



Sea surface temperature impacts on winter cropping systems in the Iberian Peninsula



Mirian Capa-Morocho^{a,b,*}, Belén Rodríguez-Fonseca^{a,c,d}, Margarita Ruiz-Ramos^{a,b}

^a Campus of International Excellence Moncloa, UCM-UPM, Madrid 28040, Spain

^b CEIGRAM-AgSystems—Producción Agraria, ETSI Agrónomos, Technical University of Madrid, 28040, Spain

^c Departamento de Geofísica y Meteorología, Facultad de Ciencias Físicas, Complutense University of Madrid, Spain

^d Instituto de Geociencias (CSIC-UCM), Plaza de Ciencias 1, Madrid 28040, Spain

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ABSTRACT

Climate variability is the main driver of changes in crop growth, development and yield, especially for rainfed production systems. In Iberian Peninsula (IP), wheat yields are strongly dependent on the rainfall amount and its temporal distribution during the growing season. The major source of precipitation interannual variability in IP is the North Atlantic Oscillation (NAO), which has been partially related with changes in the Tropical Pacific (El Niño) and Atlantic (TNA) sea surface temperature (SST). Therefore, existence of some predictability of precipitation opens the possibility to reach some predictability of wheat yield in the IP using SSTs anomalies as predictor. For this purpose, a crop model, site specific calibrated and validated for the NE of IP, and several reanalysis climate datasets have been used to obtain long time series of attainable wheat yield and to relate their variability with SST anomalies. The results show that the TNA and El Niño influence rainfed wheat development and yield in IP and these impacts depend on the concurrent state of the NAO. Although crop-SST relationships do not equally hold during the whole analyzed period, they can be explained by an understood and stationary ecophysiological mechanism. During the second half of the twenty century, the positive (negative) TNA index is associated to a negative (positive) phase of the NAO, which exerts a positive (negative) influence on the minimum temperature and precipitation during winter and, thus, wheat yield increases (decreases) in IP. In relation to El Niño, the highest correlation takes place in the period 1981–2001. For these decades, high (low) yields are associated with an El Niño to La Niña (La Niña to El Niño) transitions or to El Niño (La Niña) events finishing. For these events, the regional associated atmospheric pattern resembles the NAO, which also influences directly on the maximum temperatures and precipitation experienced by the crop in spring, during flowering and grain filling. The combined effects of the two teleconnection patterns increase (decrease) the rainfall and decrease (increase) maximum temperature in IP, and thus to increase (decrease) wheat yield. The results from this study could have important implications for predictability issues in agricultural planning and farmers' management, such as for decisions on insurance coverage, changes in sowing dates and choice of species and varieties.

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1. Introduction

The variability of weather conditions is the main driver of yield variability in most of areas, especially for rainfed production systems, ie. those for which the only water supply for crops is rainfall

(Hoogenboom et al., 2010; Olesen et al., 2007; Ray et al., 2015). Previous works have shown the influence of climate variability and extremes on regional agricultural yields and crop performance in Iberian Peninsula (IP) using historical yield data (Iglesias and Quiroga, 2007; Rodríguez-Puebla et al., 2007). Recent works have used crop models and climate data (observed, reanalysis, outputs from General Circulation Models “GCM” and Regional Circulation Models “RCMs”) to isolate the climate variability effect and to obtain long time series of yield (Capa-Morocho et al., 2014, 2015). Crop models are suitable tools to simulate potential and attainable (water limited) yield, which for a given crop variety, soil and management, are only influenced by climate variability and inte-

* Corresponding author at: M. Capa Morocho, C/ Senda del rey 13 - Campus Sur de prácticas, CEIGRAM-AgSystems- Producción Agraria, ETSI Agrónomos, Technical University of Madrid, Madrid 28040, Spain.

E-mail addresses: mi.capa@upm.es (M. Capa-Morocho), brfonsec@fis.ucm.es (B. Rodríguez-Fonseca), margarita.ruiz.ramos@upm.es (M. Ruiz-Ramos).

grate the effect of the meteorological variables during the crop cycle (Capa-Morocho et al., 2014; Saue and Kadaja, 2009). Potential yield is defined as the yield of a cultivar when grown in environments to which it is adapted (ie. the crop phenology reasonable fits the environment) under optimal management (without limitation of water and nutrients) and the absence of biotic stress (pests, diseases, weeds) (Evans and Fischer, 1999). Attainable yield in relation to water or water limited yield potential is defined similar as potential yield, but crop growth is only limited by water supply, and hence influenced by soil type and field topography (<http://www.yieldgap.org/glossary>). A yield gap between the observed (actual yield obtained by farmers) and the potential or attainable yield typically exists (Lobell et al., 2009).

Wheat is the main cereal grain grown in the European Union (Eurostat, 2015) and globally the second most widely cultivated cereal crop after rice (FAO, 2014). In most Mediterranean regions in the world, it is grown under rainfed conditions and yields are water-limited. In the Mediterranean, wheat growing season may span from October to June. Previous studies have shown that the wheat yields in this region are strongly dependent on seasonal rainfall amount and its temporal distribution during the growing season, particularly during December-January-February (vegetative phase) and March-April-May (reproductive, grain filling phase) (Acevedo et al., 1999; Austin et al., 1998; McAneney and Arrúe, 1993; Rodríguez-Puebla et al., 2007).

