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A B S T R A C T

The MARS-Crop Yield Forecasting System (M-CYFS) is used since 1993 to forecast the yields of all major crops in the European Union (EU) based on gridded runs of the WOFOST crop model. Using 28 years of observation, from 1988 to 2015, we quantified the variability in crop yield reported by all 28 EU Member States (MS) that can be explained by each individual WOFOST crop model based predictors and a few simple meteorological variables. A linear regression is used as a screening tool to quantify the relationship between each predictor and the yield residuals from the trend throughout the crop cycle for 168 country/crop combinations, assuming the yield residuals from the trend depend on the inter-annual climate variability. The results are plotted and analyzed at different level: every 10 days for each country crop/combination and each predictor; synthetized every 10 days for each country/crop combination keeping the predictor showing the best relationship with the yield residuals; finally, the best predictor found for each MS during the entire growing season is used to evaluate the ability of the model to estimate yield variability of each crop at European scale.

While 61% of the grain maize (*Zea mays* L.) yield variability can be anticipated 80 days before harvest with the simulated water limited biomass for countries where rainfed maize prevails, 41% of the soft wheat (*Triticum aestivum* L.) yield variability can be reproduced a month before harvest, the best estimates being obtained where wheat is predominantly exposed to water stress. For the other crops analyzed, the results are also found to be reliable for crops predominantly exposed to water stress and becoming unreliable in agricultural systems exposed to an oceanic climate with a high level of inputs. The agro-meteorological processes related to an excess of water (nitrogen losses, diseases, anoxia, harvest conditions) would need to be disentangled and better integrated into the crop modeling system to improve the predictors.

The monthly cumulated meteorological predictors are performing only slightly worse than the crop model predictors and help to characterize the main processes responsible for the yield variability. Nevertheless, the predictive capacity of the meteorological predictors is spatially and temporally incoherent and differs according to the crop phenology. In comparison, the M-CYFS crop model predictors are more consistent since the predictors summarize the succession of agro-meteorological conditions determining the yield throughout the entire growing season.

1. Introduction

Crop yield forecasting has a growing importance in the public and private sector, to anticipate crop production and market fluctuations, ensure food security, optimize agro-management practices and resource use (Macdonald and Hall, 1980; Meinke and Stone, 2005). From farmers to national and international private and public institutions, various individuals need to anticipate crop production and markets. Initiatives like AMIS (Agricultural Market Information System) illustrate the usefulness of monitoring agricultural production at global scale to stabilize agricultural markets (Islam and Grönlund, 2010). The aim of the MARS Crop Yield Forecasting System (M-CYFS), developed and maintained by the Joint Research Center (JRC), is to contribute to the cereal supply balance sheets of the European Union published by the European Commission, which can aid to stabilize prices of the main commodities and prevent market fluctuations, impacting directly farmers and Member States (MS). Such initiatives have a growing importance since inter-annual yield variability depends largely on weather conditions, which will be particularly altered by climate change. Expected changes in temperature trends, rainfall distribution, and extreme climatic events are foreseen to impact the yields of major crops and increase their variability (Asseng et al., 2011; Iizumi and Ramankutty,

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2016; Lesk et al., 2016; Lobell et al., 2011; Powell and Reinhard, 2016; Ray et al., 2012).

Monitoring and forecasting crop yield is generally accomplished using several sources of information, from field observations, meteorological data, remote sensing images to crop growth simulation models (Basso et al., 2013). The approach of the M-CYFS is rather unique as it is one of the few forecasting systems relying on the use of gridded crop simulations at large scale, over the European Union (Van Diepen et al., 2004). Remote sensing time series are completing the information available and also used operationally to forecast the yields (Kerdiles et al., 2017; López-Lozano et al., 2015).

Gridded crop models are commonly used for applications such as studying yield gaps or to simulate future crop yields under different climate scenarios (Mueller et al., 2012; Müller and Robertson, 2014; Rosenzweig et al., 2014; Van Ittersum et al., 2013). Only a few validations of these large scale gridded crop models have been done to identify their ability to reproduce crop yield variability and characterize their weaknesses and their strengths (Bassu et al., 2014; Müller et al., 2017). Since the launch of the M-CYFS in 1993, the crop model predictors of the Crop Growth Modeling System (CGMS) have been only validated partly and the relative performance of crop model predictors *vs.* meteorological predictors has not been evaluated (Reidsma et al., 2009; Supit, 1997). This study intends to highlight the ability of the M-CYFS to forecast the yields of the main arable crops, considering 28 years of meteorological data, yield statistics and crop model simulations.

The M-CYFS approach to forecast yields is relying on the assumption that the yield variability is composed of 1- a trend, depicting the technological improvements (new varieties, the use of fertilizers, fungicides, mechanization) and impacting the yields on the long term, and 2- the residual from the trend, depending on inter-annual climate variability (Lobell, 2010). In this study, considering this last approach, the gridded WOFOST crop model output predictors and a set of simple cumulated meteorological predictors aggregated at national scale are compared to the crop yield residuals, using a simple linear regression analysis, to identify and quantify the impact of the main agro-meteorological processes responsible for the crop yield variability. The use of such a simple statistical method was motivated assuming that the output of the crop model simulations, and more particularly the biomass and storage organs weight, should be linearly related to the statistical yields residuals.

In an operational context, two statistical methods are commonly used in the M-CYFS to establish the yield forecast using the crop model output simulations: a Principal Component Analysis (PCA) used to identify similar years and forecast the yield according to the similarities found, and a simple or multiple regression analysis on the residuals from the trend. A more complex statistical method could have been used in this study to assess the reliability of the M-CYFS, however, the goal is to evaluate the ability of the crop model predictors to reproduce the yield variability and determine for which crop and which countries the model is valid. Beyond the evaluation of the model, the aim is to highlight which agro-meteorological processes are explaining the yield variability of the main crops in Europe.

2. Material and methods

2.1. Input data

This study is focusing on the main cereals, oilseeds and root crops produced by the MS of the European Union (EU-28): Soft wheat (*Triticum aestivum* L.), spring and winter barley (*Hordeum vulgare* L.), grain maize (*Zea mays* L.), durum wheat (*Triticum turgidum* L.), rye (*Secale cereale* L.), triticale (×*Triticosecale* Wittm. ex *A. Camus*), rapeseed (*Brassica napus*), sunflower (*Helianthus annuus*), sugar beet (*Beta vulgaris* L.) and potato (*Solanum tuberosum* L.). The input data are extracted exclusively from the M-CYFS: the yield statistics at country scale, the spatially aggregated crop model simulations and the daily meteorological data aggregated at national scale on arable land.

2.1.1. Yield statistics

National yields statistics of all the MS of the EU-28 published by Eurostat are used and were preferred to other data sources, such as the FAO statistics, as the yields are detailed by cultivars, distinguishing soft wheat from durum wheat, spring barley from winter barley (Eurostat, 2017). The analysis is conducted for each cultivar, considering their spatial distribution varies and their sensitivity to meteorological conditions can differ. For example, durum wheat is cultivated predominantly in southern Europe and does not have a vernalization requirement while most of the soft wheat is cultivated in northern Europe and does need a period of vernalization which might explain part of the yield variability.

