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RESEARCH DOCTORATE IN ECONOMICS, ECOLOGY AND PRESERVATION OF AGRICULTURAL AND LANDSCAPES ENVIRONMENTAL SYSTEM

Modelling and predicting durum wheat yield and quality in Mediterranean environments.

PhD Student

Piero Toscano

SUPERVISOR Prof. Alessandro Peressotti

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Summary

Durum wheat (Triticum turgidum L. var durum) is mainly produced and consumed in the Mediterranean environments, where yield and grain protein content are usually constrained by environmental variables.

A 1.4 million ha of durum wheat are currently grown in Italy with an average production of 4 million tons and an average yield of 3.8 t/ha. 73% of the production, which accounts for 65% of total production, is located in South Italy, while in the Northern regions yield is usually higher due to different pedology and climatic conditions. The cultivation of durum wheat in Italy generates a vast range of allied activities, “upstream” such as seed and technical supplies industries, and “downstream” such as storage centries, primary and secondary transformation industries. Due to the strategic importance of the durum wheat production, a tool able to accurately predict yield and grain protein content before harvesting and an assessment of the agronomic and environmental variables that most influence the quantitative and qualitative parameters in the Mediterranean environments, can be of great value in policy planning. Currently the national and international agricultural statistics services provide regular updates during the growing season of total acreage planted with a specific crop, as well as the expected yield levels. Traditionally, forecasts have been based on a combination of scouting reports as well as statistical techniques based on historical data. Based on the expected yield, the price of grain can vary significantly, with a high impact on both commodity prices and farmers incomes. Growing season forecasts of crop yields are therefore of considerable interest also to commodity market participants and price analysts. Crop simulation models can play a critical role in crop yield and quality forecasting applications: the relatively low cost and

speed of assessment makes crop growth simulation models promising for areas where meteorological information is readily available. The overall aim of the present study was to test the predictive capability of Delphi system, based on the AFRCWHEAT2 model, for yield and quality forecast at local and regional scale in long-term analysis and to determine the general principles underlying how Mediterranean environments affects grain protein content (GPC). General findings allowed us to implement a new simple model with high predictive ability in terms of GPC, only based on gridded climate data, supporting strongly the key role played by weather pattern for a crop such as durum wheat under rainfed conditions.

Abstract 1

Crop models are frequently used in ecology, agronomy and environmental sciences for simulating crop and environmental variables at a discrete time step. The aim of this work was to test the predictive capacity of the Delphi system, calibrated and determined for each pedoclimatic factor affecting durum wheat during phenological development, at regional scale. We present an innovative system capable of predicting spatial yield variation and temporal yield fluctuation in long-term analysis, that are the main purposes of regional crop simulation study. The Delphi system was applied to simulate growth and yield of durum wheat in the major Italian supply basins (Basilicata, Capitanata, Marche, Tuscany). The model was validated and evaluated for three years (1995-1997) at 11 experimental fields and then used in operational mode for eleven years (1999-2009), showing an excellent/good accuracy in predicting grain yield even before maturity for a wide range of growing conditions in the Mediterranean climate, governed by different annual weather patterns. The results were evaluated on the basis of regression and normalized root mean squared error with known crop yield statistics at regional level.

Abstract 2

Durum wheat is one of the most important agricultural crops in the Mediterranean area. In addition to yield, grain quality is very important in wheat markets because of the demand for high-quality end products such as pasta, couscous and bulgur wheat. Grain quality is directly affected by several agronomic and environmental factors. Our objective is to determine the general principles underlying how, in Mediterranean environments, grain protein content (GPC) is affected by these factors and provide a system model with high predictive ability. We initially evaluated the capability of the Delphi System to simulate GPC in the major Italian supply basins (Basilicata, Capitanata, Marche, Tuscany) for 9 years (1999-2007) a month ahead of harvesting and we then analyzed relations between Delphi system errors and selected environmental variables during flowering and grain filling stages. The results were evaluated on the basis of regression with observed GPC, while errors were calculated performing a linear correlation analysis with environmental variables. The model showed a high capability to reproduce the inter-annual variability, with important year to year differences, with better performance in the southern study areas (Basilicata and Capitanata). In this study the highest overestimation occurred in conjunction with the year (2004) characterized by the lowest quality in terms of GPC, lowest average temperature in May and highest yield production for the whole study period.

Abstract 3

The production of durum wheat in the Mediterranean basin is expected to experience increased variability in yield and quality as a consequence of climate change. To assess how environmental variables and agronomic practices affect grain protein content (GPC), a novel empirical modeling approach based on monthly gridded input data has been developed, and validated on historical time series to assess its capability to reproduce spatial and inter-annual GPC variability. The model was applied in four Italian regions and at the whole national scale, proving to be reliable and usable for operational purposes also in forecast mode before harvesting. Precipitable water during autumn to winter and air temperature during anthesis to harvest resulted extremely important in controlling GPC; these and additional variables, included in a linear model, were able to reproduce 95 % of the variability that occurred in the last 15 years in Italy. These results provide experimental evidence to improve crop growth modeling and are an useful tool to better understand and forecast the impacts of future climate change projections on durum wheat production.

Durum wheat modelling: the DELPHI system, 11 years of observations in Italy

P. Toscano[*ab], R. Ranieri[cd], A. Matese[a], F.P. Vaccari[a], B. Gioli[a], A. Zaldei[a], M. Silvestri[d], C. Ronchi[d], P. La Cava[d], J. R. Porter[f], F. Miglietta[ae]

[a]*Institute of Biometeorology (IBIMET – CNR), via G.Caproni 8, 50145 Firenze, Italy.*

[b]*Department of Agricultural and Environmental Sciences, University of Udine, via delle Scienze, 206, 33100 Udine, Italy.*

[c] *Currently in Open Fields S.r.l., Collecchio (Pr), Italy.*

[d]*Barilla G. e R. F.lli S.p.A., via Mantova 245, 43122 Parma, Italy.*

[e]*E. Mach Foundation – Iasma, via E. Mach 1, 38010 S. Michele all'Adige (Tn), Italy*

[f]*Department of Agriculture and Ecology, University of Copenhagen, Faculty of Life Sciences, Højbakkegård Allé 30, DK-2630 Taastrup, Denmark*

**Corresponding author:*

Piero Toscano

IBIMET – CNR

Via Caproni 8,

50145 Firenze, Italia

Tel. +390553033711

Fax +39055308910

E-mail address: p.toscano@ibimet.cnr.it

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1 Introduction

1.4 million hectares of durum wheat are currently grown in Italy, which is the main world producer (IGC,2010), with an average production of 4.0 million tons of grain and an average yield of 3.06 t/ha in the period 2006-2010 (ISTAT). 73% of the cultivation, which accounts for 65% of total production, is located in southern Italy, while yield in the north is higher due to the different pedology and climatic conditions (Bianchi, 1995), (Table 2). Durum wheat is the leading cereal crop in Italy, responsible for almost 40 percent of total cereal production (Istat, Italian statistical center). This generates a vast range of allied activities, both “upstream” (seed and technical supplies industries) and “downstream” (storage centres, primary and secondary processing industries), hence the strategic importance of the entire production chain. This is the result of a gastronomy in which pasta, an end product of durum wheat, is universally recognized as a symbol of Italian cuisine, one of its cornerstones and of great value for the Italian economy (1.7% GDP, Nomisma 2011, http://www.nomisma.it/index.php?id=157&no_cache=1&tx_ttproducts_pi1[backPID]=157&cHash=ee38ce6558). For these reasons, the effect of weather patterns on winter durum wheat production is of primary interest. Due to a high variability of water supply and climatic adversities that characterize the cultivation areas, the qualitative and quantitative planning of production is highly uncertain and represents an important challenge (Dalla Marta, 2011).

The features of durum wheat production are determined by both management and natural variables: sowing time, crop density, soil fertility, genetic characteristics interact with important weather variables, such as solar radiation, rainfall, frosts and high temperatures during grain filling, creating a “risky” environment at local scale (farmers) but also for the whole production at regional or country level (Pecetti, 1997). Low rainfall amounts and their temporal distribution explain as much as 75% of the wheat yield variability (Blum and Pnuel, 1990), while rainfall and temperatures during grain formation and ripening are critical for durum wheat quality (Garrido-Lestache et al., 2005). A decreasing trend in the wheat production area has occurred in recent years (1999 – 2009, FAO global data) as outlined by Mifflin (Mifflin, 2000), due to several factors in addition to the effects of interannual weather variability: global warming and increasing occurrence of extreme weather events, limitations in available land, increasing soil erosion, reduction of available water in irrigated areas and increasing salinization negatively affect total production, while the new agricultural policy guidelines have steered farmers to more profitable crops (Aggelopoulos 2008, Pastatrend http://www.agricoltura24.com) .

In the last years, crop growth simulation models have been widely used as an important tool to investigate crop growth and development and the responses of crops and varieties to different pedoclimatic conditions in order to minimize risk. Studies have addressed a wide range of issues including the impact of climate change on crops, mixed cropping, breeding applications, water and nitrogen management, while only few studies on durum wheat modelling are available for typical Mediterranean climate conditions (Pecetti 1997, Rinaldi 2004, Rezzoug 2008, Richter 2010, Dettori 2011, Motzo et al. 1996, Pala 1996, Latiri, 2010). A model assessing durum wheat development at regional scale, could be of great value for agronomists and help researchers to study the impact of climate change on agriculture. The potentials and limits of dynamic simulation models as predictive tools have been discussed (de Wit and Penning de Vries 1985, McCown 2002, Ahuja 2002), concluding that crop modelling could provide unique advantages in several situations: for example providing a quick response when new needs arise, allowing time and space, dimensions that are often difficult to represent adequately using field experimentation, to be added to agronomic research (Bindi 2001). In general, the applications of dynamic crop simulation models can be defined as strategic, tactical, and forecasting, with a service aimed at farmers, consultants, policy-makers, or companies directly involved with agricultural management and production (Vogel and Bange 1999). The main objective of such applications is to accurately predict yield before harvesting, which can be of great value in policy planning. Currentlly the national and international agricultural statistics services provide regular updates during the growing season of total acreage planted with a specific crop, as well as the expected yield levels. Traditionally, forecasts have been based on a combination of scouting reports as well as statistical techniques based on historical data. Based on the expected yield, the price of grain can vary significantly (Hoogenboom, 2000), with a high impact on both commodity prices and farmers incomes. Growing season forecasts of crop yields are therefore of considerable interest also to commodity market participants and price analysts. For example, future grain prices tend to be quite volatile during crop growing seasons, with the markets being quite sensitive to weather information that affects the yield potential of the growing crop. It is important for market operators to be able to predict the market price in order to maximize economics returns, but if high and volatile prices attract the most attention, low prices and volatility are problematic.

Volatile prices create uncertainty and risk for producers, traders, consumers and governments and can have extensive negative impacts on the agriculture sector, food security and the wider economy in both developed and developing countries (OECD-FAO,2011 http://www.agri-outlook.org/document/63/0,3746,en_36774715_36775671_47923007_1_1_1_1,00.html).

However, it seems that crop simulation models can play a critical role in crop yield forecasting applications: the relatively low cost and speed of assessment makes crop growth simulation models promising for areas where meteorological information is readily available.

Although there is an abundant literature on crop growth simulation model studies, typically these do not translate in tools that can run operationally on entire regions, and that can forecast future yields expected on the basis of scenario weather conditions. Actually in Europe, periodic information on expected yields is provided by the MARS (Monitoring Agriculture with Remote Sensing) Crop Yield Forecasting System operated by the Joint Research Centre (de Wit 2007), but bulletins and outlooks refer to national scale. The Delphi system, object of this study, was implemented to overcome this lack of information and forecast durum wheat yields at regional and sub-area scale. In 1998, in collaboration with one of the largest pasta producers in the world, Delphi was implemented as an integrated forecast system based on the AFRCWHEAT2 model (Porter 1984, 1993a, 1993b), in the major supply basins of southern and central Italy. Delphi consists of a network of weather stations in the regions of interest that acquire meteorological inputs required by the model, a tool to handle management information like sowing date, seed and fertilization amounts, a database for soil, a statistical tool for scenario data reconstruction and gap-filling, and a geographical information system for output visualization and spatialization. This study is based on the capability of a specific crop growth simulation model, driven by a combination of both measured past weather data and forecast future scenario weather data, to predict durum wheat yield, integrated into an operational seasonal forecasting tool focused on the need of crop production managers. We first assessed the ability of AFRCWHEAT2 model simulations to reproduce crop growth at 11 experimental sites by comparing model outputs and site observations and subsequently we implemented Delphi system as an operational tool at regional scale. The results were stored in a database and spatially aggregated to administrative regions, in order to be compared with official durum wheat yields provided by the National Institute for Statistics (ISTAT, http://agri.istat.it/) over a period of 11 years. Moreover we assessed the performance of Delphi as a forecast tool, in terms of accuracy and lead-time of yield forecasts that are produced operationally during the growing season.

2 Materials and methods

2.1 AFRCWHEAT2 simulation model

The Delphi system is based on AFRCWHEAT2 model (Porter, 1984, 1993a, 1993b, Semenov, 1993, Semenov and Porter, 1995). The model has been calibrated and “tuned” for durum wheat and Italian conditions since 1995 and is currently used by one of the major pasta manufacturers to make yield and quality predictions for durum wheat in the major Italian supply basins. AFRCWHEAT2 is a FORTRAN-based mechanistic model that incorporates crop response to water and nitrogen constraints. AFRCWHEAT2 is a complex model of wheat growth and development, describing the phenological development, dry matter production and dry matter distribution between the organs for various environmental parameters on a daily time scale. The model includes a description of plant transpiration and soil evaporation, water and nitrogen movement in the soil, and their uptake by the plant in the course of growth (Harnos, 2006).

AFRCWHEAT2 model simulates wheat development by thermal time accumulation using vernalization and photoperiod factors. Dates of emergence, double ridges, terminal spikelet, anthesis, beginning and end of grain-filling and physiological maturity are calculated by the model for a specific cultivar. Constant intervals in thermal time between developmental events are calculated separately for each pair of developmental stages. Temperature is accumulated above a base temperature and, according to developmental stage, its effects are modified by photoperiod and vernalization. To account for the range of cultivars currently grown in the study areas, model parameters calibrated using experimental data performed for 4 different cultivars grown in experimental sites (Table 1) (Simeto, Duillio, Iride and Svevo) which are among the most widely cultivated in Italy, (http://www.agraria.org/coltivazionierbacee/granoduro.htm) in order to parameterize an ideal cultivar (Harrison 2000). Incoming photosynthetically active radiation (PAR) is calculated from the daily incoming short-wave radiation, leaf area index (LAI) is used to calculate the fraction of intercepted PAR and photosynthesis, Ps (mg (CO2) m–2 s–1) is calculated using a quadratic equation fitted to the photosynthesis–light response curve (Marshall and Biscoe, 1980), after subtracting photorespiration (Weir 1984). AFRCWHEAT2 model was calibrated for durum wheat during a 3-years experimental period (1995-

1996-1997) and then implemented in the core of the Delphi system that allows the management of input data and analysis and spatialization of model results.

2.2 Simulations and yield forecast

An operational tool has been developed in the Delphi system, to estimate phenological development, biomass growth and quantity of grain in durum wheat. A database that stores and updates meteorological data from weather stations, the main characteristics of soil and agronomical data and is linked to the crop simulation model.

Input data are daily values of maximum, minimum, dry and wet bulb temperature, solar radiation, sunshine hours, rainfall, wind and humidity. The weather station database is updated with the meteorological data coming through GSM and transmitted by several stations distributed over the territory (Figure 1). The data are checked for consistency and gap-filled. In order to use crop simulation models to predict crop yield, unobserved daily weather, an important input for crop models, must be forecast in some way. Due to the chaotic nature of weather and the non-linear response of crop simulation models to weather input, this forecast weather cannot simply be a single weather series (e.g. average historical weather for the upcoming growing season), but must be a set of weather series, incorporating site-specific climatic variability (Lawless, 2005).

From this point of view, the database for each weather station also includes also the climatic reconstruction based on long-term conditions (1960-1990 WMO-World Meteorological Organization) in order to define the wettest, driest and average year and create three scenario files ("dry", "wet", "average"), which are used for the forecast.

The Delphi system, requires input data of the main physiological parameters of the durum wheat cultivar, sowing date and number of seeds/m^2 (phenological data input); the soil hydrological profile (2m in 40 layers, hydrological data input) (Addiscott and Whitmore 1991, Addiscott 1993); soil total nitrogen content profile (2m in 40 layers), agronomic data on quality and quantity of nitrogen (NH_4 NO_3, nitrogen data input); roots growth data (roots data input). To compute phenological development of durum wheat an operational tool has been set up with a clear graphical interface. It uses all input data described above to simulate the phenological development of durum wheat, leaf area and biomass growth day by day and display it on a map. The first output is the phenological phase, then the biomass and grain quantity calculated (yield data output). Then using GIS technology it is possible choose which data to show (biomass, grain yield, etc.) as a map or extrapolate for a single location. The system starts to simulate plant growth from 1st September to harvest date. In the operational version, the model runs simulations from January to June and, in forecast, the model uses the scenario files in a sort of ensemble forecast. Rather than rely on just the present information of the growth stage, we consider three forecasts that start from the same initial conditions (present information). The growth stage is determined by the actual weather conditions during the period from 1st September, while the entire development till harvest will follow the conditions of the three scenarios. The variation in simulated yields using different scenarios could be considered as an indication of the effect of climatic uncertainty on yield prediction for a given site. This produces a narrower distribution of grain yields. As time passes and the amount of observed data available for prediction increases, the simulated prediction becomes more accurate.

2.3 Study area

The study was carried out in four Italian macroareas/regions: Basilicata, Capitanata, Marche, Tuscany, each characterized by different climatic conditions, although in a typical Mediterranean environment (Table 3). The climate in Capitanata Plain (Apulia region) is Mediterranean subtropical with a thermic soil temperature regime, where the rainiest months are October and November, while the dry period is from May to September. In Basilicata, while Metapontum Plain has climatic conditions similar to those of Capitanata, the central and northern area of Basilicata is characterized by a Mediterranean and Mediterranean suboceanic climate. November is the rainiest month, while July and August are the driest. From an environmental point of view, Tuscany is peculiar for its extremely heterogeneous morphological and climatic features. The climate in Tuscany ranges from Mediterranean oceanic and suboceanic, partially mountainous, to a Mediterranean to subcontinental and continental climate. Under Mediterranean oceanic and suboceanic, the rainiest months are October and November, while July and August are dry. Under Mediterranean to subcontinental and continental climate the rainiest period is between October-December, while there is a dry period between June-August. In Marche region climate ranges from Mediterranean and Mediterranean suboceanic to a Mediterranean mountainous climate. Under Mediterranean and Mediterranean suboceanic climate the rainiest month is November while July and August are dry. Under Mediterranean mountainous climate the rainiest months are November and January while the dry months are July and August.

The meteorological data used to implement the model during the eleven years of forecast Delphi system are collected from 104 stations distributed over the four areas of study (Figure 1). For Marche, Tuscany and Basilicata we used weather data gathered by ASSAM (Marche Regional Agency for Agro-food Industry, 27 weather stations), ARSIA (Regional Agency for Development and Innovation in Agriculture and Forestry, 28 weather stations), and ALSIA (Lucana Agency for Development and Innovation in Agriculture, 14 weather stations) respectively, which supplied all the weather parameters required by the model as input on a daily basis. For the Capitanata area we used weather data collected by a proprietary network that includes 35 weather stations. The weather station supports the main meteorological parameters sensors with 0÷5 Volts output: temperature and air humidity, soil temperature, global solar radiation, wind speed, wind direction, rainfall, connected to a data-logger (with 8 analog channels, 10 digital channels with I/O functions and an input counter channel for the rain gauge) contained in a rugged box (IP56 protection class) where the main board of the data-logger and electronic sensor are placed. The data-logger program and data retrieval are performed by the specific D.O.S. environment software and an RS-232 interface port. Weather sensors of the proprietary network were calibrated at the beginning and end of each crop year, and monthly maintenance was carried out.

Soil data were retrieved from the soil maps of Regional Agencies and from the National Center for Soil Mapping (http://www.soilmaps.it/) and constitute a compromise between data generalization and intensity of soils surveys conducted in the study areas during the experimental period (Table 1). Crop management inputs typically considered include sowing date, plant density, fertilizer date (type and amount), while irrigation is not required because Italian durum wheat is basically not irrigated (Bazzani, 2004). The agronomic data were provided by the Agricultural Consortia and by Barilla G. e R. F.lli SpA.

