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Monthly-to-seasonal predictions of durum wheat yield over the Mediterranean Basin

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ABSTRACT: Uncertainty in weather conditions for the forthcoming growing season influences farmers' decisions, based on their experience of the past climate, regarding the reduction of agricultural risk. Early within-season predictions of grain yield can represent a great opportunity for farmers to improve their management decisions and potentially increase yield and reduce potential risk. This study assessed 3 methods of within-season predictions of durum wheat yield at 10 sites across the Mediterranean Basin. To assess the value of within-season predictions, the model SiriusQuality2 was used to calculate wheat yields over a 9 yr period. Initially, the model was run with observed daily weather to obtain the reference yields. Then, yield predictions were calculated at a monthly time step, starting from 6 mo before harvest, by feeding the model with observed weather from the beginning of the growing season until a specific date and then with synthetic weather constructed using the 3 methods, historical, analogue or empirical, until the end of the growing season. The results showed that it is possible to predict durum wheat yield over the Mediterranean Basin with an accuracy of normalized root means squared error of <20%, from 5 to 6 mo earlier for the historical and empirical methods and 3 mo earlier for the analogue method. Overall, the historical method performed better than the others. Nonetheless, the analogue and empirical methods provided better estimations for low-yielding and high-yielding years, thus indicating great potential to provide more accurate predictions for years that deviate from average conditions.

KEY WORDS: Yield predictions · Seasonal forecasts · Analogue forecasts · Stochastic weather generator · Empirical forecasting models · Durum wheat · Crop modelling · Mediterranean Basin

1. INTRODUCTION

Among human activities, agriculture is probably the most dependent on climate. Crop development and growth are strongly related to weather behaviour during the growing season. Accordingly, interannual climate variability is one of the main drivers of year-to-year yield variability, especially in rain-fed agricultural systems (Hoogenboom 2000). Crop management is aimed at reducing such variability, and the related economic risks, by opportunely protecting crops and supplying them with nutrients and irrigation (Lawless & Semenov 2005). However, the uncertainty related to weather conditions in the forthcoming season leads farmers to adopt crop management strategies based on their own experience of the climate of the region. On the one hand, such strategies allow farmers to reduce the economic risks

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related to unfavourable climatic conditions; on the other hand, these strategies may prevent the crop from taking advantage of more favourable conditions (Jones et al. 2000).

Knowing in advance the climate behaviour for the coming season might help farmers in their management decision processes (Jones et al. 2000, Hansen & Indeje 2004), increase profits and reduce economic risks (Jagtap et al. 2002). Methodologies capable of predicting crop yields, such as those based on coupling weather forecasts and crop simulation models, might allow farmers to modulate crop inputs such as fertilizers, water and pesticides, thus maximizing the difference between the value of expected yield and the costs of inputs (Lawless & Semenov 2005). For instance, when a low-yielding season is forecast, farmers may rearrange the management of the crop so as to reduce the costs of inputs. By contrast, they could increase the inputs, aiming at higher yields, in seasons that are predicted to be more favourable for the crop (Asseng et al. 2012, Vermeulen et al. 2012). In addition, predicting in advance the occurrence of specific phenological stages might be useful for planning the timing of farm activities (e.g. fertilizer and pesticide distribution) (Lawless & Semenov 2005) and better organizing the allocation of economic and labour resources. Furthermore, adjusting crop management in response to expected climate variability in the forthcoming season is considered one of the most important and feasible adaptation options that farmers may adopt to cope with the challenges of climate change (Olesen et al. 2011, Vermeulen et al. 2012).

In recent years, several studies have focused on the possibility of predicting crop phenology and yield in the current growing season. Some have investigated the utility of different methodologies for producing seasonal forecasts to be used for yield predictions (Semenov & Doblas-Reyes 2007, Moeller et al. 2008, Shin et al. 2010). Others have explored approaches linking long-term forecasts with crop simulation models (Bannayan et al. 2003, Baigorria et al. 2008, Apipattanavis et al. 2010). Most of these studies were conducted in the United States (Baigorria et al. 2008, Quiring & Legates 2008, Shin et al. 2010), Australia (Hansen et al. 2004, Wang et al. 2008, Asseng et al. 2012) and Africa (Hansen & Indeje 2004, Zinyengere et al. 2011). In these regions, climate variability is related to some strong climate signals; thus, the capability of producing reliable predictions of seasonal meteorological fluctuations is higher than in regions where those signals are not clear or do not exist (Petersen & Fraser 2001, Cantelaube & Terres 2005, Baigorria et al. 2008). This, in turn, can explain why very few studies so far have been conducted over Europe at both regional (Cantelaube & Terres 2005) and local scales (Marletto et al. 2007, Semenov & Doblas-Reyes 2007, Pavan & Doblas-Reyes 2013) and, in particular, over a complex area, from the climatic point of view, such as the Mediterranean Basin (Toscano et al. 2012).

Durum wheat, *Triticum turgidum* L. subsp. *durum* (Desf.) Husn. is a rain-fed crop that is widely cultivated over the Mediterranean Basin. This area contributes more than half of the 36 million tonnes of durum wheat produced globally. The peculiar grain protein concentration and composition makes durum wheat suitable for several food products, such as pasta, couscous, bulgur and flatbread. These represent an important dietary component for many populations living on the shores of the Mediterranean Sea but are also niche products for European, North American and former USSR markets (Lidon et al. 2014). Accordingly, durum wheat is an economically important crop for Mediterranean countries. In these countries, durum wheat yield, in terms of both quantity and quality, is greatly affected by the variability of the weather pattern characterizing Mediterranean environments (Diacono et al. 2012). In particular, low and irregular rainfall distribution as well as high temperatures during sensitive phenological stages, such as flowering and grain filling, may alter the final yield and its quality. A system capable of producing early yield forecasts for durum wheat is, therefore, a desirable tool for more effective crop management (Dalla Marta et al. 2015).

In this study we compared the quality of within-season predictions of durum wheat yield based on a wheat simulation model and 3 different methods for producing estimates of weather parameters up to 6 mo ahead of time over the Mediterranean Basin. The main aims of the study were to evaluate whether it is possible to produce within-season predictions of durum wheat yield across the Mediterranean Basin as well as exploring whether there are differences in levels of skill in prediction depending on the method, the climatic conditions of the area considered or the period in which the forecasts are produced.

2. MATERIALS AND METHODS

The crop simulation model SiriusQuality2 (SQ2) was applied across the Mediterranean Basin to produce predictions of yield at a monthly time step using 3 different methods for generating weather parameters from the date of prediction to the end of the growing season.

