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Simulating Future Wheat Yields' Response to Climate Change and Evaluating the Efficiency of Early Sowing in Spain

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by

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Abstract

Global food security is one of the main concerns of this century. Moreover, the increasing negative impacts of climate change on different sectors including agriculture are further expected to exacerbate these challenges. The main aim of this thesis is to assess the future impacts of climate change on wheat yields in Spain by 2050 and to evaluate the efficiency of early sowing as an adaptation strategy. This was done by using the LPJ-GUESS model. The model was calibrated and validated against reported experimental wheat data in the most productive regions of Spain. Moreover, future simulations were run using future climate data obtain from two GCMs (ESM2 and CM3), the embedded sowing algorithm in LPJ-GUESS and applied deviations in sowing dates. The results show that wheat will be influenced by climate change in Spain and that earlier sowing dates generally results in increases in yields depending on the location. Finally, this study insists on the need for exploring more adaptation measures as changing sowing dates only would not be a viable option for the second half of the century.

Keywords: ***Ecosystem Analysis, Physical Geography, Food Security, Climate Change, Adaptation, Early Sowing, Spain, Wheat***

Popular Summary

بسم الله الرحمن الرحيم والصلاة والسلام على أشرف المرسلين

لا شك أن الأمن الغذائي أصبح هاجسا يؤرق المجتمع الدولي في هذا القرن، مما جعله يتصدر أولويات التفكير وتعميق البحث والدراسة بسبب تكاثر الآثار السلبية للتغيرات المناخية التي تزداد شدتها وبسرعة كبيرة في قطاعات متعددة.

ومن المعلوم أن القطاع الفلاحي أصبح عرضة لهذه التغيرات المناخية والمتمثلة في ارتفاع درجات الحرارة وانخفاض تساقطات الأمطار مما يؤدي إلى أضرار بالغة على المنتوجات الزراعية.

هذا البحث تناول بالدراسة تقدير آثار التغيرات المناخية على إنتاج القمح بإسبانيا على مدى 50 سنة، وقد تبين أن إنتاجه سيستفيد من ارتفاع تركيزات ديوكسيد الكربون إلى غاية 2030، ومن المتوقع أن ينخفض الإنتاج في معظم المناطق بسبب ارتفاع دراجات الحرارة التي تؤدي الى تضاءل فترة نمو القمح.

كما قام هذا البحث كذلك بتقييم مدى فعالية الزراعة المبكرة في ارتفاع الإنتاج، وتبين أن تعجيل زراعة القمح ب 30 يوما سيؤدي إلى ارتفاع الإنتاج بما يقارب 40٪ في بعض المناطق إلى غاية سنة 2050، كما أن ازدياد فترات الجفاف في البلاد تستلزم اتخاذ تدابير أخرى ذات فعالية مرتفعة لحصر الأضرار التي سيعاني منها نمو القمح في المستقبل.

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Finally, I take this opportunity to express my sincerest gratitude to my parents and close friends who supported me and believed that I could finish this work well and in due time. I would not have done it without them.

Contents

Introduction

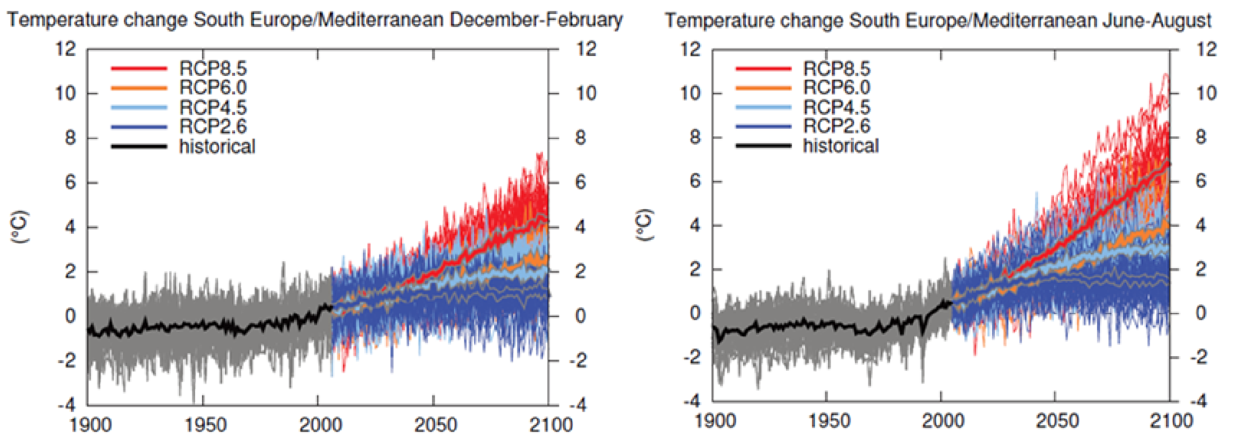
"Food security exists when all people, at all times, have physical and economic access to sufficient, safe and nutritious food to meet their dietary needs and food preferences for an active and healthy life" (FAO 1996). In addition to this definition given by the FAO at the 1996 World Food Summit, food security depends on the different processes of the food system including food production, storing, processing, transporting and disposing of food waste (Porter et al. 2014).

One of the main challenges of this century is attaining global food security. Indeed, the first United Nation's (UN) Millennium Development Goal aims at eradicating hunger and poverty and has focused so far on halving the number of people suffering from hunger by 2015 (1.C MDG target) (UN 2014). Over the past 20 years, global food production increased by 18% (FAO 2012) which enabled 63 developing countries to reach the 1.C MDG target (FAO et al. 2014). However, there are still about 800 million chronically undernourished people in the world mainly due to the high volatility of food prices and the lack of access to food in the poorest regions (FAO et al. 2014) . Moreover, in order to keep up with the expected increase in the world population (up to 9 billion people) by 2050, cereal yields will also have to increase by 40% (FAO 2009). This means, that by the middle of the century, food security will no longer be an issue of food accessibility but also of availability in more regions of the world. Securing enough food for the global population will become an even bigger challenge with the acceleration of climate change in many parts of the world (Porter et al. 2014).

Climate change has mostly been driven by human activity since the Industrial revolution of the 1800's. The intensive dependence on fossil fuels and land use changes since the industrial era has continuously increased greenhouse gases' (GHG) emissions to the atmosphere which in turn is leading to global warming. Climate change is thus the response of the Earth system to changes in radiative flux (Myhre et al. 2013). In order to assess the changes in climate due to both anthropogenic and natural factors, radiative forcing (RF) is used. It is a metric that "represents the net change in the energy balance (radiative flux) of the Earth system" which results in a warming of the planet (Myhre et al. 2013). Between 1750 and 2005 RF has increased by 0.2 W/m2 mainly due to the increase in CO_2 concentrations (from 278 ppm in 1750 to 390.5 ppm in 2011). Methane (CH4), dichlorodifluoromethane (CFC-12) and nitrogen dioxide (NO2 - N2O) are other GHG that considerably contribute to global warming in addition to natural factors such as volcanic eruptions and solar irradiance (Myhre et al. 2013).

In order to simulate future climate, climate models rely on a range of emission scenarios for estimating RF based on the possible future global socio-economic, environmental and technological development (Moss et al. 2010). In earlier IPCC assessment reports, these scenarios started from the range of future human behaviors to derive the potential resulting GHG emissions. However, this approach has proven to be time consuming and data extensive and a simpler alternative has been chosen (Moss et al. 2010). The latest IPCC report presented a new set of scenarios called Representative Concentration Pathways (RCPs) going from best case (RCP 2.6) to a worst case (RCP 8.5) scenario. They describe potential future CO_2 concentrations by 2100 compared to 1750 (IPCC 2013). The responsible levels of RF could be assessed for each of the RCPs and potential socio-economics, technological advancement can be derived from them. Mitigation and adaptation policies necessary to reach each of the scenarios could also be developed (Moss et al. 2010). The RCP 2.6 represents a strict mitigation scenario with a RF target of 2.6 W/m2 due to CO_2 concentrations of 421ppm by 2100 and leading to a mean global warming of 1°C by 2065 (IPCC 2013b; Moss et al. 2010). On the other hand, the RCP 8.5 represents a business as usual scenario with an RF target of 8.5 W/m2 and 936 ppm of CO_2 concentrations by 2100 that would lead to 2°C of global warming by 2065 and 3.7°C by 2100 (IPCC 2013b; Moss et al. 2010).

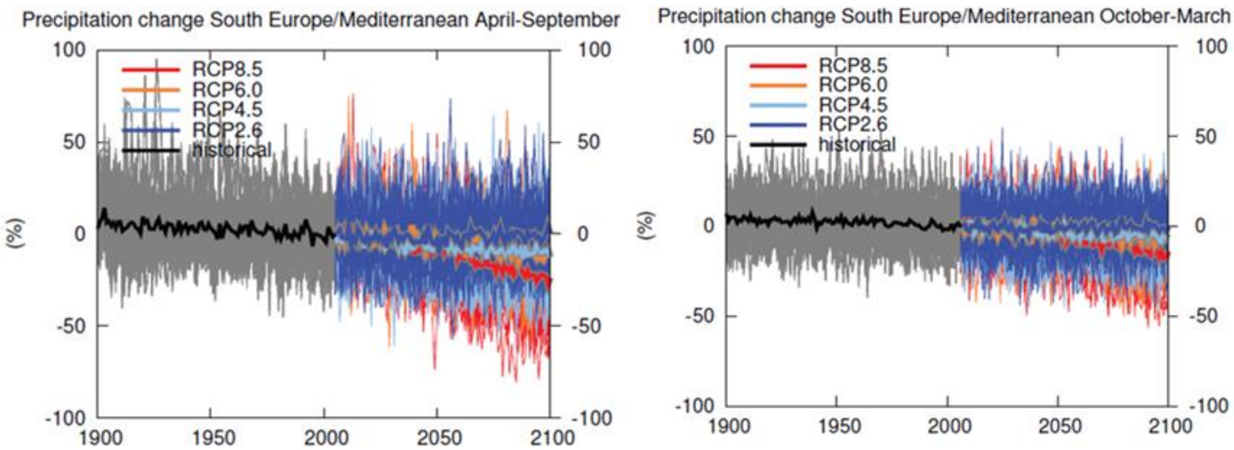
Over the past 50 years, the world has faced more extreme climate events, higher surface temperatures as well as variability in precipitation patterns both seasonally and regionally (Kovats et al. 2014). In Europe, an increase of 1.3°C in temperatures (over the 1850-1899 average) has been observed in the past 10 years. The highest increases have been recorded over Scandinavia in winter and the Iberian Peninsula in summer. For its part, precipitation has considerably increased in Northern Europe and decreased in the Mediterranean region (Kovats et al. 2014). Based on the latest assessment report of the IPCC, these regional climate fluctuations as well as occurrences and strength of extreme events (droughts and heat waves) are expected to further increase during the rest of this century. It has also been shown that the Mediterranean represents the European region most at risk of such climatic changes (Kovats et al. 2014). Indeed, precipitation is projected to decrease by 50% from its level in 2005 while temperatures could increase by up to 10°C in 2100 according to the RCP 8.5 (figures 1 and 2). These new climatic trends will have consequences on different sectors including but not limited to forestry, energy and agriculture (Kovats et al. 2014).



Time series of temperature change relative to 1986–2005 averaged over land grid points in the region South Europe/Mediterranean in December to February. Thin lines denote one ensemble member per model, thick lines the CMIP5 multi-model mean.

Time series of temperature change relative to 1986–2005 averaged over land grid points in the region South Europe/Mediterranean in June to August. Thin lines denote one ensemble member per model, thick lines the CMIP5 multi-model mean.

Figure 1: Seasonal temperature change in Southern Europe (IPCC 2013a)



Time series of relative change relative to 1986–2005 in precipitation averaged over land grid points in the region South Europe/Mediterranean in April to September. Thin lines denote one ensemble member per model, thick lines the CMIP5 multi-model mean.

Time series of relative change relative to 1986–2005 in precipitation averaged over land grid points in the region South Europe/Mediterranean in October to March. Thin lines denote one ensemble member per model, thick lines the CMIP5 multi-model mean.

Figure 2: Seasonal precipitation change in Southern Europe (IPCC 2013a)

Changes in cereal production have already been observed in Europe as a result of the massive heat waves of 2003 and 2010 amounting to a 20% decrease in yields and the 2004-2005 drought in the Iberian Peninsula that led to a 40% decrease in yield (EEA 2010). Furthermore, Southern Europe already suffers from water scarcity and often pains to satisfy the increasing demand for water by agriculture, tourism and the energy sector; especially in summer (EEA 2010). These already observed physical conditions are expected to be further aggravated by climate change effects. As a matter of fact, crop yields in Europe are expected to decrease by 10% and up to 27% in Southern Europe in the 2080's given a regional increase of 5.4 °C (Ciscar et al. 2010). Fresh water availability will also decrease in the Mediterranean region inhibiting an increase in irrigation (Kovats et al. 2014). Finally, even though a CO_2 increase would have a fertilization effect that increases yields, it will be counteracted by an increase in temperatures of more than 3 °C (Porter et al. 2014).

In view of the projected negative impacts of climate change on agriculture in Europe, mitigation and adaptation policies have been developed at the level of the European Union but also at the national and local levels (Kovats et al. 2014). Adaptation is considered as the minimization of the risks and impacts of climate change by taking advantage of the current situation (MAGRAMA 2014). Iglesias et al. (2011) define three types of adaptation measures; technical, managerial and infrastructural. These measures can either be adopted by the farmers themselves (managerial and some technical measures) or be implemented at a national or regional scale through policies, large investments and research (infrastructural measures). Technical measures include improving the efficiency of drainage and irrigation systems by increase rainwater collection in winter for irrigation use in summer (Iglesias et al. 2011b). On the other hand, the technical aspect, which is a priority in the Mediterranean zone, is to develop cultivars and crops more resistant to heat stress and low water availability (Iglesias et al. 2011b). Finally, the main managerial adaptation measures include changing fertilization amounts and timing as well as irrigation and drainage methods and emphasizing on increasing the water-holding capacity of soils. Changing sowing dates should also be applied to avoid that crop maturation coincides with high temperatures and thus reducing crop yields (Iglesias et al. 2011b).

According to Porter et al. (2014), adaptation measures lead to a 10% (15% to 18% for managerial measures and up to 23% in the Mediterranean region) increase in crop productivity on average. However, crops respond differently to these measures across regions (Porter et al. 2014). It has also been argued that changing crop cultivars or planting dates are more effective strategies than for example optimizing irrigation (Porter et al. 2014). Nevertheless, there is still uncertainty and a research gap on monitoring and evaluating the actual effects of these adaptation strategies (Kovats et al. 2014).

The aim of this research is thus to evaluate the efficiency of earlier planting dates as an adaptation strategy in the Mediterranean region with a special focus on the case of wheat in Spain. In order to do so, future wheat yields are simulated using the LPJ-GUESS model and differences in yields are analyzed. Spain was chosen as it is one of the most vulnerable countries to climate change impacts in Europe and it is also the fourth most productive agricultural country in the EU (Tudela et al. 2005). For its part, wheat is considered to be the third most produced crop in the world (Asseng et al. 2011 in Bralow 2014) and it is also mainly rainfed in Spain and thus most vulnerable to changes in climate (Iglesias and Minguez 1997).

The objectives of this project are thus to calibrate the model in order to simulate wheat yields in Spain, then, to compare the future yields obtained from the present planting dates to sowing dates obtained using a climate based sowing algorithm. Moreover, more comparisons will be performed by deviating the sowing dates in order to derive an optimized sowing period for Spain in 2050.

Background:

Crop models are process-based simulation models used to evaluate the dynamic response of crop production to climate change by taking into account managerial conditions at a broad scale (Angulo et al. 2013; Porter et al. 2014). The first crop models were used to simulate climate change impacts only on one specific crop at a particular site (Ewert et al. 2014). This was the case of Iglesias and Minguez (1997) who used General Circulation Models' (GCM) outputs as inputs to the CERES Wheat and Maize models to determine yield changes and future irrigation needs for wheat and maize in Spain. The CERES models simulate the phenology of wheat and maize based on physical properties of soil and weather as well as management options (irrigation, cultivar and planting date) at farm level (Iglesias and Minguez 1997).

With the increasing technological developments and scientific advances, new studies have been made using GCM models with atmospheric-oceanic coupling as well as Regional Climate Models (RCM) accounting for more climatic variability within regions (Guerena et al. 2000 in Tuleda at al. 2005). As there is still a considerable level of uncertainty related to RCMs, ensembles of nested RCMs are used in order to further reduce the climate model uncertainties. This is the case of a study conducted by Ruiz-Ramos et al. (2011) analyzing the impacts of high temperatures on wheat and maize in the Iberian Peninsula. This study derives a range of future crop yields from the ensemble climate model's outputs and uses the CERES models to derive phenology, yield, biomass and water use of the crops (Ruiz-Ramos et al. 2011).

As crop models are in principle simplifications of the complex bio-geophysical relations of the field and climate systems, it goes without saying that they contain a certain amount of uncertainty in their predictions. A study by Palosuo et al. (2011) compared eight commonly used crop models in order to assess their ability to adequately capture the climate variability impacts on wheat yields and phenology in Europe but also to determine the source and level of uncertainties related to each model. The study emphasized on the different sources of uncertainty. First, there is always uncertainty or incompleteness in the input data, then there are model related uncertainties as different models consider different processes and/or define them differently leading to different results (Palosuo et al. 2011). Finally, human error is also a considerable source of uncertainty. Observed data to which the simulation results are compared also contain their fair share of uncertainty as there are always errors in yield measurements and specific controlled field experiments cannot be considered to be fully representative of the situation in regular farm fields (Palosuo et al. 2011). Finally, most models do not account for yield limitations due to pests, diseases, pollutants and weeds or nitrogen fertilization (Iglesias and Minguez 1997; Palosuo et al. 2011; Semenov et al. 2014).

On the other hand, Dynamic Global Vegetation Models (DGVM) represent an improvement in climate science as they include vegetation dynamics to global coupled atmospheric-oceanic circulation models. Indeed, land use changes over the past 300 years have considerably affected the biochemical and biophysical properties of the Earth including albedo, energy balance and GHG emissions (refered to by Bondeau et al. 2007). As agriculture (crop land and management practices) influences biogeochemical cycles in a specific way, different crop model components were added to DVMs in order to account for agriculture-climate feedbacks (Kucharik and Brye 2003; Gervois et al. 2004 in Bondeau et al. 2007).

In order to model vegetation dynamics in response to climate change, several DGVMs have been developed (Foley et al. 1996; Smith et al. 2001; Sitch et al. 2003). These models simulate the behavior of different plant functional types (PFTs including types of trees and grasses) both spatially and temporally as well as their ecosystem functions (primary production and evapotranspiration) by assessing CO_2 effects (Bondeau et al. 2007). As the initial purpose of these models was to estimate land use land cover changes (Bondeau et al. 2007; Lindeskog et al. 2013), only grassland and trees were considered with a focus on NPP. Nowadays, more models account for the phenology, carbon allocation and productivity of specific crops in addition to natural vegetation (Bondeau et al. 2007; Lokupitiya et al. 2009; Berg et al. 2010; Lindeskog et al. 2013).

Finally, Smith et al. 2014 and Olin et al. 2015 made changes to the DGVM Lund-Potsdam-Jena General Ecosystem Simulator (LPJ-GUESS) to account for carbon (C) and nitrogen (N) cycling together; thus simulating the combined impacts on different plants. Indeed, accounting for C-N interactions changed the way in which LPJ-GUESS simulates plant productivity, establishment and competition, and C storage; with higher difference between C-only and C-N observed for regional simulations (Smith et al. 2014).

