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Integration of components for the simulation of biotic and abiotic stresses in model-based yield forecasting systems

Ph.D. Thesis

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ABSTRACT

The raising global demand for agricultural products and the exacerbated inter-annual fluctuations of food productions due to climate change are increasing world food price volatility and threatening food security in developing countries. In this context, the availability of reliable operational yield forecasting systems would allow policy makers to regulate agricultural markets. However, the reliability of the current approaches (the most sophisticated being based on crop models) is undermined by different sources of uncertainty. In particular, large area simulations can be affected by errors deriving from the uncertainty in input data (e.g., sowing dates, information on cultivar/hybrid grown, management practices) and upscaling assumptions, as well as from the incomplete adequacy of crop models to reproduce the effects of key factors affecting inter-annual yield fluctuations (e.g., extreme weather events, pests, diseases).

The aim of this Ph.D. project was to reduce the uncertainty affecting the existing model-based forecasting systems through: (i) the implementation of approaches for the estimation of the impact of biotic and abiotic stressors on crop yields (based on dynamic models and on dedicated agro-climatic indicators), and (ii) the integration of remote sensing information within crop models. Concerning the first objective, the approaches for the simulation of transplanting shock and cold-induced spikelet sterility in rice included in Oryza2000 and WARM models, respectively, were improved, by increasing the model adherence to the underlying systems. Moreover, generic approaches for the simulation of the impacts of extreme weather events on crop yields were developed and evaluated, as well as approaches specific for sugarcane. For the second objective, remote sensing information was used to derive rice-cropped areas and sowing dates varying with time and space, as well as for the assimilation of exogenous leaf area index data using both recalibration and updating techniques (to account for factors not explicitly reproduced by the model within large-area applications).

The application of the improved forecasting systems to different crops and agro-climatic contexts worldwide led to marked improvements compared to existing approaches. This was achieved through an increase in the percentage of inter-annual yield variability explained. On the one hand, the simulation of the impact of weather extremes (cold shocks, heat waves, water stress and frost) allowed to reduce the tendency of CGMS (the monitoring and forecasting system of the European Commission) to overestimate cereal yields in case of unfavorable seasons. Moreover, the integration of dynamic crop models and of agro-climatic indicators led to enhance the predicting capacity of available approaches. On the other hand, the integration of remote-sensing information within high resolution simulation chains allowed to decidedly reduce the uncertainty of the standard CGMS-WARM system when applied to the main European rice districts.

Keywords: agro-climatic indicators; assimilation; blast disease; Brazil; Canegro; CGMS; cold damage; crop model; direct sowing; extreme weather events; *Oryza sativa* L.; remote sensing; seedbed; sowing technique; spikelet sterility; sugarcane; transplanting, WARM model; WOFOST; yield forecast.

CONTENTS

INTRODUCTION

1.1. Large area crop monitoring and yield forecasting

Timely and reliable crop yield forecasts and early warnings in case of adverse conditions are increasingly needed by a variety of actors within the agricultural sector, and their availability is considered as increasingly important in both developed and developing countries (Wang et al., 2010; Son et al., 2014). Among the main reasons explaining the interest in crop monitoring and forecasting systems, a key role is played by the need of tools for supporting the regulation of agricultural markets and the management of food-supply chains through procurement, stock management, marketing, and distribution networks (Bannayan and Crout, 1999; Atzberger, 2013). Other crucial reasons deal with the need of mitigating the volatility of prices of food commodities (OECD and FAO, 2011) and of planning post-harvest operations (e.g., milling) along the whole production chain (Everingham et al., 2002).

A variety of yield forecasting systems were proposed in the last decades. The first methods, based on field surveys, were strongly subjective and suffered from a lack of consistency. For this reason, more complex and rigorous approaches were developed starting from the mid ‘90s, based on information retrieved from agro-climatic indicators, remote sensing and crop simulation models (Bouman et al., 1997; Bannayan and Crout, 1999). Simple systems – based, e.g., on agro-climatic indicators (Balaghi et al., 2012) or basic vegetation indices (Fernandes et al., 2011) – demonstrated their usefulness under conditions characterized by large year-to-year fluctuations in crop yields and where these fluctuations are driven by one or two key factors (e.g., rainfall distribution in summer months) severely limiting crops productivity. The most complex and reliable approaches – used by policy makers for yield forecasts at national and regional levels – rely on remote sensing (Mkhabela et al., 2005; Wang et al., 2010; Duveiller et al., 2013; Son et al., 2014) or crop simulation models (Vossen and Rijks, 1995; Supit, 1997; Bezuidenhout and Singels, 2007a-b; de Wit et al., 2005; Kogan et al., 2013).

According to the authors’ knowledge, the most sophisticated operational (since 1994) crop yield forecasting system is the Crop Growth and Monitoring System (CGMS) of the European Commission. The system was developed at the Joint Research Centre within the Monitoring Agricultural

ResourceS (MARS) activities to provide short-term (in-season) independent forecasts of the yield of the main food crops in Europe (Vossen and Rijks, 1995; Lazar and Genovese, 2004; de Wit et al., 2005). The MARS system is based on the WOFOST model (van Keulen and Wolf, 1986; Rabbinge and van Diepen, 2000) for the simulation of the development and growth of all crops but rice, for which the rice-specific WARM model (Confalonieri et al., 2009; Pagani et al., 2014) is used.

Despite modern forecasting systems are often based on sophisticated technologies, their reliability is threatened by different sources of uncertainty, which limit their applicability in specific environments and decrease their capability to interpret the underlying systems in case of unusual conditions, that is, when stakeholders are more interested in their predictions (Kogan et al., 2013). These sources of uncertainty strictly depend on the type of technology used. Forecasting systems solely based on remote sensing are normally unsuitable in contexts characterized by a good yield potential, since signal saturates because of the favorable conditions and optimized management techniques (Sader et al., 1989; Dobson et al., 1995; Zhao et al., 2016) even before the reproductive phase. This type of systems normally fails also in contexts where specific abiotic stressors (e.g., cold or heat waves during the reproductive period) can severely affect crop yields even without relevant damages to the canopy.

Systems based on crop simulation models, instead, can be affected by sources of uncertainty deriving from their incomplete adequacy to reproduce the effects of the main factors affecting crops productivity under the conditions explored. Other important sources of uncertainty derive from the fact that they are used for large-area applications despite they were originally developed to perform simulations at point-scale, i.e., on ideal spatial units homogeneous for soil, climate, management, pathogen pressure, etc. Different authors, indeed, observed how crop models – when applied at regional scale – may lead to biased simulations because of aggregation assumptions (Hansen and Jones, 2000; Hoffman et al., 2016), which cause the so-called nonlinear aggregation error (Cale et al., 1983) or aggregation effect (Hoffmann et al., 2015). However, even regardless of output aggregation, large-area simulations are affected by errors deriving from the uncertainty in input data at the spatial scale (elementary simulation unit) at which simulations are run. Indeed, in case of regional or national forecasting systems, it is practically impossible to get high-resolution and reliable information on soil, weather and management practices (e.g., sowing dates, cultivar/hybrid grown, dates and amounts of irrigation water, nutrients, chemicals, etc.). Besides uncertainty in inputs and in information for output aggregation, simulations can be affected by uncertainty due to model structure (Sándor et al., 2016; Confalonieri et al., 2016a) and to the experience of model users (Diekkrüger et al., 1995; Confalonieri et al., 2016), as well as by the uncertainty in the data used for the calibration of model parameters (Kersebaum et al., 2015; Confalonieri et al., 2016).

The predictive ability of available forecasting systems is also strictly dependent on the number and typology of processes simulated with respect to the factors affecting seasonal yield fluctuations in the specific context of interest like, e.g., nutrient availability, weeds, pests, diseases, extreme weather events. As an example, the simulation tools used within forecasting systems are largely based on models of plant response to environment that were developed for conditions of good adaptation and were often designed for temperature and precipitation regimes typical of temperate environments. Consequently, the effects of unusual weather events on crop performance – including crop failure – are often overlooked or unsatisfactorily reproduced by available forecasting systems (Eitzinger et al., 2013; Sanchez et al., 2013). The fact that they are – although to a different extent – unsuitable to handle weather extremes explain their ability to adequately predict mean yields but not the related inter-annual variability.

1.2. Key issues

1.2.1. Yield forecast and extreme weather events

The ongoing climate change is expected to increase the year-to-year fluctuations in crops productivity and to decrease mean yields in many regions of the world (Parry et al., 1999; IPCC, 2007b), thus reducing the global food production. The relevance of climate change impact on the agricultural sector is demonstrated by the variety of recent studies aimed at identifying adaptation strategies to alleviate projected yield losses (Falloon and Betts, 2010; Reidsma et al., 2010; Olesen et al., 2011). The significant increase in temperature projected for the 2030s is expected to affect winter crops in northern Europe, as well as summer crops in southern and central European countries (IPCC, 2007a). Moreover, the increase in the frequency, intensity and duration of extreme weather events that severely affected yields starting from the late 1990s is expected to further exacerbate in Europe. Major events will be related to heat waves (Calanca, 2007; Trenberth et al., 2007), heavy rainfall (Christensen and Christensen, 2003), and cold shocks, the latter including both chilling and freezing injuries (Kasuga et al., 1999; Lang et al., 2005).

Most of the abiotic stressors affecting plant growth (e.g., heat and cold waves, frost events, water shortage) are characterized by dynamics in weather variables for which the crop is not able to provide a suitable physiological response during the most sensitive phenological phases. In recent years, agro-climatic indices (e.g., Confalonieri et al., 2010; Rivinngton et al., 2013) and modelling approaches were proposed to reproduce the effects of extreme weather events on crop productivity. Concerning dynamic impact models, approaches to reproduce cold/heat effects on crop growth and yield formation were developed (Challinor et al., 2005; Shimono et al., 2005; Confalonieri et al., 2009; van Oort et al., 2015). Different models were also proposed to account for the effects of frost on leaf area development (CERES-Wheat – Jones et al., 2003; InfoCrop – Aggarwal et al., 2006), leaf senescence (APSIM – Holzworth et al., 2014), and total biomass accumulation (EPIC – Williams et al., 1989). Among these approaches, some are detailed enough to include algorithms for the effects of hardening/dehardening on winter crops cold tolerance (e.g., Ritchie et al., 1991) or for the effects of interval between tiller emission on susceptibility to thermal shocks-induced sterility (e.g., Shimono et al., 2005). Concerning the stress caused by water shortage, most of the existing simulation models include approaches to reproduce soil-water-plant dynamics and the resulting effects on crop productivity (Cavero et al., 2000; Raes et al., 2006; Singh et al., 2008). For other typologies of extreme weather events (e.g., hail, wind-induced lodging, flooding) the relationship with crop growth and production may be less straightforward, and the circumscribed nature of these events makes difficult to obtain reliable input data for large-area simulations. Despite this, a few studies are available where approaches for the impact of this kind of weather extremes were proposed, as the approach by Baker et al. (1998) for estimating the risk of stem and root lodging.

However, operational simulation platforms used within crop monitoring and yield forecasting systems rarely implement approaches for the impact of extreme weather events, being available impact models often unsuitable for operational contexts and too demanding in terms of data needs in case of regional applications.

1.2.2. Integration of remote sensing information within crop models

The integration of remote sensing and crop modelling is considered as a powerful system to increase the spatial applicability of simulation tools, being able to reduce the uncertainty related with the poor quality of input data for regional applications (Launary and Guerif, 2005). The combined use of these two kinds of technology, indeed, can markedly reduce their intrinsic limits (and related uncertainty), because the potentialities of both technologies are maximized by their integration (Fang et al., 2011; Ines et al., 2013; Ma et al., 2013).

Remote sensing information can be directly used as inputs before the simulation. As an example, the uncertainty in sowing dates for regional modelling studies can be reduced through the analysis of temporal profiles of remote sensing products (e.g., Boschetti et al., 2009). Other applications refer to the assimilation of remote sensing-derived leaf area index data varying in time and space (Launay and Guèrif, 2005; Dorigo et al., 2007) during the simulation. This allows implicitly accounting for possible differences in vigour between different varieties or for the effects of factors not accounted for by simulation models (e.g., insects, Wu and Wilson, 1997; weeds, Kropff et al., 1992). In particular, remote sensing information can be assimilated into crop models using two main strategies, each presenting pros and cons for different species and agroclimatic/operational contexts (Dorigo et al., 2007): recalibration and updating. The recalibration method is based on the automatic adjustment of model parameters targeting the minimization of the error between model outputs and remote sensing-derived state variables (e.g., Bouman et al., 1995). The updating method is instead based on the update of model state variables when the remote sensing data are available, using algorithms to convert them into simulated variables and to reinitialize all model state variables accordingly (Mc Laughlin, 2002). If not properly applied, the recalibration method can be considered as more risky, since the values of model parameters – likely deriving from calibration activities based on many detailed experimental datasets – are changed using completely unsupervised optimization algorithms and few uncertain remote sensing-derived reference data. This could alter the process-based logic behind the crop model itself, and lead to unpredictable errors in model outputs. On the other hand, the updating method can be considered as more robust, since the biophysical coherence of the simulation is not affected between two assimilation events. However, the simulation lose consistency from sowing to harvest, since crop state variables appear as discontinuous and state variables referring to soil (e.g., water and nutrient contents) cannot be updated, since not linked to crop states with strict relationships like those existing between, e.g., the biomass of different plant organs. However, under specific conditions, each of these technologies – if correctly applied – demonstrated its capability of decreasing model uncertainty. Moreover, the availability of consistent archives (e.g., long-term MODIS-derived leaf area index data; https://modis.gsfc.nasa.gov/data/dataprod/mod15.php) and a new generation of remote sensing products (those provided by the Sentinel satellites from the Copernicus program; Lefebvre et al., 2016) are increasing the potential of forecasting systems based on the integration of crop modelling and remote sensing technologies.

1.3. Objectives and organisation of the research

The aim of the PhD project was to reduce the uncertainty affecting the existing yield forecasting systems through:

- the development and improvement of modelling approaches for the simulation of the impact on crop yield of major abiotic stressors;
- the integration of the new impact models within yield forecasting systems to increase their capability to predict crop yields in case of anomalous seasons;
- the integration of remote sensing information within crop model-based forecasting systems to reduce errors due to uncertainty in management practices (i.e., sowing dates changing in time and space) and due to factors not explicitly reproduced by the model (e.g., different varieties).

The improved yield forecasting systems were evaluated for a variety of crops and in different agro-climatic contexts.

1.4. Outline of the thesis

The study is articulated in five chapters.

Chapter 1 presents the development of a yield forecasting system for sugarcane based on agro-climatic indicators and on the Canegro model. As a case study, the system was evaluated for the Brazilian State of São Paulo, by quantifying its forecasting reliability in different stages of the sugarcane growth cycle. In particular, given sugarcane is grown under rainfed conditions in the study area, the impact of water stress on the inter-annual yield fluctuations was analyzed. The Canegro model was linked to existing approaches for the simulation of water dynamics in the plant-soil system, that is, a cascading model for soil water redistribution and the EPIC approach for root water uptake.

Chapter 2 presents the development of a new algorithm to allow the rice specific WARM model to reproduce the effects of both manual and mechanical transplanting. Indeed, transplanting (which is still the main technique used to establish rice in developing countries, especially in tropical and sub-tropical Asia) can largely affect rice productivity, and the magnitude of the transplanting shock is strictly dependent from the environmental conditions experienced by the plants before and after the transplanting event. The new transplanting algorithm improves the approach implemented in Oryza2000 by including algorithms for the simulation of the effect of the competition for solar radiation on canopy structure, as well as for estimating the percentage of mortality in the seedbed.

Chapter 3 presents the improvement of the spikelet sterility model implemented in WARM. In particular, the existing approach for cold-induced sterility (affecting the crop during the young microspore stage) was refined and extended to reproduce damages during anthesis. Moreover, the model was extended to account for heat-induced sterility during anthesis. The improved approach was evaluated using datasets collected in northern Italy between 2004 and 2010, characterized by heterogeneous weather conditions and cold-air outbreaks occurring in different moments during the reproductive phase.

Chapter 4 presents the results of activities aimed at improving the European Commission CGMS system for its capability of predicting the impact of weather extremes (heat, cold, frost and water stress) on the yields of cereal crops (maize, barley, soft and durum wheat) in Europe. The developed approaches are based on the hypothesis that yield variations due to extreme events are mediated by changes in the harvest index for water, heat and cold stresses and by damages to leaf area (or even crop failure) in case of frost events.

Chapter 5 presents the development of a high-resolution rice yield forecasting system based on the deep integration of remote sensing information within a simulation platform based on the WARM model. Remote sensing information were used to derive the rice-cropped area and sowing dates varying with time and space, as well as for the assimilation of exogenous leaf area index data using both the recalibration and updating techniques. The high spatial resolution and the production of forecasts at district level (for the main six European rice districts) allowed including modelling approaches for the simulation of the key biotic (blast disease) and abiotic (cold shocks) factors affecting rice production in temperate environments.

Note

Chapter 1 is submitted to Agricultural Systems. Chapter 2 is published in European Journal of Agronomy. Chapter 3 is submitted to Field Crops Research. I would like to acknowledge the editorial board of European Journal of Agronomy for the permission to include the papers in this thesis.

FORECASTING SUGARCANE YIELDS USING AGRO-CLIMATIC INDICATORS AND CANEGRO MODEL: A CASE STUDY IN THE MAIN PRODUCTION REGION IN BRAZIL

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To be resubmitted to Agricultural Systems after “moderate revisions”

2.1. Abstract

Timely crop yield forecasts at regional and national level are crucial to manage trade and industry planning and to mitigate price speculations. Sugarcane is responsible for 70% of global sugar supplies, thus making yield forecasts essential to regulate the global commodity market. In this study, a sugarcane forecasting system was developed and successfully applied to São Paulo State, the largest cane producer in Brazil. The system is based on multiple linear regressions relating agro-climatic indicators and outputs of the sugarcane model Canegro to historical yield records. The resulting equations are then used to forecast the yield of the current season using 10-day period updated values of indicators and model outputs as the season progresses. We quantified the reliability of the forecasting system in different stages of the sugarcane cycle by performing cross-validations using the 2000-2013 time series of official stalk yields. Agro-climatic indicators alone explained from 38% of inter-annual yield variability (at State level) during the boom growth phase (i.e., January-April) to 73% during the second half of the harvesting period (i.e., September-October). When Canegro outputs were added to the regressor set, the variability explained increased to 63% for the boom growth phase and 90% after mid harvesting, with the best performances achieved while approaching the end of the harvesting window (i.e. at the beginning of October, SDEP = 0.8 t ha^{-1}, R^2_{cv} = 0.93). It is concluded that the overall performances of the system are satisfactory, considering that it was the first attempt based on information exclusively retrieved from the literature. Further improvements to operationalize the system could be possibly achieved by the use of more accurate inputs possibly supplied by the collaboration with local authorities.

Keywords*:* sugarcane; yield forecast; Canegro; agro-climatic indicators; Brazil

2.2. Introduction

Sugarcane (Saccharum spp. L.) is a semi-perennial crop widespread in tropical and sub-tropical environments. It is grown on about 27 million ha worldwide, for an annual production of 1.89 billion tonnes as fresh cane (FAOSTAT, 2014), corresponding to 70% of global sugar supply (Lakshmanan et al., 2005). Moreover, it is efficiently used for ethanol production (Goldemberg, 2008; Langeveld et al., 2014), contributing for 60% to the global bioethanol demand (Demirbaş, 2005). The sucrose stored in the stalk, which depends on genetic, management and environmental factors, is about 12-15% of the fresh weight (Humbert, 2013).

Brazil is the main sugarcane producing country worldwide, accounting for 40% of global production (FAOSTAT, 2014). The cultivated area in the country sharply increased from 2002 to 2009, mainly due to incentives aimed at replacing or blending gasoline with ethanol in the transport sector (Scarpare et al., 2016). After this period, the global financial crisis and the fall of international sugar prices slowed down the Brazilian sugar sector (Marin, 2016). The State of São Paulo is the most important producer, being responsible for more than half of national sugarcane production (UNICA, http://www.unicadata.com.br/).

Its prominent role in global production places emphasis on the timely estimation of sugarcane yields in Brazil. Indeed, early warning in case of anomalous seasons at regional and national scale allows stakeholders to properly assure imports and regulate the agricultural market (Atzberger, 2013, Bannayan and Crout, 1999). Moreover, the process of sugar production involves different sectors, like agriculture, transportation, milling and marketing. In such a complex scenario, early knowledge on seasonal supplies may support selling strategies and industry competitiveness, besides being a valuable information to plan milling operations and sugar shipments (Everingham et al., 2002). Finally, transparent forecasts made available to the public and early warnings in case of unfavorable conditions can mitigate the volatility of prices that often affect the main food commodities because of unexpected production falls and speculative actions (OECD and FAO, 2011).

These considerations led to the development of a variety of yield forecasting systems in the past decades. The first methods were based on farm surveys and crop scouting (Bannayan and Crout, 1999); however, these methodologies are strongly subjective and suffer from a lack of consistency. Since the 1990s, systems based on information retrieved from agro-climatic indicators, remote sensing and crop simulation models became more common (Bouman et al., 1997). The latter approaches present major advantages regarding coherence and objectiveness, and applicability at the regional to global scales. However, these methods also present some tenacious constraints, that undermine the accuracy of model-based yield forecasting systems: (i) the uncertainty regarding input data at regional scale (i.e., agro-management practices, soil properties, weather data, crop distribution, cultivated varieties), largely depending on the aggregation assumptions (Hoffmann et al., 2016), (ii) the difficulty to simulate all the factors that significantly influence crop yield (e.g. nutrient availability, competing weeds, pests, diseases, extreme weather events), (iii) the uncertainty in parameterizations. In order to reduce the impact of these factors on the forecast uncertainty, the European Commission Joint Research Centre – within the MARS (Monitoring Agricultural ResourceS) activities – supported the development of a forecasting system based on the statistical post-processing of model outputs and time series of official yields (Vossen and Rijks, 1995), operational at the level of the EU and its Member States (https://ec.europa.eu/jrc/en/research-topic/crop-yield-forecasting).

Regarding sugarcane, various systems have been developed to forecast cane yields in the world's main production regions. These systems are based on the estimation of climatic-edaphic parameters (Scarpari and Beauclair, 2004; Suresh and Krishna Priya, 2009), on information retrieved from remote sensing indices (Everingham et al., 2005; Fernandes et al., 2011; Gonçalves et al., 2012; Mulianga et al., 2013; Nascimento et al., 2009) and on the use of crop simulation models often integrated with climatic outlooks (Everingham et al., 2005, Everingham et al., 2002). These methods were mostly tested within small areas or over limited time windows, thus without evidence of their applicability in operational contexts at national level. Notable exceptions are the national-scale systems developed by Bezuidenhout and Singels (2007a, 2007b) in South-Africa and by Duveiller et al. (2013) in Brazil. In particular, the system developed in South Africa, based on the Canesim model, provides since the early 2000s operationally monthly forecasts of sugarcane production at mill and industry level.

In this paper we present a yield forecasting system for sugarcane based on agro-climatic indicators and on the Canegro model (Inman-Bamber, 1991; Singels and Bezuidenhout, 2002; Singels et al., 2008) as implemented in the BioMA framework. As a case study, we evaluated the system for the State of São Paulo by quantifying its forecasting reliability in different stages of the sugarcane growth cycle.

2.3. Materials and Methods

2.3.1. The study area

The State of São Paulo (44°10’/53°5’W, 19°46’/25°18’S) is located along the Atlantic Ocean coast in the south-eastern part of Brazil (Fig. 1.a). The State is responsible for 56% of Brazilian sugarcane production, with 369 million tons harvested in the 2015/2016 season (UNICA, 2015). The crop covers about 20% of the State’s surface: according to the 2008 CANASAT cover map (Fig. 1.b) (CANASAT Project; Rudorff et al., 2010), it is concentrated in the central and north-eastern areas, which presents optimal climatic conditions for sugarcane. The climate is tropical to subtropical, with annual average temperature of 23°C and cumulated rainfall of 1400 mm according to the historical weather series for the period 1990-2009 (Instituto Nacional de Meteorologia, www.inmet.gov.br/). Rainfall events are concentrated in the north-eastern part of the State from September to March; temperature follows a north-west/south-east decreasing trend, with maximum values recorded during January and February. Sugarcane is usually harvested 12 or 18 months after sprouting both for planted and ratoon crops (i.e., canes resprouting from the stubbles of the previous crop), with the latter covering about 80% of cultivated area (Marin et al., 2016). On average, the ratoon crop is replanted every five years, due to the progressive yield decrease over successive ratoons. Fig. 2 highlights the main growth phases of 12 and 18 months sugarcane compared to monthly average mean temperature and cumulated rainfall in the State of São Paulo. Highest biomass accumulation rates are achieved in the most rainy and warmest periods of the year (i.e., boom growth phase in Fig. 2), whereas mild water stress (Inman-Bamber et al., 2008) and cooler temperatures

(Singels and Inman-Bamber, 2002) reduce crop vegetative growth and favor sucrose storage in the stalks (i.e., ripening and harvest periods in Fig. 2). Rainfall amounts and distribution in 90% of South-East Brazil allow the growing of sugarcane under rainfed conditions. According to the varietal census of RIDESA (2014), about 27% of the sugarcane area of the most productive Brazilian states (i.e., São Paulo and Mato Grosso do Sul) is currently covered by RB867515, a medium-ripening cultivar (Barbosa et al., 2008). According to the Brazil System of Soil Classification (EMBRAPA, 2013), the main soil classes characterizing the sugarcane areas are Ferralic Acrisols and Rhodic/Haplic Ferralsols, both displaying – although to a different extent – a sandy-clay texture. The soil map (https://www.embrapa.br/solos) was processed with a GIS software, assigning the most representative soil to each simulation unit (see beginning of Section 2.3.1 for more details).