2.1. Study area

With the aim of exploring the aptitude of the 3 methods in predicting yields under different climatic conditions, the forecasting exercise was conducted at 10 different sites across the Mediterranean Basin (Fig. 1), where durum wheat is usually cultivated. According to the environmental classification produced by Metzger et al. (2005), 8 out of 10 of the selected sites are classified as Mediterranean, with typically hot and dry summers and mild and wet winters. The exceptions are the 2 sites located in Central and Southern France, in which the climate is characterized by relatively low summer temperatures, winter temperatures not far below 0°C and precipitation much more evenly distributed during the year, although maintaining a somewhat Mediterranean-like distribution (i.e. with maximum in winter).

2.2. Meteorological data

For each of the selected sites, a complete series of observed meteorological data was extracted from the Crop Growth Monitoring System (CGMS) of the Joint Research Centre (JRC) archive (http://mars.jrc.ec.europa.eu). This is an observational interpolated meteorological dataset, specifically created for agricultural modelling purposes. Site-specific daily weather data, collected from more than 3000 sites in Europe since 1975, have been interpolated into a regular grid with a spatial resolution of 25 km. The interpolation procedure adopted (van der Goot & Orlandi 2003) accounts for the agricultural areas within a cell and makes these data representative of an agricultural site typical of a cell (Semenov et al. 2010). For this study, the meteorological variables extracted were minimum and maximum temperature, rainfall and global radiation covering the period from 1975 to 2010. For the calibration of the forecasting methodologies (see Section 2.5), the years from 1975 to 2000 were adopted as a common baseline. Although this period is a bit shorter than usual climatological reference periods (i.e. 30 yr), it allowed us to test the forecasting methods over a longer period, i.e. from 2001 to 2010 (testing period).

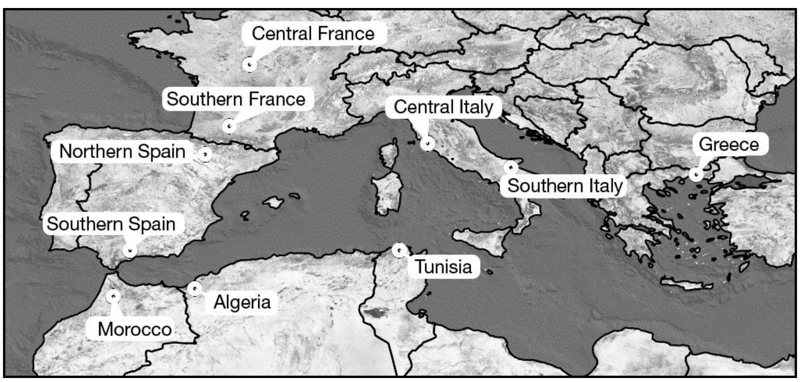

Fig. 1. Map of the Mediterranean Basin showing the 10 study locations

2.3. Crop simulation model

For the simulation of durum wheat phenology and yield, the model SQ2 was adopted. SQ2 is the latest version of a process-based wheat simulation model that is able to reproduce crop development and growth in response to weather and crop management. The model simulates crop phenology based on the phyllochron and the final leaf number as estimated from daylength and vernalization requirements. Crop growth is calculated on a daily time step from intercepted solar radiation and radiation use efficiency. The potential growth is then limited depending on nitrogen and water availability. Simple partitioning rules determine the accumulation of biomass and nitrogen into the grain after anthesis. The model allows users to specify soil properties, cultivar-specific parameters and crop management options. For an in-depth description of the model, the reader is referred to Martre et al. (2006).

SQ2 has been extensively used to simulate wheat phenology and yield in several environments and climates (Martre et al. 2007, Asseng et al. 2013). The model was calibrated for simulating phenology and yield of a medium-cycle durum wheat variety using data from a field experiment conducted in Central Italy (Ferrise et al. 2010). The ability of the model to reproduce observed durum wheat yields at local and regional scale across the Mediterranean Basin was tested against independent data, showing good agreement between simulated and observed yields in diverse environments (Ferrise et al. 2011).

2.4. Crop model input data

Crop yield is the result of complex interactions between environment, genotype and management. This study was aimed at investigating the utility of the 3 forecasting methods in predicting yield under diverse climatic conditions. Accordingly, with the aim of isolating the effect of climate from other factors and allowing direct comparison across the sites, the same soil, cultivar and management parameters were assumed for the crop model at all sites.

In all the simulations, the cultivar parameters adopted were those representing durum wheat cultivar Creso (Ferrise et al. 2010). The crop management consisted of a sowing date of 15 November using 500 seeds m^{-2} and a single nitrogen fertilization of 50 kg N ha^{-1} distributed at sowing. The soil was 1 m deep with a moisture content of 47% at saturation, 26% at field capacity and 13% at wilting point, resulting in an available water content of 130 mm. Organic N content was set to 8 t ha^{-1} with a mineralization rate constant of 0.3 kg mineral N t^{-1} organic N ha^{-1} d^{-1}. To avoid any carryover effects from the previous year, the model was re-initialized at the beginning of each growing season. Specifically, the initial inorganic N was set to 20 kg ha^{-1} split over the entire soil profile (50% in the top third and 40% in the middle third of the profile), and the soil water deficit was set to 0.

2.5. Forecasting methods

Three different methods for producing the meteorological data needed to feed the crop simulation model from the moment of estimation to the end of the growing season were compared.

2.5.1. Historical climatology (H)

This first methodology is based on the use of a weather generator. This is a tool capable of creating synthetic time series of meteorological variables with statistical properties similar to the observed climate at a site (Wilks & Wilby 1999). In this study, the LARS Weather Generator (LARS-WG, Semenov & Barrow 1997, Semenov et al. 1998) was used to simulate possible meteorological trends during the season according to historic climate in a stochastic fashion. The procedure for generating the data includes, firstly, a calibration phase. During calibration, LARS-WG analyses observed daily weather data of a specific site, thus providing a statistical characterization of the observed time series. This implies the calculation of a set of parameters describing the probability distributions of atmospheric variables and the relevant correlations between them. This set of parameters is then used to stochastically produce synthetic meteorological time series for the selected site.

Following this procedure, in this study, LARS-WG was firstly calibrated at each site using a common baseline (1975–2000). Then, 100 yr of synthetic daily weather data were produced and used to feed the crop model on each prediction date.

2.5.2. Analogue methodology (A)

The analogue methodology has already been analysed and studied in the past both for weather forecasting and for analysis and seasonal forecasts (Lorenz 1969, Livezey & Barnston 1988). This methodology is based on the assumption that the atmospheric pattern for the coming days in the current year reproduces what has already happened in the past. Thus, the methodology aims to identify patterns of rainfall and temperature similar to those of the current year in the weather history.