The availability of statistics depends on the accession of the MS to the EU and the geopolitical context, with most of them being available since 1988. A total of 256 crop/country combinations were considered but, excluding *de facto* yield statistics time series with one or more missing data and considering 1988 as the first year of analysis, 168 crop/country combinations are remaining. Thus, 28 years are considered, focusing on the period 1988–2015.

2.1.2. Crop model simulations

WOFOST is a mechanistic point-based crop model based on light use efficiency, developed originally in 1965 and is used operationally in the M-CYFS since 1993 (De Wit, 1965; Van Diepen et al., 1989). Light use efficiency, which determines the amount of radiation absorbed, is used to simulate the photosynthetic activity considering the characteristics of leaves, and depends on the daily radiation and the current Leaf Area Index (LAI). The photosynthetic activity is then used to simulate the carbon assimilation rate. The maintenance respiration is subtracted from the daily gross carbon assimilation rate and weighted by the conversion efficiency of assimilates to simulate the net carbon assimilation rate (*i.e.* the daily dry biomass formation). The assimilates are partitioned between the roots, the leaves and the storage organs with a partitioning coefficient varying depending on the development stage of the plant, being determined in growing degree-days since sowing or emergence. The soil water model implemented in WOFOST uses a simplified representation of soils and considers a single layer, simplifying the soil in a single reservoir. Conceptually, two levels of crop production are distinguished in WOFOST: potential production (determined variety properties, radiation and temperature), water limited production (water availability limits potential production). More details on the model structure and principles behind are described by Supit and Goot (2003) and De Wit et al. (this Virtual Special Issue). In the CGMS, crop model simulations are starting in 1976, corresponding to the first year of acquisition of meteorological data, and are updated every 10 days in real time for the following crops: soft wheat, durum wheat, grain maize, spring barley, winter barley, rapeseed, rye, triticale, sunflower, potato and sugar beet. In order to limit the amount of data stored in the M-CYFS database, the simulations are saved at a 10-daily time step, called a dekad, and the following output variables are stored: the development stage (DVS), potential and water limited biomass (respectively PB and WLB), potential and water limited storage organs (PSO and WLO), potential and water limited LAI (PLAI and WLAI), the relative soil moisture (SM), the total water consumption and requirements (TWC and TWR).

2.1.2.1. Crop model calibration. Considering the lack of eco-physiological data available and the heterogeneity of cultivars that can be found both temporally and spatially at national, regional or even at the grid level, the generic calibration published in 1993 is used and only the definitions of the specific LAI and temperature sums defining the main development stages simulated by WOFOST have been improved over years: sowing, emergence, flowering and maturity

(Boons-Prins et al., 1993).

Winter crops simulations (soft wheat, durum wheat, winter barley, triticale, rye, rapeseed) start on 1 January instead of sowing dates, this choice having been done in the past to facilitate the management of the database for winter crops, growing on two calendar years, and following the assumption that most of the yield variability is explained by agro-meteorological conditions from tillering to harvest. Consequently, the temperature sum between emergence and flowering (TSUM1) was shortened to approximate the flowering stage of winter cereals. Soft wheat simulations are used as a proxy to forecast winter barley and triticale, despite their phenology being differing.

Considering there is no more technical limitations to simulate winter crops during the whole crop cycle and starting the model at sowing would improve the simulations of winter cereals, winter soft wheat was recalibrated recently and simulations run at sowing instead of 1 January (Ceglar et al., this Virtual Special Issue). The old simulations starting on 1 January and the new one are used and compared in this study, the new calibration of soft wheat appearing as “Soft wheat N.”.

2.1.2.2. Meteorological data. The meteorological data of the CGMS are retrieved daily in real time from a network of > 4000 stations. The network density depends on the national meteorological services and the priority has been given to the acquisition of meteorological data close to or within agricultural areas. Considering that the global radiation is not available for each station, it is estimated whether using the sunshine duration, the cloud cover, or minimum and maximum temperatures, depending on the data availability. After a quality check, minimum temperatures, maximum temperatures, precipitations and global radiation are interpolated at a resolution of 25 km. A complete description of the meteorological data acquisition and processing can be found in the CGMS version 9.2 manual (Baruth et al., 2007).

2.1.2.3. Soil data. Soil data are derived from the European soil database (ESDB) (Panagos, 2006). The ESDB is structured in mapping units defined as Soil Mapping Units (SMU), which corresponds to a group of Soil Typological Units (STU) containing the soil characteristics used to derive the soil hydraulic properties required by the model. The location of the STUs within the SMUs is unknown, only the share of each STU within a SMU is given. The parameters needed to run the WOFOST crop model, the water content at wilting point, field capacity and maximum rooting depth, have been derived in 2006 during the SINFO project (Baruth et al., 2006). For each STU of the ESDB, the water content at wilting point was estimated using the Wösten pedotransfer functions (Wösten et al., 1999), while the available water capacity, used to determine the water content at field capacity, was estimated using the method described in Le Bas (1997). A set of pedotransfer rules have been used to determine the maximum rooting depth based on the agricultural limitations defined in the ESDB, the depth of textural change and the presence of impermeable layers. Considering not all STUs are cultivated, a few rules were applied to identify the STUs suitable for the cultivation of arable crops, excluding STUs based on their slope, drainage class, salinity, alkalinity, chemical toxicity and rooting depth.

2.1.2.4. Simulation units and aggregation of output simulations. The elementary simulation units are defined as the intersection of meteorological gridded data, at 25 km resolution, and the soil data. For a given meteorological grid at 25 km resolution, the simulations are run on each STUs found within the SMUs intersecting a 25 km grid cell. The output simulations, at STU level, are weighted according to their share within a SMU and aggregated at grid level considering the area of the SMUs intersecting the meteorological grid.

The aggregation of the gridded simulations to the national scale is done in several steps. First, the gridded simulations are spatially aggregated to NUTS-3 level considering the arable land area of each grid, derived from GLOBCOVER and CORINE Land Cover (Bontemps et al., 2011; Nunes de Lima, 2005). From NUTS-3 to NUTS-2 level and country scale, the cultivated area of the crop considered for the current year, retrieved from Eurostat, is used to weight and aggregate the simulations to the next administrative level (Eurostat, 2017).

2.1.3. Cumulated meteorological predictors

The meteorological daily data of the CGMS, spatially aggregated a national scale on arable land, are cumulated on a monthly basis and yearly basis (from sowing to maturity). The monthly predictors are cumulated for each dekad, corresponding to the crop model output, on the 30 days preceding the end of a dekad. This leads to an overlap of 20 days of meteorological daily data between two consecutive dekads but allows comparing the meteorological predictors to the crop model predictors for the exact same dates during the crop cycle. The yearly meteorological data are cumulated for each crop from sowing to harvest, using the sowing dates available in the CGMS database. Minimum temperatures (Tmin), maximum temperatures (Tmax) and average temperatures (Tavg) are cumulated excluding the negative temperatures.

2.1.4. Predictors selection

For each set of predictors (*i.e.* crop model predictors, monthly meteorological predictors, yearly meteorological predictors), a correlation matrix was calculated to identify the strongest collinearities and synthetize the analysis by selecting the most pertinent predictors. The correlation matrices are calculated considering the entire time series of predictors for all crops aggregated together. The predictors showing a r Pearson coefficient higher or equal to 0.95 are kept out of the analysis.