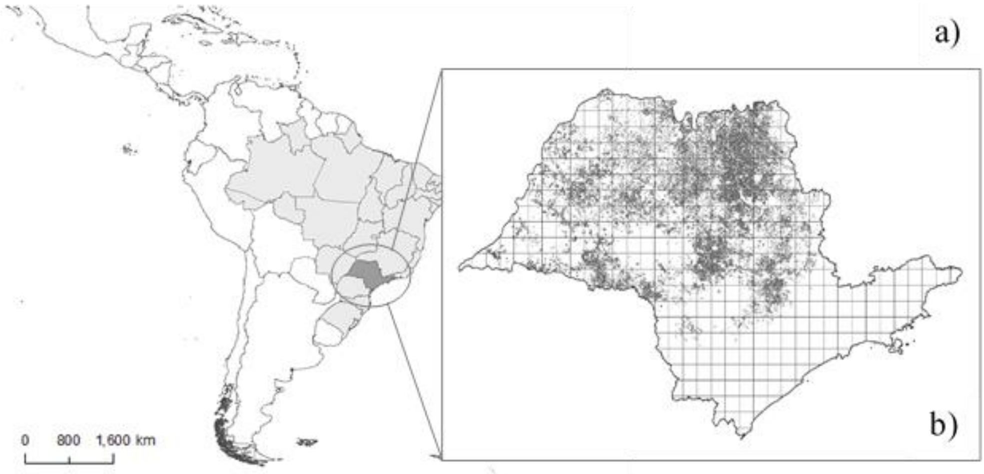


Figure 1: *a) Position of the State of São Paulo in South America and b) 0.25° latitude ×0.25° longitude simulation grid and sugarcane cover map (CANASAT, 2008).*

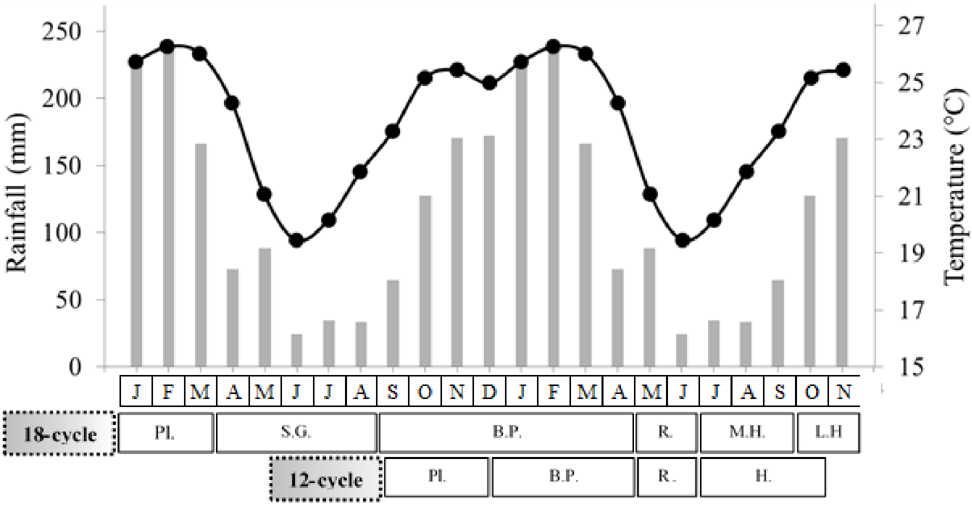


Figure 2: *main growth and management phases of 12 and 18-month cycle sugarcane plant crops (Source: Castro, 1999) and average monthly temperature (black circles) and rainfall (grey bars) in São Paulo state (average of the period 1990-2009, www.inmet.gov.br/). Pl=Planting; S.G.=slow growth; B.P.=Boom growth phase; H.=harvest; R.=ripening; M.H.=medium harvest; L.H.=late harvest.*

2.3.2. Simulation environment

The Canegro model (Inman-Bamber, 1991; Singels et al., 2008) dynamically simulates sugarcane growth and development from daily weather data, cultivar features, soil properties and agro-management information. Phenological development is estimated according to thermal time accumulation. After planting or ratooning, germination of primary tillers occurs when a specified thermal time has elapsed (longer for plant cane than for ratoon cane). Starting from this stage, a number of sequential tiller cohorts (i.e., groups of homogeneous tillers) are emitted until a peak population is reached and tiller senescence phase begins. Row spacing and water stress modify tiller appearance and senescence. Photosynthesis is driven by solar radiation interception, calculated according to Beer’s law using leaf area index (LAI) and extinction coefficient for solar radiation: LAI is derived from thermal time-driven development of individual leaves and tiller cohorts. On each tiller, leaf appearance is based on the phyllochron, i.e., the thermal time between the emergence of subsequent leaves. Increase in individual leaf length and width is derived from plant elongation rate, a variable determined by cultivar characteristics, average daily air temperature and water stress. Leaves stop expanding once they reach a maximum blade area, which varies according to cultivar and leaf position on the tiller. Senescence of green leaves is modulated by a variety-specific maximum number of active leaves: once this number is reached, the emission of a new leaf forces the oldest one on the tiller to die. The total number of leaves on the primary tiller is used to determine the extinction coefficient of solar radiation within the canopy. Tiller leaf area is scaled up to canopy level by multiplying, for each cohort, leaf area per tiller by the number of elements in the cohort per unit area. Daily increments of total biomass depend on the amount of intercepted photosynthetically active radiation (PAR), crop water stress, maintenance and growth respirations. PAR conversion efficiency and maintenance respiration depend on temperature as described by Singels et al. (2008). Partitioning of assimilates between above- and below-ground organs is simulated as a non-linear function of total biomass, with a large fraction of photosynthates partitioned to roots during early growth. Partitioning to roots support increase of both root mass and root length density, in turn influencing water uptake and water stress. A temperature-dependent fraction of aboveground biomass increment is partitioned to stalk; partitioning of stalk dry matter between sucrose and stalk structure is regulated by sink capacity for stalk structural growth and the source-to-sink ratio (Singels and Bezuidenhout, 2002). Sink capacity for structural growth and sucrose storage are modulated by growing conditions, stalk mass and cultivar characteristics, considering a variable distribution of sucrose within the stalk.

For this study, a customized modelling solution (MS) was developed for potential and water limited (rainfed) simulations. The MS links models belonging to different software components and manages their communication. Sugarcane growth and development is simulated using the algorithms made available by the UNIMI.CaneML component (http://www.cassandralab.com/components/2), which provides the MS with an implementation of Canegro explicitly designed to be coupled to other models (Stella et al., 2015). In particular, those belonging to CRA.AgroManagement component (Donatelli et al., 2006) are used to trigger crop management events (i.e., planting, harvest), whereas models from the UNIMI.SoilW software library (http://www.cassandralab.com/components/6) simulate soil water dynamics in order to account for water limitation to crop production. More specifically, a cascading model (Ritchie, 1998) and the EPIC approach (Williams et al., 1989) estimate, respectively, the downward movement of water through the soil profile and root water uptake. Given the target spatial scale, such approaches were selected in light of their limited input requirements.

The MS is implemented as a Microsoft C# class library managing the interactions between the I/O data produced by models belonging to the different software components. The entry point of the MS contains instances of Adapter classes (Gamma et al., 1994) and manages their call. Adapter classes, in turns, encapsulate the logic to perform dynamic simulation, by calling specific models selected among those provided by software components. The components implemented in the MS communicate in each integration time step (daily), by sharing information produced during the simulation. This information is stored in dedicated objects, i.e., DataTypes, containing instances of the data structures of all the components.

2.3.3. Yield forecasting

2.3.3.1. Spatially distributed simulations

Simulations were run for 0.25° latitude × 0.25° longitude grid cells covering the sugarcane area of the State of São Paulo (see Fig. 1b), according to the spatial resolution of the weather data obtained from the European Center for Medium-Range Weather Forecasts (ECMWF) Era-Interim database (Dee et al., 2011). Simulations were performed only on grid cells with a sugarcane cover greater than 7% (i.e., 215 simulation units). For each cell, average physical soil properties were attributed to three soil layers (i.e., 0-30 cm, 30-70 cm and 70-120 cm) according to information provided by the EMBRAPA soil database (https://www.embrapa.br/solos). Soil texture, organic carbon content and soil bulk density allowed estimating the parameters of the van Genuchten water retention curve (van Genuchten, 1980) via the pedotransfer functions proposed by Wösten et al. (1999). Canegro was parameterized according to Marin et al. (2011), who calibrated model parameters using a set of experimental data for the variety RB867515. For each cell, simulations were performed for both 12- and 18-month sugarcane cycles. For the first, resprouting was triggered at the end of November, and harvest at the beginning of November in the following year. For 18-month cycle, resprouting was set in February and harvest in November in the following year. In both cases, crop was harvested at the end of harvest window of sugarcane (Fig. 2). Due to its relative abundance, only ratoon crop was simulated. Ratooning was reproduced by initializing at resprouting root depth and root length density distribution in soil according to their values simulated at the previous harvest. Soil water content was simulated continuously during the whole period (2000-2013). For each cell and for each 10-day period, selected potential and water limited model state variables together with two soil-water balance indicators were stored in a database for both the 12- and 18-month cycles (Table 1).

Table 1*: List of Canegro model outputs and agro-climatic indicators stored each 10-day period and used for yield forecast.*

Indicator name	**Unit**	**Crop cycle** (months)	**Production level**	**Description**
Model outputs				
Stalk Dry Mass (SDM)	t ha^{-1}	12, 18	P*, WL**	Total stalk biomass (dry matter, including sucrose plus structural biomass)
Stalk Sucrose Mass (SSM)	t ha^{-1}	12, 18	P, WL	Dry sucrose biomass stocked in the stalk
LAI	m^2 m^{-2}	12, 18	P, WL	Total leaf area index
Water content indicator (WCI)	unitless	12, 18	WL	Average soil water content in the rooted zone from resprouting, as a fraction of plant available water
Water stress indicator (WSI)	unitless	12, 18	WL	Cumulated water uptake to cumulated potential evapotranspiration ratio from resprouting
Agro-climatic indicators				
TMAX	°C	12, 18	P,WL	Cumulated daily maximum temperature from resprouting
ET0	mm	12, 18	P,WL	Cumulated reference evapotranspiration (Hargreaves and Samani, 1985) from resprouting
Rain	mm	12, 18	WL	Cumulated rainfall from resprouting

**Potential production; **Water-limited production*

In particular, stalk dry and sucrose mass were selected since directly related with sugarcane productivity, whereas leaf area index and soil-water balance indicators were selected as synthetic representation of crop potential and to focus on the importance of water availability for sugarcane growth in Brazil. In order to make available yield data for each year, 18-months sugarcane was simulated twice by setting resprouting in even and odd years, respectively. For forecasting purposes, only the variables and indicators related to the crop harvested in the solar year were taken into account. In the same database and with the same frequency, the following agro-climatic indicators were stored: daily maximum temperature, rainfall and reference evapotranspiration cumulated from resprouting every 10-day period of forecast (Table 1). Finally, both Canegro model outputs and agro-climatic indicators were aggregated at State level according to the percentage of crop cover in each simulation unit obtained overlapping the grid and the CANASAT map (Fig. 1b).

2.3.3.2. Statistical analysis

Model outputs and agro-climatic indicators (Table 1) were related as independent variables of multiple linear regressions to the time series 2000-2013 of stalk biomass yields (IBGE, www.ibge.gov.br) for each of the 10-day period from January to October. Historical yield statistics were previously examined to identify and possibly remove the presence of significant technological trends. This allowed removing from the statistical analysis the factors not reproduced by the modelling solution (e.g., introduction of higher-yielding cultivars, changes in management practices). Regressors were first divided in three groups: agro-climatic, Canegro-potential and Canegro-water limited (Canegro-WL), in order to analyze separately the influence of the three categories of factors on sugarcane yields. Such categories were merged in a second step, which allowed identifying through a step-wise analysis the combinations of regressors able to explain the largest inter-annual yield variability.

A maximum of four independent variables were used in the regressions to reduce collinearity and overfitting problems. For each regression model the degree of multicollinearity was evaluated with the Variance Inflation Factor (VIF, Eq. 1, 1 to +∞, optimum = 1):

$$VIF_i = \frac{1}{1 - R_i^2} \qquad (1)$$

where R_i^2 represents the proportion of variance in the ith independent variable that is associated with the other independent variables in the model. A t-test was applied to verify the significance (p-value) of regression coefficients associated to each indicator. The influence of each indicator was also evaluated using the standardized coefficients. The absence of serial correlation among the residuals was verified via the Durbin-Watson statistic (Durbin and Watson, 1971; Eq. 2):

$$d = \frac{\sum_{t=2}^{n}(e_t - e_{t-1})^2}{\sum_{t=1}^{n} e_t^2} \quad (2)$$

where e_t is the difference between observed and predicted yield in the tth year of the time series; n is the number of years. The null hypothesis (i.e., absence of autocorrelation among residuals) is (i) accepted if the result of the test is higher than the upper critical value (d_U), (ii) rejected if the result is smaller than the lower critical value (d_L), and (iii) inconclusive if the result is between d_L and d_U (Savin and White, 1977).

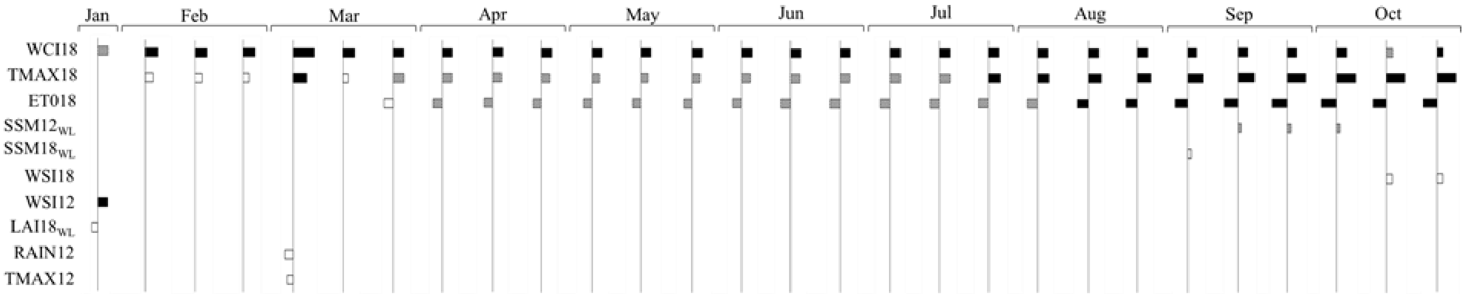
The predictive ability of the regression models was then tested performing a leave-one-out cross-validation on the available time series. Forecasted yields, obtained by excluding each time a single year during the cross-validation, were compared with historical yields. The prediction capability of each regression model was then evaluated through the calculation of the standard deviation error in prediction (SDEP, t ha^{-1}, 0 to +∞, optimum = 0), and the cross validation-coefficient of determination (R^2_{CV}) of the linear regression equation between official and predicted yields.

2.4. Results and discussion

The trend in the historical series of official yields was not significant, thus no de-trending was applied to the analysis.

Figure 3 displays, for each forecasting window, the best statistical model selected after the cross-validation among those proposed by the step-wise analysis. The significance level for all the combinations of regressors was lower than 0.05 regardless of the 10-day period. The only exceptions were observed for the first 20 days of January, since in this case the growth stages were too early to explain a sufficient part of the variability characterizing the season. For this reason, results for the first two 10-day periods are not further discussed.

Figure 3: *Standardized coefficients (bars), Durbin-Watson (D.W.) test (Eq. 2) and maximum VIF (Variance Inflation Factor) values (Eq.1) of regression models constructed with the best combination of Canegro-water limited (WL) outputs and agro-climatic indicators during sugarcane season (WCI=water content indicator; SSM=stalk sucrose mass; WSI=water stress indicator; LAI=leaf area index; TMAX=cumulated maximum temperature; ETO=cumulated potential evapotranspiration; Rain=cumulated rainfall; 12= the regressor was cumulated within the 12-month sugarcane cycle; 18= the regressor was cumulated within the 18-month sugarcane cycle), followed by the cross validation-coefficient of determination (R^2_{CV}), the slope and intercept of the linear regression equation between official and predicted yields The different items of the bars represent the significance level of the regression coefficients.*



D.W.	1.14	1.89	2.06	2.24	2.32	2.05	2.15	2.09	1.99	1.87	1.85	1.92	1.98	1.86	1.77	1.72	1.76	1.74	1.83	1.87	1.87	1.97	1.65	1.77	1.81	1.93	1.76	2.40
VIF	1.49	1.52	1.38	1.28	3.35	1.13	2.90	2.66	2.41	2.33	2.11	2.02	2.18	2.33	2.43	2.47	2.64	2.52	3.00	2.74	3.00	3.45	3.65	3.69	4.37	4.57	4.49	4.73
Slope	0.80	0.85	0.83	0.83	0.92	0.89	0.83	0.84	0.87	0.88	0.90	0.92	0.92	0.93	0.94	0.93	0.93	0.93	0.92	0.93	0.93	0.93	0.92	0.93	0.93	0.94	0.93	0.92
Int	16.3	12.3	13.7	14.0	6.03	9.25	13.6	13.2	10.8	9.37	8.12	6.23	6.69	5.32	4.67	5.44	5.38	5.97	6.52	5.74	5.34	5.97	6.72	5.40	5.34	4.48	5.97	6.31
R^2_{CV}	0.55	0.48	0.51	0.55	0.81	0.61	0.65	0.67	0.71	0.72	0.75	0.77	0.76	0.79	0.81	0.81	0.81	0.80	0.81	0.83	0.85	0.85	0.88	0.91	0.91	0.93	0.89	0.89

$p < 0.05$ *$p < 0.01$* *$p < 0.001$*

VIF values of selected regressors never exceeded five, which is lower than the threshold usually recommended to avoid multicollinearity (e.g., Hair et al., 2010; Rogerson, 2014) (Fig. 3). The null hypothesis (i.e., absence of correlation among residuals) of the Durbin-Watson test was accepted in all but two cases (i.e., January, 10th; September, 10th). In these cases, the test was inconclusive and null hypothesis could not be rejected (Fig. 3).

Once verified the absence of serial collinearity and autocorrelation, the use of multiple linear regressions allowed to clearly identify the factors (i.e., independent variables) influencing the final yield (i.e., dependent variable) for each of the 10-day periods when the forecasting events were triggered.

Both the significance level and the standardized coefficients underlined that the largest percentage of inter-annual yield variability was explained by WCI simulated for the 18-month sugarcane cycle (Fig. 3). This is consistent with conditions affecting sugarcane productivity in São Paulo, which is largely influenced by water availability, in turns depending on rainfall and on water redistribution in the soil layers explored by roots. Cumulated TMAX and ET0 were selected in almost all moments when the forecast was triggered, with the addition of some water-limited Canegro outputs in the harvesting months (e.g., water-limited state variables related with stalk sucrose content). Instead, Canegro outputs simulated under potential conditions for water were never selected by the stepwise regression, as further demonstrated by the low performance of the models including only Canegro-potential state variables in the statistical analysis (Fig. 4.b).

The forecasting reliability of the system significantly increased while proceeding along the growing season, with the exception of the seventh 10-day period (i.e., 10th March), for which the achieved uncertainty was smaller than the mean for the period (Fig. 3; Fig. 4.d,). The fact that the step-wise selected three agro-climatic indicators out of the four independent variables underlined how the trend of temperature and rainfall in this period, i.e., during the boom-growth phase, is – per se – critical for the final production. The best performances were achieved during the medium-late harvesting period (i.e., September-October), with an average SDEP lower than 1 t ha^{-1} (Fig. 4.d) and an amount of explained inter-annual variability that reached 93% on October 10th (Fig. 3). However, the system showed satisfactory performances also in early stages, with R^2 always exceeding

0.48 and RMSE never larger 2.01 t ha^{-1}. Figure 5 shows the system performance along the season for each year of the time series. It is interesting to note that the variability in forecasted yields along the same season tends to be smaller than the inter-annual yield variability.

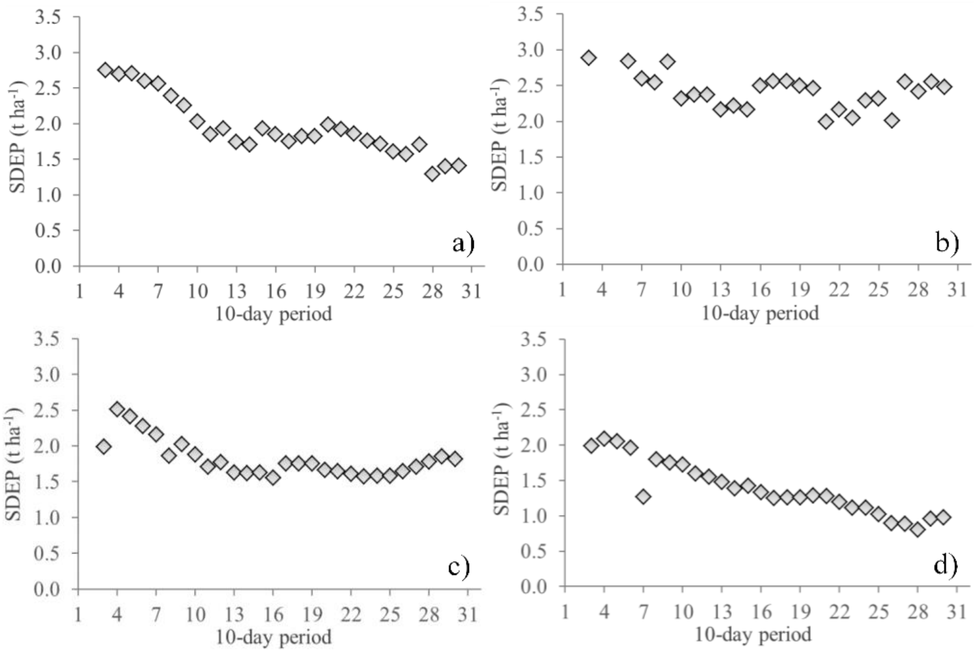


Figure 4: *Standard deviation error in prediction (SDEP) values (averaged for all the available years) derived from the comparison between official and predicted yields achieved by the forecasting system during the season. The four charts refer to cross validation of models from stepwise regressions when the following information was used: (a) agro-climatic indicators, (b) Canegro potential outputs, (c) Canegro water limited outputs, and (d) agro-climatic indicators + Canegro water limited outputs.*

The years with the highest yields in the official series (2008, 2009 and 2010) were identified as the most productive also by the forecasting system for the forecasting events triggered at medium-late harvesting time. However, yields were slightly underestimated in those cases. The marked overestimation observed for 2011 can be attributed to anomalous conditions that influenced sugarcane productivity while being uncommon in the historical period considered, i.e., prolonged droughts during 2010 winter months, occurrence of frost at the beginning of the 2011 harvest season, and abundant flowering (which causes a reduction of the sucrose and an increase of fiber) (UNICA, 2015).

Agro-climatic indicators, when used alone in the regression analysis, led to markedly decrease the forecasting error while proceeding along the sugarcane growing period (Fig. 4.a). At the end of the growing season, they allowed explaining about 80% of inter-annual yield variability, with an SDEP slightly lower than 1.5 t ha-1. However, during the boom growth phase (before April) when biomass accumulation rates are usually higher, the system based on agro-climatic indicators was characterized by larger errors, with RMSE ranging between 2.5 and 3 t ha-1. In this early phase, instead, water limited outputs of Canegro led to a substantial improvement compared to what achieved using only agro-meteorological indicators, with SDEP values falling below 2 t ha-1 (Fig. 4.d). The contribution of the water limited model outputs to the overall system reliability is less evident after the beginning of the harvest period. After this stage, indeed, plant starts to allocate resources towards the synthesis of sucrose and to reduce the percentage of photosynthates partitioned to the stalk structural components, leading water limited model outputs to keep a nearly constant predictive power until the end of the sugarcane cycle (Fig. 4.c).

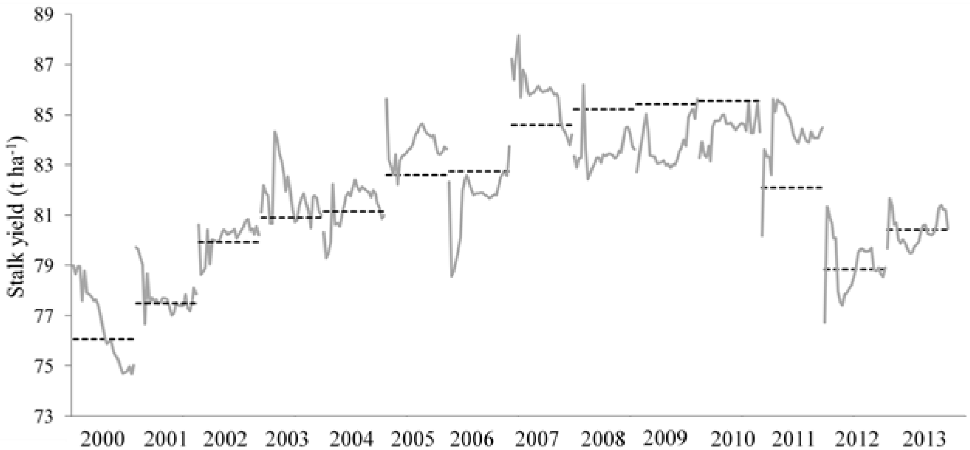


Figure 5*: Comparison between official stalk yield records (dotted lines) and yields forecasted after the cross-validation for each 10-day period within the selected window (January-October).*

The system we developed is based on a simplification of the actual management of the 12 and 18-cyle sugarcane in Brazil, a planting schedule that has been slightly modified in the last decade to reduce costs. In particular, the model configuration could be affected by non-negligible sources of uncertainty, since based exclusively on information retrieved from the literature. Indeed, the model was parameterized for one variety, the same resprouting date was used for all seasons and simulation units, and soil data were characterized by low-resolution. The Canesim-based system developed for South African millers by Bezuidenhout et al. (2007a,b) is more complex and based on more detailed information. As an example, input weather data were collected from a network of ground stations and the system was tested after the historical series of yield data was de-trended with information on mill closures and cane diversions, harvest age, and changes in irrigated area. Moreover, forecasting results were provided at industry and mill level. For the former, mean error and modelling efficiency were 6.6% and 0.57 at harvest. Results are slightly poorer than those obtained in this study; however, the system proposed by Bezuidenhout et al. (2007a,b) provided information at a spatial scale that makes the information more useful for farmers and other actors of the production chain involved, e.g., with milling operations and sugar shipments. A different system was developed by Duveiller et al. (2013) for the state of São Paulo using remotely-sensed information as independent variables of multiple linear regressions with official yields. The system achieved satisfactory results, with values of the agreement metrics consistent with those achieved in this study. However, a forecasting system solely based on remote sensing could be partly unsuitable in case of stressors affecting yields or product quality without clear damages to the canopy, or in contexts characterized by high yields, since the vegetative vigor could saturate the signal (Dobson et al., 1995; Zhao et al., 2016).

