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Influence of climate variability on European agriculture — analysis of winter wheat production

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ABSTRACT: European agricultural production is influenced by the space-time distribution of regional climate. Because regional distributions of temperature and precipitation in Europe are affected by changes in the wintertime atmospheric circulation, this paper aims at identifying the relationships between the wintertime Euro-Atlantic variability and wheat yield for the Member States of the European Union. An empirical orthogonal function (EOF) decomposition of the 500 hPa geopotential height fields is used to describe the wintertime climate variability, associating the leading 4 components of the EOF decomposition into known climatic patterns (such as North Atlantic Oscillation or Eastern Atlantic patterns). Using statistical methods such as ANOVA, linear regression and 'leave-one-out' cross-validation, those patterns are related to time series of wheat yield anomalies. It is shown that, depending on the country, there is a link between wheat yield and modes of winter climate variability, and this link differs from the relationship between temperature and precipitation with the modes. Looking ahead to the improvement of seasonal climate forecasts, it is expected that such meteorological patterns may be predicted with some accuracy, which in turn could improve crop yield forecasts.

KEY WORDS: Euro-Atlantic climate variability · Wheat yield · Europe · NAO

1. INTRODUCTION

With a production of around 100 million t of common wheat *Triticum aestivum*, the European Union (EU15) is the second largest producer in the world (after Asia and slightly in front of North America). Furthermore, the budget of the Common Agricultural Policy (CAP) devoted to arable crops was around €17 billion in 2000. Therefore, the Directorate General for Agriculture (DG AGRI) of the European Commission (EC) requires timely forecasting of EU agricultural production to support the CAP and to manage the European cereals market appropriately.

Climate is one of the major factors that directly or indirectly influence the space-time distribution of agricultural production. Thus, agricultural systems are vulnerable to climate variability, with regard to both extreme events and changes in the historical patterns of regional climate (Hoogenboom 2000, Ogallo et al. 2000). During the last few decades, scientists have shown that, at a global scale, some climate variability is related to large-scale interactions between the oceans and the atmosphere (Wallace & Gutzler 1981). This is the case over the Pacific Ocean with the El Niño Southern Oscillation (ENSO) phenomenon (Neelin et al. 1998).

Relationships between the climate and agriculture have been studied in cases such as ENSO and crop production in the US (Hansen et al. 1998, Alexandrov & Hoogenboom 2001), ENSO-related climate variability and maize production in Argentina (Ferreyra et al. 2001), climate-variability impacts on rice yields in Java (Amien et al. 1999), ENSO-related rainfall patterns and maize yield variability in Zimbabwe (Philips et al. 1998).

However, ENSO impacts mainly the tropics and countries bordering the Pacific Ocean. The climate variability in the North Atlantic and European regions

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is associated with other modes of variability such as the Eastern Atlantic pattern, the Euro-Atlantic blocking or the North Atlantic Oscillation (NAO). These have a non-uniform impact on temperatures and precipitation over Europe, which are the main drivers for crop development (temperatures) and for yield variability (spatial and temporal distribution of precipitation).

Empirical orthogonal function (EOF) decomposition of climate fields is frequently used to characterise the leading variability with a small number of patterns associated to those modes, and thus it describes the interannual variability of the large-scale flow over Europe and the Atlantic region during winter. Pavan et al. (2000) have shown that the 4 leading EOFs of the 500 hPa geopotential height fields explain >80% of the North Atlantic variability. Thus, analyses of the patterns associated with these 4 leading EOFs may help to characterise the influence of climate variability on agricultural production in Western Europe.

Furthermore, since European agriculture uses mainly intensive farming practises (high levels of inputs: fertilisers, pesticides), crop-yield variations are mostly dependent on weather conditions. Therefore, a better understanding of the link between European climate variability and crop yield is necessary to improve the crop yield prediction systems.

In this study, the objective is to identify and quantify the empirical relationships between the EOFs and yield of winter wheat for each Member State of the EU15 and for the EU15 as a whole.

2. METHODS

2.1. Wheat yield data

Winter wheat is sown under European conditions from late September to December (depending on the country). At mid-European latitudes, stem elongation occurs at the beginning of April, flowering in May and maturity is reached in July, while the latter can range from June in the southern countries to August in northern Europe.

Wheat yield data for EU15 Member States were extracted from the Food and Agriculture Organisation (FAO) database for 1961–2000. As an example, Fig. 1 shows the observed wheat yield in the 15 Member States of the EU15 for 1961–2000. The yield time series has 2 components: a technological trend, due notably to improvements in farm management practices, and a weather-related component, which explains the yield variability around the trend. Thus, to study the effect of the wintertime climate variability on crop yield, the technological time trend was removed from the raw time series, using a low-pass filter smoothing algorithm (Friedman 1984), in order to work on yield anomalies only. The fraction of observations in the span is chosen by a leave-one-out cross-validation, and the smoothness was increased until a linear or quasi-linear trend was obtained. Yield anomalies were then normalised by subtracting the time-series mean and dividing by the standard deviation.

