboom G, Kimball BA, Wall GW (2011) Methodologies for simulating impacts of climate change on crop production. Field Crops Research 124(3):357–368, DOI 10.1016/j.fcr.2011.07.001

Wilks D (2006) Statistical methods in the atmospheric sciences, 2nd edn. Academic Press

WMO (2012) Standardized Precipitation index. User Guide. Weather Climate Water, CH 1211 Geneva 2, Switzerland

WMO (2013) The global climate 2001-2010. a decade of climatic extremes. summary report. Report

Wold S, Sjostrom M, Eriksson L (2001) Pls-regression: a basic tool of chemometrics. Chemometrics and Intelligent Laboratory Systems 58(2):109–130, DOI 10.1016/s0169-7439(01)00155-1

Wu J, Liu M, Lu A, He B (2014) The variation of the water deficit during the winter wheat growing season and its impact on crop yield in the north china plain. International Journal of Biometeorology 58(9):1951–1960, DOI 10.1007/s00484-014-0798-4

Wu Z, Huang NE, Long SR, Peng CK (2007) On the trend, detrending, and variability of nonlinear and nonstationary time series. Proceedings of the National Academy of Sciences of the United States of America 104(38):14,889–14,894, DOI 10.1073/pnas.0701020104

Wu ZH, Huang NE, Wallace JM, Smoliak BV, Chen XY (2011) On the time-varying trend in global-mean surface temperature. Climate Dynamics 37(3-4):759–773, DOI 10.1007/s00382-011-1128-8

Xiao D, Tao F, Liu Y, Shi W, Wang M, Liu F, Zhang S, Zhu Z (2013) Observed changes in winter wheat phenology in the north china plain for 1981-2009. International Journal of Biometeorology 57(2):275–285, DOI 10.1007/s00484-012-0552-8

Xiao DP, Tao FL (2014) Contributions of cultivars, management and climate change to winter wheat yield in the north china plain in the past three decades. European Journal of Agronomy 52:112–122, DOI 10.1016/j.eja.2013.09.020

Yu Q, Li L, Luo Q, Eamus D, Xu S, Chen C, Wang E, Liu J, Nielsen DC (2014) Year patterns of climate impact on wheat yields. International Journal of Climatology 34(2):518–528

Yue S, Wang CY (2004) The mann-kendall test modified by effective sample size to detect trend in serially correlated hydrological series. Water Resources Management 18(3):201–218, DOI 10.1023/b:warm.0000043140.61082.60