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Using reanalysis in crop monitoring and forecasting systems

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ABSTRACT

Weather observations are essential for crop monitoring and forecasting but they are not always available and in some cases they have limited spatial representativeness. Thus, reanalyses represent an alternative source of information to be explored. In this study, we assess the feasibility of reanalysis-based crop monitoring and forecasting by using the system developed and maintained by the European Commission- Joint Research Centre, its gridded daily meteorological observations, the biased-corrected reanalysis AgMERRA and the ERA-Interim reanalysis. We focus on Europe and on two crops, wheat and maize, in the period 1980–2010 under potential and water-limited conditions.

In terms of inter-annual yield correlation at the country scale, the reanalysis-driven systems show a very good performance for both wheat and maize (with correlation values higher than 0.6 in almost all EU28 countries) when compared to the observations-driven system. However, significant yield biases affect both crops. All simulations show similar correlations with respect to the FAO reported yield time series.

These findings support the integration of reanalyses in current crop monitoring and forecasting systems and point to the emerging opportunities linked to the coming availability of higher-resolution reanalysis updated at near real time.

1. Introduction

Weather and climate are among the main drivers of variability in agricultural production. Climate extremes, which intensity and frequency are projected to increase (e.g. Russo et al., 2014; Toreti et al., 2013a), can have serious consequences on crop production, security and safety. Extremes can affect food availability, quality and accessibility and trigger market instabilities, thus inducing impacts on local, regional and potentially global economy (IPCC, 2014; Schmidhuber and Tubiello, 2007). Crop monitoring and forecasting systems can become an essential climate service tool for end-users at different levels, from farmers to policy makers. For instance, they can be used to implement technical mitigation measures and to prevent agricultural market instabilities and reduce price volatility (Challinor, 2009).

Crop monitoring and forecasting systems heavily rely on observed daily meteorological data (e.g. Baruth et al., 2007) that influence crop development and then final yield (e.g. Delincé, 2017; Zampieri et al., 2017; Ceglar et al., 2016). The primary source of meteorological observations is represented by weather stations measuring the main meteorological parameters at regular time intervals, e.g.: 2-meter air temperature, cumulated precipitation, solar radiation, wind and relative humidity. The availability of such data, especially with near-real-time updates, strongly depends on the region of interest. While in regions such as Europe data are often available and retrievable with daily updates, strong limitations often characterise other regions of the world. Nevertheless, even in regions such as Europe, there are issues linked to the density of weather observations and their representativeness of local weather conditions. The density of observations is a crucial factor for meteorological parameters like precipitation, characterised by shorter spatial decorrelation scale (e.g. Gervais et al., 2014; Hofstra and New, 2009). Furthermore, the meteorological time series of observations are usually affected by inhomogeneities caused by non-

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climatic factors such as station relocations, changes of instruments, etc. (e.g. Toreti et al., 2010a and references therein).

Besides observations, other products combining different sources of information have been developed in the last decades. For instance, reanalyses have become an essential tool in climate and climate-impact related sciences (e.g. Ceglar et al., 2017a, 2017b; Toreti et al., 2013b; Toreti et al., 2010b). Reanalyses combine observations from different sources (e.g. weather stations, satellites) and numerical models through data assimilation (Kalnay, 2012) to provide a representation, as reliable as possible, of past and current weather conditions at the global scale. The spatial resolution of these products varies, e.g. ~55 km for JRA55 (Kobayashi et al., 2015) and 80 km for ERA-Interim (ERA-I; Dee et al., 2011), and their quality is regional and parameter dependent (e.g. Ceglar et al., 2017a, 2017b). Some reanalyses focus on longer time scales, e.g. since 1900 (ERA-20C; Poli et al., 2016) and since 1871 (2OCR; Compo et al., 2011), while others cover the last decades (e.g. ERA-Interim, JRA-55) and offer higher spatial resolution. Moreover, some of these reanalyses have been bias-corrected to get closer to observations, e.g. ERA-Interim Land (Balsamo et al., 2015), JRA-55 (Iizumi et al., 2017), and AgMERRA (based on NASA Modern Era Retrospective-analysis for Research and Applications; Ruane et al., 2015 and Rienecker et al., 2011). It is worth to mention that the last one has been specifically developed to investigate the impact of past climate on agricultural productions in the framework of the Agricultural Model Intercomparison and Improvement Project (AgMIP; Rosenzweig et al., 2013) and it has been already used in several gridded crop model exercises (e.g. Müller et al., 2017; Schauberger et al., 2017).

Reanalyses could offer a valid alternative to observations in regions of the world with sparse data and/or limited accessibility and/or unavailability of daily updates. Even in regions such as Europe, these products could bring added value for crop monitoring systems; for instance, in terms of reliability and weather representation in areas affected by lower station density and/or temporal gaps. As for maize in the U.S., Glotter et al. (2016) explored the sensitivity of a crop model on the driving climate data by mainly comparing simulations based on observations, reanalysis and bias-corrected reanalysis. The use of older reanalyses, such as ERA-40 and JRA-25, was also investigated by Challinor et al. (2005) and Iizumi et al. (2013), respectively.

This study explores the feasibility of a crop monitoring system driven by climate reanalysis over Europe, a data-rich region that makes possible the comparison with high quality meteorological observations. This evaluation is timely as new reanalyses having higher spatial resolution will be made available in the coming years.

2. Data and methods

In the following sub-sections we shortly introduce the crop yield forecasting system on which this study is focused on, describe the meteorological data here used, the two case studies and the associated simulation settings.

2.1. Crop yield monitoring and forecasting system

The MARS Crop Yield Forecasting System (MCYFS) of the European Commission-Joint Research Centre is used to monitor the weather conditions, the crop growth and development, and to provide monthly crop yield forecasts for all countries of the European Union (EU28) as well as neighbouring regions. The system is based on five components (Baruth et al., 2007; Genovese and Bettio, 2004): observed weather data and forecasts, remote sensing data, crop growth model simulations, statistical models, expert evaluation and expert-driven risk-assessment. Here, we focus on the meteorological component and the one based on crop growth model simulations (the Crop Growth Monitoring System-CGMS; Supit and Van der Goot, 2003).

2.2. Weather observations and reanalysis

The weather monitoring component of the MCYFS (Van der Goot et al., 2004) is currently based on daily collection of data coming from approx. 4000 weather stations in Europe (Fig. S1 in the Supplementary material) interpolated on a regular grid with a resolution of 25 km (hereafter MarsMet). Archived meteorological data start in 1975 and are updated in near-real-time. To evaluate the feasibility of the same system driven by reanalysis, AgMERRA (Ruane et al., 2015) is here used. As mentioned in the previous section, this reanalysis offers at 0.25 degree resolution: bias-corrected daily temperatures with respect to CRU (Harris et al., 2013) and WM (Willmott and Matsuura, 1995) gridded observations; bias-corrected daily cumulated precipitation with respect to CRU, WM, GPCC (Schneider et al., 2011) gridded observations and satellite data (see Ruane et al., 2015 for more details); radiation data from satellite observations, modelled wind and relative humidity. Since AgMERRA is bias-corrected with global observational datasets, a raw reanalysis is also tested as benchmark: ERA-I (Dee et al., 2011). It is worth to note that an earlier version of the MCYFS driven by this reanalysis was tested for a limited number of years by de Wit et al. (2010).