2.2. Climate data

The wintertime variability in the Euro-Atlantic region is described by an EOF decomposition of the 500 hPa geopotential height fields (Pavan et al. 2000). The 4 time series corresponding to the leading principal components (PC) — calculated in this study from the winter mean December–January–February (DJF) NCEP reanalyses data (Kalnay et al. 1996) for 1948–2001 — will be used to relate to the crop yield anomalies. Their features are similar to the relevant large-scale patterns that characterise the interannual variability over the Euro-Atlantic region (e.g. Pavan et al. 2000). A brief description of these modes of variability follows.

The first mode (PC1) is similar to the historically defined winter NAO (see Marshall et al. 2001, Hurrell

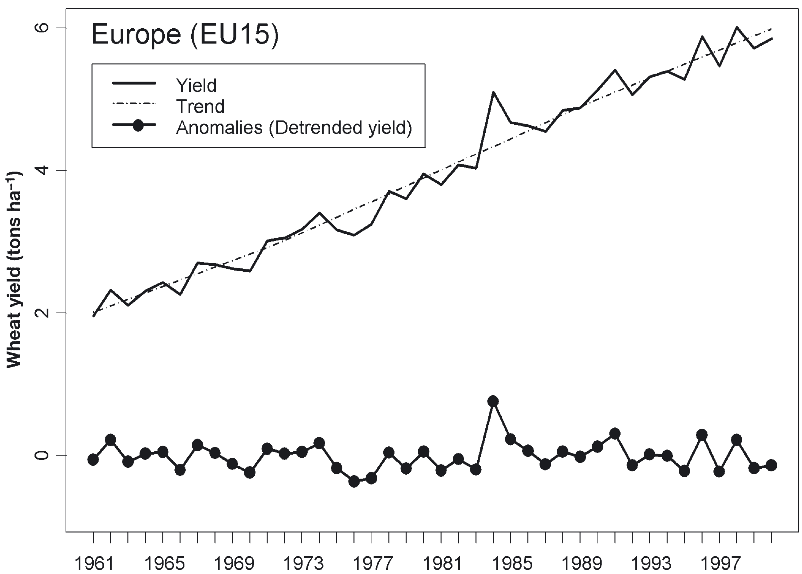

Fig. 1. Time series of wheat yield in Europe, 1961–2000: yield (solid line), general trend (dashed line) and anomalies or detrended time series (dotted line with points)

et al. 2003 for a complete review). It is characterised by an index based on the difference of normalised sea-level pressures between Ponta Delgada on the Azores Islands and Stykkisholmur/Reykjavik, Iceland (Hurrell 1995). NAO phases are characterized by their sign. Positive NAO phases are associated with warmer wetter-than-normal weather in northern Europe. During negative NAO phases, winters are wetter around the Mediterranean Sea, while NW Europe remains dry and cold. The high positive index of the early 1990s indicates a strong positive NAO phase, whereas the 1960s were characterised by frequent negative NAO phases. Correlation between PC1 and the NAO winter index is 0.95.

PC2 defines a mode of variability associated with latitudinal excursions of the North Atlantic dipole, and it is close to the 500 hPa height East Atlantic (EA) pattern (Wallace & Gutzler 1981, Castro-Diez et al. 2002). This EOF, along with the fourth one, is linked to the occurrence of ENSO events (Pavan et al. 2000). PC3 represents variability linked to the Euro-Atlantic blocking events (Tibaldi et al. 1994). It is the most spatially confined of the 4 patterns; its main centre of action is located west of the British Isles (Quadrelli et al. 2001). PC4 is similar to the Eurasian type-1 pattern (Barnston & Livezey 1987) and shares some features with the Southern Europe–North Atlantic (SENA) and Scandinavian (SCAN) patterns (Rogers 1990). Its positive phase increases zonal winds over the NE Atlantic, Scandinavia and Siberia, while its negative phase resembles a blocking dipole with centres over Scandinavia and France (Pavan et al. 2000).

The 4 time series obtained from the PCs characterise the leading climate variability over the Euro-Atlantic region using a small number of patterns that together explain about 70% of the total variability (PC1 explains about 31%, PC2 17%, PC3 12% and PC4 10%) (Pavan et al. 2000). However, relationships and impacts of these climatic patterns on European temperature and precipitation are complex. As an example, Castro-Diez et al. (2002) found that temperatures in southern Europe are sensitive to NAO phases, and also to the exact location of the NAO centres of action, but they did not find such a sensitivity to location over northern and central Europe. Furthermore, Trigo et al. (2002) showed that the NAO signal is stronger for minimum temperature than for maximum temperature and that NAO influence on 2 different precipitation-related variables (precipitation rate and precipitable water) displays different patterns.

Nevertheless, to illustrate the links between climatic patterns and weather parameters, Fig. 2 shows the correlations of the PCs with winter temperature and precipitation. Winter temperature was computed as an average of the mean daily minimum and maximum temperature for December–March (DJFM) and precipitation as cumulative precipitation for the DJFM period. Data were extracted from the Joint Research Centre database: daily weather ground station observations interpolated onto 50 × 50 km grids (Terres 1999). These maps show the link between PC1 and temperature in northern Europe (in particular, the south of Sweden and Finland, Denmark and the Baltic countries) and precipitation in southern Europe (a very high negative correlation is found between precipitation and the first PC for the Iberian Peninsula). The second PC impacts mostly southern countries for temperature and the Atlantic fringe of western countries for precipitation. PC3 is correlated with temperature in SE Europe and with rainfall in west-central Europe (France, Benelux, the south of England, Ireland and Denmark). The direct impact of PC4 on winter temperature and precipitation is less clear.

