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In silico evaluation of climate change impacts on the qualitative aspects of rice productions in the main Italian rice-growing district

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ABSTRACT

The definition of food security provided by the Food and Agriculture Organization of the United Nations (FAO) includes the quality of agricultural products as a principal pillar, intended as the production of nutritious food to allow people to meet dietary needs and food preferences for an active and healthy life. In a world that is undergoing major physical, social, and economic transitions, the achievement of global food security is undermined by the projected increase of human population to 9 billion people by 2050.

Nowadays, even if the current total food production would be capable to provide humankind with enough calories, the latest FAO statistics estimate that hundreds of millions of people live in hunger or lack a suitable supply of food. This is why the world governments are acting to meet the need of higher quality diets as a main objective. The challenge to improve the quality and the nutritional value of crop productions is also threatened by the climate change issue, with agriculture representing the most vulnerable economic sector due to the deep influence of weather conditions on the performances of cropping system.

The only viable solution to gain information on the future trends of the qualitative aspect of crop production and to provide farmers and stakeholders in agriculture with effective adaptation strategies is the use of process based simulation models, which are capable to reproduce the responses of biophysical systems to changing boundary conditions.

This doctorate gives answers to these research questions, by developing a reference methodological framework to assess the quality of rice (Oryza sativa L.) –the first staple food crop in the world – in current and future climatic conditions.

The first chapter presents a software library of models to simulate the dynamics of the main aspects of rice grain quality as a function of agro-meteorological conditions. This research product is released as a framework independent component, fostering extension with new models and reuse by third parties intended as collaborations between research entities.

In the second chapter the performances of the rice quality models in reproducing observed field data of milling quality and functional properties of grains are tested in a multi-site and multi-year evaluation, prior to be used to assess climate change impacts.

The third chapter deals with the development of a forecasting system targeting the simulation of qualitative and quantitative rice productions in Northern Italy, the main European producing area. This pilot study is realized by coupling the WARM rice model with rice quality models, taking the head rice yield, i.e., the percentage of entire grains as a case study.

The fourth chapter presents the complete workflow to assess the climate change impacts on crop productivity in the Lombardy plain via the application of process based models at a fine spatial resolution. An exploratory analysis of the impacts of climate change on giant reed crop is performed to illustrate the potentialities of the methodology.

This work led the basis to the last chapter, where a comprehensive evaluation of the impacts of climate change on rice milling quality and technological suitability is performed in Europe. The main sources of uncertainties in climate change projections were taken into account, i.e., General Circulation Models and emission scenarios, to give an ensemble of future weather scenarios as input data to the models. The implementation of remote sensing to detect rice sowing dates and the assimilation of local farmers management led to a tight adherence between simulated and real system.

The main perspective of this work is the application of the methodological framework developed here in top producing rice countries, in order to allow moving a step forward the mere focus on the quantitative trends of crop production in a changing climate.

Keywords: amylose, end-use-value, high-temperature stress, global warming, head rice yield, grain filling, milling quality, protein, starch viscosity.

CONTENTS

INTRODUCTION

1.1. Climate change and pre-harvest crop quality

Empirical records provide evidences of the impacts of climate change on several aspects concerning human life as health, food security, social and economic development, hydrological resources and infrastructures. According to the Intergovernmental Panel on Climate Change (IPCC), the steadily increasing anthropogenic GHG emissions are expected to even exacerbate global changes in the coming years in case effective adaptation and mitigation strategies will not be implemented in the short-mid term (e.g., Bernard et al., 2001; Roessig et al., 2004; Tol, 2009). Climatologists agree in projecting global raising thermal regimes up to 4.8 °C by the late-21st century, together with marked sub seasonal changes in precipitation patterns and a rising frequency and severity of weather extremes (IPCC, 2013).