AgMERRA covers the period 1980–2010; thus, all the analyses are here based on these 31 years. An assessment of the main differences between AgMERRA and MarsMet is performed at the grid level by analysing seasonal/monthly mean temperatures and cumulated precipitation, cumulated radiation in the period April to July, the monthly Standardised Precipitation-Evapotranspiration Index (SPEI-1;Vicente-Serrano et al., 2010), events with daily maximum temperatures above 31 °C (TX31). The significance of the seasonal differences is assessed by applying a Welch test, the spatial representation of AgMERRA-based monthly SPEI-1, cumulated precipitation and mean temperature is compared to the one of MarsMet by using a reference-varying Taylor diagram (Taylor, 2001). While, the TX31 events are evaluated by using the Fractions Skill Score (FSS; Roberts and Lean, 2008) at several different spatial scales. Although this comparison of AgMERRA and MarsMet is partial, it provides a very good overview of the main differences in the key parameters. As ERA-I is here used as a benchmark and considering that it has been extensively evaluated over Europe (e.g. Lavaysse et al., 2018; Cornes and Jones, 2013; Belo-Pereira et al., 2011, Trager-Chatterjee et al., 2010), the meteorological analysis is restricted to AgMERRA.

2.3. Crop growth simulations and yield data

As case studies, two among the most important staple crops in the world are selected: winter wheat and grain maize. In the EU28, winter wheat is the most important crop with a cultivated area of more than 24 Mha and 152 Mt. of production, while grain maize is the third most important crop (after barley) with a cultivated area of 9 Mha, and 59 Mt. of production (EUROSTAT 2015, http://ec.europa.eu/eurostat). In this study, MarsMet, AgMERRA and ERA-I daily data are used to feed the crop growth model of CGMS: WOFOST (Boogaard et al., 2014 and references therein). The growth and eventually the yield of wheat and maize are simulated for the entire European region from 1980 to 2010. The reanalysis-driven and the observation-driven simulations share the same standard crop parameters (Boons-Prins et al., 1993; Van Heemst, 1988), soil, and crop sowing calendars settings used in the CGMS. The soil data of the Soil Geographic Database of Europe (v4.0) is used in the CGMS. This soil database contains a list of soil typological units (STUs) described by attributes and grouped into soil mapping units (SMUs). STUs include information about the soil chemo-physical properties such as soil depth (defining the potential rooting depth), wilting point, field capacity, saturation, salinity and alkalinity (Baruth et al., 2006; Lazar and Genovese, 2004). At the grid level, WOFOST simulations are run primarily on each suitable STU of each SMU, then the outputs are aggregated by weighting according to the share of the SMU in the grid cell considered.

Here, the two crops are simulated under potential and water limited conditions (van Ittersum et al., 2003). The final yields are then evaluated by using the CGMS aggregation schemes and the Nomenclature of Territorial Units for Statistics (NUTS) classification. The NUTS classification divides the territory of the European Union (EU28) in several levels of spatial aggregation for statistical analysis of socio-economic relevance. At the NUTS3 level (i.e. district), the CGMS aggregation scheme is based on agricultural land; while at the NUTS0 level (i.e. country), it is based on reported yield statistics by the EU28 countries. Two measures are used for the evaluation: Spearman correlation and mean difference, with the significance being assessed by the Welch test.

Furthermore, simulated crop yields are evaluated w.r.t. the EU-28 crop yield statistics recorded by FAO (www.fao.org/faostat) from 1980 to 2010. Since the FAO-time series are in most cases affected by significant trend (mainly caused by technological development, improved agro-management practices, etc.), a detrending procedure based on LOESS (Cleveland and Devlin, 1988) is applied before testing the simulated crop yield series. The same detrending is applied to the simulated yield time series exhibiting significant non-stationarities.

3. Results and discussion

3.1. A comparison of AgMERRA and MarsMet

At the seasonal scale (by using the standard meteorological seasons), AgMERRA reproduces reasonably well mean temperatures w.r.t. MarsMet and significant differences are mainly detected in the Mediterranean region (Fig. S2 in the Supplementary material). As for precipitation cumulated at the seasonal scale, some significant differences can only be observed in mountainous regions (Fig. S3 in the Supplementary material), where weather stations are sparse and have less spatial representativeness. As for the cumulated radiation (from April to July), Fig. 1 shows significant differences detected in southern Spain, Italy, eastern and south-eastern Europe with lower cumulated radiation provided by AgMERRA w.r.t. MarsMet (especially in July).

At the monthy time scale, the spatial pattern of mean temperature is very well reproduced by AgMERRA (Fig. 2) in all four seasons. In summer, the performance slightly degrades but still remains very good (i.e. with correlations higher than 0.9). Concerning monthly cumulated precipitation, AgMERRA achieves good performance although not comparable (as expected) with the one of temperature (Fig. 2). In all seasons, there is a higher variability in the spatial correlation with the

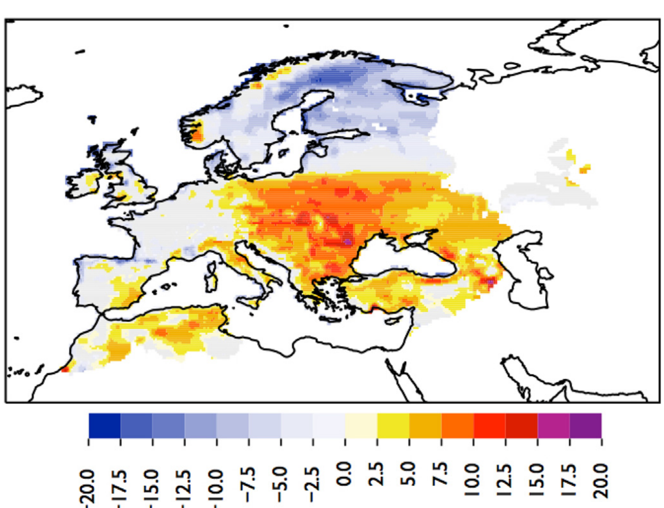

Fig. 1. Differences in cumulated (from April to July) radiation (%) in MarsMet and AgMERRA. Significant grid-values (at 95% level) are shown according to the colour scale. Grey denotes grid-points with non-significant differences.

observations. Furthermore, some winter and autumn months show a very pronounced spatial variability w.r.t. the observed pattern (Fig. 2). However, these are less important in determining the final yields.

As for the SPEI-1 analysis, Fig. 3 shows the relatively good agreement of AgMERRA and MarsMet with spatial correlations centred around 0.8 and root mean squared error between 0.5 and 1.

Concerning the TX31 events, four spatial scales are here analysed: 0.25, 0.5, 1 and 2 degrees. These values represent the spatial tolerance allowed in comparing the events reproduced by AgMERRA to the ones given by MarsMet. As the FSS is equal to 1 only when the events are perfectly reproduced (within the given spatial tolerance), Fig. 4 shows the very good agreement of AgMERRA and MarsMet with FSS values above 0.8 already at the 0.25 degree scale. The better results at higher spatial scales are expected as an effect of the increased tolerance.