Precipitation in the IP is characterized by a strong interannual variability (Vicente-Serrano et al., 2011), whose major source is the North Atlantic Oscillation (NAO) (Serrano et al., 1999; Zorita et al., 1992). The NAO is one of the most prominent and recurrent patterns of atmospheric circulation variability over the mid and high latitudes of the Northern Hemisphere (Hurrell et al., 2003). NAO influences total and extreme precipitation in IP mainly during the winter months (Muñoz-Díaz and Rodrigo, 2006; Queralt et al., 2009). In turn, previous studies have suggested that sea surface temperature (SST) in the tropical Atlantic may affect the NAO variability with some months in advance. The energy released from the ocean when the thermal equilibrium with the atmosphere is broken, is propagated far apart from the SST anomaly through atmospheric teleconnection mechanisms, as those related to Rossby waves (horizontal atmospheric undulation that separates cold polar air from warm tropical air) (Okumura et al., 2001; Robertson et al., 2000). In addition, the variability of SST in subtropical North Atlantic region influences the anomalies of winter rainfall in the IP (Rodríguez-Fonseca and de Castro, 2002; Rodríguez-Fonseca et al., 2006). These relationships open the possibility for analyzing the predictability of the wheat yield variability in the IP.

It is well known that SST is one of the most convenient variables to be used as predictor of climate variability due to the high thermal inertia of the ocean. The warming or cooling of the tropical SST impacts convection, which influences the global atmospheric circulation. Thereby, it influences global and regional climate and therefore regional crop production. Several studies have revealed the tropical Pacific SST impacts on wheat yields in many parts of the world (Hsieh et al., 1999; Iizumi et al., 2014; Podestá et al., 1999; Potgieter et al., 2002; Travasso et al., 2003), and it has been used for crop forecasting purposes (Hammer et al., 2000; Mauget et al., 2009; Ramirez-Rodriguez et al., 2014). Nevertheless, there are few studies that relate tropical SST with crop production variability in Europe and even less in IP (Capa-Morocho et al., 2014; Gimeno et al., 2002). Recently, a non-stationary relationship between the Tropical Pacific SST anomalies (El Niño 3 region) and maize yield anomalies in IP was found using crop simulation models run with reanalysis datasets (Capa-Morocho et al., 2015).

The objective of this study is to evaluate the variability of rainfed wheat development and yield in IP and its predictability using

a model chain methodology (climate + crop) to generate reliable long time series of attainable yield. For that purpose, several steps are needed: (1) to evaluate the performance of simulated yield in comparison with observed (historical and experimental) data; (2) to assess the reliability of reanalysis datasets for generating long series of attainable crop yield in IP, (3) to investigate possible links between yield anomalies and several indexes of SST anomalies, and (4) to propose mechanisms to explain the yield-sea interactions involved in the established connections by analyzing the variability pattern of atmospheric climate behind crop response.

2. Materials and methods

2.1. Study site

The study area is located in the Northeast (NE) of IP and it is representative of one of the most important Spanish cropping systems, in which the wheat, other cereals and field crops are grown under rainfed conditions (Fig. 1a). Two locations in this area were selected because of the availability of field data for crop model calibration and evaluation: Agramunt (41.79°N, 1.10°E, altitude 337 m) and Gimènells (41.65°N, 0.39°E, altitude 258 m). These locations are 80 km apart within the province of Lérida (Cartelle et al., 2006). These sites are located within the same climatic region: “Cfa”, warm temperature, fully humid and hot summer according to Köppen-Geiger climate classification (Kottek et al., 2006). However, they have different soil type and depth and therefore different soil water holding capacity, which in turn determines the amount of water available for the crops, especially under rainfed conditions, and thereby strongly influences their yield under this climate regime. In Agramunt, the soil was a Xerofluvent Typic (Soil Survey Staff, 1999) of 1.40 m depth, with a silty-clay texture; meanwhile in Gimènells it was a Petrocalcic Calcixerept (Soil Survey Staff, 1999) of 1 m depth, with a loam texture. In both locations, the sowing of wheat crop spans from October to February and the growing season ends in June. Wheat winter cultivars are typically sown in November.

2.2. Crop simulations

Wheat yield response to weather inputs is simulated with CERES-Wheat crop model v 4.5 (Ritchie and Otter, 1985), which is included in the Decision Support System for Agrotechnology Transfer (DSSAT) (Hoogenboom et al., 2010). CERES requires, at least, daily data of maximum and minimum temperature (Tmax, Tmin), precipitation (Prec) and incoming solar radiation (Rad) to simulate plant growth and development processes on a daily basis from sowing to crop maturity and harvest. The crop model uses these weather data to calculate the potential evapotranspiration using the Priestley and Taylor (1972) method. FAO-Penman Monteith (Allen et al., 1998) was not selected because not all the used climate datasets have wind speed and relative humidity, needed for using this method. The crop model also uses daily mean temperature to compute the thermal time, which is defined as the sum of temperatures above a threshold temperature that makes crop development to progress (Hodges, 1991).

The CERES-wheat model is calibrated and validated in the two studied locations for a winter wheat variety currently grown in the area, Soissons, which is a common commercial cultivar of wheat in IP with high yield potential. Model performance are evaluated with the root mean square percentage error “RMSPE”, defined as the root mean square error normalized by the average of observed values (
$$\text{RMSPE} = \sqrt{\frac{\sum_1^n ((Y_{obs} - Y_{sim}) / Y_{obs})^2}{n}} \times 100$$
, being Y_{obs} = Observed yield, Y_{sim} = Simulated yield and n = total number of data). For this purpose, three years of data (2003, 2004, 2005) of crop phenology (sowing, flowering and maturity dates), yield and biomass from

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