Furthermore, over the past 20 years, much effort has been made to take into account current knowledge of crops' development and climate interactions to create models more suitable for large scale simulations of climate change impacts (Ewert et al. 2014; Porter et al. 2014). CO_2 concentrations, temperatures, solar radiation are defining factors in cereal development. Nutrients and water for their parts are limiting factors of crop growth while pests, diseases and extreme events of frosts and heat shocks are considered to be reducing factors of potential yields (van Ittersum et al. 2003). First of all, increasing temperatures increase evapotranspiration and decrease the length of the growing period (Iglesias and Minguez 1997). Moreover, impacts of high temperatures differ based on which stage of growing cycle they happen in (Porter and Gawith 1999; Barlow et al. 2015). Indeed, exposure to frost during the reproductive stage causes considerable damage to wheat and leads to "seedling death, sterility and abortion of grains" which results in yield reductions (Barlow et al. 2015). For their parts, high temperatures (exceeding 33°C) mostly affect wheat during anthesis and grain filling as they shorten the grain filling stage, reduce photosynthesis and reproduction of wheat grains (Rezaei et al. 2014; Barlow et al. 2015). Porter and Gawith (1999) gathered a range of suggested cardinal temperatures (minimum, optimum and maximum) for each development stage of wheat. In general, wheat develops optimally between 17°C and 23°C with a minimal temperature of 0°C and a maximal temperature of 37°C beyond which the crop gets damaged (Porter and Gawith 1999). Nevertheless, the influence of temperatures on crops vary according to their location, cultivar and photosynthesis pathway as more negative impacts are observed for C4 summer crops (Ruiz-Ramos et al. 2011). Second, increases in CO_2 concentrations have a fertilization effect on C3 plants as they increase the efficiency of photosynthesis and water use (Iglesias and Minguez 1997). Finally, Nitrogen (N) is considered to be the most limiting nutrient of plant growth as N interacts with carbon (C) and reduces the CO_2 fertilization effects (Cramer et al. 2001). Including N fertilization rates in the management options for crops could considerably improve simulation results (Olin et al. 2015).

In view of the challenges facing increasing cereal production under future warming, it is important to extend the grain filling duration of crops which in turn will increase the harvest index and improve drought tolerance of crops in water scarce environments (Semenov et al. 2014). This can be done by choosing earlier planting dates that would enable the crops to develop during cooler periods and avoid heat and water stress periods thus avoiding a reduction in the length of the growing cycle (Iglesias and Minguez 1997; Ruiz-Ramos et al. 2011; Barlow et al. 2015). It is also important however to be careful about planting too early because the crops would then face a risk of frost that would be just as damaging (Barlow et al. 2015). Other adaptation strategies have also been suggested such as improving irrigation systems (Iglesias and Minguez 1997), changing cultivars (Ruiz-Ramos et al. 2011) and increasing nitrogen fertilization to increase the floral survival rate (Semenov et al. 2014).

Finally, in order to reduce model specific uncertainties by taking into account the above mentioned phenological knowledge, all models need a level of calibration based on known agronomic data in order to effectively assess a specific crop growth at a particular location and thus reducing the differences between observed and simulated yields (Iglesias and Minguez 1997; Palosuo et al. 2011; Ruiz-Ramos et al. 2011; Angulo et al. 2013; Semenov et al. 2014). Crop phenology, growth and yield parameters can be calibrated; with values based on literature or field experiments (Iglesias and Minguez 1997; Angulo et al. 2013). Angulo et al. (2013), attempt to evaluate the importance of calibrating regional models in Europe by using a search algorithm that looks for the best values for each parameter. The study presents three calibration strategies; region-specific parameters for phenology only, for phenology and the yield correction factor, and finally, for phenology and growth parameters (Angulo et al. 2013). The results show that none of the calibration strategies gives a perfect fit between observed and simulated yields, however, taking into account phenological parameters together with growth parameters gives the best results and is expected to give even better results if more growth parameters are considered (Angulo et al. 2013).

Study Area:

Spain is a country located in the Mediterranean basin in Southern Europe. It has two agro-climatic zones; the Mediterranean South and Mediterranean North (Iglesias et al. 2011a). It is one of the most agriculturally productive countries in Europe contributing to 12.1% of the total production of the EU after France, Germany and Italy (Tuleda et al. 2005). About 30% of the surface of the country is used for agriculture (Tuleda et al. 2005). Most of the farmed area is not irrigated in Spain (Tudela et al. 2005).

Furthermore, wheat is the third main crop produced in the world (Barlow et al. 2015) and the first in Europe (Palosuo et al. 2011). In Spain, most of the wheat is grown in winter and is rainfed (Iglesias and Minguez 1997). The largest wheat producing regions in Spain are Andalucia, Cataluna, Castilla la Mancha, Castilla y Leon and Aragon as shown in figure 3 (Secretaria General Tecnica Subdireccion General de Estadistica 2013). A regional map of Spain can be found in Annex 1.

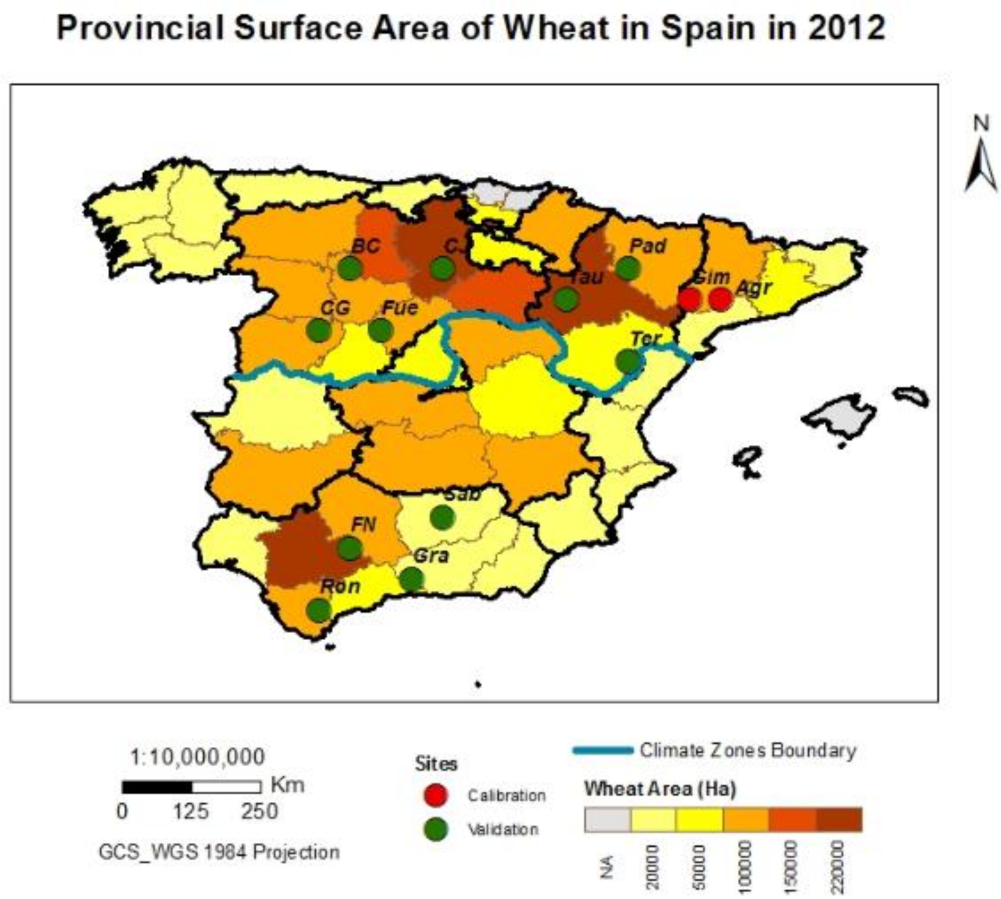


Figure 3: Provincial Areas for Wheat in Spain in 2012 (borders from GADM 2009; climatic zone boundary from Iglesias et al. 2011a and surface areas from Secretaria General Tecnica Subdireccion General de Estadistica 2013)

Moreover, as was previously mentioned, Spain is expected to experience large climatic variability and a high vulnerability to climate change especially in the agricultural sector. The Spanish government thus launched a National Climate Change Adaptation Plan (PNACC) aiming at evaluating and assessing climate change impacts and implementing adaptation policies in the different sectors influenced by climate change (MAGRAMA 2014). A specific focus is put on research and development for implementing highly accurate regional models and evaluating potential impacts of future climate change scenarios. It has already been shown that temperatures are expected to increase and precipitation to decrease across the whole country. This would lead to decrease of available water by 5 to 14% by 2030 and to 20-22% by the end of the century (MAGRAMA 2014). Knowing that 30% of the country is arid and semi-arid areas, conflicts regarding water use between farming, energy production and household consumption are expected to increase drastically.

Methods:

LPJ-GUESS

The representation of LPJ-GUESS used in this study was built on the LPJmL model (Bondeau et al. 2007) representing crops as Crop Functional Types (CFTs) (Lindeskog et al. 2013). CFTs represent groups of crops that are considered to behave similarly. This version of LPJ-GUESS was further improved by Olin et al. (2015) to account for nitrogen cycling and include nitrogen fertilization in the management practices for crops.

Sowing Algorithm:

Identifying the optimal sowing date of a crop based on favorable climatic conditions is of upmost importance since high temperatures, low precipitation and soil moisture at the start of the growing season can lead to crop failures (Waha et al. 2013). When no data on planting periods is available, the sowing algorithm is used within LPJ-GUESS to dynamically allocate planting times based on the climate data at each grid cell. The algorithm used is based on the implemented method in LPJmL accounting for temperature and crop water thresholds. It is based on the heat unit theory which is in turn dependent on growing degree days (*GDD*) (Bondeau et al. 2007). This approach was further improved by Waha et al. (2012) by using seasonality coefficients representing annual variations in precipitation and temperature instead of absolute values of temperature and precipitation. It is then the seasonality of temperature or precipitation that determines the start of the growing season. It is based on the heat unit theory with the temperature threshold set to the base temperature of the crop when there is a temperature seasonality and on the ratio of precipitation over potential evapotranspiration when precipitation seasonality is considered (Waha et al. 2012). If no seasonality is observed, sowing could actually happen at any moment based the algorithm's setting (Waha et al. 2012).

Calibration tool:

In order to be representative in relation to the observed data, the most important crop related parameters in the model characterizing phenological, crop growth and yield components should be calibrated (Iglesias and Minguez 1997; Minet et al. 2015). In order to do so, the calibration tool (Olin, unpublished) based the Markov Chain Monte Carlo sampling approach (Minet et al. 2015) was used. This Bayesian method "generates samples from complex high-dimensional distributions" (Andrieu and Thoms 2008). The approach is based on the Metropolis-Hastings algorithm that generates transitions for the Markov Chain based on statistically sound distributions. Monte Carlo estimators are used to optimize the transition probabilities in order to get the best samples (Andrieu and Thoms 2008). When applying the calibration tool, the parameter values obtained that present the highest likelihood were chosen.

Data:

In order to run LPJ-GUESS, data on soil types, climate (temperature, precipitation and solar radiation) and CO_2 concentrations are needed. Moreover, LPJ-GUESS also takes into account managerial components when it comes to croplands and thus requires data on sowing dates, nitrogen fertilization amounts and timing and whether or not the crops are irrigated. A set of data was common in all the simulations and that is the soil type data taken from the WISE 3.0 dataset (Batjes 2002) as fractions of silt, clay and sand. Global nitrogen deposition was obtained from the ACCMIP dataset (Lamarque et al. 2010; Smith et al. 2014). Finally, global atmospheric CO_2 concentrations from 1850 to 2100 follow the RCP 8.5 simulations (Meinshausen et al. 2011). The specific climate data, sowing dates and fertilization practices used for each simulation will be described for each step as they often differ. All these datasets present information in 0.5° x 0.5° grid cells. Finally, for all the simulations, a spin-up is needed to equilibrate the carbon and nitrogen pools. In this case the spin-up was set for 500 years.

Process:

In order to complete this project, five main steps were followed (figure 4). First, the model was calibrated (Step 1) and validated (Step 2) then it was applied to the whole country during the 2000's in order to obtain a base line to future simulations (Step 3).

After that, an iterative process was taken in simulating future wheat yields by using different sowing dates. All the outputs were compared and a future sowing date map was suggested (Step 4). Finally, different elements were analyzed in order to identify the main drivers and limitations of wheat yields in Spain by 2050 (Step 5). In order to avoid increased uncertainties in future climate data and based on the assumption that adaptation strategies should be applied for the short term, only the period from 2000 to 2050 is analyzed in this project. Moreover, since there is no apparent distinction between RCPs before 2050 (figures 1 and 2), only the RCP 8.5 is considered in the future simulations.

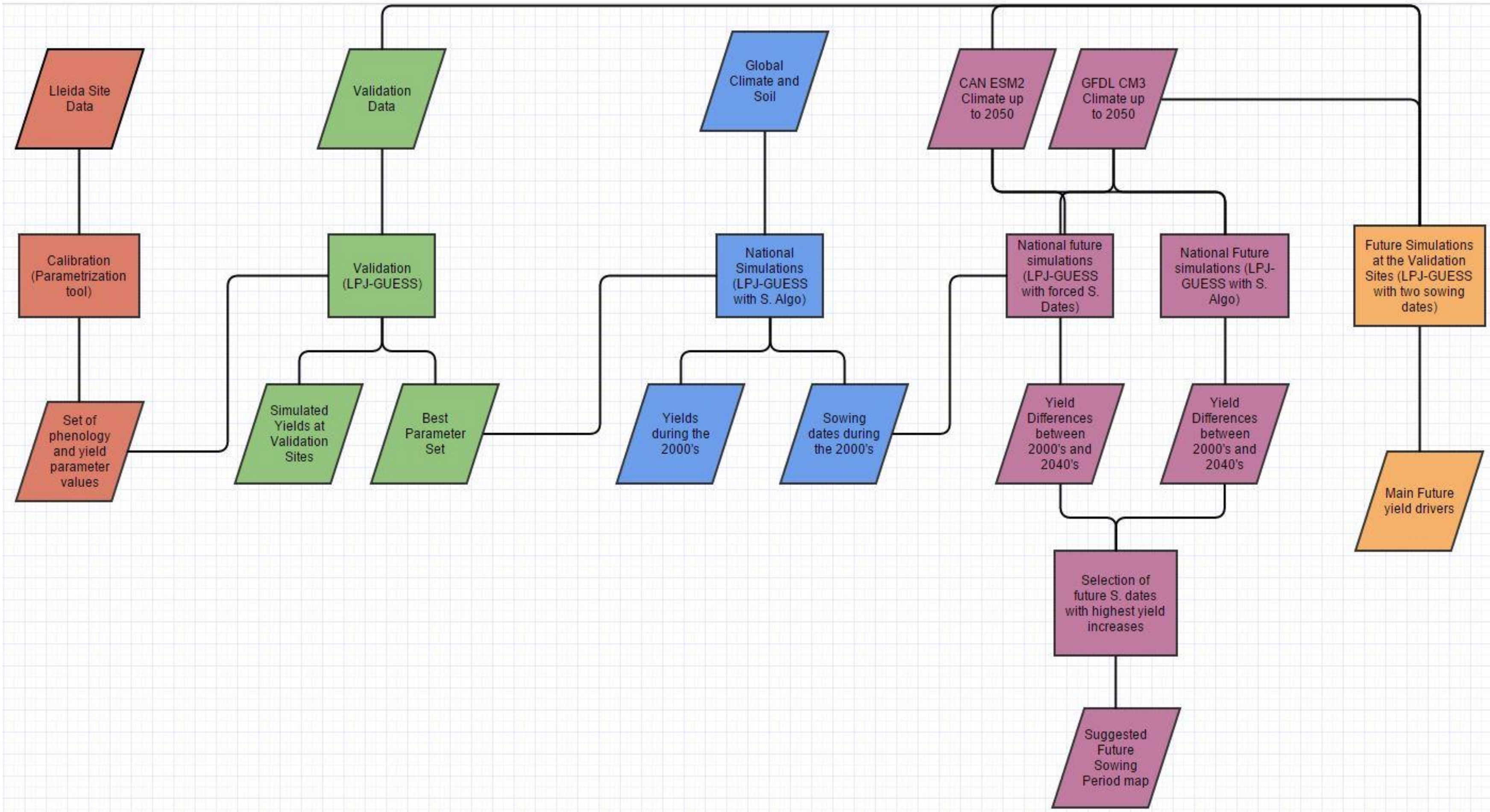


Figure 4: Flowchart of the process followed in this project

Step1: Calibration

As LPJ-GUESS is used to represent crops at a global scale, the default parameters characterizing wheat should be adapted to the local varieties produced in Spain. Therefore, the model was calibrated using data obtained from different field experiments conducted in two sites in Lleida, Cataluña (Gimenells and Agramunt) between 2003 and 2006 (Cartelle et al. 2006; Abeledo et al. 2008).The experiments also account for different management practices including tilling, sowing dates, irrigation and fertilization practices. Moreover, flowering and harvest dates as well as the harvested yield and biomass for each experiment are provided. Moreover, all the experiments present a spring wheat cultivar ANZA (very low vernalization requirements) by using different fertilization (amounts and timing) and irrigation treatments as well as different sowing dates. The climate data used was obtained from the closest meteorological station in Lleida. It comprises of daily mean, maximum and minimum temperatures, precipitation and solar irradiance.

As the experiments used for calibration give specific dates for the fertilization applications, modifications were made to the model to account for dates of fertilization instead of the default growing stages. Moreover, since in Spain both winter and spring wheat cultivars are sown in autumn, the cultivar specific parameters were given the values of winter wheat (Olin et al. 2015).

There are two types of parameters chosen for the calibration (table 1). First, phenological parameters were calibrated against the observed flowering and harvest dates. Then, when the values with the highest likelihood were chosen, a second set of calibration was performed to account for yield related parameters which results were compared against the observed yield and biomass. The range of values for known parameters was obtained from the literature. For those parameters where no value was found in the literature, a very large range was used deviating from the default values set by the model. Thus, in order to avoid using very unrealistic values, three sets of parameters were obtained from the calibration tool and were all used in the validation step.

Table 1: Phenology and Yield Parameters Calibrated

Parameter	Denomination	Reference
Phenology Parameters		
Photoperiod sensitivity factor	(Ω)	(Wang 1998)
Critical photoperiod	(Hpc)	(Wang 1998)
Vegetative Development Rate	(Veg_dev_rate)	(Wang 1998)
Reproductive Development Rate	(rep_dev_rate)	(Wang 1998)
Minimum Vegetative Temperature	(T_Veg_min)	(Porter and Gawith 1999)
Optimum Vegetative temperature	(T_Veg _opt)	(Porter and Gawith 1999)
Maximum Vegetative Temperature	(T_Veg_max)	(Porter and Gawith 1999)
Minimum Reproductive temperature	(T_Rep_min)	(Porter and Gawith 1999)
Optimal Reproductive Temperature	(T_Rep_opt)	(Porter and Gawith 1999)
Maximum Reproductive Temperature	(T_Rep_max)	(Porter and Gawith 1999)
Yield Parameters		
Specific Leaf Area (ratio of leaf area to dry mass)	Sla	
Minimum Carbon to Nitrogen Ratio in leaf	$C:N_{leaf}$	
Maximum (evapo)transpiration rate	Emax	
Root distribution for water	Rootdist_up	

uptake in the upper soil layer		
Minimum stromatal conductance	Gmin	
Drought tolerance	Drought toler	
Extinction coefficient for light in canopy	Kbeer	
Photosynthetic Active Radiation efficiency coefficient	Alpha a	
Base nitrogen in leaf not used for the photoperiod	Nb	
Ratio between allocation to stem and leaf at the end of the development stage	B2	
Shape parameter (part of photosynthesis)	Theta	
leaf respiration coefficient for C3 plants	b_{C3}	

Step 2: Validation

Three sets of parameters were obtained from the calibration tool that compare well with the yields reported in Lleida. In order to choose the most representative set of parameter values, they were all used to simulated yields in the validation sites.

More simulations were run to determine whether or not the parameter set obtained after the parameterization is reliable for simulating wheat in other locations in Spain. In order to do so, more field data was combined from reported experiments conducted in Aragon, Castilla y Leon and Andalucía (Table 2). These locations were chosen as they are the most productive wheat regions in Spain. For each region data was obtained for two different years. The reported data was composed of sowing date, yield, fertilization and irrigation treatments. This sowing and fertilization data was used for comparing the simulated yields. For these simulations, the observed global climate dataset from 1979 to 2012 from the Climate Research Unit (CRU) at the University of East Anglia was used. Each site was represented by one grid cell (0.5x0.5).