2.4 Calibration

AFRCWHEAT2 model, developed for bread wheat, was calibrated for durum wheat in order to determine each pedoclimatic factor that affects durum wheat during phenological development, at regional scale. The calibration procedure to minimize the difference between measured and corresponding simulated data was performed for three years (1995-1997) at 11 experimental sites (Table 1) with the following activities:

- soil core sampling at 5 depths (0-10 cm, 10-30 cm, 30-50 cm, 50-70 cm, 70-90 cm) for pH, soil texture, and organic component analysis;

- 7 samplings for each field and for 4 cultivars (Simeto, Duillio, Iride, Svevo) during different phenological phases (average seed weight, LAI, grain yield, biomass);
- hourly meteorological variables (air temperature, soil temperature, global radiation, rainfall, wind speed, relative humidity).

Shape parameters for the LAI simulation, rate of carbon translocation to the grain, rate of nitrogen translocation, biomass accumulation for a single “mean” cultivar as average of the 4 sown cultivars, on a daily time-step and grain yield, dry matter production and harvest index were tuned on the basis of data collected during the experimental period.

Collected data were divided into two datasets, to calibrate with one subset and then validate with a different subset (Power, 1993, Hansen, 2000) (Table 1). The subset used for calibration includes 5 experimental sites and crop variables: water and nitrogen contents in different soil layers, grain yield, above-ground biomass, below-ground biomass and phenological stages. The data for the years 1995-1996 were used for calibration, while data for 1997 were used for validation.

2.5 Sensitivity

A sensitivity analysis is useful to indicate which input parameters have the most significant effect on the model output, with particular focus on the measurement or calibration of those parameters. The sensitivity of a certain model output to a given parameter can be defined as the rate of change in the output value resulting from a change of this input parameter while keeping all other parameters constant (Wöhling, 2005).

During the experimental period a sensitivity analysis of the model was conducted for soil hydrological and chemical properties, to differentiate the weight of input data required by the model (phenological, hydrological, nitrogen, roots).

Analysis was performed on 3 years of meteorological data collected from the network of 11 weather stations (Table 1).

2.6 Spatial aggregation and validation

Crops are produced in an environment that varies in both space and time. Scaling up entails applying models that assume a homogeneous environment (i.e. a point in space) to larger areas that can encompass a considerable range of spatial variability. Inputs to crop simulation models typically include daily weather, soil properties (including topography and initial conditions) and management (including cultivar characteristics); collectively these inputs define the environment of the modelled system. All three types of environment inputs vary spatially. Valid predictions of yields for a particular year or crop response to interannual climate variability averaged over a region depends on appropriate representation of variability of inputs in space (Hansen 2000). The work that we propose in this study follows a simplified approach for the characterization and prediction of durum wheat production at regional scale. On the one hand we implemented a detailed model that at local scale (single point), captures much of the mechanism of crop response to weather variability and its interaction with management. On the other we selected a wide range of weather stations for each basin of interest in order to capture the spatial variability range (Figure 2). This choice allows us to characterize almost all the areas that usually grow arable crops, such as durum wheat in Italy, as indicated by Barilla, which annually provided sowing and management data for each local point annually, simulation studies have inferred regional crop response (yield and production) to climate variability based on the average of representative locations. The decision to simulate only representative sites and evaluate the average of the output, instead of aggregating the input data, was taken to avoid “fallacy of the averages” (Templeton and Lawlor, 1981).

The average of yields simulated at representative locations were compared, for the 11 years study period, with official durum wheat yield provided by the National Institute for Statistics (ISTAT, http://agri.istat.it/), such as surface (area under production), total production and harvested yield at regional scale. In this paper, we assume that these statistical values represent the true crop yield for a region.

2.7 nRMSE

Crop yields at regional scale vary from season to season primarily because of the variability of weather. Because of interactions between plants, soil and weather, spatial patterns of yields can also vary between years. For example, normalized root mean squared error (nRMSE) of crop yield predictions (S) can be calculated based on deviations from observed yields (O) accumulated over time represented by n years:

$$nRMSE = \sqrt{\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}} \times \frac{100}{\overline{O}}$$

nRMSE gives a measure of the relative difference (percentage of the mean value, O) of simulated versus observed data. The simulation is considered excellent with nRMSE less than 10%, good if nRMSE is greater than 10 and less than 20%, fair if nRMSE is greater than 20% and less than 30%, and poor if nRMSE is greater than 30% (Jamieson, 1991; Bannayan and Hoogenboom, 2009). Assuming that applications of crop models related to climate variability and prediction are concerned primarily with response to interannual variability of areal-average model results over some region of interest, we applied this statistical approach and description in order to evaluate the performance of our system.

3 Results

The purpose of the simulation experiment was to implement and calibrate AFRCWHEAT2 model, for different geographical areas and for 4 cultivars, in order to simulate the entire phenological development in different climatic conditions and define variables that really affect the production of durum wheat performing and adapting the model for a single “mean” cultivar.

Simulated and observed data for grain yield and biomass at harvesting are shown in Figure 3, for the model without calibration (NO CAL) and after calibration (CAL) for 6 validation sites. Before model calibration, an over-forecast for biomass is shown, while an under-forecast for yield, which led to a redefinition of shape parameters for the LAI simulation and of harvest index, as average of 4 sown cultivars. After calibration, errors were found to be acceptable between predictions and observed data from field experiments (Harrison et al 2000). The average RMSEs for total final above-ground biomass and final grain yield, calculated from the 6 validation sites, were 0.71 and 0.299 t ha^{-1}.

For the sensitivity analysis, vertical distribution of total nitrogen content (40 layers) was modified and model output for biomass and grain yield are shown in Table 4. Modified nitrogen content led to a not significant change (± 5 %, mode 1) on durum wheat production. Hydrological parameters (40 layers as input) were then modified, as DUL (drained upper limit) and RLL (lower limit for crop extraction). Perturbations for DUL and RLL induced significant changes on the production of grain yield and biomass (Table 5): a negative percentage variation of DUL parameter (-20%) affects strongly biomass and yield (-136% and -147%), while a positive percentage variation (+10 and +20%) results in an increase of biomass and yield, but with lower magnitude (+31% and +39%); in a different way percentage variation of RLL parameter affects biomass and yield with a low increase (+19% and +27%) for negative variation and a strong reduction (-74% and -77%) due to positive variation (+20%).

Finally the importance of using meteorological data validated and without systematic errors, caused by sensor or system problems, was evaluated comparing a reference simulation (Tref) with two simulations, increasing/decreasing Tref by 2℃. The 2 ℃ tempera ture rise allowed the crop to advance its phenological development by 13 days, while decrease in temperature delayed it by 15 days. Simulated biomass and grain yield are shown in Table 6.

After the experimental period (1995-1997) to calibrate and evaluate the system, Delphi has been used in operational mode for the four study areas that for eleven years (1999-2009) produced an average of 50% of Italian durum wheat. A comparison between simulated and ISTAT grain yields for the whole operational period and for each study area is shown in Figure 4, with results of the Delphi system at harvest for each crop year aggregated at the regional scale to compare them with data provided by ISTAT. Spatial heterogeneity, such as climate, management and soil, leads to a considerable effect on the grain yield, as highlighted by the standard error in Figure 4, while bias of spatial average was not taken into account because the model runs only for representative sites. Regression of simulated yields and ISTAT yields indicated that there was a statistically significant fitting with an r^2 of 0.84, with best performance for Tuscany (^{r2} 0.85) and Basilicata (r^2 0.76), lower for Capitanata (^{r2} 0.72, without 2007 r^2 0.85) and Marche (r^2 0.4, without 2003 0.7).

Latitude dependence of yields can be observed by the results shown in Figure 4 and 5, with lowest average production in Basilicata (2.41 ± 0.54 t/ha) and Capitanata (2.79 ± 0.58 t/ha), highest values in Toscana (3.17 ± 0.47 t/ha) and Marche (3.95 ± 0.21 t/ha). Despite the interannual variability, in the North (Tuscany and Marche) yield is higher due to different weather and soil conditions (Bianchi, 1995).

Evaluating the results for different years, climates and areas, the model adequately reproduced yield. The simulated grain yields follow the interannual variability for each area (Figure 5), and in terms of the relative difference between simulated and observed values, are always below 0.5 t ha^{-1}, except for three crop years, two for the Marche region (2001 and 2003) and one for Capitanata (2007).

An analysis of all the simulations run for 104 locations, for each of the 104 weather stations in the 4 study areas during each crop year and excluding 2001 for Marche region, based on three scenarios (wet, dry, average) used for the forecasting system, highlights that the Delphi system provided a very consistent grain yield forecast even before crop maturity (Figure 6).

The forecasting system monthly (the first day of each month from January to June) on the basis of three scenarios provided the distributions of crop development under wet, dry and average conditions. As the growing season progressed, so the proportion of historic meteorological data in these sets decreased, the distribution means converged towards the true values, allowing us to make predictions with a high level of confidence before crop maturity. Figure 6 shows as the wet scenario initially tends to overestimate slightly, while the dry scenario, simulating extreme conditions, leads to pronounced underestimation.

Since correlation coefficient and linear regression are not entirely satisfactory for model evaluation (Kobayashi and Salam, 2000), model performances were evaluated computing an index based on squared differences between estimated and observed values.

nRMSE values (Table 7) were calculated for all 11 years, based on three scenarios, and each year for the six months of simulation (January, February, March, April, May, June) on 104 stations for a total of 20592 simulations. Basically yield forecasts based on the “dry” scenario are poor and tend to converge to good values on 1st May, as the worst weather conditions for given phenological stages have been contemplated for this scenario.

The forecasts based on the "wet" and "average" scenarios are excellent/good from 1st January for Marche and Tuscany regions, while for the southern areas (Basilicata and Capitanata) they are “good” on 1st May, before the harvest (usually harvested between the second week of June and first week of July) (Raciti, 2003, Rosenmund 2005, Castrignanò 2002) and approach almost excellent values on 1st June.

4 Discussion

Analysis shows that a proper hydrological characterization is required to perform a reliable simulation, while the characterization of nitrogen content, however necessary, is not crucial. Positive variations for DUL parameter (+10 % and +20 %) led to positive changes on the production of biomass and yield. Instead, positive variations for RLL parameter (+10 % and +20 %) induced negative changes of biomass and grain. The difference is due to RLL parameter (wilting point) which represents the not available soil water for crop growth and its increase has a negative impact on production, vice versa for DUL parameter, which represents the field capacity.

During the operational mode the lowest yield values were in conjunction with the warmest average temperature/drought or adverse weather conditions during the period between anthesis and maturity, showing some discrepancy between the model and ISTAT data. The interannual variability is mainly caused by adverse weather conditions (2001 and 2003), or favourable to the crop development (2004 and 2005). The 2001 crop year in the Marche region (overestimation of 0.98 t ha^{-1}) was affected by a late frost event in mid-April that was reported as limiting (http://meteo.regione.marche.it/agrometeo/notizie/provedim.htm) and is not integrated into the Delphi system, while in the 2003 crop year low rainfall in spring and above average temperature in June caused "stretta" phenomena (seed shrivelling due to high temperatures during kernel ripening), reducing the specific weight of grains (Frascarelli, 2009), (http://www.informatoreagrario.it/bdo/RIA03325.asp). These latter conditions were simulated by the model as severe water stress, causing a drastic reduction in yield (underestimation of 0.68 t/ha).

The 2007 crop year in Capitanata area was characterized by pronounced climatic extremes, which translated into a reduction in yield indicated by the simulations, but with an overestimation of 0.77 t ha^{-1}. It is likely that the simulation underestimated the severe stress damage due to pronounced climatic extremes which caused in reality a drastic production reduction. However, also for this season, the model performed well if compared with the results by other study conducted on durum wheat in adverse weather conditions (Pecetti, 1997) or in general with study based on different models in terms of correlation (Dettori 2010, Moriondo 2007).

Is notable how the Delphi system, except for 2001 year crop in Marche region, captured the year-to-year pattern of response to climate variability, validating the methodology implemented for scaling up crop model predictions, from single plot level to broader spatial scales and higher system levels.

In addition, a slight overestimation (less than 2 %) of the grain yield has been noted for Marche, Tuscany and Capitanata that in any case does not appear to be linked the model parameterization.

Considering that the system simulates for a wide range of growing conditions in the Mediterranean climate, a large initial ensemble prediction, although increasing forecast uncertainty, allows the assessment of any risks associated to drought conditions, especially in southern Italy, where are more limiting.

In general, the accuracy of yield forecasts decreased with increasing lead-time. This is expected because an increasing proportion of weather is observed rather than estimated from the climatological distribution as the growing season progresses, but is not equally clear for each study area. The difference that emerged in the capacity to predict yields well in advance for the various regions is linked to interannual variability of production for each region, as shown in Table 7. Low values of standard deviation reflect the capacity of the system to predict with high accuracy even five months before harvest (Marche and Tuscany, with a standard deviation of ± 0.21 t ha^{-1} and ± 0.47 t ha^{-1} respectively), while a high interannual variability allows the model to achieve high accuracy two months before harvest (Capitanata and Basilicata, with a standard deviation of ± 0.58 t ha^{-1} and ± 0.54 t ha^{-1}, respectively).

5 Conclusions

When we implemented Delphi system and used for the first time as operational tool in 1999, yield forecast for durum wheat and for several crops in Italy were based only on field surveys and farmer interviews. Over the last years national and international agency developed forecast systems for staple crops including durum wheat. Several elements and independent modules (remote sensing, GCM, weather stations, crop models) are integrated to monitor crop behaviour and produce crop yield forecasts (MARS Crop Yield Forecasting System, http://mars.jrc.ec.europa.eu/mars/About-us/AGRI4CAST/MARS-Bulletins-for-Europe), but actually bulletin provide forecast only at national scale.

With Delphi system we demonstrated that durum wheat yields can be accurately predicted under Mediterranean conditions, providing valuable information on the final regional production of durum wheat, thanks to its ability to simulate the entire growing season. We demonstrated that it is possible to predict yield in advance with confidence and regional estimates can be produced using a detailed crop simulation model, but it requires detailed description of the distribution of soil-types, climate and cropping techniques over the region. Simulations of grain yield indicated ‘excellent’ to ‘good’ predictions for all study areas, with a clear ability of the model to predict production before crop maturity. Basically the Delphi system captures year-to-year patterns of response to climate variability and for crop years affected by drought and those with average climatic conditions.

The results of this study, based on long-term datasets, support the conclusion that a predictive crop model needs proper calibration and validation in different environments in order to simulate accurately and have a significant forecasting value over wide areas. This is particularly crucial taking into account that durum wheat is cultivated under different climatic conditions and often in rainfed and water limiting conditions.

Research can play a role in narrowing the gap between technology, agriculture and sectors directly involved in production and agribusiness. The development of a model, carefully calibrated through field experiments and then implemented in a user-friendly forecasting system, is crucial in managing the risks associated with the production process, supporting a reduction in the volatility of returns and planning storage and distribution strategies as well as the importance, influence and potential to meet the requirements of stability of supply.

Advance knowledge of the likely volume of future harvests is thus a crucial factor in the market. Prices fluctuate as a function of the expected production, with a major psychological component. In fact, prices depend more on the production that the traders anticipate than on actual production. Accurate forecasts are, therefore, an useful planning tool. They can also often act as a mechanism to reduce speculation and the associated price fluctuations of end products.

In the future, it will be interesting to apply and evaluate the Delphi system estimating the protein content of grain or further implement the system in the form of a decision support system (DSS) (Fedra, 1995, Lilburne 1998, Bonfil 2004, Bazzani, 2005) at lower level based on a direct exchange of information with farmers using platforms such as social forum, in order to increase grain yield because of a tendency to a decline in the growth trend in many European countries (Brisson, 2010).

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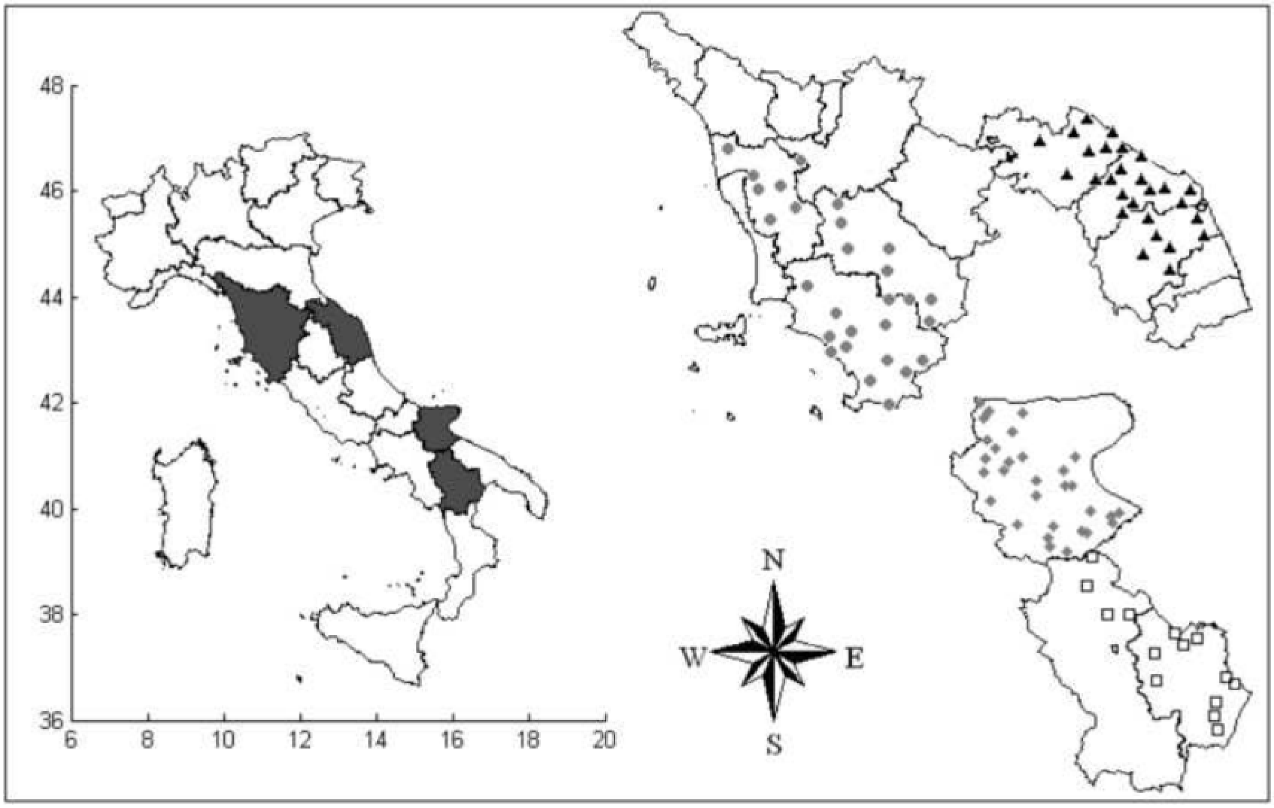
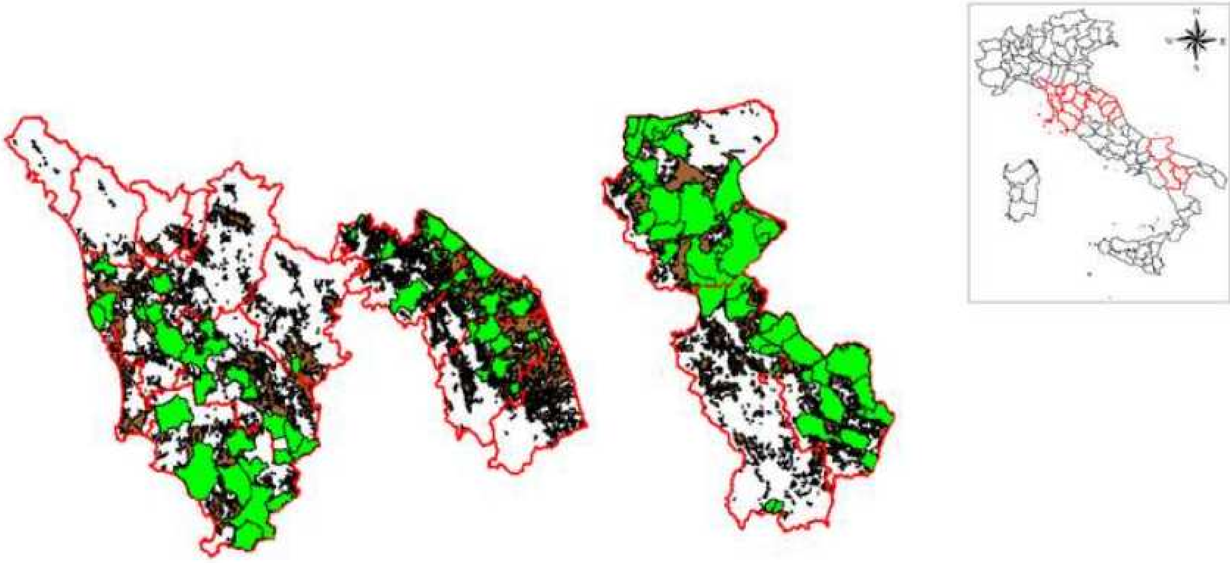


Figure 1 Map of Italy with study area in grey and locations of weather stations (Marche ▲, Tuscany ●, Basilicata □ and Capitanata ♦)



Region	Not irrigated arable crops (ha)	WS municipality coverage (ha)	Coverage (%)
Tuscany	637466	466461	73.17
Marche	411990	313348	76.05
Capitanata	747146	717646	96.05
Basilicata	859494	769707	89.55

Figure 2 Study area map based on Corine Land Cover (2006 Level II) for not irrigated arable crops (brown), with the municipalities where weather stations are located (green). The table gives the surface area defined as not irrigated arable crops, the surface of municipality and regional percentage cover.