Considering the performances of the existing approaches, the overall predictive ability of our system is satisfactory, proving that sensible forecasts can be achieved even by using a simplified system. Moreover, this type of approach is quite simple to automate and thus easily transferable to other contexts. The performances of the system, especially at the beginning of the season, could be further improved by using more accurate information provided by local authorities and institutions.

2.5. Conclusions

A forecasting system was developed for sugarcane yields, based on outputs from the Canegro simulation model and agro-climatic indicators. As case study, the system reliability was quantified for the State of São Paulo, Brazil. The overall system performance was satisfactory, with the most reliable predictive ability achieved when the forecasting event was triggered during the medium-late harvesting period (i.e., September-October). In this case, average values for SDEP and R^2_{CV} were 0.92 t ha^{-1} and 0.90, respectively, with the largest amount of inter-annual yield variability (93%) achieved at the beginning of October. Despite the discrete performance obtained when only agro-climatic indicators were used, the addition of the Canegro model outputs allowed getting a marked increase in the system's capability to capture yearly yield fluctuations, especially during the boom growth phase of the sugarcane cycle.

The results achieved by the forecasting system – applied here for one of the largest and most productive sugarcane districts worldwide – were satisfactory also considering that the historical series of official yields (2000-2013) had no significant trend, thus the system itself explained the greatest part of the inter-annual yield variability, without portions of variance explained by technological trends.

These observations allow considering the forecasting system we developed as suitable for sugarcane yield forecasts in operational contexts in Brazil, thus supporting multiple actors in the Brazilian sugarcane sector. Marketers are interested in yield predictions both during early stages of the sugarcane growing cycle and during harvesting months. Indeed, on the one hand, early forecasts of productivity are crucial to plan market operations; on the other hand, yield estimates during the harvesting months are important as well, since official yield data are not immediately available at the end of the season.

Further improvements to operationalize the system could be possibly achieved by the integration within the system of more accurate input data provided by the collaboration with local institutions.

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EVALUATION OF WARM FOR DIFFERENT ESTABLISHMENT TECHNIQUES IN JIANGSU (CHINA)

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3.1. Abstract

WARM is a model for rice simulation accounting for key biotic and a-biotic factors affecting quantitative and qualitative (e.g., amylose content, chalkiness) aspects of production. Although the model is used in different international contexts for yield forecasts (e.g., the EC monitoring and forecasting system) and climate change studies, it was never explicitly evaluated for transplanting, the most widespread rice establishment method especially in tropical and sub-tropical Asia. In this study, WARM was tested for its ability to reproduce nursery growth and transplanting shock, using data on direct sown and transplanted (both manual and mechanical) rice collected in 24 dedicated field experiments performed at eight sites in Jiangsu in 2011, 2012 and 2013. The agreement between measured and simulated aboveground biomass data was satisfactory for both direct sowing and transplanting: average R^2 of the linear regression between observed and simulated values was 0.97 for mechanical transplanting and direct sowing, and 0.99 for manual transplanting. RRMSE values ranged from 5.26% to 30.89%, with Nash and Sutcliffe modelling efficiency always higher than 0.78; no notable differences in the performance achieved for calibration and validation datasets were observed. The new transplanting algorithm – derived by extending the Oryza2000 one – allowed WARM to reproduce rice growth and development for direct sown and transplanted datasets (i) with comparable accuracy and (ii) using the same values for the parameters describing morphological and physiological plant traits. This demonstrates the reliability of the proposed transplanting simulation approach and the suitability of the WARM model for simulating rice biomass production even for production contexts where rice is mainly transplanted.

Keywords: direct sowing; *Oryza sativa* L.; seedbed; sowing technique; transplanting.

3.2. Introduction

Rice (Oryza sativa L.) is the staple food for more than three billion people worldwide, providing 35-75% of their dietary calories (Krishnan et al., 2011). Global rice production amounts to more than 720 million tonnes (FAO, 2011). The cultivated area is concentrated in Asia, with China accounting, alone, for the 28% of the total production (FAO, 2011).

The two main methods for establishing rice plants are direct sowing and transplanting, with the latter implying growing rice seedlings in a nursery bed near the main field before manually or mechanically transplanting them about 15-40 days after sowing (IRRI, 2009). Although transplanting requires significantly more labour than direct sowing, it is still the main technique used to establish rice in developing countries, especially in tropical and sub-tropical Asia. Transplanting, indeed, favours rice over emerging weeds and allows a higher degree of intensification because rice takes up the main field for less time (IRRI, 2009). In the last two decades, transplanting was partially replaced by direct sowing in important producing countries like Malaysia and Thailand (Pandey et al., 2000). However, the price of herbicides still makes manual transplanting the preferred solution in most low-income areas (Chen et al., 2009; IRRI, 2009).

In some temperate Asian countries like Japan, Korea, Taiwan and part of China, the reduced availability of manpower in the countryside and the increasing cost of labour are leading to gradual abandonment of manual transplanting in favour of mechanical techniques (Pandey et al., 2000). Mechanical transplanting is much more efficient than manual in terms of manpower use (1-2 ha $person^{-1}day^{-1}$ compared to 0.07 ha $person^{-1}$ day^{-1}), although it requires more financial and technological resources (IRRI, 2009) and is hardly feasible in hilly-terraced regions, like, e.g., those present in northern Philippines.

Among the widespread models for rice simulation, only CERES-Rice (Jones et al., 2003), ORYZA2000 (Bouman et al., 2001; Bauman and van Laar, 2006), APSIM-Oryza (Gaydon et al., 2012a; 2012b), NIAES-Rice (Hasegawa and Horie, 1997) and RIBHAB (Salam et al., 2001) reproduce the key processes involved with nursery growth and transplanting shock. The latter is crucial because of its effect in arresting the main physiological processes involved with crop growth and development after the event, thus extending the length of the crop cycle (Salam, 1992). The duration of the shock depends on seedling age, pulling methods, handling during transplanting, cultivar characteristics and weather conditions before and after transplanting (SARP, 1987).

It is possible to find in the literature various studies where the transplanting algorithms of the above-mentioned rice models were tested under different environmental and management conditions. Sudhir-Yadav et al. (2011) tested the ability of ORYZA2000 to simulate the effects of different water management techniques on transplanted rice in north-western India. Mahmood et al. (2004) applied CERES-Rice to 16 locations representative of the major rice growing regions in Bangladesh to study the effect of water stress on transplanted rice. However, an effective evaluation of the algorithms involved with transplanting should be performed by using datasets with the same (or similar) cultivars established using both the techniques (e.g., Hossain et al., 2002; San-oh et al., 2004), whereas – according to the authors' knowledge – the available studies refer only to either direct sowing or transplanting datasets. The risk, in this case, is to include the effect of biophysical processes dealing with transplanting in the values of parameters that should instead describe only morphological and physiological plant features, or – vice versa – to include cultivar features involved with, e.g., phenology, in the parameters of the transplanting shock algorithms. The assumption behind these considerations is obviously that a model should work with exactly the same set of crop parameters for both the establishment methods, when cultivars with similar features are used. This would demonstrate the reliability of the transplanting algorithm and the coherence of the way it is coupled to the crop model.

WARM (Confalonieri et al., 2009) is a model specific for the simulation of rice-based cropping systems, operationally used by the European Commission for rice monitoring and yield forecasts since 2006, and adopted in different international projects (e.g., EU-FP7 E-AGRI, MODEXTREME, ERMES, World Bank AZS) and networks (i.e., AgMIP). The possibility of reproducing the interaction between fungal pathogens and the host plant, and the impact of abiotic factors (e.g., temperature shocks, lodging) on qualitative and quantitative aspects of productions make this model particularly suitable for evaluating the impact of climate and management scenarios. The main restriction of the first version of the model was the absence of an algorithm for the simulation of processes involved with transplanting.

The objectives of this study were:

- to develop a new algorithm within WARM to reproduce the dynamics involved with both manual and mechanical transplanting;
- to evaluate WARM using datasets where the same (or similar) varieties were grown under both direct sowing and transplanting conditions, in order to verify the capability of the model to reproduce – using the same parameter set – the effect of different establishing methods on rice growth and development.

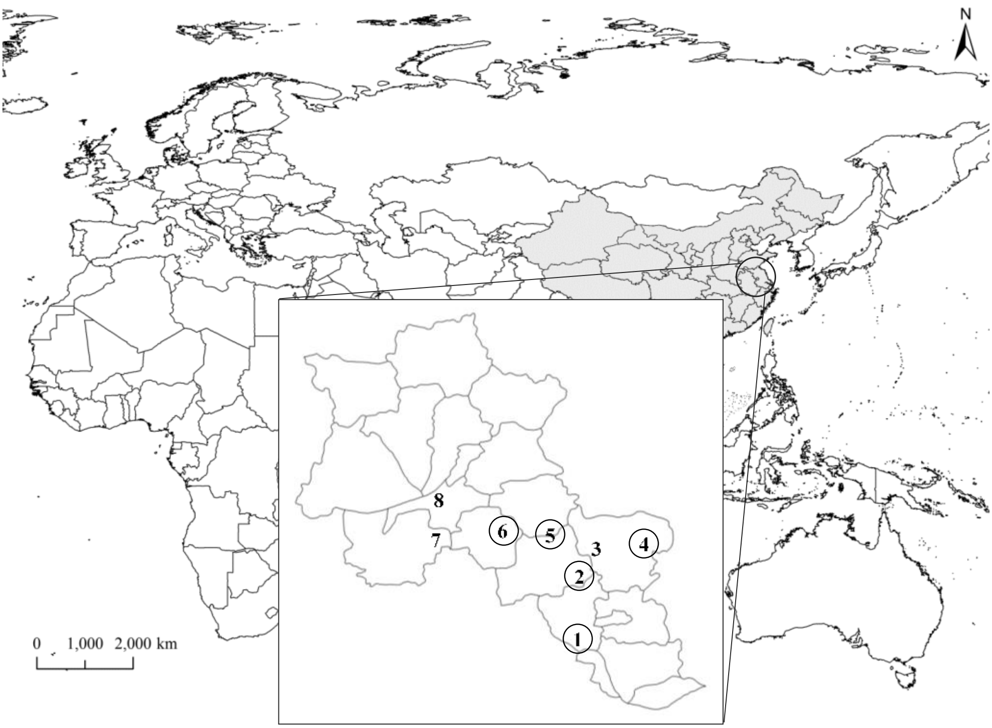

Figure 1: *Experimental sites (see Table 1 for details). Calibration datasets are enclosed by circles.*

3.3. Materials and methods

3.3.1. Experimental data

Data were collected in the Jiangsu province of the People's Republic of China in 2011, 2012 and 2013, at eight sites located in the central-western part of the province (Fig. 1). The climate in the experimental area is humid subtropical; mean annual temperature is about 15°C, and daily values often exceed 30°C in summer. Cumulated rainfall ranges between 800 and 1200 mm. During the period when experiments were carried out, 2011 was characterized by abrupt temperature fluctuations in the sowing periods and temperature slightly lower than the average during the flowering phase; in the same year, the highest cumulated rainfall during the crop cycle was gauged, whereas the highest temperatures during summer were recorded in 2013. The soils in the sites located in the southern part of the province (experiments 1 to 5) were clay, whereas those in the central part of the province (experiments 6 to 8) were clay loam (USDA classification). All the soils presented a medium organic matter content, although higher values were measured in the southern sites (about 25 g kg^{-1} against 20 g kg^{-1} of the central sites), and pH was always subacid, ranging from 6.5 to 6.8. For all the sites, soils had sufficient available phosphorous and medium potassium content. For all the experimental sites, rice was grown under flooded conditions, thus soil moisture never limited crop growth and development. In the same way, fertilizers (distributed pre-sowing and in one top-dressing event), herbicides and pesticides assured potential conditions for plants in all sites and years. Information on the main characteristics of the experimental sites, on the varieties grown and on management techniques is summarized in Table 1. According to the site and year, rice was directly sown between the first and the second week of June, or transplanted between the third and the fourth week of June. In case of manual transplanting, the mean seedling age at transplanting was 40 days and the seed density in the nursery was around 3000 seeds m-2, coherent with values normally found in literature (e.g., Sharma and Ghosh, 1999; Pasuquin et al., 2008). In case of mechanical transplanting, 58 cm × 28 cm plastic plates were used for the nursery, with 150 g of seeds for each tray (Fisher et al., 2004; FAO, 2012) and seedlings transplanted after about 30 days.

Table 1: *Datasets used for model calibration and evaluation. DS: direct sowing; MT: mechanical transplanting; MM: manual transplanting.*

Exp. ID	District	Town/City	Lat N Long E	Year	Sowing date	Hybrid	Cultivation method	Used in calibration
1	Yangzhou	Shatou, Hanjiang	32°16' 119°33'	2011	26-May	Yangjing 4227	MT	×
				2012	20-May			×
				2013	28-May	Wuyunjing 24		
2	Yangzhou	Fanchuan, Jiangdu	32°40' 119°40'	2011	12-Jun	Huaidao 5	DS	×
				2012	6-Jun			×
				2013	8-Jun			
3	Taizhou	Lincheng, Xinghua	32°50' 119°47'	2011	12-Jun	Huaidao 5	DS	
				2012	9-Jun			
				2013	10-Jun			
4	Taizhou	Changrong, Xinghua	32°56' 120°05'	2011	11-Jun	Huaidao 5	DS	×
				2012	7-Jun			×
				2013	8-Jun	Zhendao 88		
5	Yangzhou	Xiaji, Baoying	33°02' 119°32'	2011	13-Jun	Huaidao 5	DS	×
				2012	12-Jun			×
				2013	14-Jun			
6	Huaian	Tugou, Jinhu	33°03' 119°13'	2011	10-May	C Liangyou 608	MM	×
				2012	5-May	C Liangyou 343		×
				2013	5-May	Huiliangyou 3		
7	Huaian	Dailou, Jinhu	33° 118°53'	2011	5-May	Y Liangyou 1	MM	
				2012	8-May	Y Liangyou 464		
				2013	5-May	Huiliangyou 996		
8	Huaian	Zhuba, Hongze	33°14' 118°53'	2011	20-May	Huaidao 5	MT	
				2012	7-Jun	Xudao 3	DS	
				2013	22-May	Huaidao 5	MT	

Plant state variables were determined eight/nine times during the crop cycle on 10 to 20 randomly selected plants per plot according to the variable (Gomez, 1972; Confalonieri et al., 2006). Phenological stages of emergence, booting, heading, flowering and physiological maturity were determined (codes 09, 41, 59, 65 and 92 of the BBCH scale for rice; Lancashire et al., 1991), and physical and chemical properties of soils were measured at the beginning of each experiment. In this study, aboveground biomass (AGB; determined on 20 plants) data were used for model calibration and validation.

Available data were split into calibration and validation datasets as shown in Fig. 1 and Table 1, with the aim of providing each of the two datasets with data from rice cultivated in the three establishment methods analyzed in this work (direct sowing, mechanical and manual transplanting).

3.3.2. WARM model

WARM (Confalonieri et al., 2009) is a model specific for rice simulations, and reproduces crop growth and development with daily (used in this study) or hourly time step. It was developed using a component oriented approach, and it is available both as stand-alone package for field level simulations (at cassandra.lab@unimi.it) and as a modelling solution within the BioMA platform (Donatelli et al., 2012). The model simulates quantitative (e.g., biomass, yield) and qualitative (e.g., amylose content, chalkiness, percentage of fissured grains; Cappelli et al., 2014) aspects of rice production under conditions limited by water availability and by a variety of biotic (interaction between rice and fungal pathogens) and a-biotic factors (spikelet sterility due to pre-flowering temperature shocks, lodging), as well as agrochemicals fate. In case of flooded conditions, the floodwater effect on the vertical thermal profile is reproduced via the micrometeorological model TRIS (Confalonieri et al., 2005), providing temperature at the meristematic apex to routines involved with development and spikelet formation, and mid-canopy temperature to photosynthesis and leaf aging algorithms.

Crop development is simulated as a function of thermal time, with an option to account for the effect of photoperiod. Aboveground biomass accumulation is simulated using the concept of net photosynthesis and a monolayer representation of the canopy, with a modified radiation use efficiency (RUE) approach based on RUE response to temperature, saturation of the enzymatic chains, senescence and diseases. Photosynthates are daily partitioned to leaves, stems and panicles using a set of quadratic and beta functions driven by development stage and a parameter representing the amount of biomass partitioned to leaves at emergence. During grain filling, translocation to panicles due to leaf senescence is simulated by accounting for the efficiency of the conversion from leaf to grain N-rich compounds. Leaf area index (LAI) is derived from leaf biomass and specific leaf area (SLA), with the latter varying according to development stage and the two input parameters (SLA at emergence and at mid-tillering). Daily-emitted leaf units live until a threshold amount of degree-days is reached, and leaf senescence is calculated by subtracting the dead LAI units from the total one.

Further details on the model algorithms are available in the seminal literature and in the documentation of the components used in the WARM modelling solution (http://agsys.cra-cin.it/tools/help/)

3.3.3. The transplanting algorithm

Algorithms for rice transplanting must deal with four key processes: the determination of leaf area index when seedlings emerge in the seedbed, the proper simulation of post-emergence growth in the seedbed, the dilution of photosynthetic area per unit soil surface when plants are transplanted, and the duration/impact of the transplanting shock.

In Oryza2000 (Bouman et al., 2001), the simulation of seedlings growth in the nursery is based on the initialization of LAI at emergence, whereas Ceres-Rice (Jones et al., 2003) and RIBHAB (Salam et al., 2001) models use empirical functions for the simulation of the endosperm mobilization from seeds to seedlings. We decided to start from the Oryza2000 approach since it was considered as the most coherent with the level of detail used by WARM for reproducing emergence and post-emergence dynamics in case of direct sown rice.

The new solution developed for WARM extends the Oryza2000 algorithm by calculating (i) the initial value of LAI in the seedbed (without needing an user-specified initialization value), (ii) changes in plant traits (extinction coefficient and specific leaf area at emergence) due to the plant adaptation to high seedbed densities, and (iii) the mortality of plants in the seedbed. These improvements to the Oryza2000 algorithm refer to Equations 1 to 4, whereas Equations 5 and 6 refer to steps of the original algorithm that were not altered.

Initial LAI in the seedbed is estimated using Equation 1:

$$LAISB_{ini} = LAIF_{iniOpt} \cdot \frac{SBD}{FD_{opt}} \tag{1}$$

where $LAISB_{ini}$ ($m^2\ m^{-2}$) is the initial value of LAI in the nursery bed; $LAIF_{iniOpt}$ ($m^2\ m^{-2}$) and FD_{opt} are, respectively, the initial LAI and the plant density for optimal rice establishment in case of direct sowing; SBD is the seedbed density in the nursery (plants m^{-2}). $LAIF_{iniOpt}$ and FD_{opt} were set, respectively, to 0.007 m^2 m^{-2} (unpublished data) and 125 plants m^{-2} (Ottis and Talbert, 2005), whereas *SBD* ranged – according to the different datasets – from 3000 seeds m^{-2} to 30000 seeds m^{-2} for manual and mechanical transplanting, respectively.

In order to improve the pre-transplanting simulation, seedbed conditions were reproduced by means of Eqs. 2 to 4, derived from unpublished data collected in two of the experimental sites. In particular, the effect of the high seedbed density on extinction coefficient for solar radiation (k) – important especially for the high seedbed density used for mechanical transplanting – was simulated using Eq. 2.

$$k = -0.054 \cdot \ln(SBD) + 0.81 \tag{2}$$

Many authors demonstrated how the high competition for solar radiation leads plants to increase the leaf area to mass ratio (i.e., SLA, m^2 kg^{-1}) (e.g., Williams et al., 1965; Asch et al., 1999). This effect was reproduced using Eq. 3:

$$SLASB_{em} = \begin{cases} SLA_{em} \cdot \sqrt{\dfrac{SBD + 3775}{3900}} & SBD < 5000\, plants \cdot m^{-2} \\ 1.5 \cdot SLA_{em} & elsewhere \end{cases} \tag{3}$$

where $SLASB_{em}$ (m^2 kg^{-1}) and SLA_{em} (m^2 kg^{-1}) are, respectively, the value of SLA at emergence as affected by seedbed density, and SLA at emergence measured/calibrated for direct sowing.

The mortality (α, %) of plants in the seedbed was estimated using Eq. 4.

$$\alpha = \begin{cases} \dfrac{\left[\left(\dfrac{SBD}{15000}\right) \cdot \left(\dfrac{30000 - SBD}{15000}\right)\right]^{1.6}}{2} & SBD < 15000\, plant \cdot m^{-2} \\ 0.5 & elsewhere \end{cases} \tag{4}$$

For the dilution of photosynthetic area per unit soil surface at the transplanting event, the Oryza2000 approach was used (Eq. 5):

$$LAIF_{tr} = LAISB_{btr} \cdot \frac{FD}{SBD_{btr} \cdot (1-\alpha)} \quad (5)$$

where $LAIF_{tr}$ and $LAISB_{btr}$ (m^2 m^{-2}) are the LAI values in the field after transplanting and in the seedbed before transplanting, respectively; *FD* (plants m^{-2}) is the plant density in the field after transplanting; SBD_{btr} is the seedlings density, SBD_{btr} is here assumed to be affected by the survival rate 1–α.

When transplanting occurs, rice development and growth stop until the end of the shock period. Even in this case, the Oryza2000 algorithm (Eq. 6) – based on the relationship between shock duration (*TSHCKL*, °C $days^{-1}$) and seedling age at the moment of transplanting (*SA*, °C $days^{-1}$) – was used:

$$TSHCKL = SA \cdot SHCKD \quad (6)$$

where *SHCKD* is a parameter used to modulate the relationship between seedling age and shock duration according to the different cultivar sensitivity. The value of *SHCKD* was here set to 0.5.

3.4. Results

Calibrated parameters were those identified with the sensitivity analysis performed by Confalonieri et al. (2012), in light of the low model plasticity underlined by the authors. For both calibration and validation, simulations were performed under potential conditions. Parameter values and sources of information are shown in Table 2, whereas Figs. 2 and 3, and Table 3 present the results of the comparison between measured and simulated aboveground biomass data for the calibration and validation datasets.

The calibration led to good agreement (R^2 = 0.97) between measured and simulated AGB data in case of direct sowing (Fig. 2.a-f), as confirmed by the average relative root mean square error (RRMSE; %, 0 to ∞; optimum = 0; normalized for the mean of observations) of 20.14%, and by modelling efficiencies (EF; unitless, -∞ to +1; optimum +1; if negative indicates that the average of observations is a better predictor than the model; Nash and Sutcliffe, 1970) always higher than 0.80 (Table 3). Results also highlighted the general slight overestimation of the model, although the values of coefficient of residual biomass (CRM; unitless, -∞ to +∞, optimum 0; if positive indicates underestimation and vice versa; Loague and Green, 1991) were never lower than -0.23. Figs. 2.a-f show that the model overestimation especially concerns the final biomass values collected in experiments 2 and 4 performed in 2012 (Figs. 2.b, 2.d and Table 3). Figs. 2.g-j show that the accuracy of the model in reproducing AGB values for transplanting is similar to that achieved for direct sown rice. Even in this case, RRMSE never exceeded 20% and EF was always higher than 0.90 (Table 3), although a slight underestimation was obtained for the 2012 datasets (Figs. 2.h, 2.j; CRM = 0.15).The performances of the model in reproducing manual and mechanical transplanting were very similar, with average RRMSE equal to 15.79% and 14.36%.