The performance of this methodology is dependent upon how much similarity is quantified. Thus, depending on the size and complexity of the region under consideration, as well the aim of the application, an extensive archive of historical weather observations is required for successful implementation (Hamill & Whitaker 2006). However, this methodology is easily applicable and presents 2 further advantages for yield forecast applications: the conservation of spatial covariance structure of local-scale weather in the simulated fields due to the use of observed weather; and the possibility of building scenarios for variables that are not normally distributed, such as daily precipitation (Matulla et al. 2008).

In this study, an easy selection process in which the specific similarity measures are computed over the common baseline (1975–2000) was applied. Among the baseline, the year most similar to the current one was identified through the calculation of the Euclidean distances (Kruizinga & Murphy 1983, Martin et al. 1996, Ribalaygua et al. 2013). At each specified location, the values of the leading principal components (PCs) of the joint monthly rainfall and monthly average temperature were calculated. The resulting scores were used as elements of a metric providing information about the similarity between the current period before a specific prediction date and all other similar periods within the common baseline. To identify and select the closest year, the minimum Euclidean distance for PC scores was then used. This procedure was applied 6 times per year in an iterative way for any given prediction date: in January, the observed monthly rainfall and monthly average temperatures from September to December were compared with all the series of the baseline archive; in February, January values were also included, and in March, February values were also included and so on until the last process included the entire period from September to May.

Based on this procedure, the pattern from the historical data most similar to that of the current year was found and was designated as the most likely meteorological sequence for the remainder of the current year, thus providing site-specific atmospheric scenarios.

2.5.3. Empirical forecasting model (E)

Climate variability, from monthly to quarterly time scales, is often captured by relevant spatio-temporal low-frequency features, such as empirical orthogonal functions (Barnston & Livezey 1987). Accordingly, global circulation atmospheric and oceanic indices can be used as predictors to build up seasonal forecasting statistical models (Kim et al. 2007, Kim & Kim 2010, Magno et al. 2014).

In the present study, a multi-regressive approach based on a linear combination of atmospheric and oceanic observed indices (predictors) was used to forecast monthly temperature and precipitation anomalies (predictands) with respect to the common baseline (1975–2000). The empirical model adopted is of the form:

$$a_k(s,t) = \beta_1(s,t)\mathrm{Pred}_1 + \beta_2(s,t)\mathrm{Pred}_2 + \ldots + \beta_n(s,t)\mathrm{Pred}_n + \varepsilon\,(s,t) \tag{1}$$

where a is the monthly anomaly of temperature or precipitation for the kth month after the prediction date (t) at a specific site (s); β is the coefficient of the predictor (Pred) computed for the specific site (s) and prediction date (t); and ε is the independent, identically distributed error associated with the model. A complete list along with a brief description of the predictors adopted is shown in Table S1 in the Supplement (see www.int-res.com/articles/suppl/c065p007_supp.pdf).

For each prediction date, a specific set of predictors (Table S2 in the Supplement) was identified based on the evaluation of corrected R-squared and Fisher's test metrics. The latter were calculated, over the reference period, between the predictands and the whole set of predictors. To prevent intrinsic correlations, each time series was detrended by subtracting its pure linear time regression component from the original signal. Further, to increase its Gaussian distribution form, the precipitation field was processed using an analytical Box-Cox transformation (Box & Cox 1964) with a power law formulation with an exponent of 0.5.

Finally, for each location and prediction date, the coefficients of the predictors in the multi-regressive model (summarized in Tables S3 & S4 in the Supplement) were computed using an ordinary least squares algorithm and chosen with a best-fit procedure between observed and hindcast rainfall and temperature anomalies over the reference baseline (1975–2000). The LARS-WG model was forced by the computed anomalies to generate 100 yr of daily weather.

2.6. Creating input meteorological data for yield predictions

To simulate crop development and growth, SQ2 needs weather inputs for the whole growing season. To allow the model to provide estimates of yield during the growing season (i.e. with incomplete meteorological inputs) on a specific prediction date, sets of mixed observed/forecast daily weather data must be generated. The first part of these data coincides with the observed values, while the remaining part represents the possible continuation for the site.

Depending on the forecasting methodology, different procedures were used to produce mixed weather data. The analogue methodology identifies a specific year in the past with characteristics similar to those of the current year. In this case, the input meteorological data constituted a single realization, in which the daily weather for the remainder of the season is the relevant data for the 'analogue' year. For the other 2 methodologies, LARS-WG was used to create an ensemble of synthetic site-specific weather scenarios representing samples of possible future outcomes (Lawless & Semenov 2005). In the historical methodology, LARS-WG was adopted to generate synthetic data with characteristics similar to those of the reference climatology (1975–2000). In the empirical model forecasting methodology, LARS-WG was forced with monthly anomalies forecast by the empirical model to generate synthetic series of daily weather data deviating from the reference climatology, as predicted by the empirical model. In both cases, LARS-WG was used to generate probabilistic ensembles of 100 yr of possible future meteorological series. Thus, SQ2 was run for each year in the ensemble and the average yield was calculated and used as an estimator of the expected yield (Semenov & Doblas-Reyes 2007).

2.7. Evaluating the performance of forecasts

To assess the value of forecasts, the approach described in Semenov & Doblas-Reyes (2007) was adopted. The approach is based on the assumption that a crop simulation model can correctly simulate crop development and growth once complete input information is provided. Based on this premise, SQ2 was first used to generate a vector of reference yields over the testing period. Reference yields were calculated by feeding the model with observed weather data for the whole growing season (i.e. from sowing date to maturity). Then, predictions of yield were produced at a monthly time step, from 1 January to 1 June, using mixed observed/synthetic daily weather data as model inputs.

At each site and on each prediction date, the estimated yields were compared to the reference yields (i.e. those produced with observed meteorological data for the whole growing season) to assess the performance of the forecasting methodologies in predicting yield. To this end, 3 different statistics were adopted, as they provide different information on the quality of predictions. More specifically, the normalized root means squared error (nRMSE) of yield estimates (Sim) from reference yields (Ref) accumulated over testing years was calculated as:

$$\mathrm{nRMSE} = \frac{100}{\overline{\overline{\mathrm{Ref}}}} \sqrt{\frac{1}{n} \sum_{i=1}^{n} (\mathrm{Sim}_i - \mathrm{Ref}_i)^2} \qquad (2)$$

This is a measure of the relative difference (as a percentage of the reference average yield at a site) of simulated versus reference yield data. The lower the value of nRMSE, the higher the ability of the methodology in capturing the interannual variability of yields. Assuming that deviations of simulated yields from the reference ones are mainly related to the effect of climatic uncertainty due to the forecast weather, this statistic may be used to give a measure of the ability of the forecasting methodologies in predicting weather conditions for the remainder of the growing season.