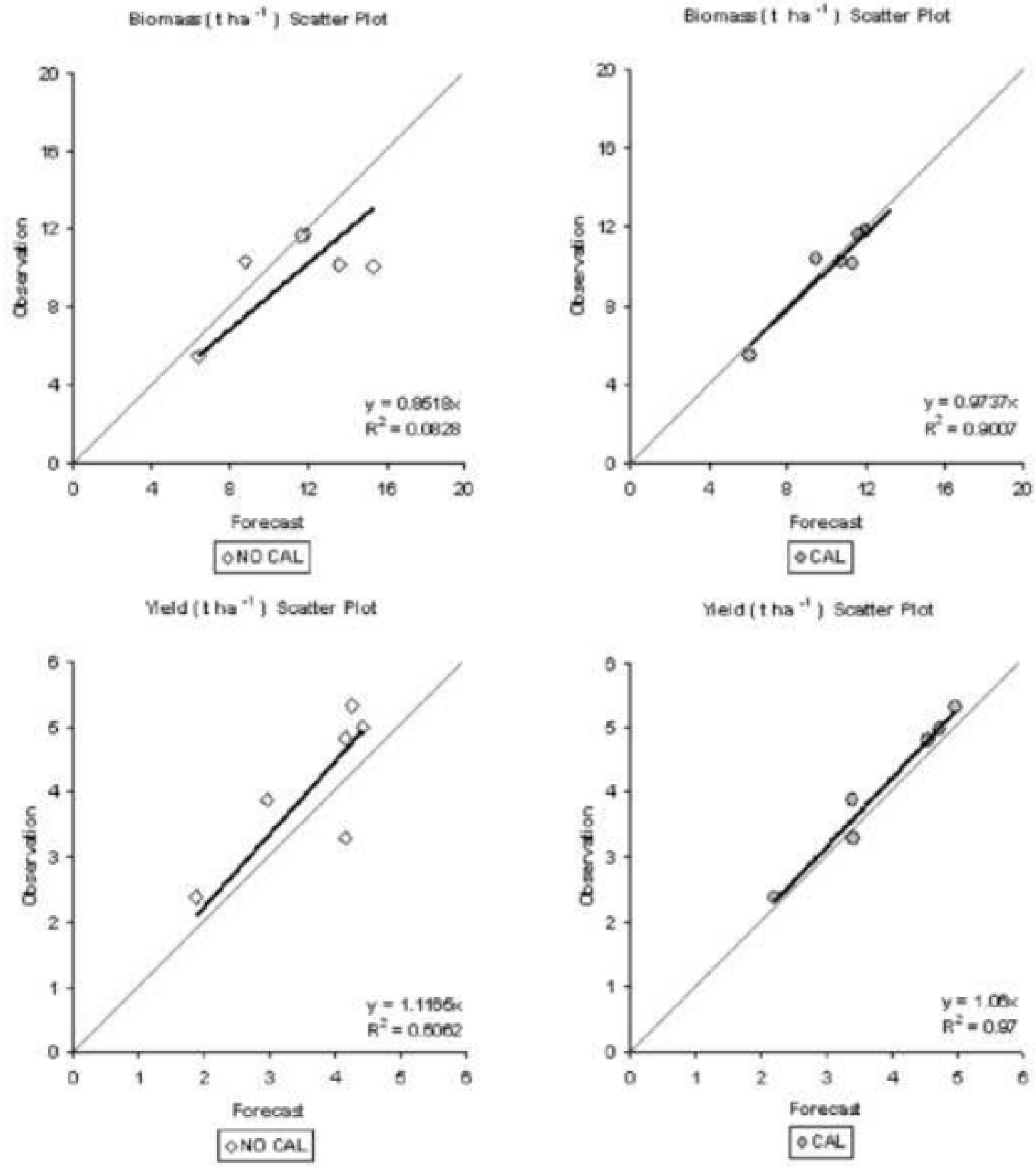


Figure 3 Validation for non-calibrated (left) and calibrated (right) model results of AFRCWHEAT2 for ideal cultivars at 6 experimental sites (Table 1). The 1:1 line is shown in each panel

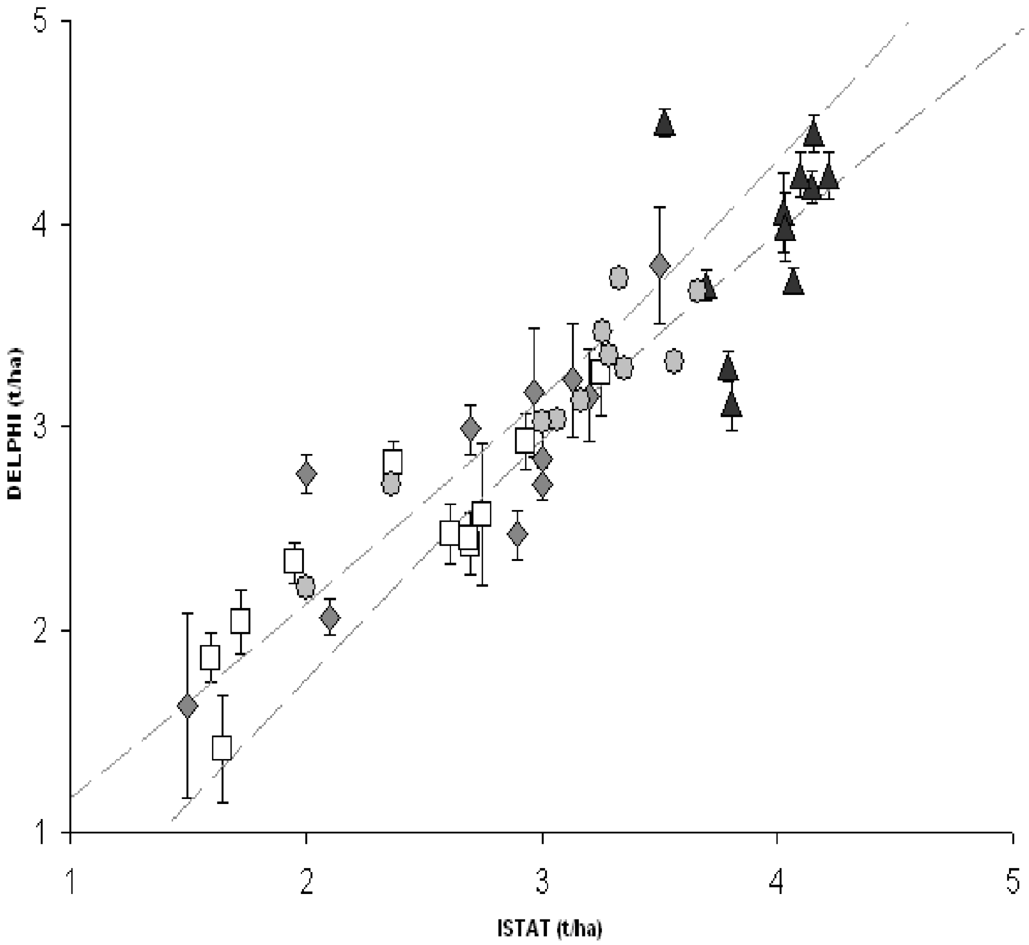


Figure 4 Comparison between national durum wheat yield statistics (ISTAT) and simulated yield (Delphi) over 4 study areaa in Italy (Marche ▲, Tuscany ●, Basilicata □ and Capitanata ♦), for a period of 11 years. Statistically significant correlation (0.92) with an r of 0.84 and p-value<0.01. Confidence interval (0.95) grey dashed lines.

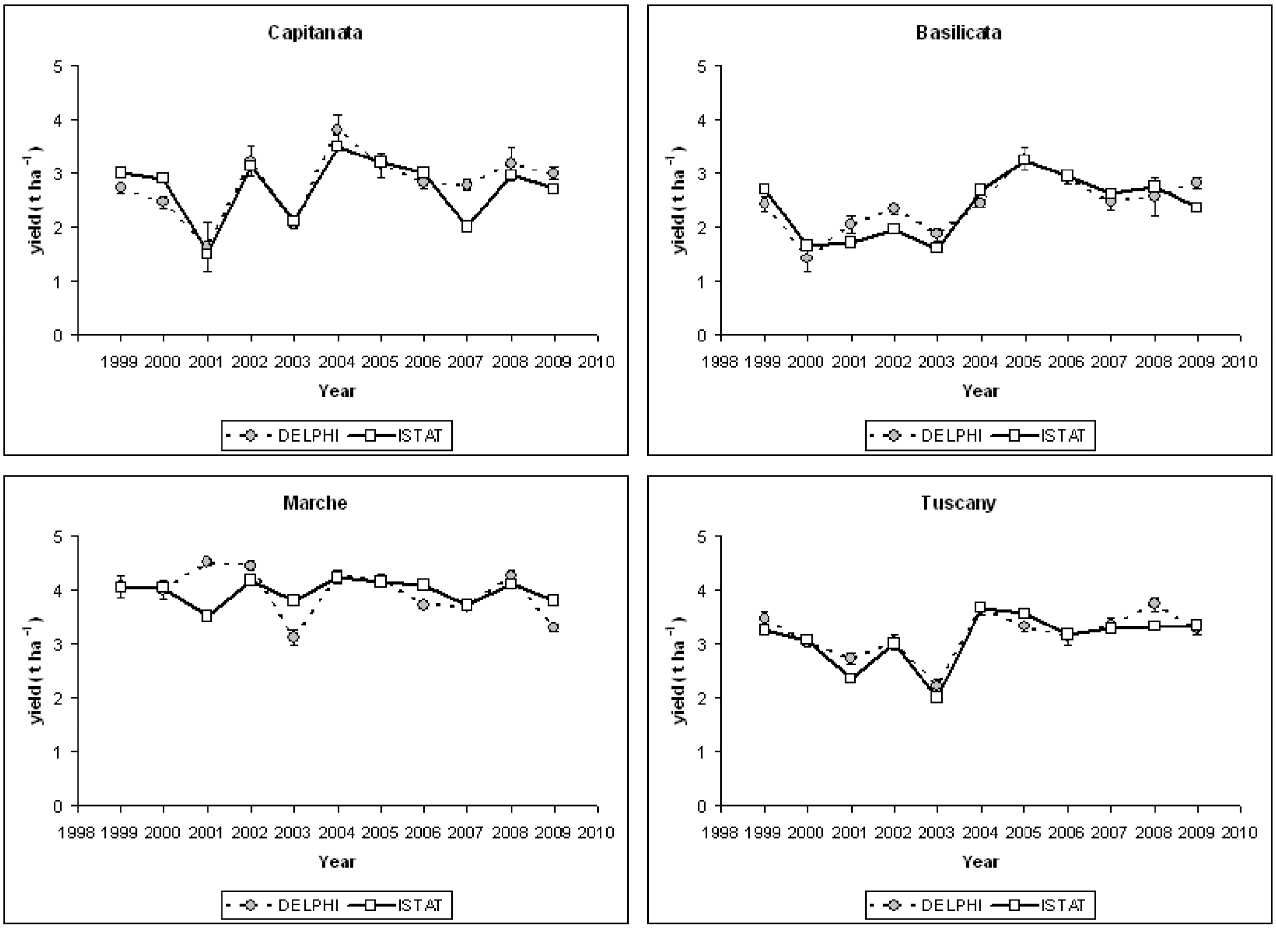


Figure 5 Durum wheat grain yield (t/ha) trends of 11 years simulated (Delphi System) and observed crop (ISTAT) for each study area.

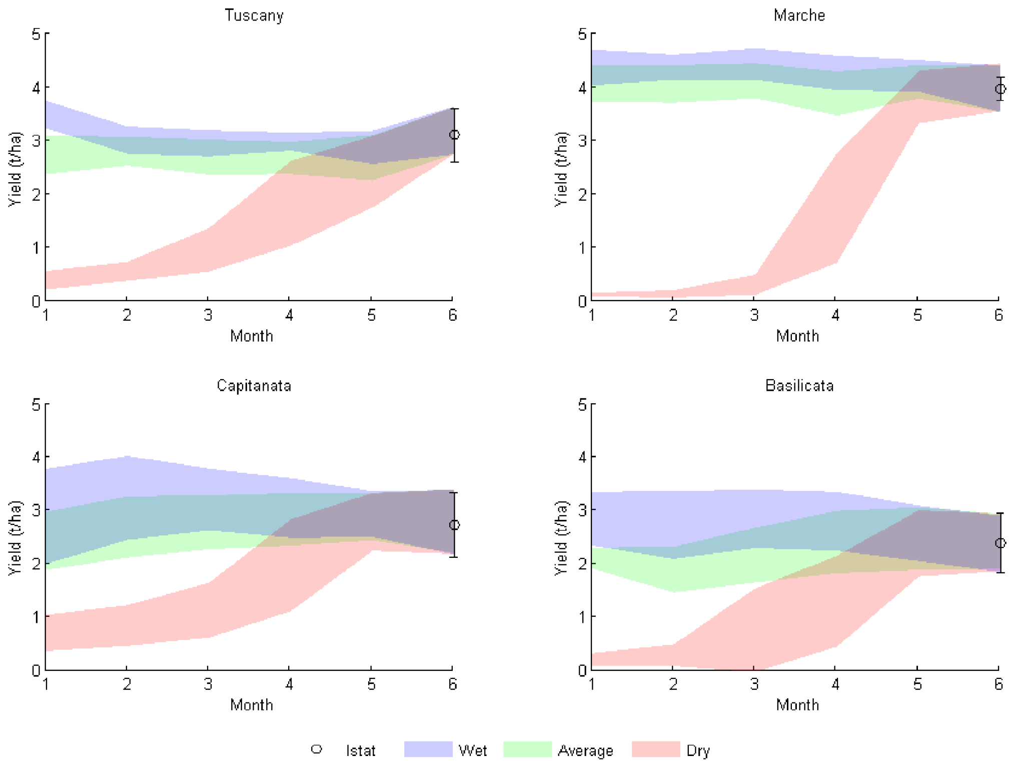


Figure 6 Time evolution of the yield forecast as mean and standard deviation of 11 years simulated for each study area, using three different scenario simulations. The black circle is the official mean yield for the same period as reported by the National Institute for Statistics (ISTAT).

Experimental Sites	Coordinates	Stones (%)	Sand (%)	Silt (%)	Clay (%)	pH in H_2O	Organic Matter (%)	Total nitrogen (g/kg)	Phosphoric Anhydride (g/kg)	Potassium Oxide (g/kg)	Nitrate (meq/100g)
Corial – Foggia *	41.42 N 15.62 E	0.34	62.50	23.00	14.50	8.23	2.43	0.07	2.33	20.94	1.40
Torremaggiore °	41.71 N 15.19 E	4.77	64.00	16.50	19.50	8.45	1.32	0.18	1.44	8.71	3.65
Senigallia *	43.68 N 13.23 E	0.20	55.00	23.50	21.50	8.24	1.03	0.13	1.62	4.36	1.23
Basentello °	40.66 N 16.20 E	0.10	57.50	18.50	24.00	8.44	1.33	0.18	2.13	5.63	1.58
Braccagni *	42.88 N 11.01 E	0.10	48.00	27.00	25.00	8.14	3.30	1.31	2.04	2.97	0.71
Apricena °	41.78 N 15.45 E	0.22	54.00	23.00	23.00	5.27	1.29	0.81	1.84	4.18	1.60
Tolentino °	43.22 N 13.38 E	0.62	41.50	22.00	36.50	7.90	1.90	1.37	2.48	5.19	2.89
Rovereto *	44.75 N 11.03 E	0.32	51.00	27.50	21.50	8.22	1.62	1.10	2.52	2.18	2.07
Conselice °	44.52 N 11.73 E	0.07	49.00	22.00	29.00	8.11	1.85	0.59	1.97	3.41	1.88
Rapolano *	43.28 N 11.60 E	6.01	81.50	7.50	11.00	6.00	0.84	0.61	2.19	1.56	1.39
ITAS – Firenze °	43.76 N 11.32 E	1.31	61.00	19.00	20.00	7.39	1.98	0.01	2.51	4.11	1.36

Table 1 Experimental campaign: sites description (* calibration site, ° validation site). Soil physical and chemical characteristics (0-30 cm depth) are reported for each site.

	Surface cultivated (ha)	%	Total Production (t)	%	Yield (t/ha)
North Italy	77682	5.61	419545	9.89	5.4
Central Italy	277999	20.08	1083960	25.53	3.9
South Italy	1028786	74.31	2742261	64.58	2.6
Italy	1384467		4245766		3.06

Table 2 Durum wheat cultivated surface area, total production and yield in Italy (ISTAT, 2006/2010).

Study Area	Durum wheat surface (ha)	Mean Annual Temperature Range (°C)	Mean Annual Rainfall Range (mm)	Montly mean temperature < 0 °C
Basilicata	175000	12.5 - 16	700 - 1000	--
Capitanata	400000	12 - 17	400 - 800	--
Tuscany	135000	10 - 17	620 – 1600	--
Marche	125000	9.5 - 16	700 - 1000	--

Table 3 Study area description: mean durum wheat cultivated surface area, mean annual temperature range, mean annual rainfall range and months with an average temperature below 0 °C are reported.

Nitrogen content perturbation (%)	Biomass Variation (%)	Grain Yield Variation (%)
- 20	- 5.5	- 4.9
- 10	- 2.8	- 2.0
+ 10	+ 2.9	+ 4.2
+ 20	+ 5.3	+ 5.3

Table 4 Relationship between nitrogen content perturbation and model output (biomass and grain yield). A broad range of variation ± 20% does not significantly vary production values.

Parameter Modified	Perturbation (%)	Biomass Variation (%)	Grain Yield Variation (%)
DUL	- 20	- 136	- 147
DUL	- 10	- 54	- 59
DUL	+ 10	+ 20	+ 26
DUL	+ 20	+ 31	+ 39
RLL	- 20	+ 19	+ 27
RLL	- 10	+ 13	+ 17
RLL	+ 10	- 47	- 43
RLL	+ 20	- 74	- 77

Table 5 Relationship between DUL (drained upper limit), RLL (lower limit for crop) perturbation and model output (biomass and grain yield). Positive changes for DUL parameter result in increase of production, while for the parameter RLL positive changes result in a decrease. Output variations show extreme variability and an accurate determination of the hydrological parameters is necessary.

	Tref	+2 ℃	-2 ℃	% Variation (+2 ℃)	% Variation (-2 ℃)
Grain Yield (t/ha)	**3.24**	**3.12**	**2.95**	**- 3.7**	**- 8.95**
Biomass (t/ha)	**9.16**	**9.47**	**8.34**	**+ 3.38**	**- 8.95**

Table 6 Durum wheat simulated biomass and grain yield with three different climate scenarios: reference, +2 ℃ and -2 ℃ with respect to reference scenario. Sc enario +2 ℃ has a positive effect on biomass, but a negative impact on grain yield. A decrease in temperature (-2 ℃ scenario) causes a delay in crop development, resulting in a decrease in both biomass and yield.