3.2. Wheat

Overall, the simulated AgMERRA driven and MarsMet driven wheat yields are very well correlated in almost all regions (NUTS3) for both the potential and water-limited simulations (Fig. 5). 16 and 17 countries (potential and water-limited simulations, respectively) out of 34 show no regions with no-significant correlation; and only 9 and 5, respectively, show a percentage of regions with no-significant correlations above 15%. However, there are some countries having a relatively high percentage of no-significant regions. For instance, 38% and 21% of the Austrian regions do not show significant correlations between AgMERRA-driven and MarsMet driven water-limited and potential simulated yields, respectively (Fig. 5). These results are spatially homogeneous (with very limited spatial variability) in countries such as Belarus, Denmark, Latvia, Lithuania and the Netherlands (Fig. 5). While, higher spatial differences can be observed in countries such as Italy (in the potential yield simulations) and Romania (for water-limited simulations). The ERA-I driven simulations are also well correlated with the MarsMet driven yield simulations for both potential and water-limited conditions (Fig. S4 in the Supplementary material).

Considering mean yield differences, in many countries a very high percentage of regions does not show any significant difference between the values obtained by driving the crop model with AgMERRA and the ones obtained by using MarsMet (Fig. 6). This holds, for instance, in the Netherlands under potential conditions where 92% of the regions (40 NUTS3 regions) achieves similar (in statistical terms) yields using AgMERRA and MarsMet (Fig. 6). Overall, Fig. 6 points to more favourable conditions for yields given by AgMERRA, and higher mean yields in the regions where there are significant differences. This holds both under potential and water-limited conditions.

Concerning ERA-I driven simulations, the first countries in terms of production have more regions showing significant mean differences in yield especially under water-limited conditions (Fig. S5 in the Supplementary material). Similarly to AgMERRA, more favourable conditions are given by ERA-I, with generally higher mean yield in both potential and water limited conditions (Fig. S5 in the Supplementary material).

At NUTS0 in the EU28 countries, the water-limited simulations driven by AgMERRA show very high correlation with the ones driven by MarsMet. Estimated values are above 0.8 in western, central and north-eastern Europe as well as in Hungary and Romania, and between 0.6 and 0.8 elsewhere (Fig. 7). The only exception is Croatia with a significant estimated correlation value between the AgMERRA and MarsMet driven simulations equal to 0.46 (Fig. 7). In the potential yield simulations, correlation decreases (remaining above 0.6) in France, Italy, Slovenia, Spain, and Romania (Fig. 7). The lowest correlations are observed in Croatia and Greece (0.38 and 0.59, respectively). The differences between AgMERRA and MarsMet driven yields are not significant in most of the countries under both potential and water-limited conditions (Fig. S9 in the Supplementary material). As for the potential conditions, AgMERRA induces higher mean yields in Spain and Greece

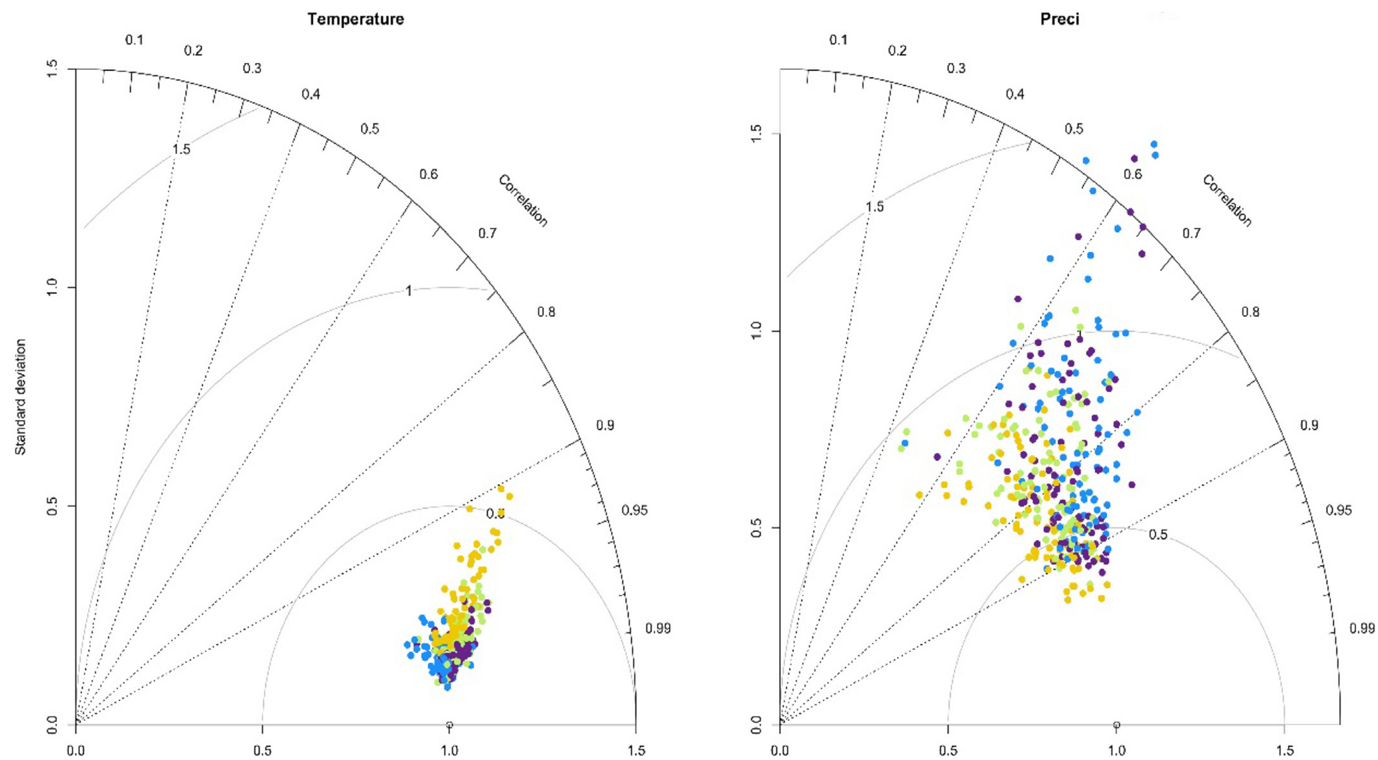

Fig. 2. Taylor diagram of the monthly mean temperature (left panel) and cumulated precipitation (right panel) derived from AgMERRA with respect to MarsMet, here used as time-varying reference in the period 1980–2010. Each point in the diagram reports the comparison of the AgMERRA monthly variables in a specific month with the MarsMet variables of the same month. Colours are associated with the four meteorological seasons. Blue, green, yellow and violet represent, respectively, winter, spring, summer and autumn. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

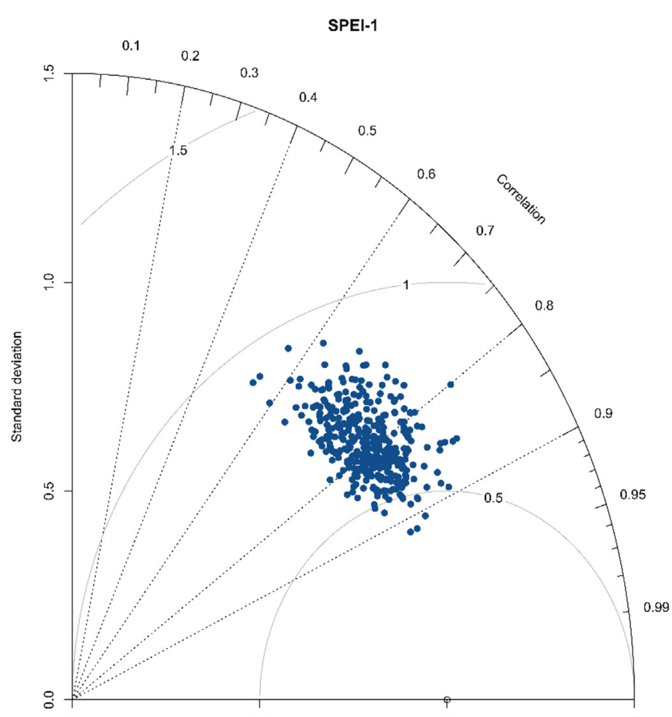

Fig. 3. Taylor diagram of the SPEI-1 derived from AgMERRA with respect to the MarsMet SPEI-1, here used as time-varying reference in the period 1980–2010. Each point in the diagram reports the comparison of AgMERRA SPEI-1 in a specific month with MarsMet SPEI-1 of the same month.

with mean differences not exceeding 0.6 t ha^{-1}. It results in lower mean yield in Austria, Hungary, Slovakia, the Czech Republic, Poland and Sweden with mean differences not exceeding 0.8 t ha^{-1}. In the water-limited simulations significant differences are identified only in 5 countries out of 28, all showing higher mean yield when driven by AgMERRA, especially in Spain, Luxembourg and Slovakia (Fig. S6 in the Supplementary material).