Table 2: *Parameters values and source of information (C: calibrated parameters; L: literature). GDD: growing degree days. AGB: aboveground biomass.*

Parameter	Units	Value	Description	Source
			Development	
TbaseD	°C	12	Base temperature for development	LSié et al. (1998)
TmaxD	°C	42	Maximum temperature for development	LSié et al. (1998)
GDDem	°C-days	90	Thermal time from sowing to emergence	C
GDDem-fl	°C-days	1175	Thermal time from emergence to flowering	C
GDDfl-mat	°C-days	600	Thermal time from flowering to maturity	C
			Growth	
RUEmax	g MJ^{-1}	2.50	Maximum radiation use efficiency	C
k	unitless	0.47	Extinction coefficient for solar radiation	C
TbaseG	°C	13	Base temperature for growth	C
ToptG	°C	26	Optimum temperature for growth	C
TmaxG	°C	38	Maximum temperature for growth	C
SLAini	m^2 kg^{-1}	33	Specific leaf area at emergence	C
SLAtill	m^2 kg^{-1}	19	Specific leaf area at tillering	C
RipL0	unitless	0.77	AGB partition to leaves at emergence	C
LeafLife	°C-days	820	Leaf duration	C

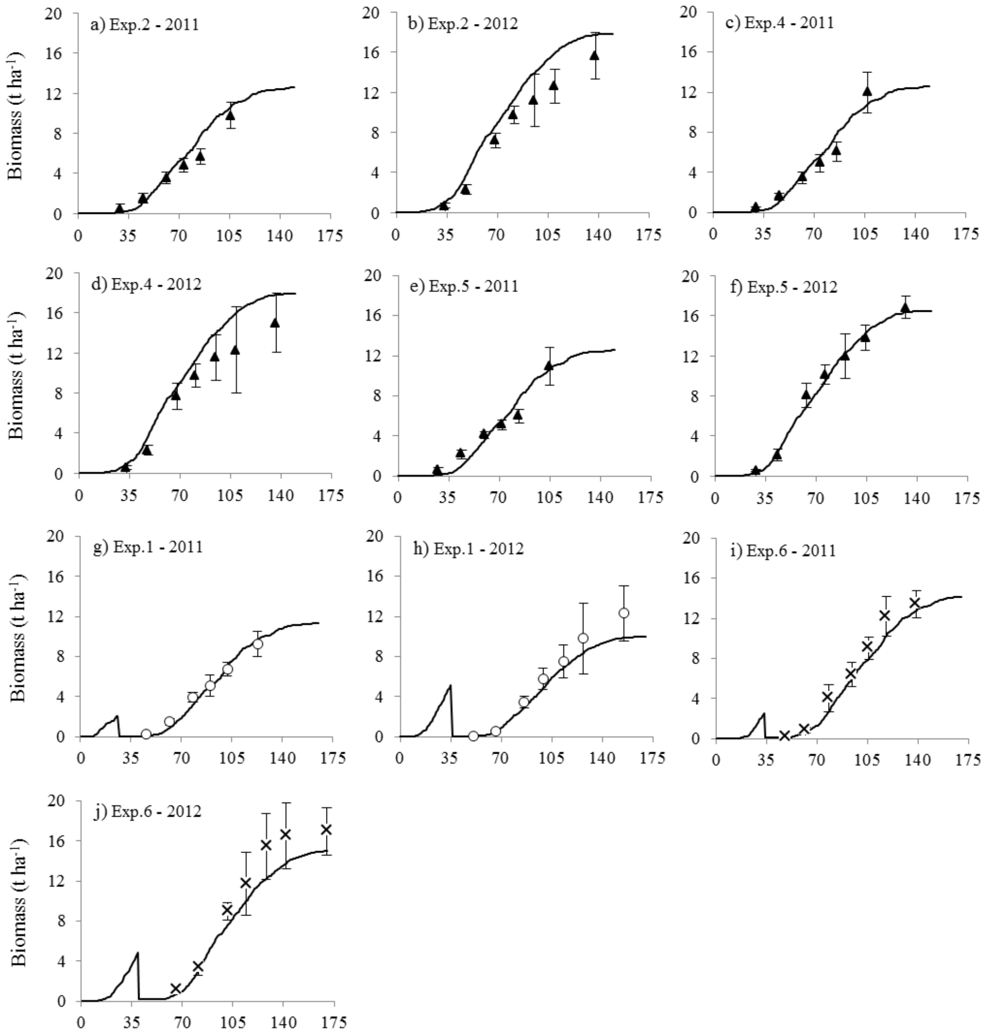

Figure 2*: Comparison between measured and simulated aboveground biomass (AGB) data for the calibration datasets. Days after sowing on the X-axis. Black triangles, white circles and crosses refer to direct sowing, mechanical and manual transplanting, respectively. Continuous line represents simulated AGB. For the transplanting datasets, the AGB peak before the typical S-shaped curve describing AGB accumulation refers to seedling growth in the nursery (before plants are diluted in the main field).*

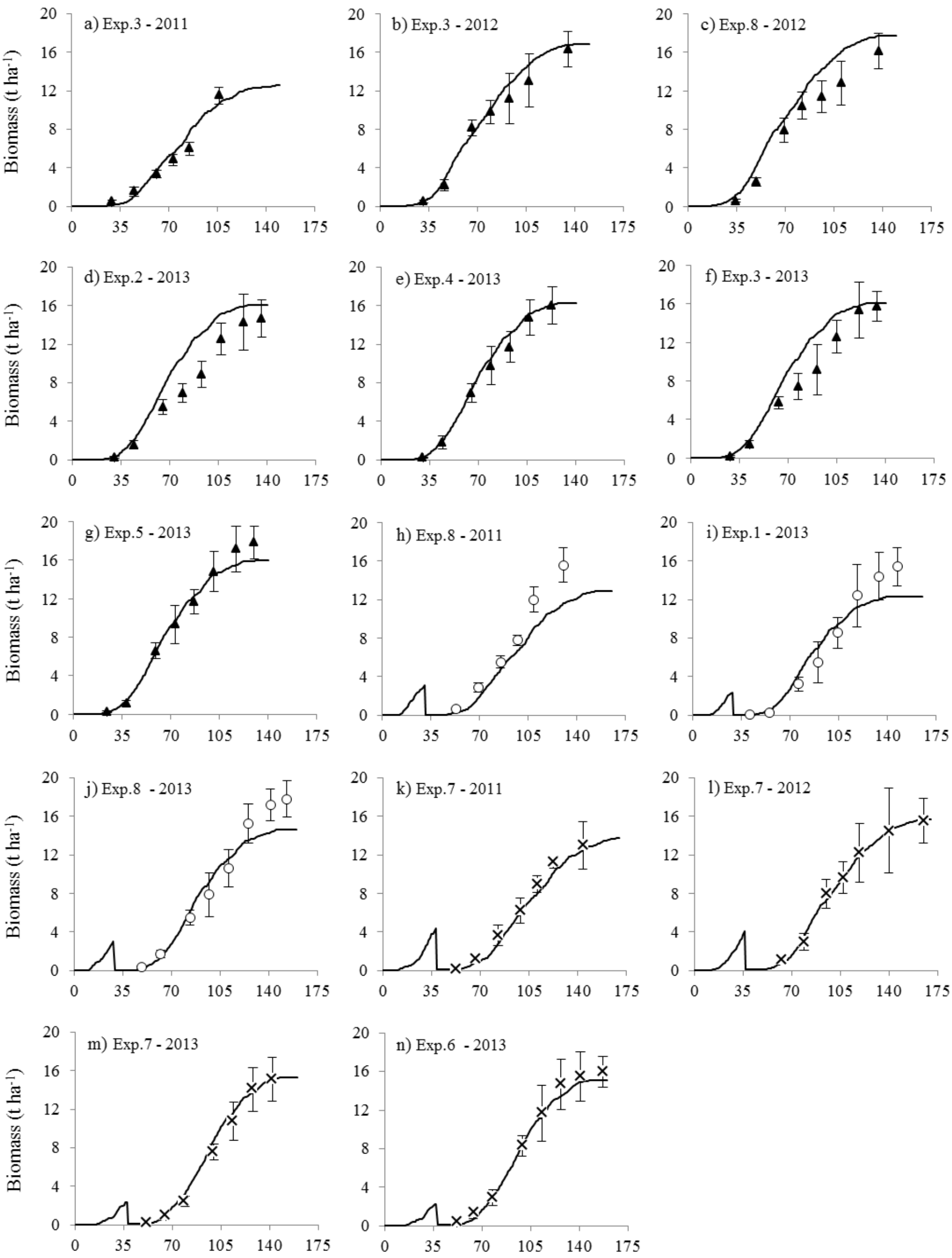

Figure 3: *Comparison between measured and simulated aboveground biomass (AGB) data for the validation datasets. Days after sowing on the X-axis. Black triangles, white circles and crosses refer to direct sowing, mechanical and manual transplanting, respectively. Continuous line represents simulated AGB.*

The set of parameters obtained from the calibration was tested using the remaining 2011 and 2012 datasets, and using all the data collected during 2013. The results obtained for the validation datasets confirmed the satisfactory performances achieved by WARM after calibration. Figs. 3.a-g show that the agreement between measured and simulated AGB data for direct sown rice reflects the one achieved for calibration, with RRMSE ranging from 7.39% to 30.07% and average EF equal to 0.91. For manual transplanting, the WARM performances for the validation datasets were even better than those achieved after calibration (Figs. 3.k-n), with average RRMSE and EF equal to 7.93% and 0.99. The model performances during validation for mechanical transplanting (Figs. 3.h-j) confirmed the slight underestimation tendency during the pre-harvest phases discussed for some of the calibration datasets. However, the model achieved even in these cases satisfying results, with average RRMSE and EF equal to 23.68% and 0.88.

3.5. Discussion

Calibrated parameter values (Table 2) are in the range of those available in the literature. Cardinal temperatures for thermal limitation to photosynthesis are consistent with those estimated by Yin and Kropff (1996) and Sié et al. (1998), and used in modelling studies by Mall and Aggarwal (2002). The value of maximum radiation use efficiency (RUEmax) is coherent with those measured by Kiniri et al. (2001) and used for Chinese rice varieties by Confalonieri et al. (2009). Parameters involved with leaf area evolution, i.e., specific leaf area at emergence (SLAini) and at mid-tillering (SLAtill), are similar to those proposed by Dingkuhn et al. (1998), as well as the extinction coefficient for solar radiation (k).

In general, the WARM accuracy while reproducing AGB values was similar to the one achieved by other rice specific models for the same variable (e.g., Salam et al., 2001; Bouman and van Laar, 2006; Belder et al., 2007), and to what was achieved by the same model under different agro-climatic and management conditions (Confalonieri et al., 2009). The satisfactory reliability of WARM in reproducing growth dynamics for both transplanted and direct sown rice was confirmed by the validation activity carried out using the eight datasets collected in 2013, characterized by weather conditions not explored during calibration. According to the threshold-based classification proposed by Jamieson et al. (1991), RRMSE values for the validation datasets can indeed be considered as excellent in six out of 14 cases (RRMSE <10%), good in three out of 14 cases (RRMSE between 10% and 20%), and acceptable in four out of 14 cases (RRMSE between 20% and 30%). Only for one dataset, the 30% threshold was slightly exceeded (30.07% for experiment 2 in 2013, direct sowing). The satisfying performances are also demonstrated by comparing the values of RMSE with the observed experimental variability. RMSE values, indeed, were often lower than 1 t ha^{-1}, whereas the standard deviation of observations was always larger after flowering. However, the coefficient of variation of observed AGB values was always around 15%, in agreement with Belder et al. (2007), who considered this as the typical uncertainty in yield determination during field experiments.

The goodness of the new transplanting algorithm – and its suitability for different transplanting techniques – is demonstrated by the results obtained by performing the calibration and evaluation with the WARM model coupled to the original (unmodified) Oryza2000 transplanting algorithm. The model, using this configuration, adequately simulated rice growth and development for the datasets where rice was manually transplanted (average RRMSE and EF equal to 29.12% and 0.80), whereas it completely failed while reproducing rice growth in the nursery in case of mechanical transplanting, where plants density is decidedly higher than those the algorithm was developed for. Indeed, results underline a marked underestimation of biomass values (average CRM = 0.77), with average RRMSE and EF equal to 93.46% and -0.74. The algorithm proposed in this study, instead, succeeded in reproducing crop growth throughout the crop cycle even for mechanical transplanting, thanks to an improved representation of nursery dynamics in case of the high seedling densities that characterize this establishment technique.

The importance of reproducing seedling growth and post-transplanting shock via a dedicated algorithm is demonstrated by the performances of the WARM model in case the dynamics involved with transplanting are completely ignored. The exclusion of the transplanting algorithms for datasets where rice was transplanted, indeed, led to mean RRMSE of about 70% for both the transplanting methods, with values for this metric ranging from 34.55% to 127.16%. This is confirmed also by negative modelling efficiencies achieved in six out of 11 datasets.

Table 3: *Indices of agreement between measured and simulated aboveground biomass (t ha^{-1}) values. DS: direct sowing; MT: mechanical transplanting; MM: manual transplanting.*

Activity	Establishment method	Exp. ID	Year	RRMSE %	EF	CRM	Slope	Intercept t ha^{-1}	R^2
Calibration	DS	2	2011	23.73	0.89	-0.12	0.81	0.38	0.97
		4	2011	20.24	0.93	-0.02	0.98	-0.02	0.94
		5	2011	19.92	0.92	0	0.86	0.65	0.94
		2	2012	24.9	0.83	-0.23	0.88	-0.64	0.99
		4	2012	26.01	0.8	-0.23	0.84	-0.3	0.99
		5	2012	6.05	0.99	0.01	1	0.1	0.99
	Mean			20.14	0.89	-0.1	0.9	0.03	0.97
	MT	1	2011	10.84	0.97	0.04	0.9	0.6	0.99
		1	2012	20.83	0.92	0.15	1.21	-0.14	0.99
	MM	6	2011	13.68	0.97	0.1	1.07	0.28	0.99
		6	2012	17.89	0.9	0.15	1.2	-0.25	1
	Mean			15.81	0.94	0.11	1.09	0.12	0.99
Validation	DS	3	2011	19.86	0.94	-0.05	0.95	0.03	0.94
		3	2012	10.92	0.97	-0.06	0.93	0.05	0.98
		8	2012	22.27	0.85	-0.2	0.9	-0.69	0.98
		2	2013	30.07	0.78	-0.25	0.87	-0.65	0.95
		4	2013	7.39	0.99	-0.05	0.97	-0.13	0.99
		3	2013	23.19	0.87	-0.17	0.92	-0.7	0.95
		5	2013	9.38	0.98	0.04	1.08	-0.36	0.99
	Mean			17.58	0.91	-0.11	0.95	-0.35	0.97
	MT	8	2011	30.89	0.8	0.25	1.31	0.16	0.99
		1	2013	21.82	0.92	0.05	1.2	-1.05	0.95
		8	2013	18.33	0.92	0.07	1.16	-0.71	0.95
	MM	7	2011	9.97	0.98	0.08	1.03	0.3	0.99
		7	2012	5.26	0.99	-0.03	1	-0.27	0.99
		6	2013	7.1	0.99	0.06	1.03	0.24	1
		7	2013	9.39	0.99	-0.05	0.99	-0.33	0.99
	Mean			14.68	0.94	0.06	1.1	-0.24	0.98

3.6. Conclusions

WARM was here calibrated and evaluated on data collected in eight sites and three seasons in Jiangsu under potential conditions, with the aim of testing its suitability for different rice establishment techniques, i.e., direct sowing, manual and mechanical transplanting. Overall, the effect of transplanting shock on rice growth and development – mainly due to a reduction of leaf area expansion rate after the event – was correctly reproduced.

The good performances obtained by the model when the same parameter set was used to describe rice growth for both direct sowing (average RRMSE for AGB = 18.76%) and transplanting (RRMSE = 15.09%) datasets demonstrate the suitability of the transplanting algorithm implemented, and provide guarantees on the general coherence on the way processes are formalized. The need for modifying the original transplanting algorithm implemented in Oryza2000 (Bouman et al., 2001) was due to its incomplete suitability in case of the high seedbed densities that characterize the advanced mechanical transplanting techniques adopted in the study area. The improved version of the algorithm, instead, allowed the model to properly reproduce rice establishment for both manually and mechanically transplanted rice.

The results obtained in this study demonstrate the model suitability for aboveground biomass simulation for all the establishment techniques used for rice, thus extending the applicability of the model to most of the production contexts worldwide.

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A NEW APPROACH FOR THE SIMULATION OF COLD-INDUCED STERILITY FOR RICE CROPS

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Submitted to Field Crops Research

4.1. Abstract

Cold is one of the most important abiotic stressors affecting rice that could cause substantial yield losses especially in temperate environments. While many physiological and genetic studies have been carried out in order to improve rice cold tolerance, few existing works are focused on the development of models for the simulation of cold-induced sterility. In this study, an existing approach for the simulation of cold shocks effects on spikelet fertility was improved in order simulate cold stress during the entire most sensitive period of rice cycle (i.e., from panicle initiation to flowering). The model was calibrated using data collected in Vercelli and Castello d'Agogna by Ente Nazionale Risi in the period 2004-2010 for Japonica and Tropical Japonica types. First, rice phenology was differentially calibrated for each variety group using the WARM model; then the threshold temperature below which cold damages occurred was fixed. The agreement between measured and simulated values of percentage of spikelets sterility was satisfactory with an average R^2 and MAE of 0.65 and 1.9%, respectively, with overall performances slightly better in calibration than validation. Despite all the key factors involved with temperature-induced sterility are explicitly considered, the proposed approach needs only few easily accessible inputs, thus resulting particularly suitable for operational contexts.

Keywords: cold damage; extreme weather event; *Oryza sativa* L.; spikelet sterility; WARM model.

4.2. Introduction

Cold and freezing are among the most important abiotic stressors affecting growth and development of cultivated plants (Kasuga et al., 1999; Lang et al., 2005). Among herbaceous crops, rice is particularly exposed to low temperatures because of its tropical origin and its frequent cultivation in temperate environments (e.g., northern districts in Italy, Japan, China, and southern ones in Australia). As an example, rice yield losses due to spikelet sterility (the main cold-injury during the reproductive phase) caused by 2-3 days summer cold-air outbreaks can reach 25–50% in northern Italy for susceptible varieties (Confalonieri et al., 2005). Like for most damages caused by weather extremes, the degree and type of injury depend on the phenological stage and on the severity/duration of the cold event (Li et al., 1981). According to most authors, the young microspore stage (around booting) is the most susceptible to cold temperatures (Imin et al., 2004; Gothandam et al., 2007; Shimono et al., 2007; Sakata et al., 2014) that, in this case, may cause the abortion of pollen (Mackill et al., 1996). However, other authors reported how low temperatures can also affect rice around anthesis (Pereira da Cruz et al., 2006; Sánchez et al., 2014) because of problems to anther development or to pollen ripening/germination (Ito et al., 1970).

The threshold temperature inducing sterility largely depends on the rice cultivars adopted in the different environments. As an example, temperatures lower than 20°C are considered as cold enough to cause sterility in southern Japan (Satake, 1976, Shimono et al., 2005), whereas Mariani et al. (2009) suggested 14°C for the cultivars grown in the Po Valley (northern Italy). The floodwater effect in smoothing thermal extremes is one of the reasons why rice growers were used to increase floodwater level in the first part of the reproductive phase (Confalonieri et al., 2005). However, the young panicle is below the water surface – where the smoothing effect is maximum – only for a few days (panicle initiation – beginning of stem elongation), whereas the floodwater effect on temperature is perceived by the plant only in the first centimeters above the air/water interface (Confalonieri et al., 2005). This means that, for most of the susceptible phase, the sensitive organs are exposed to air temperatures regardless to the water management.

Among the rice models classified by Confalonieri et al. (2016) within the activities of the AgMIP (Agricultural Model Intercomparison and

Improvement Project) rice team, ten include the reproduction of cold-induced spikelet sterility. The most reliable approaches are based on the concept of cooling degree-day (Uchijima, 1976), applied on a daily basis during the most cold-sensitive period (i.e., before flowering). Shimono et al. (2005) added a “weighting” function to account for changes in the sensitivity of the panicle in the different growth stages of reproductive period. Available approaches use – as driving variable – average (e.g., Godwin et al., 1994) or minimum (e.g., Dingkuhn et al., 1995) daily temperatures, others provide estimates with a hourly time-step, generating hourly temperatures from daily values (e.g., Confalonieri et al., 2009). Input temperature can refer to the air or to floodwater, being water temperature estimated using energy balance models (e.g., Godwin et al., 1994); other approaches select water or air temperature according to the young panicle height (e.g., Shimono et al., 2005) or to the development stage (e.g., van Oort et al., 2015). Despite floodwater affects the vertical thermal profile throughout the canopy, the magnitude of this effect is often considered as not relevant enough compared to the uncertainty of energy balance models to justify the use of canopy temperature when the young panicle is above the water surface (Confalonieri et al., 2005). However, regardless of the algorithms, the evaluation of most of these models was performed under controlled environment (greenhouses or growth chambers) through the application of cool treatments, or tested on limited field datasets.

The aims of this study were (i) improving the sterility model implemented in the WARM model (Confalonieri et al., 2009; Pagani et al., 2014) and (ii) evaluating it using datasets collected in northern Italy between 2004 and 2010, characterized by heterogeneous weather conditions and cold-air outbreaks occurring in different moments during the reproductive phase.

4.3. Materials and methods

4.3.1. The sterility model

The model derives from the one available in the WARM model (Confalonieri et al., 2009; Pagani et al., 2014), which estimates daily stress values (in turn calculated from hourly ones) and weights them using a bell-shape function representing the combined effect of the different susceptibility to low temperatures along the period between panicle initiation and heading, and the within- and between-plant heterogeneity in panicle development. The new approach includes the simulation of cold-induced damages around anthesis (pollen ripening/germination) and presents a quadratic function instead of a bell-shape one, the former considered more suitable to represent the underlying processes because of the actual differences in flowering dates of secondary and tertiary culms compared to the main one. The model is described in Eq. 1:

$$S = \begin{cases} \sum_{i=d1.6}^{d1.9} \left\{ \left[\sum_{h=1}^{24} \left(T_{Th}\, p - T_{i,h} \right) \right] \cdot \left[-44.4 \cdot DVS_i^{\,2} + 155.5 \cdot DVS_i - 135.1 \right] \right\} & 1.6 < DVS < 1.9 \cap T_{Th}\, p > T_{i,h} \\ \sum_{i=d1.9}^{d2.1} \left\{ \left[\sum_{h=1}^{24} \left(T_{Th}\, f - T_{i,h} \right) \right] \cdot \left[-100 \cdot DVS_i^{\,2} + 400 \cdot DVS_i - 399 \right] \right\} & 1.9 < DVS < 2.1 \cap T_{Th}\, f > T_{i,h} \\ 1 & elsewhere \end{cases} \quad (1)$$

where $T_{Th}p$ (°C) and $T_{Th}f$ (°C) are the pre-flowering and flowering sterility threshold temperatures; $T_{h,i}$ (°C) are the hourly air temperatures for the ith day generated from daily values according to Denison and Loomis (1989); DVS is a development stage code (unitless; 0: sowing, 1: emergence, 2: flowering; 3: maturity, 4: harvestable; 1.6, 1.9, 2.1 correspond to panicle initiation, heading, end of flowering); DVS_i is the DVS at the ith day; *d1.6* is the day when DVS = 1.6 (the same for *d1.9* and *d2.1*). As shown in Eq. 1, the quadratic functions used to weight the daily sterility values have the axes of symmetry in the middle of the pre-flowering and flowering periods (DVS = 1.75 and DVS = 2, respectively). The use of air temperature is here considered an admissible approximation, given that floodwater level was around 5 cm during the experiments, and thus the young panicle was exposed to air temperature for most of the duration of the sensitive periods. The new sterility model was tested in the WARM simulation environment.

4.3.2. Evaluation datasets

Data for model evaluation were collected by the National Rice Authority (Ente Nazionale Risi; www.enterisi.it) in Castello d'Agogna (45°14' N, 8°41' E) and Vercelli (45°19' N, 8°25' E) during the seasons 2004-2010. Four cultivars were grown: Thaibonnet (Tropical Japonica ecotype, long cycle), Gladio, Sirio (Tropical Japonica ecotype, medium-length cycle), and Loto (Japonica ecotype, short cycle). For all the experiments, rice was scatter seeded and grown under flooded conditions and unlimited nutrients supply; management allowed keeping the fields weed, pest and disease free.

Table 1: *Datasets used for the calibration and validation of crop phenology and of the model for the simulation of cold-induced sterility.*

Variety group	Variety	Site	Year	Sowing/flowering/ harvest dates	Sterility (%)	Cal*
Japonica *short cycle*	Loto	Castello d'Agogna	2004	17 May/8 Aug/6 Oct	1.2	
		Vercelli	2005	27 May/17 Aug/8 Oct	11.5	●
			2007	18 May/8 Aug/4 Oct	6.1	
Tropical Japonica *long cycle*	Thaibonnet	Castello d'Agogna	2004	7 May/18 Aug/7 Oct	8.6	●
			2005	29 Apr/8 Aug/27 Sep	8.2	
			2006	2 May/10 Aug/29 Sep	5.6	●
Tropical Japonica *medium-length cycle*	Gladio	Castello d'Agogna	2009	19 May/5 Aug/30 Sep	0	●
			2010	24 May/12 Aug/16 Oct	9.3	●
	Sirio	Vercelli	2009	28 May/19 Aug/5 Oct	0	

*Cal: ● indicates datasets used for calibration (the others were used for validation).

Available data were split into calibration and validation datasets as shown in Table 1. First, the values of the WARM parameters involved with plant phenology were defined for the three variety groups using observed dates of flowering/harvest. Then, the threshold temperature for sterility was calibrated using the measured percentage of fertility (Table 1).

Meteorological data were collected by the weather stations of the Regional Agency for Environmental Protection (ARPA, www.arpalombardia.it and www.arpa.piemonte.it), placed in the close proximity of the experimental fields in Vercelli and Castello d'Agogna.

4.4. Results and discussion

Datasets collected in 2005 and 2010 were characterized by the highest percentage of sterility, regardless of the site and cultivar. Concerning the season 2004, cultivars Loto and Thibonnet showed different responses to cold, the latter being more affected by cold-induced sterility. This was caused by the longer duration of the Thaibonnet vegetative phase, which led the flowering to fall during a period of a cold air outbreak. Intermediate sterility values were observed for the datasets collected in 2006 and 2007.

Table 2 shows the values for the WARM parameters involved with crop development and sterility. The flowering date, which is one of the two periods when the crop is susceptible to cold shocks, was satisfactory reproduced during calibration, with a mean absolute error (MAE) of 3.2 days. The performances for the validation datasets were less reliable, with a value of MAE of 6.5 days.

Table 2: *WARM parameters involved with crop development and the cold-induced sterility. (J = Japonica; TJL = Tropical Japonica, long cycle; TJM = Tropical Japonica, medium-length cycle).*

Parameter	Unit	Description	Value		
			J	TJL	TJM
GDD_{em}	°C-day	Growing degree days from sowing to emergence	70	70	70
$GDD_{em\text{-}fl}$	°C-day	Growing degree days from emergence to flowering	880	1008	740
$GDD_{fl\text{-}mat}$	°C-day	Growing degree days from flowering to maturity	370	460	350
T_{base}	°C	Base temperature for development	11	12	
T_{max}	°C	Maximum temperature for development	42		
$T_{Th}p$	°C	Threshold temperature for pre-flowering cold-induced sterility	13.3		
$T_{Th}f$	°C	Threshold temperature for cold-induced sterility around flowering	13.3		

The same value of threshold temperature for sterility (13.3°C) was used for the two sensitive periods (pre-flowering and flowering) and for all the groups of cultivars, without differences for Japonica and Tropical Japonica. The calibrated value for the sterility threshold is coherent with values found in the literature for Italian varieties (Mariani et al., 2009; Dreni et al., 2012) and, in general, for rice varieties grown in temperate environments (e.g., Satake et al., 1987).

Figure 1 shows the comparison between measured and simulated percentage of sterility. The inter-annual variability of spikelets fertility was satisfactory reproduced by the model, with the highest damages simulated for 2005, 2010 and 2004 (the latter only for Thaibonnet). Lower sterility values were simulated for 2006 and 2007 for Japonica and Tropical Japonica long cycle varieties, respectively, despite a slight underestimation compared to measured data. The model simulated a low percentage of sterility because of cold events during pre-flowering period in 2009 for Tropical Japonica medium-length cycle varieties in Castello d'Agogna and Vercelli, although no empty spikelets were detected in the field experiments.