Table 2: Validation Data Used

Region	Growing Season 1	Source 1	Growing Season 2	Source 2
Aragon	2006-2007	(Perez Berges 2007)	2011-2012	(Gutierrez Lopez 2012)
Castilla y Leon	2003-2004	(Casta 2004)	2009-2010	(Casta 2010)
Andalucia	2006-2007	(Gimenez 2007)	2010-2011	(Catedra Ceron et al. 2011)

Step 3: National simulations for the 2000's

After selecting the best set of parameters, the model was applied to simulate wheat yields for the entire country between 2001 and 2010. The sowing algorithm was used to dynamically determine the planting dates in the whole country based on the climate data. Moreover, as the national simulation will act as a baseline to the future simulations, the yields and sowing dates obtained where average over the 10 year period.

The national simulation was performed by using the same CRU data as for the validation data and was applied to all the 0.5° x 0.5° grid cells of mainland Spain. The nitrogen fertilization applied was taken from the AgGrid dataset (Elliott et al. 2015). Finally, as no data was available on crop calendars for the whole country, sowing dates were derived from the sowing algorithm.

Step 4: Future simulations up to 2050

For the future simulations, the potential applied nitrogen fertilization was also taken from the AgGrid dataset. The climate data for its part was derived from previously bias corrected GCMs against the CRU data (used for the simulations from 2001 to 2010). This was done using a relative delta change for precipitation approach added to the bias corrected Watch Forcing Data (Era Interim) (WFDEI) (Weedon et al. 2014). Moreover, the monthly data available was roughly downscaled into daily climate data to be used by LPJ-GUESS. The used GCMs are CAN-ESM2 and GDFL-CM3 based on the RCP 8.5

from 2007 to 2050. The CAN-ESM2 is an Earth System Model representing Land-Ocean-Land carbon exchanges coupled with the Canadian Ecosystem Model that focuses on human activity and ecosystems interactions (Chylek et al. 2011). On the other hand, the GFDL-CM3 is a physical model representing cloud-aerosol interactions and focusing on atmospheric chemistry (GFDL 2014). The future simulations use a range of sowing dates that will be described in more details in the next sections.

The future simulations were applied over the whole country between 2010 and 2050. In order to smoothen the influence of the high variability in the climate data, decadal yield averages were used. The focus was put on evaluating the differences in yield between the 2000's and the 2040's. The simulations are presented as sets comprised of four simulations focusing on both rainfed and irrigated wheat; and using climate data from two GCMs (ESM2 and CM3). The first set of simulations was run by using the sowing algorithm. Then, a second set of simulations used the same sowing dates as the ones obtained by the sowing algorithm for the 2000's. After that, a range of simulations was run by deviating the 2000's sowing dates by 10, 20 and 30 days earlier and later. The resulting changes in yield for these simulations were compared between each other and the sowing dates resulting in the highest increases in yields were combined to suggest potential future optimum sowing dates.

Step 5: Drivers of yield change

In order to evaluate the influence of different factors on yields in the future, the validation data was used again together with the climate data from the two GCMs.

Since the previous simulations only focused on yield differences between the 2000's and the 2040's, other future simulation sets were applied on the validation sites in order to analyze more temporal variations in future yields. Moreover, the validation sites were chosen since actual sowing dates are available which reduces the uncertainty resulting from using the sowing date algorithm. These simulations also presented the yields resulting from different sowing dates starting by keeping the current dates constant and then by planting 10, 20 and 30 days earlier.

Finally, decadal averages were used again for these sites in order to identify the reasons behind a change in wheat yield in the future. To do so, changes in yields were compared to changes in temperature and the length of the growing period (LGP) by keeping the sowing dates constant and by planting 30 days earlier. Moreover, impacts of CO_2 were also evaluated by running simulations with dynamic CO_2 and constant CO_2 (using the CO_2 concentrations in 2011).

Results and Discussion

Calibration

From the parameter optimization, three sets of parameter values were obtained using the parameterization tool. They are slightly different but they are within the ranges found in literature except for C: N_{leaf} and Kbeer (Table 1). Moreover, the model results of biomass, yield and phenology compare well with the observed ones using both the site climate data as well as the global one (RMSE values).

Table 3: Parameter Values Resulting from the Model Calibration

	Default	Set 1	Set 2	Set 3
	Phenology Parameters			
Omega	0.34	0.21	0.35	calculated
Hpc	9.5	8.8	8.8	9.1
Veg dev rate	0.03	0.024	0.018	0.017
Rep dev rate	0.042	0.035	0.092	0.071
T Veg min	0	1	0	0
T Veg opt	24	18	18	19
T Veg max	35	33	32	34
T Rep min	8	8	9	8
T Rep opt	29	24	33	32
T Rep max	40	38	40	40
	Yield Parameters			
Sla	45	29	39	28
$C:N_{leaf}$	7	5	4	7
Emax	5	8	9	7
Rootdist_up	0.9	0.8	0.9	0.8
Gmin	0.5	0.3	0.2	0.1
Drought toler	0.1	0.1	0.1	0.1
Kbeer	0.5	0.37	0.93	0.8
Alpha a	1	0.96	0.94	0.98
N b	0.00068	0.0007	0.0004	0.0002
B2	0.2	0.09	0.09	0.1
Theta	0.7	0.85	0.82	0.9
Bc3	0.015	0.0008	0.05	0.0001

Simulations were run with each set of optimized parameter values and the resulting flowering dates and yields were compared against the observed values used within the optimization.

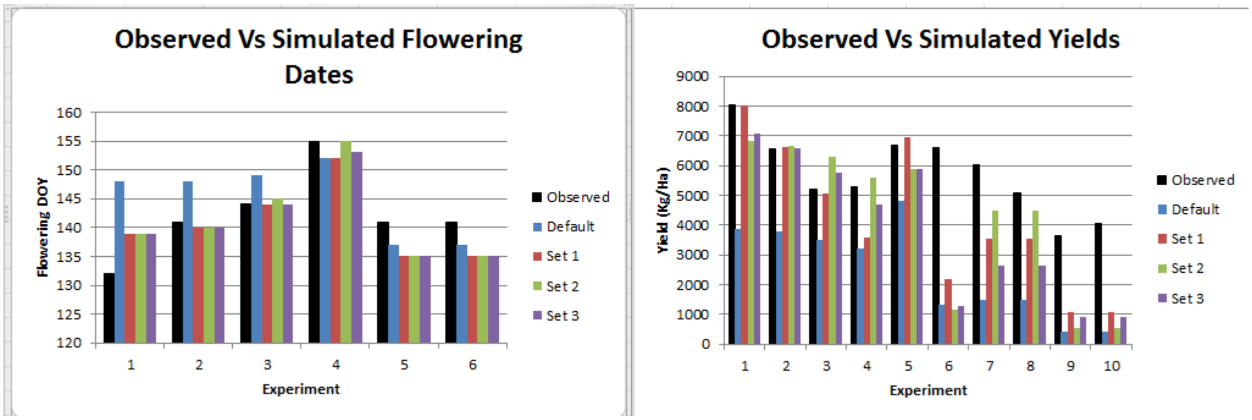


Figure 5: Differences between Observed and simulated Flowering dates and Yields in Lleida

From figure 5, it can be seen that the difference in flowering dates obtained from the three parameter sets is small. However, the default parameters overestimate the flowering date for the first three experiments. On the other hand, the default parameter set clearly underestimates the simulated yield for all the experiments. The three optimized sets produce comparable yields to the observed ones for the first five experiments but they all underestimate the yields for the last five experiments. This might be explained by the fact that observed phenological and biomass values were only available at Gimenells (the site of the first six experiments) which means that the parameterization tool was mainly focusing on results of the first site. Moreover, experiments 6, 9 and 10 show the lowest simulated yields as these are actually rainfed experiments. The model is clearly unable to capture the rainfed yield at these sites as the crops are simulated to be extremely water stressed. One reason for that could be that natural water bodies are not included in the model and the water available for the crops is only obtained from precipitation. Another reason might be that there were droughts and massive heat waves in Catalonia between 2003 and 2010 which might explain the very low yields as the model does not have a heat stress component and cannot handle extreme events.

Validation

As the model was calibrated for one specific site in Cataluña (Gimenells), it is important to verify that it can still give good results in other locations of the country. Thus, all the parameter sets were used again to model yields in different sites of Spain at which observations were available.

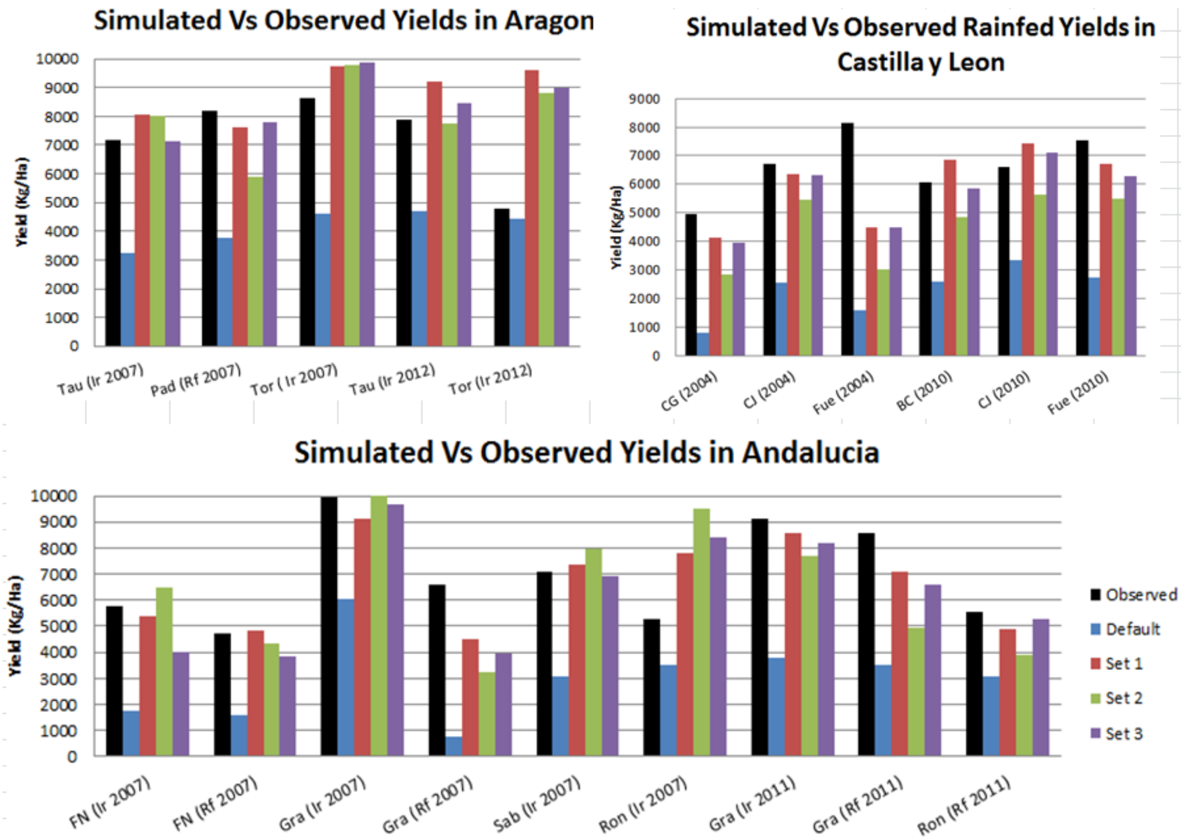


Figure 6: Comparisons of Simulated and Reported Yields in different sites in Castilla y Leon, Aragon and Andalucia

For all the locations (Figure 7), the default set of parameters always considerably underestimates yields. Moreover, the model has a general tendency to slightly overestimate a bit the yields for irrigated wheat and underestimate the one of rainfed wheat. While the possible reasons for underestimated yields were previously explained, overestimations could actually be due to the fact that the model irrigates the crops whenever they are water stressed which means that they will always receive enough water to develop correctly. This is not the case in many locations in Spain as the water available for irrigation is often limited; thus the crops do not always benefit from the optimal amount of irrigation they might need.

On the other hand, the model provides acceptable results for almost all the simulated locations (except Segovia and Zamora in Castilla y Leon). Another source of uncertainty in this case is that the original experiments were conducted on very small fields when compared to the size of the modeled grid cell and might thus not be representative of the whole grid cell. Finally, eventhough there is still no big distinction visible between the results obtained from each parameter set, the first and the third set proved to be more compatible with the observed values and it is the first set that was chosen to simulate future yields in Spain.

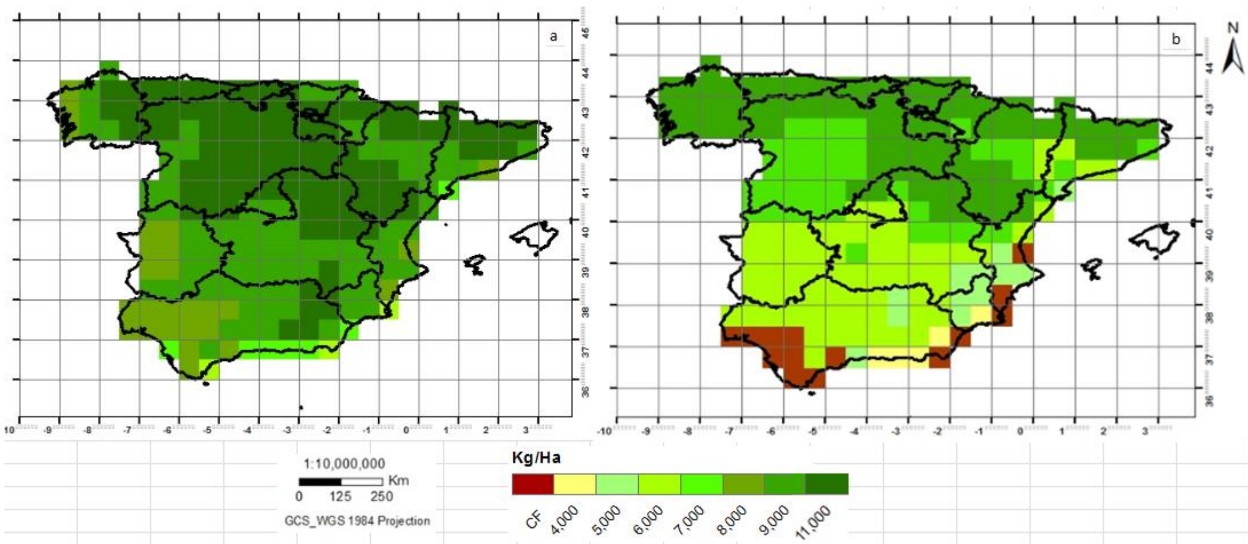


Figure 7: Simulated Yield in Spain in the 2000's for (a) Irrigated and (b) Rainfed Wheat (using the sowing algorithm).

The simulations in figure 8 were obtained by applying the sowing algorithm and forcing it to chose a sowing date in autumn. The resulting simulated planting periods by the sowing algorithm are presented in frigure 9.

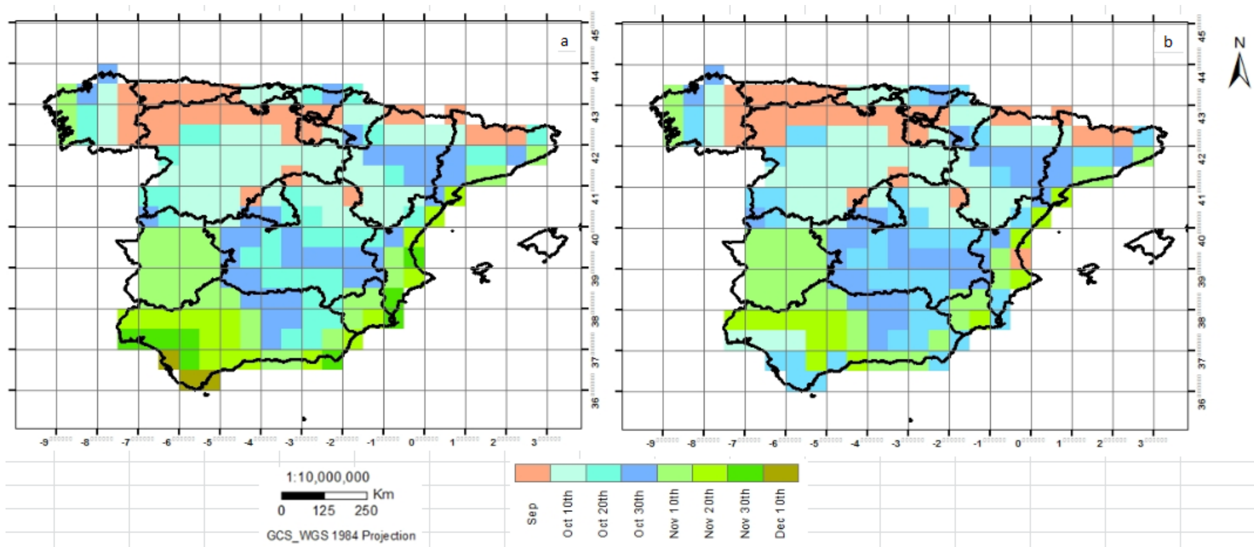


Figure 8: Simulated Sowing Dates for (a) Irrigated and (b) Rainfed Wheat in Spain in the 2000s (Sowing Algorithm)

Overall, rainfed wheat is usually planted earlier than irrigated wheat in order to increase the length of the growing season as the crop would need more time to develop when rainfed. Moreover, the highest yields could be found in the north of the country where wheat is planted in September and October. However, in the south and parts of the east coast, the yields are lower and wheat is planted in November and December. The model also simulated crop failures in the south west of Andalucia and in the south east of the country for rainfed wheat. This could be due to the fact that the model does not contain a detailed hydrology component and thus does not account for the full amount of water available in the soil. It could also be due to the inability of the sowing algorithm to determine the appropriate planting period in that region. However, since no data is available on sowing dates for the whole country, these sowing periods will still be considered as a base line to the future projections.

Future yield projections

The first set of simulations used the same sowing dates as simulated for the 2000's while the second set relied on the sowing algorithm to identify the new optimum planting dates based on the changes in climate.

Irrigated Wheat:

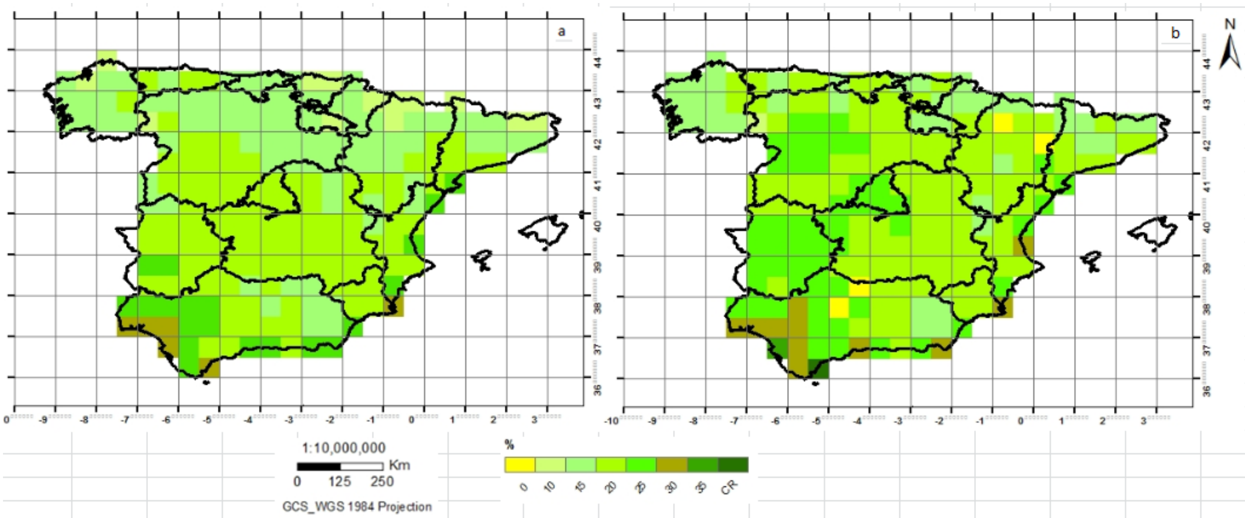


Figure 9: Percentage difference in irrigated wheat yields in Spain from the 2040's to the 2000's using (a) the ESM2 and (b) the CM3 GCMs (Same sowing dates as simulated for the 2000's)

When keeping the same sowing dates as in the 2000’s, the yields of irrigated wheat increase in the whole country. The relative increase varies between regions and also depends on the GCM used. For ESM2 simulations, the yields will increase by up to 15% in the north of the country, by 20% in the center and up to 25 to 30% in the western parts of Andalucia. On the other hand, when using the CM3 model, the yields usually increase more than for the ESM2, with increases of up to 20-25% in most of the county and 30% in the south west of Andalucia. Moreover, the grid cells in the south of Andalucia that presented a crop failure (CF) in the 2000s now show a much higher increase in yield and could be considered as recovered crops (CR).