ERA-I driven simulations are also very well correlated with the MarsMet-driven ones for both potential and water-limited conditions (Fig. S7 in the Supplementary material). In terms of mean differences, the ERA-I driven water-limited simulations are not statistically different from the MarsMet-driven ones, except in Greece and Bulgaria (Fig. S8 in the Supplementary material). While, they are significantly higher (w.r.t. the Mars-Met mean yield values) in western, central and south-eastern Europe (Fig. S8 in the Supplementary material).

When compared to the FAO reported yield values, the AgMERRA driven simulations in the EU28 countries perform reasonably well (w.r.t. the MarsMet driven simulations), except for Germany, Denmark, Austria, Slovakia and the Czech Republic (Fig. 8). While, AgMERRA outperforms MarsMet in Poland, Lithuania and Latvia. ERA-Interim also performs well when compared to MarsMet in reproducing the FAO reported yield time series, except for Germany, Denmark and Greece. Moreover, it is characterised by (weak) significant correlations also in Ireland, the Netherlands and Lithuania (Fig. S9 in the Supplementary material).

3.3. Maize

The results for maize yield simulations are very similar to the wheat ones. At NUTS3 level, correlations between AgMERRA and MarsMet driven simulations are good in almost all countries for both potential and water-limited conditions (Fig. 9). 11 and 15 countries (for potential

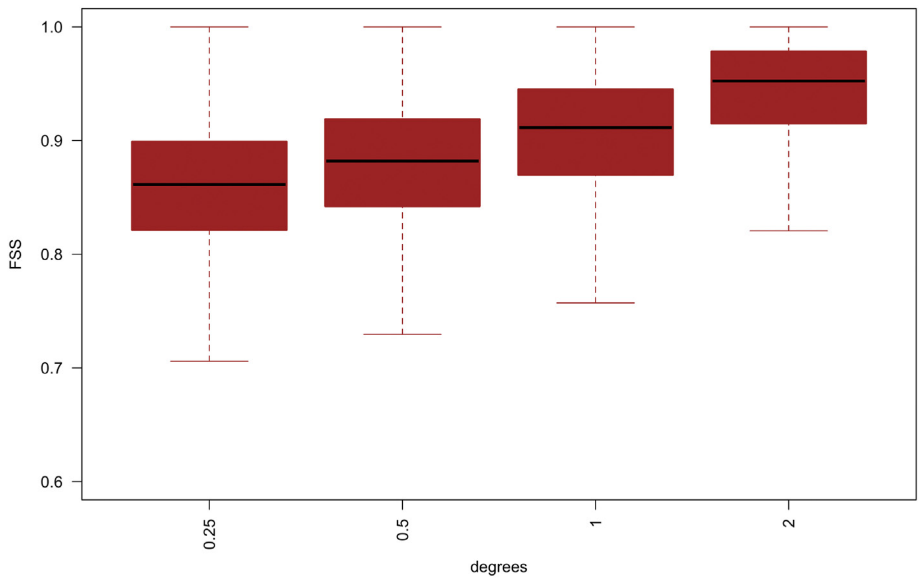

Fig. 4. FSS at four different spatial scales of TX31 events as reproduced by AgMERRA and compared with the one given by MarsMet in the period 1980–2010.

and water-limited simulations respectively) show no regions with no significant correlation, and only 10 and 4 countries showing regions with more than 15% of regions with no significant correlation. In a few countries, there is also a very high spatial homogeneity in the estimated correlation (e.g., the Netherlands and Lithuania under potential conditions; Fig. 9). Whereas, there are other countries having a relatively high percentage of regions showing no-significant correlations, e.g., Slovenia (36%, potential conditions; Fig. 9) and Austria (30% for both potential and water-limited conditions; Fig. 9).

ERA-I driven simulations are also very well correlated with the MarsMet ones (Fig. S10 in the Supplementary material).

Concerning the mean yield differences, Fig. 10 shows a different behaviour under potential and water-limited conditions. As for the potential simulations, AgMERRA driven simulations achieve lower mean yield in most of the countries with respect to the MarsMet simulations. Conversely, higher mean yields result for the AgMERRA-driven simulations under water-limited conditions (Fig. 10). Under both settings (potential and water-limited), many countries show a high percentage of regions having no significant differences between the AgMERRA and the MarsMet driven simulations, e.g., in the Netherlands (98%, potential conditions; Fig. 10) and Germany (68%, water-limited conditions; Fig. 10).

Concerning ERA-I driven simulations, there is an overall positive bias under potential conditions, although a high percentage of regions does not show any significant difference (Fig. S11 in the Supplementary material). While, the water-limited simulations show a more heterogeneous behaviour without a clear common tendency (Fig. S11 in the Supplementary material).

At NUTS0 level in the EU28 countries, the correlation between the AgMERRA and the MarsMet driven simulations is very high under both potential and water limited conditions (Fig. 11). In the water limited simulations, values are above 0.8 in western, central and south-eastern Europe; while they range between 0.6 and 0.8 in eastern Europe (Fig. 11). In the potential simulations, they are above 0.8 except for:

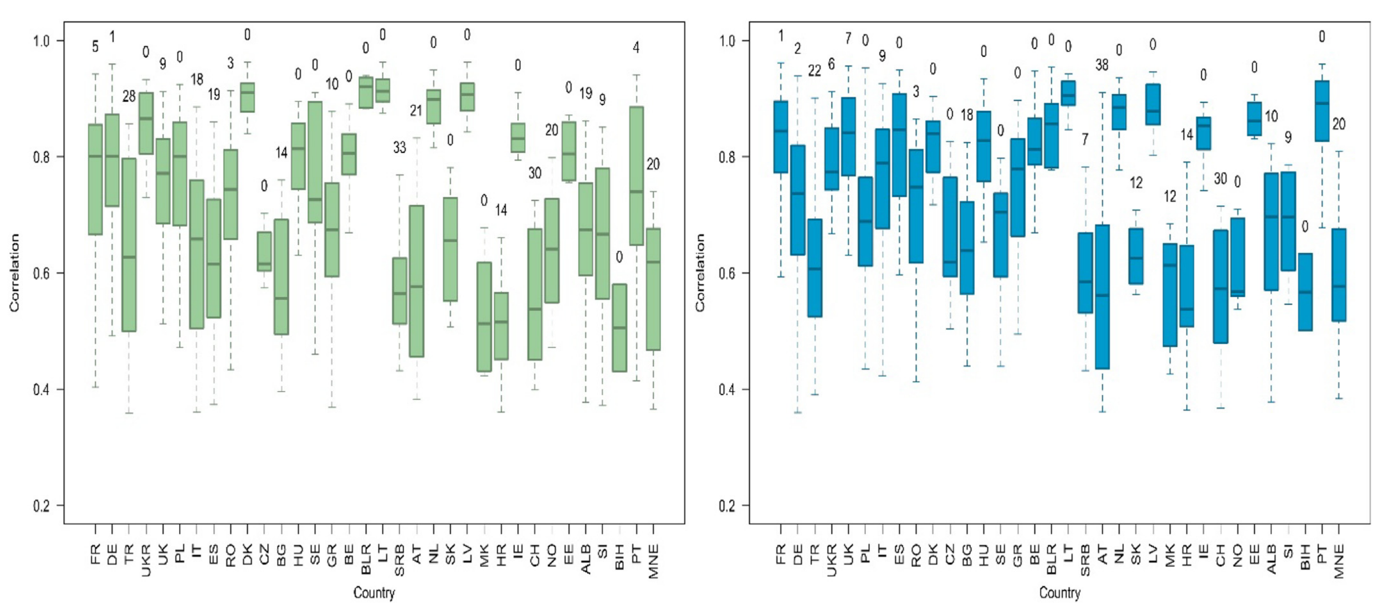

Fig. 5. Estimated significant (at 95% level) correlation between wheat yield at NUTS3 level simulated by using AgMERRA and MarsMet under potential (left panel) and water-limited (right panel) conditions. The numbers above each boxplot show the percentage of regions having no-significant correlation. Countries are ranked according to the reported production in 2010 (FAOSTAT).

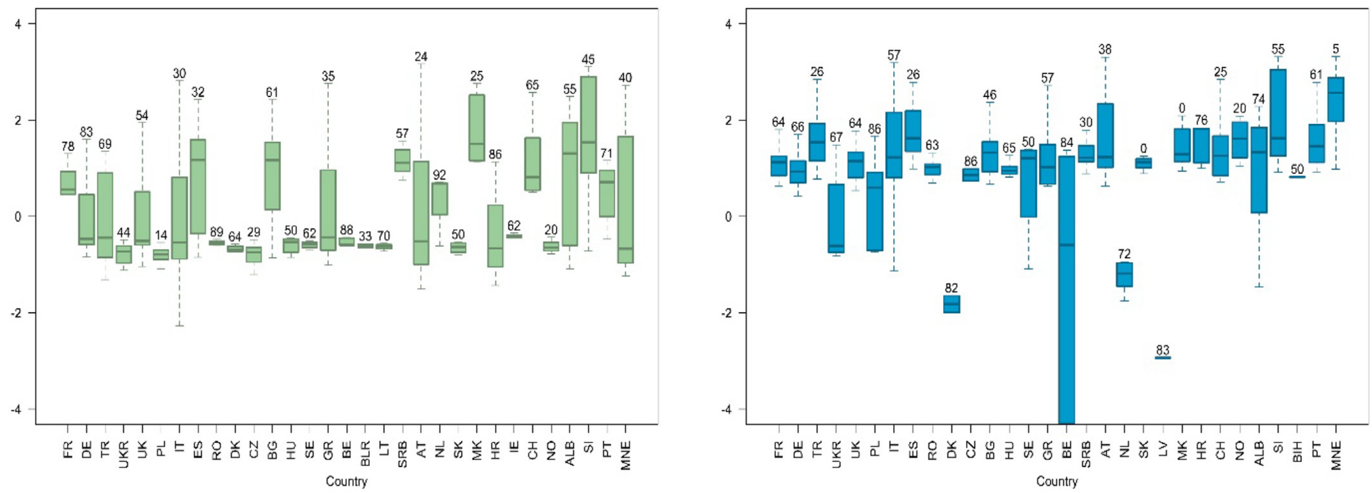

Fig. 6. Estimated significant (at 95% level) mean differences ($t\,ha^{-1}$) between wheat yield at NUTS3 level simulated by using AgMERRA and MarsMet under potential (left panel) and water-limited (right panel) conditions. The numbers above each boxplot show the percentage of regions having no-significant differences. Countries are ranked according to the reported production in 2010 (FAOSTAT).

Italy, the Czech Republic and Croatia (where correlation values between 0.6 and 0.8 are estimated); Austria and Slovakia (with correlation values between 0.4 and 0.6); Slovenia (where no significant correlation is estimated). Similar findings characterise the ERA-I driven simulations at NUTS0 in the EU28 countries (Fig. S12 in the Supplementary material).

When compared to the reported FAO maize yield values, MarsMet and AgMERRA show a very similar behaviour, the main difference being a slightly weaker correlation for the latter one in Germany (Fig. 12). Similar results are shown for the ERA-I driven simulations (Fig. S13 in the Supplementary material).

In terms of mean yield differences at NUTS0 level in the EU28 countries, most of them do not show any significant difference between the AgMERRA and the MarsMet driven simulated yields under water limited conditions (Fig. S14 in the Supplementary material). In Hungary, Bulgaria, Slovakia and the Czech Republic, significant mean differences range from 0.8 to $1\,t\,ha^{-1}$, while in Spain it is equal to $0.58\,t\,ha^{-1}$. Under potential conditions, AgMERRA driven simulations achieve significant lower yields in eastern Europe and Spain with mean differences up to $1\,t\,ha^{-1}$ (Fig. S14 in the Supplementary material).