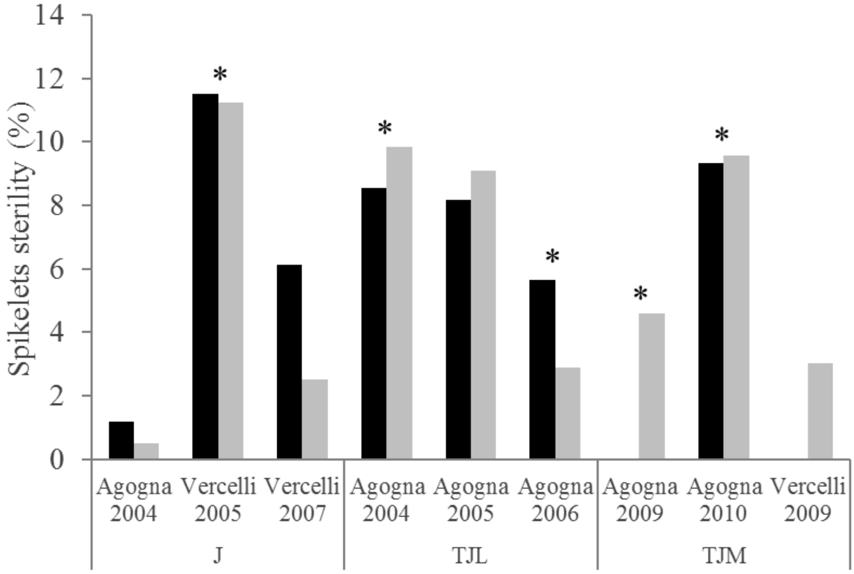

Figure 1: *Comparison between measured (black bars) and simulated (grey bars) percentage of cold-induced spikelet sterility (J = Japonica; TJL = Tropical Japonica, long cycle; TJM = Tropical Japonica, medium-length cycle; * = datasets used for calibration).*

Despite the young microspore stage is considered as the most critical for rice (Gothandam et al., 2007; Sakata et al., 2014), damages were mainly due to events occurred around flowering for most combinations site × year × varieties. Figure 2 shows the time trend of daily air minimum temperature measured in Vercelli in 2005 and in Castello d'Agogna in 2010, i.e., the two datasets characterized by the highest measured percentage of cold-induced sterility. In 2005 at Vercelli minimum temperatures fell below the sterility threshold for seven days (with a minimum of 11.6° C) around flowering, i.e., between DVS 1.9 and DVS 2.1. The situation was similar for Castello d'Agogna in 2010 (minimum temperature below the threshold for four days around flowering), although in this case slight damages were also caused by a cold event occurred at the young microspore stage.

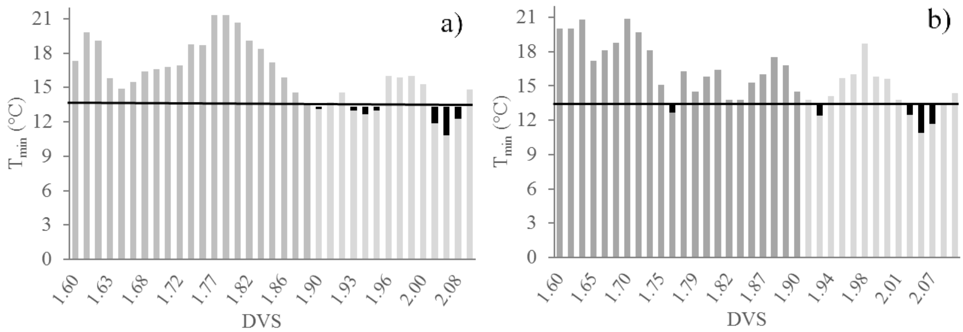

Figure 2: *Trend of daily minimum temperature within DVS windows 1.6-1.9 (dark grey bars) and 1.9-2.1 (light grey bars) at a) Vercelli station in 2005 and b) Castello d'Agogna station in 2010. Black bars show days with minimum temperature lower than the threshold (black horizontal line).*

The overall performances of the model during calibration were satisfactory: the relative root mean square error (RRMSE %, 0 to +∞, optimum = 0) was 35.2%, and the modelling efficiency (EF, unitless, -∞ to +1, optimum = +1, if negative indicates that the average of observations is a better predictor than the model, Nash and Sutcliffe, 1970) and the coefficient of determination (R^2) were 0.61 and 0.64, respectively. The model accuracy during validation was slightly lower; however, EF was positive (0.48), more than 50% of the total variance was explained (R^2 = 0.53), and the absolute error was around 2.4%. The lower accuracy during validation was probably caused by the lower reliability in the simulation of flowering occurrence.

Model performances are coherent with those reported in other studies. van Oort et al. (2015) tested approaches for heat- and cold-induced sterility in two sites in Senegal during 2006-2007. In this study, authors estimated cold sterility damages using a linear model based on air and water temperature, the latter being calculated using an empirical model. The comparison between measured and simulated sterility led to achieve good values for the evaluation metrics (EF = 0.7). The approach developed by Shimono et al. (2005) is based on a logistic function that includes air or water temperature according to the panicle height. The model was tested on 23 datasets collected in nine sites from 1996 to 1999. Despite the approach is more complex than the one presented in this study and requires empiric coefficients to be defined, the performances obtained using air temperature as a driver (R^2 = 0.65, RRMSE = 33.4%) are similar to those we achieved. However, when the authors used as driving variables both air and water temperature, with the latter directly measured with dedicated sensors, their model showed a decidedly high accuracy (R^2 = 0.94, RRMSE = 9.6%). This indirectly demonstrates the uncertainty affecting approaches for estimating water temperature.

4.5. Conclusions

A new approach for the simulation of spikelets sterility caused by cold shocks during the young microspore stage and flowering was calibrated and evaluated using nine datasets collected in six different seasons and two sites in Northern Italy for Japonica and Tropical Japonica rice cultivars. Compared to the original model proposed by Confalonieri et al. (2009), the extension to the simulation of cold-induced sterility around flowering (the original model was targeting only the young microspore stage) proved to be essential for the correct reproduction of the underlying processes. The results achieved in this study also confirmed the relevance of the effects of cold shocks on spikelet fertility around anthesis, as observed and discussed by Pereira da Cruz et al. (2006). Despite the model proposed in this study requires less inputs (i.e., daily minimum temperature and the threshold temperature inducing sterility) compared to other approaches available in the literature, it allowed achieving satisfactory performances. Moreover, the approach proposed does not include empirical coefficients difficult to measure or estimate. The consideration of all the key factors and the reliability in reproducing observations makes this model suitable for being used in research and operational contexts like, e.g., for yield forecasts and early estimate of damages in case of extreme weather events. Further studies will target the evaluation of the model also for heat-induced sterility, a type of damage which is expected to increase its relevance even in temperate environments because of the rise in temperatures characterizing most climate change projections.

IMPROVING CEREAL YIELD FORECASTS IN EUROPE – THE IMPACT OF WEATHER EXTREMES

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5.1. Abstract

A model-based yield forecasting system is presented that accounts for the impact of extreme weather events on crop production. It is motivated by a key observation, i.e., the impact of extreme events (such as prolonged droughts, heat waves and cold shocks) is poorly represented by most crop simulation models, and by a corollary expectation, that is, extreme drought and heat wave events are projected to increase in frequency and intensity with climate change. Simple relations – consistent in the degree of complexity with most generic crop simulators – impacting on leaf development and yield formation are proposed to explicitly model the impact of these events as well as cold shocks and frost. The incorporation of these relations into the Crop Growth Monitoring System (CGMS) of the European Commission is proposed as a way to improve yield forecasts. The system was assessed for the main micro- and macro-thermal cereal crops grown in highly productive European countries. The forecasting reliability of selected agro-climatic indicators (accounting for drought and cold/heat stress), used alone or integrated with model outputs, was also evaluated. Based on the statistical post-processing of model outputs aggregated at national level with historical series (1995-2013) of official yields, the workflow was evaluated via cross-validation (CV) for forecasting events triggered at flowering, maturity and at an intermediate stage. The system based on agro-climatic indicators showed satisfactory performances limited to crop production systems mainly driven by rainfall distribution, such as microthermal crops grown in Mediterranean environments (e.g., $R^2_{CV} = 0.82$ for soft wheat in Spain at maturity). The CGMS-standard system showed satisfactory predictive ability with maize, which appeared not to be particularly impacted by extreme weather events (e.g., $R^2_{CV} = 0.89$ for maize in Germany at flowering). In most cases where CGMS-standard system performed poorly, the explicit simulation of extreme impacts by water, frost, cold and heat stress improved the reliability of forecasts by explaining a large part of the interannual variability (up to 44% for spring barley in Poland). The addition of agro-climatic indicators to the workflow mostly enhanced the forecasting reliability, adding accuracy to an already satisfactory forecasting system.

Keywords: agro-climatic indicators; CGMS; crop model; extreme weather events; WOFOST; yield forecasting.

5.2. Introduction

The agricultural sector needs timely and reliable crop production forecasting and early warning systems, which are increasingly becoming important in both developed and developing countries (Bouman, 1995; Atzberger, 2013). This need reflects increasing pressures from food demand, price-competition induced by market globalization as well as food price levels and volatility (G20 Agriculture Action Plan, http://www.amis-outlook.org/fileadmin/user_upload/amis/docs/2011-agriculture-plan-en.pdf). In addition to several agronomic and economic factors, agricultural production strongly depends on the varying weather conditions from season to season and year to year (Supit, 1997). Policy decisions relating to food security (that is, food-supply chains through procurement, stock management, marketing, and distribution networks) would be enhanced if supported by a reliable system for food crop production forecasting (Lazar and Genovese, 2004). For instance, early warning in case of anomalous seasons (e.g., owing to severe heat and water stress) may enhance the capacity of regional and national decision makers to assure food imports and regulate the agricultural market (Bannayan and Crout, 1999; Atzberger, 2013). The variety of systems developed in the last decades for the forecasting of crop yields are usually nationwide (e.g., Bezuidenhout and Singels, 2007a, b; Duveiller et al., 2013). Most of these systems are based on the single or combined use of agro-climatic indicators (e.g., Balaghi et al., 2012), remote-sensing information (Wang et al., 2010; Fernandes et al., 2011; Son et al., 2014) and crop models (Vossen and Rijks, 1995; de Wit et al., 2010; Kogan et al., 2013). The effect of weather conditions on agricultural production can be quantified by predictive models built on statistical relationships between a few agro-climatic indicators and crop yields. However, only where crop production fluctuations are driven by a few main meteorological factors these simple relationships can accurately explain the inter-annual variability of crop productivity and reliably forecast final yields (Balaghi et al., 2012). Other, more reliable methods, are used by policy makers in the provision of crop yield forecasts based on simulation modelling. To the best of authors' knowledge, the most sophisticated forecasting system in agriculture at present is the Crop Growth and Monitoring System (CGMS). It was developed by the European Commission Joint Research Centre, within the Monitoring Agricultural ResourceS (MARS) activities, to provide short-term (in-season) forecasts of the yield of the main food crops in Europe (Vossen and Rijks, 1995; Lazar and Genovese, 2004; de Wit et al., 2005). The MARS system is based on the WOFOST crop model (van Keulen and Wolf, 1986; Rabbinge and van Diepen, 2000), used to simulate development and growth for all crops but rice. For the latter, the rice-specific WARM model (Confalonieri et al., 2009) is used.

The simulation tools used within forecasting systems are based on models of plant response to environment, which were developed for conditions of good adaptation and often designed for seasonal patterns reflecting temperature and precipitation regimes of temperate environments. Consequently, the effects of unusual meteorological events over crop performance – including crop failure – are thus often overlooked or unsatisfactorily simulated by the available crop models. In general, they are able to adequately predict mean yields but not the inter-annual variability of productivity, due to their inability to handle climate extremes (Eitzinger et al., 2013; Sanchez et al., 2013). This limitation is critical to investigate the crop response under ongoing climatic change, which is expected to bring increased levels of extreme weather and problems for the agricultural sector in many regions of the world (Parry et al., 1999; IPCC, 2007b). Europe (the focus of this study) is one of the most productive food suppliers in the world. The harvested production of cereals in the EU-28 represented about 13% of global production in 2014 (FAO; http://www.fao.org/faostat/en), making EU a major world producer of cereal grains. Many studies have been focused on the impacts and adaptation of European crop productivity to climate change (Falloon and Betts, 2010; Reidsma et al., 2010; Olesen et al., 2011). Significant warming is projected by the 2030s, affecting winter season in the North of Europe, and summer months in southern and central European countries (IPCC, 2007a). Moreover, an increase in the frequency, intensity and duration of extreme weather events, which have already caused huge yield losses in the past years, is expected in Europe. An increased occurrence of heat waves and related drought events have already been registered in large parts of western and eastern countries, especially in the Mediterranean belt (Trenberth et al., 2007). As an example, in 2003, the combined occurrence of heat and drought in large parts of Europe led to considerable losses in agriculture (Ciais et al., 2005). It is very likely that the frequency and severity of drought spells and heat waves will further increase especially in southern and central parts of the continent (Beniston et al., 2007; Calanca, 2007). An increase of the intensity of rainfall events has been observed in most parts of the continent with severe damages caused by summertime flooding (Christensen and Christensen, 2003). In spite of the warming climate, cold shocks, including both chilling and freezing injuries, is still an important abiotic stress factor for agricultural plants (Kasuga et al., 1999; Lang et al., 2005). Indeed, the current trend toward an increased number of days with frost events in some areas is expected to remain stable until the mid-2030s (Crimp, 2014).

Most of the abiotic shocks affecting plant growth (e.g., heat and cold waves, frost events, water shortage) are caused by dynamics in weather variables for which the crop is not able to provide a suitable physiological response during the most sensitive phenological phases. Studies do exist in which models have been developed to better reproduce the effects of extreme weather events on crop yields. For instance, the effect of high (Prasad et al., 2008) and low (Thakur et al., 2010) temperatures on spikelet sterility during the reproductive phase of crop plants were extensively studied. Different approaches were developed to reproduce cold/heat effects on crop growth and yield formation (Challinor et al., 2005; Shimono et al., 2005; Confalonieri et al., 2009; van Oort et al., 2015). Damages on winter crops caused by frost stress have been observed at each growing stage (Fuller et al., 2007), with increased frost sensitivity during new shoot development (vegetative recovery) in spring. Different approaches were developed which account for frost effects on leaf area development (CERES-Wheat – Jones et al., 2003; InfoCrop – Aggarwal et al., 2006), leaf senescence (APSIM – Holzworth et al., 2014) and total biomass accumulation (EPIC – Williams et al., 1989). The crop model STICS (Brisson et al., 2003) quantifies the impact of frost on seedling density, leaf senescence and grain number. For other extreme weather events (e.g., hail, wind-induced lodging, flooding) the relation with crop growth and production may be less straightforward. The circumscribed nature of these events makes difficult to obtain reliable input data for the modelling purpose and it is essentially for these reasons that only a few studies are available that look at the impact of weather extremes on crop production. For instance, the approach by Baker et al. (1998) calculates the risk of stem and root lodging from crop parameters and soil characteristics.

In this paper, we present novel approaches for the simulation of the impacts of extreme weather events (i.e., heat, cold, frost and water stress), as developed within the activities of the EU FP7 project MODEXTREME -

Modelling vegetation response to extreme events (http://modextreme.org) and incorporated within the CGMS forecasting system.

We evaluated the new system for the most representative cereal crops in Europe.

5.3. Materials and methods

5.3.1. Study crops and countries

The CGMS forecasting system was applied to major cereal crops grown in Europe, i.e., wheat (soft and durum), grain maize and spring barley. These crops cover 47% (about 45% and 2% for soft and durum wheat, respectively), 23% and 9% of the cereal production in EU-28 (Eurostat, 2014; http://ec.europa.eu/eurostat/web/agriculture). For each crop, the main producing countries were selected (Fig. 1). Notably, France accounts for more than one fifth (i.e., 21.8%) of the EU-28's cereal production (Eurostat, 2014), followed by Germany, for which statistics show high production levels for winter cereals.

Countries located along the Mediterranean belt (i.e., France, Italy, Spain, Romania) have milder weather conditions than central and northern European countries.

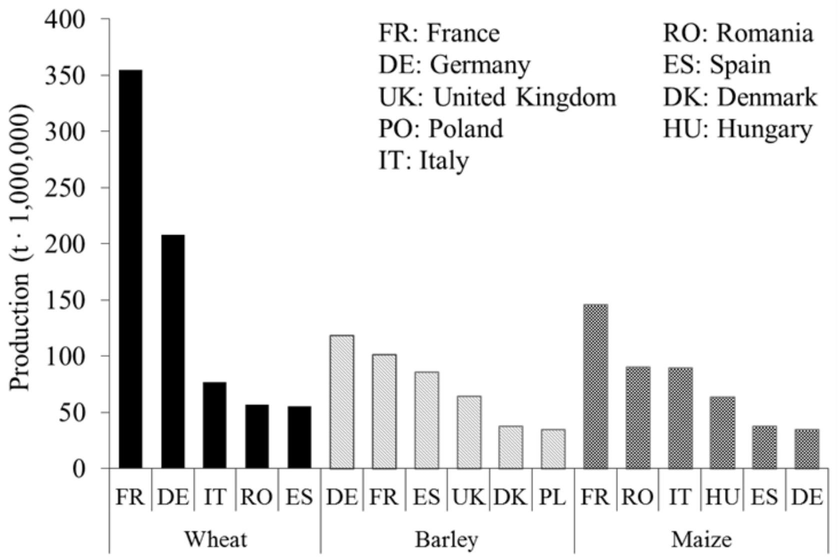

Figure 1*: Main European cereal (wheat, barley and maize) producing countries (Faostat, 2014).*

5.3.2. Models of the impact of extreme weather events

A general framework was developed based on the hypothesis that yield variations due to extreme events are mediated (i) by changes in the harvest index (HI, proportion of harvested biomass on the total aboveground biomass) for water, heat and cold stresses (e.g., Stöckle et al., 1994; Edmeades et al., 1999; Prasad et al., 2006), and (ii) by damages to leaf area (or even crop failure) in case of frost damages (e.g., Porter and Gawith, 1999), whereas the main effects of weather on crop performance (e.g., thermal limitation to photosynthesis) are already captured by existing crop models. Extreme events affect crop performance differentially because crop susceptibility changes during the crop cycle (e.g., Li et al., 1981). This was accounted for by using different thresholds for inducing the damage at different development stages. The latter is represented in this study using a SUCROS-type numerical code (DVS; unitless; 0: emergence; 1: anthesis; 2: maturity; van Keulen et al., 1982).

The response function to extreme water stress (F_W, unitless) around anthesis (i.e., $0.9 \leq \mathrm{DVS} \leq 1.1$) is calculated using Eq. 1.

$$F_W = \begin{cases} \dfrac{F_E}{F_{Ecrit}} & F_E \leq F_{Ecrit} \\ \\ 1 & elsewhere \end{cases} \tag{1}$$

where F_E (unitless) is the fraction of transpiration that is not reduced (depending on the actual to potential transpiration ratio and on the allowable soil water depletion); F_{Ecrit} (unitless) is a crop dependent parameter, set to 0.7 for all the study crops.

The approach used for simulating the impact of heat shocks (F_{HT}, unitless; Eq. 2) is a linear response to maximum canopy temperature (T_{Cmax}, °C) driven by threshold (T_{0heat}, °C) and critical ($T_{100heat}$, °C) temperatures during the crop reproductive phase (i.e., $0.9 \leq \mathrm{DVS} \leq 2$).

$$F_{HT} = \begin{cases} 1 & T_{C\max} \leq T_{0heat} \\ \\ \dfrac{T_{C\max} - T_{100heat}}{T_{0heat} - T_{100heat}} & T_{0heat} < T_{C\max} < T_{100heat} \\ \\ 0 & T_{C\max} \geq T_{100heat} \end{cases} \tag{2}$$

A similar approach was used to simulate the impact of cold shocks (F_{CD}, unitless; Eq. 3) during the crop reproductive phase (i.e., 0.9 ≤ DVS ≤ 2). In this case, minimum canopy temperature (T_{Cmin}, °C) is used as input.

$$F_{CD} = \begin{cases} 0 & T_{C\min} \leq T_{100cold} \\ \dfrac{T_{C\min} - T_{100cold}}{T_{0cold} - T_{100cold}} & T_{100cold} < T_{C\min} < T_{0cold} \\ 1 & T_{C\min} \geq T_{0cold} \end{cases} \tag{3}$$

Canopy temperatures (T_{Cmax} and T_{Cmin} in Eqs. 2 and 3) used to modulate temperature-related damages are derived using a dedicated energy balance model (Villalobos et al, 2015; Villalobos et al., 2017).

Both F_{HT} and F_{CD} range between 0 and 1, and modulate HI in a different way if the extreme event occurs around flowering (Eq. 4) or from anthesis to maturity (Eq. 5).

$$HI_{AA} = \left[\left(\frac{1}{d_A}\sum_{1}^{d_A} F_W\right) \cdot \left(\prod_{1}^{d_A} \min\left(F_{HT}, F_{CD}\right)\right)\right] \cdot HI_{\max} \tag{4}$$

$$HI = HI_{AA} \cdot \left[\left(1 - F_{HT}, F_{CD}\right) \cdot \frac{t}{d_{PA}} + F_{HT}, F_{CD}\right] \tag{5}$$

where HI_{AA}, HI_{max} and HI (unitless) are the actual (after anthesis), potential and final (at maturity) harvest index, respectively; t is any time (e.g., days) after anthesis; d_A and d_{PA} are the duration of the flowering and anthesis-maturity phases, respectively. Around flowering, the effects of water stress are averaged, whereas the effects of heat and cold stresses are multiplied. During the reproductive phase, each event of cold or heat stress has an impact on the HI.

The same equation used for the simulation of cold shocks on HI was used to reproduce the effect of frost on leaf area index from emergence to ripening, by defining different threshold and critical temperatures on the basis of the phenological stage. The effects of hardening and de-hardening on the critical temperature are also simulated (Pomeroy et al., 1975).

A customized modelling solution was built by coupling the impact models for extreme weather events to the crop model WOFOST.

5.3.3. Agro-climatic indicators

Five agro-climatic indicators were selected to reflect the effects of extreme temperatures and drought. The indicators for heat and cold are simple counts of days with maximum/minimum temperatures above/below fixed thresholds (Rivington et al., 2013). The effect of water shortage was evaluated using the ARID – Agricultural Reference Index for Drought – (Woli et al., 2012) and Fu (Fu, 1981; Zhang et al., 2004) indicators. The former is a simple, general, soil-plant-atmosphere metric (Narasimhan and Srinivasan, 2005), whereas the latter is based on the assumption that the equilibrium water balance is controlled by water availability and atmospheric demand.

5.3.4. The forecasting methodology

For each combination crop × country, WOFOST simulations were run according to the standard MARS workflow (http://marswiki.jrc.ec.europa.eu/agri4castwiki/index.php/Main_Page; Vossen and Rijks, 1995). In particular, the model was run on elementary simulation units defined by homogeneous weather, soil and crop characteristics. Meteorological data were acquired by weather stations irregularly distributed over Europe, and then interpolated on a regular grid with spatial resolution of 25 km × 25 km. Soil properties (e.g., depth, texture, water capacity) were retrieved from the version 4 of the Soil Geographical Database of Europe at 1:1,000,000 (http://eusoils.jrc.ec.europa.eu/esbn/SGDBE.html), as documented by Lambert et al. (2003). Data for crop characterization (including information on morphological and physiological features and crop calendars; Djaby et al., 2013) were provided by the MARS team of the Joint Research Centre (JRC).

After the simulations, model outputs were aggregated at NUT0 level by using information on crop masks, soil suitability and regional statistics.

Two different modelling solutions were run:

- CGMS-WOFOST (CGMS, hereafter) for potential (driven by temperature, day length, solar radiation) and water-limiting (including possible water shortages) conditions. This solution is the standard one used at the JRC-MARS for crop yield forecast in Europe;

- CGMS-WOFOST-MODEXTREME (MODEXTREME, hereafter), including the impact models for extreme weather events described in section 2.2. This solution was run for water-limiting conditions.

Agro-climatic indicators were aggregated at national level using the same methodology used for crop model outputs.

For each combination crop × country group (i.e., Mediterranean and northern countries), forecasting events were triggered at three moments during the growing season, i.e., around flowering, at maturity and at an intermediate moment. For each forecasting moment, model outputs and agro-climatic indicators were related as independent variables of multiple linear regressions (with a maximum of four regressors) to the 1995-2013 series of official Eurostat yields. Before the regression analysis, historical yield statistics were analyzed to identify and remove significant technological trends. This allowed removing from the statistical analysis factors not reproduced by the two modelling solutions (e.g., improved genotypes and/or management practices).

Four groups of regressors were analyzed separately to quantify the role of each category in explaining inter-annual crop yield fluctuations (Table 1):

- agro-climatic indicators;
- CGMS outputs (standard system, hereafter);
- CGMS outputs together with MODEXTREME outputs (improved system, hereafter);
- all the outputs of the three previous categories (hybrid system, hereafter).

A step-wise analysis followed by a cross-validation allowed selecting the best-predicting regression model for each combination crop × country × moment when the forecasting event was triggered. Forecasted yields, obtained by excluding each time a single year during the cross-validation, were compared with historical yields. The prediction capability of each regression model was then evaluated through the calculation of the cross validation (CV)-relative root mean square error of prediction (%, 0 to +∞, optimum = 0), modelling efficiency (unitless, -∞ to +1, optimum = +1; Nash and Sutcliffe, 1970) and coefficient of determination (R^2_{CV}) of the linear regression equation between official and predicted yields.