For the monthly and yearly meteorological variables, temperatures (Tmin, Tmax, Tavg) are highly correlated (Tables 1 and 2), thus only

Table 1
Correlation matrix between monthly meteorological predictors.

Name	Tmin	Tmax	Tavg	P	Et0	Rad	VP	CWB
	Minimum temperatures	Maximum temperatures	Average temperatures	Rainfall	Potential evapotranspiration	Global radiation	Vapour pressure	Water balance
Unit	(°C)	(°C)	(°C)	(mm)	(mm)	(kJ/m2)	(mbar)	(mm)
Tmin	1							
Tmax	0.96	1						
Tavg	0.98	0.99	1					
P	0.25	0.14	0.19	1				
Et0	0.88	0.93	0.91	0.05	1			
Rad	0.81	0.89	0.87	0.02	0.98	1		
VP	0.98	0.94	0.97	0.29	0.82	0.76	1	
CWB	−0.61	−0.72	−0.68	0.52	−0.83	−0.83	−0.54	1

Table 2
Correlation matrix between the yearly meteorological predictors.

Name	Tmin	Tmax	Tavg	P	Et0	Rad	VP	CWB
	Minimum temperatures	Maximum temperatures	Average temperatures	Rainfall	Potential evapotranspiration	Global radiation	Vapour pressure	Water balance
Unit	(°C)	(°C)	(°C)	(mm)	(mm)	(kJ/m2)	(mbar)	(mm)
Tmin	1							
Tmax	0.99	1						
Tavg	1	1	1					
P	0.86	0.84	0.85	1				
Et0	0.97	0.99	0.98	0.8	1			
Rad	0.96	0.98	0.98	0.83	0.99	1		
VP	0.99	0.98	0.98	0.91	0.96	0.97	1	
CWB	−0.58	−0.64	−0.62	−0.14	−0.71	−0.67	−0.51	1

the average temperatures is kept. Potential evapotranspiration (Et0) is highly correlated to global radiation (Rad), and considering that the climatic water balance (CWB) is a more realistic variable to account for water deficit, only Rad and CWB are used. Vapour pressure (VP) is highly correlated to Tmin and Tavg and is thus excluded from the analysis.

For the crop model predictors, Total Water Consumption (TWC) and Total Water Requirements (TWR) are removed as their correlation with Potential Biomass (PB) and Water Limited Biomass (WLB) is higher than 0.95 (Table 3). PLAI shows to be highly correlated to WLAI, and WLB to PB. Nevertheless, these collinearities are not observed for all the crops when analyzed independently (Table S1). Thus, PLAI, WLAI, PB, WLB were kept, considering some differences might be seen only for some specific dekads where water stress is impacting crop growth.

2.2. Regression analysis

2.2.1. Determination of the trend and yield residuals

Yield statistics are first detrended before analyzing their relationship with the predictors. In an operational context, an analyst is parameterizing the trend on an expert-knowledge basis for each country/crop combination. Considering the high number of country/crop combinations and the heterogeneity of tendencies that could be observed, a LOWESS function is used as a common method to detrend the yield time series (Cleveland, 1981). In order to limit the influence of local variations, a large span is used corresponding to 2/3 of the yield time series, the goal being to isolate the inter-annual variability. The entire statistical yield time series were considered when available (from 1976 onward) to limit any overfitting. The LOWESS function tends to be close to a second and third order polynomial trend (Figs. S1 and S2).

2.2.2. Yield coefficient of variation

For each country/crop combination, the coefficient of variation (*CV*) is calculated on the yield statistics considering the time series from 1988 to 2015, in order to highlight the dispersion of the yield distribution and explain if the relationships found between the yield residuals and the predictors are depending on the amplitude of variability.

2.2.3. Linear regression analysis

For each country/crop combination, each dekad during the crop cycle, a linear regression is calculated between the yield residuals and each predictor. The statistical relationships are evaluated using the *r* Pearson moment coefficient, *p* value, determination coefficient (R^2), calculated between yield residuals and the predictors, while Relative Root Mean Square Error (*RRMSE*) is calculated between the observed yields and the estimates, adding back the trend.

The results are plotted independently for each country/crop combination from sowing to harvest, giving a picture of the dynamic of the relationship between the predictors and the yield residuals (Fig. S3).

In a second step, the information is synthetized by dekad, keeping the predictor showing the highest relationship with the yield residuals for each country/crop combination:

$$r_{i\,dekad} = \max_{i\,\mathrm{var} \in n\,\mathrm{var}}(|r_{i\,var}|) \tag{1}$$

where r_{i_dekad} is the maximum *r* of all predictors for a specific dekad, *n_var* is the number of variables used, r_{i_var} is the *r* correlation coefficient of one predictor for a specific dekad.

The associated statistics of the best relationship found, R^2, *p* values, *RRMSE* and the yield estimates of the corresponding dekad and predictor are stored and used further in the analysis. This information is

Table 3
Correlation matrix of the crop model predictors for all the crops simulated from sowing to maturity.

Name	DVS	PB	WLB	PSO	WLO	PLAI	WLAI	SM	TWC	TWR
	Development stage	Potential biomass	Water limited biomass	Potential storage organs	Water limited Storage organs	Potential leaf area index	Water limited LAI	Relative soil moisture	Total water consumption	Total water requirements
Unit	(−)	(kg/ha)	(kg/ha)	(kg/ha)	(kg/ha)	(ha/ha)	(ha/ha)	(%)	(mm)	(mm)
DVS	1									
PB	0.92	1								
WLB	0.88	0.95	1							
PSO	0.84	0.87	0.8	1						
WLO	0.78	0.8	0.84	0.92	1					
PLAI	0.51	0.53	0.57	0.22	0.24	1				
WLAI	0.46	0.48	0.56	0.17	0.23	0.98	1			
SM	−0.74	−0.72	−0.62	−0.59	−0.44	−0.54	−0.45	1		
TWC	0.91	0.96	0.97	0.83	0.83	0.52	0.49	−0.68	1	
TWR	0.92	0.96	0.88	0.87	0.75	0.46	0.39	−0.76	0.95	1

plotted for all countries in order to highlight the main predictors and agro-meteorological processes explaining the yield variability during the crop cycle (Figs. 4, 5, 7, 8).

Next, for each country/crop combination, the best predictor found during the crop cycle and its associated statistics are used to assess the crop model reliability per country/crop combination:

$$r_{country/crop} = \max_{i\,dekad \in n\,dekad}(|r_{i\,dekad}|) \quad (2)$$

where $r_{country/crop}$ is the maximum r observed for one country/crop combination during the entire crop cycle, n_dekad is the number of dekads covering the crop cycle, r_{i_dekad} is the maximum correlation coefficient from the whole set of predictors of a specific dekad.

Finally, for each crop, the yield estimates obtained at national scale using the best predictor found during the growing season are compared altogether to the yield residuals of all countries and the R^2, *RRMSE* is calculated on the ensemble of estimates and observed yields to deliver a picture of the amount of variability reproduced by the best predictors found at European scale.