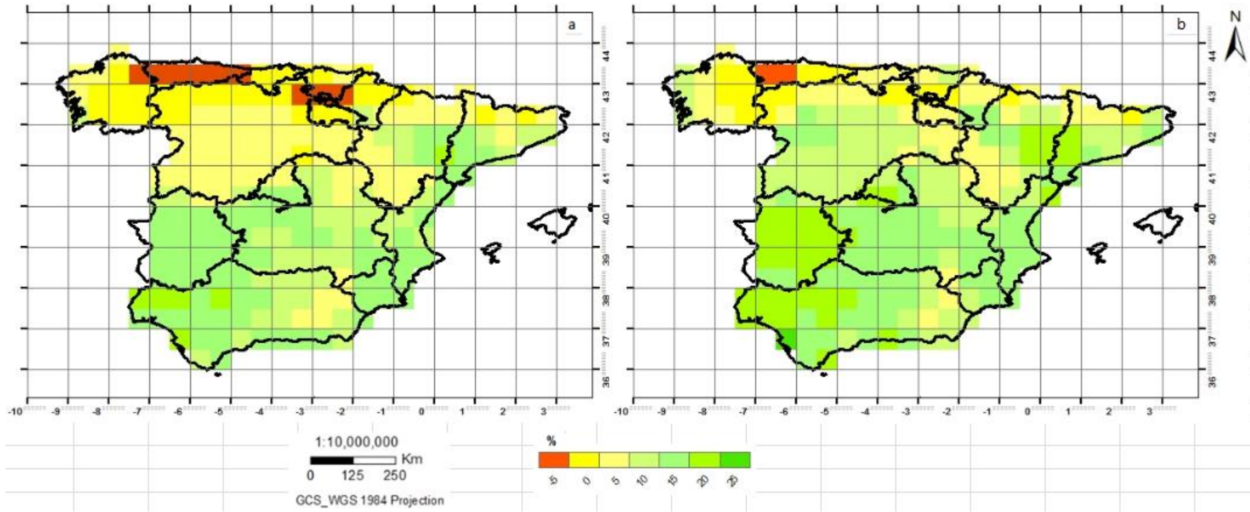


Figure 10: Percentage difference in irrigated wheat yields in Spain from the 2040's to the 2000's for (a) the ESM2 and (b) the CM3 GCMs (Sowing dates simulated using the sowing algorithm for each decade)

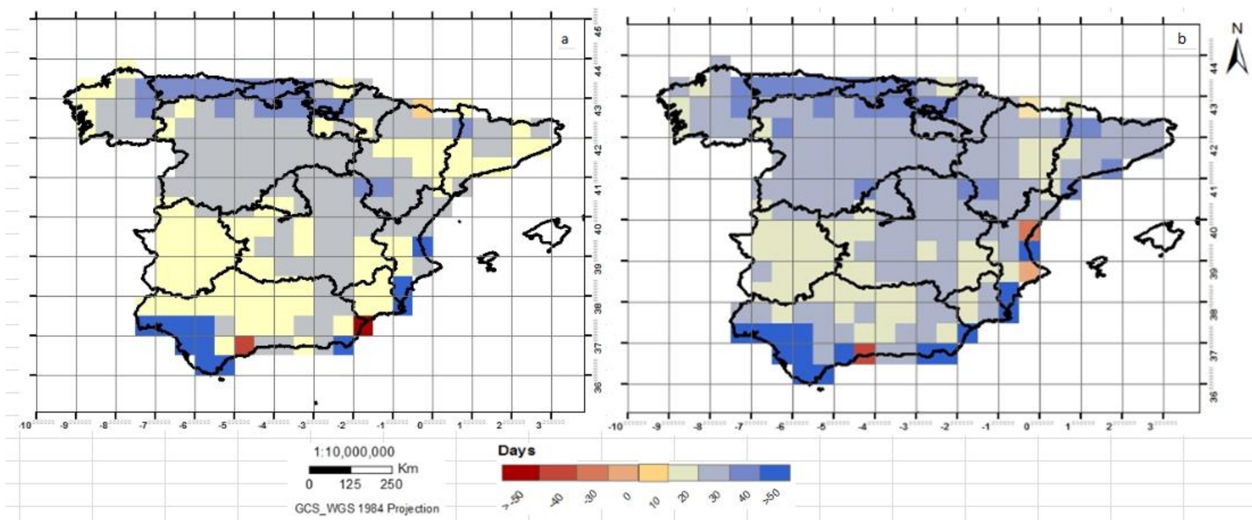


Figure 11: Day difference in simulated sowing dates from the 2040's to the 2000's for irrigated wheat in Spain using (a) the ESM2 and (b) the CM3 GCMs with sowing dates simulated by the sowing algorithm for each decade

When considering the simulations using the sowing algorithm, it also seems that the yields of irrigated wheat will increase by 2050 in the whole country to the exception of Asturias and some sites in the Pais Vasco where there will be a decrease of up to 5% in yield. Simulated yieds using climate from the CM3 model are slightly higher than those from the ESM2. Moreover, the sowing algorithm simulates different planting dates in the future delayed by 20 to 30 days compared to the 2000's in most of the country. The main exceptions are in the south west of Andalucia and in Asturias, Cantabria and the Pais Vasco with a suggested shift of more than 40 days. Furthermore, the yields obtaied using the sowing algorithm are lower than those obtained when keeping the sowing date constant which proves that changing sowing dates influences yields.

Rainfed Wheat:

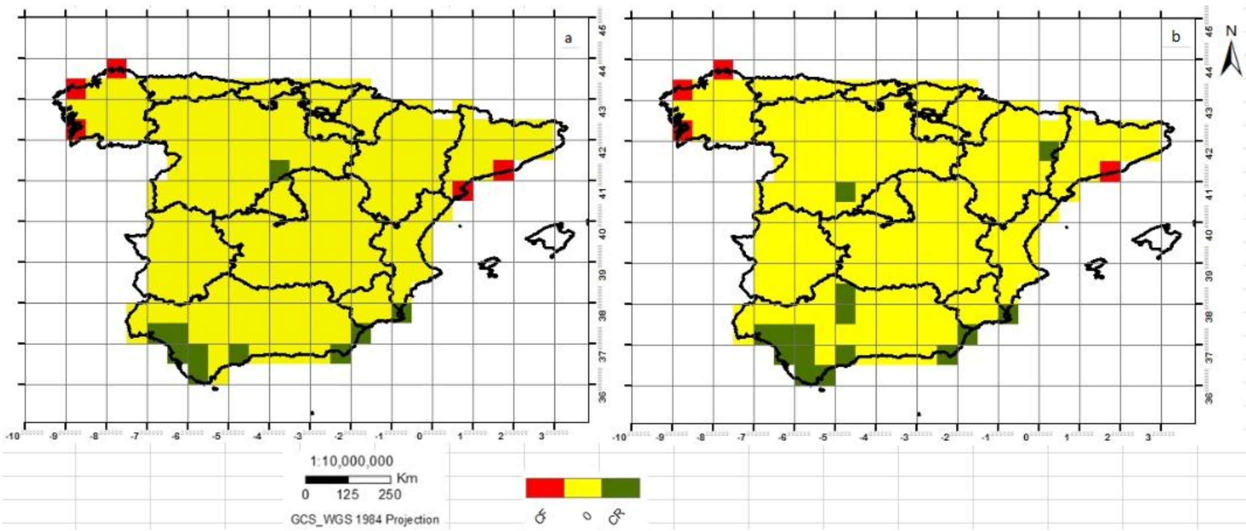


Figure 12: Difference in rainfed wheat yields in Spain from the 2040's to the 2000's using (a) the ESM2 and (b) the CM3 GCMs with the same sowing dates as simulated for the 2000's)

When keeping the same sowing dates, simulations of rainfed wheat for both GCMs show approximately the same yields. From figure 12, it seems that there will not be much change in yield between the 2000's and the 2040's in most of the country. However, areas in southern Andalucia that were simulated as crop failures now appear to have recovered while coastal areas in Galicia are now presenting crop failures.

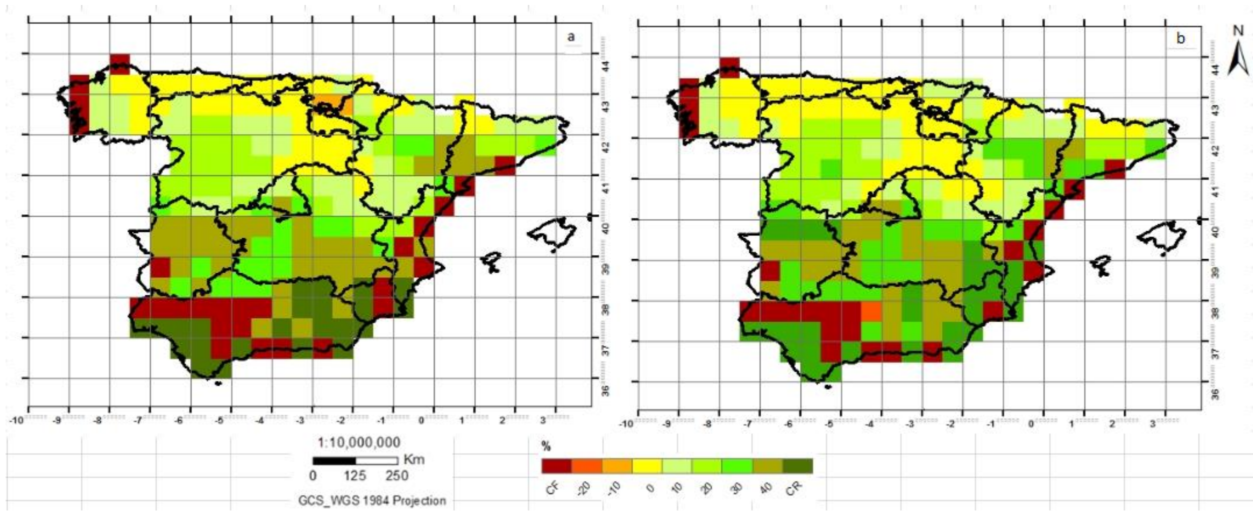


Figure 13: Percentage difference in rainfed wheat yields in Spain from the 2040's to the 2000's for (a) the ESM2 and (b) the CM3 GCMs with sowing dates simulated using the sowing algorithm for each decade

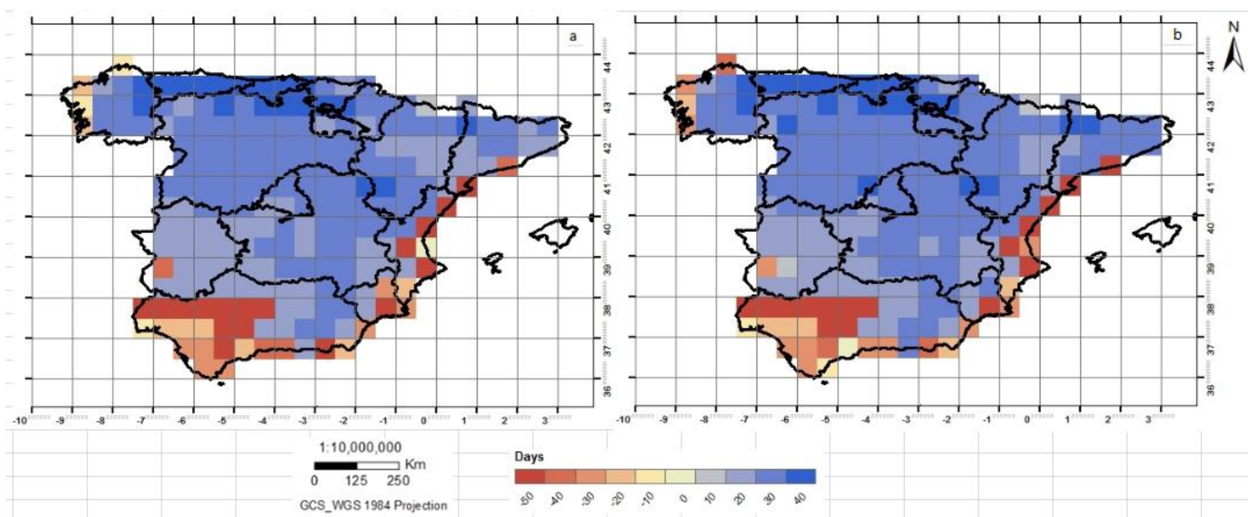


Figure 14: Day difference in simulated sowing dates from the 2040's to the 2000's for rainfed wheat in Spain using (a) the ESM2 and (b) the CM3 GCMs with sowing dates simulated by the sowing algorithm for each decade

Looking at the simulations using the sowing algorithm for rainfed wheat, there are again no major differences between the two GCMs in both yield and sowing date changes. Moreover, the presented sowing dates for rainfed wheat are slightly more shifted from the base line than the irrigated dates are. Indeed, wheat is now planted 30 to 40 days later in most parts of the country and more than 50 days earlier in Andalucia and the East coast of Valencia and Cataluna. These regions where wheat is planted too early result in crop failures in both simulations. On the other hand, the yields will tend to stagnate or increase by up to 20% in the north of the country while they will increase by up to 40% in the south. Some southern areas that previsouly presented a crop failure would also recover in the rainfed simulations. Finally, wheat benefits from higher increases in yield when the sowing algorithm is used than when the sowing dates are kept constant. There is however an exception in the southern and eastern coastal parts of the country where sowing too early would cause crop failures.

Optimizing sowing dates

As there does not seem to be a big difference in yield changes between the two GCMs, the ESM2 was used again in a third set of simulations that explores the changes in yields when the sowing dates are changed. This new set of simulations deviated the base line sowing dates by 10 day periods and the results obtained for sowing 10, 20 and 30 days earlier and later are shown below.

Irrigated yield:

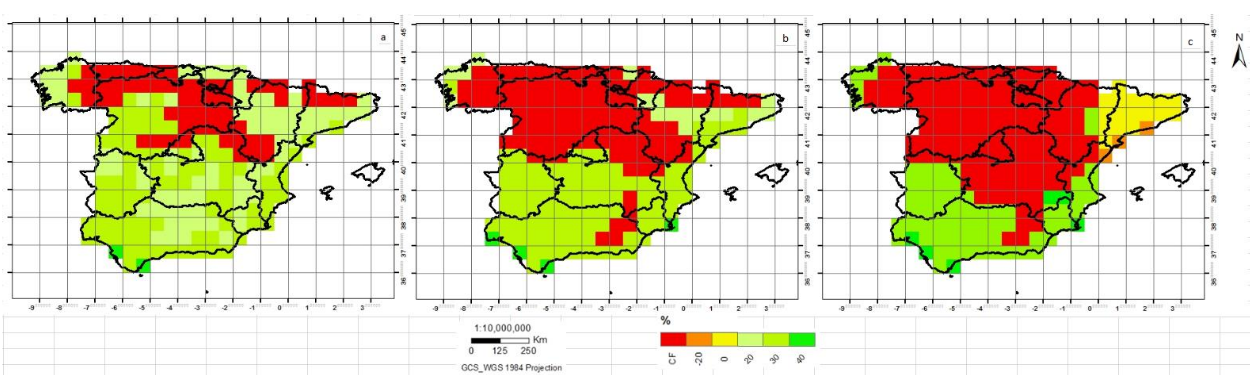


Figure 15: Percentage Difference in Irrigated Wheat Yields in Spain from the 2040's to the 2000's by planting (a) 10 days, (b) 20 days and (c) 30 days earlier than the Simulated Sowing Dates in the 2000s using the ESM2 GCM

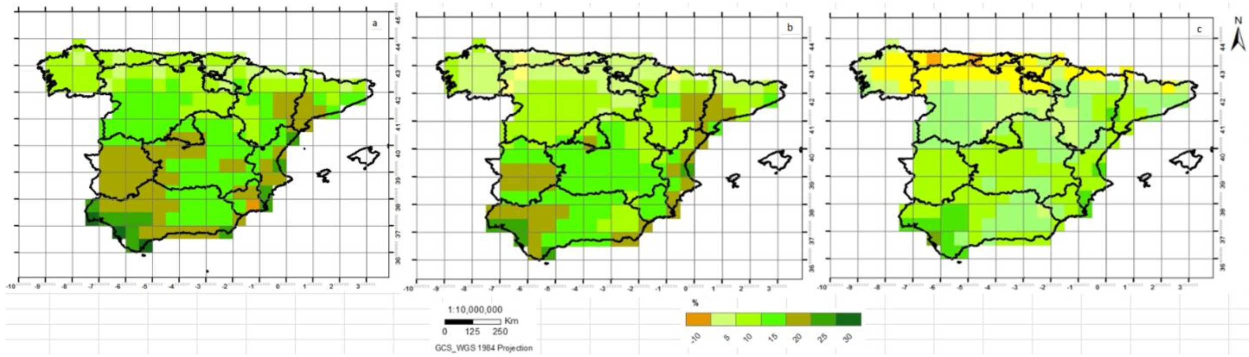


Figure 16: Percentage Difference in Irrigated Wheat Yields in Spain from the 2040's to the 2000's by planting (a) 10 days, (b) 20 days and (c) 30 days later than the Simulated Sowing Dates in the 2000s using the ESM2 GCM

When comparing the different simulations (figures 15 and 16), it appears that wheat planted in northern and in the southern parts of the country reacts differently to changed planting dates. Indeed, while the northern parts would benefit more from being planted later, as they experience crop failures when planted early; the southern parts will have higher increases when wheat is planted earlier. The highest increases in wheat yields (without any crop failures) could be observed when it is planted 10 days earlier in the south with an increase in yield between 20 and 30%. Moreover, some areas in Andalucia, Extremadura and Castilla la Mancha could benefit from a 30% increase if planted 20 days earlier. On the other hand, the northern areas (to the exception of Cataluna and the coast of Galicia) seem to be less influenced by specific planting dates, but they seem to have some kind of threshold. Indeed, for most parts, when wheat is planted early, a crop failure is observed while a slight increase in yield could be obtained if the wheat is planted later. Finally, the highest increases in yield could be observed when wheat is planted between 10 and 20 days later.