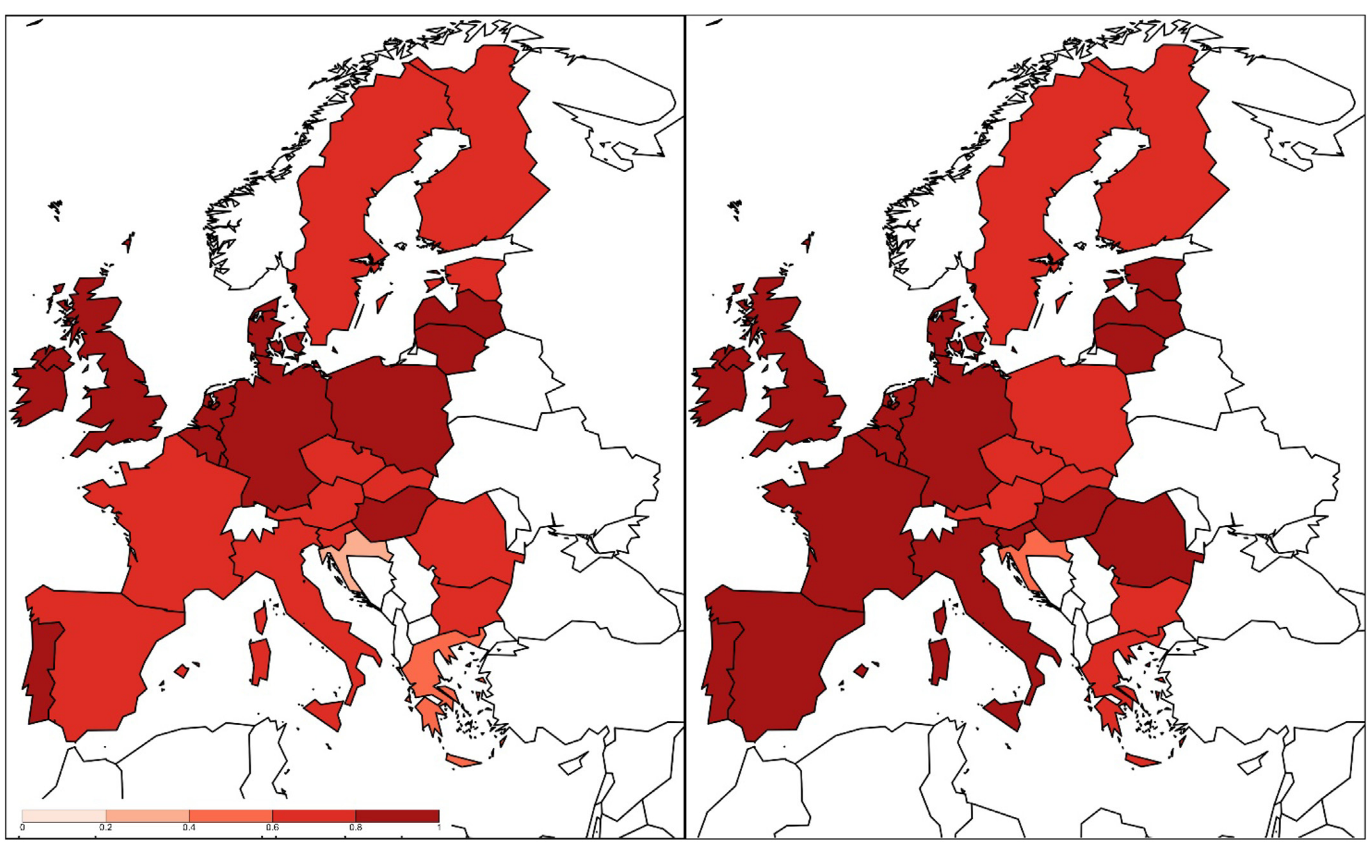

Fig. 7. Estimated significant (at 95% level) correlation between the AgMERRA and the MarsMet driven wheat yield simulations in the EU28 countries under potential (left panel) and water-limited (right panel) conditions.

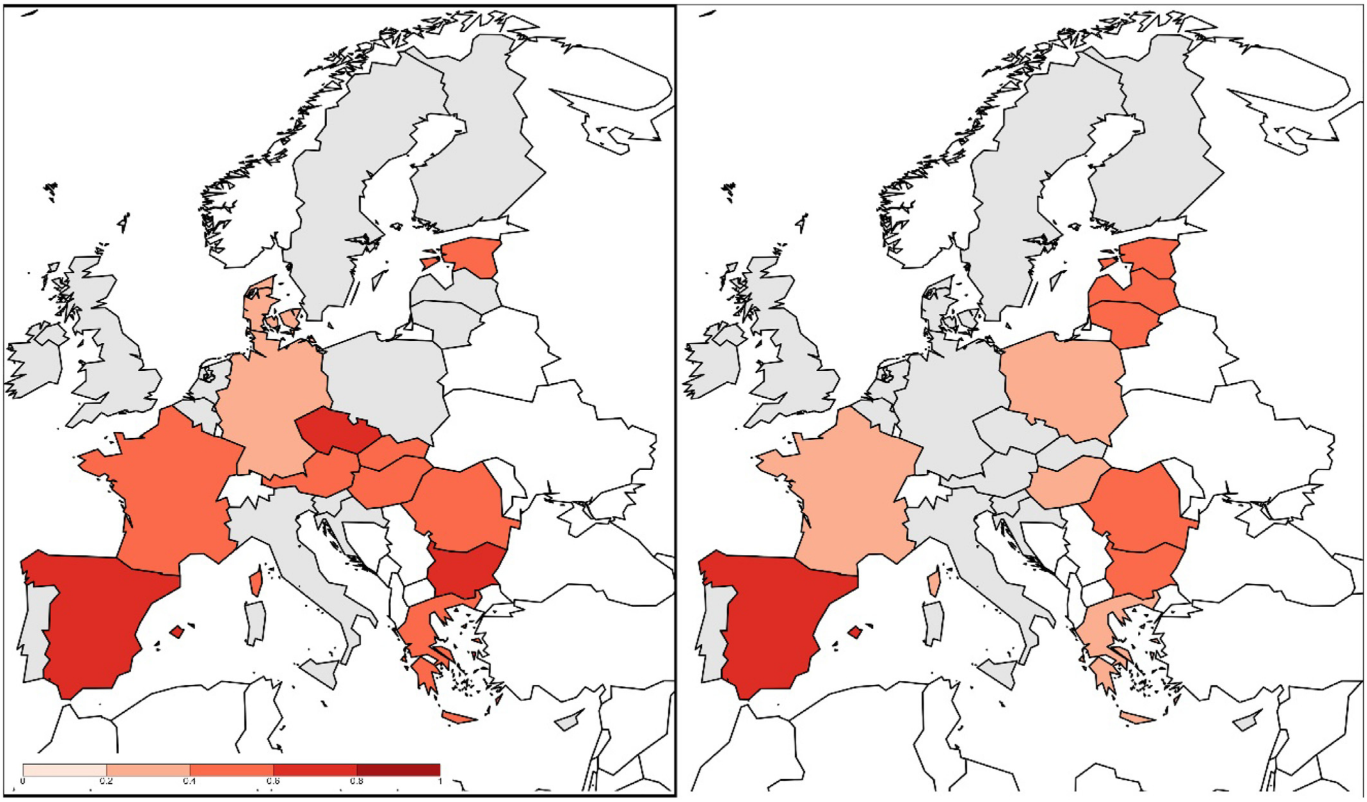

Fig. 8. Estimated significant (at 95% level) correlation between the MarsMet driven (left panel), the AgMERRA driven (right panel) wheat yield simulations and the FAO reported yields in the EU28.

Concerning ERA-I, simulations under potential conditions show significantly higher mean yields in almost all countries of western and central Europe (Fig. S15 in the Supplementary material). While under water-limited conditions, only 4 countries have significantly different mean yields (Fig. S15 in the Supplementary material).

4. Conclusions

The comparison of the Crop Growth Monitoring System-CGMS driven by AgMERRA, ERA-I and MarsMet meteorological data has revealed the good performance of both reanalysis driven systems. At the seasonal scale, significant differences between the selected bias-corrected AgMERRA reanalysis and the gridded observational dataset are mainly found in regions characterised by complex orography and in the Mediterranean region. While, significant differences have been detected for cumulated radiation especially in eastern and south-eastern Europe. These differences, however, seem to have a reduced influence on the mean yield difference. This could be explained by a delay in the AgMERRA simulated flowering due to a slightly lower thermal accumulation (w.r.t. the MarsMet driven simulations). This delay gives the crop more time to accumulate biomass and leads to a higher LAI and thus a better radiation interception during the grain filling that can