3. Results

3.1. Results per crop at European scale

Considering the estimates provided by the best predictor found in each country, the crop model predictors are reproducing 61% of the variability of grain maize, 42% for sugar beet, 41% for soft wheat considering new soft wheat calibration, 41% for durum wheat, 39% for potato, 36% for rye, 34% for triticale, 33% for rapeseed, 31% for winter barley and becomes insignificant for sunflower with 26% of the variability explained (Fig. 1). The yearly meteorological predictors appear to be insignificant for winter cereals and shows a weaker relationship with the yield than the crop model and monthly meteorological predictors. The monthly meteorological predictors are reproducing a smaller part of the variability than the crop model predictors and using those predictors improves only the yield estimates for rapeseed and winter barley. The use of soft wheat simulations as a proxy for winter barley simulations is found to be a weakness and a proper calibration could also improve the simulations of triticale. The recent calibration of soft wheat improves substantially the relationship between the predictors and the yield residuals, the R^2 of the crop model predictors starting on 1 January reaching 0.35 against 0.41 for simulations starting at sowing.

The *RRMSE* of the trend depends on the dispersion of the residues from the trend and shows the crops for which the variability is high at European scale, a higher *RRMSE* being related to a higher *CV*. Using one crop model predictor, the yield estimates of durum wheat, triticale and grain maize - having a high variability - are improved, while the improvement is not significant for sunflower and rapeseed. Oilseed crops (sunflower and rapeseed) could be more sensitive to adverse meteorological conditions during flowering and those specific processes not being considered by the crop model could explain the low relationship found. For the remaining crops analyzed - having a lower variability - (sugar beet, potato, spring barley, soft wheat, winter barley and rye), the relative improvement compared to the trend is weaker than for the crops having a higher yield variability.

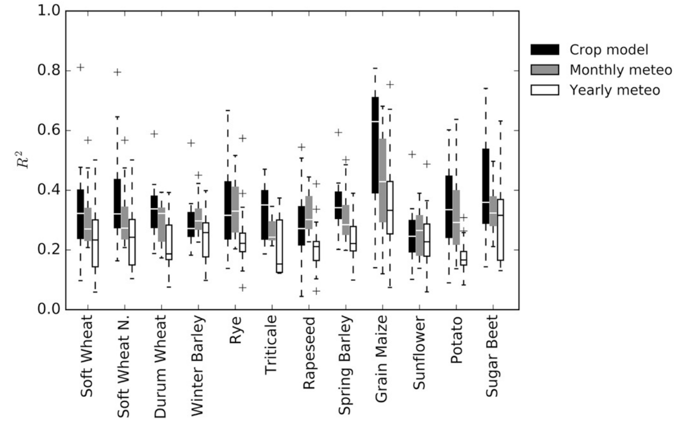

Fig. 2. Distribution of the R^2 obtained of the best predictor found during the growing season and the yield residuals for the EU-28 MS, using the crop model predictors, monthly and yearly meteorological predictors.

3.2. Spatial variability of the results

The reliability of the predictors used to estimate the yield variability is largely depending on the MS considered as the best R^2 obtained for grain maize can range from 0.19 in Belgium to 0.81 in Bulgaria and, for soft wheat, from 0.19 in Latvia to 0.8 in Spain (Fig. 2).

For soft wheat, the crop model predictors are found to correlate well with the yield variability for the MS where the yield varies highly as in Spain (R^2 = 0.8), Romania (R^2 = 0.65), Bulgaria (R^2 = 0.57), Hungary (R^2 = 0.52), and to a lesser extent Slovakia (R^2 = 0.44) and Ireland (R^2 = 0.43) (Fig. 3).

Less than 35% of the yield variability is explained for the United Kingdom, Belgium, the Netherlands, France, Italy, Denmark, Czech Republic and Austria, countries where the yield *CV* is lower than 0.15. For Lithuania and Latvia, despite a relatively high yield variability, with a $CV > 0.2$, the crop model predictors and meteorological predictors are showing a weak relationship with the inter-annual yield variability.

For grain maize, results are shown to depend on agro-management

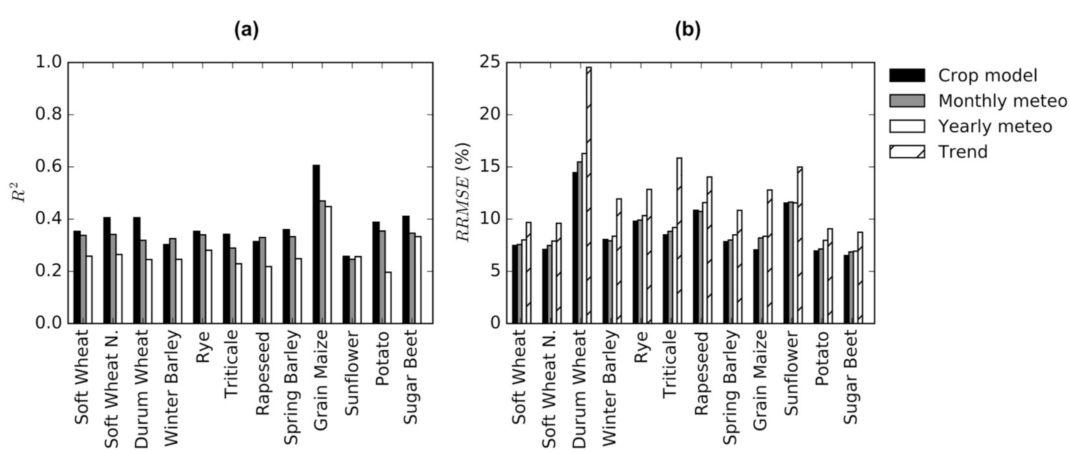

Fig. 1. (a) R^2 between crop yield residuals and the best predictors found for each MS during the crop cycle, and (b) *RRMSE* between the observed and estimated yields obtained using the best predictor for each crop, considering countries where yield statistics are available since 1988.