The literature also provides some information at a more local scale. Xoplaki et al. (2000) observed that the changes in Greek precipitation conditions during wintertime are primarily related to the first and second EOFs of the 500 hPa geopotential height. Sáenz et al. (2001) showed that in the north of the Iberian Peninsula the correlation of local temperature with the East-Atlantic pattern is higher than with any other common climatic pattern in the Northern Hemisphere, such as the NAO. Quadrelli et al. (2001) found that the NAO (PC1 here) explains most of the Alpine precipitation variance, and also found a strong link with Euro-Atlantic blocking events (PC3).

The PCs computed from the climatic data for this paper were detrended in order to be consistent with crop yield data (detrended as well). This is justified by the fact that the yield trend may contain contributions other than just technological farm practices. Furthermore, trends in the PCs are indeed physically meaningful and not artificial. The trend of PCs was estimated in the same manner as for the crop data (see Sect. 2.1).

Finally, it must be kept in mind that NCEP reanalysis data were used in this study, and reanalysis data should not be considered as observations. However, the use of gridded analyses avoids the caveat of uneven spatial distribution of the observations over such a large region as Europe. Moreover, a comparison of the NCEP EOFs with the ECMWF re-analysis dataset (ERA40) EOFs shows that they are very similar (correlation between the 2 sources of EOFs is 0.95). In these conditions, if the analysis were repeated with the EOFs computed from the ERA40 data, the results would be similar to those in this study.

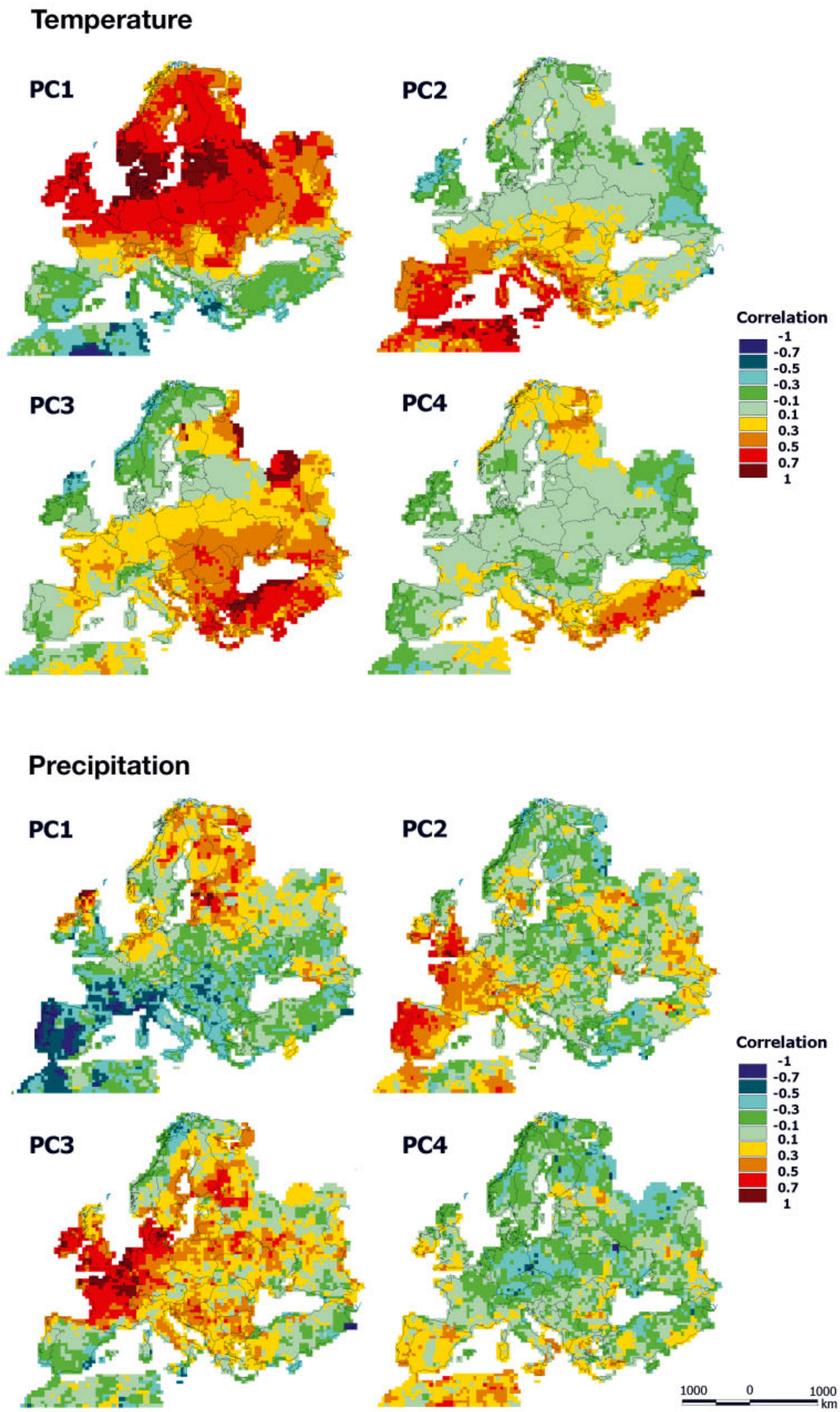

Fig. 2. Correlation coefficients of Principal Components PC1 to PC4 of the 500 hPa geopotential height EOFs for December–March 1976–2000. Top: Winter temperatures (average DJFM daily temperatures). Bottom: Total precipitation (sum of DJFM precipitation)