Table 1: *Agro-climatic indicators (Type: AI), crop and soil state variables simulated by CGMS-WOFOST (Type: CW), state variables and response functions for extreme events simulated by CGMS-WOFOST-MODEXTREME (Type: MW). Variables included in each of the four forecasting systems: A=agro-climatic; S=standard CGMS; I=improved system (including MODEXTREME impact models); H=hybrid (including regressors from all systems).*

Type	Regressor	Description	A	S	I	H
AI	$TMAX_{cr}$	No of days with Tmax higher than a fixed threshold (°C)	●			●
	$TMIN_{cr}$	No of days with Tmin lower than a fixed threshold (°C)	●			●
	$ARID_{mean}$	Average value of the ARID indicator (Woli et al., 2012) (-)	●			●
	$ARID_{cr}$	No of days with ARID higher than a fixed threshold (-)	●			●
	Fu	Average value of the Fu indicator (Fu, 1981) (-)	●			●
CW	DVS	Development stage code (-)		●	●	●
	AGB	Aboveground biomass (t ha^{-1})		●	●	●
	YIELD	Storage organs biomass (t ha^{-1})		●	●	●
	LAI	Leaf area index (-)		●	●	●
	AGB_{WL}	Aboveground biomass limited by water stress (t ha^{-1})		●	●	●
	$YIELD_{WL}$	Storage organs biomass limited by water stress (t ha^{-1})		●	●	●
	LAI_{WL}	Leaf area index limited by water stress (-)		●	●	●
	WC	Crop total water consumption (sum of water-limited transpiration) (mm)		●	●	●
	WR	Crop total water requirement (sum of potential transpiration) (mm)		●	●	●
	FSM	Volumetric soil moisture content in rooted zone (%)		●	●	●
MW	AGB_{FL}	Aboveground biomass limited by frost stress (t ha^{-1})			●	●
	$YIELD_{FL}$	Storage organs biomass limited by frost stress (t ha^{-1})			●	●
	LAI_{FL}	Leaf area index limited by frost stress (-)			●	●
	f_{HT}	Heat stress response function (-)			●	●
	T_{Cmax}	Cumulated maximum crop temperature (°C)			●	●
	f_{CD}	Cold stress response function (-)			●	●
	T_{Cmin}	Cumulated minimum crop temperature (°C)			●	●
	f_{W}	Water stress response function (-)			●	●

5.4. Results and discussion

Tables from 2 to 5 show the performances of the regression models identified by the step-wise procedure as the most reliable for the forecasting system evaluated: based on agro-climatic indicators (A), standard CGMS (S), improved with MODEXTREME impact models (I) and hybrid systems (H). Results are shown for the 66 combinations crop × country × forecasting moment analyzed. The regressors selected were sorted on the basis of the regression coefficients. Models for which the values of R^2_{CV} between official yield statistics and predicted values were lower than 0.01 are not shown. The best performances were obtained for maize (Table 2), for which the values of R^2_{CV} and EF were always higher than 0.65 when the forecast was triggered after the flowering stage. For the same crop the most satisfactory results were achieved in Spain and Germany, although for the former a large part of the inter-annual variability in official yields was explained by the introduction of technological innovations (technological trend). The worst performances were obtained for spring barley (Table 3) in Germany, France and Denmark, although EF was always positive. For the same crop, results were better for United Kingdom, Poland and Spain, regardless of the moment when the forecasting event was triggered (e.g., in Spain, R^2_{CV} and EF were larger than 0.7 and 0.8, respectively).

Concerning wheat (both durum and soft), more than 50% of the inter-annual variability in yields was explained in at least one of the moments when the forecast event was triggered in all the selected countries (Tables 4 and 5).

In general, the standard, improved and hybrid systems achieved the best forecasting performances in 4, 36 and 24 combinations crop × country × forecasting moment, respectively (gridded, stripped and dotted items in Fig. 2). In two cases (i.e., the 1st and 2nd forecasting moment for spring barley in Germany; indicated by items without dithering) the R^2_{CV} of all forecasting systems was lower than 0.01. However, results showed that the improvement in terms of predictive capability of the best option compared to simpler systems was frequently slight. In eight combinations crop × country × forecasting moment, the improvement of the R^2_{CV} of the best system compared to the system based on agro-climatic indicators was lower than 0.10. In particular, most of the cases occurred when the system based on agro-climatic indicators was applied to microthermal crops (barley and wheat) in Spain. Indeed, three out of five agro-climatic indicators used as regressors were related with plant available water and, in Spain (mainly characterized by a Mediterranean climate), crop production for winter and spring cereals is mainly driven by rainfall volumes and distribution during the growing season. Under those conditions, the system based on agro-climatic indicators explained 79%, 81% and 82% of the inter-annual variability of soft wheat yields in the three moments when the forecasting events were triggered.

Table 2: *Performance metrics derived from the comparison between 20-year series of official and predicted maize yields achieved when the forecasting event was triggered at flowering (1), maturity (3) and an intermediate moment (2). Results achieved by the most reliable regression model for each system (i.e., based on agro-climatic indicators (A); standard CGMS (S); improved (I, by including MODEXTREME impact models); hybrid (H, including all regressors) are shown.*

Country	Moment	Syst.	Regression model	RRMSE %	EF	R^2 model	R^2 trend	R^2 TOT
France	1	I	LAI_{WL}, WC, $YIELD_{Pot}$, AGB_{FL}	4.45	0.61	0.63	0	0.63
	2	S	LAI_{WL}, LAI_{Pot}, AGB_{WL}, $YIELD_{WL}$	3.79	0.72	0.72	0	0.72
	3	H	f_{CD}, f_{HT}, f_W, TMIN_{cr}	3.17	0.80	0.8	0	0.80
Romania	1	I	f_{CD}, f_{HT}, LAI_{WL}	16.4	0.57	0.58	0	0.58
	2	I	FSM, WR, T_{Cmax}, $YIELD_{WL}$	12.8	0.74	0.74	0	0.74
	3	I	f_W, $YIELD_{Pot}$	13.1	0.73	0.73	0	0.73
Italy	1	I	f_W, T_{Cmax}, $YIELD_{Pot}$, AGB_{WL}	5.23	0.40	0.41	0	0.41
	2	H	Fu, f_{HT}, f_{CD}, WC	3.94	0.66	0.67	0	0.67
	3	I	f_{HT}, f_{CD}, WR, DVS	4.39	0.58	0.59	0	0.59
Hungary	1	I	LAI_{WL}, WC, WR, T_{Cmin}	15.4	0.47	0.49	0	0.49
	2	I	T_{Cmax}, $YIELD_{Pot}$, AGB_{WL}, AGB_{Pot}	9.44	0.80	0.81	0	0.81
	3	S	LAI_{Pot}, DVS, AGB_{WL}, $YIELD_{WL}$	10.3	0.76	0.77	0	0.77
Spain	1	H	Fu, WR, f_W, T_{Cmin}	3.30	0.86	0.12	0.75	0.87
	2	I	LAI_{Pot}, f_{CD}, DVS, WC	3.33	0.86	0.11	0.75	0.86
	3	H	LAI_{Pot}, f_{CD}, DVS, $TMIN_{cr}$	2.83	0.90	0.15	0.75	0.90
Germany	1	I	FSM, LAI_{FL}, $YIELD_{Pot}$, AGB_{Pot}	3.45	0.88	0.43	0.46	0.89
	2	I	DVS, AGB_{WL}, AGB_{FL}, $YIELD_{Pot}$	2.94	0.91	0.46	0.46	0.92
	3	I	LAI_{FL}, T_{Cmin}, $YIELD_{Pot}$, AGB_{WL}	3.15	0.90	0.44	0.46	0.90

Table 3: *Performance metrics derived from the comparison between 20-year series of official and predicted spring barley yields achieved when the forecasting event was triggered at flowering (1), maturity (3) and an intermediate moment (2). Results achieved by the most reliable regression model for each system (i.e., based on agro-climatic indicators (A); standard CGMS (S); improved (I, by including MODEXTREME impact models); hybrid (H, including all regressors) are shown.*

Country	Moment	Syst.	Regression model	RRMSE %	EF	R^2 model	R^2 trend	R^2 TOT
Germany	1	-	-	-	-	-	-	-
	2	-	-	-	-	-	-	-
	3	H	FSM, $TMIN_{cr}$, $YIELD_{WL}$	10.40	0.1	0.18	0	0.18
France	1	I	LAI_{WL}, WR, $T_{MIN}Crop$	9.10	0	0.13	0	0.13
	2	I	FSM, f_{COLD}, $T_{MIN}Crop$, $YIELD_{WL}$	9.26	0	0.12	0	0.12
	3	H	f_{WS}, ,DVS, $ARID_{cr}$, $T_{MIN}Crop$	8.00	0.3	0.29	0	0.29
Spain	1	S	LAI_{Pot}, WR, $YIELD_{WL}$, AGB_{WL}	10.4	0.8	0.81	0	0.81
	2	H	WC, FSM, $ARID_{cr}$, AGB_{FL}	9.69	0.8	0.82	0	0.82
	3	H	FSM, $ARID_{mean}$, $TMAX_{cr}$, AGB_{FL}	11.5	0.8	0.75	0	0.75
United Kingdom	1	H	Fu, f_{COLD}, $T_{MAX}Crop$	5.35	0.5	0.24	0.25	0.49
	2	I	LAI_{WL}, LAI_{POT}, f_{HEAT}	4.75	0.6	0.36	0.25	0.61
	3	I	LAI_{Pot}, f_{COLD}, DVS, f_{WS}	5.87	0.4	0.17	0.25	0.42
Denmark	1	S	WC, AGB_{WL}	5.60	0.2	0.19	0	0.19
	2	H	LAI_{WL}, $TMAX_{cr}$, $YIELD_{Pot}$, AGB_{WL}	6.13	0	0.10	0	0.10
	3	H	$ARID_{mean}$, Fu, f_{WS}	4.78	0.4	0.41	0	0.41
Poland	1	H	FSM, f_{HEAT}, f_{COLD}, $TMIN_{cr}$	5.71	0.7	0.65	0	0.65
	2	H	WC, $TMIN_{cr}$, $T_{MAX}Crop$, AGB_{Pot}	5.57	0.7	0.67	0	0.67
	3	I	f_{COLD}, WC, $YIELD_{WL}$, AGB_{WL}	6.94	0.5	0.50	0	0.50

Table 4: *Performance metrics derived from the comparison between 20-year series of official and predicted soft wheat yields achieved when the forecasting event was triggered at flowering (1), maturity (3) and an intermediate moment (2). Results achieved by the most reliable regression model for each system (i.e., based on agro-climatic indicators (A); standard CGMS (S); improved (I, by including MODEXTREME impact models); hybrid (H, including all regressors) are shown.*

Country	Moment	Syst.	Regression model	RRMSE	EF	R^2 model	R^2 trend	R^2 TOT
France	1	I	$FSM, DVS, T_{MAX}Crop$	4.62	0.38	0.4	0	0.4
	2	I	$WR, DVS, T_{MAX}Crop, AGB_{WL}$	4.38	0.4	0.46	0	0.46
	3	I	$FSM, f_{HEAT}, AGB_{WL}, YIELD_{Pot}$	3.86	0.6	0.59	0	0.60
Germany	1	I	$LAI_{FL}, f_{HEAT}, T_{MIN}Crop, AGB_{FL}$	5.66	0.1	0.18	0	0.18
	2	I	$f_{HEAT}, WR, DVS, T_{MIN}Crop$	4.27	0.5	0.51	0	0.51
	3	H	$LAI_{FL}, DVS, ARID_{cr}, AGB_{Pot}$	4.26	0.5	0.51	0	0.51
Italy	1	I	$LAI_{Pot}, DVS, f_{MIN}, AGB_{WL}$	5.49	0.6	0.04	0.55	0.60
	2	H	$ARID_{mean}, Fu, TMAX_{cr}, AGB_{FL}$	2.84	0.9	0.34	0.55	0.89
	3	H	$ARID_{mean}, FSM, Fu, AGB_{WL}$	3.89	0.8	0.26	0.55	0.81
Romania	1	I	$FSM, T_{MIN}Crop, YIELD_{Pot}, AGB_{FL}$	15.17	0.6	0.61	0	0.61
	2	H	$f_{COLD}, WR, TMAX_{cr}, YIELD_{FL}$	15.68	0.6	0.57	0	0.57
	3	I	$f_{COLD}, WR, YIELD_{WL}, YIELD_{FL}$	14.13	0.6	0.65	0	0.65
Spain	1	I	$FSM, LAI_{Pot}, WC, T_{MIN}Crop, AGB_{WL}$	7.92	0.8	0.81	0	0.81
	2	H	$ARID_{mean}, WC, f_{COLD}, AGB_{Pot}$	5.47	0.9	0.91	0	0.91
	3	H	$ARID_{mean}, Fu, f_{COLD}, AGB_{FL}$	6.22	0.9	0.88	0	0.88

Table 5: *Performance metrics derived from the comparison between 20-year series of official and predicted durum wheat yields achieved when the forecasting event was triggered at flowering (1), maturity (3) and an intermediate moment (2). Results achieved by the most reliable regression model for each system (i.e., based on agro-climatic indicators (A); standard CGMS (S); improved (I, by including MODEXTREME impact models); hybrid (H, including all regressors) are shown.*

Country	Moment	Syst.	Regression model	RRMSE	EF	R^2 model	R^2 trend	R^2 TOT
France	1	I	$LAI_{WL}, LAI_{Pot}, f_{COLD}, f_{HEAT}$	5.07	0.75	0.51	0.24	0.75
	2	I	$DVS, T_{MAX}Crop, YIELD_{FL}$	7.65	0.4	0.18	0.24	0.42
	3	H	$ARID_{mean}, FSM, Fu, YIELD_{Pot}$	7.95	0.4	0.16	0.24	0.40
Germany	1	I	WC, AGB_{FL}	6.84	0.3	0.30	0	0.30
	2	I	$f_{COLD}, DVS, T_{MIN}Crop$	5.49	0.5	0.54	0	0.54
	3	I	$LAI_{FL}, DVS, WC, AGB_{WL}$	6.67	0.4	0.33	0	0.33
Italy	1	I	$LAI_{Pot}, f_{COLD}, DVS, AGB_{WL}$	8.68	0.5	0.06	0.43	0.49
	2	H	$FSM, ARID_{cr}, TMAX_{cr}, T_{MAX}Crop$	5.23	0.8	0.39	0.43	0.82
	3	H	$ARID_{mean}, FSM, Fu, AGB_{WL}$	4.42	0.9	0.45	0.43	0.88
Romania	1	I	$FSM, LAI_{FL}, f_{COLD}, WC$	25.30	0.3	0.38	0	0.38
	2	I	$f_{HEAT}, f_{WS}, AGB_{FL}$	28.60	0.2	0.19	0	0.19
	3	H	$FSM. Fu, WC, YIELD_{FL}$	18.99	0.6	0.66	0	0.66
Spain	1	I	$DVS, T_{MAX}Crop, YIELD_{FL}, AGB_{FL}$	19.49	0.6	0.64	0	0.64
	2	H	$LAI_{FL}, DVS, TMAX_{cr}, AGB_{FL}$	17.77	0.7	0.70	0	0.70
	3	I	$LAI_{WL}, DVS, YIELD_{Pot}, AGB_{FL}$	21.07	0.6	0.59	0	0.61

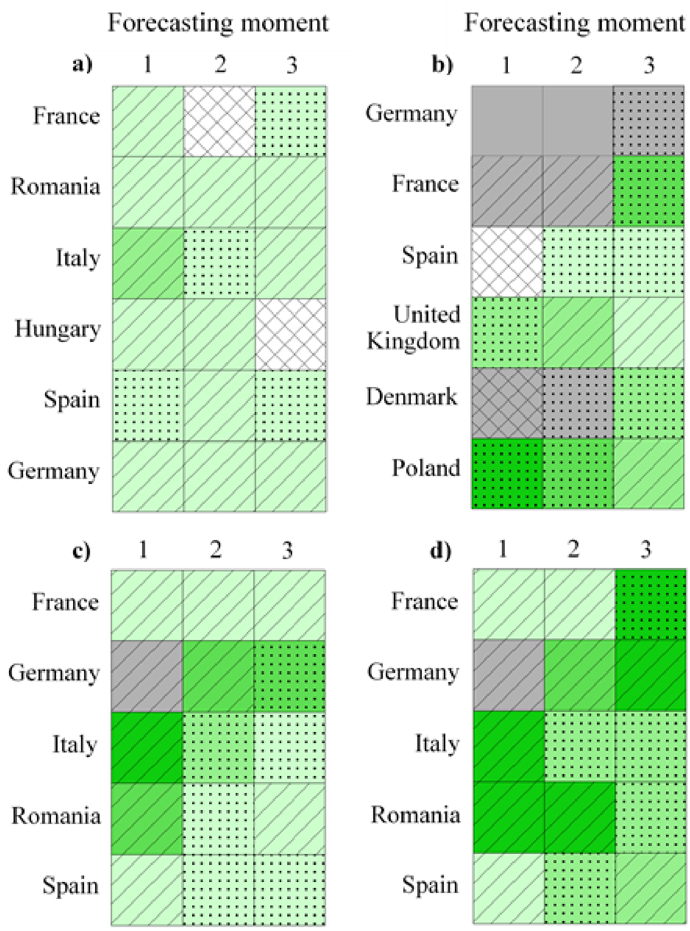

Figure 2: *Forecasting performances for maize (a), spring barley (b), soft wheat (c), and durum wheat (d). Green shades indicate four classes of R^2_{CV} improvement compared to the standard CGMS system: 1-25%, 26-50%, 51-75%, 76-100% for green shades ranging from the lightest to the darkest. Gridded (standard CGMS system), stripped (improved system, including new impact models for weather extremes) and dotted (hybrid system, including agro-climatic indicators) items refer to the forecasting system that achieved the best performance. Grey items refer to the combinations crop × country × forecasting moment for which the final R^2_{CV} was lower than 0.20. Items without dithering indicate that R^2_{CV} for all systems was lower than 0.01.*

Considering the cases where the final R^2_{CV} was higher than 0.20, the standard system achieved the best performance in three combinations crop × country × forecasting moment: two for maize and one for spring barley (gridded white items in Fig. 2), with more than 60% of inter-annual variability explained. Concerning the improvement in the forecasting reliability (compared to the standard system) obtained by the

MODEXTREME and the hybrid systems, results can be divided in four main categories (indicated with four shades of green in Fig. 2). For these categories, the percentage increase in the systems' capability of explaining the inter-annual yield fluctuations was between 1% and 25% (lightest green), 26% and 50%, 51% and 75%, and 76% and 100%. Grey squares represent the combinations crop × country × forecasting moment for which the value of R^2_{CV} for the best forecasting system was lower than 0.20.

In 20 out of the 32 cases when the improved system showed the best performances (stripped items in Fig. 2) – most of which referring to grain maize (Fig. 2.a) – the inclusion in the regressor set of outputs from the impact models for weather extremes allowed obtaining less than 25% increase in the amount of variance explained (lightest green in Fig. 2). Indeed, the standard system demonstrated satisfactory performances for grain maize in most of the countries, with forecasting reliability usually increasing after the flowering stage. As an example, in Hungary (ranked third in Europe according to grain maize production), CGMS explained 46%, 71% and 77% of interannual yield fluctuations in the three moments when the forecasting event was triggered, even without the presence of a significant technological trend. The inclusion of regressors from the MODEXTREME models for the impact of extreme weather events further increased the predictive capacity of the system. The minor improvement achieved for grain maize is likely due to the already good performance of the standard system and to the lower impact of weather extremes on maize compared to the other crops analyzed. Indeed, grain maize is mostly irrigated in the study areas and – where it is grown under rainfed conditions – crop water demand is normally satisfied by rainfall (both for amounts and seasonal distribution). This contributes to the lower susceptibility to thermal extremes around anthesis compared to other species grown in Europe (Spiertz et al., 2006; Shimono et al., 2007), given yield losses normally deriving from the combined effect of temperature and water stress (Carter et al., 2016). However, in some cases, the improvement in the predictive performances derived from the inclusion of the outputs simulated by the MODEXTREME modelling solution was relevant, as in the case of the combined occurrence of heat and drought which characterized large parts of Europe in 2003, causing considerable yield losses. In that season, the crop most affected in Italy was maize, that is grown in the north of the Country where extremely high temperatures were recorded (Ciais et al., 2005; grey circles in Fig. 3). The standard system, which explained 53% of the inter-annual yield variability, showed a marked overestimation in 2003 (Fig. 3.a). The slight increase in the predictive ability of the improved system (59% of variance explained) was almost totally explained by the complete elimination of the 2003 overestimation.

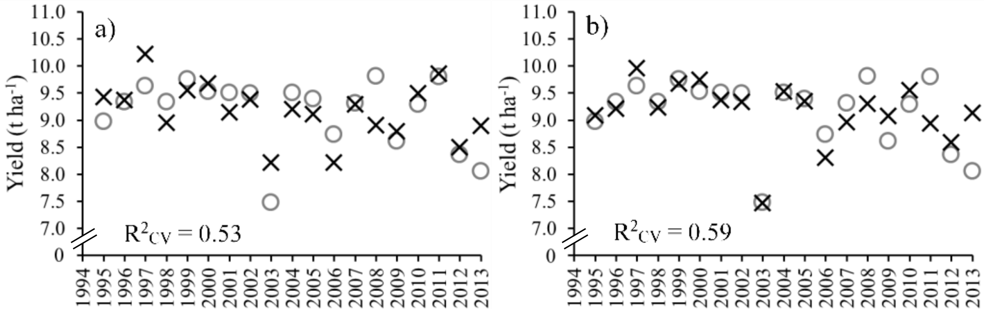

Figure 3: *Comparison between official statistics (grey circles) and predicted yields (black crosses) for maize in Italy. a) standard system; b) improved system. The forecasting event was triggered at maturity.*

In eight out of 32 cases (all referring to soft and durum wheat, Figs. 2.c and 2.d), the improved system increased the explained variability in yields for more than 50% compared to standard one (the two darkest green shades in Fig. 2).

Concerning the hybrid system, the combined use of agro-climatic indicators and variables simulated by the MODEXTREME solution allowed achieving the best performances in 22 cases (dotted items in Fig. 2). However, the addition of agro-climatic indicators led to a slight enhancement (increase in R^2_{CV} lower than 0.10) of the forecasting performances of the improved approach in most of the study cases, thus revealing a predominant role of dynamic models compared to agro-climatic indicators. The only combinations crop × country × forecasting moment for which the hybrid system assured a considerable improvement in the predictive capability were the cases where agro-climatic indicators alone explained more variance than the model outputs. As an example, the hybrid system explained more than 80% of the yield variability for soft and durum wheat in Italy when the forecast event was triggered after the flowering stage; the improvement compared with the system purely based on agro-climatic indicators ranged between 15 and 26%.

In most of the cases referring to durum wheat, the system including the outputs of the impact models for weather extremes led to R^2_{CV} values lower than 0.60. However, in these cases, the inter-annual variability was explained almost entirely by the variables simulated by the MODEXTREME modelling solution. These results should be considered as relevant in light of the poor performances obtained with the standard system, for which the R^2_{CV} was frequently lower than 0.01. Concerning soft wheat, the values of R^2_{CV} for the improved systems were larger than 0.60 in most of the combinations crop × country × forecasting moment. However, similar results were sometimes achieved also for spring barley. Indeed, looking at this crop in Poland as an example (Fig. 4), the use of variables affected by extreme weather events (improved solution) allowed increasing the amount of variance explained from 22% to 66%. In particular, Fig. 4.a distinctly shows that the poor performances of the standard system were caused by the marked overestimation of 2000 yield, which was instead correctly reproduced by the system based on the MODEXTREME impact models (Fig. 4.b). The spring barley season in Poland in 2000 was characterized by a severe heat wave with maximum temperature exceeding 30°C (with a peak of 34°C) for some consecutive days in the mid of June (corresponding to the flowering period). Different studies demonstrated that temperature higher than 27 -31°C around anthesis (in particular during stem elongation and the booting-anthesis phases) are responsible for sterile grains in microthermal cereals, by reducing grain number and size and thus limiting the sink size (Ferris, 1998; Ugarte et al., 2007; Deryng et al., 2014).

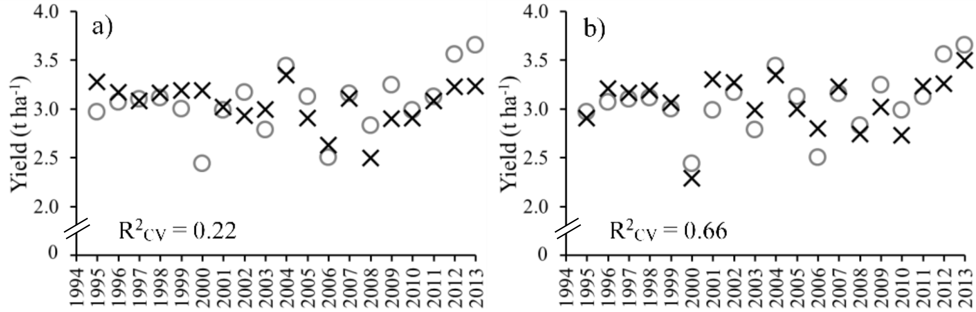

Figure 4: *Comparison between official statistics (grey circles) and predicted yields (black crosses) for spring barley in Poland. a) standard system; b) improved system. The forecasting event was triggered between flowering and maturity.*

The regressors most frequently selected by the step-wise procedure were the response function to cold (f_{CD}) and the minimum temperature of the canopy (T_{Cmin}). This is explained by considering that spikelets sterility caused by low temperatures is more frequent than damages caused by heat shocks in most of the European countries for which the analysis was performed. Moreover, for the winter crops (i.e., soft and durum wheat), state variables influenced by frost (LAI_{FL}, AGB_{FL}, $YIELD_{FL}$) were often selected as independent variables.

The overall forecasting performances for each crop (including results from all the study countries) demonstrated the usefulness of the activities performed for improving the standard CGMS system (Fig. 5). Graphs in left and right columns refer to the standard and improved systems, respectively. In general, the most reliable forecasting systems explained more than 70% of the inter-annual variability in crops yields. Figures 5.a and 5.b confirm that the best performances were achieved for maize and that the enhancement due to the improved and hybrid systems was mostly light (R^2_{CV} = +0.06). On the other side, the improvement was decidedly more relevant for spring barley (Figs. 5.c and 5.d), soft wheat (Figs. 5.e and 5.f), and durum wheat (Figs. 5.g and 5.h). For these crops, indeed, both the increase in R^2_{CV} (+0.12, +0.13 and +0.19, respectively) and the parameters of the linear regression equation between official and predicted yields (slope and intercept) were consistently closer to those of the ideal 1:1 line.

It is important to notice that the improvement compared to the standard CGMS was mostly explained by the higher capability of predicting yields in unfavorable years (Fig. 5), i.e., the years characterized by yields lower than the average. This is a crucial feature for crop yield forecasting systems, since stakeholders are mostly interested in early yield forecasts in case of adverse conditions (e.g., Kogan et al., 2013).