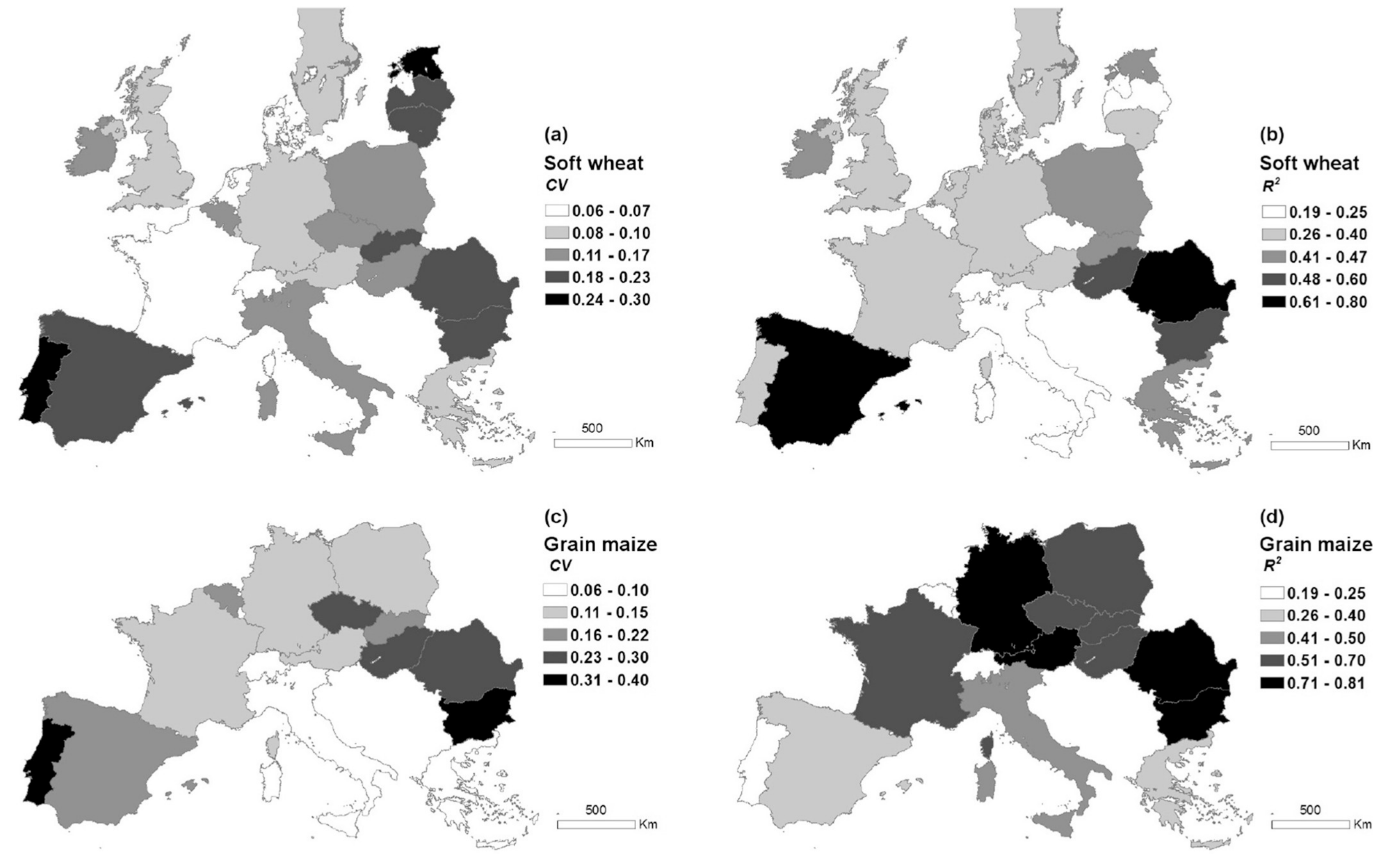

Fig. 3. Maps of the yield coefficient of variation of soft wheat and grain maize (a)(c) and R^2 between the yield residuals and the best crop model predictor identified during the growing season (b)(d).

practices, particularly irrigation (Fig. 3). In Spain, the low yield variability ($CV = 0.18$) is not well reproduced ($R^2 = 0.31$) and 99% of the maize cultivated area is irrigated. In Bulgaria, where grain maize is not irrigated and the yield variability is high ($CV = 0.38$), the WLB reproduces 81% of the yield variability. Except for Portugal, Spain, Greece, Italy and Belgium, the crop model predictors are explaining > 60% of the yield variability.

3.3. Timings of predictors and processes explaining yield variability

3.3.1. Grain maize

Except for countries where maize is predominantly irrigated as cited previously, most of the yield variability is explained by the WLB, from the dekad following anthesis until maturity, while during the early vegetative growth, before anthesis, soil moisture already allows to anticipate part of the yield variability (Fig. 4). WLAI around anthesis shows also to be a consistent predictor for a large part of the countries analyzed, before WLB becomes the best predictor. Two months before harvest (8 dekads), around the 10 August, the model delivers already some reliable estimates of the yield residuals. This result was underlined previously for Hungary and can here be extended to countries where maize is predominantly not irrigated (Bussay et al., 2015).

The results obtained with the meteorological predictors are following the one obtained with the crop model predictors, with, despite a lower correlation for all the countries analyzed, a large part of the yield variability explained around 31 July (Fig. 5). CWB is found to be the predictor providing the best estimates of the yield variability around anthesis, while later in August, a negative correlation with Tavg is observed. It is not clear if CWB is correlated to Tavg for these specific dekads and those predictors are collinear and water stress is the main limiting factor, or if temperature intervenes as another limiting factor of grain maize yield. Heat stress has been identified as one of the main drivers of grain maize yield variability in the United States (Lobell et al., 2013; Singletary et al., 1994; Wilhelm et al., 1999).

Compared to the monthly meteorological predictors, the crop model simulations have the advantage of preserving the relationships found around anthesis up to the end of the growing season, while the meteorological predictor are explaining the yield variability only around anthesis (Fig. 6). Considering the heterogenity of phenological stages around Europe, the crop model simulations tend to homogeneize the information used to forecast the yield.

3.3.2. Soft wheat

For soft wheat, the analysis is conducted considering the newest calibration (Soft Wheat N.) with simulations starting at sowing, described in Ceglar et al. (this Virtual Special Issue), as it explains a larger part of the yield variability than the simulations starting on the 1st of January.

The crop model predictors are slightly better related to the yield statistics than the monthly meteorological predictors, and in most cases, the reliability of the predictors improves toward the end of the growing season (Fig. 7). The meteorological variables explaining the yield variability are temporally scattered, depending on the phenology in each country, and contrarily to grain maize, there is no general improvement of those predictors at a specific development stage.

For Spain, the yield variability can be anticipated, first with SM in April, next in May with WLAI and finally with the WLB mid-June (Fig. 8). Water stress appears clearly as the main process explaining the yield variability considering the CWB is positively related to the yield (Fig. 8). A highly significant relationship (***p value < 0.001) between yield residuals and WLB is also observed for Bulgaria, Romania, Hungary, Poland, Greece and Estonia, from the first dekad of June

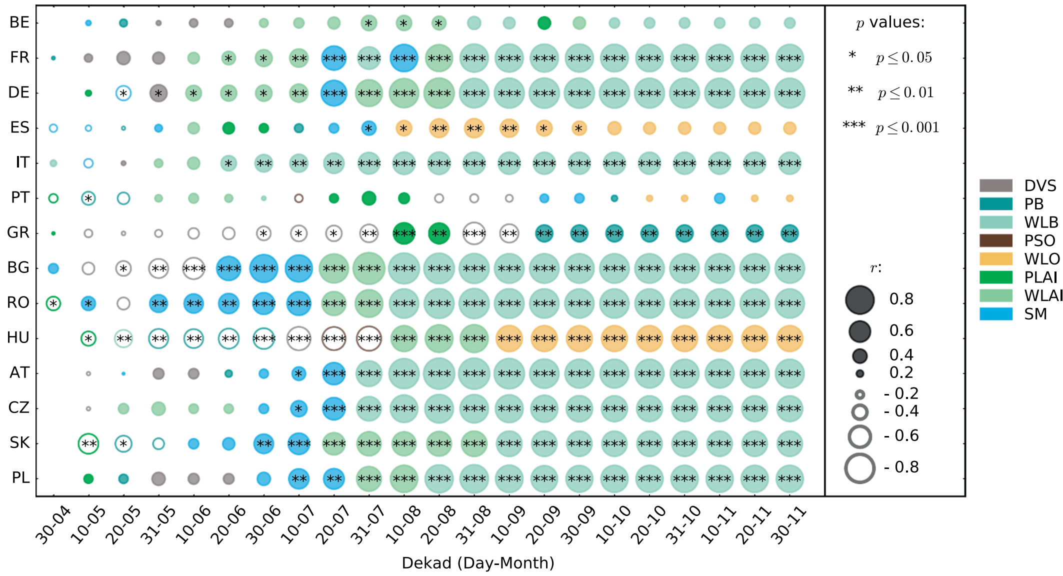

Fig. 4. Evolution of the correlation between grain maize yield residuals and the best crop model predictor found per dekad, from sowing to maturity, for the MS of the EU-28 providing yield statistics since 1988.