Rainfed yields:

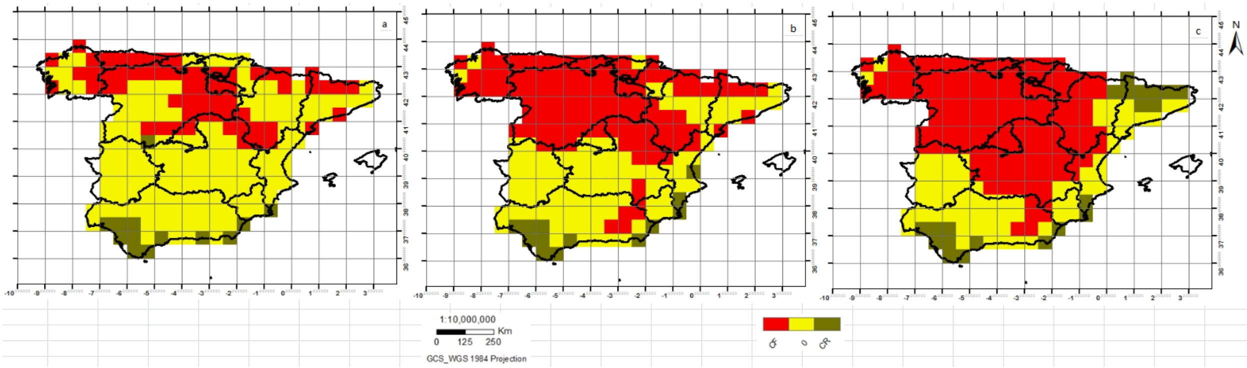


Figure 17: Difference in Rainfed Wheat Yields in Spain from the 2040's to the 2000's by planting (a) 10 days, (b) 20 days and (c) 30 days earlier than the Simulated Sowing Dates in the 2000s using the ESM2 GCM

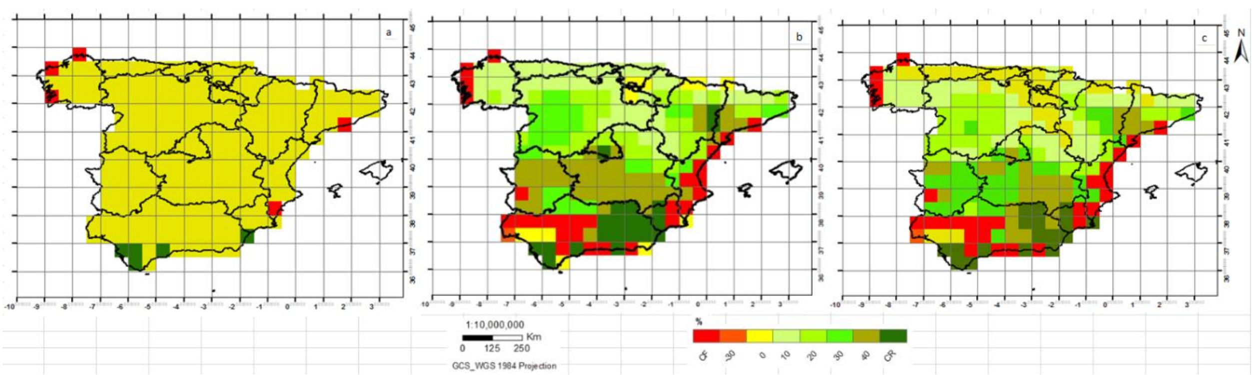


Figure 18: Difference in Rainfed Wheat Yields in Spain from the 2040's to the 2000's by planting (a) 10 days, (b) 20 days and (c) 30 days later than the Simulated Sowing Dates in the 2000s using the ESM2 GCM

When looking at the rainfed wheat (figures 17 and 18), it also appears that most parts in the north of the country would experience crop failures if wheat is planted earlier; again to the exception of the south of Catalunia and parts of Galicia where yields would stagnate and would increase by up to 30% in the north of Cataluna. However, if planted 20 days later, northern rainfed wheat would increase by 10 to 20% and up to 30 to 40% in parts of Castilla y Leon, Aragon and Cataluna. On the other hand, the southern parts would mostly benefit from planting 20 days later as yields would increase by 30 to 40% and more than that in the west of Andalucia. Finally, the crop failures that were simulated in Andalucia and the coast of Valencia in the 2000's would only recover if wheat is planted 10 to 30 days earlier. However, in all the simulated planting dates, the coast of Galicia would always experience crop failures for rainfed wheat.

By combining all these results, it is now possible to suggest an optimization of the sowing periods for wheat in 2050.

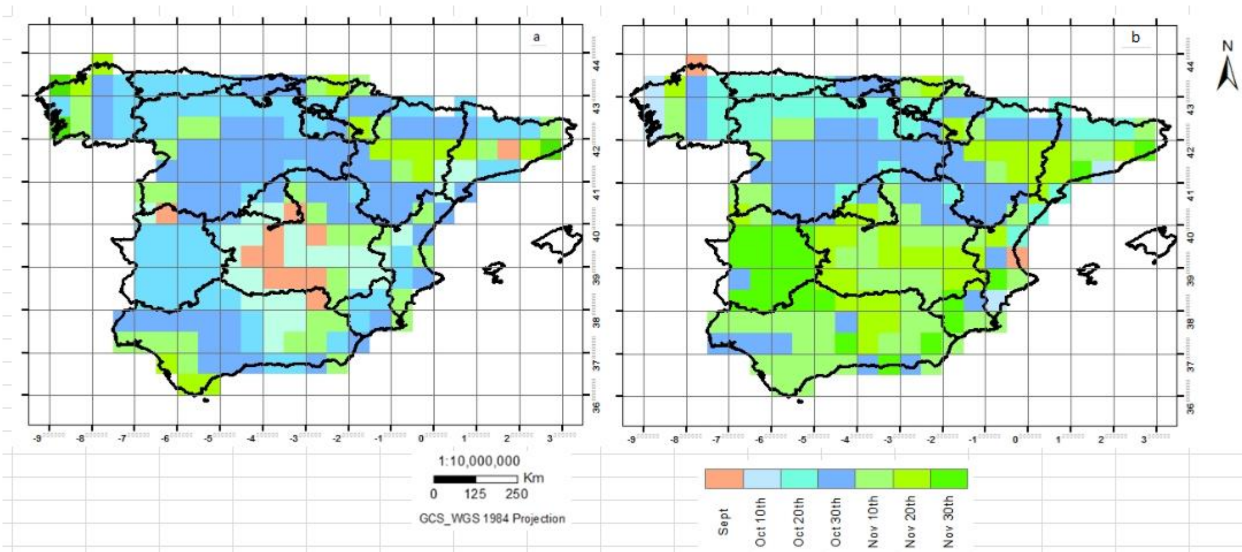


Figure 19: Optimized Future Sowing Periods for (a) Irrigated and (b) Rainfed Wheat in Spain by 2050

The suggested sowing dates were compared to the sowing dates at the validation site and it seems that overall, most of the optimized planting periods occur 30 days earlier than the current reported ones (table). It is also obvious from table 3 that the sowing algorithm did not represent the 2000's sowing dates accuratelty. Thus, it cannot be expected from the sowing algorithm to accrurratly represent future sowing dates especially considering the high uncertainties emanating from daily future climate data. It is thus possible to accept the optimized sowing dates as actually being earlier planting dates compared to current dates. Indeed, Sacks et al. (2010) present sowing dates for wheat in Spain as neither temperature nor precipitation limited which means that the start of the growing season for wheat in Spain does not depend on either temperature or precipitation. This further explains the inability of the sowing algorithm to present accurate sowing dates for wheat in Spain (Sacks et al. 2010; Waha et al. 2012). The suggested optimized sowing dates on average correspond to an advancement of 30 days in planting dates. However, the warmer temperatures in this new planting period increase the risks of damage by pests and insects as they would survive longer (Sacks et al. 2010). Moreover, there are rotation cycles in Spain and thus wheat cannot be planted before the previous crop is harvested. This might add an extra constraint on earlier planting of wheat.

On the other hand, a study on future climate change impacts on cereal phenology in central and northern Europe was conducted by Olesen et al. (2012). This study showed that an increase in temperatures would lead to earlier flowering and maturity dates for both winter and spring wheat (Olesen et al. 2012). The study also shows that early flowering would lead to higher yields provided sufficient soil moisture and precipitation (Olesen et al. 2012). Finally, it predicts 1 to 3 weeks earlier sowing dates for spring wheat (Olesen et al. 2012). These findings could also be expanded to Spain and justify that the suggested earlier wheat sowing is acceptable.

Table 3: Observed, Simulated and Optimized Sowing Dates for Rainfed Wheat at the Validation Sites

		Reported (current)	*Sowing Algo in the 2000's*	*Sowing Algo in the 2040's*	*Optimized for the 2040's*
CL	***Zamora (CG)***	Nov 30th	Oct 10th	Nov 10th	Oct 30th
	Segovia (Fue)	Nov 20th	Oct 10th	Nov 10th	Oct 30th
	Burgos (CJ)	Nov 20th	Sep	Oct 30th	Oct 20th
	Palencia (BC)	Nov 20th	Oct 10th	Nov 10th	Oct 30th
AR	***Huesca (Pad)***	Nov 10th	Oct 10th	Nov 10th	Oct 20th
	Zaragoza (Tau)	Dec 10th	Oct 30th	Nov 20th	Nov 20th
	Terruel (Tor)	Dec 10th	Oct 10th	Nov 10th	Oct 30th
AN	***Granada (Gra)***	Dec 10th	Oct 30th	Nov 20th	Nov 20th
	Malaga (Ron)	Jan 20th	Nov 20th	Sep	Nov 10th
	Cordoba(FN)	Jan 20th	Nov 20th	Sep	Nov 10th
	Jaen (Sab)	Dec 10th	Oct 30th	Nov 20th	Nov 20th
CAT	***Lleida (Gim)***	Dec 20th	Oct 30th	Nov 20th	Nov 20th
	Lleida (Agr)	Dec 10th	Oct 20th	Nov 20th	Nov 10th

Drivers of yield change

In view of these results, it is clear that changing sowing dates influences yields but the reason for it cannot be derived from the previous maps (figures 16 to 19). Moreover, the maps only show the differences in yields between the 2000's and the 2040's but do not account for any variation in time. That is why more simulations were run on the validation sites by deviating the planting dates by 10, 20, 30 and 40 days before their current ones. The resulting graphs accounting for decadal yields could be found in the Annex1.

In all the simulations, the earlier the planting date, the higher the yields except for Pardinilla in Huesca, Aragon where the highest yield was obtained for wheat sown 30 days earlier but collapsed when sown 40days earlier. Moreover, in almost all the locations, if the sowing date is kept constant, the yields were projected to increase by 2050 from 2% in Burgos (CL) to 20% in Jaen (AN) when considering the ESM2 GCM and from 17% to 35% when considering the CM3 simulations. However, rainfed yields in Malaga were projected to decrease by 41% (CM3) to 54% (ESM2) and would collapse in Cordoba (Table). On the other hand, the trends in yield variations over time differ in each location and for each irrigation system. While most of the irrigated yields follow a continuous increase, the rainfed yields usually peak around the 2030's and then start decreasing (Annex 2).

Table 4: Simulated Wheat Yield Differences from the 2040's to the 2000's at the Validation Sites using the same sowing dates as currently reported (table 3)

		ESM2		CM3	
		Irrigated	*Rainfed*	*Irrigated*	*Rainfed*
CL	*Zamora*	15%	17%	21%	35%
	Segovia	15%	15%	17%	28%
	Burgos	8%	2%	17%	17%
	Palencia	12%	8%	21%	26%
AR	*Huesca*	13%	15%	19%	26%
	Zaragoza	18%	18%	22%	32%
	Terruel	16%	18%	20%	31%
AN	*Granada*	14%	16%	18%	33
	Malaga	15%	-54%	23%	-41%
	Cordoba	17%	Crop failure	22%	Crop failure
	Jaen	18%	20%	19%	34%
CAT	*Gimenells, Lleida*	18%	17%	22%	30%
	Agramunt, Lleida	16%	17%	21%	31%

In order to determine which factors play an important role in the changes in yield, more simulations were run by keeping CO_2 concentration to their level in 2011 and by comparing yields to changes in temperature and the length of the growing season for two sowing dates (the current reported dates and 30 days earlier dates than that).

From figure 20, it appears that there is a positive correlation between yields and LGP as the highest yields are obtained for the longest growing periods. The geographical differences are also well represented in this figure as the lowest yields and LGPs are observed in Andalucía while the highest are in Cataluña. Moreover, it appears that rainfed wheat suffers from shorter growing seasons than irrigated wheat especially in Andalucía. Finally, CO_2 does not seem to have a major impact on LGP.

On the other hand, it appears that exposure to lower temperatures leads to higher yields no matter if irrigated or not. However, rainfed yields are more sensitive to temperature changes as they decline when temperatures increase while irrigated yields continue increasing. It also appears in the figure that there is a threshold to this correlation as the lowest temperatures are observed in Castilla y Leon, but the resulting yields are lower than in Andalucia (where wheat is exposed to the highest temperatures). This can explain the multiple crop failures observed across Castilla y Leon in (Figure 15) when wheat is planted too early. Furthermore, when keeping the CO_2 concentrations constant, it appears that both irrigated and rainfed wheat yields decrease compared to when dynamic CO_2 concentrations are used. This shows that the simulated future increases in yields are due to CO_2 fertilization especially for irrigated wheat. CO_2 fertilization also prevents crop failures in some locations in Andalucía for rainfed wheat as it compensates for the negative effects of temperature. These results explain the lack of change in yields in (figure 12) when the sowing dates are kept constant.

Finally, there is a clear correlation between LGP and temperature as higher temperatures lead to shorter growing periods which in turn lead to lower yields. This does explain why planting at lower temperatures would increase yields as the growing season is extended.

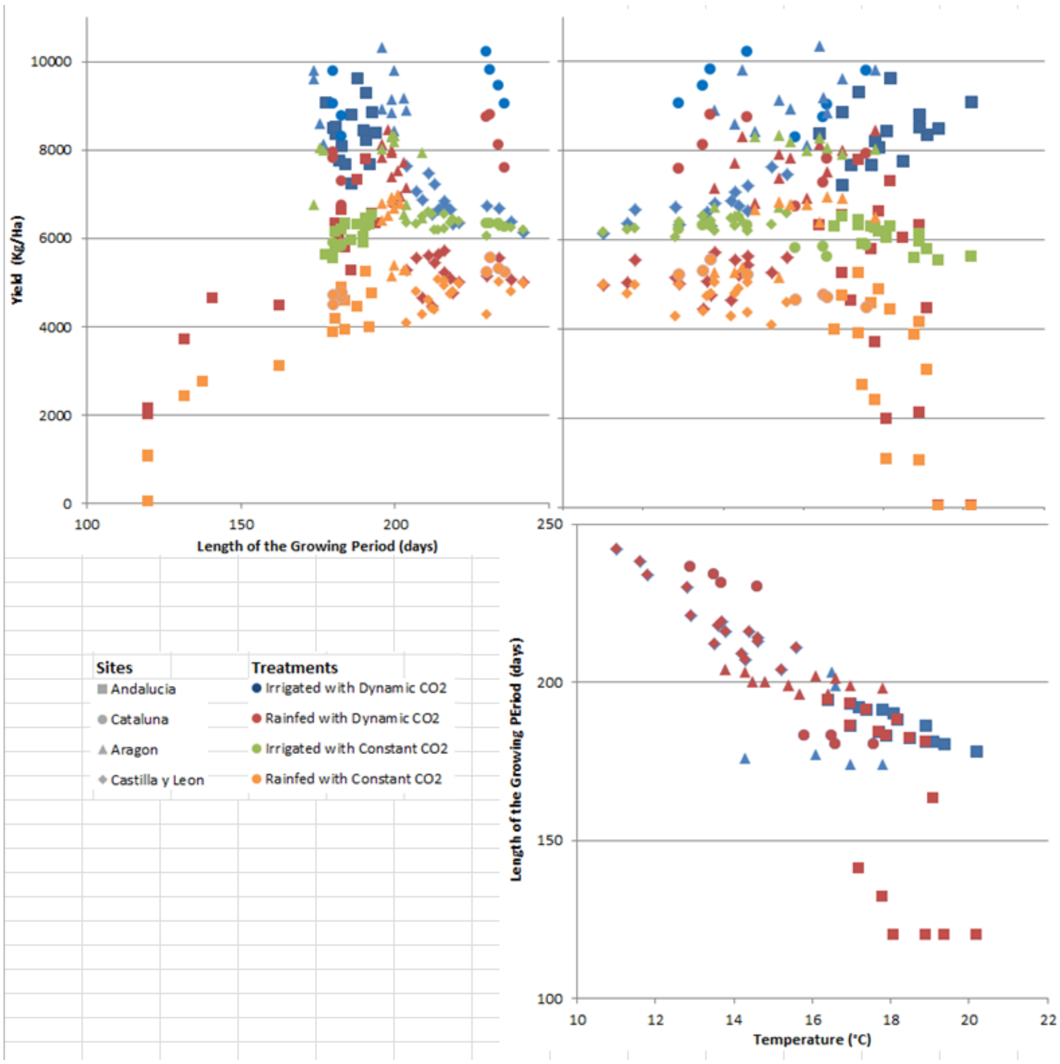


Figure 20: Simulated Response of Wheat Yields to Temperature and LGP in the 2040's using same sowing dates as currently reported (table 3) with the ESM2 GCM

When planted earlier (figure 21), wheat yields generally increase compared to when the sowing dates are kept constant as less crops are exposed to high temperatures and the LGP is higher. Here, even though wheat in Castilla y Leon is still exposed to the lowest temperatures, there is no crop failure observed in this location, which means that the critical threshold has not yet been attained and that the suggested advancement of 30days in the optimization is acceptable for this region. Moreover, planting earlier also benefits rainfed crops in Andalucia as less crop failures are observed.

Finally, the decadal variability in yield together with LGP is presented in Annex 3 for Padrinilla in Huesca, Aragon where the highest yield was obtained and Ronda in Malaga, Andalucia where the lowest yield was simulated.

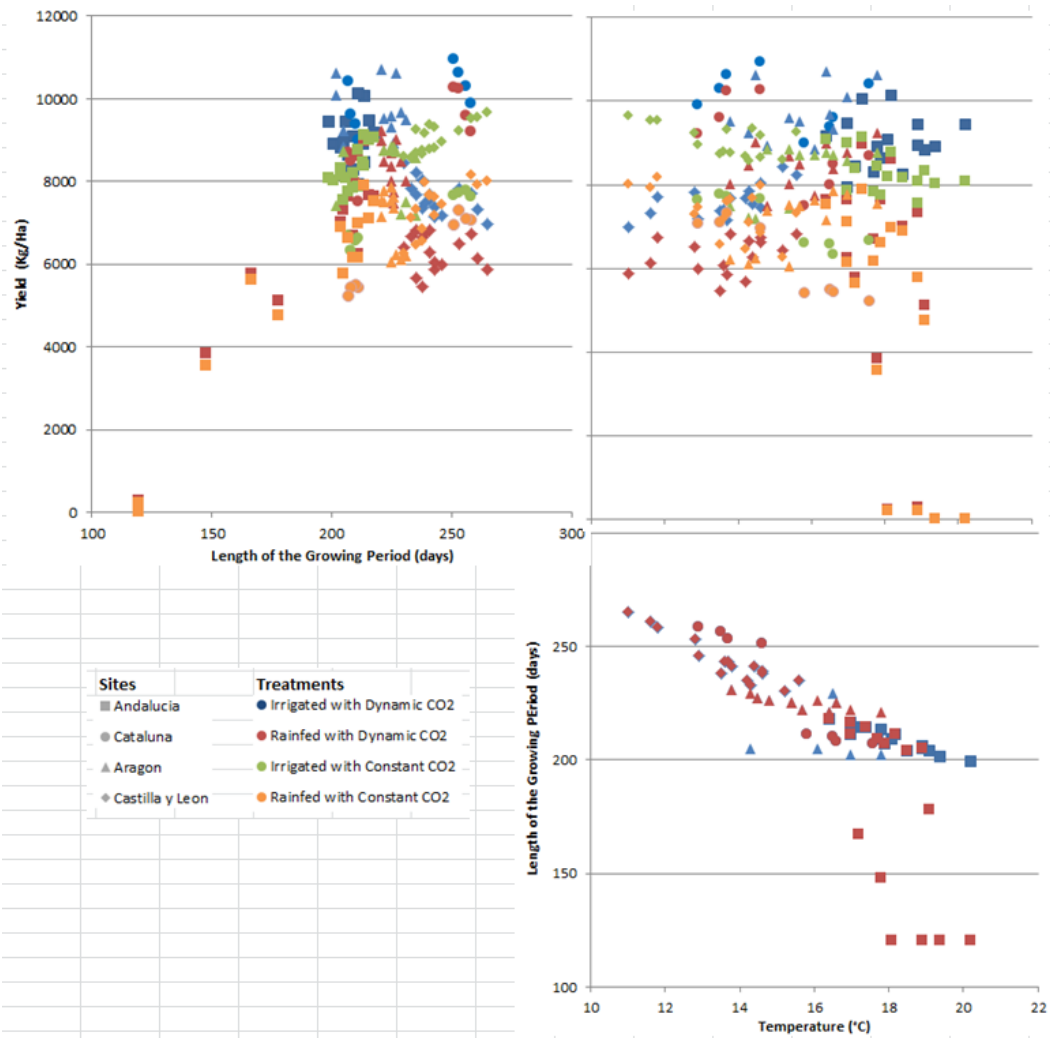


Figure 21: Simulated Response of Wheat Yields to Temperature and LGP in the 2040's using currently reported sowing dates advanced by 30 days with the ESM2 GCM

An evaluation of the response of yield to evapotranspiration was performed (Annex 4) but was inconclusive for irrigated wheat as the increase in evapotranspiration could be either attributed to high temperatures or high irrigation amounts. Moreover, there was no clear relationship between yield and AET between December and February, but a clearer correlation was observed with AET between March and May in the CM3 simulations. Lower AET values were also obtained when rainfed wheat was planted earlier resulting in higher yields. That was the only case observed where CO_2 seemed to have a positive impact on AET as better water use efficiency was obtained. Better results could have been obtained if the AET was analyzed together with the exact amount of precipitation, runoff and irrigation at each site.