However, this index does not provide specific information on the size of the deviation from reference yields. Accordingly, we used the median of the cumulative distribution of the relative absolute errors (MRAE) to give quantitative information on the differences between simulated and reference yields. The relative absolute error (RAE) between reference (Ref) and estimated (Sim) yields was calculated as:

$$\mathrm{RAE}_i = 100 \, \frac{|\mathrm{Sim}_i - \mathrm{Ref}_i|}{\mathrm{Ref}_i} \qquad (3)$$

where RAE_i is the relative absolute error for a prediction i, Ref_i is the reference yield value and Sim_i is the estimated yield. The MRAE accumulated over years in the testing period was computed and was used to evaluate how much closer the estimated yields were to the reference yields.

These metrics provide information about the size of the error but not about the prediction method behaviour. Information about the efficiency of the forecasting method in estimating reference yields was then provided by calculating the Pearson's correlation coefficient (r) according to the following:

$$\mathrm{r} = \frac{\sum_{i=1}^{n} (\mathrm{Ref}_i - \overline{\mathrm{Ref}})(\mathrm{Sim}_i - \overline{\mathrm{Sim}})}{\sqrt{\sum_{i=1}^{n} (\mathrm{Ref}_i - \overline{\mathrm{Ref}})^2} \sqrt{\sum_{i=1}^{n} (\mathrm{Sim}_i - \overline{\mathrm{Sim}})^2}} \qquad (4)$$

To provide a measure of the variability of reference yields at a site, the coefficient of variation (CV, %) was calculated as the percentage of the ratio between the standard deviation and the mean of reference yields at each site.

3. RESULTS AND DISCUSSION

The main climatic characteristics of the selected sites calculated over the period adopted for the calibration of the 3 methods (1975–2000) are reported in Table 1. Mean annual temperatures span a wide range, from more than 17°C in the southwestern sites to ca. 15°C in the central–eastern regions and less than 13°C in the northwestern locations. The spatial

Table 1. Location of the selected sites and main climatic characteristics. Climatic indices were calculated over the period 1975–2000

Site	Latitude (°N)	Longitude (°E)	Altitude (m a.s.l.)	Mean annual temperature (°C)	Mean annual precipitation (mm)
Tunisia	37.06	9.63	10	18.2	553
Morocco	34.60	5.57	150	17.7	620
Algeria	35.01	1.25	350	17.3	320
Southern Spain	37.05	4.69	400	17.0	442
Southern Italy	41.43	15.56	75	15.8	458
Central Italy	42.72	11.13	10	15.0	636
Greece	41.07	25.42	50	14.2	480
Central France	46.91	1.67	150	12.6	749
Northern Spain	42.15	0.69	420	11.9	557
Southern France	43.64	0.59	130	11.1	757

distribution of mean annual precipitation presents a similar pattern. The southwestern part of the basin is the driest (on average 480 mm), and the northwestern the wettest (690 mm, on average). The central and eastern sites are medium rainfall sites with ca. 525 mm of annual rainfall.

On average, nRMSE in January ranged from 17.0% with the H methodology to 19.0% with the E methodology and 24.1% with the A methodology (Fig. 2). Regardless of site and forecasting methodology, nRMSE progressively decreased as the prediction date approached crop maturity, thus indicating an increasing accuracy of yield estimates. The accuracy of the forecasting methodologies in estimating yield as measured by nRMSE varied across sites and prediction dates. At the southwestern sites (Morocco, Tunisia, Algeria and Southern Spain), the H and E methodologies provided very similar results. From January, yield estimations produced with these methodologies presented good accuracy, with nRMSE usually lower than 20%. In contrast, the A methodology gave less accurate estimates on the first 3 prediction dates, for which nRMSE tended to be higher than 25%. Starting from March–April, the predictions with A became comparable to those of the other methodologies. At the other sites, the differences between the methodologies were not so clear, although the H methodology performed better than the others overall. In some sites, such as Central Italy and the Southern France, the A and E methodologies produced values for nRMSE that were clearly higher than (almost double) those of the H methodology on each prediction date. At the remaining sites, the performance of the empirical model was comparable to that of the H methodology, with values of nRMSE that were similar (Greece and Central France) or just a bit higher (Southern Italy and Northern Spain). At these sites, up to March, the A methodology produced values of nRMSE higher than those of the other 2 methods; then its accuracy increased and leveled up with the other methodologies or even overtook them, such as in Southern Italy.

Similar patterns were observed for the evolution of the Pearson's correlation coefficient (r) (Fig. 3). H and E produced comparable results except in the Southern France, where r-values produced with E were lower. Overall, H and E always produced positive values of r. From the earliest prediction dates, r was higher than 0.5 at most of the selected sites. Only in Tunisia, Algeria, Southern Spain and Southern Italy was r lower for yield estimates produced in January. Compared with H and E, predictions performed with A gave analogous results in Morocco, Central Italy and Southern Spain. At the earliest prediction dates, results produced with A clearly diverged from those of the other 2 methods at the other sites, sometime showing negative values (Tunisia, Southern Spain, Southern Italy, Greece and Southern France). At all of the sites, values of r increased as the season progressed. As a result, from March to April the performance of the 3 methodologies became comparable.

MRAE varied across prediction dates, sites and methodologies (Fig. 4). At 5 to 6 mo before harvest, MRAE ranged, on average, from 17.6% with A to 13.7% with E and 12.5% with H. The MRAE was progressively reduced as the season went on, to less than 5% on the last 2 prediction dates. At some sites, such as Morocco, Tunisia, Southern Spain, Greece and Central France, the H and E methodologies produced very similar values for MRAE that were generally lower than those of the A methodology. In Algeria, although the values for MRAE of the 3 methodologies were quite similar, methodologies A and E produced results that were always lower than those of H. In Central Italy, A and H produced the same results, while E performed worst. In Southern Italy, results for H and E were similar, except in April when the MRAE produced with E was lower. The MRAE produced with A initially increased to 35% in March and then decreased, being the lowest in May and June. In Southern France and Northern Spain, values for MRAE produced with H were, overall, lower than with the other 2 methodologies, although these 2 showed a certain level of variability and in some cases gave better results.