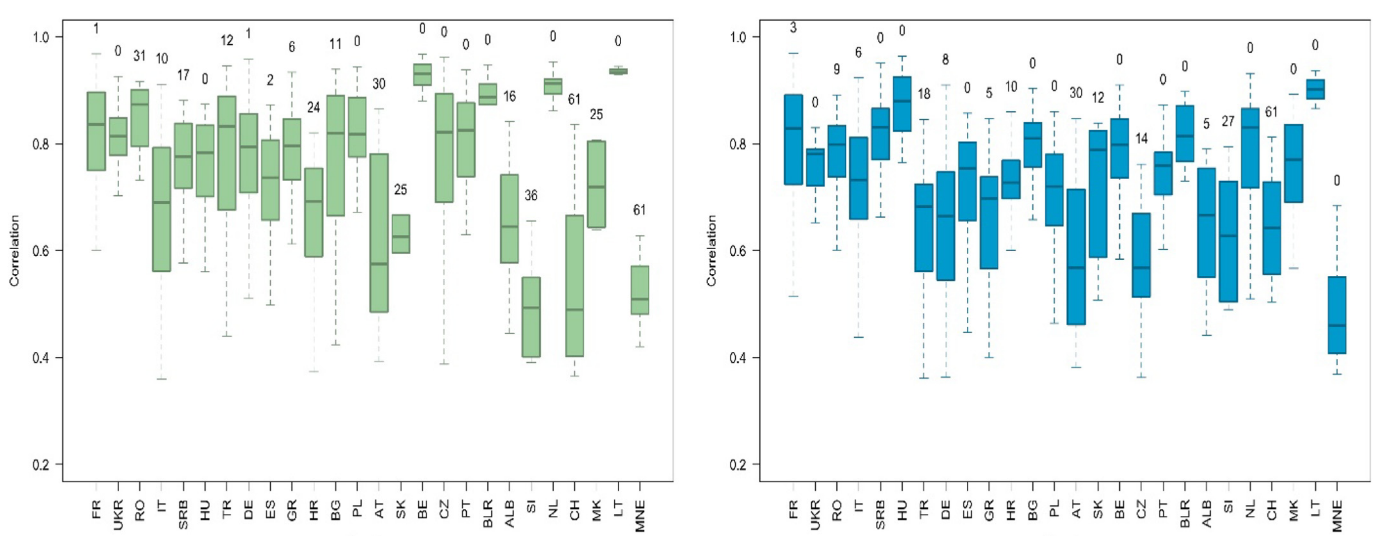

Fig. 9. As Fig. 5 but for maize.

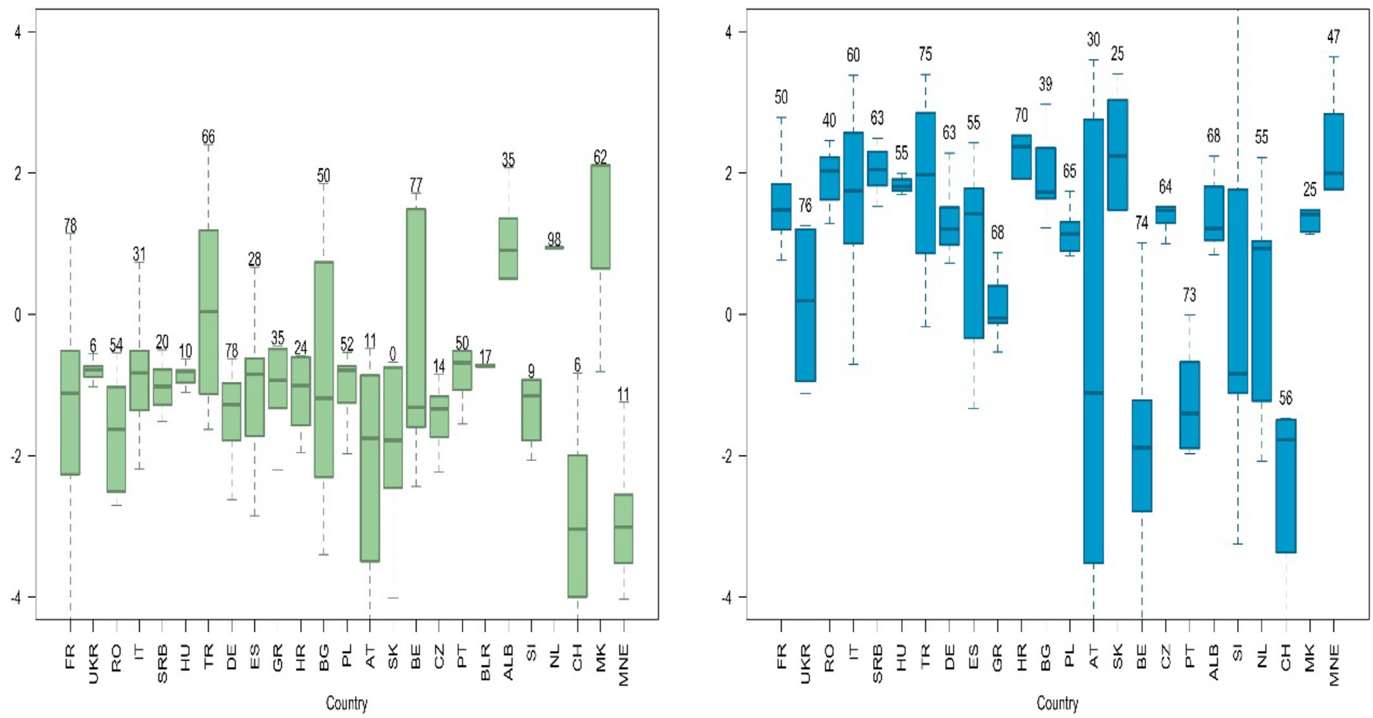

Fig. 10. As Fig. 6 but for maize.