onward, 20 to 30 days before harvest (Fig. 8). For the aforementioned countries, the improvement of the WLB is associated to a negative relationship between Tavg and the yield residuals emphasizing the impact of warm temperatures on the yield (Fig. 9). This result shows that the reduction factor applied on the maximum leaf CO_2 assimilation rate for suboptimal temperatures in WOFOST reproduces the impact of heat stress during the grain filling stage.

For the other countries, the crop model predictors are explaining < 43% of the yield variability and some predictors other than the biomass or storage organs stands out of the analysis. In north-western Europe (Ireland, United Kingdom, the Netherlands), a significant negative relationship with soil moisture is found, significant in Ireland (***$p \leq 0.001$), where it explains 42% of the yield variability the 20th of June, while in the United Kingdom and the Netherlands, this relationship is observed around the 20th of July with a lower significance (**$p \leq 0.01$). This negative relationship with soil moisture is associated to positive anomalies of cumulated rainfall (Fig. 9). In a study published by Landau et al. (1998), the storage organs simulated by different crop models failed to reproduce soft wheat yield in the UK while a relationship between the yield and cumulated rainfall was found using long field experiments (Chmielewski and Potts, 1995). In our analysis, soil moisture and cumulated rainfall are explaining the same amount of yield variability in the UK ($r = -0.55$ for cumulated rainfall and $r = -0.58$ for soil moisture).

For France, all the relationships are largely insignificant. As pointed by Gouache et al. (2015) and Ceglar et al. (2016) the predictors and processes responsible for the soft wheat yield variability are differing in-between regions and a regional analysis would be more relevant. Soft wheat in France is exposed to different climatic conditions and a large inter-annual variability, thus the heterogeneity of agro-meteorological processes explaining the yield variability cannot be synthetized in a single predictor at national scale. Some of the relationships found are not linear, such as the one found with the simulated soil moisture around the 10th of May, where an extremely high or low soil moisture

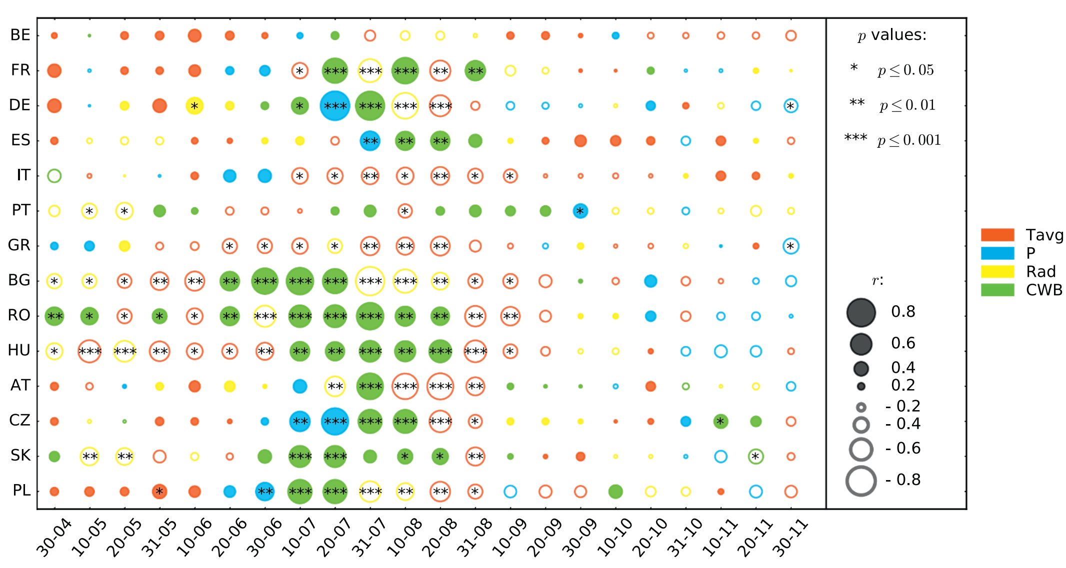

Fig. 5. Evolution of the correlation per dekad between grain maize yield residuals and the best monthly meteorological predictor found, from sowing to maturity, for the MS of the EU-28 providing yield statistics since 1988.

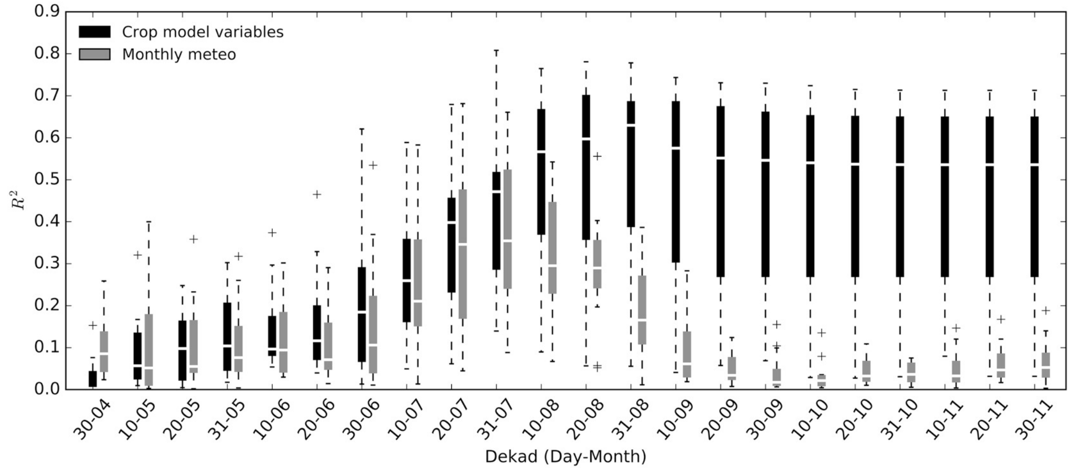

Fig. 6. Evolution of the distribution of the best relationship (R^2) found per dekad between the crop model predictors, the monthly meteorological variables and the yield residuals of grain maize, for the MS of the EU-28 providing yield statistics since 1988.

explains the yield losses (Fig. 10).

In Sweden, and less significantly Estonia and Lithuania, Tavgs in February and March is correlated to the yield residuals while from the crop model side, the DVS is positively correlated to the yield. In the literature, the negative yield anomalies are associated to long winters and short winters to positive anomalies (Enquist, 1929; Holmer, 2008). In Denmark, the DVS in March is also related to the final yield as well as SM in July and August, and despite the relationships being weak, those drivers were highlighted at field scale in the literature (Olesen et al., 2000). The impact of an earlier tillering stage on yield is emphasized by the DVS, but the simulated biomass and LAI do not reflect these beneficial conditions on crop growth.