Area	Scenario	Jan	Feb	Mar	Apr	May	Jun
Tuscany	**Dry**	*88.3*	*83.5*	*70.7*	*46.4*	*29.1*	***6.1***
	Average	*16.5*	*16.5*	*17.5*	*19.6*	*18.9*	***6.5***
	Wet	***8.8***	*11.1*	*12.9*	*14.9*	*15.4*	***6.1***
Marche	**Dry**	*98*	*97.8*	*94.3*	*66.4*	*14.5*	***8***
	Average	***8.2***	***8.9***	***8.8***	*12.4*	***8.7***	***7.7***
	Wet	*12.4*	*10.8*	*12.7*	*10.8*	***9.7***	***7.9***
Capitanata	**Dry**	*78.5*	*71.8*	*63.2*	*42.6*	*14.5*	*12.1*
	Average	*20.9*	*24.7*	*22.4*	*22.7*	*14.4*	*11.7*
	Wet	*35.1*	*42*	*30.5*	*25*	*15.9*	*12*
Basilicata	**Dry**	*91.8*	*87.5*	*75.8*	*54.5*	*13.7*	*10.3*
	Average	*31.8*	*33.8*	*28.8*	*22.5*	*12.7*	*11*
	Wet	*32.1*	*31.6*	*28.6*	*25.2*	*15.4*	*10.8*

Table 7 Statistical analysis results are shown for grain yield in terms of normalized root mean square error (nRMSE). For the Marche region the series does not include the 2001 crop year affected by late frost and not integrated into the Delphi system. Grey cells indicate “good” values of nRMSE, with bold for “excellent” values.

Durum wheat quality prediction in Mediterranean environments: from local to regional scale.

P. Toscano[*ab], B. Gioli[a], A. Crisci[a], L. Genesio[a], F.P. Vaccari[a], A. Zaldei[a], E. Ferrari, F[c]. Bertuzzi[c], P. La Cava[c], C. Ronchi[c], M. Silvestri[c], A. Peressotti[b], J. R. Porter[d], F. Miglietta[ae]

[a]*Institute of Biometeorology (IBIMET – CNR), via G.Caproni 8, 50145 Firenze, Italy.*

[b]*Department of Agricultural and Environmental Sciences, University of Udine, via delle Scienze, 206, 33100 Udine, Italy.*

[c]*Barilla G. e R. F.lli S.p.A., via Mantova 245, 43122 Parma, Italy.*

[d]*Department of Agriculture and Ecology, University of Copenhagen, Faculty of Life Sciences, Højbakkegård Allé 30, DK-2630 Taastrup, Denmark*

[e]*E. Mach Foundation – Iasma, via E. Mach 1, 38010 S. Michele all'Adige (Tn), Italy*

**Corresponding author:*

Piero Toscano

IBIMET – CNR

Via Caproni 8,

50145 Firenze, Italia

Tel. +390553033711

Fax +39055308910

E-mail address: p.toscano@ibimet.cnr.it

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1. Introduction

Europe accounts for more than 26% (9.1 Mt) of the global durum wheat production and this is mainly concentrated in Mediterranean countries: Italy (4.1 Mt), Greece (1.3 Mt) and Spain (0.9 Mt) for a total cultivated surface of approximately 3 Mha (IGC, 2012).

Durum wheat is grown mainly in sub-humid dry lands under non-irrigated conditions, which makes grain yield uncertain, but offers the opportunity for high quality productions in terms of total protein content (Borghi et al., 1997).

Environmental and agronomical variables such as climate, soil and agronomic practices exert a strong influence on technological quality parameters of durum wheat. This effect is particularly marked in Mediterranean environments, where the climate, characterized by sustained water deficit and thermal stress during grain filling, may cause large fluctuations in both grain yield and grain quality traits (Baenziger et al., 1985). The most important agronomic practices and variables that affect wheat protein content are: soil water content, nitrogen fertilization rate, time of nitrogen application and residual soil nitrogen (Campbell et al., 1981; Rao et al., 1993; Uhlen et al., 1998; Rharrabti et al., 2001). About two-thirds or more of the proteins stored in the grain at maturity are present in the plant at anthesis (Austin et al., 1977), while the remainder is absorbed from the soil during the period of grain development (Kramer, 1979).

The complexity of plant growth and development processes that interact with each other and the weather have made experimental studies of grain protein development and management rather difficult. Results from field experiments have been highly variable from site to site and season to season (e.g. Spiertz and Ellen, 1978; Delroy and Bowden, 1986; Fischer et al., 1993; Rao et al., 1993).

If durum wheat yield and quality responses to climatic conditions can be predicted early, precisely and accurately, this information could be widely used: by farmers to optimize their agronomic decisions and by durum wheat markets, for hedging or forward contracting (Smith and Gooding, 1999; Woolfolk et al., 2002).

Crop models have been used to predict protein content of wheat, because of the importance of gluten, about 80% of the total protein content. Gluten affects the technological characteristics of the dough. Attempts have been made to estimate grain protein concentrations under various growing conditions with either site-specific (Makowski et al., 1999) or generic simulation models (Otter-Nacke et al., 1986; Meinke, 1996; Jamieson and

Semenov, 2000; O'Leary and Connor, 1996; Porter, 1993; Brisson, 1998; Martre, 2003; Asseng et al., 2002a). Between generic models, the grain protein routine of the APSIM-Nwheat model has already been quantitatively tested for *Triticum aestivum* L., showing good agreement between simulated and measured protein concentrations under various growth conditions and environments including temperate, Mediterranean and sub-tropical areas. The root mean squared deviation (RMSD) was 2% variation in grain protein concentration (Asseng et al. 2002). The model also projected a decline in grain protein concentration with increased genetic yield potential, thus presenting an opportunity to explore issues related to the response of grain protein to environmental, management and genetic factors. Good progress has also been made in modelling total and fractional grain protein content and concentrations (Martre et al., 2006; Jamieson et al., 2001), but only for winter and spring wheat.

In this paper, we i) explore the capacity of an existing state-of-the-art durum wheat modelling system (Delphi) to forecast grain protein content (GPC) a month ahead of harvest; ii) evaluate the capability of the system to reproduce the inter-annual variability of durum wheat GPC for four regional study areas from 1999 to 2007 by assessing its performance against observed data; iii) analyze relations between system errors and selected environmental variables during flowering and grain filling stages, to investigate key areas of system improvement.

The Delphi System (Toscano et al., 2012) is based on the AFRCWHEAT2 mechanistic crop model (Porter et al., 1993), and predicts GPC by modelling crop response to water and nitrogen constraints, driven by a combination of actual and scenario weather conditions.

2. Materials and methods

2.1 Delphi System - AFRCWHEAT2

Delphi system is based on AFRCWHEAT2, a model developed for bread wheat (*Triticum aestivum L.*) that has been calibrated and validated for different environments and pedo-climatic conditions (Porter,1984, 1993; Porter et al., 1993; Semenov et al., 1993; Semenov and Porter, 1995 Jamieson et al., 1998; Jamieson and Ewert, 1999). In the Delphi system the model was calibrated for durum wheat by parametrizing pedo-climatic factors that affect durum wheat phenological development, at a regional scale. The calibration procedure (Toscano et al., 2012) was performed for three years (1995–1997) by accounting for dry matter partitioning of C and N that determine the grain yield and protein concentration. Protein concentration, in particular, depends on the capacity of the plant to accumulate both carbon and nitrogen in the grains. The demand for crop nitrogen is calculated from the difference between the concentration levels at the current crop development stage and their maximum value (Hay and Porter, 2006) and in this study the maximum value of demand for nitrogen by grain is set at 0.001625 g N grain−1 ℃ day, lower than 0.0017 g N gra in−1 ℃ day as reported in Vos, 1981 and Porter et al., 1995, to balance for the increased grain number per unit area (Gnum, grain m^{-2}) following the calibration procedure performed in Toscano et al., 2012. A factor (GFN) was introduced to reduce grain N demand when shoot pool for C is equal to 0: i) GFN=1 when shoot pool is greater than zero (SPOOL>0), ii) GFN=0.3 when shoot pool is 0 (SPOOL=0) for less than 4 consecutive days, iii) GFN=0 in all other cases. Final simulated grain nitrogen value was then multiplied by a factor of 5.7, that expresses the N concentration in the grain, and by 100 to calculate the simulated GPC in %, hereafter referred to simply as GPC_{DEL}, and compare it with the observed GPC.

The Delphi System upgraded with the algorithm for the characterization and prediction of durum wheat protein content, was applied in four study areas (Figure 1, Basilicata, Capitanata, Marche, Tuscany) for the period 1999-2007. Soil data were retrieved from soil maps of Regional Agencies and from the National Center for Soil Mapping (http://www.soilmaps.it/). Crop management inputs include sowing date, plant density, fertilizer date (type and amount), while irrigation is not required because durum wheat is sparingly irrigated in Italy (Bazzani et al., 2004). Agronomic data were provided by the Agricultural Consortia and by Barilla G. e R. F.lli SpA.

Input meteorological data include daily values of maximum, minimum and average temperature, solar global radiation, rainfall, wind speed and relative humidity, collected from 104 weather stations located in durum wheat production areas across the four study areas as described in Toscano et al., 2012. The database for each weather station also includes the climatic reconstruction based on long-term conditions (1960-1990 WMO-World Meteorological Organization) in order to define the average year and create the scenario file used for the forecast.

2.2 Datasets and model testing

2.2.1 Grain Protein Content data

Detailed surveys of GPC were made by Barilla for the period 1999-2007 during the project “Quality Map”, hereafter referred to simply as GPC_{BAR}. This dataset of 863 samplings consists of annual sampling of protein content from the 4 study areas (Table 1) across a large range of growing conditions, including different combinations of soil types, water and N supplies, and cultivars.

Data were averaged at regional and country level for each year of the whole available dataset.

2.2.2 Gridded climatic variables: Air Temperature and Precipitable water

The air temperature (AIRT) and precipitable water (PW) (Table 2) were selected as climatic variables potentially controlling yield and protein content, since they are directly related to vapour pressure deficit (VPD) that is known to regulate photosynthesis. We obtained these data by spatially gridded global numerical simulations from NCEP/DOE AMIP-II Reanalysis (Reanalysis-2) (hereafter referred to simply as NCEP) (Kanamitsu et al., 2002); the web data hub is available online at http://www.cdc.noaa.gov/data/gridded/data.ncep.reanalysis2.html.

Both PW and AIRT parameters were downloaded in netcdf format and processed and analyzed using Matlab (http://www.mathworks.it/it/help/matlab/ref/netcdf.html). The NCEP dataset has a temporal resolution of 6 h (4x/day) and data are available in several different coordinates systems, such as a 17 pressure level stack on 2.5x2.5 degree grids, 28 sigma level stack on 192x94 Gaussian grids and 11 isentropic level stack on 2.5x2.5 degree grids. For this work we used the 28 sigma level stack on 192x94 Gaussian grids, with AIRT at 2m level and PW referring to the entire atmospheric column, considered as a single layer. Both variables were selected as independent dataset to investigate the environmental conditions that control model performance. Data were extracted for the 4 study areas as indicated in Figure 1.

2.2.3 N : C ratio in grain and accumulation/remobilization timing

To better understand the controlling factors related to the model performance, we calculated several simulated variables associated with the C and N translation: the N:C ratio in grain; the number of days taken for the accumulation/remobilization in the grain. In post-anthesis for each day we calculated the differential of carbon and nitrogen and then the ratio. For each year, we then calculated the average of all calculated ratio. Regarding the accumulation/remobilization timing we calculated the number of days taken until the total accumulation of N in the grain and then we calculated the average for each year.

2.3 Statistical analysis

The analysis was performed using a linear regressive scheme, while the evaluation metric is the coefficient of determination, denoted as R^2.

A linear correlation analysis was also performed between gridded environmental variables (air temperature and precipitable water) and GPC by using Person's linear correlation coefficient.

3. Results

Simulated and observed GPC data for the four study areas and for nine crop years (1999-2007) are shown in Figure 2; correlations show a higher predictive capacity of the model in the southern durum wheat area than in the central regions, with R^2 values of 0.84 and 0.73 for Basilicata and Capitanata respectively. In the two central regions R^2 values were lower at 0.57 and 0.46 for Marche and Tuscany respectively. GPC values range over the nine year period from 11.59% to 13.43% in Basilicata, 12.01% to 13.61% in Capitanata, 12.62% to 14.22% in Marche and 11.21% to 14.66% in Tuscany. During the nine crop years the Delphi system tends to overestimate GPC and the absolute difference between simulated and observed values is on average +0.24% ± 0.11% (Tuscany -0.26% ± 0.27; Marche +0.07% ± 0.12; Capitanata +0.34% ± 0.09; Basilicata +0.81% ± 0.10). The maximum absolute difference between model and observations was 1.69% in Tuscany in 2000. Clustering the values of observed and predicted GPC for the four areas leads to an R^2 of 0.71 (Figure 3). Both simulations and observations show an overall decreasing GPC trend over the study period, with a slope of similar magnitude for both observed and simulated values (-0.12% and -0.11% for GPC_{BAR} and GPC_{DEL} respectively, Figure 4a). Figure 4a also highlights how the Delphi system, although overall overestimating the observed data (except in 2007), is capable of reproducing the GPC interannual variability, with important year to year differences: in 2004 the model had the worst performance, with an overestimation of 0.78% of the absolute total GPC (12.22% observed, 13.00% simulated), while the average for the other 8 years is 0.18% of the total GPC (13.14% observed, 13.32% simulated). If we consider 2004 as an outlier (Figure 4b) the relation between simulated and observed GPC values increases further with an $R^2 = 0.87$.

We then calculated the errors on an annual basis as the difference between the predicted and observed values. The errors denoted as (GPC_{DEL} – GPC_{BAR}) show a strong negative correlation with the monthly gridded values of precipitable water in May ($r = -0.895$, $p = 0.0011$) and mean air temperature ($r = -0.714$, $p = 0.0308$) (Table 3). Figure 5a reports the strong negative relationship between the precipitable water during the months of May and residues GPC_{DEL} – GPC_{BAR}, a $R^2 = 0.79$ and showing how the poorest model performance coincides with the lowest value of precipitable water. The ratio of differential nitrogen and carbon in grain (Figure 5b) was lowest in 2004 simulations, not showing any significant relation with precipitable water in May (Figure 5c), but showing a low correlation ($R^2 = 0.47$) with the average temperature during the first 10 days of grain filling (data not shown).

Moreover, analyzing the days taken for the total accumulation/remobilization in grain, the longest period was again in 2004 (Figure 5d), with a mean number of days for the 4 study areas of 29.3 compared to an average of 21 days in the other 8 years analyzed. The time taken for the total accumulation/remobilization results as being correlated ($R^2 = 0.73$) with the ratio of differential nitrogen and carbon (DN : DC, data not shown).

4. Discussion

The observed GPC showed a high variability in the 1999-2007 period in all four study areas, with the lowest values for Basilicata, Marche and Capitanata observed in 2007. This was a year characterized by pronounced climatic extremes for the whole plant development period (mean air temperature 1.8 °C higher and mean rainfall 19.4 mm lower with respect to the 1975-2005 average) resulting in a substantial reduction in both production and quality (Toscano et al., 2012). In Tuscany the decline in GPC in 2004 (lowest value observed for the whole period) was instead associated to high yields as generally also happened for the other study areas.

GPC high inter-annual variability is a reflection of variations in weather patterns, between years and between sites, which are characteristic of the Mediterranean region, and that significantly influence grain yield and GPC (Pinheiro, 2013; Rharrabti, 2003a; Rharrabti, 2003b; Diacono, 2012).

The Delphi System is able to capture this variability with a relatively high correlation coefficient (r= 0.71). The higher predictive performance of the Delphi System in the two southern regions is likely to be due to the shorter time-lag between the issuing of the forecast (1st June) and harvest date in southern areas: wheat is harvested on average 20 days later in central/northern regions and therefore the forecast time-lag is longer.

In general the Delphi System tends to overestimate GPC in southern regions, probably related to the model parameterizations that do not account for lower yields, while a slight underestimation in northern regions is probably due to the non inclusion in the model of farming techniques that are known to affect productivity such as weed control, use of certified seed and more adequate fertilization (Bianchi, 1995). Although there is a negative correlation (r= -0.47, data not shown) between protein content and yields specially due to adverse weather conditions (2001 and 2003) with low yield production and high GPC, or favourable to crop development (2004 and 2005) with high yield and GPC below the average for the period 1999-2007, it should be highlighted that high protein content also occurred in years of good yield performance (1999 and 2002), probably as a consequence of improvements in breeding and release of new genetic material with good expression of both yield and quality parameters.

The Delphi System showed the lowest forecast capability in 2004, the year reported as the one with the highest production of durum wheat in Italy and, for the study period, the only one to have exceeded domestic demand but with a lower average quality (Frascarelli and Oliverio, 2009; ISTAT, http://agri.istat.it/).

From a climatic point of view, 2004 was characterized by low air temperatures in May, on average 2.63 °C below the average for the period 1999-2007. These conditions led to a prolonging of both anthesis and post-anthesis stages.

It should be noted that Delphi System also correctly captured the year-to-year pattern of response to climate variability for 2004 (Figure 4a) forecasting a lower GPC than in 2003.

In 2004 there was a prolonged grain filling stage (Figure 5), as a consequence the low predictability is likely to be linked to the longer time-lag of the forecast compared to other years; this is supported by the fact that running simulations without scenario weather data (i.e. with observed meteorological data until maturity) led to a difference between observed and simulated GPC of 0.56% instead of 0.76%, confirming the low predictability of 2004.

A prolonged grain filling accompanied by cool conditions and not limiting water as in 2004 led to a prolonged green leaf area duration through delayed leaf senescence in a sort of “stay green” status (Borrell and Hammer, 2000; Spano et al., 2003), allowing the photosynthetic activity to continue and enabling the plant to assimilate more carbon and use more N for biomass production and increasing yield and grain weight (Dimmock and Gooding, 2002). Stay-green properties would be beneficial for total biomass production, an important character for feed and/or feedstock purposes (Christopher et al., 2008), but may not be desirable in bread-making as they could be associated with reduced N relocation to the grain. The environmental conditions during grain filling can have impacts on grain protein concentration, high temperatures (above 20 ℃) in the grain filling period have a greater effe ct on C than on N accumulation, generally giving smaller grains with high N concentrations (Gooding et al., 2003). The low GPC in 2004 was instead due to lower than average temperatures, that led to an increase in C supply to the grain mostly due to increases in growth duration, especially after anthesis, with a reduction in grain protein concentration as reported in Triboi et al., 2006.

Analyzing the ratio DN : DC over the years it emerges that the Delphi System correctly predicted 2004 as the lowest value (Figure 5b), but this did not reflect in a marked dilution, thereby leading to an overestimation by simulations.

One reason could be related to transport of N to the harvested organs that in our system is “sink regulated” and not “source regulated” as described in Jamieson and Semenov, 2000; Martre et al., 2003. AFRCWHEAT2 implicitly assumes that N has to be transported from the shoots to satisfy the demand of grains, this implies that the transport system is controlled by the sink, through the product of grain number and the demand of individual grains. This approach probably led to the overestimation in a stay-green condition as happened in 2004, underestimating the use of more N for biomass production and overestimating grain N accumulation.

A further insight to improve the performance derives from the relation between the model error (i.e. the difference between observed and simulated values, GPC_{DEL} – GPC_{BAR}) and the two environmental variables, precipitable water and air temperatures: a strong and significant relation was found for both variables in the month of May, which is the month of anthesis and beginning of grain filling in Italy. Flagella et al., 2010;

Garrido-Lestache et al., 2005 similarly reported a positive correlation, for Mediterranean environments, between GPC and May and June air temperature.

In this study the highest overestimation occurred in conjunction with the year (2004) characterized by lowest quality in terms of GPC, lowest average temperature and lowest value of precipitable water in May.

Precipitable water successfully acted as a proxy for atmospheric water demand and VPD, and helps to better understand the dynamics of the VPD being closely linked to the dew point as reported by many authors (Karalis et al., 1974; Yang and Xue, 1996; Reber and Swope, 1972; Li et al., 2009). VPD, a highly significant variable for physically based crop simulation models (Huang, 2010), has a significant effect on the amount of water required by the crop to maintain optimal growth, but data required to calculate the mean VPD on a daily basis are rarely available, and the model implemented in the Delphi System uses an approximation to estimate it, as in other models (Wang et al., 2004). In fact, VPD is estimated from daily maximum and minimum temperatures with the assumption that the minimum temperature equals dew point, and there is little change in vapour pressure or dew point during any one day. Daily minimum temperature was found to be a poor estimate of dew point temperature, being higher than dew point in summer and lower in winter, but at same time VPD estimated in the Delphi System (data not shown), resulted as lower on average in May 2004 than other crop years.