Limitations

With any model simulation, the results cannot be considered as absolute truth as there are always uncertainties related to the model and input data used. The major sources of data uncertainty in this research are related to the future climate data. Indeed, there are already uncertainties within the different GCMs when it comes to simulating future climate, and this was further increased by roughly downscaling monthly data to daily data. Using decadal averages limited the high variability in the climate data; however a better option would have been to also use an ensemble approach to account for the variations between different climate models and to include more RCPs. This would have resulted in a more reliable confidence interval for the outputs. Moreover, the effects of extreme events were not considered in this project. As their occurrence and intensity is expected to increase in the future especially in Spain, it could be expected that they would have more negative impacts on wheat yields than was simulated.

Furthermore, due to the lack of available data on current crop calendars in Spain, the sowing algorithm was used. This algorithm tries to approximate the most appropriate sowing period based on the climate data. Thus, accounting for the uncertainties arising from the use of such an algorithm, combined with the uncertainties in the climate data, it is not possible to consider the resulting sowing periods as highly accurate. If more time was available, a field visit combined with satellite imagery processing would have enabled to derive the start of the growing season in most of the country (Jönsson and Eklundh 2004). Another possibility would have been to also parameterize the sowing algorithm to better fit the region.

Finally, the nitrogen fertilization amounts were also obtained from global projections and cannot be considered as representative of the actual values as these would be restricted to country level by different policies. Indeed, it could be expected that the use of nitrogen fertilization would decrease in Spain in the years to come. A base line of fertilization amounts could have been obtained in Spain (for the 2000's) if at least the actual sowing dates were available by using the calibration tool (Olin unpublished) the future amounts would have then been derived by analyzing different nitrogen limitation policies across the country.

On the other hand, there are various limitations to the model as the embedded hydrological model is very simplified and thus cannot account for the complete water cycle's influence on crops. It also does not consider the influence of diseases and pests on the crops' development.

Moreover, when simulating irrigated wheat, the model assumes the perfect irrigation treatment that would always provide enough water to the crop and avoid any kind of water stress. In Spain, this seems to be very optimistic as the country already faces water availability problems and tends to reduce the amount of water used for irrigation (Iglesias and Minguez 1997). It is thus expectable that a perfect irrigation treatment would almost never happen in the future. This means that the future irrigated yields are probably overestimated.

Furthermore, crop rotations were not considered in the simulations. Indeed, it was assumed that there was only wheat planted in all the grid cells at all times. This would probably have consequences on soil characteristics and thus on yields.

Finally, the calibration approach used is not optimal. Indeed, it was only used for two sites and better results would have probably been obtained faster if it was used in more locations. Moreover, many of the parameters used are still not very well understood and their values unknown by the scientific community.

Conclusion

As a conclusion, climate change will influence wheat yields in Spain. As the changes in climate will vary between the regions, so will the impacts on yield. Indeed, the highest percentage increases will be observed in the southern parts of the country, while, the highest yields will still be obtained in the northern parts by 2050. Moreover, there is a distinction in the influence of climate on irrigated and rainfed wheat. Indeed, irrigated wheat will benefit more from CO_2 fertilization and would be less sensitive to the increases in temperatures across the country. Conversely, even though rainfed wheat will also benefit from an increase in CO_2 concentrations, its yield will on average increase up to the 2030's after which point, the CO_2 will not be able to compensate the adverse effects of high temperatures and yields are expected to further decrease after 2050.

Furthermore, this paper showed that planting dates have a considerable influence on wheat yields. Indeed, changes in sowing dates can lead to yield increases of up to 40% or complete crop failures. After analyzing multiple sowing periods, an optimized map of sowing periods was obtained for 2050 (figure 19). On average, this optimization suggests advancing the sowing period by approximately 30 days in order to avoid crop failures. It is however still unable to avoid failures in the coast of Galicia as modeled by LPJ-GUESS. Finally, while a positive correlation was found between earlier planting and higher yields, thresholds still need to be identified for each region. As the risk of frost would lower due to increases in temperatures, it would be possible to plant wheat much earlier in Andalucia, however this will not be the case in Castilla y Leon or in Aragon where crop failures were simulated when planting in September to early October.

Nevertheless, future yields cannot only be maintained by only applying earlier sowing dates as other non-climatic factors are involved such as the future presence and distribution of pests and their resulting effects on wheat. This might represent a major limitation to earlier sowing in the south of Spain. Moreover, regulations and policies on limiting excessive irrigation and fertilization are increasing which might cause extra managerial limitations on wheat yields.

On the other hand, the presented results contain some levels of uncertainty, first related to the use of LPJ-GUESS that tends to overestimate irrigated yields and underestimate rainfed yields. Indeed, when irrigated, LPJ-GUESS assumes a perfect irrigation system where wheat will always receive the necessary amount of water for its growth which is not the case in Spain. Moreover, LPJ-GUESS does not account for the surrounding hydrology and thus underestimates the soil water content which leads to less water available for a better development of rainfed wheat. Furthermore, even though the model was successfully calibrated and validate against various observations, there are still uncertainties related to the calibration of the model as it was performed only against two sites in Cataluña. Moreover, many calibrated crop growth parameters used are not fully understood by the scientific community and there are no default values available for them. Finally, the sowing algorithm used did not adequately represent the cropping calendar in Spain. Future improvements could make use of actual sowing dates as well as flowering and harvest dates obtained at farm level or from image analysis. It would also be interesting to account for future extreme events and to also consider the period between 2050 and 2100 based on different RCPs and RCMs.

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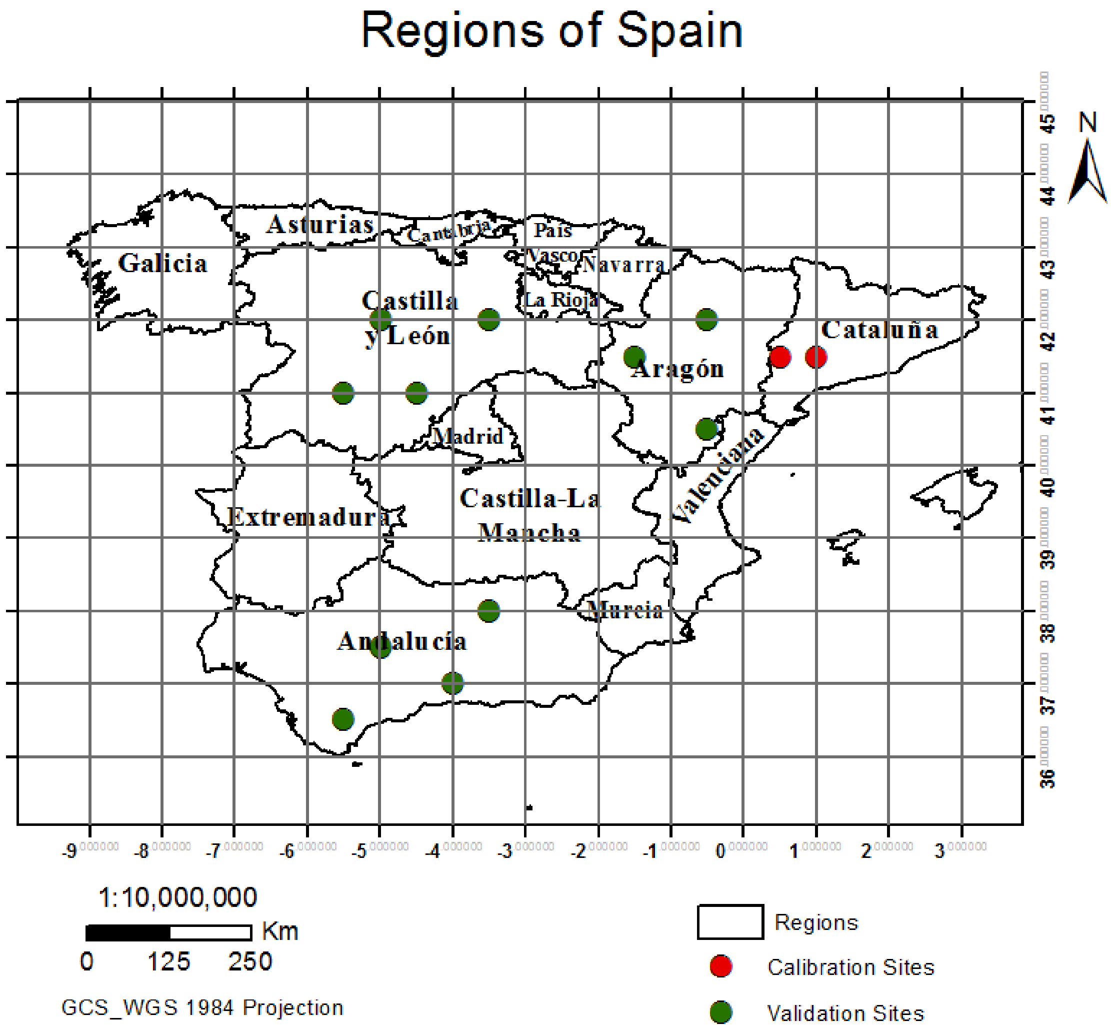
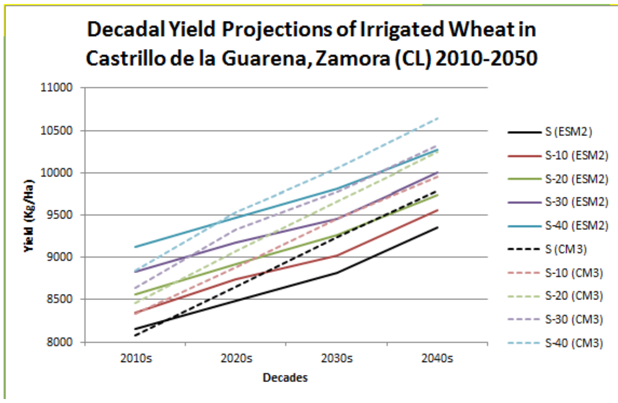
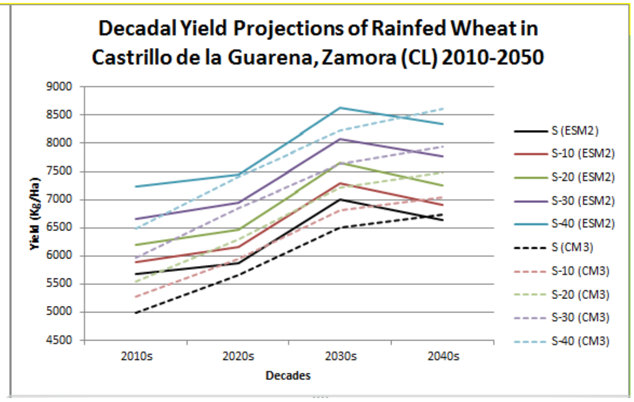
Annex 1: Map of Regions in Spain

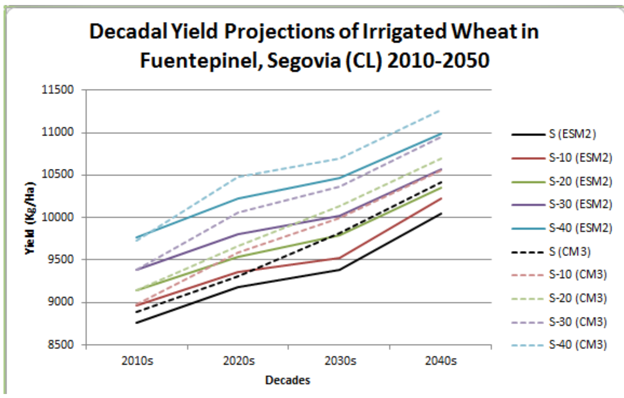


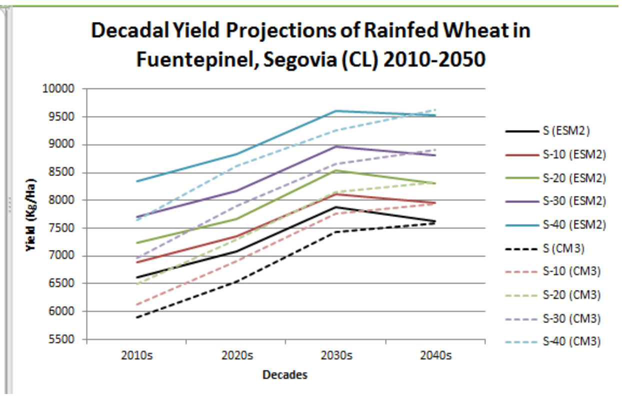
Annex 2: Future simulations in validated locations with different sowing dates

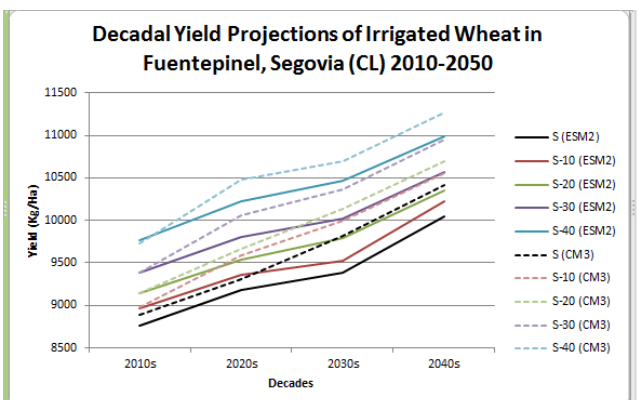
Castilla y Leon

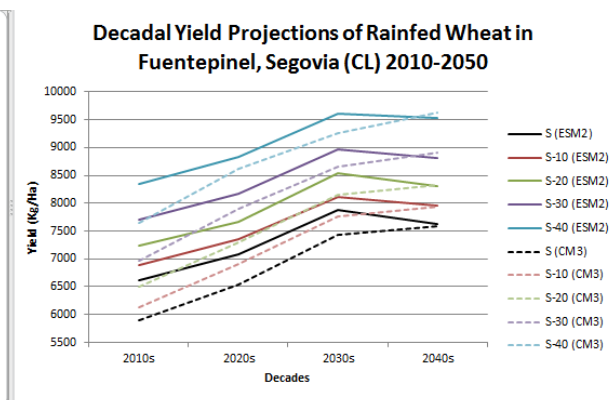


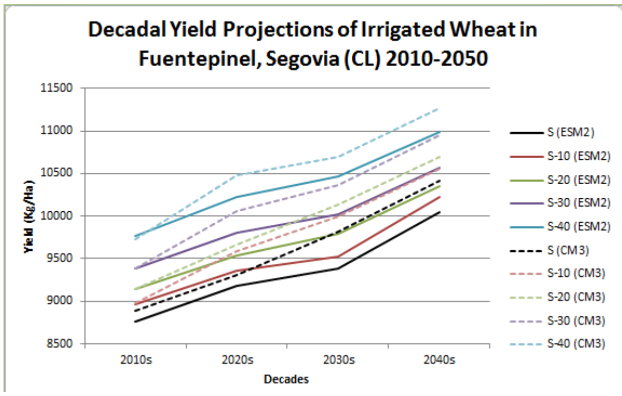


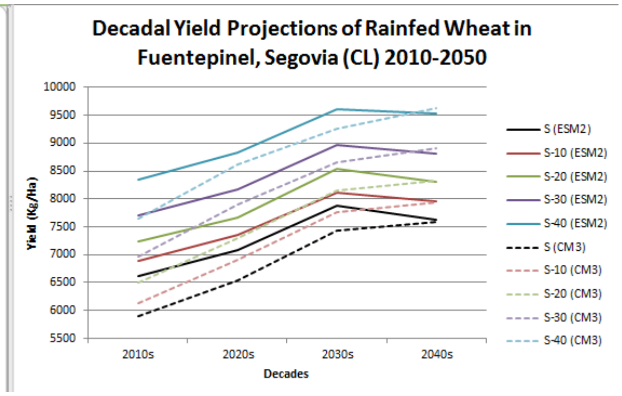




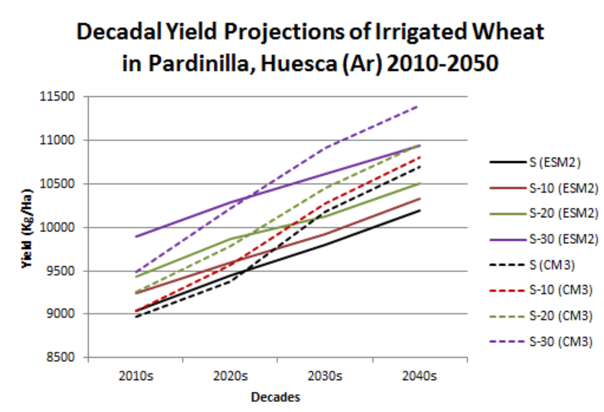


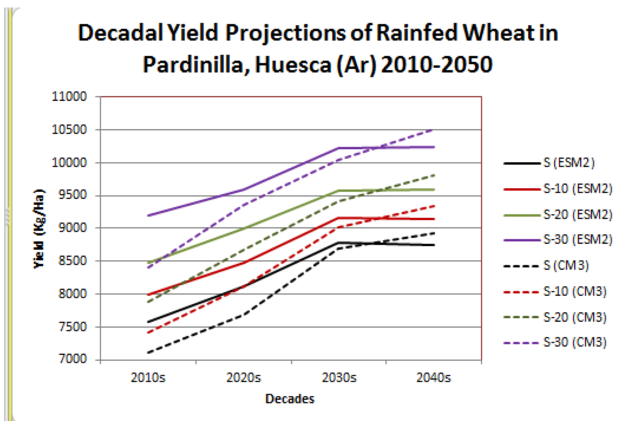


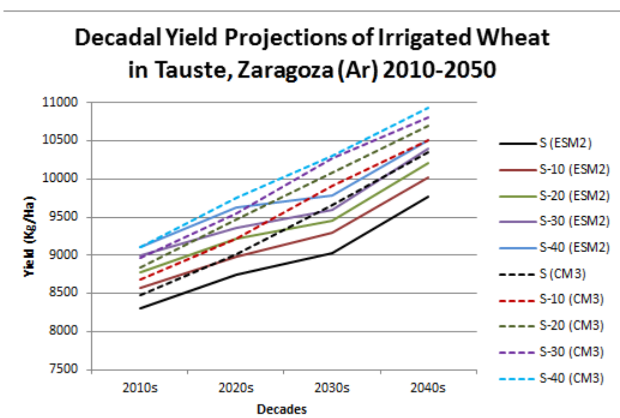

Decadal Yield Projections of Irrigated Wheat in Fuentepinel, Segovia (CL) 2010-2050
11500
11000
10500
10000
9500
9000
8500
Yield (Kg/Ha)
2010s
2020s
2030s
2040s
Decades
S (ESM2)
S-10 (ESM2)
S-20 (ESM2)
S-30 (ESM2)
S-40 (ESM2)
S (CM3)
S-10 (CM3)
S-20 (CM3)
S-30 (CM3)
S-40 (CM3)