4. Discussion

The WOFOST crop model simulations in the CGMS reproduce the yield variability induced by water stress and suboptimal temperatures using the simulated biomass and storage organs. Nevertheless, some other processes explaining the crop yield variability in Europe are clearly not simulated, more particularly those related to wet conditions as those are only highlighted by the simulated soil moisture. For winter cereals, the simulated biomass at anthesis, known to be related to the yield of winter cereals, fails to explain the yield variability. The second limitation of the crop model as implemented in the M-CYFS is the lack of consideration of agro-management practices, including the fertilization, irrigation and variety selection, which also importantly contribute to the yield formation.

4.1. Agro-meteorological processes

Crop yield losses induced by wet conditions are not reflected by the simulated biomass and soil moisture appears to be an appropriate proxy to estimate the yield variability in northwestern Europe. Several processes depending on water excess can explain the yield losses, which all have different timings and impacts depending on the development stage of the crop: Nitrogen losses through leaching and denitrification (Jamieson et al., 1999), lodging during the grain filling period (Fischer and Stapper, 1987), diseases such as yellow spot toward the end of the season or fusarium head blight at anthesis (De Wolf et al., 2003; Rees and Platz, 1983; Thomas et al., 1989), waterlogging diminishing the plant density before tillering (Cannell et al., 1980).

The complexity of the aforementioned processes explaining crop yield, with heterogeneous timings and impacts depending on the phenological stages makes that an indicator focusing on the pre-anthesis period will only partly explain yield variability (Siebert et al., 2017; Zampieri et al., 2017). Some of these processes depend on the soil and their capacity to drain the excess of water, thus soil data as well as the soil water model would need to be improved. Diseases would need to be considered, but their impacts depend on the varieties used, the fungicides sprayed, the crop rotations and the management of residues, making it a complex process to model, particularly at large scale given the limited data available (Champeil et al., 2004; Maiorano et al., 2008).

Another weakness of the crop model simulations is highlighted when analyzing the predictors for soft wheat, where the simulated

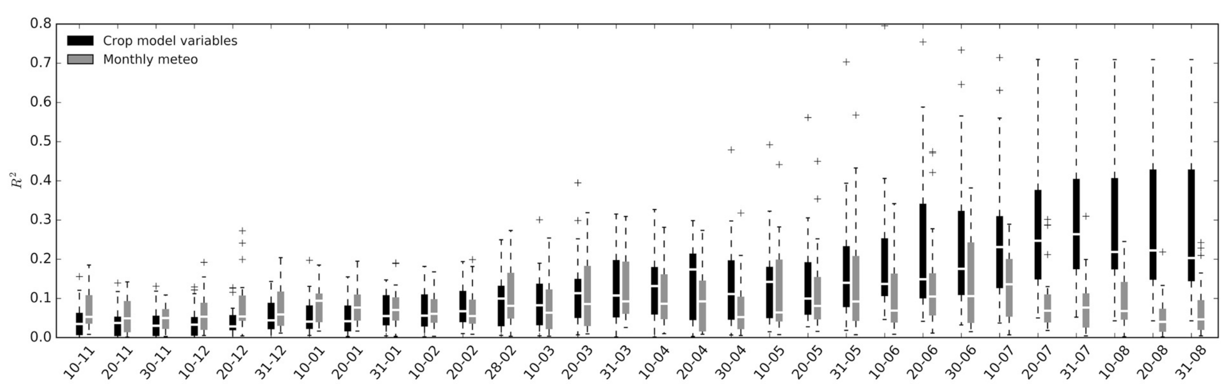

Fig. 7. Evolution of the distribution of the best relationship (R^2) found per dekad between the crop model predictors, the monthly meteorological variables and the yield residuals of soft wheat, for the MS of the EU-28 providing yield statistics since 1988.

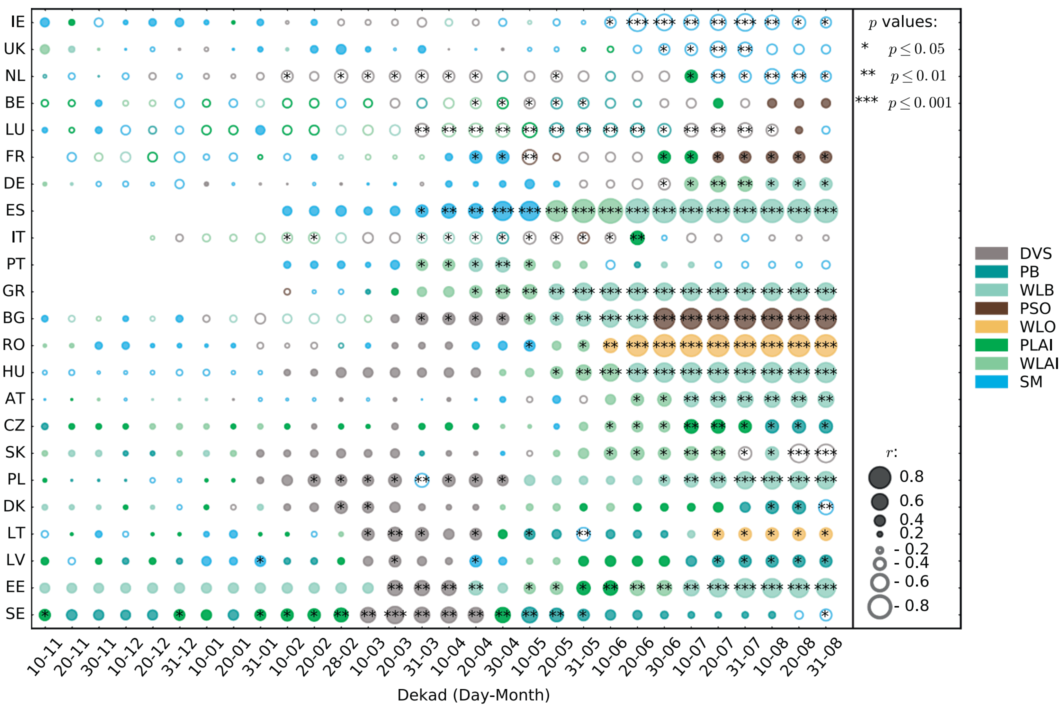

Fig. 8. Evolution of the correlation between soft wheat yield residuals and the best crop model predictor found per dekad, from sowing to maturity, for the MS of the EU-28 providing yield statistics since 1988.