A particular case was observed in Central France. Here, in January all 3 methods already resulted in good predictions with approximately 10% error, and later in the season the level of skill in prediction remained unchanged. This may be attributed to the lower climate variability observed at this site. In fact, the range of variability and the spread of ensemble model outputs are a direct result of the variance in the model inputs (i.e. in this study, observed atmospheric data) and reflect the climatic conditions that characterize the development and growth of the crop. This is particularly true for durum wheat over the Mediterranean environments, for which high temperatures and drought are the major climatic constraints (Porter & Semenov 2005, García del Moral et al. 2003). During the years 1975 to 2000, adopted for the calibration of the forecasting methodologies, the Central France study area registered the lowest variability in terms of accumulated precipitation (CV = 25.9%, data not shown) and a low variability in terms of thermal summation (CV = 6.6%,

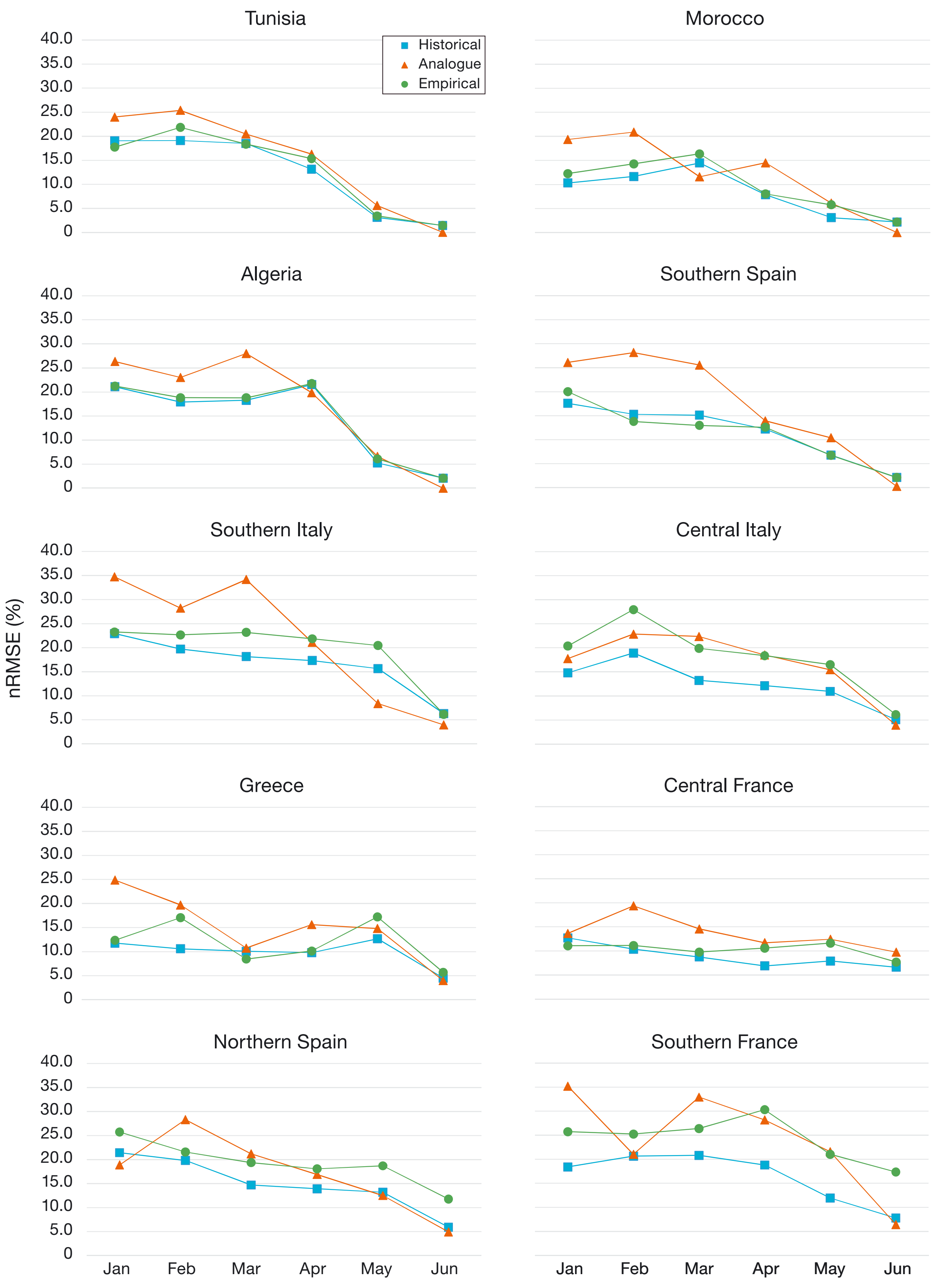

Fig. 2. Normalized root mean squared errors (nRMSE). Errors were calculated as the difference between predicted and reference yields for each of the 10 study locations at monthly time steps from January to June