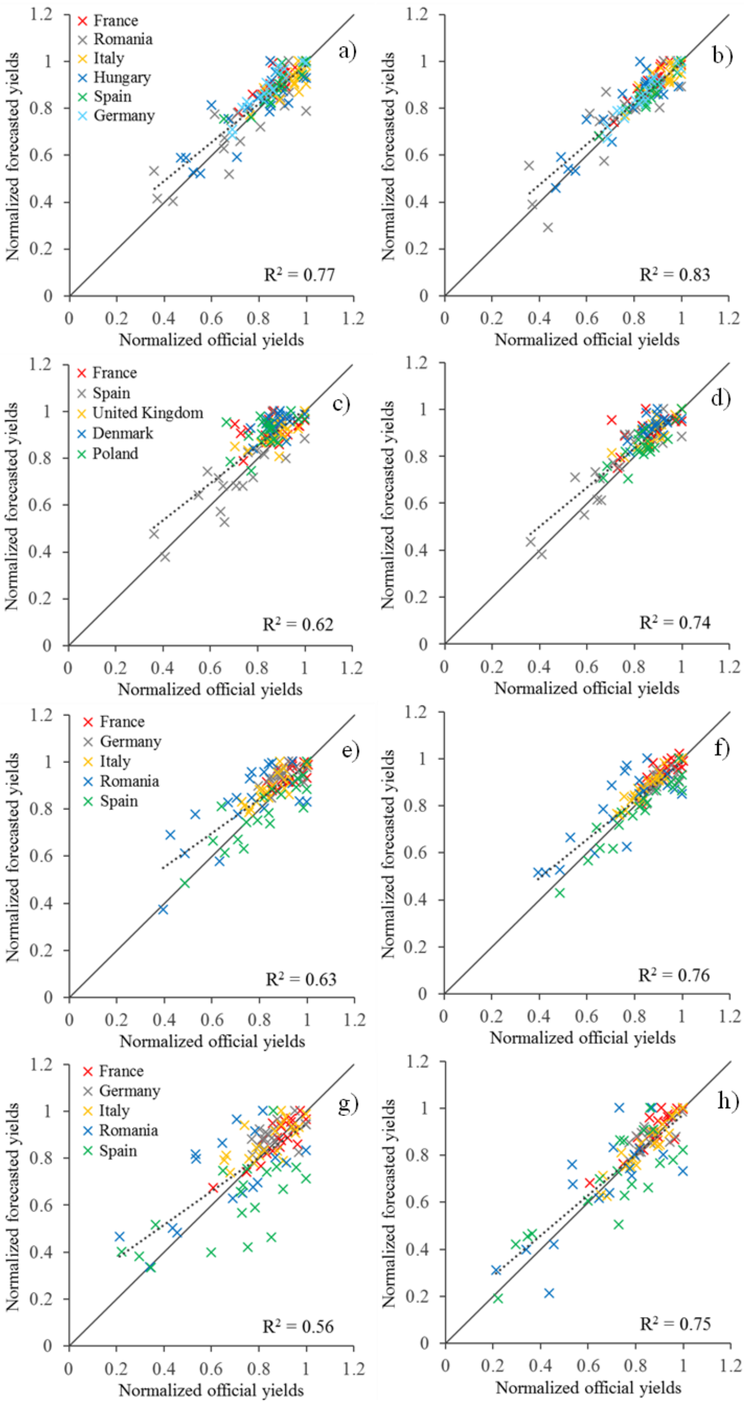

Figure 5*: Comparison between official records of all the study countries and yields obtained from the cross-validation applied to the 20-year series applying the CGMS system (a, c, e, g) and the most reliable system (b, d, f, h) to maize (a,b), spring barley (c,d), soft wheat (e,f) and durum wheat (g,h). Yields for each county are normalized on the highest value of the series.*

5.5. Conclusions

The inclusion of (i) process models for the simulation of the impacts of extreme weather events (i.e., cold, heat, water and frost stress) on crop productivity and (ii) specific agro-climatic indicators (for cold, heat and drought) within the CGMS-standard system allowed improving the forecasting reliability for cereals in Europe in 62 out of 66 combinations crop × country × moment when the forecasting event was triggered. For maize, the CGMS system showed satisfactory performances in most of the study countries, and the inclusion of variables simulated by the MODEXTREME impact models led only to a slight increase in the forecasting reliability. For microthermal cereals, the improved system led, in most of the countries, to a marked increase (up to 44%) of the amount of variance explained compared to the standard system. In particular, with the simulation of the impact of weather extremes the inter-annual yield fluctuations were better captured by the crop forecasting system. As a consequence, it was reduced the marked overestimation observed with the standard system in some combinations crop × year. The performances achieved suggest that the forecasting system using process models and indicators specifically addressing impacts of extreme weather events on crop productivity can be used for operational forecasting purpose in Europe. This is even more important considering the need to secure food in a warming world, more likely producing extreme weather patterns. Our contribution to the challenges related to food security research is particularly relevant for policy implementation in Europe because the forecasting system evaluated here is consistent, and fully compatible, with the operational requirements of the MARS forecasting system already in use at the European Commission. It can therefore readily be applied to crop yield foresting in Europe though more evaluation is needed to confirm the results obtained in the current study with a wider set of crops, countries and climate conditions. The results of this study demonstrate the challenge of using 25-km spatially aggregated weather data to capture thresholds of extreme weather conditions and their effects on crop yields. However, considering the sparse resolution of weather extremes, the reliability of the system need to be assessed with higher spatial resolution (e.g. at finer administrative levels) that would better capture the distribution of extreme weather events.

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A HIGH RESOLUTION, INTEGRATED SYSTEM FOR RICE YIELD FORECAST AT DISTRICT LEVEL

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6.1. Abstract

To meet the growing demand from public and private stakeholders for early yield estimates, a high-resolution (2 km × 2 km) rice yield forecasting system based on the integration between the WARM model and remote sensing (RS) technologies was developed. RS was used to identify rice-cropped area and to derive spatially distributed sowing dates, as well as for the dynamic assimilation of exogenous leaf area index (LAI) data within the crop model. The system – tested for the main European rice production districts in Italy, Greece and Spain – allowed achieving satisfactory performances: more than 66% of inter-annual yield variability was explained in six out of eight combinations ecotype × district, with a maximum of 89% of variability explained for Tropical Japonica cultivars in the Vercelli district (Italy). In seven out of eight cases, the assimilation of RS-derived LAI allowed improving the forecasting capability, with minor differences due to the assimilation technology used (updating or recalibration). In particular, RS allowed reducing the uncertainty by capturing factors not properly reproduced by the simulation model (given the uncertainty due to large-area simulations). As an example, the season 2003 in the Serres (Greece) district was characterized by severe blast epidemics, whose effect on canopy vigor was captured by RS-derived LAI products. The system – extending the one used for rice within the MARS project – was pre-operationally used in 2015 and 2016 to provide early yield estimates to private companies and institutional stakeholders within the EU-FP7 ERMES project.

Keywords: assimilation; blast disease; Oryza sativa L.; remote sensing; WARM model.

6.2. Introduction

There is an increasing demand for systems able to provide timely yield forecasts, given the potential interest for a variety of actors within the agricultural sector, including private companies and institutional stakeholders (e.g., Supit, 1997; Bannayan and Crout, 1999; Wang et al., 2010; Fang et al., 2011). While industries and private companies are interested in crop yield forecast for reasons such as the need of defining selling strategies or of planning milling operations (Everingham et al., 2002), the interest of public institutions deals with the need of regulating agricultural markets and mitigating volatility of prices in case of speculative actions on food commodities (e.g., OECD and FAO, 2011; Kogan et al., 2013, G20 initiative Agricultural Market Information System" -AMIS, http://www.amis-outlook.org/ and "Global Agricultural Geo-monitoring Initiative" - GEOGLAM, http://www.geoglam-crop-monitor.org/). Simple forecasting systems – based, e.g., on agroclimatic indicators (Balaghi et al., 2012) – demonstrated their usefulness under conditions characterized by large year-to-year fluctuations in yields and when those fluctuations are driven by one or two key drivers or, in general, in contexts where crops are grown under severely limiting conditions. Other approaches are more complex, relying on remote sensing (Mkhabela et al., 2005; Wang et al., 2010; Duveiller et al., 2013; Son et al., 2014) or crop simulation models (Vossen and Rijks, 1995; Supit, 1997; Bezuidenhout and Singels, 2007a/b; de Wit et al., 2010; Kogan et al., 2013). Crop models – if properly used – are indeed able to interpret reality in quite a fine way, thus being able to capture the effect of weather anomalies or other factors affecting crop yields better than simpler systems. As an example, they are able to simulate the effect of thermal shocks-induced spikelet sterility (Shimono et al., 2005), which, for some cereals, can lead to relevant yield losses. A forecasting system solely based on remote sensing – for its own nature – would fail in contexts where sterility is an issue, since sterility can severely affect yields even without any damage to the canopy. Forecasting systems solely based on remote sensing are unsuitable also in contexts characterized by a good yield potential, because the favourable conditions for soil and climate and the optimized management techniques lead vegetative vigour to saturating signal (both in case of optical and radar techniques) (Sader et al., 1989; Dobson et al., 1995;

Zhao et al., 2016) even before the reproductive phase. However, crop model-based forecasting systems are quite demanding in terms of data needs and, when applied on large areas, they can be affected by many sources of uncertainty, due to the poor quality of input data (weather, soil), to the lack of information on management (e.g., sowing dates, irrigation practices, cultivars/hybrids grown) variable in space and time, as well as to the model structure (Sándor et al., 2016; Confalonieri et al., 2016a), to the experience of the model users (Diekkrüger et al., 1995; Confalonieri et al., 2016b) and to the uncertainty in the data used for their calibration (Kersebaum et al., 2015; Confalonieri et al., 2016c).

The availability of powerful platforms for gridded model runs and for automatic calibration of parameters, as well as the availability of consistent archives (e.g., leaf area index estimates for the period 2000 - 2016 from ESA - Copernicus http://land.copernicus.eu/global/products/lai or NASA – MODIS https://modis.gsfc.nasa.gov/data/dataprod/mod15.php) and new generation (e.g., Sentinel satellites from the Copernicus program; Lefebvre et al., 2016) of remote sensing products is increasing the potential of forecasting systems integrating crop models and remote sensing technologies.

The combined use of these two kinds of technology can markedly reduce their intrinsic limits and forecasting uncertainty when exploited in single use, because the potentialities of both technologies are maximized by their integration (Fang et al., 2011; Ines et al., 2013; Ma et al., 2013). As an example, the uncertainty in the sowing dates provided to crop models can be reduced through the analysis of temporal profile or remote sensing products (e.g., Boschetti et al., 2009) or differences in vigour between different varieties or effects of factors not accounted for by simulation models (e.g., insects, Wu and Wilson, 1997; weeds, Kropff et al., 1992) can be implicitly included in the simulation via the assimilation of remote sensing-derived leaf area index data varying in time and space (Launay and Guèrif, 2005; Dorigo et al., 2007).

Two main strategies are available to integrate remote sensing information into crop simulators, each presenting pros and cons for different species and agroclimatic/operational contexts (Dorigo et al., 2007): calibration and forcing. The calibration method is based on the automatic adjustment of model parameters targeting the minimization of the error between model outputs and remote sensing-derived state variables (e.g., Bouman et al., 1995). The forcing method is instead based on the update of model state variables when the remote sensing data are available, using algorithms to convert them into simulated variables and to redefine all model outputs accordingly (McLaughlin, 2002).

The aim of this study was to develop and test a high-resolution rice yield forecasting system targeting the main European rice districts, and based on the deep integration of remote sensing information in crops models. This was achieved in the framework of the EU-FP7 ERMES project, whose aim was developing services and disseminating added-value information for the rice sector (www.ermes-fp7space.eu).

6.3. Materials and methods

6.3.1. Study areas

The system was developed targeting Italy, Spain and Greece, which are responsible of 52%, 25% and 7% of the total European rice production, respectively (FAOSTAT, 2014). The rice production districts selected for each of the three countries are shown in Fig. 1. For the Italian district "Lombardo-Piemontese", we considered the province of Vercelli and the area of Lomellina (located in the Pavia province), including 31% and 27% of the Italian rice area (National Rice Authority [Ente Nazionale Risi]; www.enterisi.it). For Spain, the system included the areas of the Ebro delta and of the "Parc natural de l'Albufera", with the two rice districts located in the provinces of Tarragona and Valencia representing about 30% of the Spanish rice production. In Greece, the Central Macedonia region was selected, with rice districts located around Thessaloniki (the main Greek producing site), and Serres. According to the Koppen climate classification, Spanish and Greek areas are characterized by a Mediterranean climate, with hot and dry summers, whereas the climate in the Italian district is temperate with warm and humid conditions during the summer months. In general, the rice season in the three countries starts in March/April and ends in September/October, even though the length of the cycle strictly depends on the cultivated variety and on the seasonal weather conditions. The most common water management adopted in the three countries is based on continuous flooding; however, dry sowing (usually coupled with delayed flooding at the 3rd-5th leaf stage) is increasingly used in Italy. According to data made available by Italian National Rice Authority, Japonica varieties belonging to the market category "Lungo A" are the most cultivated in Italy, followed by Japonica varieties "Tondo" and the Tropical Japonica varieties "Lungo B", with the latter – especially grown in the province of Vercelli – representing about 15% of the national rice production. In Spain and Greece, the most cultivated varieties belong to Japonica and Tropical Japonica groups, respectively, with the exception of the Greek district of Serres, where the colder climate is more suitable for the cultivation of Japonica varieties.

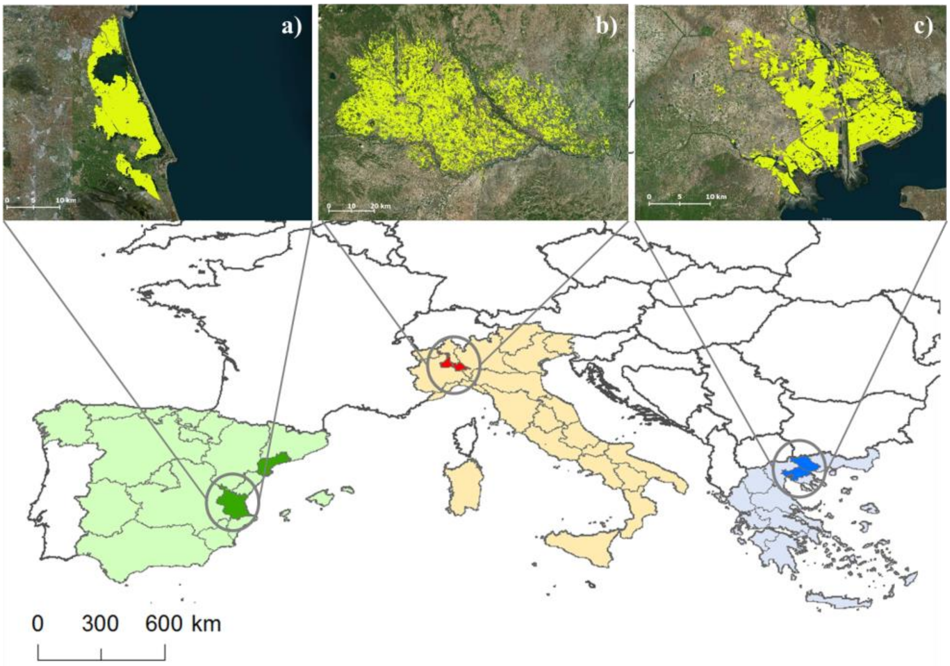

Figure 1: *rice production districts and related 2016 rice distribution maps for the a) Spanish (Valencia district), b) Italian (Lomellina and Vercelli districts) and c) Greek (Thessaloniki district) study areas.*

6.3.2. Crop model and assimilation tool

This study was carried out using the rice-specific model WARM (e.g., Confalonieri et al., 2009; Pagani et al., 2014), fully described in the seminal literature. The model is used since years in both research and operational contexts (e.g., it is one of the rice models used within the AgMIP project and it is used by the European Commission for rice yield forecasts in Europe; http://ies-webarchive-ext.jrc.it/mars/mars/About-us/AGRI4CAST/Models-Software-Tools/Crop-Growth-Modelling-System-CGMS.html).

WARM estimates biomass accumulation using a net photosynthesis approach, based on the concept of radiation use efficiency, the latter being modulated according to temperature limitation, saturation of enzymatic chains in case of high radiation levels, senescence, sterility, and diseases. Daily accumulated biomass (using alternatively a daily or hourly time step) is partitioned to the different plant organs using a set of beta and parabolic functions driven by a single parameter (partitioning to leaves at emergence). Green leaf area index increase is daily computed by multiplying daily increase in leaf biomass by a development stage-dependent specific leaf area. Each day, leaf senescence is calculated by subtracting the dead leaf area index (because of daily-emitted leaf area units reaching a thermal time threshold) to the total one. Radiation interception is based on the Beer's law. Spikelet sterility due to cold shocks around young microspore stage and at flowering, as well as due to heat stress at flowering, are simulated by calculating hourly stresses and weighting them using development-dependent bell-shape functions to reproduce the between- and within- plant heterogeneity in development. Concerning leaf and neck blast, disease onset is estimated based on hydrothermal time (Arai and Yoshino, 1987; Kim, 2000), whereas the daily infection efficiency is computed according to Magarey et al. (2005). Duration of the phases of latency, incubation and infectious is based on hourly air temperature. Leaf area affected by blast lesions (reducing radiation absorption) is estimated using a compartmental susceptible-infected-removed model. Effects of neck blast are reproduced by reducing the fraction of assimilates partitioned to panicles after the panicle initiation stage (Bregaglio et al., 2016).

The assimilation of remote sensing information was carried out using recalibration and updating techniques. The former is theoretically most advanced and provides a fully consistent and coherent simulation after each assimilation event (Bouman et al., 1995). However, it could expose to risks (Dorigo et al., 2007), since parameter values – normally calibrated using data from many field experiments – are changed using very few uncertain data (normally leaf area index values derived from low resolution remote sensing images). The optimization method used is a multi-start and bounded (for parameter ranges) version of the downhill simplex (Nelder and Mead, 1965). The simplex has N+1 vertices interconnected by line segments and polygon faces in an N-dimensional parameter hyperspace, and it moves through this space according to three basic rules: reflection, contraction, and expansion. Although other optimization methods not using derivatives are available (e.g., Kirkpatrick et al., 1983; Glover, 1986), the simplex guarantees a very favourable ratio between performance and complexity (Matsumoto et al., 2002; Press et al., 2007).

Using the updating method, instead, parameter values are not changed during the simulation, thus lowering the risk of degrading the process-based logic behind the biophysical model. Using the updating assimilation method, indeed, exogenous leaf area index data and model specific leaf area can be used to derive leaf biomass. Then, the relationships between relative weight of different plant organs at the previous time step can be used to update all state variables related to the simulated plant. Of course, this method cannot guarantee a coherent simulation after updating events, since simulated state variables are discontinuous by definition. Moreover, it cannot be used to update soil-related state variables, such as contents of water or mineral nitrogen in the different soil layers. However, this does not represent a constraint here, since simulations were carried out under potential conditions for water and nutrients.

Regardless of the assimilation methods, the procedure was triggered only (i) before flowering (to avoid uncertainty due to green or senescent leaf area), (ii) in case at least three exogenous data were available for each elementary simulation unit, and (iii) for leaf area index data within a biophysical range for rice in each specific phenological stage. Concerning recalibration method, parameters whose values were optimized were specific leaf area at emergence and at mid-tillering and radiation use efficiency.

6.3.3. Input data

Dedicated processing chains were developed to produce the near real-time weather data and RS-derived information used to feed the WARM simulation model.

6.3.3.1. Weather data

An archive (continuously updated for near real-time simulations) of weather data at 2 km × 2 km spatial resolution was created starting from 1st of January 2003 to provide daily input to the WARM model. Source data were derived from the European Centre for Medium-Range Weather Forecast ERA-Interim (for the historical series) and TIGGE (for near real-time) databases (ECMWF; www.ecmwf.int; de Wit et al., 2010) for the following daily variables: maximum and minimum air temperatures, maximum and minimum air relative humidity, rainfall, average wind speed, global solar radiation. Leaf wetness duration, needed for the simulation of blast infections, was estimated according to Sentelhas et al. (2008). The spatial resolution of the ECMWF database used in this study was 0.125° (about 17 km). Data were downscaled to a regular 2 km × 2 km grid based on kriging methodology (Cressie, 1993). To allow correcting biases detected for some of the variables, dedicated calibration procedures were developed by targeting the EC-JRC MARS weather database as a reference (http://agri4cast.jrc.ec.europa.eu/DataPortal/Index.aspx).

6.3.3.2. Satellite remote sensing data

Satellite data were exploited to retrieve information on (i) rice cultivated area (for identifying the area covered by rice in each 2 × 2 km elementary unit) to perform the upscaling of model outputs), (ii) spatially distributed, season-specific sowing dates, and (iii) leaf area index (LAI) for the updating/recalibration of the model.

6.3.3.2.1. Rice distribution maps

Spatial explicit information on rice cultivated areas for the three study sites was derived at 20 m resolution from Sentinel 1 SAR data processing (Fig.1.a,b,c). The map was produced using the processing chain module within MAPscape-RICE (Sarmap®). The mapping method involved two main steps: automatic pre-processing of SAR data and rule-based classification. Firstly, the multi-temporal spaceborne SAR Single Look Complex data were converted into terrain geocoded backscattering coefficient (σ0) following strip mosaicking, co-registration, time-series speckle filtering, Terrain geocoding, radiometric calibration and normalization, anisotropic Non-Linear Diffusion (ANLD) Filtering, Removal of atmospheric attenuation. Secondly, a SAR specific multitemporal σo rule-based rice detection algorithm (MSRD) was then applied (Nelson at al. 2014). In this work, for Greece and Spain exclusively Sentinel-1A 12 days VV/VH Ascending (12 in Greece, 13 in Spain) and Descending (12 in Greece, 13 in Spain) data have been used (hence enabling an almost weekly monitoring) to produce the maps. For Italy, due to the complex agricultural system, 4 Landsat-8 images acquired between March 2016 and June 2016 were additionally used. In this second case, EVI (Huete et al. 2002) and NDFI (Boschetti et al., 2014) were used as additional info to improve the differentiation between rice and other summer crops (maize, sunflower, soybean).

6.3.3.2.2. Sowing dates maps

Spatially distributed estimates of sowing date at district level were based on the use of the PhenoRice algorithm (Boschetti et al., 2009). Currently the method works on integrated time series of TERRA and AQUA 250 m 16-days composite MODIS vegetation indices products (MOD13Q1 and MYD13Q1, respectively). The algorithm identifies a MODIS pixel as a rice crop when 1) a clear and unambiguous flood condition is detected using NDFI, and 2) a consistent rapid crop growth is recognized analyzing EVI. In synthesis, sowing date was estimated in correspondence of agronomic flooding and a minimum in the EVI curve, more details can be found in Boschetti et al. (2009). The PhenoRice approach was applied in three study areas (Italy, Greece and Spain) to estimate dates of crop establishment to be used primarily as direct input to crop modelling solutions, providing spatially and temporally dynamic crop calendars. MODIS imageries acquired from 2003 to 2014 were used to analyze the inter-annual and spatial variability of rice growth dynamics. Fig. 2 provides the statistics derived for sowing dates in Italy (a), Spain (b) and Greece (c). It is interesting to notice that the method was able to detect the anomalous condition that occurred in Italy in 2013 (Fig. 2.a), when crop establishment was 1-month delayed compared to the 10-year average. This observation was confirmed by the National Rice Authority in the 2013 Rice Season Report, that described how an extremely rainy and cold spring forced farmers to delay rice sowing up to mid-June (ENR, 2013).

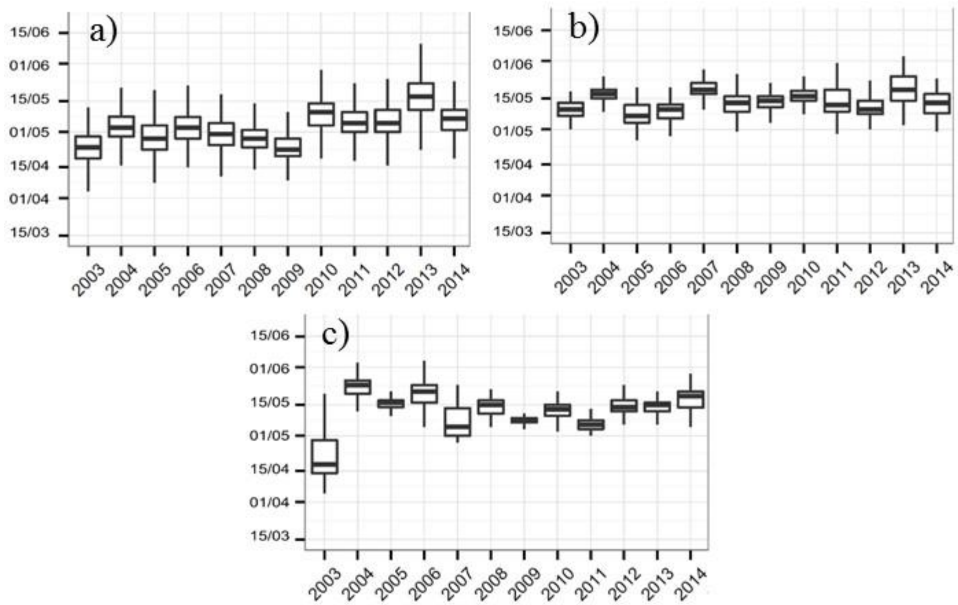

Figure 2: *Inter-annual variability of rice sowing from 2003 to 2014 in a) Italy, b) Spain and c) Greece.*

6.3.3.2.3. Leaf Area Index maps

LAI values (Fig. 3) – used for being assimilated into the WARM model – were derived from operational multi-temporal biophysical products derived from SPOT/VEGETATION and PROBA-V in the framework of the Copernicus Global Land Services. The GEOV1 dataset is a multisensory product, developed to guarantee temporal continuity of biophysical variables over the globe on the near real-time basis. The GEOV1 LAI retrieval processing chain relies on neural networks trained using MODIS and CYCLOPES products (Baret et al., 2013) to generate remote sensing LAI estimates from SPOT/VEGETATION (1999 to May 2014) and PROBA-V (June 2014 up to date) sensors at 1/112° spatial resolution in a Plate Carrée projection (regular latitude/longitude grid) every 10 days. LAI maps were downloaded from Copernicus servers and downscaled at the 2 km × 2 km regular grid used as elementary simulation unit. The downscaling was performed using only values with quality flags indicating the best confidence estimates and using dedicated crop masks for the study areas.