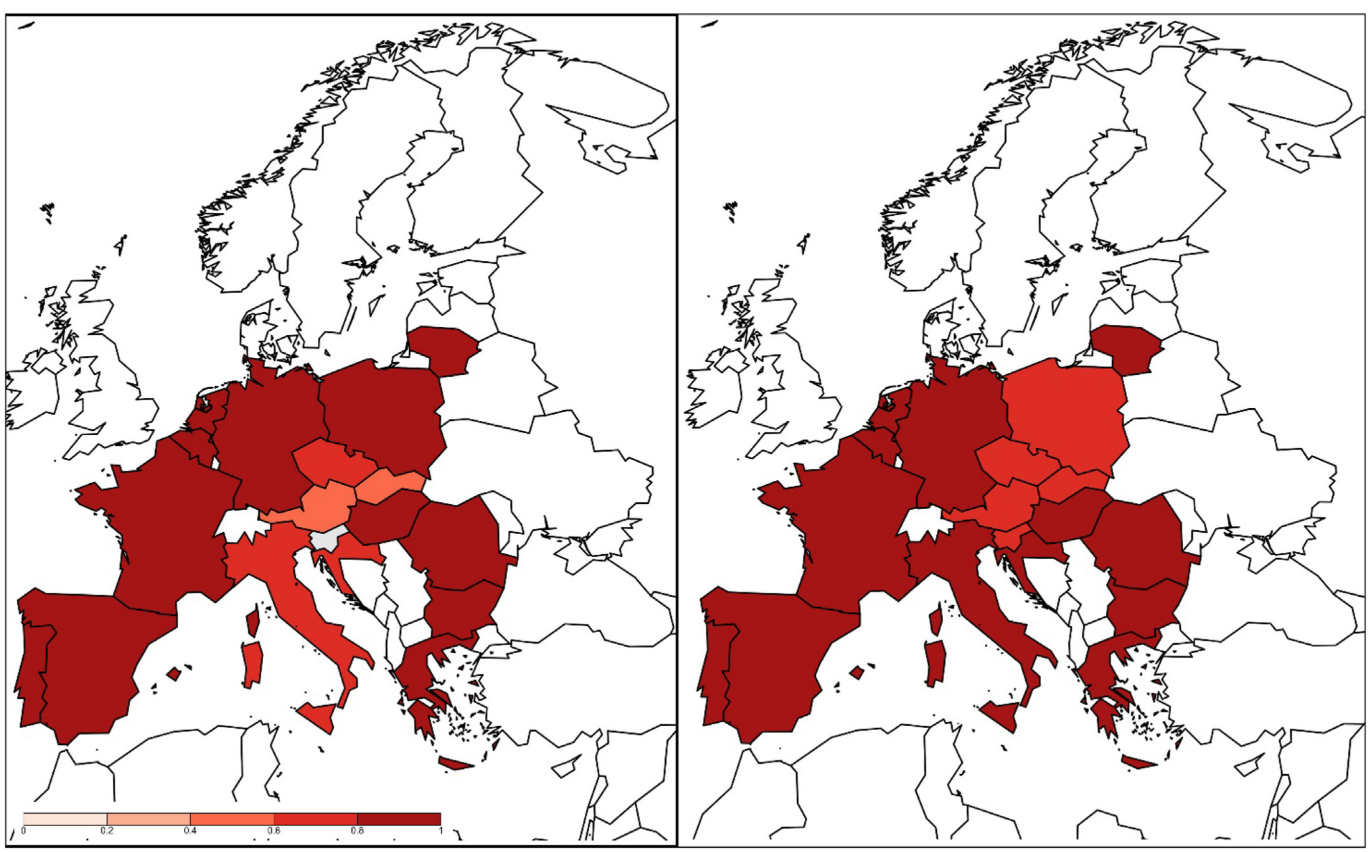

Fig. 11. As Fig. 7 but for maize.

partially counterbalance the lower radiation of AgMERRA.

In terms of yield, similar findings characterise wheat and maize. For both crops, simulated yields are well correlated at the NUTS3 level and very well correlated at the country scale in the EU28 region. Although the mean differences between the AgMERRA, ERA-I and the MarsMet simulated yields are quite relevant at NUTS3 level, they are significantly reduced at NUTS0 in the EU28 countries. The identified differences between AgMERRA and MarsMet are relatively limited,

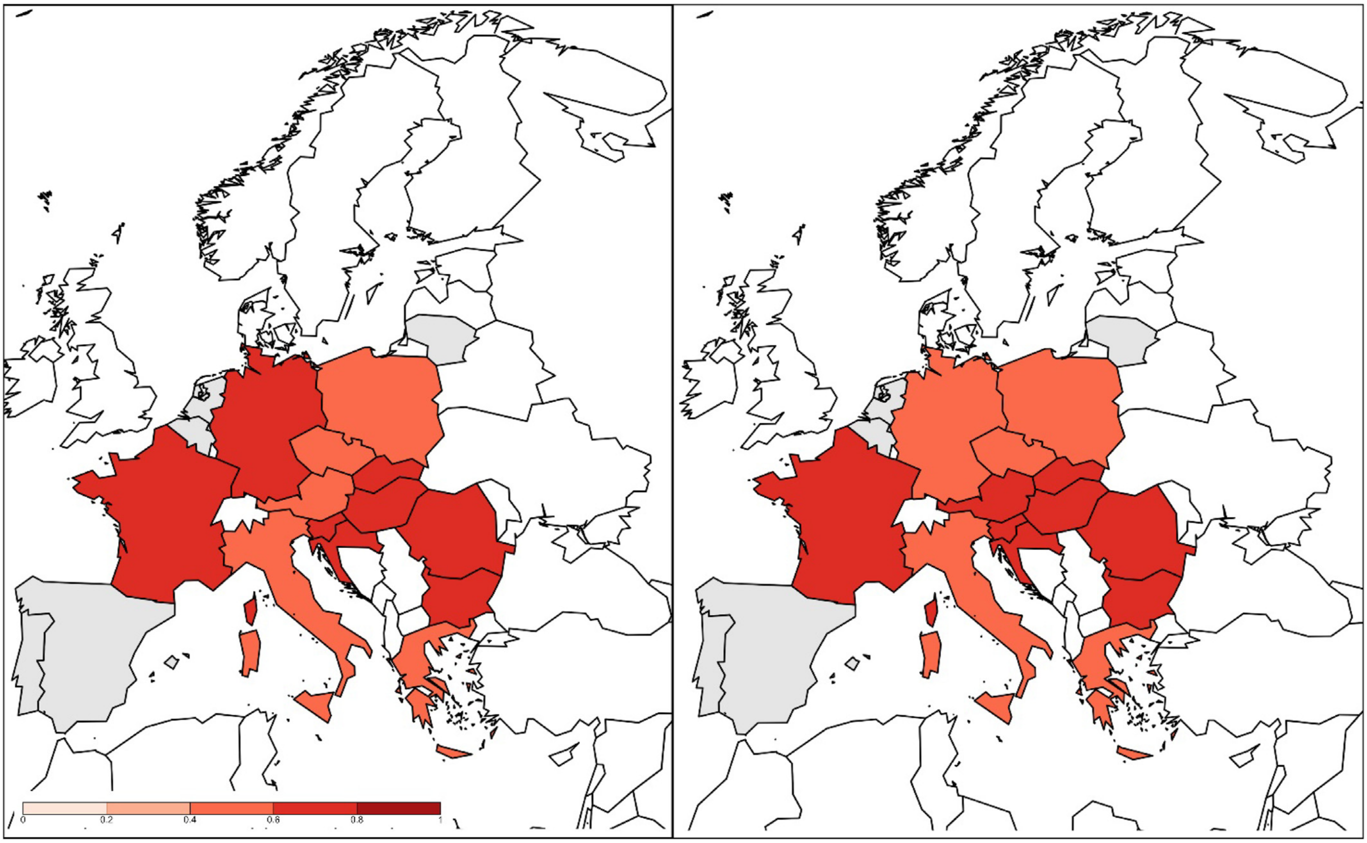

Fig. 12. As Fig. 8 but for maize.

however can still induce significant yield differences. Concerning the meteorological differences, they could reflect issues either in the reanalysis or in the observations (e.g. lack of stations, inhomogeneities).

When compared to the reported FAO yields, both AgMERRA and ERA-I achieve performance similar to the MarsMet driven simulations. This demonstrates the similarity of the analysed systems in the key European producing areas of both wheat and maize. Interestingly, both the bias-corrected AgMERRA and the raw ERA-I achieve very good results in terms of correlation. This could be explained by the use of global observational dataset in the AgMERRA bias correction and by the high number of observations assimilated in Europe by ERA-I. Since the bias-correction approach implemented by AgMERRA requires observations to be updated in near-real-time, a distributional bias-correction of ERA-I (that would not require near-real-time observations; e.g. Iizumi et al., 2014) could in principle offer a valid alternative. As in a few countries (e.g. Poland), the reanalysis driven system outperforms the MarsMet driven one, a spatially dependent bias-correction should be developed to take into account the different station density/quality available. Finally, it is important to highlight the spatial scale dependence of all these results (e.g. Challinor et al., 2003) and the associated uncertainties coming, for instance, by the aggregation procedures, the reported yields and the scale-dependent uncertainties of the meteorological data.

All these findings support the feasibility of reanalysis driven crop monitoring and forecasting system. Thus, a reanalysis-based complementary tool could be used both as backup solution when near-real-time data retrieval from weather stations fails and/or for areas characterised by sub-optimal weather station availability. Furthermore, interesting opportunities are about to emerge since in the coming years new higher resolution reanalyses are going to be released.

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2018.07.001.

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