3. RESULTS

3.1. Correlation analysis

In the first stage, the correlation between yield anomalies (at EU15 and at national level) and principal components was computed. Wheat yield anomalies for EU15 are mostly correlated with PC4 (correlation coefficient R = 0.35). Correlation with PC1 and PC2 is very weak, and no correlation is found for PC3 (Table 1).

At the national level, results are heterogeneous (Fig. 3, Table 1). Correlation coefficients are never higher than 0.5 and are close to zero in several cases. Countries where yield anomalies are most strongly correlated with NAO (PC1) are the Scandinavian countries Sweden (R = 0.49), Denmark (R = 0.27) and Finland (R = 0.19), as well as Portugal (R = 0.26) and Greece (R = 0.23). Wheat yield anomalies are not correlated with the EA pattern (PC2); the highest R is found for The Netherlands (–0.19). PC3 shows a higher correlation mostly in NW Europe (United Kingdom, Ireland and Denmark). Higher correlation coefficients are in general found for PC4. The Scandinavian countries (especially Finland and Sweden, R = 0.46 and 0.36, respectively) as well as Portugal (R = 0.47), Belgium–Luxembourg, France and Germany have a positive correlation.

These overall weak correlations indicate a low percentage of yield variability explained by the different climate patterns. For instance, a correlation coefficient between yield anomalies and PC1 equal to 0.4 means that only 16% of winter wheat yield variability is explained by the NAO. However, it must be kept in mind that each PC is only one pattern of climate variability. They should also be considered together because they explain up to 70% of the winter climate variability. Thus, these results may be interpreted as an imprint of the influence of the wintertime variability on the annual anomalies of wheat yield over Europe.

Table 1. Correlation coefficients of Principal Components PC1 to PC4 of the 500 hPa geopotential height EOFs with wheat yield anomalies for EU and single European countries (1961–2000)

	PC1	PC2	PC3	PC4
Europe (EU 15)	0.1	0.09	−0.02	0.35
Austria	0.19	0.06	−0.05	0.10
Belgium-Luxembourg	−0.09	−0.14	−0.1	0.34
Denmark	0.27	0.05	0.29	0.14
Finland	0.19	0.03	0.05	0.46
France	0.1	0.1	−0.07	0.31
Germany	−0.21	0.08	0.15	0.25
Greece	0.23	−0.1	0.14	0.06
Ireland	−0.02	0.12	0.26	0
Italy	0.13	−0.09	−0.11	0.09
The Netherlands	0.15	−0.19	0.19	0.05
Portugal	0.26	−0.15	−0.11	0.47
Spain	−0.16	0.07	−0.19	0.06
Sweden	0.49	−0.07	−0.12	0.36
United Kingdom	−0.04	−0.01	0.31	0.21

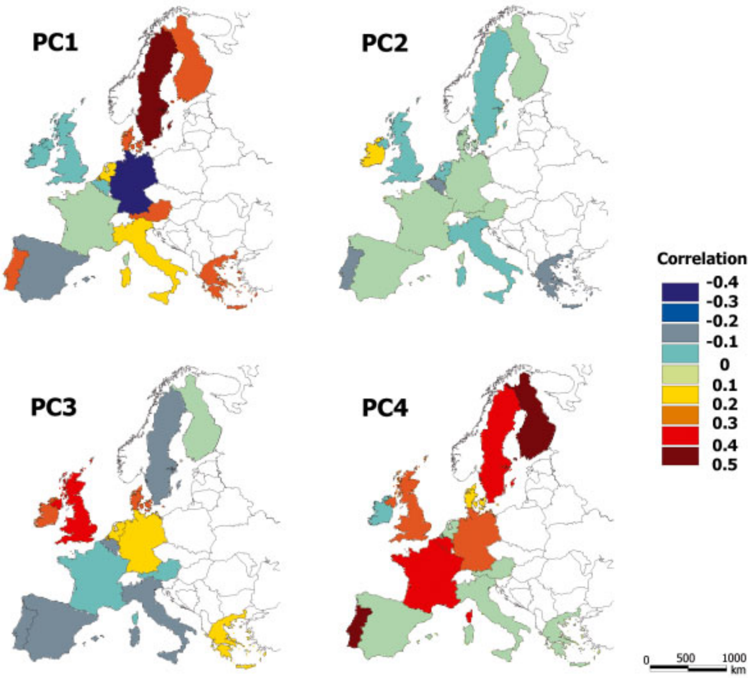

Fig. 3. Correlation coefficients of Principal Components PC1 to PC4 of the 500 hPa geopotential height EOFs with wheat yield anomalies at the national level (1961–2000)