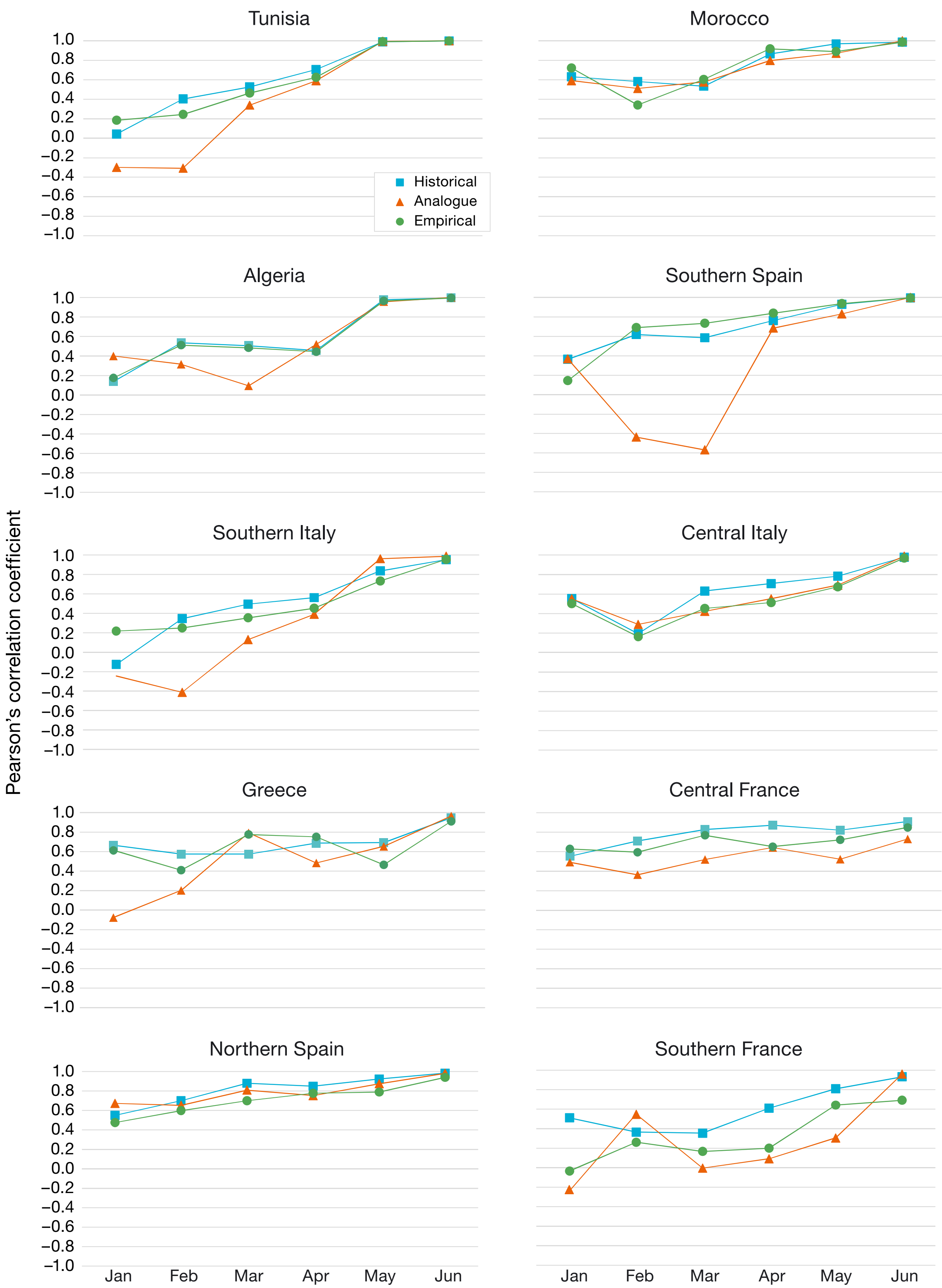

Fig. 3. Pearson's correlation coefficient of simulated versus reference yields for each of the 10 study locations at monthly time steps from January to June

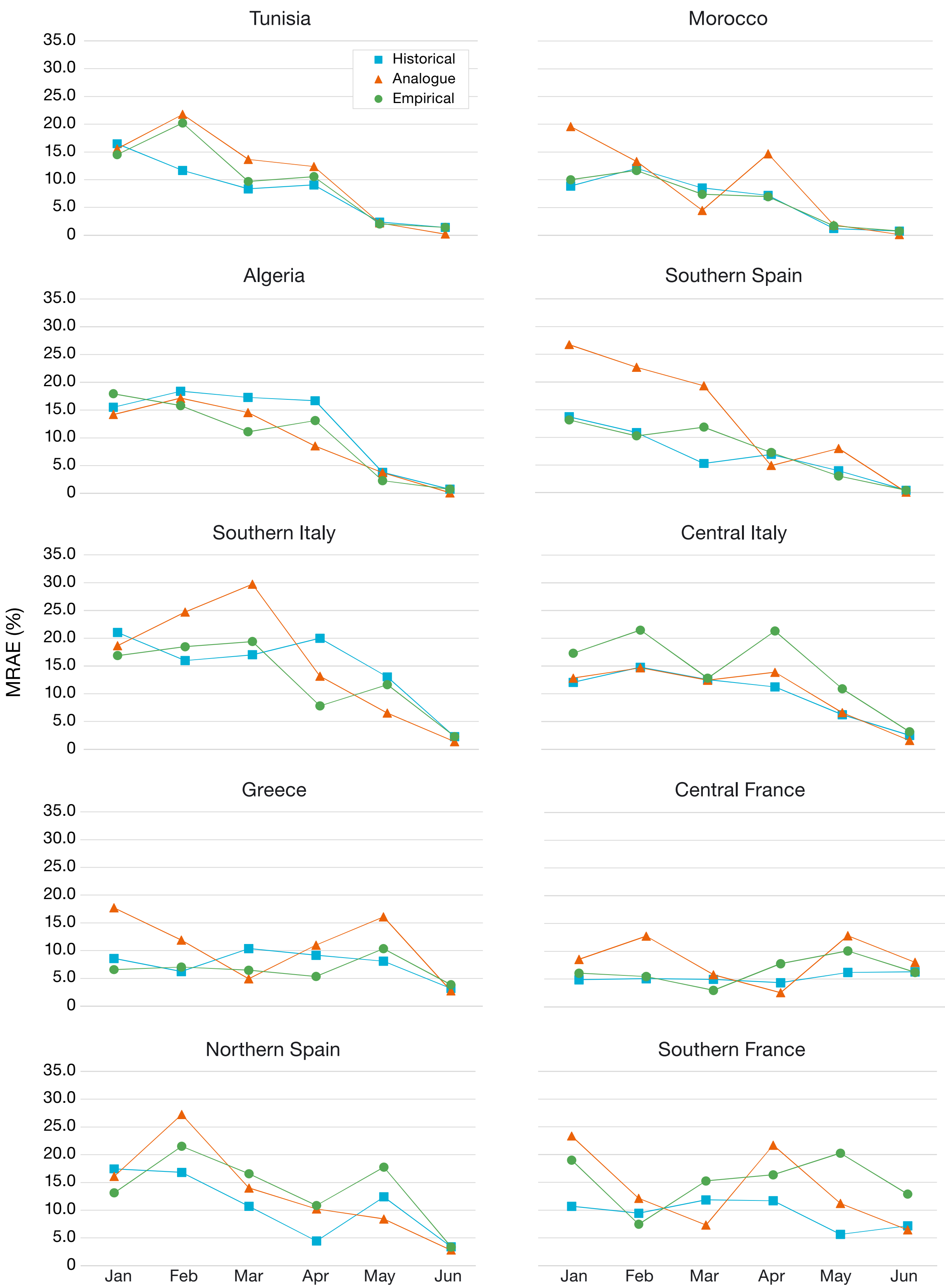

Fig. 4. Medians of the relative absolute errors (MRAE). Errors were calculated as the difference between predicted and reference yields for each of the 10 study locations at monthly time steps from January to June

data not shown). This turns into a reduced variability in the input data for the scenario generation that results in an even more marked reduction in the cumulative rainfall variability recorded during the 9 yr of simulation (CV = 15.1%, data not shown), during which water and thermal requirements were, however, fully satisfied. In terms of predictability, this translates into a very low nRMSE as early as January (Fig. 2) for Central France, with the 3 methodologies able to estimate the yield with high accuracy, contrasting with the results across the other sites, where a greater interannual variability of the weather conditions greatly affected the forecast accuracy.