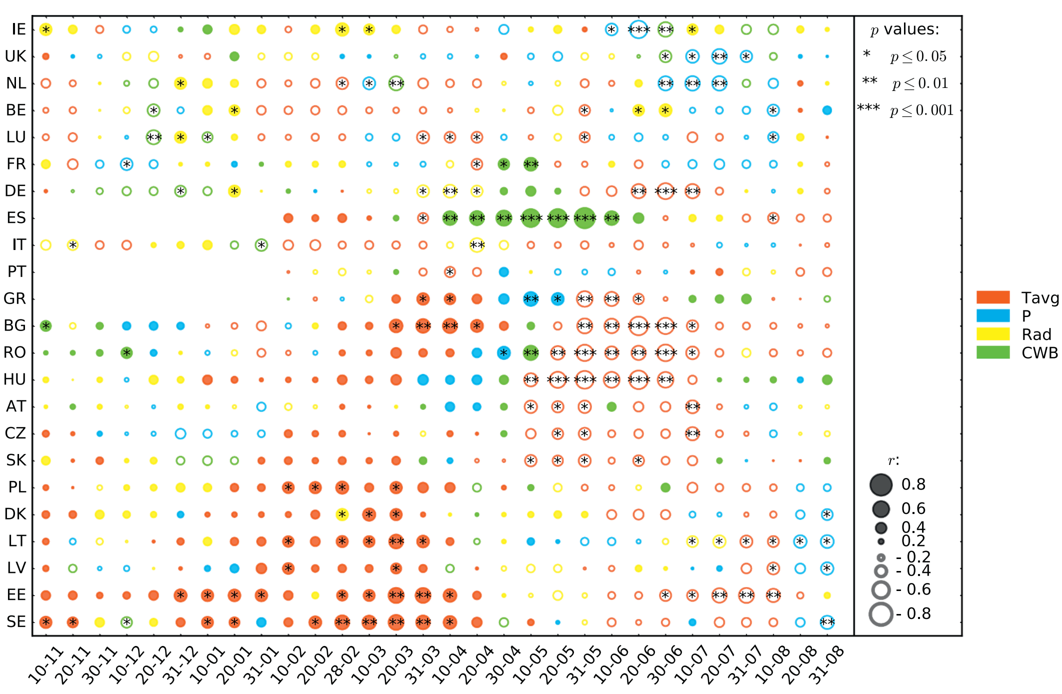

Fig. 9. Evolution of the correlation between soft wheat yield residuals and the best monthly meteorological predictor found per dekad, for the MS of the EU-28 providing yield statistics since 1988.

storage organs weight, which theoretically should be highly correlated to the yield, is rarely the best predictor explaining its variability, leading us to question the simple partitioning approach of WOFOST. The insignificant relationship observed between the simulated biomass at anthesis and the yield would tend to demonstrate that the harvest index of winter cereals depends predominantly on meteorological conditions within a short number of days around anthesis (Unkovich et al., 2010) and during the grain filling stage. It has been demonstrated that simulating a few specific processes around the flowering stage, such as the impact of heat stress, slightly improves the yield forecast done using the CGMS simulations for soft wheat (Pagani et al., 2017). Nevertheless, the biomass simulated at anthesis is used in several crop models to estimate the kernel number of winter cereals like CERES-Wheat (Ritchie and Otter, 1985), AFRCWHEAT2 (Porter, 1993), STICS (Brisson et al., 1998). In the literature, wheat yield is found to be strongly related to the kernel number rather than the weight of the

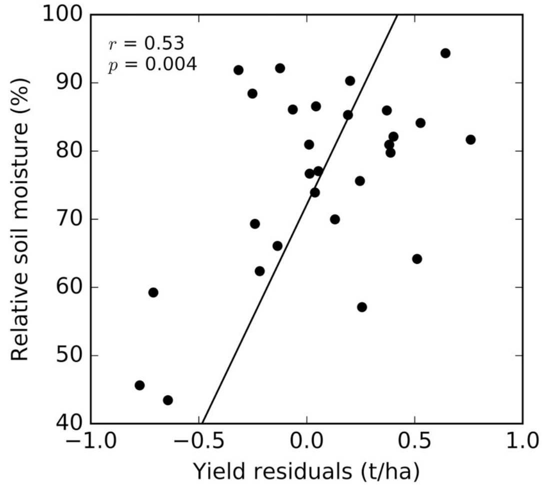

Fig. 10. Relationship between the yield residuals of soft wheat and the simulated relative soil moisture in France for dekad 13 (10 May).

grains, as reported by Frederick and Bauer (1999) who demonstrate that soft red winter wheat yield is largely related to the kernel numbers ($R^2 = 0.84$) rather than individual kernel weight ($R^2 = 0.48$). Agro-meteorological conditions one month prior to anthesis, during the vegetative stage and the spike weight have been shown to be related to the kernel number and yield (Abbate et al., 1997; Fischer, 1993; Fischer, 1975; Frederick and Bauer, 1999; González et al., 2005; Midmore et al., 1984; Savin and Slafer, 1991; Sayre et al., 1997; Sinclair and Jamieson, 2006). A deeper analysis should be conducted to determine why the biomass simulated at anthesis in the CGMS is not well related to the yield of winter cereals and another approach, considering the processes determining the kernel number, might improve the results obtained.

4.2. Agro-management practices

The lack of consideration of agro-management practices is clearly shown to be a limitation. Irrigation is driving yields of grain maize in Mediterranean areas and including it in crop simulations, assuming relevant data are available on a yearly basis, could improve the forecast. Some improvements could also be foreseen by including fertilizers, more particularly nitrogen as it impacts the inter-annual yield variability while phosphorus and potassium are more determinant on the long term (Girma et al., 2007). Nitrogen has been shown to be related to the kernel number of winter cereals, which could also improve the yield simulated (Ratjen et al., 2012). Variability in sowing dates are also explaining part of the crop yield variability, but are not included in the CGMS while it exposes the crops to water stress or heat stress later during the growing season (Bindi and Olesen, 2011). The evolution of varieties and its diversification over years is not considered either, while the new varieties tend to have a higher resistance to diseases, different responses to nitrogen and different phenology.

The lack of input data at large scale, already limiting the calibration of the crop model parameters, should be deplored and is challenging for the future development of the M-CYFS.

4.3. Statistical approach

The statistical method used does not give a complete picture of the M-CYFS ability to forecast yield and a multiple regression method with a selection of the input variables would improve the yield estimates (Sharif et al., 2017). Nevertheless, the strength of this simple analysis using a linear regression is to highlight the weakness of the crop model. Another way to tackle some of the deficiencies found in the crop model would be to use an ensemble of crop models, as done within the Agmip initiative, which may allow to explain a larger part of the yield variability (Palosuo et al., 2011; Rosenzweig et al., 2013; Rötter et al., 2012). Downscaling the analysis at regional scale (see *e.g.*Ceglar et al., 2016; Gouache et al., 2015) and extending the period of analysis could also improve the characterization of the yield variability, more particularly for large heterogeneous countries such as France and Germany, where the current predictors are not allowing to reproduce the yield variability at national scale.

5. Conclusion

The WOFOST crop model, as implemented in the M-CYFS, reproduces relatively well the yield of crops exposed to drought or positive thermal anomalies during the grain filling stage. Compared to the meteorological predictors, the crop model predictors tend to better reproduce crop yield variability and harmonize spatially and temporally the information, the meteorological predictors being dependent on the country analyzes and the phenological stages. The crop model simulations suffer from the lack of consideration of agro-management practices and impacts of processes induced by humid weather conditions. Despite the simplicity of the statistical method used, the main agro-meteorological conditions responsible of crop yield variability in Europe can be identified as well as the main weaknesses of the crop model.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2018.03.002.

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