Furthermore, once the PCs that contribute most strongly are identified, one should qualify the impact of the different climate patterns on yield anomalies — aiming at knowing anomaly behaviours according to these PCs. For example, according to the correlation analysis, yield anomalies in Sweden appear mainly linked to the NAO (PC1, R = 0.49), while Portuguese anomalies are mostly driven by PC4 (R = 0.47). The box-plot shown in Fig. 4 displays the yield anomaly in Sweden distributed into 3 clusters stratified according to the NAO phase. It shows that the anomalies tend to be high and negative for negative NAO and positive for positive NAO. Average anomalies for both phases (–0.86 t ha^{-1} for the negative phase and +0.7 t ha^{-1} for the positive one) are significantly different at the 99% confidence level (Student's *t*-test; p = 0.004). Anomalies present a large variability for neutral phases. A similar behaviour is observed for all other countries with a positive correlation >0.2 with the winter NAO. The opposite is observed in countries with a negative correlation between PC1 and yield anomalies. For instance, a negative NAO is associated with positive

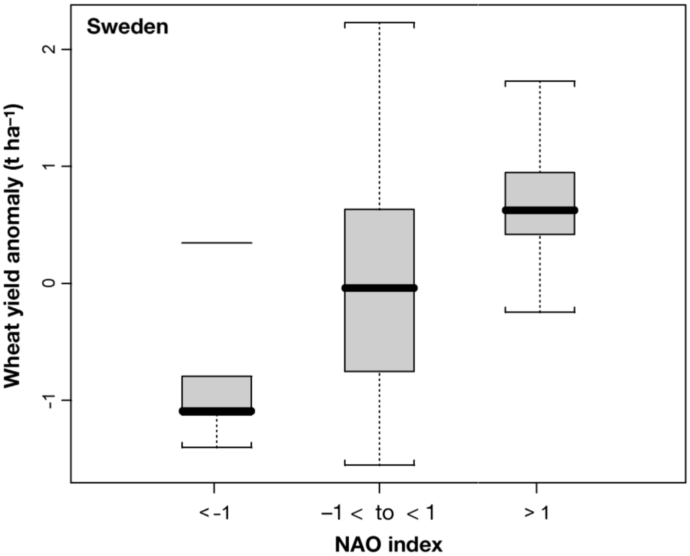

Fig. 4. Box-plot of wheat yield anomalies (1961–2001) classified in 3 clusters according to the NAO DJF index (EOF PC1) for Sweden. Each whisker contains 25% of the yield anomalies of each cluster. The central box contains half of the values and is divided by the median of the yield anomalies in each cluster.

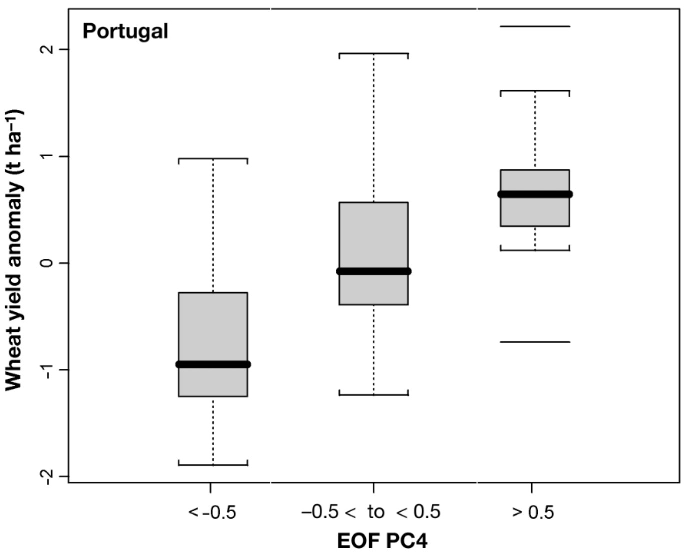

Fig. 5. Box-plot (box-and-whisker representation) of wheat yield anomalies (1961–2001) classified in 3 clusters according to the EOF PC4 for Portugal. Details as in Fig. 4

yield anomalies in Germany and Spain. Fig. 5 shows that median yield anomalies in Portugal for PC4 < –0.5 (–0.71 t ha^{-1}) and > +0.5 (+0.69 t ha^{-1}) are significantly different at the 95% confidence level ($p < 0.001$). These thresholds to categorize the PCs (respectively +/–1 for PC1 in Sweden and +/–0.5 for PC4 in Portugal) are issued from a cluster analysis and are the optimum values allowing to distinguish between yield anomalies in Sweden as a function of PC1 or in Portugal as a function of PC4, respectively.

3.2. Regression of yield anomalies on the PCs

Considering that the information provided by all patterns or combinations of patterns may provide better results, a multiple linear regression was carried out in the second stage of the analysis. The winter wheat anomalies were regressed against the 4 PCs. This allows the analysis of the combined effect of these 4 patterns on wheat yield anomalies. The regression was done for the EU15 and at the national level. A stepwise selection of predictors based on the Akaike information criterion (Sakamoto et al. 1986) was chosen. Some of the cross-factor interactions between the 4 PCs, starting from the whole set of 2-, 3- and 4-factor interactions, were considered (combined effect of 2, 3 or the 4 PCs on wheat yield anomalies). The results are described below separately for the EU15 and the national yields.