The H methodology provided the best accuracies overall. Nonetheless, a detailed analysis of the performances of the methodologies in years with the highest yield deviations from the site-specific reference mean revealed that the other 2 methodologies can provide more accurate forecasts. Assuming that the final yield is the result of the weather conditions occurring during the growing season (Lawless & Semenov 2005) at each site, we selected the years with the highest and the lowest reference yields. In each specific area, these years are supposed to be those in which the best and the worst weather conditions for durum wheat growth occurred. The deviations of estimated yields in such extreme years were then analysed to evaluate the methodologies. In years with the lowest yields, although all forecasts provided by the 3 methodologies tend to overestimate the reference yield (Table 2), the predictions based on the A methodology appear to be more accurate. After all

Table 2. Relative deviation (%) of predicted yields in years with the lowest and highest reference yield

	Jan		Feb		Mar		Apr		May		Jun	
	Lowest	Highest	Lowest	Highest	Lowest	Highest	Lowest	Highest	Lowest	Highest	Lowest	Highest
Historical												
Tunisia	5.1	−3.2	9.8	−0.1	7.4	4.4	14.2	7	9.5	1.1	7.6	0
Morocco	35.7	−23.9	2.0	−27.8	6.3	−24.8	4.8	−19.2	1.4	0.4	1.9	−2.6
Algeria	62.0	−15	43.7	−20.6	40.0	−27.5	17.2	−38.1	4.6	−8.8	−1.3	0.7
Southern Spain	29.1	−17.1	10.9	−13	17.2	−23.8	15.6	−4.1	−3.6	3.9	−7.9	−0.9
Southern Italy	35.6	−21.1	31.5	−16	28.4	−6	22.0	2	21.7	9.2	2.5	−2.2
Central Italy	34.6	−14.6	41.2	−18.8	30.1	−12.6	14.6	−11.3	9.8	−2.8	−0.7	6.8
Greece	15.5	−1.9	4.9	−6.6	10.3	−11.9	10.9	0.1	−5.9	−12.6	−8.1	2.1
Central France	59.7	−10.9	65.4	−13.4	64.5	−14.5	46.1	−6.5	25.6	−4.4	13.0	10.4
Northern Spain	72.2	−21.4	26.2	−34.6	21.2	−24.2	21.6	−20.6	26.9	−2.1	2.5	−0.9
Southern France	13.8	−24	1.4	−21.9	8.9	−16	8.5	−13.1	15.7	−5.3	1.9	−7.8
Mean	36.3	−15.3	23.7	−17.3	23.4	−15.7	17.6	−10.4	10.6	−2.1	1.1	0.6
Empirical												
Tunisia	−9.9	−18.9	12.7	−5.7	−2.5	1.2	6.8	5.6	19.1	3	7.6	0
Morocco	36.8	−20.7	−2.6	−28.5	−1.5	−23	3.4	−23	0.2	2.9	1.9	−2.6
Algeria	66.4	−17.8	50.5	−23.3	51.3	−26.7	22.4	−40.4	0.9	−10.3	−1.3	0.7
Southern Spain	32.8	−16.1	9.4	−2.4	6.0	−11.8	11.3	−1.1	2.9	1.5	−7.9	−0.9
Southern Italy	−4.6	−20.2	34.8	−18.5	7.2	−5.4	4.3	6.5	14.7	7.9	4.7	−2.3
Central Italy	29.4	−1.9	56.1	−1.6	45.1	−8.1	30.1	−2.5	2.0	6.9	−0.8	8.8
Greece	18.9	11.1	7.0	2.3	8.2	4.9	5.3	4.9	−10.3	−21.6	−7.8	3
Central France	78.4	−13.3	81.4	−4.4	62.3	−12	93.1	−1.6	−2.0	−7.8	20.1	13.6
Northern Spain	99.1	−10.6	39.3	−30.4	13.9	−16.6	−6.2	−13.4	19.8	6.1	1.5	8.6
Southern France	3.9	−13.7	−4.1	−20.1	3.0	−20.7	9.9	−18.2	15.9	−6.7	5.8	−9.4
Mean	35.1	−12.2	28.5	−13.3	19.3	−11.8	18.0	−8.3	6.3	−1.8	2.4	2.0
Analogue												
Tunisia	−3.6	18.2	4.2	−13.2	−2.5	−5.5	15.1	14.6	18.3	7.6	0.0	0
Morocco	34.6	−41.3	24.3	−37.3	−5.3	−25.9	23.9	−6.7	−0.6	10.9	0.0	0
Algeria	41.5	−52.7	74.7	2	36.0	−47.9	−2.8	−38.3	3.3	4.4	0.0	0
Southern Spain	−26.7	−6.6	34.2	−32.2	23.7	−38.2	−0.2	−0.1	11.3	7.9	0.0	−0.4
Southern Italy	25.7	−18.7	39.3	−32.6	36.8	19.7	6.7	−8.6	−4.0	10.1	0.0	−1.4
Central Italy	40.9	−12.9	39.5	−13.6	12.5	−19.8	42.2	−20.1	2.3	−17.9	1.7	5.2
Greece	22.2	17.6	−3.5	−17.4	−26.4	−1.4	−9.0	3.6	−19.9	1.5	−4.9	1.1
Central France	103.5	−8.4	37.2	−12.1	98.3	−2.2	44.4	−21.6	48.8	−11.2	4.6	−4.6
Northern Spain	25.1	−19.2	40.6	−31	−8.2	34.5	3.8	−30.5	−3.8	−6.2	1.9	−8.2
Southern France	16.4	−22.6	−5.8	−31.5	0.8	−26	−23.8	−21.4	19.2	−12.6	−4.0	−11
Mean	28.0	−14.7	28.5	−21.9	16.6	−11.3	10.0	−12.9	7.5	−0.6	−0.1	−1.9

the years characterized by minimum yield for all case studies were aggregated, A emerged as the first to return a prediction with a margin of error lower than 10% 1 mo in advance (April) compared with the H and E methodologies. By contrast, during the years with maximum yield, the forecasts provided by the 3 methodologies have a tendency to underestimate the yield (Table 2); under these conditions the predictions based on the E methodology appear to be the most accurate, on average, with a 13% absolute error in January that falls below 10% in April. In those extreme years, the analysis of thermal accumulation (i.e. the sum of mean daily temperature) and total rainfall from January to June did not reveal any clear pattern that could explain such separated behaviour. This is likely due to the combined effect on crop development and growth of temperature and precipitation anomaly patterns both acting, as atmospheric forcing, at sub-monthly time scales. The performance of the E methodology was probably related to a better identification of large-scale dynamic forcing leading to emerging atmospheric regimes in the synoptic variability range but with a marked bias highlighted by the difficulty of correctly identifying critical periods leading to low yields. In contrast, the difficulties of the A methodology in identifying the better conditions for high yield may be ascribed to a low probability of finding in the past analogue year with similar weather patterns.