Agriculture is one of the most vulnerable human sector to climatic changes since atmospheric CO_2 enrichment and meteorological variables are the main drivers influencing the growth and development of crops (e.g., Rosenzweig et al., 2002; Tubiello, 2005; Lhomme et al., 2009). Over the last two decades, while the crop yield level is progressively increased due to genetic and management advancements (Cassman, 1999), the crop quality attributes have levelled off or even decreased for a large variety of products such as grain legumes (Graham and Vance, 2003), oilseeds, fresh fruits and cereals (Oury et al., 2003). The few available studies indicate that the increased temperature and enriched CO_2 concentration will determine an overall decline in grain quality in the future for many cereal crops (DaMatta et al., 2010), with rice being particularly interested (Nagarajan et al., 2010; Sreenivasulu et al., 2015). The exposure to elevated temperature regimes during ripening period will be responsible for the alteration of sink strength and storage composition of rice grains, leading to a decay of the nutritional, rheological and milling attributes of this key food crop (Sreenivasulu et al., 2015). The physiological causes behind these alterations mainly rely on the shortage of grain filling duration (Ishimaru et al., 2009), on the reduced allocations of nitrogen from leaves to ears (Cheng et al., 2010), on the predominance of nighttime respiration versus photosynthesis (Sreenivasulu et al., 2015), on the non-uniform moisture desorption from the grain surface before harvest (Lan et al., 1999) and on

the reduced biosynthesis of starch and its concurrent degradation by α-amylase enzyme (Yamakawa et al., 2007). These projections are pushing the demand for mid-term analyses of the economic and social sustainability of current rice productions, especially in Europe, where recent policies concerning food safety and the responsible use of resources induced farmers to improve the qualitative aspects of processes and products. Crop quality is a key determinant of the economic and nutritional value of agricultural products, since it directly affects their acceptability to buyers and consumers (Koutroubas et al., 2004). The achievement of superior quality is gaining unprecedented importance as an efficient way to gain a competitive market advantage against countries exporting low price products (Griglione et al., 2015). This frame is exacerbated by the changing climatic conditions, given that rice represents the staple food of world’s half population (GRiSP, 2010) and its consumption is steadily increasing even in non rice-eating countries (Suwannaporn and Linnemann 2008).
Italy is the first rice producer in EU-27 and the fourth-largest rice-exporting country at global level. More than 90% of Italian rice is grown in the Italian Lombardo-Piemontese district, representing the leading rice area in Europe with 1,380,000 t produced on 216,000 ha in 2014 (Ente Nazionale Risi, ENR; www.enterisi.it), leading to a turnover of about one billion euros (National Institute of Agricultural Economics Research, INEA, 2014). A large number of varieties is grown in the district, with 2/3 belonging to the Japonica type (average yield of 6.5 t ha^{-1}) and 1/3 to the Indica type (average yield of 7 t ha^{-1}), with a cycle length ranging from short (120-140 days) to medium-long (140-170 days). Among Japonica cultivars, long rice with chalky grains and high amylose content predominated over bold and medium grains, and they are mainly used in the domestic market for parboiling process and the preparation of risotto dishes. The non-chalky Japonica and Indica cultivars are almost entirely exported to European and non EU countries (above 60% of total milled rice), contributing to the value of domestic rice sector with approximately accounted for € 500,000 in 2013 (INEA, 2014). The leading role of Italy in the EU rice production is nowadays undermined by the decrease of CAP incentives to farmers and by the rising global market competition. Furthermore, the increase in the occurrence of weather extremes during the rice growing season is threatening Italian rice productions, leading to a severe decay in grain quality and consequent

losses of market value (Cappelli et al., 2014a). National breeding programs to enhance the quality of rice productions were thus recently funded for Japonica and Indica varieties. The main traits Italian breeders are focusing on are the improvement of milling quality, cooking properties and nutritive characteristics of rice productions (Russo and Callegarin 1997) and the certification of the supply chain, considering the chance to implement low impact agronomic practices (i.e., organic and Protected Geographical Indication rice varieties, Griglione et al., 2015). The availability of plausible indications targeting rice cropping systems performances in the mid-long term could support multiple stakeholders in the rice sector to plan financial investments according to available resources and local priorities.

1.2. Modelling pre-harvest crop quality in climate change studies

In light of their proved ability in reproducing crop responses under a wide range of agro-meteorological conditions (Porter and Semenov 2005), process-based models are routinely used to forecast the potential impacts of climate change on agricultural systems and to define adaptation strategies. In this context, crop quality is still scarcely investigated, in spite of its expected decay for many cereals, with consequences on food security issues and market losses worldwide. Although the availability of a number of simulation models for crop quality, the studies on the climate change impact are mainly focused on the evaluation of crop phenology, productivity and water use efficiency aspects (White et al., 2011). Very few attempts were carried out to assess the nitrogen concentration in wheat grains (Erda et al., 2005; Porter and Semenov 2005; Asseng et al., 2013) and the incidence of chalky grains in rice (Okada et al., 2011).