3.2.1. Results for Europe (EU15)

According to the regression model[1] built for the EU15, the influence of the 4 PCs on the wheat yield anomalies is significant. The model R^2 is 0.61 (fraction of the total variability in the response that is accounted for by the model) and the final *F*-statistic is 4.5 (on 9 and 30 degrees of freedom) with $p = 0.001$. This suggests that the contribution of all parameters to the model is not negligible, the *F*-statistic being used for testing overall regression model coefficients, i.e. to test the null hypothesis (all regression coefficients are zero, which is rejected here) against the alternative hypothesis (at least 1 of the regression coefficients is not zero). The regression diagnostics are summarised in Table 2. The combined effect of the different modes has a significant influence on the European wheat yield anomalies, which are influenced mainly by the combined effects of PC1 with PC3 ($p = 0.0026$) and of PC2 with PC3 ($p = 0.0097$), as shown in Table 2. Since those p-values are significant, the PCs point towards a significant impact on European yield anomalies.

A 'leave-one-out' cross-validation (CV) was performed to make an assessment that is as realistic as

[1]Statistics and tests computed for regression models depend on assumptions about random disturbances in the model equation. For all models presented in this paper, the residuals appear to behave randomly, and quantile–quantile plots have been used to verify their normality. This suggests that these assumptions can be supported

Table 2. Regression diagnostic for Europe (EU15, 1961–2000): best model selected for wheat yield anomalies function of PC1 × PC2 × PC3 × PC4; 95 % significance level).

ANOVA

Source	df	SS	*F*	p > *F*
Model	9	23.783	4.532	0.001
Error	30	15.213		
Total	39			
$R^2 = 0.61$				

Analysis of coefficients

Parameters	p > (Student's *t*)
PC1	0.4890
PC2	0.6376
PC3	0.2331
PC4	0.1021
PC1 × PC3	0.0026
PC2 × PC3	0.0097
PC3 × PC4	0.0371
PC1 × PC2 × PC4	0.0465
PC2 × PC3 × PC4	0.0168

Correlation (observed, cross validation hindcasts) = 0.30

Table 3. Diagnostic for the selected regression models at the national level. R^2: model multiple R^2; R.CV: correlation coefficient between observed and cross-validated hindcast anomalies; N_{out}: no. of points outside 95 % confidence interval (out of 40 points)

	R^2	p of *F*	R.CV	N_{out}
United Kingdom	0.68	0.000	0.46	2
Germany	0.64	0.003	0.33	2
Belgium-Luxembourg	0.45	0.001	0.23	2
Portugal	0.42	0.004	0.27	2
Sweden	0.46	0.006	0.15	2
France	0.59	0.015	0.25	3
Ireland	0.46	0.015	0.13	3
Finland	0.35	0.031	0.12	3
The Netherlands	0.32	0.039	-0.24	2
Denmark	0.16	0.039	-0.34	2
Greece	0.21	0.092	0.04	4
Italy	0.26	0.119	-0.28	3
Austria	0.31	0.162	0.10	3
Spain	0.27	0.220	-0.26	3

possible of the sensitivity of the yield anomalies to the PCs found with the previous linear regression model. The leave-one-out CV consists in building a regression model as was done before, but omitting 1 of the 40 years. Then the anomaly for the omitted year is predicted using this model (CV hindcast). This value is thus not 'fitted' but 'predicted', because information for this year was not used to build the regression model. This process is repeated for every 1 of the 40 yr of the study. Fig. 6 presents these yield anomaly CV hindcasts, their 95 % confidence intervals and the actual yield anomalies. It appears that only 2 out of 40 (5 %) CV hindcasts are outside the 95 % confidence intervals. The CV correlation coefficient is 0.3.

3.2.2. Results at the national level

Selected models are different from country to country, with different parameters and interactions of parameters selected with different skill level. Results from the regression analysis are summarised in Table 3. Models for the United Kingdom and Germany show particularly high accuracy, higher or comparable to the one found for the EU15 model. R^2 is higher than 0.6 for both, and the *F*-statistic $p \leq 0.003$, which is highly significant. This is an interesting result, since Germany and the United Kingdom are the largest wheat producers in Europe after France. For these countries, PC-based regression models predict accurately the yearly wheat yield anomalies. Those results are confirmed by the CV, which shows good hindcasts for these countries (only 2 hindcasts fall outside the 95 % confidence intervals). The *F*-statistic p is also significant for Belgium–Luxembourg, Sweden and Portugal ($p < 0.006$), even if the R^2 is slightly lower (values of 0.45, 0.42 and 0.46, respectively).