This study provides evidence that, even if seasonal forecasting skills in the Mediterranean Basin are still limited, the chance of providing useful information on durum wheat yield several months in advance is real, even on a monthly time scale, with a clear tendency towards skill improvement as the forecast lead time shortens. Such useful information is not limited to a single option among the methods shown; instead, our results highlight some prevalent performance behaviour for each method, regardless of the geographical location. The historical methodology provided good predictive power in years with monthly to seasonal anomalies closer to their long-term mean values and thus with a low level of potential yield hazard. The empirical method, in turn, illustrated positive skill levels when climatic anomalies generated high levels of wheat yield, that is, in good years with a marginal to negligible level of low yield risk. In contrast, the analogue method showed positive skill levels in years with low yields, that is, years with a potentially high level of risk. Results reveal that there is useful information embedded among all of the forecast options provided by the different methodologies. Accordingly, it could be possible to build a simple multi-option approach for providing potential scenarios for wheat production several months in advance. This potential skillful prediction behaviour is particularly important in years when no strong atmospheric/oceanic forcing is present and thus no clear mechanism is acting.

The results confirmed the need to further develop the methods presented here to better account for adverse weather events, especially in the context of climate change that predicts an increase in frequency and magnitude of adverse weather events affecting crop production (Moriondo et al. 2010, 2011, Trnka et al. 2014). The A methodology can be further improved by introducing additional parameters (e.g. precipitable water, Toscano et al. 2014) and indices (e.g. North Atlantic Oscillation and El Niño–Southern Oscillation, Gimeno et al. 2002) defining similarity of weather patterns in the historical time series. Further, implementing different classification and selection techniques instead of the conventional Euclidean norm can be a way to improve skill in prediction (Akbari et al. 2011, Crochet 2013). Improvements of the E methodology could be achieved by applying local calibration, e.g. using a site-specific selection of predictors instead of the same list of predictors for different sites and prediction dates. Defining a site-specific list of predictors by eliminating those that have only a marginal impact on climate variability of a specific geographical region is expected to result in a reduction of noise as well as an improvement of the signal-to-noise ratio, with improved overall performance.

The 3 methodologies analysed were able to provide yield forecasts with good accuracy, with a lead time that, in some cases, is sufficient to allow intervention (with a view to reducing losses) and planning strategy. From the earliest prediction dates, the metrics indicated a good overall ability of the H and E methodologies to reproduce the interannual variability of yields. In contrast, the A methodology gave poorer estimations for the first prediction dates, but tended to level up with the results of the other methodologies from March–April onwards. As expected, as the season progressed, the increasing proportion of observed weather constituting the mixed meteorological data allowed the estimates to become much more accurate. Nonetheless, with very few exceptions, from January (i.e. 5 to 6 mo earlier than maturity) the trueness of the estimations is notable, as can be seen by comparing the MRAE with the CV of the reference yields at each site (Table 3). At each specific site, the MRAE was generally lower than the CV, thus indicating that all the methodologies can provide reliable results in predicting durum wheat

Table 3. Coefficient of variation (CV) of the distribution of reference yields. Reference yields were those obtained by running the crop model with observed meteorological data for the whole growing season

Site	CV (%)
Tunisia	15.9
Morocco	11.2
Algeria	21.1
Southern Spain	18.3
Southern Italy	20.4
Central Italy	16.5
Greece	12.1
Central France	13.3
Northern Spain	25.4
Southern France	20.2

yield over the Mediterranean Basin well in advance of maturity.

Such results support the idea that applying these methods to gain within-season yield predictions may provide end-users with useful information, thus allowing them to make or plan tactical changes during the crop year. For instance, an important contribution can be provided for modulating the distribution of nitrogen fertilizer, in terms of timing and quantity. In this respect, due to their higher lead times, the H and E methodologies might be useful for optimizing the quantity of fertilizer that could be distributed at the beginning of stem elongation (3–4 mo before harvest), avoiding over-fertilization in low-yielding years or providing the crop with adequate nitrogen supply in potential high-yielding years. All the methodologies tested may provide useful indications for late nitrogen applications such those distributed around anthesis (1–2 mo before harvest), with the aim to increase the protein content. Similarly, due to their higher accuracy, predictions of yield produced 2–3 mo ahead of harvest may be used for planning supplemental irrigation to avoid detrimental droughts during grain filling.

In this paper, our analysis has only focused on the utility of the 3 forecasting methods for predicting yield. We made 2 main theoretical assumptions: (1) the crop model is able to reproduce crop growth and yield once a complete set of input data are provided, and (2) deviations of simulated yields from the reference yields are mainly related to the effect of climatic uncertainty due to the forecast weather. These 2 assumptions allowed us to isolate the effect of climate from all other sources of uncertainty and variability, and, in the end, investigate the predictive power of the forecasting methodologies as dependent only on local climate.

With the aim of incorporating these methods in a decision support system to be used for practical farming, the effect of other sources of uncertainty affecting yield predictions should be considered. For instance, although mechanistic, crop models may contain several empirical assumptions that do not completely represent actual plant processes. In addition, the process-based algorithms used for simulating crop growth dynamics as well as water and nutrient balance in the soil–plant system may differ and can produce different responses. Several other factors affecting yield, such as weeds, pests and extreme climate events, are not considered or are roughly simulated, thus representing another source of uncertainty. Exploring such uncertainties, considering the adoption of several crop models as well as the coupling with pest and disease models, would be an interesting topic for further studies.

4. CONCLUSIONS

In this study, the performances of 3 methodologies to calculate within-season yield estimates of durum wheat over the Mediterranean Basin were evaluated. Yield estimates produced at specific dates during the growing season at 10 sites were compared to the reference yields calculated using the observed weather for the whole growing season. The results showed that it is possible to predict durum wheat yield over the Mediterranean Basin with an accuracy of nRMSE < 20%, from 5 to 6 mo earlier for the H and E methodologies and 3 mo earlier for the A methodology. Although the H methodology performed better overall than the others, the A and E methodologies provided better estimations for both low- and high-yielding years. This indicates that the A and E methodologies have great potential as they can provide more accurate predictions for those years that deviate from average conditions.

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