From an operational perspective, although the Delphi System succeeded in providing early predictions of GPC, improving its predictive ability seems related to a better characterization of protein accumulation in grain, accounting for an impact factor of precipitable water/VPD or air temperature in May by creating an empirical relationship at local and regional scales. It would also be useful to evaluate the performance of a more mechanistic approach (source regulated) for durum wheat in a particular year such as 2004.

5. Conclusions

Weather conditions strongly influenced the GPC over the whole period analyzed and we demonstrate that the Delphi System is capable of reproducing GPC variation and temporal fluctuation in a long-term analysis but it still requires model improvement and better climatic characterization to improve accuracy and precision at local and regional scales.

This is the first study, to our knowledge, of a modelling forecast of pre-harvest GPC in durum wheat in Mediterranean environments. Therefore, opportunities for comparison with other data and simulation forecasts are limited. On the basis of our findings there is a need to develop joint modelling and experimental studies of this topic to provide the quantitative responses that will permit the modelling effort to progress.

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YEAR	BASILICATA	MARCHE	CAPITANATA	TUSCANY
1998	*22*	*31*	*30*	*14*
1999	*24*	*28*	*28*	*19*
2000	*17*	*27*	*24*	*12*
2001	*17*	*27*	*23*	*13*
2002	*24*	*30*	*21*	*19*
2003	*17*	*26*	*20*	*16*
2004	*21*	*25*	*29*	*11*
2005	*15*	*31*	*20*	*13*
2006	*22*	*29*	*20*	*17*
2007	*16*	*31*	*18*	*16*

Table 1 Sampling numbers during the Barilla Quality Map Project. Samples refer to a mix of different cultivars

	SOURCE	*PERIOD*	*UNIT*	*DESCRIPTION*
AIRT_1	NCEP	1999-2007	℃	Mean Air Temperature January
AIRT_2	NCEP	1999-2007	℃	Mean Air Temperature February
AIRT_3	NCEP	1999-2007	℃	Mean Air Temperature March
AIRT_4	NCEP	1999-2007	℃	Mean Air Temperature April
AIRT_5	NCEP	1999-2007	℃	Mean Air Temperature May
AIRT_6	NCEP	1999-2007	℃	Mean Air Temperature June
AIRT_7	NCEP	1999-2007	℃	Mean Air Temperature July
AIRT_8	NCEP	1999-2007	℃	Mean Air Temperature August
AIRT_9	NCEP	1999-2007	℃	Mean Air Temperature September
AIRT_10	NCEP	1999-2007	℃	Mean Air Temperature October
AIRT_11	NCEP	1999-2007	℃	Mean Air Temperature November
AIRT_12	NCEP	1999-2007	℃	Mean Air Temperature December
PW_1	NCEP	1999-2007	kg/m^2	Precipitable Water January
PW_2	NCEP	1999-2007	kg/m^2	Precipitable Water February
PW_3	NCEP	1999-2007	kg/m^2	Precipitable Water March
PW_4	NCEP	1999-2007	kg/m^2	Precipitable Water April
PW_5	NCEP	1999-2007	kg/m^2	Precipitable Water May
PW_6	NCEP	1999-2007	kg/m^2	Precipitable Water June
PW_7	NCEP	1999-2007	kg/m^2	Precipitable Water July
PW_8	NCEP	1999-2007	kg/m^2	Precipitable Water August
PW_9	NCEP	1999-2007	kg/m^2	Precipitable Water September
PW_10	NCEP	1999-2007	kg/m^2	Precipitable Water October
PW_11	NCEP	1999-2007	kg/m^2	Precipitable Water November
PW_12	NCEP	1999-2007	kg/m^2	Precipitable Water December
GCP_{BAR}	BARILLA	1999-2007	%	Grain Protein Content Observed
GCP_{DEL}	DELPHI	1999-2007	%	Grain Protein Content Simulated
N	BARILLA	1999-2007	N/ha	Unit of Nitrogen applied for fertilization

Table 2 List of environmental and agronomic variables

Month	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	
GPC_{DEL} - GPC_{BAR}	-0.123	0.590	0.162	-0.271	-0.030	-0.480	0.342	-0.895**	0.455	0.290	Precipitable Water
	-0.505	0.29	-0.028	-0.446	-0.205	-0.573	-0.375	-0.714*	0.083	0.128	Mean Air Temperature

Table 3 Correlations with significance for Precipitable water (PW, kg/m2) monthly values, Mean air temperature (AIRT, °C) monthly values and GPC_{DEL} - GPC_{BAR} values at regional scale for the period 1999-2007. Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

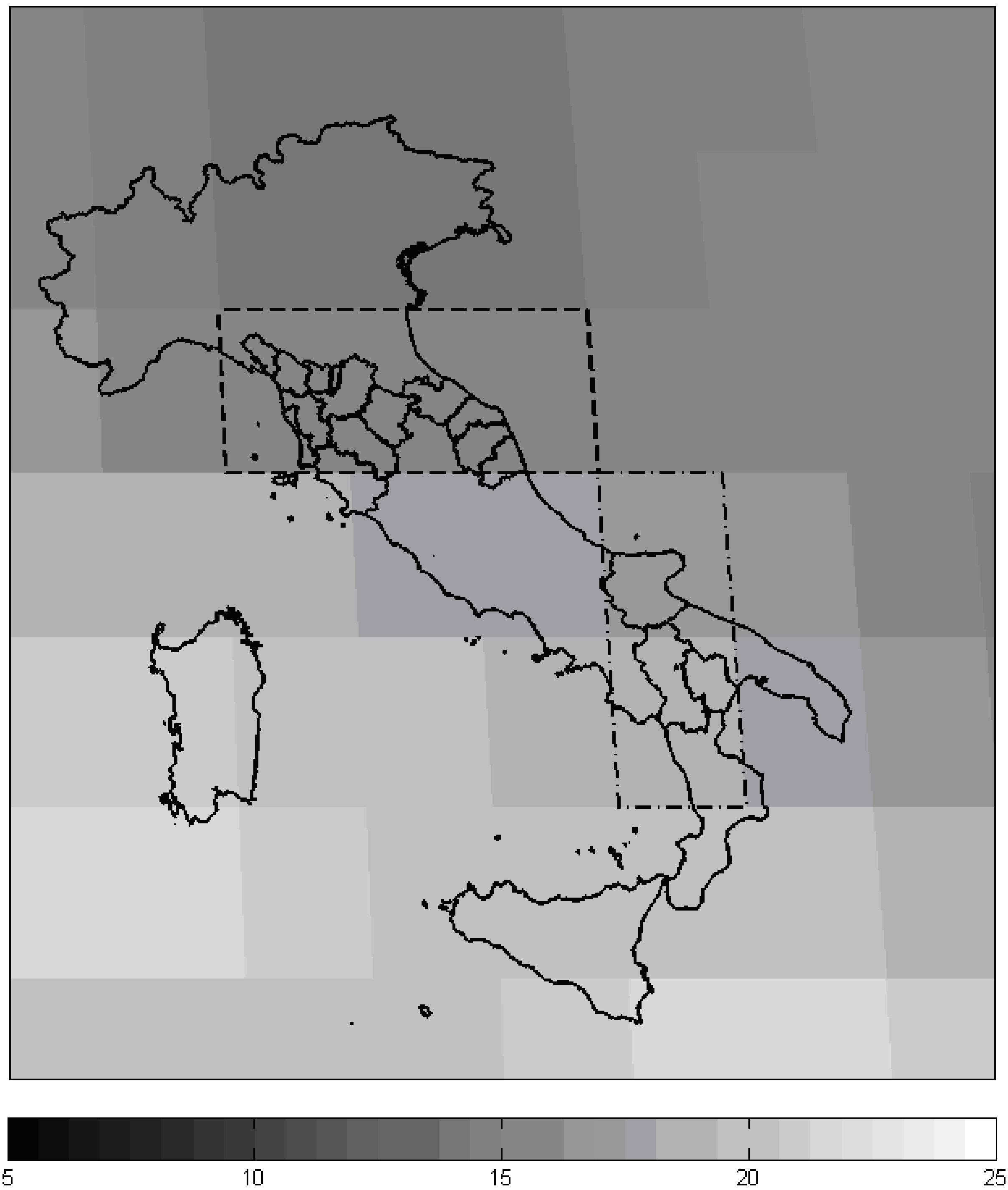

Figure 1 Mean Precipitable Water (kg/m^2) for the year 2012. Map of Italy with study area (Tuscany, Marche, Capitanata, Basilicata) for the Delphi Model implementation. Dashed line and dash-dot line highlight the grid selected for Tuscany–Marche and Capitanata–Basilicata for the extraction of monthly gridded values of precipitable water and mean air temperature

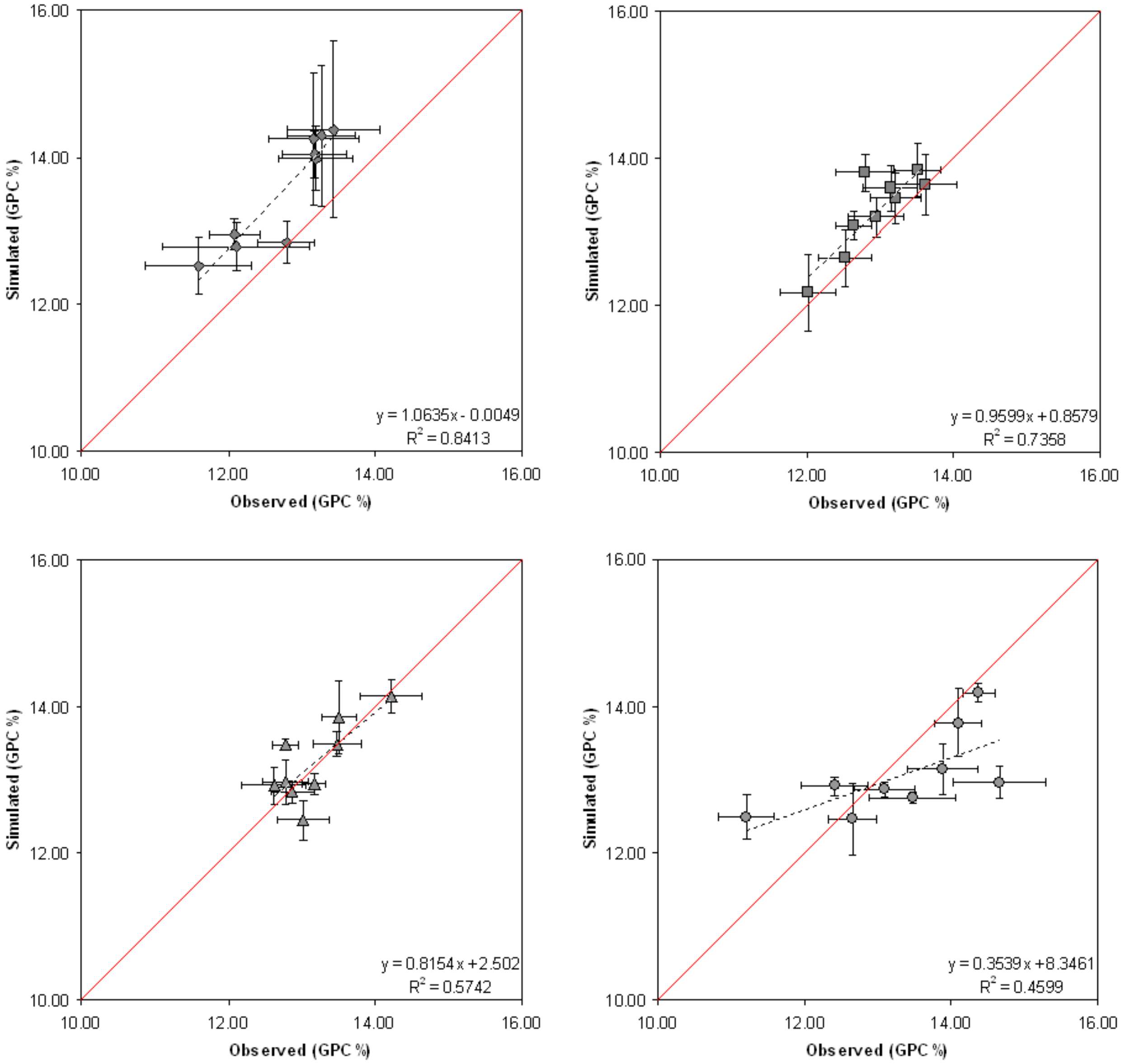

Figure 2 Comparison between GPC_{BAR} and simulated Grain Protein Content with Delphi System over four study areas in Italy (Marche ▲, Tuscany ●, Basilicata ♦ and Capitanata □), for the period 1999-2007. The 1:1 line is shown in each panel

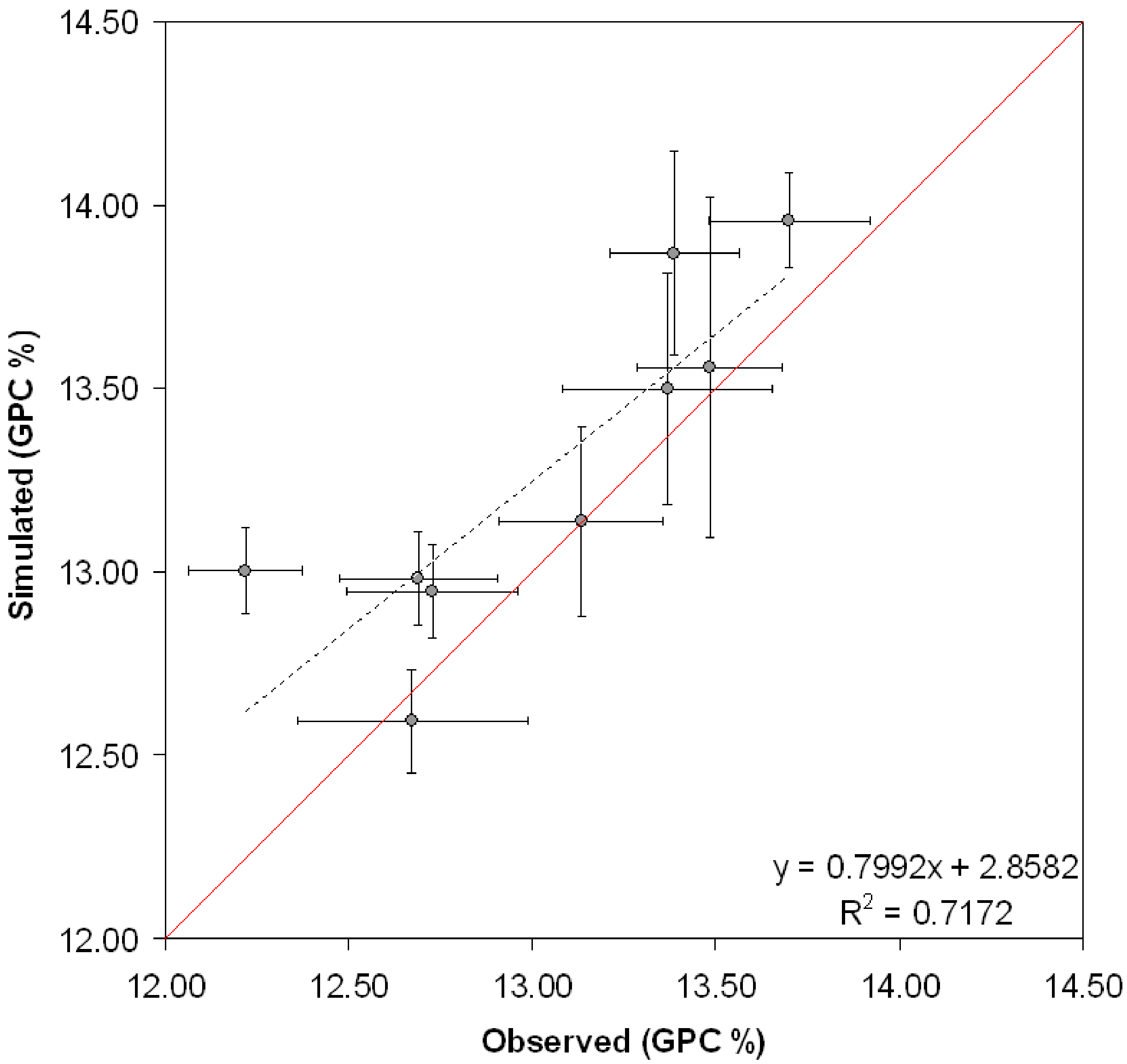

Figure 3 Comparison between observed GPC_{BAR} and simulated GPC_{DEL} over four study areas for the period 1999-2007 aggregating results. The 1:1 line is shown.

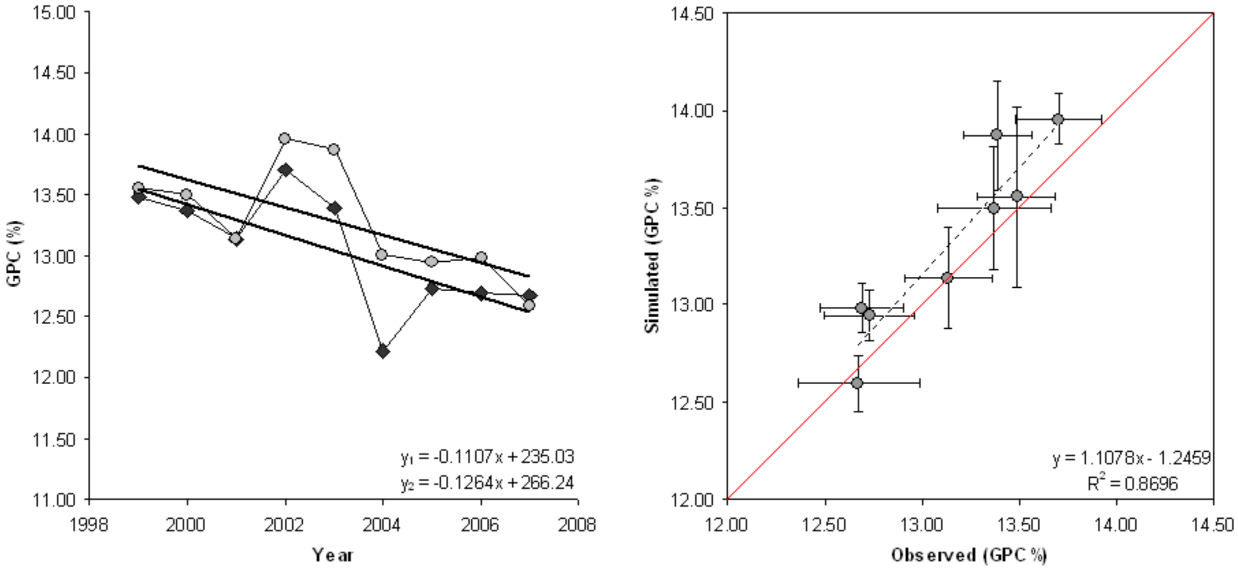

Figure 4a Trend in GPC simulated (Delphi ● , y1) observed (Barilla ♦, y2); **Figure 4b** Comparison between GPC_{BAR} and GPC_{DEL} over four study areas for the period 1999-2007 aggregating results, excluding 2004. The 1:1 line is shown in figure 4b

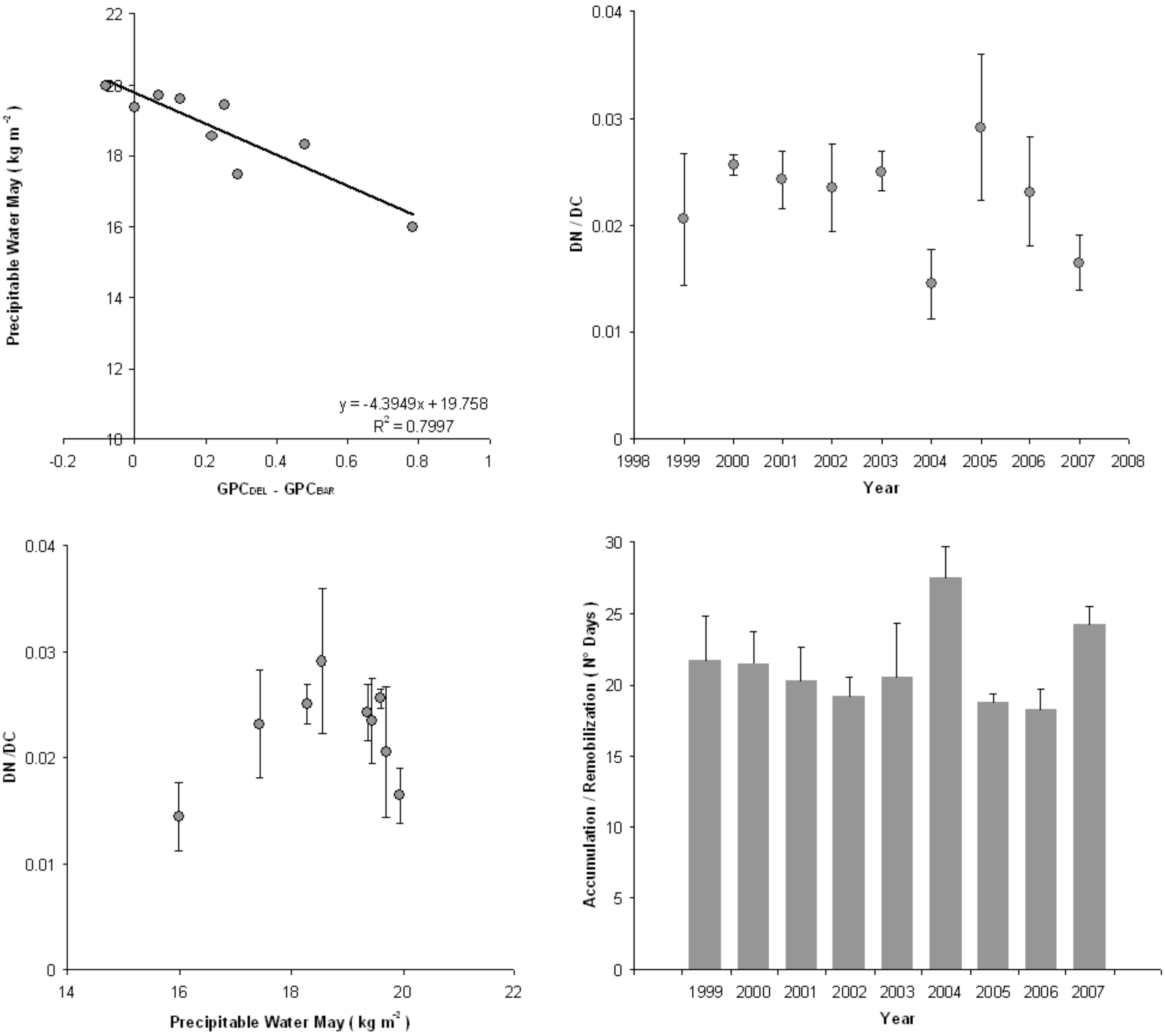

Figure 5a Comparison between residual (GPC_{DEL} – GPC_{BAR}) and Precipitable water in May. **Figure 5b** DN : DC ratio during the 9 year study period as average for the 4 study areas. **Figure 5C** Comparison between DN : DC ratio and Precipitable water in May. **Figure 5d** number of days taken for total accumulation/remobilization during grain filling.