For 3 other countries (France, Ireland and Finland) the models present a lower skill, but still significant in spite of the *F*-statistic p between 0.01 and 0.03 (in addition, the R^2 is high). Models for Denmark and The

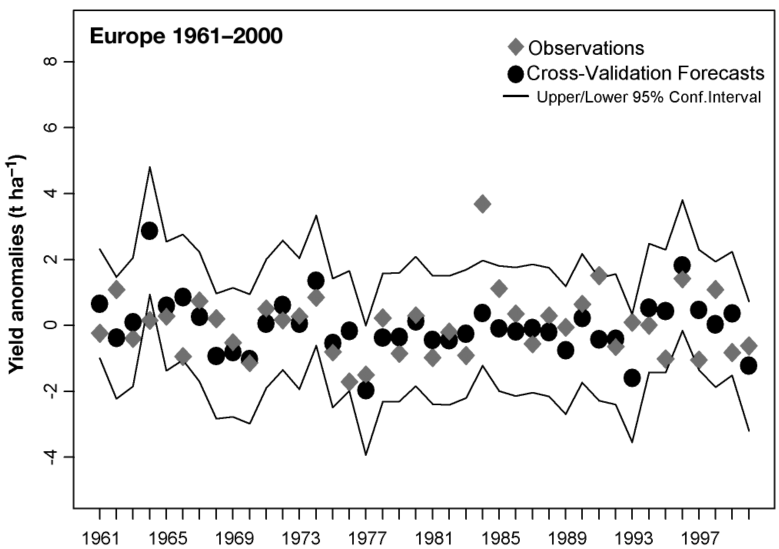

Fig. 6. Wheat yield wintertime variability, cross-validation (leave-one-out). Cross-validated hindcasts (●) and 95 % confidence interval (solid lines) along with the corresponding observations (◆)

Netherlands have a slightly higher *F*-statistic p (0.039) but a negative (and quite high) CV correlation coefficient.

Finally, for Greece, Austria, Italy and Spain, the impact of the EOFs on yield anomalies was not found to be statistically significant. Greece and Austria have poor CV hindcasts; for Italy and Spain the CV correlation coefficient is negative and relatively high. For these countries, CV allows the identification of years which deteriorate model quality. For instance, for Spain, by removing 1992, the model R^2 goes up to 0.42 (instead of 0.27, see Table 3) and the *F*-statistic p = 0.03 (instead of 0.22).

The most important parameters (single PCs or PC interactions) for each national model are shown in Table 4. This table suggests that the cross effects of 2 or even 3 PCs on wheat yield are often as important as single PCs. The interaction between PC2 and PC3 is the most important for the United Kingdom ($p < 0.0001$), and has non-negligible effects for Germany and France. Considering that those 3 countries are the main wheat producers in Europe, representing together around 75% of total production, the influence of the cross-effect of PC2 and PC3 is not negligible for European wheat production. PC1 × PC4 is also important in the United Kingdom, ($p < 0.002$). The PC1 × PC3 interaction contributes significantly to the Belgium–Luxembourg model ($p < 0.0001$), and is also important again for Germany and France. Furthermore, wheat yield anomalies in Ireland are mainly linked to the 3-factor interaction PC2 × PC3 × PC4 (p-value = 0.009). Nevertheless, Table 4 also shows that single effects contribute significantly to several national models. As was suggested by the correlation analysis, PC4 is the most important predictor in the regression for Finland and Portugal, while for Sweden it is PC1. (Table 1 shows that these 3 countries have the highest correlation coefficient between yield anomalies and single PCs).

Table 4. Most important parameters (PCs and interactions between PCs) for selected regression models at the national level. The right column indicates the *t*-test p (test of the contribution of a single PC or interaction in the model)

	PC	p (> | *t* |)
United Kingdom	PC3	0.0057
	PC2 × PC3	0.000
	PC1 × PC4	0.002
Belgium-Luxembourg	PC4	0.01
	PC1 × PC3	0.000
Germany	PC1	0.08
	PC1 × PC3	0.04
	PC2 × PC3	0.04
Portugal	PC4	0.009
Sweden	PC1	0.007
France	PC1 × PC3	0.0214
	PC2 × PC3	0.0223
Ireland	PC2 × PC3 × PC4	0.0091
Finland	PC4	0.003
The Netherlands	PC1 × PC4	0.03
	PC3 × PC4	0.06
Denmark	PC1	0.06
	PC3	0.08
Greece	PC1	0.06
	PC2 × PC4	0.01
Italy	PC3 × PC4	0.0880
Austria	PC3 × PC4	0.05
	PC2 × PC4	0.03
Spain	PC3	0.05
	PC1 × PC2 × PC4	0.05

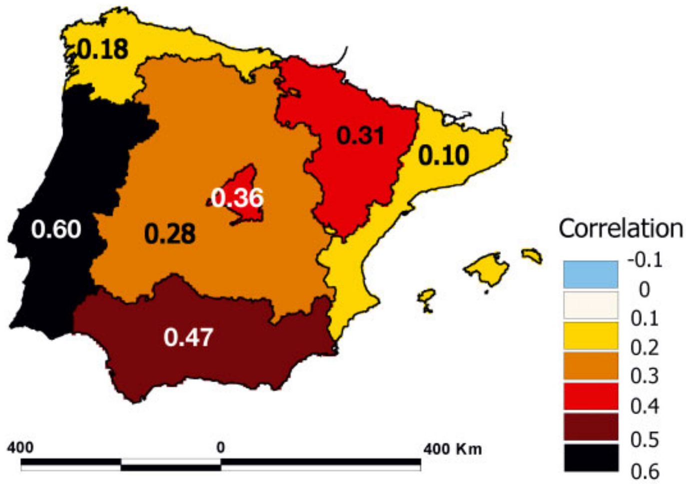

Fig. 7. Correlation coefficient of PC4 with wheat yield anomalies for the Iberian Peninsula (1975–1995)