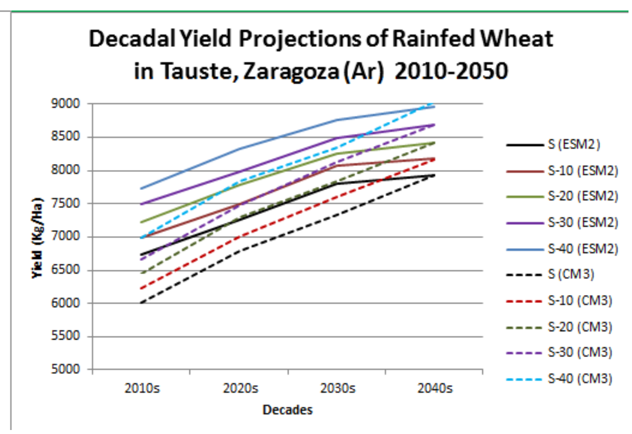

Decadal Yield Projections of Rainfed Wheat in Fuentepinel, Segovia (CL) 2010-2050
10000
9500
9000
8500
8000
7500
7000
6500
6000
5500
Yield (Kg/Ha)
2010s
2020s
2030s
2040s
Decades
S (ESM2)
S-10 (ESM2)
S-20 (ESM2)
S-30 (ESM2)
S-40 (ESM2)
S (CM3)
S-10 (CM3)
S-20 (CM3)
S-30 (CM3)
S-40 (CM3)

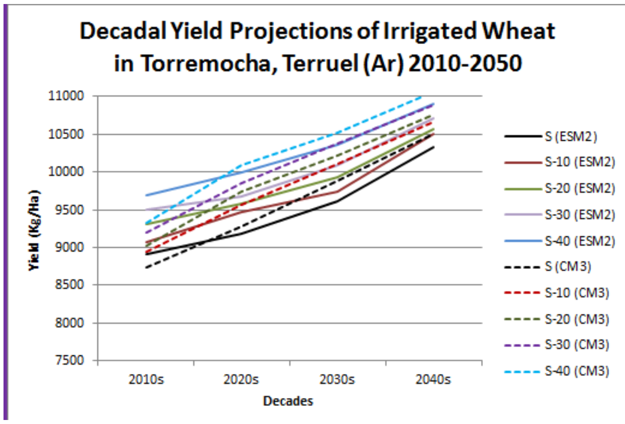
Aragon:

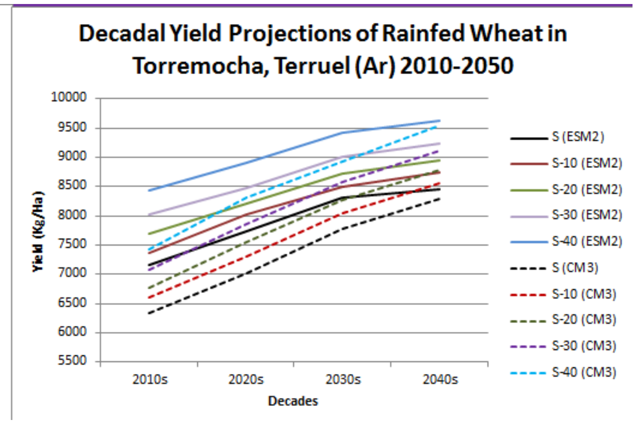

Decadal Yield Projections of Irrigated Wheat in Pardinilla, Huesca (Ar) 2010-2050
11500
11000
10500
10000
9500
9000
8500
Yield (Kg/Ha)
2010s
2020s
2030s
2040s
Decades
S (ESM2)
S-10 (ESM2)
S-20 (ESM2)
S-30 (ESM2)
S (CM3)
S-10 (CM3)
S-20 (CM3)
S-30 (CM3)


Decadal Yield Projections of Rainfed Wheat in Pardinilla, Huesca (Ar) 2010-2050
11000
10500
10000
9500
9000
8500
8000
7500
7000
Yield (Kg/Ha)
2010s
2020s
2030s
2040s
Decades
S (ESM2)
S-10 (ESM2)
S-20 (ESM2)
S-30 (ESM2)
S (CM3)
S-10 (CM3)
S-20 (CM3)
S-30 (CM3)

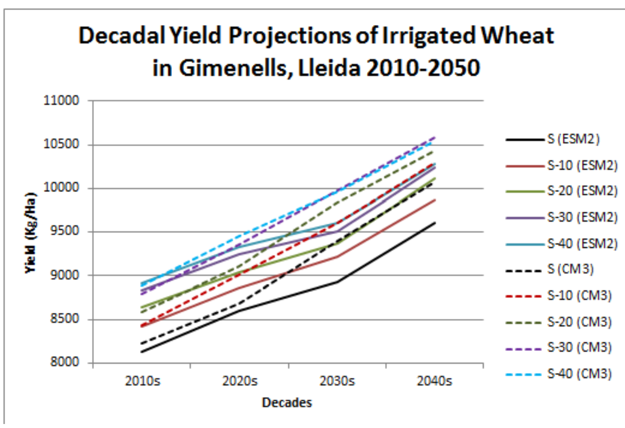

Decadal Yield Projections of Irrigated Wheat in Tauste, Zaragoza (Ar) 2010-2050
11000
10500
10000
9500
9000
8500
8000
7500
Yield (Kg/Ha)
2010s
2020s
2030s
2040s
Decades
S (ESM2)
S-10 (ESM2)
S-20 (ESM2)
S-30 (ESM2)
S-40 (ESM2)
S (CM3)
S-10 (CM3)
S-20 (CM3)
S-30 (CM3)
S-40 (CM3)

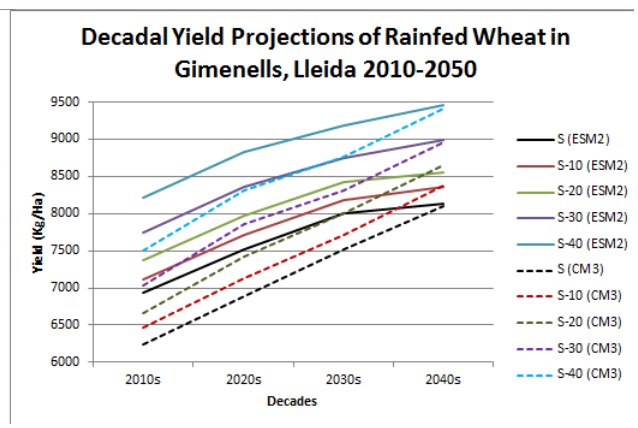

Decadal Yield Projections of Rainfed Wheat in Tauste, Zaragoza (Ar) 2010-2050
9000
8500
8000
7500
7000
6500
6000
5500
5000
Yield (Kg/Ha)
2010s
2020s
2030s
2040s
Decades
S (ESM2)
S-10 (ESM2)
S-20 (ESM2)
S-30 (ESM2)
S-40 (ESM2)
S (CM3)
S-10 (CM3)
S-20 (CM3)
S-30 (CM3)
S-40 (CM3)

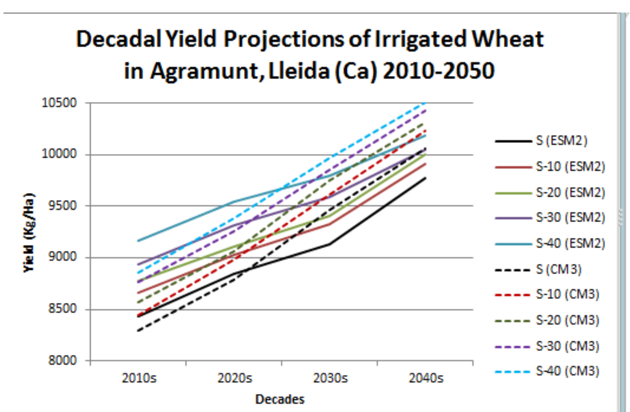

Decadal Yield Projections of Irrigated Wheat in Torremocha, Terruel (Ar) 2010-2050
Yield (Kg/Ha)
11000
10500
10000
9500
9000
8500
8000
7500
2010s
2020s
2030s
2040s
Decades
S (ESM2)
S-10 (ESM2)
S-20 (ESM2)
S-30 (ESM2)
S-40 (ESM2)
S (CM3)
S-10 (CM3)
S-20 (CM3)
S-30 (CM3)
S-40 (CM3)

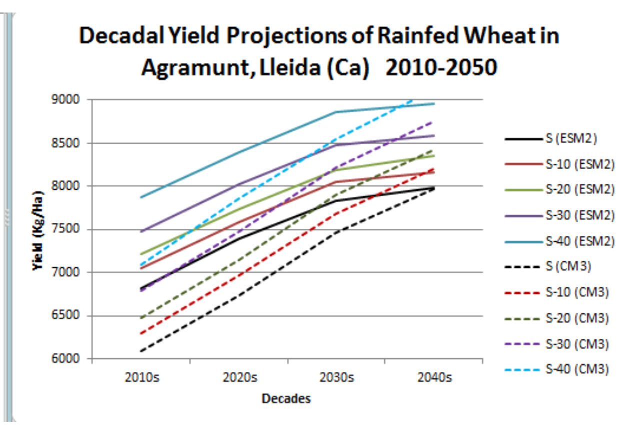

Decadal Yield Projections of Rainfed Wheat in Torremocha, Terruel (Ar) 2010-2050
Yield (Kg/Ha)
10000
9500
9000
8500
8000
7500
7000
6500
6000
5500
2010s
2020s
2030s
2040s
Decades
S (ESM2)
S-10 (ESM2)
S-20 (ESM2)
S-30 (ESM2)
S-40 (ESM2)
S (CM3)
S-10 (CM3)
S-20 (CM3)
S-30 (CM3)
S-40 (CM3)

Cataluna

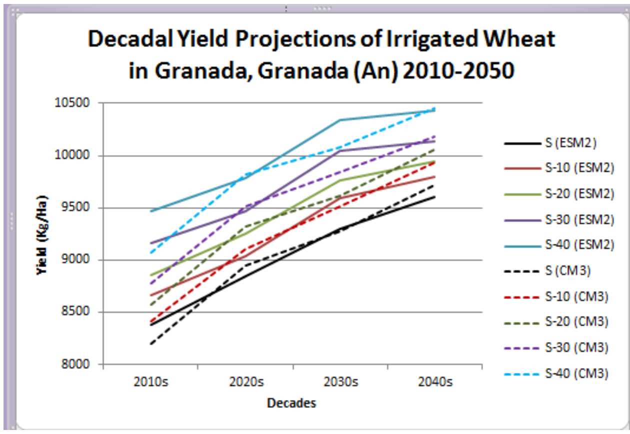

Decadal Yield Projections of Irrigated Wheat in Gimenells, Lleida 2010-2050
Yield (Kg/Ha)
11000
10500
10000
9500
9000
8500
8000
2010s
2020s
2030s
2040s
Decades
S (ESM2)
S-10 (ESM2)
S-20 (ESM2)
S-30 (ESM2)
S-40 (ESM2)
S (CM3)
S-10 (CM3)
S-20 (CM3)
S-30 (CM3)
S-40 (CM3)


Decadal Yield Projections of Rainfed Wheat in Gimenells, Lleida 2010-2050
Yield (Kg/Ha)
9500
9000
8500
8000
7500
7000
6500
6000
2010s
2020s
2030s
2040s
Decades
S (ESM2)
S-10 (ESM2)
S-20 (ESM2)
S-30 (ESM2)
S-40 (ESM2)
S (CM3)
S-10 (CM3)
S-20 (CM3)
S-30 (CM3)
S-40 (CM3)

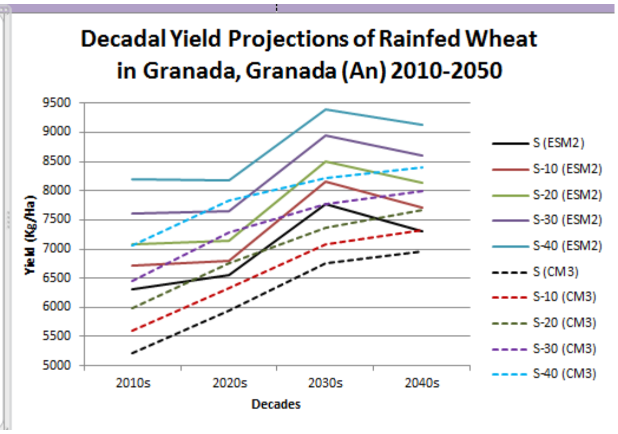

Decadal Yield Projections of Irrigated Wheat in Agramunt, Lleida (Ca) 2010-2050
Yield (Kg/Ha)
10500
10000
9500
9000
8500
8000
2010s
2020s
2030s
2040s
Decades
S (ESM2)
S-10 (ESM2)
S-20 (ESM2)
S-30 (ESM2)
S-40 (ESM2)
S (CM3)
S-10 (CM3)
S-20 (CM3)
S-30 (CM3)
S-40 (CM3)


Decadal Yield Projections of Rainfed Wheat in Agramunt, Lleida (Ca) 2010-2050
Yield (Kg/Ha)
9000
8500
8000
7500
7000
6500
6000
2010s
2020s
2030s
2040s
Decades
S (ESM2)
S-10 (ESM2)
S-20 (ESM2)
S-30 (ESM2)
S-40 (ESM2)
S (CM3)
S-10 (CM3)
S-20 (CM3)
S-30 (CM3)
S-40 (CM3)

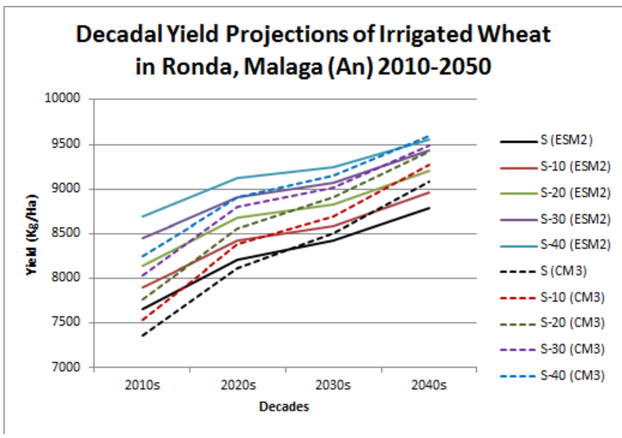
Andalucia



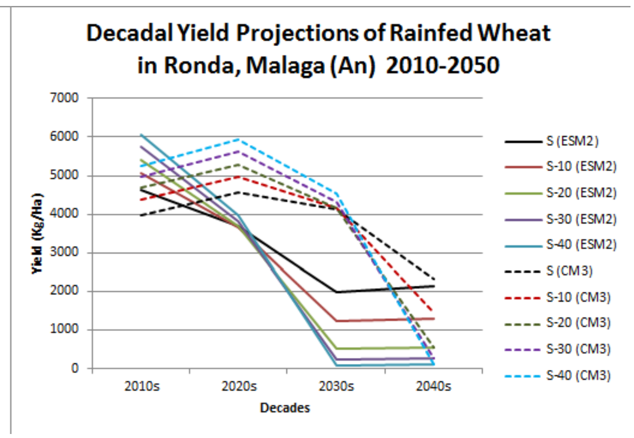
Decadal Yield Projections of Irrigated Wheat
in Granada, Granada (An) 2010-2050
Yield (Kg/Ha)
Decades
2010s
2020s
2030s
2040s
S (ESM2)
S-10 (ESM2)
S-20 (ESM2)
S-30 (ESM2)
S-40 (ESM2)
S (CM3)
S-10 (CM3)
S-20 (CM3)
S-30 (CM3)
S-40 (CM3)



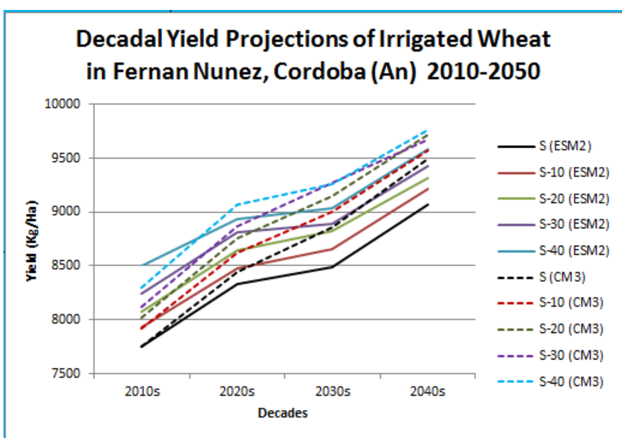
Decadal Yield Projections of Rainfed Wheat
in Granada, Granada (An) 2010-2050
Yield (Kg/Ha)
Decades
2010s
2020s
2030s
2040s
S (ESM2)
S-10 (ESM2)
S-20 (ESM2)
S-30 (ESM2)
S-40 (ESM2)
S (CM3)
S-10 (CM3)
S-20 (CM3)
S-30 (CM3)
S-40 (CM3)



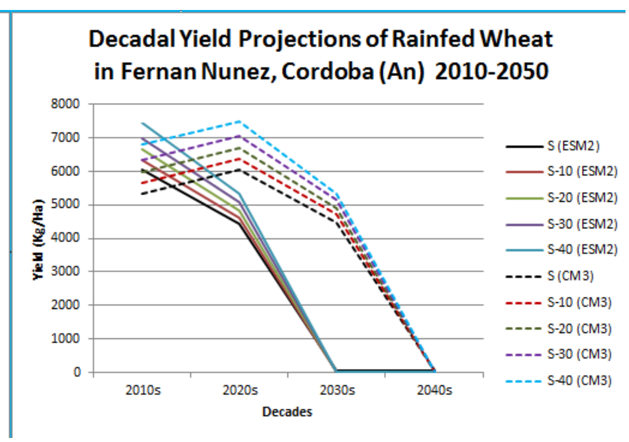
Decadal Yield Projections of Irrigated Wheat
in Ronda, Malaga (An) 2010-2050
Yield (Kg/Ha)
Decades
2010s
2020s
2030s
2040s
S (ESM2)
S-10 (ESM2)
S-20 (ESM2)
S-30 (ESM2)
S-40 (ESM2)
S (CM3)
S-10 (CM3)
S-20 (CM3)
S-30 (CM3)
S-40 (CM3)



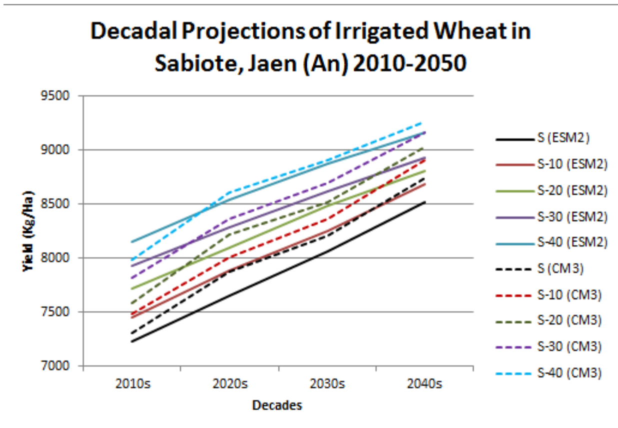
Decadal Yield Projections of Rainfed Wheat
in Ronda, Malaga (An) 2010-2050
Yield (Kg/Ha)
Decades
2010s
2020s
2030s
2040s
S (ESM2)
S-10 (ESM2)
S-20 (ESM2)
S-30 (ESM2)
S-40 (ESM2)
S (CM3)
S-10 (CM3)
S-20 (CM3)
S-30 (CM3)
S-40 (CM3)

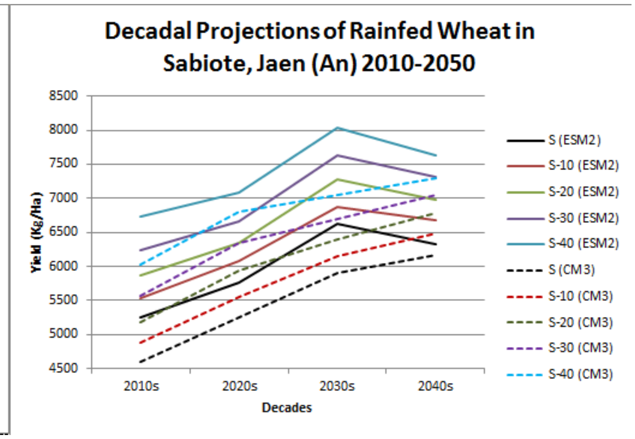


Decadal Yield Projections of Irrigated Wheat
in Fernan Nunez, Cordoba (An) 2010-2050
Yield (Kg/Ha)
Decades
2010s
2020s
2030s
2040s
S (ESM2)
S-10 (ESM2)
S-20 (ESM2)
S-30 (ESM2)
S-40 (ESM2)
S (CM3)
S-10 (CM3)
S-20 (CM3)
S-30 (CM3)
S-40 (CM3)