A simplified model for durum wheat quality prediction at regional scale in Mediterranean environments

P. Toscano[*ab], L. Genesio[a], B. Gioli[a], A. Crisci[a], A. Zaldei[a], E. Ferrari[c], P. La Cava[c], J. R. Porter[d], F.P. Vaccari[a]

[a]*Institute of Biometeorology (IBIMET – CNR), via G.Caproni 8, 50145 Firenze, Italy.*

[b]*Department of Agricultural and Environmental Sciences, University of Udine, via delle Scienze, 206, 33100 Udine, Italy.*

[c]*Barilla G. e R. F.lli S.p.A., via Mantova 245, 43122 Parma, Italy.*

[d]*Department of Agriculture and Ecology, University of Copenhagen, Faculty of Life Sciences, Højbakkegård Allé 30, DK-2630 Taastrup, Denmark*

**Corresponding author:*

Piero Toscano

IBIMET – CNR

Via Caproni 8,

50145 Firenze, Italy

Tel. +390553033711

Fax +39055308910

E-mail address: p.toscano@ibimet.cnr.it

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1. Introduction

The largest durum wheat production is concentrated in the Mediterranean basin that contributes, on average, 60% of the global production (FAOSTAT, 2013).

Environmental and agronomic variables such as climate, soil, and cropping practices exert a strong influence on productivity and quality of durum wheat, the latter typically expressed as Grain Protein Content (GPC). The effects are particularly relevant in Mediterranean environments (Nachit and Elouafi, 2004), where the climate usually leads to a sustained water deficit and thermal stress during grain filling, which may cause large fluctuations in both yield and quality (Baenziger et al., 1985). In fact about two-thirds of the protein contents in the grain at maturity are present in the plants at anthesis (Austin et al., 1977), while the remaining amount is absorbed from the soil during the grain filling phase (Kramer, 1979; Stone and Savin, 1999).

The impact of climate change on durum wheat quality will be particularly severe in the future, in view of the projected increased levels of atmospheric carbon dioxide (CO_2), rising temperatures and the increased frequency and intensity of extreme weather events (i.e. droughts and heat waves). Conroy and Hocking (1993) reported a decline in wheat protein in Australia from 1967-1990, partially attributable to the rise in atmospheric CO_2, while Free-Air CO_2 Enrichment (FACE) experiments have shown a reduction in grain quality under high levels of CO_2 (550 ppm) (Kimball et al., 2001; Ainsworth and McGrath, 2010; Erda et al., 2010), and a decrease in the grain protein content under doubled pre-industrial atmospheric CO_2 concentration (280 ppm) (Erbs et al., 2010). Wrigley (2006) reported reduced wheat grain quality for various locations, caused by heat stress associated with maximum temperatures exceeding 35 °C.

For these reasons understanding the impacts of the environmental variables on yields and quality of durum wheat is particularly important. Crop growth modeling could be a fundamental tool to assess these impacts. However most models require extensive information related to environmental and agronomic parameters that are typically unavailable, as already pointed out by Walker (1989) at the beginning of the diffusion of crop models. Moreover, the large differences in the structure and data input requirements among crop growth models limit their applicability from an operational perspective.

Previous studies have demonstrated how the model structure could bias the impact of climate change on the simulated crop (Porter et al., 1995; Wolf et al., 1996; Ewert et al. 1999) due to the uncertainties related to agronomic and climate data inputs (Aggarwal and Kalra, 1994). Because of the complexity and data requirements of simulation models, many previous studies have preferred a regression approach to a large simulation model for forecasting crop yield and quality (Yang et al., 1992; Dixon et al., 1994; Kandiannan et al., 2002; Chen and Chang, 2005; Graybosch et al., 1995; Johansson and Svensson, 1998; Smith and Gooding, 1999; Guttieri et al., 2000; Johansson et al., 2008), proving that multiple regression models have high explanatory power and can represent relationships between weather conditions and crop yield and quality. The multiple regression model approach is not only easier to use, it is also likely to be more accurate than the simulation model approach (Byoung-Hoon et al., 2013). Previous studies on the effect of weather on wheat quality have several limitations. Most quality models are not designed to produce pre-harvest predictions and have either used data from a single location or have not used the extra information provided by spatial data (Byoung-Hoon et al., 2013).

The free meteorological databases available on the web, in particular the gridded information, might easily be implemented in crop growth modeling to overcome the difficulties in data requirements (Easterling et al., 1997). However, the gridded information derived from global atmospheric models must be used with some precautions in crop models as these data are uniformly distributed for each grid cell and most are derived (Tveito et al., 2006), not directly measured. Only a few studies on crop modeling that use weather gridded databases are validated against real observations with the same grid interval (Foley et al., 2005; Lobell et al., 2008) and this limits widespread applications of these models.

In this paper, we: i) develop a statistical inference framework to assess the effects of environmental and agronomic variables on the protein content (GPC) of durum wheat; ii) define a new empirical model (TP model) based on freely available gridded global-scale datasets; iii) evaluate the capability of the TP model to simulate GPC in four Italian regions from 1999 to 2007; iv) evaluate the performance of the TP model at the Italian national scale and as a forecasting tool to be used in operational mode before crop harvesting.

2. Materials and methods

2.1 Data sources

In order to assess the inter-relations between selected agro-environmental variables and grain protein, different datasets have been considered (Table 1).

Yearly atmospheric CO_2 concentrations were obtained from the NOAA/ESRL global dataset (www.esrl.noaa.gov/gmd/), averaging monthly values for the pixel corresponding to the four study areas (Basilicata, Capitanata, Marche, Tuscany). These data have been validated by the Global Monitoring Division of NOAA/Earth System Research Laboratory, which has measured atmospheric CO_2 concentrations for several decades using a globally distributed network of air sampling sites (Conway et al., 1994).

Nitrogen fertilization datasets for each study area were provided by the Agricultural Consortia and by Barilla G. e R. F.lli SpA (Toscano et al., 2012).

Durum wheat yield data were provided by the National Institute for Statistics (ISTAT, http://agri.istat.it/) as an average of the harvested yield at the regional administrative scale for the four study areas.

Climatic variables were obtained by spatially gridded global numerical simulations from NCEP/DOE AMIP-II Reanalysis (Reanalysis-2, Kanamitsu et al., 2002), hereinafter referred to simply as NCEP; the web data hub is available online at http://www.cdc.noaa.gov/data/gridded/data.ncep.reanalysis2.html. Among the available gridded climatic variables we selected air temperature (AIRT) and precipitable water (PW) as those potentially involved in determining the durum wheat yield and protein content, mainly because they are directly related to vapour pressure deficit (VPD) that regulates transpiration, with implications on photosynthesis (Czajkowsky et al., 2002; Singh, 2010).

Both AIRT and PW were downloaded in netcdf format and processed using Matlab software (http://www.mathworks.it/it/help/matlab/ref/netcdf.html). The NCEP dataset has a temporal resolution of 6 h (4x/day) and is available in several different coordinate systems, such as a 17 pressure level stack on 2.5x2.5 degree grids, 28 sigma level stack on 192x94 Gaussian grids and 11 isentropic level stack on 2.5x2.5 degree grid. For this work we used the 28 sigma level stack on 192x94 Gaussian grids for AIRT at 2m level and columnar total (entire atmosphere considered as a single layer) PW on 2.5x2.5 degree grids. Data were extracted and averaged for the four study areas and for the whole Italian area, as shown in Figure 1.

Detailed surveys of GPC data were made by Barilla for the period 1999-2007 during the project “Quality Map” (Toscano et al., 2014), hereinafter referred to simply as GPC_{BAR}. This dataset of 863 samplings consists of annual sampling of the durum wheat GPC sampled in the four study areas (Table 2). A second dataset was obtained from the Research Unit for Cereal Quality (CRA-QCE, RU), hereinafter referred to as GPC_{CRA}, spanning 15 years (1998-2012), merging two datasets: i) the Quality Monitoring Database and ii) the Differentiated Storage Database. Those surveys are the basis of a system for quality control of the production of durum wheat, common wheat and maize, at the time of delivery of the grain to storage centres, and provide the classification of batches based on key product characteristics for the formulation of prices. (http://qce.entecra.it/RISULTATI.htm, last access 14/12/2013).

2.2 Statistical analysis

We evaluated the relationship between agro-environmental variables, and GPC_{BAR}. in the R STAT environment (2013, R Core Team), helped by the MASS package (Venables and Ripley, 2002). A linear correlation analysis was made between each single predictor (Table 1) and GPC_{BAR}, by using Pearson's linear correlation coefficient. A further variable (VART) was defined as the difference between the monthly air temperature values of June and July and added to the predictors set. This was to take into account the high climate sensitivity of grain quality in the last two months of the durum wheat cycle (Johansson and Svensson, 1998). We also graphically displayed the variability of CO_2, nitrogen fertilizer and yield for the period 1999-2007 (Figure 2b, 2c, 2d).

2.3 The TP Model

A stepwise Akaike Information Criterion (AIC) model selection (MASS R Package) was implemented to build an empirical linear model driven by gridded weather data. The inference is based on VART, monthly values of AIRT and PW for the whole period from pre-sowing through the phenological development of durum wheat to harvest (September to July), and was obtained using the yearly average of GPC_{BAR} dataset as predicted variable.

PW and AIRT data were extracted for two sub-grid boxes spatially and temporally covering the four study areas (Marche-Tuscany and Basilicata-Capitanata and the nine year study period (1999-2007); Figure 1).

A total of 23 regressors were initially evaluated (VART and monthly values of AIRT and PW, except August) and a subset of 6 regressors was then obtained following the AIC criteria (lowest AIC values)

Finally, the linear model, based on temperature and precipitable water (TP) data, was obtained as:

$$\mathbf{TP_1 = m_1{*}PW_9 \ + m_2{*}PW_{10} + m_3{*}PW_{11}\ m_4{*}PW_{12} + m_5{*}AIRT_5 + m_6{*}VART + k} \quad \textit{(1)}$$

Coefficients (m_i) and constant (k) are listed in Table 3.

A sensitivity analysis of TP_1 model was performed in terms of the rate of change in the output value resulting from a change of each input parameter while keeping all other parameters constant (Wöhling, 2005). Each input data (PW9, PW10. PW11. PW12. AIRT5, VART) was perturbed accounting for the maximum and minimum values provided by NCEP for the period 1979-1997 for each study area (Table 4).

The same approach was then applied to build a definitive TP model at national scale using the independent dataset GPC_{CRA} of grain quality as the dependent variable, while temperature and precipitable water input data (PW_9, PW_{10}, PW_{11}, PW_{12}, $AIRT_5$, VART) were extracted from a geographical box relative to the whole Italian area (Figure 1) for 15 years (1998-2012).

The second linear model (TP_2) was built implementing a test-training segmentation algorithm, with N=15 years to be evaluated (1998-2012). The procedure followed two subsequent steps:

1. The GPC_{CRA} dataset was randomly stratified into two subsets: Building Model (M1, N=10) and Test Model (M2, N=5) , corresponding to 2/3 and 1/3 of the total data respectively.
2. For TP model instanced, the metric of model performance was obtained from the normalized root mean squared error (nRMSE, equation 2) calculated comparing the predicted values (S) in testing years and the observed grain protein content (O), giving a measure of the relative difference (percentage of the mean value, O) of simulated versus observed data (Table 5):

$$nRMSE = \sqrt{\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}} \times \frac{100}{\overline{O}} \quad \textit{(2)}$$

Coefficients and constant for the TP_2 are listed in Table 3.

2.4 TP forecast tool

In the forecast version, TP_2 model runs simulations from January to June using two scenario datasets of precipitable water (PW_sce) and air temperature (AIRT_sce). The scenario data were built on climatic similarity between the actual year and the historical record: in January, the climate pattern during September - December was compared with the period 1979 – 1997, and on the basis of similarity conditions for PW and AIRT, the scenario data for the following months until harvest were constructed. The same method was repeated on the following months. The forecast tool was initially applied for the period 1998-2012 at national scale for performance assessment and then applied in the operational version for the crop year 2013. Model performances were evaluated computing an index based on squared differences between estimated and observed values.

3. **Results**

Influence of agronomic/environmental variables

High durum wheat yields are often reported to be associated with low GPC (Blanco et al., 2011), nevertheless in our study, the observed decline in GPC_{BAR} (Figure 2a) from 1999-2007, was not associated with any clear increase in average yields for the study areas (slope of 0.04, Figure 2b). In an effort to better characterize and understand the dynamics that have driven the negative trend highlighted in GPC_{BAR} data and simulated data, we analysed the correlation, in terms of significance, as between each environmental and agronomic variable and GPC_{BAR}.

A positive trend is reported for CO_2 level (slope of 2, Figure 2c), while no trend is detectable in the applied nitrogen (slope of 0.016, Figure 2d).

Figure 3 reports the results of the correlation matrix between monthly values of PW, AIRT, VART, N, CO_2, Yield and the GPC_{BAR} at the regional scales for 1999-2007. PW is always negatively correlated with GPC_{BAR} except for the months of May and July, while the temperatures of March, May, June, August and October are positively correlated. The correlation coefficient (R) for PW is higher than 0.5 only in May (p=0.032), while for AIRT in May, June and December (p=0.075, p=0.104 and p=0.132 respectively). A value of R=0.81 was obtained for VART with a high significance (p=0.007). Low levels of significance were found for Yield and N (p=0.2 and p=0.122 respectively) with a negative correlation for Yield (r = -0.47) and a low positive one for N (r = 0.12). For CO_2 the significance was p=0.038 with a negative correlation (r = -0.69).

Based on these initial findings, we decided to exclude from the model building task the variables that are not correlated with GPC (N, Yield), and those, although strongly correlated, that show no interannual variability (CO_2).

TP model performance

The analysis based on stepwise AIC model selection enabled the identification of a subset of six meteorological variables (PW_9, PW_10, PW_11, PW12, AIRT_5 and VART) converging in a single formula (the TP_1 model) that explains up to 99% of the variance of GPC_{BAR} (Figure 4a). In the TP_1 model, 67% of GPC_{BAR} variability is linked to the thermal regime in the period from flowering to maturity, while the remaining 33% is related to precipitable water (Figure 4b), a proxy for precipitation, soil moisture and relative humidity, in the period from September to December. Low values of PW (lower dew point, relative humidity and higher VPD) correlate positively with higher GPC.

For the sensitivity analysis, precipitable water, air temperature and VART were modified accordingly with their variability range during 1979-1997 (Table 4). The use of modified PW9 (range 19.52 – 24.98 kg m^{-2}) and PW10 (range 15.33 – 23.93 kg m^{-2}) led to a lower change in final GPC, while perturbations for PW11 (range 11.05 – 18.95 kg m^{-2}), PW12 (8.04 – 15.06 kg m^{-2}), AIRT5 (13.03 °C – 17.96 °C) and VART (range 0.30 – 5.12 °C) induced substantial changes in GPC. In particular lower values for PW11 and AIRT5 affected GPC (-3.46% and -7.25% respectively), while higher values resulted in an increase of GPC (+3.09 and +3.72% respectively); in a different way lower values for PW12 and VART positively affected GPC with an increase (+4.77% and +2.17% respectively) while higher values translated into a reduction of GPC (-3.51 % and -2.07% respectively).

Subsequently, by implementing a test segmentation algorithm, the TP_2 model has been built on a national scale enabling its evaluation in terms of nRMSE (2.84%) and coefficient of determination (R^2 = 0.96) (Table 5). TP_2 explains more than 95% of the GPC_{CRA} variance for a period of 15 years (1998-2012) (Figure 5a). At the national scale, 47% of the GPC_{CRA} variability is driven by the thermal regime from flowering to maturity while 53% comes from the PW of the September-December period (Figure 5b).

An analysis of all the model runs for each gridded pixel in Italy during each crop year (1998-2012), based on two scenario variables (AIRT_sce and PW_sce), highlights that the TP model provided a very consistent GPC forecast even before crop maturity (Figure 6a, 6b). The first day of each month (from January to June), the forecasting system provided the distributions of GPC based on two scenarios starting from the similarity conditions within the range of variability observed during the period 1979-1997. The PW_sce gives best performance, while the AIRT_sce tends to underestimate the final GPC at harvesting.

nRMSE values (Table 6) were calculated for all 15 years, based on two scenarios, and each year for the six months of simulation (January, February, March, April, May, June) at national scale. GPC forecasts based on both scenarios showed high accuracy since the first simulation in January (3.32% and 4.11% for PW and AIRT respectively), and provided the best performance in June (2.70% and 2.91% for PW and AIRT respectively).

The system was then used in the operational mode for the crop year 2013: the forecasting tool based on both scenarios from the first simulation (January) was able to predict with good accuracy the GPC at national scale, again showing the best performance with PW_sce (Table 7). At national scale the TP_2 model has provided a final GPC value of 11.96% ± 0.96 (std), while the observed value was 12.07% ± 1.56 (std). Analysing and aggregating GPC at regional scale for northern, central, southern and island regions revealed that the TP model maintained its predictive ability in capturing part of the interregional spatial variability. In the northern regions the simulated GPC was 13.18% ± 0.26 (std) against observed GPC_{CRA} of 12.76% ± 0.52; in the central regions it was 12.69% ± 0.24 against GPC_{CRA} of 12.79% ± 0.88; in the southern regions it was 12.06% ± 0.40 against GPC_{CRA} of 12.16% ± 0.84 and in island regions 11.52% ± 0.58 against GPC_{CRA} of 11.53% ± 0.51. Figure 7 shows the absolute difference between GPC_{CRA} and simulated GPC averaged over each region where data were available. The highest underestimations occurred in Abruzzo, Campania, Marche and Umbria (-0.89%, -0.75%, -0.74% and -0.73% respectively), while the highest overestimations occurred in Lazio and Emilia Romagna (+0.62 and +0.48% respectively).