However, analysis at a regional level shows some variability within countries. For large countries (Spain, France, Germany), regions would be more relevant units to analyse the impact of climate patterns, but the lack of long time series of regional yield data covering all EU regions did not allow such analysis. As an example, Fig. 7 shows the correlation map between PC4 and yield anomalies on the Iberian Peninsula. Correlations were computed for a 20 yr time series only (1975–1995). This figure illustrates the difference between the national and regional levels. For 1975–1995, the correlation coefficient between PC4 and the Spanish national yield anomalies is 0.27, while for 1961–2000 this same coefficient (Table 1) falls to 0.06 (for the sake of comparison, 1975–1995 and 1961–2000 correlations for Portugal are R = 0.6 and R = 0.47, respectively).

4. DISCUSSION

This study highlights the effect of climatic wintertime variability on wheat yield in Europe. At least for some individual countries and for EU15 as a whole, the influence of the leading modes of wintertime variability for the Euro-Atlantic area on yield anomalies was found to be statistically significant.

An important result is the difference in the spatial distribution between correlations of PCs and temperature and precipitation, on the one hand, and correlations of PCs and yield anomalies, on the other (in particular, for PC4). Possible explanations are as follows. (1) The correlation maps (Fig. 2) are based on winter (December–March) temperatures and precipitation whereas crop yield is the result of crop development until maturity (including the period from April to July/August). (2) Crop yield is averaged at a national level, while temperature and precipitation are not. Moreover, some studies have shown that impacts of climatic patterns on biological ecosystems could be stronger than the direct impact on physical weather-related variables such as precipitation. This ihas been suggested by Cane et al. (1994) regarding maize-yield variability in Zimbabwe in relation to ENSO. Taylor et al. (2002) studied how an ecosystem extracts a weak climatic signal that is spread across different meteorological variables. Kettlewell et al. (2002) noted that, in the United Kingdom, the biological relationship between wheat quality and NAO is stronger than the link between precipitation and NAO. Thus, one could expect these differences between the impact of the modes of climate variability on temperature and precipitation on the one hand, and crop yield on the other.

The differences between Spain and Portugal were unexpected; 3 out of the 4 PCs had very different correlations with the respective national yield anomalies in spite of the geographical proximity of the 2 countries. It must be kept in mind that yield anomalies are provided at the national level and could smooth some regional differences, while the impact of the modes of variability in terms of temperature and precipitation is regionalised (see again the example of Spain in Fig. 7).

Another important issue is that in the regression model results many interactive effects (PC cross-factors) are significant. Cross-factors take into account the fact that modes are just idealisations of the actual anomaly patterns. The anomaly pattern of a specific month could well be projected onto 2 different modes of variability. Moreover, yields at a national level could be affected by different climatic patterns, notably over long periods (wheat growth and development). Nevertheless, the interpretation of cross-factor interaction is still at a preliminary stage.

With the exception of Portugal, the link between PCs and wheat yield anomalies seems weaker in the southern countries (Italy, Spain and Greece). Comparing the wheat yield time series, those countries have large variability. Furthermore, climate patterns in Italy are characterized by the influence of Alpine climate in the north and the Mediterranean climate in the south. In Spain, the central inland climate is different from the climate of the Mediterranean coast of the country (wheat cultivation in these large countries is spread over the national territory, which is not the case in France, for instance, where wheat production is mostly concentrated in the central north). Once again, an analysis at a regional level would clarify these results. On the other hand, it is more difficult to find weather related explanations for the weak sensitivity to climatic patterns of wheat yield variability in Greece.

Finally, enlarging the theme of this paper, the link between climate variability and crop yield could be analysed through parameters such as crop quality, phenology or crop trade. Kettlewell et al. (2002) examined the relationships between the NAO and the wheat grain quality in the United Kingdom, while Chmilelewski & Rötzer (2002) studied the variation of the beginning of the growing season in Europe in relation with air temperature changes, notably with the NAO fluctuations.

5. CONCLUSION

The major result of this study is the existence of relationships between modes of climate variability and wheat yield anomalies in Europe. The link between the 4 leading EOFs of the 500 hPa geopotential height decomposition, which was used to characterise the climatic variability and yield anomalies, was found to be significant, particularly for the fourth EOF. Moreover, an interesting result is that relationships with yield differ from the relationships with temperature and precipitation between modes.

Sensitivity to wintertime variability seems local (it is likely that weather in Europe reacts differently in time and space to the different pattern described by each EOF). Relationships between wintertime variability and crop development in Europe should be further analysed, and regional analyses are required to clarify the results. Other crops could also be considered.

Crop yield is influenced by the different climatic patterns. For example, it seems possible to estimate the yearly wheat anomalies in some countries when the NAO winter index is high or in other parts of Europe when the EA pattern is negative.

The link between wheat yield and modes of variability also offers some predictive power: the expected ability of seasonal forecasts to anticipate patterns such as NAO fluctuations should improve the seasonal crop yield forecast. This is the topic of a Framework Program V Research Project funded by the European Commission, DEMETER (http:// www.ecmwf.int/research/demeter/).

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