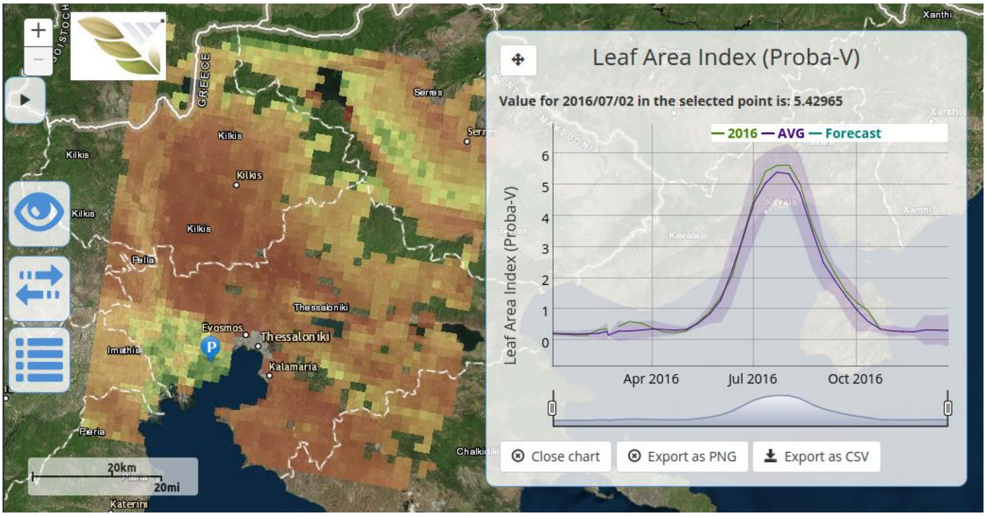

Figure 3: *LAI map over the Greek rice area derived from Proba-V on 2 July 2016 and the time-trend of LAI in 2016 (from the ERMES geoportal, http://ermes.dlsi.uji.es/).*

6.3.4. Spatially distributed simulations and forecasting methodology

WARM model simulations were run on 2 × 2 km elementary units, according to the spatial resolution of the weather database (see section 2.3.1). The model parameters for Japonica varieties (Confalonieri et al., 2009) were used for the simulations carried out in Spain (both districts) and in the Greek district of Serres, whereas the WARM parameters for Tropical Japonica varieties were used for Thessaloniki. Concerning the Italian districts, simulations were run for both the market categories “Lungo B” (belonging to the Tropical Japonica group) and “Tondo” (belonging to the Japonica group). For the latter, the available set of parameters was refined using data on phenological development, LAI and final yield provided by “Ente Nazionale Sementi Elette” (ENSE) between 2006 and 2012, and collected during dedicated experiments carried out within the ERMES project (www.ermes-fp7space.eu) in 2014-2015 in the Pavia Province. The market category “Lungo A” (belonging to the Japonica group) was excluded from the analysis since specific datasets were not available for the calibration of WARM parameters.

According to the agro-management practices in the study areas, simulations were carried out under potential conditions for water and nutrients, whereas the effects of blast disease and cold shocks around flowering (inducing spikelet sterility) were taken into account by means of dedicated WARM modules. For each elementary simulation unit (regular grid of 2 km× 2 km) and for each 10-day period, a variety of information was aggregated at district level based on the percentage of rice cover, as derived by rice maps, for each elementary simulation unit. This information included potential, blast- and cold shock-limited crop model state variables, the same state variables for model runs including the assimilation of remote sensing information (for both the updating and recalibration assimilation methods), and key agro-climatic indicators (Table 1). According to the forecasting methodology developed and used within the MARS forecasting system of the European Commission (Vossen and Rijks, 1995; https://ec.europa.eu/jrc/en/scientific-tool/agri4cast-mars-crop-yield-forecasting-system-wiki) and in related yield forecasting systems (de Wit et al., 2010; Kogan et al., 2013), model outputs and agro-climatic indicators were then related to official yield statistics for the time series 2003-2014 using multiple linear step-wise regressions. To avoid losing robustness because of overfitting, the maximum allowed number of regressor was four. The forecasting event was triggered at the10-day period corresponding to the physiological maturity. Official yield statistics for the rice ecotypes considered (with the exception of Tarragona, for which only global rice statistics were available) were supplied by the Spanish and Greek Ministries of agriculture and by the Italian National Rice Authority. Before the analysis, yield statistics were examined to identify and possibly remove the presence of significant technological trends due to, e.g., improved machineries or genotypes (not reproduced by the crop model). The predictive ability of each regression model was tested by performing a leave-one-out cross-validation on the available time series of historical yields.

Table 1*: List of crop model outputs and agro-climatic indicators used as independent variables within the forecasting system (P=potential conditions; B-l=blast-limited; C-l=cold shock-limited; U=updated; R=recalibrated).*

Indicator name	Unit	Description	Model configuration
Model outputs			
DVS	-	Development stage code	P
AGB	t	Aboveground biomass	P, B-l, U, R
SB	t	Stem biomass	P, B-l, U, R
YIELD	t ha^{-1}	Storage organs biomass	P, B-l, U, R
LAI	m^2 m^{-2}	Leaf area index	P, B-l, U, R
GLAI	m^2 m^{-2}	Green leaf area index	P, B-l, U, R
BlastInf	-	Cumulated efficiency percentage of potential blast infections	B-l
Coldster	-	Cumulated efficiency percentage of potential cold-induced spikelets sterility	C-l
Agro-climatic indicators			
T_{MAX}	°C	Cumulated daily maximum temperature	-
T_{MIN}	°C	Cumulated daily minimum temperature	-
Rain	mm	Cumulated rainfall	-

6.4. Results and discussion

The cross validation allowed identifying the best statistical models for each combination ecotype × production district identified among those proposed by the step-wise regression analysis (Table 2). The significance level for all regression models – sorted on the basis of the beta coefficients – was lower than 0.05.

The forecasting system achieved satisfactory performances in six out of eight cases. Unsatisfying forecasting reliability was indeed obtained only for Tropical Japonica varieties in Thessaloniki and Japonica varieties in Lomellina. Without considering these two cases, average $RRMSE_{CV}$ and R^2_{CV} (relative root mean square error and coefficient of determination of the cross validation, respectively) of the most reliable regression models were equal to 2.9% and 0.78, respectively. The best results were obtained for the Japonica ecotype in Valencia and the Tropical Japonica ecotype (market category “Lungo B”) in Vercelli, for which the amount of inter-annual yield variability explained was, respectively, 89% (33% of which explained by a technological trend) and 83%.

Despite the poor results obtained in terms of R^2 for Tropical Japonica in Thessaloniki and Japonica in Lomellina (Fig. 4), the values of modelling efficiency (EF; Nash and Sutcliffe, 1970) were positive (0.24 and 0.16, respectively) indicating that the forecasting system – even in these cases, is a better predictor than the mean of official yield statistics (Table 2). The marked over- and underestimations showed in some years (i.e., 2012-2014 for Thessaloniki, and 2009-2010 for Lomellina; Fig. 4.a) were mostly caused by factors not accounted for by the simulation model. As an example, the low yield recorded in Thessaloniki for 2012 was caused by an extreme heat wave during the reproductive period (process not simulated by the current modelling solution), whereas the high yields in 2013 and 2014 were due to the introduction of the successful high yielding variety Ronaldo (DEMETER – Cereal Institute of the Hellenic Agricultural Organization, personal communication).

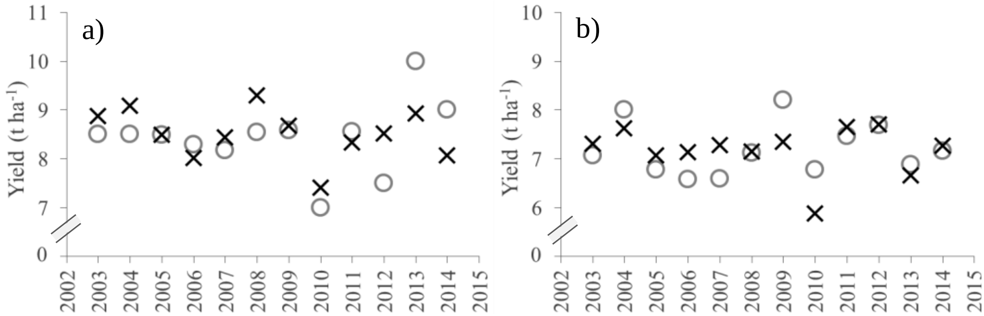

Figure 4: *Comparison between official (grey circles) and forecasted (black crosses) yields for the cross-validation for a) Tropical Japonica cultivars in Thessaloniki and b) Japonica cultivars (market category "Tondo") in Lomellina.*

In seven out of eight cases, the assimilation of remote sensing-derived LAI allowed improving the forecasting capability; in particular, the updating and recalibration assimilation methods led to improving forecasts in two and five cases, respectively. This is in agreement with results obtained by other authors: e.g., Ma et al. (2013) almost halved the error on yield estimates by assimilating MODIS-derived LAI into a forecasting system based on the WOFOST crop model. Similar results were obtained by Ines et al. (2013) for maize yield forecast using a DSSAT-based system.

For the rice district of Tarragona, simulated state variables (including blast-limited conditions) allowed achieving satisfactory predictions even without the assimilation of remote sensing information (Table 2), with EF and R^2 for cross-validation equal to 0.60 and 0.71, respectively, although 37% of the inter-annual yield variability was explained by a significant technological trend. For other combinations ecotype × district, instead, the assimilation of remote sensing information allowed to increase the predicting capability, although the forecasting system solely based on the crop model explained a relevant part of yield fluctuations in the series of historical yields series. As an example, assimilation led to increasing R^2 from 0.70 to 0.83 for Tropical Japonica in the province of Vercelli (Table 2). In other cases, the reduction of uncertainty due to the assimilation of remote sensing-derived LAI led to a substantial improvement in yield forecasts. As an example, the model showed marked under- and overestimations in most of the years for Japonica varieties in Serres, even under blast-limiting conditions (negative EF, R^2=0.09; Table 2 and Fig. 5.a), for which some of the model outputs achieved significant values when used as regressors. In particular, the yield forecasted for 2003 was in line with the average values for the time series, whereas official yield statistics for the same year were severely affected by blast disease (DEMETER – Cereal Institute of the Hellenic Agricultural Organization). Among the reasons for explaining the crop model failure in identifying 2003 as a year particularly affected by blast disease, a key role is likely played by the lower resistance of varieties grown at the beginning of the 2000s and by the general uncertainty due to the lack of information on fungicides distribution for large-area simulations.

Concerning the former, indeed, given the pathogen pressure change greatly between years, the effect of improved varieties is hardly detectable by medium-term technological trends. The assimilation of remote sensing LAI allowed reducing the uncertainty in simulations by detecting the overall lower vigor of rice canopies in the district due to the disease. Indeed, assimilation led to markedly increase the system capability to reproduce the inter-annual yield fluctuations (a value of 0.80 was achieved for both EF and R^2), including the correct estimate of the poor yields recorded for 2003 (Fig. 5.b).

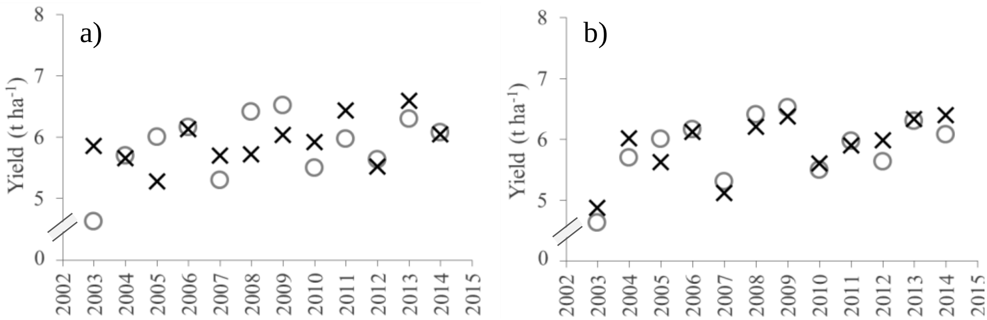

Figure 5: *Comparison between official (grey circles) and forecasted (black crosses) yields for the cross-validation for Japonica varieties in Serres. Forecasting system was based on a) crop model outputs and agro-climatic indicators, and on b) model outputs updated using remote sensing-derived LAI and agro-climatic indicators.*

In most of the cases, the statistical post-processing of simulated outputs was important for reducing the different sources of uncertainty (in model structure, parameterizations, management, upscaling procedure, etc.) affecting large area simulations and, thus, to allow the system to correctly reproducing the fluctuations along the historical series of yield statistics. However, when the model was run in contexts not severely affected by extreme weather conditions or by unreproducible (given the scale) season- or site-specific effects involved with the application of management practices, good results were obtained from the combined use of crop modelling and remote sensing technologies, even without post-processing results. As an example, in the rice district of Valencia, yields simulated by WARM under potential conditions for Japonica cultivars were sufficiently coherent – in terms of overall time trend – with official yield statistics, although they were characterized by a general underestimation during the whole time series (Fig. 6.a). The assimilation of remote sensing-derived LAI values (via recalibration of model parameters) allowed to greatly improve the forecasting capability of the crop model even in absolute term, especially in the second part of the series (Fig. 6.b). However, the statistical post-processing of simulated results led to further improve forecasts (Fig. 6.b) by including in the regression model – besides simulated yield – a second variable, i.e. the cumulated rainfall, that presented a negative correlation with official yields. The reason for the importance of cumulated rainfall is related with its role in affecting rice productivity because of less radiation available for photosynthesis (in turn due to more cloudy days) and because of higher humidity, that favored blast infections. A further negative effect of abundant rainfall in the last part of the crop cycle is the possible problems during harvesting procedures.

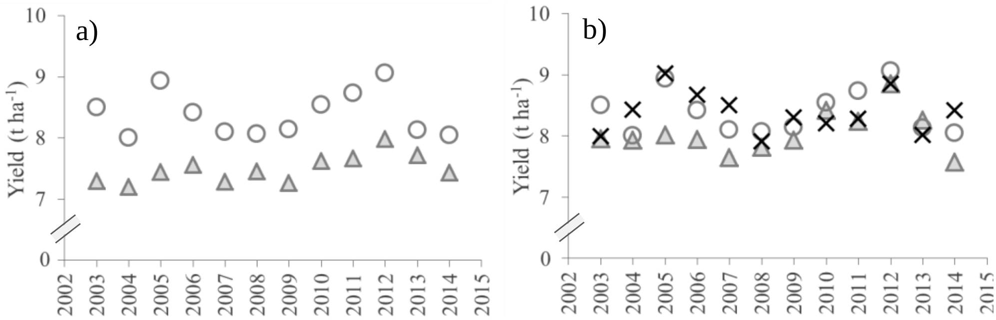

Figure 6: *Comparison between official (grey circles) and yields forecasted for Japonica cultivars in Valencia using a) only the crop model (grey triangles), b) the crop model with assimilation of remote sensing LAI (grey triangles) and the statistical post-processing of simulated results (including LAI assimilation) (black crosses).*

The forecasting reliability obtained for Italy is in line with (or better than) the best results obtained by de Wit et al. (2010) using the CGMS-WOFOST model for grain yield estimates in Europe, whereas the results we obtained for Japonica cultivars in Valencia (56% of the variance explained without considering the trend) are slightly better than those achieved by de Wit et al. (2010) for barley, field beans and sugar beets. Results achieved for other combinations rice ecotype × district are less reliable, although they can be considered as in agreement with most of the results normally obtained using generic and crop-specific (e.g., Kogan et al., 2013; Ines et al., 2013) yield forecasting systems. Comparing our system with other rice specific ones, the values of R^2 obtained by Son et al. (2014) with an approach based on MODIS-derived vegetation indices for the Mekong River Delta (Vietnam) ranged from 0.40 to 0.71. These values are similar to the ones we found, although the inter-annual yield fluctuations in Vietnam are larger than those characterizing rice cultivation in Europe, and the mean error obtained by Son et al. (2014) was often higher than those achieved in this study. However, the approach proposed by Son et al. (2014) is simpler and easier to be set-up and maintained.

Table 2: *Indices of agreement derived from the comparison between official and forecasted yields for the 2003-2014 time series. Forecasted yields derive from the statistical post-processing of simulated model outputs (M in the column "Regressors") and agro-climatic indicators (A-c) (Table 1). The best regression models (maximum allowed regressor = 4) were identified by a leave-one-out cross-validation. U and R in the column "Regressors" refer to the assimilation of remote sensing LAI in the crop model using updating and recalibration techniques, respectively. Empty cells indicate the absence of significant regression models. Cells with dashes indicate that no improvement was obtained from assimilation.*

Country	Variety group	Rice district	Regressors	Regression model	MAE	RRMSE %	EF	Slope	Int	R^2
Spain	Japonica	Valencia	M, A-c	Rain**, Yield*	0.23	3.01	0.66	1.07	-0.60	0.66
			M, A-c, **U**	-	-	-	-	-	-	-
			M, A-c, **R**	Rain***, **Yield$_R$*** **	0.11	1.72	0.89	1.04	-0.31	0.89
		Tarragona	M, A-c	GLAI$_B$*, LAI**, Yield**, AGB$_B$**	0.22	4.61	0.60	0.72	1.71	0.71
			M, A-c, **U**	-	-	-	-	-	-	-
			M, A-c, **R**	-	-	-	-	-	-	-
Greece	Tropical Japonica	Thessaloniki	M, A-c							
			M, A-c, **U**	**GLAI$_F$****, LAI$_B$**, **LAI$_F$***	0.50	8.00	0.07	0.55	3.80	0.21
			M, A-c, **R**	GLAI**, LAI*, **AGB$_R$***	0.50	7.24	0.24	0.74	2.10	0.28
	Japonica	Serres	M, A-c	Yield$_B$*, AGB$_B$*	0.41	9.08	-0.08	0.43	3.30	0.09
			M, A-c, **U**	GLAI***, **Yield$_F$*****, Tmax***	0.20	3.94	0.80	0.97	0.13	0.80
			M, A-c, **R**	LAI**, LAI$_R$*, Tmax*, Yield$_B$**	0.33	7.05	0.35	0.79	1.17	0.39
Italy	Tropical Japonica *(market category "Lungo B")*	Lomellina	M, A-c	GLAI**, DVS**, Tmax**, Tmin*	0.23	3.88	0.11	0.55	3.16	0.40
			M, A-c, **U**	DVS**, **LAI$_F$****, LAI$_B$**, **AGB$_F$****	0.16	2.78	0.54	0.75	1.78	0.62
			M, A-c, **R**	DVS**, **LAI$_R$***, Yield**, **Yield$_R$*****	0.14	2.31	0.69	0.91	0.67	0.70
		Vercelli	M, A-c	ColdSter**, LAI***	0.21	3.34	0.70	0.96	0.29	0.70
			M, A-c, **U**	-	-	-	-	-	-	-
			M, A-c, **R**	**GLAI$_R$*****, LAI***, **LAI$_R$****, **Yield$_R$****	0.16	2.50	0.83	1.00	-0.03	0.83
	Japonica *(market category "Tondo")*	Lomellina	M, A-c							
			M, A-c, **U**							
			M, A-c, **R**	**SB$_R$****, **AGB$_R$***	0.37	6.58	0.16	0.60	2.90	0.30
		Vercelli	M, A-c	LAI**	0.19	3.16	0.48	0.90	0.72	0.49
			M, A-c, **U**	**LAI$_F$****, DVS*, Rain*, AGB$_B$***	0.16	2.57	0.66	0.78	1.55	0.72
			M, A-c, **R**	-	-	-	-	-	-	-

* $p \leq 0.05$; ** $p \leq 0.01$; *** $p \leq 0.001$

6.5. Conclusions

A high-resolution rice yield forecasting system based on the WARM model was run on 2 km × 2 km elementary simulation units covering the main European rice districts in Italy, Spain and Greece. The system integrated remote sensing information to define rice-cropped area and to derive sowing dates varying in time and space, as well as for assimilating exogenous LAI information into the simulation (using both updating and recalibration techniques). Forecasting performances at maturity were satisfactory for most of the combinations ecotype × production district. The average values for mean absolute error, RRMSE and R^2 obtained from the comparison with official yield statistics were 0.23 t ha^{-1}, 4% and 0.66, respectively. The assimilation of remote sensing LAI led to improvements in seven out of eight cases, with the increase in the amount of variability explained ranging from 7% to 71%.

Although further studies are needed to increase the predicting capability in some of the districts (i.e., Thessaloniki and Lomellina), the system demonstrated its usefulness during 2015 and 2016, when it was used under pre-operational conditions during the activities performed within the EU-FP7 ERMES project (http://www.ermes-fp7space.eu/). In this context, yield forecast bulletins were regularly issued to public authorities and private companies in Italy, Greece and Spain. Feedbacks received encourage to go on running the forecasting system operationally in the next seasons.

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GENERAL CONCLUSIONS AND PERSPECTIVES

The main objective of the PhD project was to improve the reliability of existing model-based yield forecasting through the reduction of the impact of sources of uncertainty related with the quality of spatially-distributed input data, the absence of approaches for biotic and abiotic stressors, and the assumptions behind upscaling procedures.

The development or improvement of approaches for the simulation of abiotic factors affecting crop productivity allowed to better capture the inter-annual yield fluctuations, especially in case of unfavourable seasons, that is, when stakeholders are more interested in early yield estimates. Most of the approaches developed for weather extremes allowed improving the reliability of CGMS, the forecasting system of the European Commission, and will be transferred to the operational CGMS chain. In particular, the new system allowed improving the accuracy of CGMS in 93% of the analysed combinations crop × country × forecasting moments. These results have to be considered of particular interest given the projected increase in the frequency and intensity of weather anomalies.

Besides the development of dedicated approaches for extreme weather events, the research focused on increasing the capability of large-area forecasting systems to reproduce the effect of water stress on the productivity of high-yielding rainfed crops. As a case study, the integration of the dynamic Canegro model with dedicated agro-climatic indicators for sugarcane yield estimates in São Paulo (Brazil) allowed to markedly increase the predicting capability (up to 93% of the inter-annual variability explained) compared to existing approaches.

The integration of remote sensing information and crop modelling for rice yield forecasts in Europe allowed obtaining the maximum benefits from these two different technologies. Indeed, remote sensing data (used for model initialization or for the dynamic integration of exogenous information) allowed to greatly reduce the impact of the uncertainty affecting information on rice distribution, management practices, and cultivated varieties. Moreover, the system benefited from the implementation of dedicated approaches for plant-pathogen interactions.

The satisfactory results achieved allow considering the systems developed during the PhD project as suitable for operational contexts. However, further researches would allow to overcome limits that still affect the predicting capability of available systems. The integration of remote sensing information in crop modelling platform was here facilitated by the specific crop. Rice, indeed, is still mainly grown under flooded conditions in Europe, and flooded fields are clearly detected by satellite sensors. This allows deriving crop-specific remote sensing products to be used within crop models without the uncertainty due to the presence of mixed pixels. Researches are needed to evaluate the reliability of the technologies applied here on rice when extended to other species. Other areas of improvement deal with the development of more approaches for the simulation of the effects of abiotic/biotic stressors on crop productivity. However, the impact of most of the extreme events affecting crop yields is hardly reproducible within spatially-distributed simulations. Indeed, many of them (e.g., flooding, wind gusts, hail) are characterized by high-resolution spatial patterns, which are difficult to be captured by large-area agrometeorological networks. In any case, the evaluation of crop yield forecasting systems takes the highest advantage from the interaction with local stakeholders. Indeed, official yield statistics are normally recorded without metadata explaining year-to-year fluctuations, and this is a critical constraint that limits the evaluation and improvement of existing approaches.

CURRICULUM VITAE

The numbers between curly brackets refer to the publications listed at the end of this document.

Valentina Pagani was born on 10 April 1986 in Varese. In 2004/2005 she completed the high school (Second Level College of Science) with a grade of 87/100. In 2006 she started a 5-year University course (including B.Ag. and M.Sc. degrees) at the University of Milan (Faculty of Agriculture). B.Ag. and M.Sc. were completed, respectively in 2008/2009 (110/110 cum laude; dissertation on a research about a phenotyping and genotyping screening of acetic bacteria secondary symbiont of insects) and in 2011/2012 (110/110 cum laude; dissertation on a research on the evaluation of a prototype of a yield forecasting system applied to Senegal rice districts). From 2012 to 2013 she obtained a grant at the University of Milan to evaluate crop models for the simulation of growth and development of rice, maize and wheat. In the same period she was the main responsible of the calibration of crop models and of their application on large areas for yield forecasting purposes, within the activities of the work package 3 of the EU-FP7 E-AGRI project {1}. In 2013 she started a PhD project on the improvement of yield forecasting systems based on crop models and remote-sensing at the University of Milan. She was the main responsible of the development of yield forecasting systems based on the integration of crop models, weather extreme impact models {ii} and agro-climatic indicators within the activities of the EU-FP7 MODEXTREME (KBBE), grant no. 613817. She is the main author of a model for the simulation of transplanting (both manual and mechanical) shocks in rice crops {3}, and co-author of the reimplementation of the sugarcane model Canegro {4}, as well as the main responsible of its application for yield forecasting purposes {i}. She collaborated with the Institute for Electromagnetic Sensing of the Environment (Italian National Research Council) for the development of a high-resolution yield forecasting system for rice, being task leader within the work package 9 of the EU-FP7 ERMES project {iii}. She co-authored the first statistical procedures for the quantification of the amount of uncertainty in model predictions due to user subjectivity {6}.

She also co-authored two smart app for non-destructive estimates of leaf area index and nitrogen concentration in plant tissues {5}, later adapted to different operational contexts {7, 2}.
Author of 7 publications on ISI Journals with Impact Factor (1 as first author).
Inventor of a technology registered by the University of Milan on the use of digital imagery for nitrogen determination in plant tissues.

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