4. Discussion

Increases in temperature and carbon dioxide concentration associated with climate change are known to have effects on crop development and yield (Ainsworth, 2008; Long et al., 2006; Taub, 2010). The magnitude of these effects is difficult to predict due to interactions and feedbacks with other factors that may also be affected, such as water availability and pests and diseases (Coakley et al., 1999; Semenov, 2008). Similarly, although it is generally accepted that higher growing temperatures result in greater dough strength, extreme heat stress (above 30–33 °C) weakens dough and reduces quality (Blumenthal et al., 1993), but via a mechanism that is currently poorly understood (Dupont and Altenbach, 2003). At the same time, the effects of CO_2 concentration on grain quality are not clearly understood (Högy and Fangmeier, 2008). The observed declining trend in GPC in the 1999-2007 period cannot be related to a trend in nitrogen fertilization, which remained steady, nor to a trend in atmospheric CO_2 concentration that does not explain interannual GPC variability nor show any correlation with yield as might be expected (Amthor 2001, Nonhebel 1996).

However, significant correlations were found between GPC and the interaction of selected meteorological variables.

High amounts and intensity of rainfall during autumn and winter, while promoting higher yields are known to be deleterious for final quality parameters because of increased nitrogen leaching through the soil profile, particularly in sandy soils (Flagella et al., 2010; Garrido-Lestache et al., 2005). Root depth is driven by soil type and length of the vegetative period; with high water availability, the root system tends to grow superficially and does not explore deep soil layers (Lilley and Kirkegaard, 2007). If rains persist in spring, N tends to be leached to deeper soil layers below the root development profile. Further, if sub-soils are too wet, deeper rooting ability may be impaired, thus decreasing N uptake efficiency. Accordingly, in our case, in the four study areas, PW in autumn and winter was always negatively correlated to GPC, while a positive correlation was observed in May and July.

May is the month of flowering in Italy, and the observed positive correlation is in agreement with the findings of Garrido-Lestache et al. (2005), who reported a positive correlation between GPC and precipitation for the month of April (corresponding to the flowering period in Andalusia) and negative correlations during the pre-anthesis period (December to March).

GPC was positively correlated with May and June air temperatures, confirming the positive response to temperature during grain filling, as previously reported by other authors (Flagella et al., 2010; Garrido-Lestache et al., 2005).

The indicator of thermal shock, VART, showed the highest significance, being negatively correlated with GPC. This indicator shows how a high temperature in June and a temperature in July close to or lower than average, lead to the highest protein concentrations. Similarly, Johansson and Svensson (1998) at a higher latitude in Sweden reported that protein concentration was affected by the July and August (harvest) temperature.

Based on these results, the TP_1 model succeeded in adequately reconstructing the GPC temporal variability for the study period and areas (Figure 3a and Figure 4a), enabling the identification of those parameters that actually limit or promote durum wheat quality and production. PW represents the available water along the entire atmospheric column: such water may become precipitation, or not. Thus PW represents a proxy for the combination of two different drivers on wheat growth: it directly affects the availability of water to the root system through the precipitation fraction, and it affects the evaporative demand of the atmosphere (and thus the VPD) through the atmospheric water vapour fraction.

VPD, a highly significant variable for physically based crop simulation models (Huang et al. 2010), is rarely available on a daily basis. Indeed, precipitable water may help to better understand the dynamics of VPD, being closely linked to the dew point (Karalis, 1974; Yang and Xue, 1996; Reber and Swope, 1972; Li et al., 2009). Furthermore, PW variability is linked to variations in air temperature and precipitation, and the character and strength of these links vary significantly in both time and space (Zveryaev and Allan, 2005).

VPD has a significant effect on the amount of water required by the crop to maintain optimal growth, but data required to calculate the mean VPD (i.e. humidity and air temperature) on a daily basis are rarely available and not available on spatial scale, while using a proxy of both atmospheric humidity and precipitation, such as PW, can lead to a better representation of the water cycle, especially at the monthly scale where short-term variability of the atmospheric moisture profile is smoothed out (Tuller 1976).

The same approach as that used on specific regions, was then applied at national scale leading to the TP_2 model. This showed some differences in terms of description of the variability between the contribution of temperature in the post-flowering period and precipitable water in the period from September to December.

This variability is also highlighted by the magnitude of the regression coefficients (Table 3) of the two linear models (TP_1 and TP_2): in fact, a greater weight is given to the precipitable water in TP_1 and VART in TP_2. It should also be noted, even if there are two models, that the input variables are always the same and the coefficients maintain congruence in terms of sign.

The most explanatory parameter was VART (Figure 5b), because it accounts for the late phenological development in the northern regions of Italy where post-anthesis usually falls in June, with harvesting in July, while the descriptive capacity of May temperature is lower than that observed in the southern area. The total of PW (sum of PW during September-December) explains almost 57% of the variability, resulting negatively correlated with the final GPC. It is worth noting that until the late 1990s and early 2000s, at a national Italian scale, PW was negatively influenced by patterns of positive North Atlantic Oscillation (NAO) (dry air advection giving less rainfall that is more evenly distributed) during the winter. From the beginning of 2000 onwards, there has been a slight positive trend that may have contributed to increased soil moisture, relative humidity and led to more intense precipitation events even in places where total precipitation was decreasing (Meneguzzo et al., 2004; Trenberth and Shea, 2005; Pinto et al., 1999; Zveryaev et al., 2008; Durre et al., 2009). This change in precipitation distribution is coherently and negatively correlated with the observed decreases in GPC.

From an operational perspective, the TP_2 model succeeded in accurately reproducing the GPC interannual variability but showed some limitations related to the use of weather data that are not always available at harvest time (VART). This limitation was resolved adopting a methodology based on the scenarios data that led to a high accuracy of GPC forecasts well in advance, even five months before harvest, with an overall slight underestimation on average.

Although there is an abundant literature (Challinor et al., 2004; Asseng et al., 2013; Estes et al., 2013; Rinaldi et al., 2013; Boogaard et al., 2013; Kogan et al., 2013; Cola et al., 2014) on crop growth simulation with both deterministic and statistical approaches, few of these models translate into tools that can be run operationally on entire regions, and that can forecast expected GPC on the basis of seasonal weather forecast conditions. For durum wheat, an example is the tool implemented in Delphi system for both yield and GPC forecasts (Toscano et al., 2012; Toscano et al., 2014), but requiring a wide range of input variables. The approach that we propose for the TP_2 model is instead based on only two inputs, precipitable water and air temperature, as always gridded variables and on a monthly basis, to forecast GPC at regional and global scale.

The forecasting accuracy of the models was also evaluated in operational mode over the 2013 crop season. The forecast error values, for both scenarios, indicate the full capability of the TP_2 model to predict the GPC with high accuracy at national scale and showing only a reduced ability to fully reconstruct the variability within regions, due to the resolution of the input gridded data that did not allow a properly local characterization.

5. Conclusions

Weather and climatic conditions strongly influenced GPC in Italy over the last 15 years, and we demonstrated that precipitable water during autumn-winter and air temperature from anthesis to harvest are extremely important in controlling GPC in Mediterranean environments. The empirical TP model was found to be reliable and robust enough to be used for regional and national scale simulations and for operational forecasting without taking into account varying soil conditions, phenological stages, management and cultivars. In the future, it will be interesting to apply the same approach and evaluate the TP model performance in other countries and at higher spatial resolution, as new gridded meteorological datasets, such as NCEP Climate Forecast System Reanalysis (CFSR) (Saha et al., 2010), are becoming available.

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	SOURCE	PERIOD	UNIT	DESCRIPTION
AIRT_1	NCEP	1998-2013	℃	Mean Air Temperature January
AIRT_2	NCEP	1998-2013	℃	Mean Air Temperature February
AIRT_3	NCEP	1998-2013	℃	Mean Air Temperature March
AIRT_4	NCEP	1998-2013	℃	Mean Air Temperature April
AIRT_5	NCEP	1998-2013	℃	Mean Air Temperature May
AIRT_6	NCEP	1998-2013	℃	Mean Air Temperature June
AIRT_7	NCEP	1998-2013	℃	Mean Air Temperature July
AIRT_8	NCEP	1998-2013	℃	Mean Air Temperature August
AIRT_9	NCEP	1998-2013	℃	Mean Air Temperature September
AIRT_10	NCEP	1998-2013	℃	Mean Air Temperature October
AIRT_11	NCEP	1998-2013	℃	Mean Air Temperature November
AIRT_12	NCEP	1998-2013	℃	Mean Air Temperature December
PW_1	NCEP	1998-2013	kg/m^2	Precipitable Water January
PW_2	NCEP	1998-2013	kg/m^2	Precipitable Water February
PW_3	NCEP	1998-2013	kg/m^2	Precipitable Water March
PW_4	NCEP	1998-2013	kg/m^2	Precipitable Water April
PW_5	NCEP	1998-2013	kg/m^2	Precipitable Water May
PW_6	NCEP	1998-2013	kg/m^2	Precipitable Water June
PW_7	NCEP	1998-2013	kg/m^2	Precipitable Water July
PW_8	NCEP	1998-2013	kg/m^2	Precipitable Water August
PW_9	NCEP	1998-2013	kg/m^2	Precipitable Water September
PW_10	NCEP	1998-2013	kg/m^2	Precipitable Water October
PW_11	NCEP	1998-2013	kg/m^2	Precipitable Water November
PW_12	NCEP	1998-2013	kg/m^2	Precipitable Water December
GPC_{BAR}	BARILLA	1999-2007	%	Grain Protein Content
GPC_{CRA}	CRA	1998-2013	%	Grain Protein Content
Yield	ISTAT	1999-2007	t/ha	Regional yield producion
CO_2	NOAA	1999-2007	ppm	Atmospheric Carbon Dioxide Concentration
N	BARILLA	1999-2007	N/ha	Nitrogen applied for fertilization

Table 1 List of environmental and agronomical variables

	BASILICATA	MARCHE	CAPITANATA	TUSCANY
1998	*22*	*31*	*30*	*14*
1999	*24*	*28*	*28*	*19*
2000	*17*	*27*	*24*	*12*
2001	*17*	*27*	*23*	*13*
2002	*24*	*30*	*21*	*19*
2003	*17*	*26*	*20*	*16*
2004	*21*	*25*	*29*	*11*
2005	*15*	*31*	*20*	*13*
2006	*22*	*29*	*20*	*17*
2007	*16*	*31*	*18*	*16*

Table 2 Sampling numbers during the Barilla Quality Map Project. Samples refer to a mix of different cultivars

	TP_1	TP_2
m_1	*-0.0506*	*-0.1908*
m_2	*-0.0113*	*-0.2409*
m_3	*+0.1073*	*+0.1054*
m_4	*-0.1551*	*-0.1994*
m_5	*+0.2799*	*+0.2034*
m_6	*-0.1142*	*-0.2910*
k	*+10.4007*	*+20.5078*

Table 3 Coefficients and constant for the two TP models

	AVG	MIN	MAX	GPC % Variation (min value)	GPC % Variation (max value)
PW_9	*22.37*	*19.52*	*24.98*	*+ 1.10*	*- 1.03*
PW_10	*19.39*	*15.33*	*23.93*	*+ 0.35*	*- 0.40*
PW_11	*15.09*	*11.05*	*18.95*	*- 3.46*	*+ 3.09*
PW_12	*12.23*	*8.04*	*15.06*	*+ 4.77*	*- 3.51*
AIRT_5	*16.16*	*13.03*	*17.96*	*- 7.25*	*+ 3.72*
VART	*2.82*	*0.30*	*5.12*	*+ 2.17*	*- 2.07*

Table 4 Sensitivity analysis, GPC simulations perturbing gridded values (minimum and maximum) with respect to 1999 reference value.

	M1	M2	R^2	nRMSE (%)
TP_2	*1999-2000-2002-2003-2006-2007-2008-2009-2011-2012*	*1998-2001-2004-2005-2010*	*0.9695*	*2.84*

Table 5 Test segmentation algorithm and TP_2 implementation: M1 subset (10 years) for training, M2 subset (5 years) for validation.

Scenario	Jan	Feb	Mar	Apr	May	Jun
PW	*3.32*	*3.40*	*4.59*	*2.80*	*4.45*	*2.70*
AIRT	*4.11*	*2.92*	*3.14*	*4.18*	*4.27*	*2.91*

Table 6 Statistical analysis results are shown for GPC in terms of normalized root mean square error (nRMSE) for the period 1998-2012.

Scenario	Jan	Feb	Mar	Apr	May	Jun
PW	*0.188*	*0.033*	*-0.563*	*-0.454*	*0.178*	*-0.188*
AIRT	*-0.261*	*-0.283*	*0.067*	*0.204*	*0.176*	*0.468*

Table 7 Time evolution of the difference between GPC_{CRA} for 2013 crop year at national scale and GPC forecast simulated using two different scenarios.

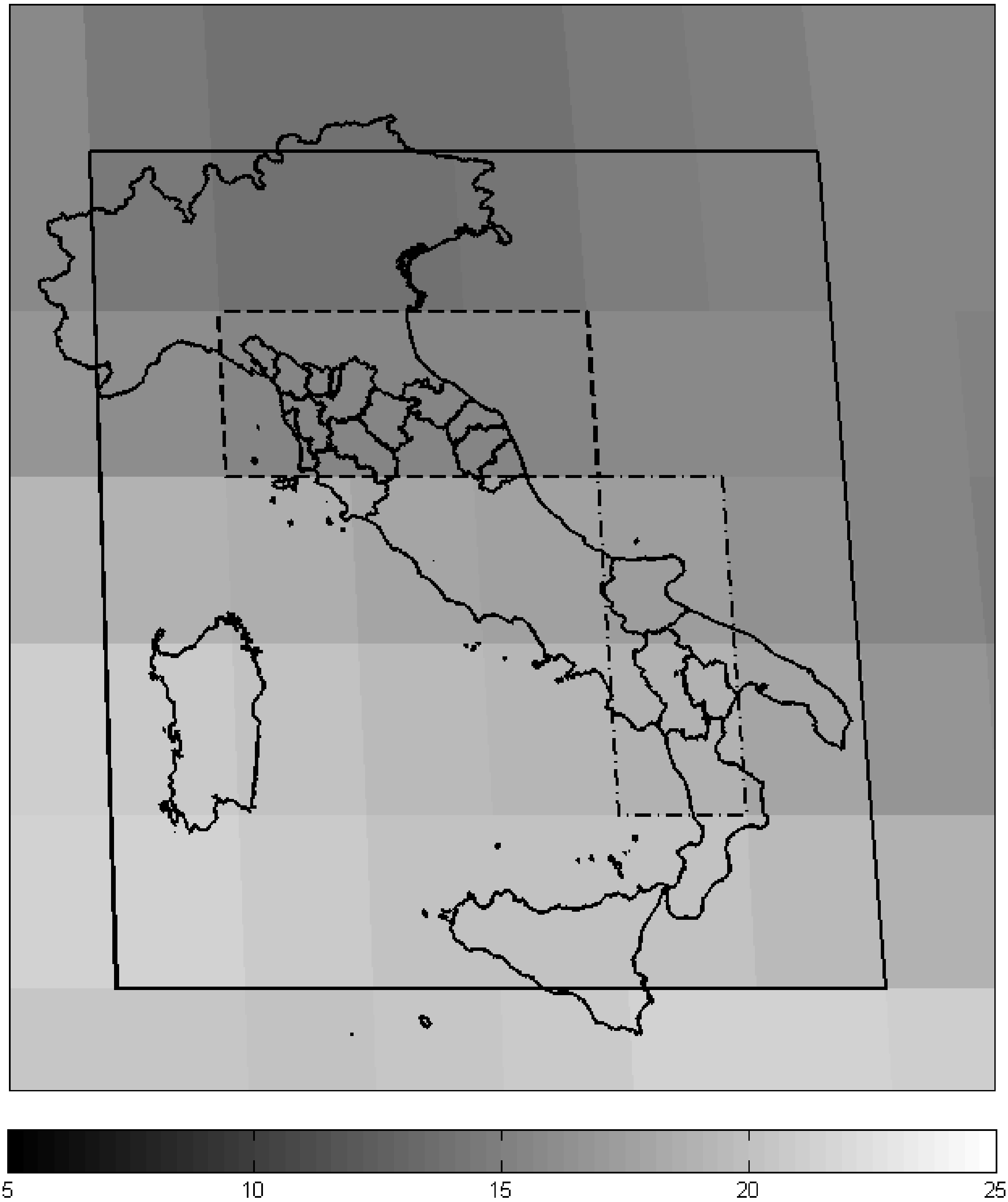

Figure 1 Mean Precipitable Water (kg/m^2) for the year 2012. Map of Italy where dashed line and dash-dot line highlight the grid selected for Tuscany-Marche and Capitanata – Basilicata for the implementation of TP_1 model at regional scale. Solid line highlights the grid selected for the implementation of TP_2 model at national scale.

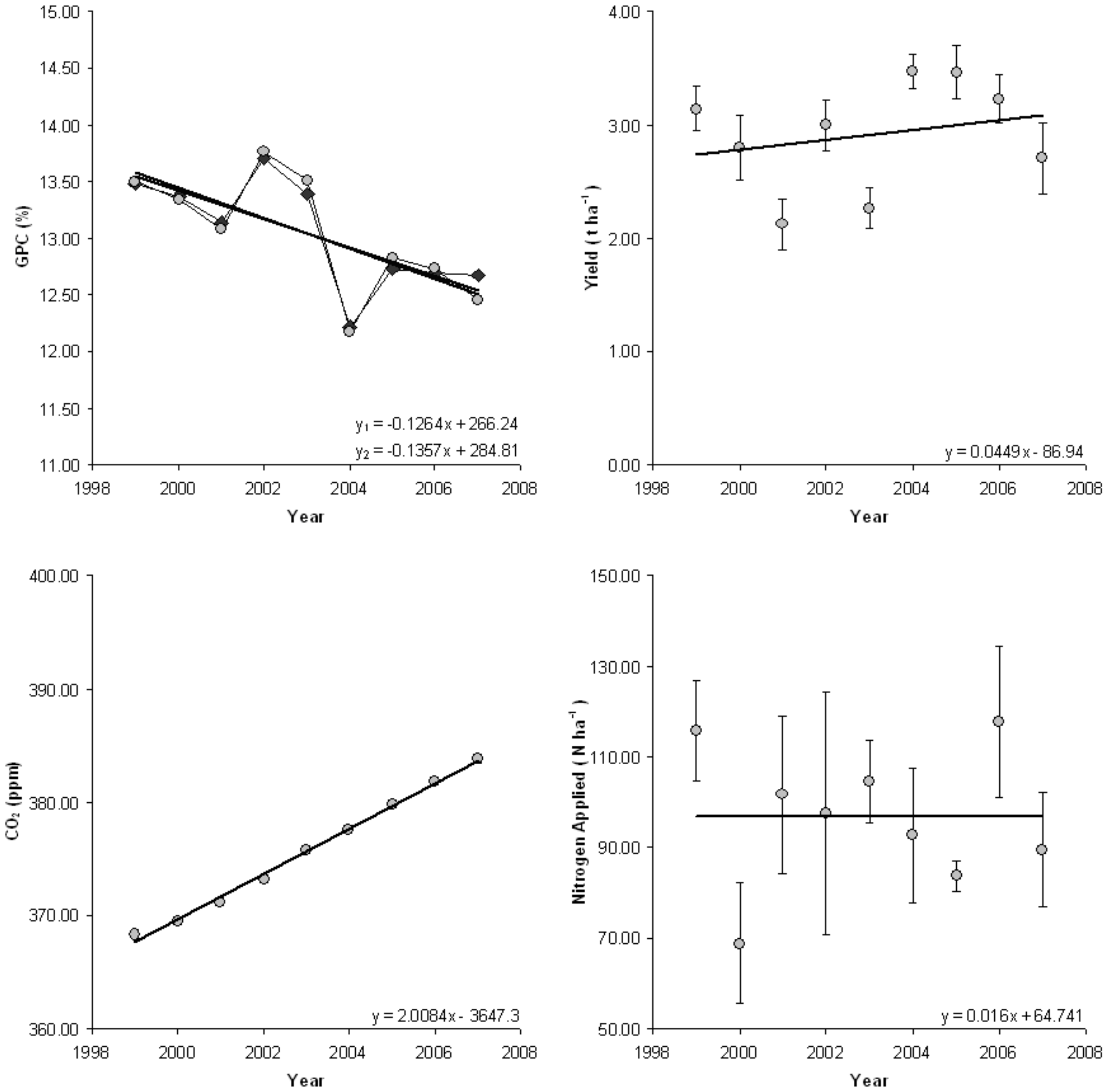

Figure 2a Trend in GPC observed (Barilla ▲, y1) and simulated (TP □ , y2) for the period 1999-2007 for the four study areas. **Figure 2b** Trend in durum wheat yield (ISTAT) for the period 1999-2007. **Figure 2c** Trend in CO_2 concentration data for the period 1999-2007. **Figure 2d** Trend in fertilization applied during the 9 crop years, as average for the four study areas