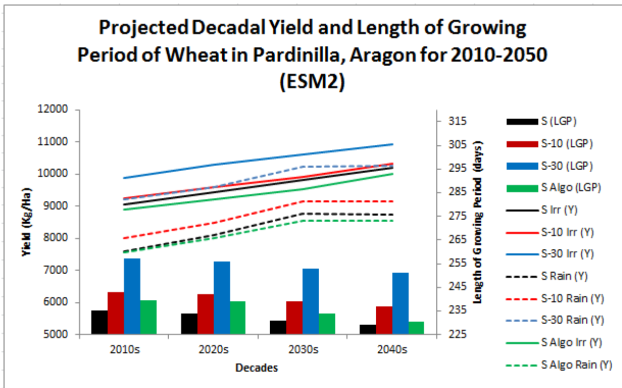
Decadal Yield Projections of Rainfed Wheat
in Fernan Nunez, Cordoba (An) 2010-2050
Yield (Kg/Ha)
Decades
2010s
2020s
2030s
2040s
S (ESM2)
S-10 (ESM2)
S-20 (ESM2)
S-30 (ESM2)
S-40 (ESM2)
S (CM3)
S-10 (CM3)
S-20 (CM3)
S-30 (CM3)
S-40 (CM3)

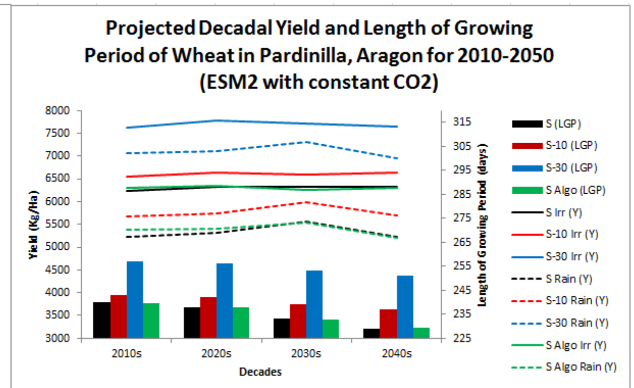

Decadal Projections of Irrigated Wheat in Sabiote, Jaen (An) 2010-2050
9500
9000
8500
8000
7500
7000
Yield (Kg/Ha)
2010s
2020s
2030s
2040s
Decades
S (ESM2)
S-10 (ESM2)
S-20 (ESM2)
S-30 (ESM2)
S-40 (ESM2)
S (CM3)
S-10 (CM3)
S-20 (CM3)
S-30 (CM3)
S-40 (CM3)

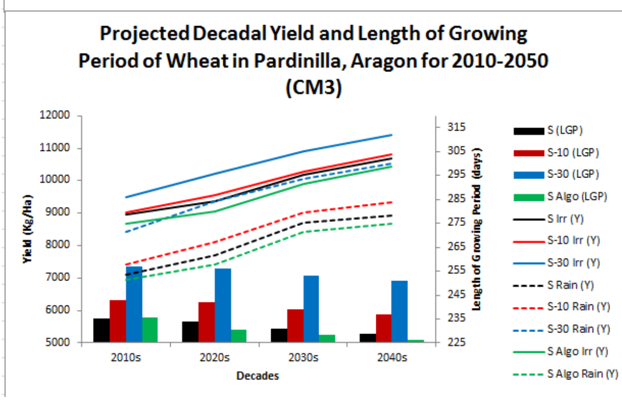

Decadal Projections of Rainfed Wheat in Sabiote, Jaen (An) 2010-2050
8500
8000
7500
7000
6500
6000
5500
5000
4500
Yield (Kg/Ha)
2010s
2020s
2030s
2040s
Decades
S (ESM2)
S-10 (ESM2)
S-20 (ESM2)
S-30 (ESM2)
S-40 (ESM2)
S (CM3)
S-10 (CM3)
S-20 (CM3)
S-30 (CM3)
S-40 (CM3)

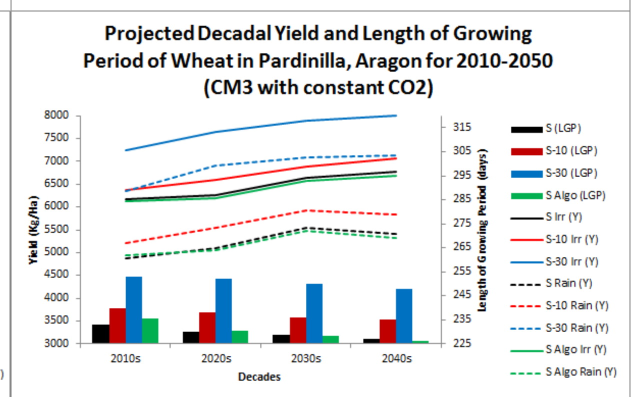
Annex 3: Decadal yield response to LGP

Aragon





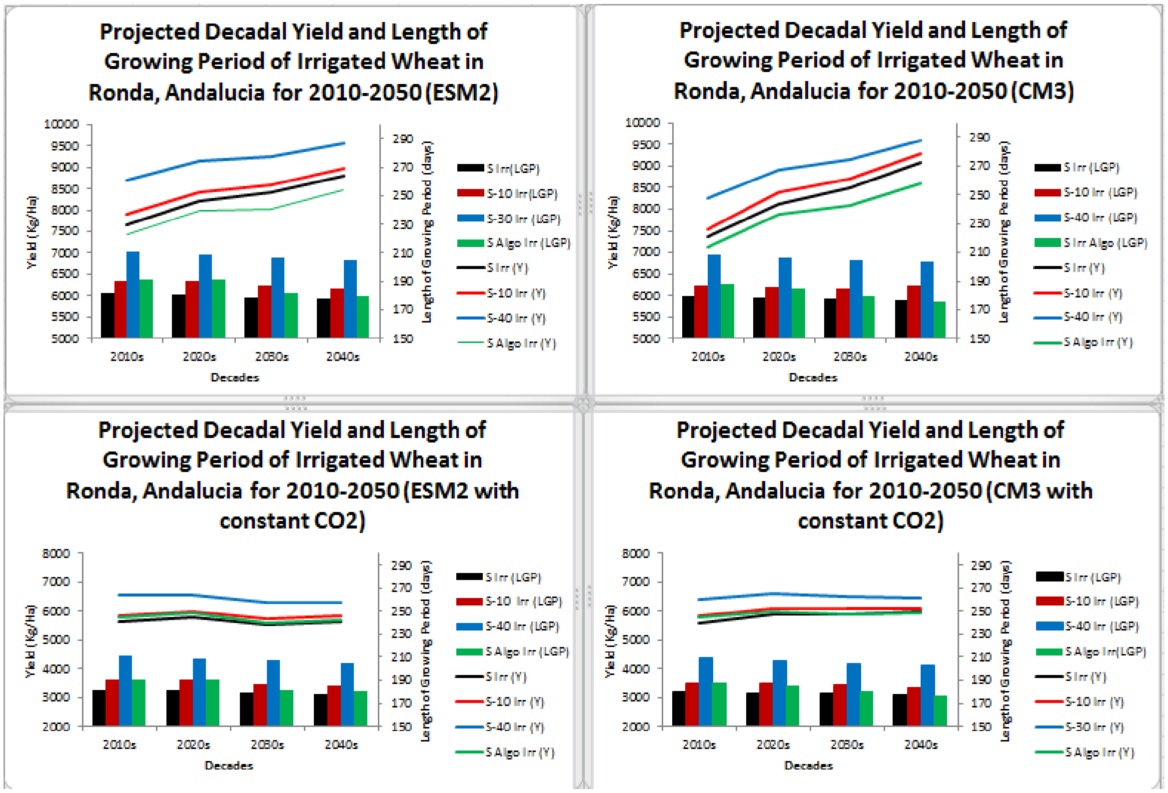




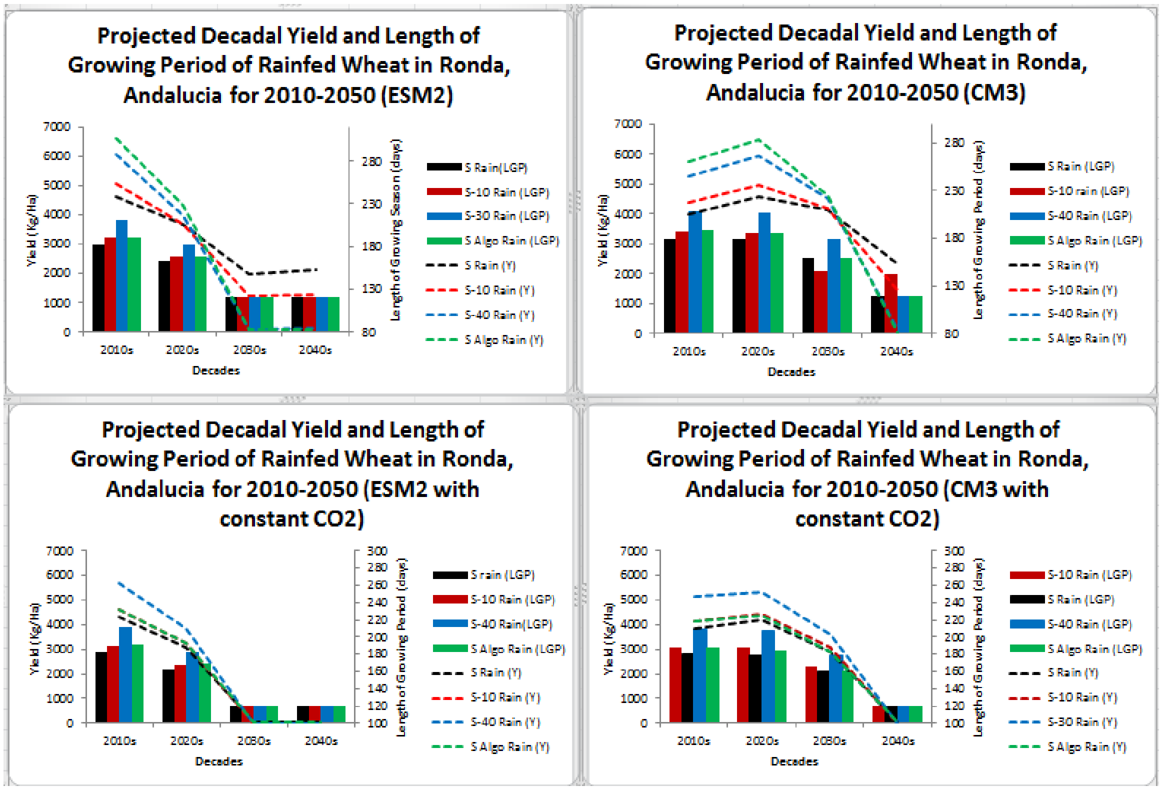
As previously mentioned, yields in Aragon increase between the 2010's and 2050's with a faster trend simulated with the CM3 model than with the ESM2. For the rainfed simulations however, the yields seem to stagnate from the 2030's onward in the ESM2 and increase much slower in the CM3 simulation. Furthermore, it appears that the growing season will shorten over time but the yields will continue to increase (for both GCMs). Moreover, earlier planting dates will actually increease both the yields and the LGP in each decade. On the other, when removing the increase in CO_2 , the yields stagnates over time in the ESM2 simulations and increase much slower in the CM3 simulation. However, the LGP does not change when CO_2 is kept constant. This means that CO_2 considerably influences yields in Aragon and could explain the simulated future increase in yields in the northern parts of Spain.

Andalucia

In Andalucia there is a distinction in the growing period of rainfed and irrigated wheat. That is why rainfed and irrigated are presented in sperate graphs.

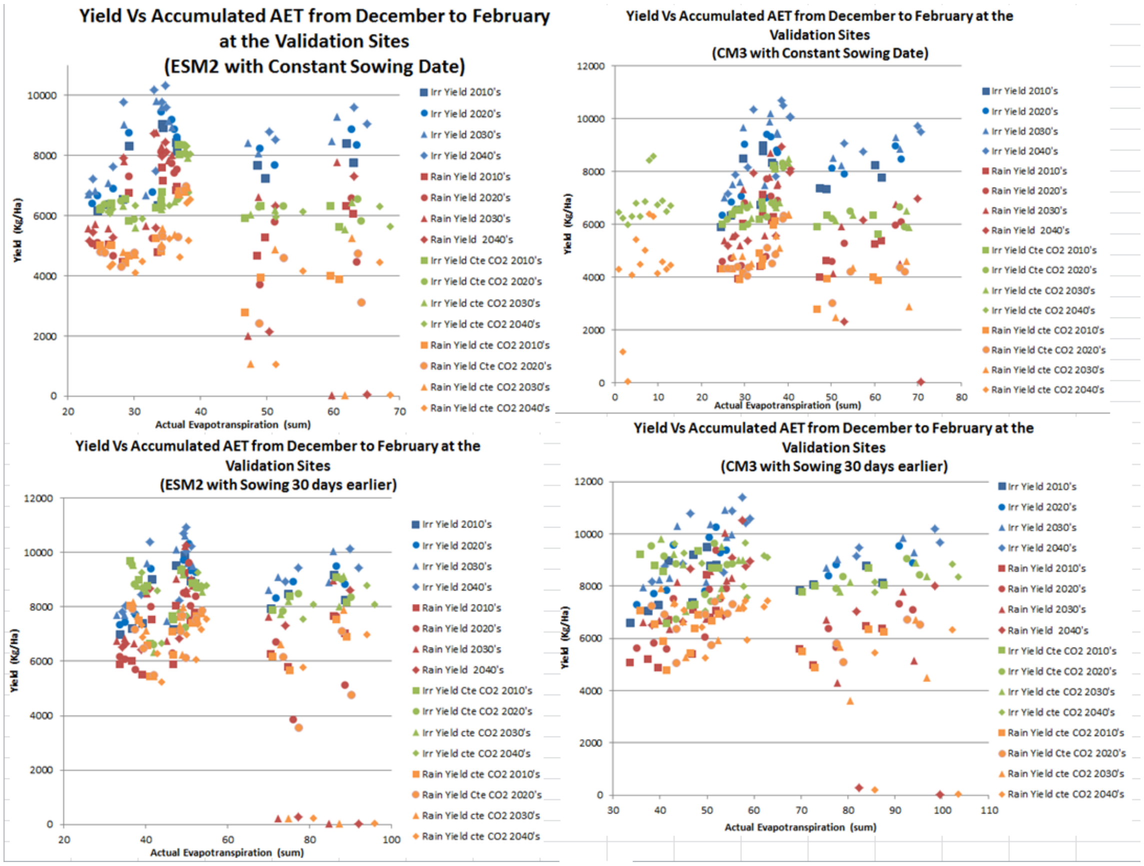


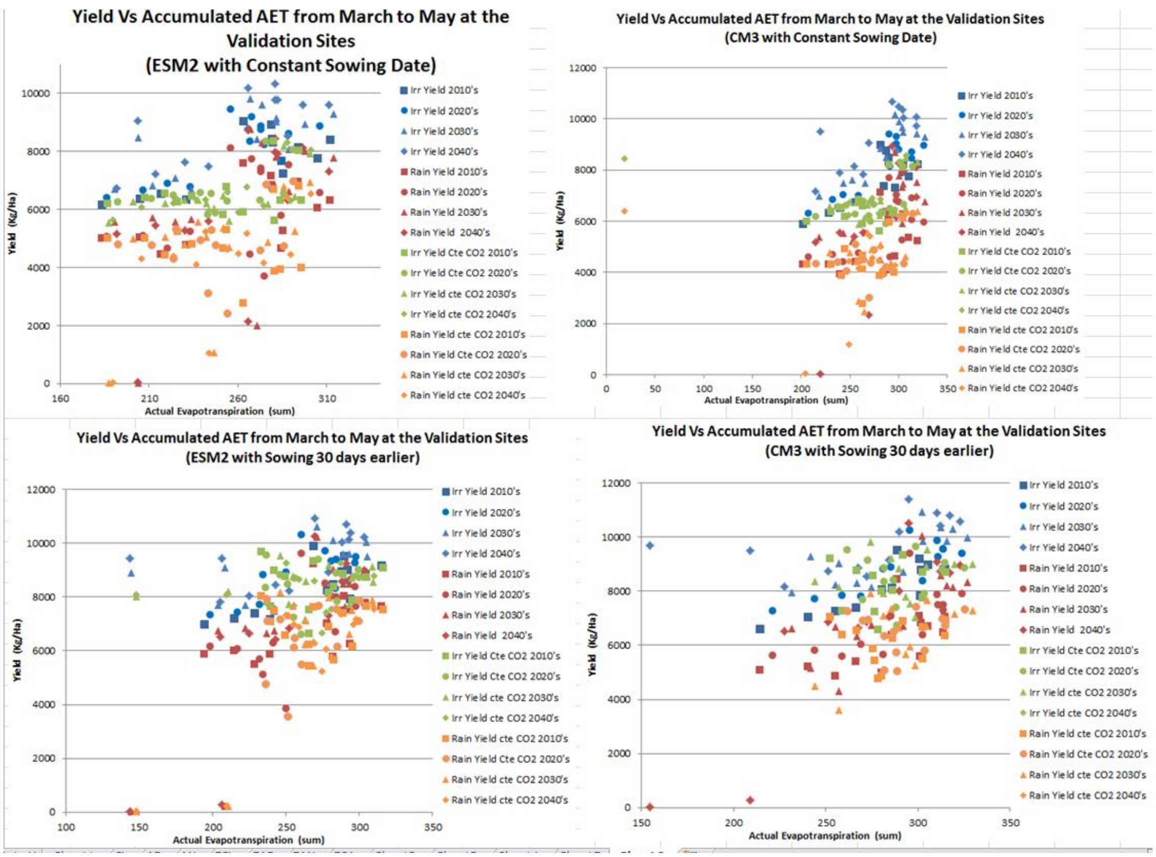
The irrigated yields in Ronda (In Malaga, Andalucia) will also increase between the 2010's and the 2040's. Besides, the growing season is expected to shorten over time, but increases in each decade when crops are planted earlier. However, eventhough the growing season decreases over time, yields continue to increase which means that the growing season does not have a major influence on yields. On the other hand, when keeping the CO_2 constant, the yields stagnates for both models and it could be concluded that CO_2 is again the major driver of irrigated yield in Andalucia.



Conversely, the rainfed wheat decreases over time with a difference in trends between the two GCMs. Indeed, while the yield decreases continuously when modeled with the ESM2 model, it first increases up to the 2020's and then decreases in the CM3 simulation. The LGP also decreases over time, reaching very low values (130 days) by the 2030's in the ESM2 and 2040's for the CM3 simulations. Furthermore, yields benefit from an earlier planting date up to the 2020's after which it is better to keep the same sowing date or maybe even plant later. On the other hand, when keeping the CO_2 constant the yields decrease faster until they collapse in the 2030's and the LGP also slightly decreases. All in all, it is obvious that CO_2 has a major influence in yields in Malaga, however, when considering the fact that irrigated yields only stagnated while rainfed yields collapse, it becomes clear that the main limiting driver in Andalucia is actually irrigation and not CO_2.

Annex 4: Yield Response to Evapotranspiration




Yield Vs Accumulated AET from March to May at the Validation Sites
(ESM2 with Constant Sowing Date)
Yield (Kg/Ha)
Actual Evapotranspiration (sum)
Irr Yield 2010's
Irr Yield 2020's
Irr Yield 2030's
Irr Yield 2040's
Rain Yield 2010's
Rain Yield 2020's
Rain Yield 2030's
Rain Yield 2040's
Irr Yield Cte CO2 2010's
Irr Yield Cte CO2 2020's
Irr Yield cte CO2 2030's
Irr Yield cte CO2 2040's
Rain Yield cte CO2 2010's
Rain Yield Cte CO2 2020's
Rain Yield cte CO2 2030's
Rain Yield cte CO2 2040's
Yield Vs Accumulated AET from March to May at the Validation Sites
(CM3 with Constant Sowing Date)
Yield Vs Accumulated AET from March to May at the Validation Sites
(ESM2 with Sowing 30 days earlier)
Yield Vs Accumulated AET from March to May at the Validation Sites
(CM3 with Sowing 30 days earlier)

Department of Physical Geography and Ecosystem Science, Lund University

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