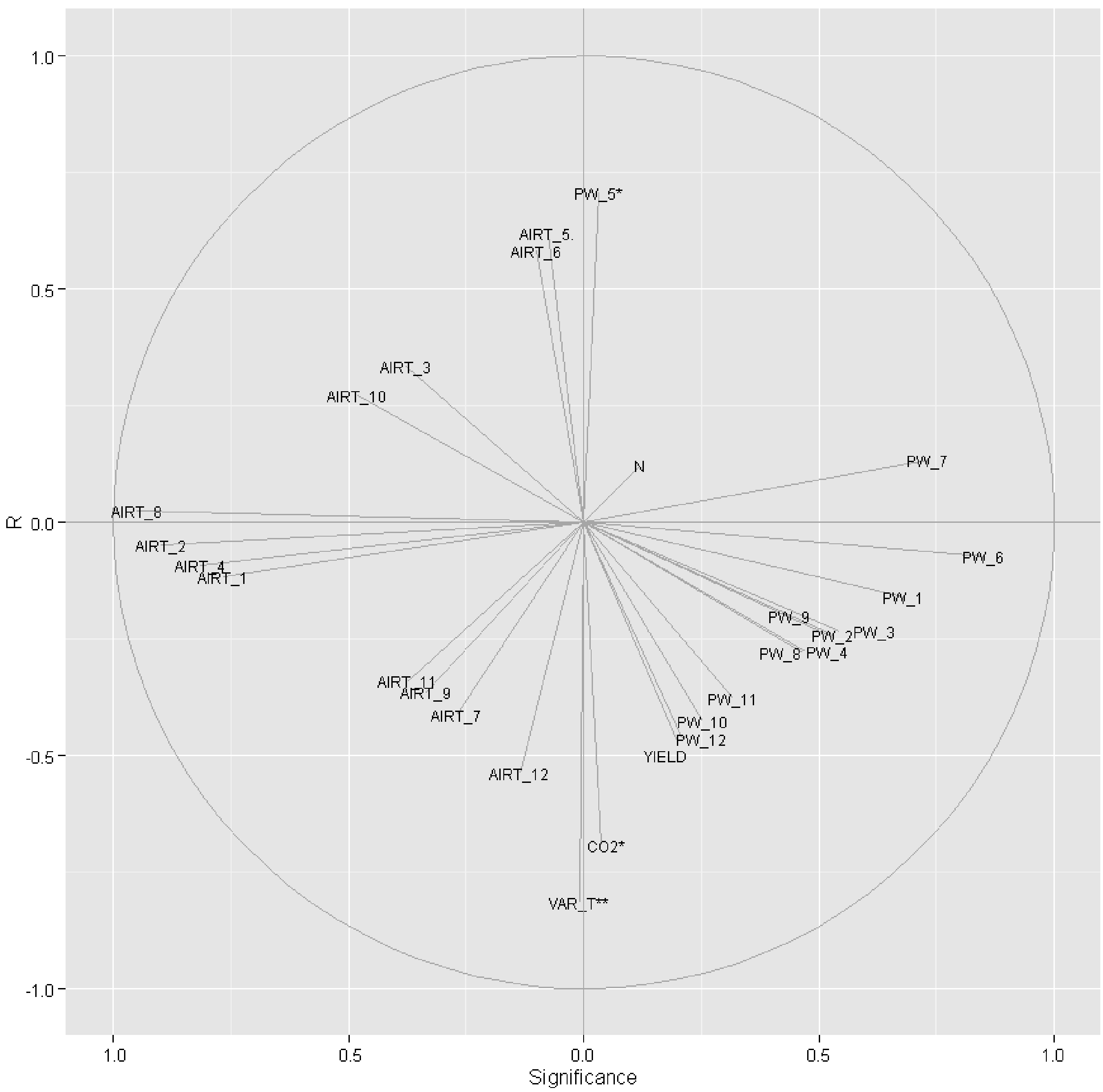

Figure 3 Circle of correlations with significance: PW (precipitable water) monthly values, N, Yield and CO_2 in the right semicircle, AIRT (air temperature) monthly values in the left semicircle for GPC_{BAR} values at regional scale for the period 1999-2007. Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1.

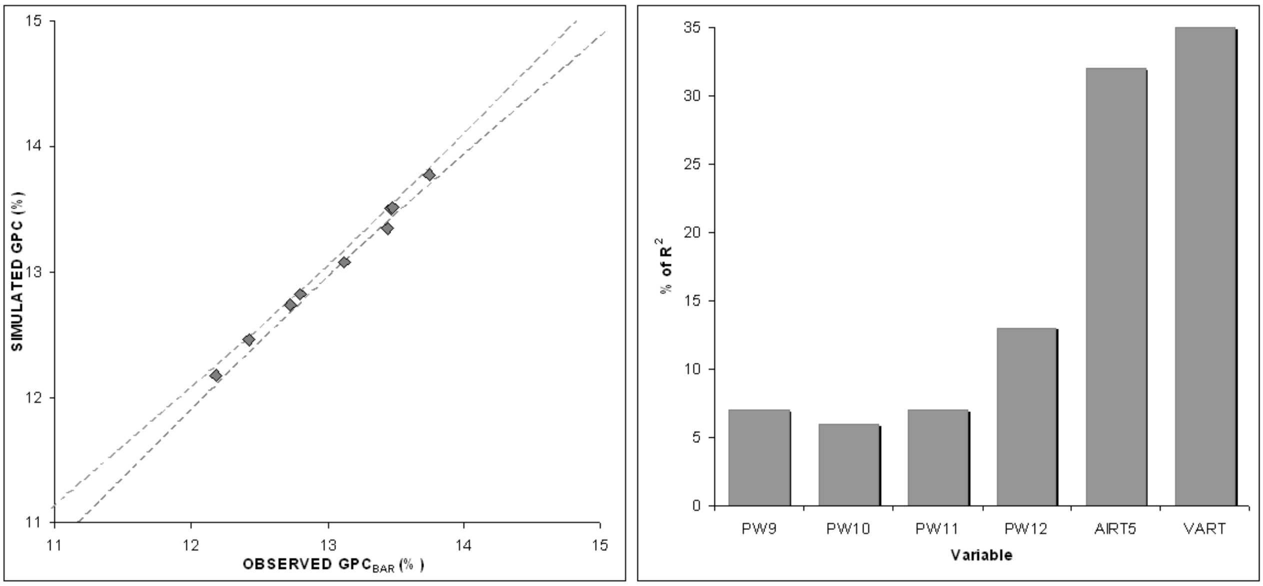

Figure 4a Comparison between Barilla Map Quality surveys for durum wheat grain protein content and simulated grain protein content (TP model) over the four study areas, for a period of 9 years (1999-2007). Statistically significant correlation with an r of 0.99 and p-value= 0.0080. Confidence interval (0.95) grey dashed lines. **Figure 4b** Relative Importance Metrics for linear model, R^2 partitioned by averaging over orders and normalized to sum 100%

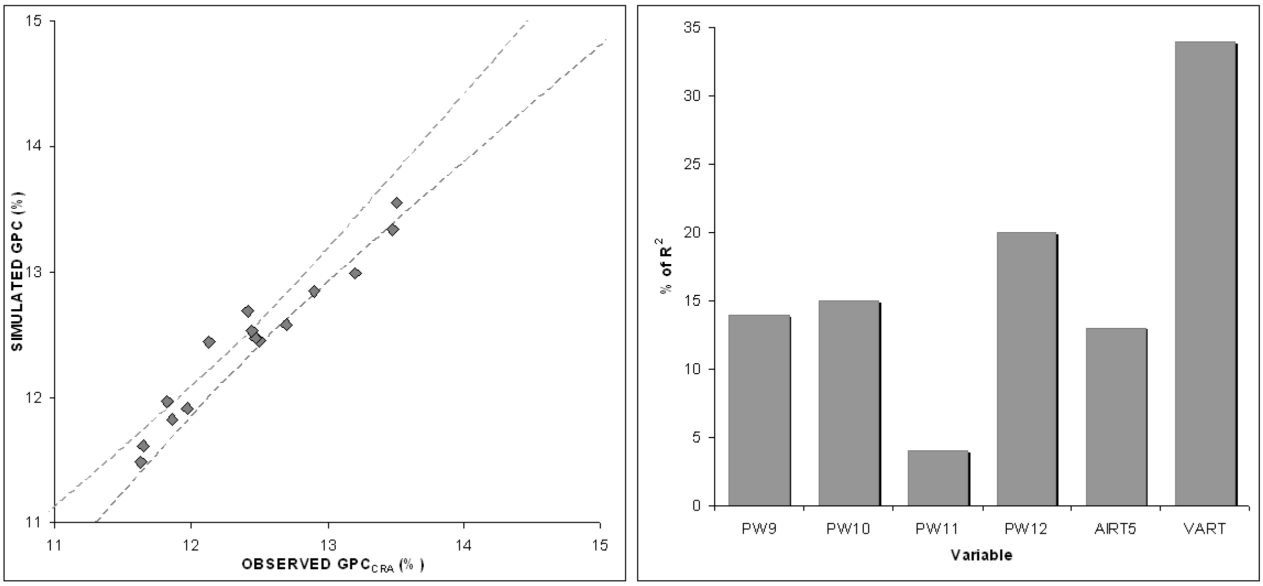

Figure 5a Comparison between national durum wheat grain protein content (CRA) and simulated grain protein content (TP model) over the whole Italian area, for a period of 15 years (1997-2012). Statistically significant correlation with an r of 0.94 and p-value< 0.0001. Confidence interval (0.95) grey dashed lines. **Figure 5b** Relative Importance Metrics for linear model, R^2 partitioned by averaging over orders and normalized to sum 100%

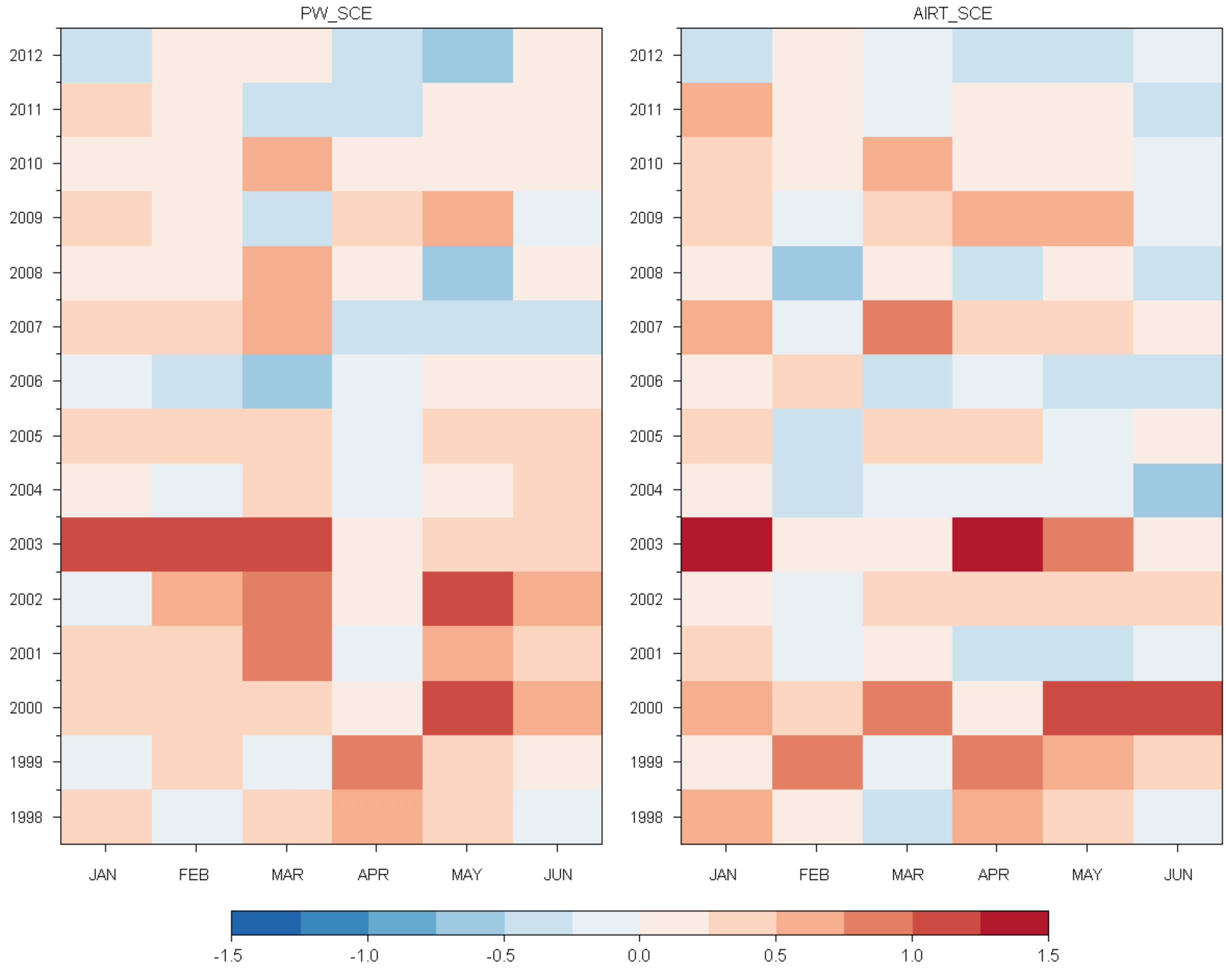

Figure 6 Time evolution of the GPC forecast as difference between simulated and observed for 15 years at national scale, using two different scenario simulations (PW_SCE left panel, AIRT_SCE right panel).

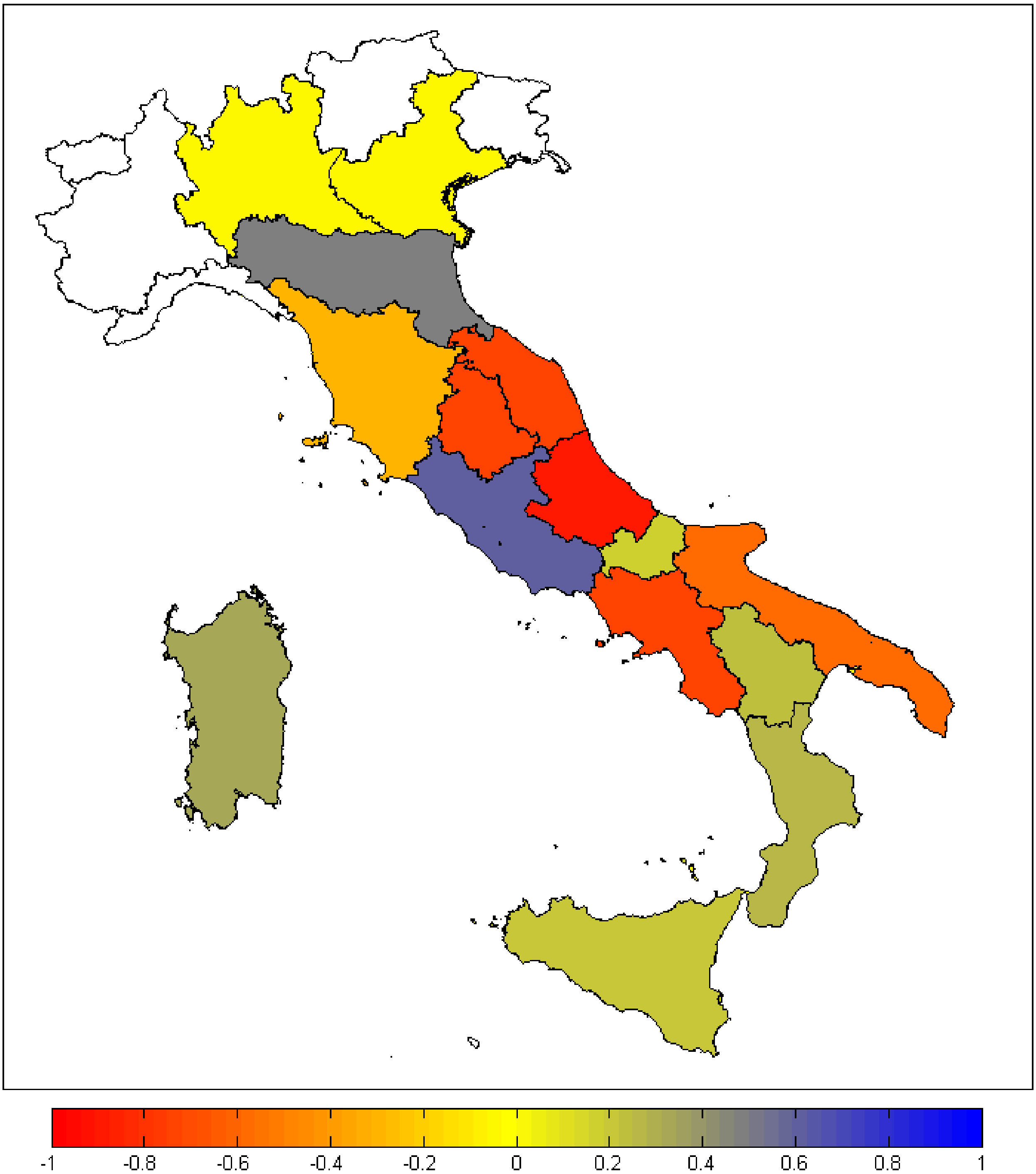

Figure 7 Difference between GPC_{CRA} and GPC simulated for 2013 crop year for each study area. GPC_{CRA} data were aggregated at regional scale and GPC simulated were extracted by gridded data.

Overall Conclusions

The capability to predict with good accuracy durum wheat yield and grain protein content (GPC) was studied combining different approaches in Mediterranean water limited environments. Several drivers of variability were analyzed, studying their simple and combined effects on quantity and quality of durum wheat productions. Observed and predicted meteorological parameters were used as input to the simulation models and statistical analysis with different approaches.

The first study, based on the development of Delphi system, demonstrated that durum wheat yields can be accurately predicted in advance with confidence and regional estimates can be produced using a detailed crop simulation model, but it requires detailed description of the distribution of soil-types, climate and cropping techniques over the region. The results of this study, based on long-term datasets, support also the conclusion that a predictive crop model needs proper calibration and validation in different environments in order to simulate accurately and have a significant forecasting value over wide areas. Delphi system efficiently captures year-to-year patterns of response to climate variability identifying crop years affected by drought and those with average climatic conditions.

In the second study we evaluated the capability of the Delphi system in estimating grain protein content proving its ability to reproduce GPC variation and temporal fluctuation in a long-term analysis. Nevertheless, model improvement is still required with better climatic characterization to improve accuracy and precision at local and regional scales. As improvements are necessary it should be noted that it is the first study, to our knowledge, of a modelling forecast of pre-harvest GPC in durum wheat in Mediterranean environments. Therefore, opportunities for comparison with other data and simulation forecasts are limited.

On the basis of these findings in the third study we developed a statistical inference framework to assess the effects of environmental and agronomic variables on GPC which allowed to define a new empirical model (TP model) based on freely available gridded global-scale datasets. Precipitable water during autumn to winter and air temperature during anthesis to harvest resulted extremely important in controlling grain protein content.

The empirical TP model, able to reproduce 95 % of the variability that occurred in the last 15 years in Italy, was found to be reliable and robust enough to be used for regional and national scale simulations and for operational forecasting without taking into account varying soil conditions, phenological stages, management and cultivars.

These results provide important inputs to improve crop growth modeling and are useful tools to better understand and forecast the impacts of future climate change projections on food production, especially in Mediterranean environments, where large fluctuations in both yield and quality in the last years are due to the water deficit and thermal stress during grain filling period.