This gap of knowledge is explained by the few process-based models for grain quality in literature, as modellers started to work on these research theme only in the last few years (Porter and Semenov, 2005; Martre et al., 2011). Given its complexity and heterogeneity, crop quality is a multi-criteria concept, which is very difficult to formalize in simulation models, given that it is the result of a complex chain of biological processes (Genard and Lescourret, 2004). The state of the art of quality models focuses on a hierarchical mechanistic representation (i.e. from cell to organ) of biological processes regulating fruit size and composition. Examples are available for fruit (peach trees, Génard and Souty, 1996; vineyards, Dai et al. 2009) and

industrial (tomato, Prudent et al., 2011) and cereal species (wheat, Porter et al., 1993; Martre et al., 2006), for which quality largely affect their processing and marketability value. However, most of these approaches are – to a certain extent – unsuitable in operational contexts since hardly compatible with the level of abstraction used by available crop models. Taking rice as an example, the quality models are involved with the simulation of grain nitrogen concentration, in turn used as a proxy for protein content (Ritchie et al., 1987; Bouman et al., 2001). Other attempts were made to estimate the accumulation of starch/amylose in the grain as affected by weather conditions (e.g. water, temperature stress; Chen et al., 2011). However, most of rice quality models rely on semi-empirical relationships with climate (e.g. temperature, solar radiation) and are driven by empirical parameters (Cappelli et al., 2014a). The performances of available models are rarely assessed in different agricultural contexts, thus preventing a clear understanding of their suitability for both research and operational purposes. This represents a crucial step towards the improvement of available modelling tools, since crop quality plays a key role in determining the economic value and the final destination of agricultural products, thus being strongly related to the humans and animals health (Koutroubas et al., 2004). Examples are provided by the occurrence of rice cracking, which usually halves the market value of head rice (Siebenmorgen et al., 2013) and can even prevent direct human consumption, redirecting products towards livestock feed or pet foods producers or brewer industry (Paranthaman et al., 2009).
The development of reliable simulation models to reproduce the multiple aspects of grain quality is then becoming a crucial issue for stakeholders in agricultural sector. The adoption of the state-of-the-art of software engineering technology is then required to manage the complexity of the underlying biophysical processes, e.g., the mutual interactions between meteorological variables, plant development, agromanagement practices, and genetic regulation of organ size and composition.

1.3. Sharing knowledge via software components

A cropping system simulation model is a set of interlinked equations each representing a single biological or physical process. They are called models, instead of the possibly more appropriate term modelling solutions

(Donatelli et al., 2014), due to the way they appear to the final user, who might even use them as black boxes driven by a graphical user interface. In the last decade, their focus has shifted from on-farm crop productivity to the integrated assessment of qualitative aspects of crop productions and losses associated with pest and diseases, thus exploring options for climate change adaptation and mitigation. This required the coupling of crop simulators with models belonging to other disciplines, such as hydrology, plant pathology and economics. Current software implementations, however, are often characterized by monolithic implementations based on procedural languages (e.g., DSSAT, EPIC) and by the lack of good software engineering principles, thus limiting cross-domain model integration. Most of the models are incompatible with each other with little or no reuse of sub-models, leading to the proliferation of software tools implementing a variety of versions of the same algorithms (Holzworth et al., 2015). In most cases, these algorithms derive from the reimplementation of very common approaches to simulate crop and soil processes, removing resources for model improvement and leading to subtle differences that are not immediately apparent. In order to overcome these shortcomings, several Authors recently claimed the need for modularity and replaceability in biophysical models (e.g., Jones et al., 2001; Donatelli et al., 2006a, Holzworth et al., 2010), to avoid duplication, improve the efficiency of use of resources and foster the development of high quality modelling units (Donatelli and Rizzoli, 2008). Component-oriented programming is currently the best option for the development of agricultural and ecological models (Reynolds and Acock, 1997; Papajorgji et al., 2004), the advantages being the ease of maintenance of the code, granularity of the approaches implemented, reusability of the tools and cross platform capabilities (Meyer, 1997). According to the modular approach at the base of component-oriented programming, the solution of a modelling problem is encapsulated in a discrete, replaceable, and interchangeable software unit, i.e., a software component (Szypersky et al., 2002), that can be deployed independently and is subject to composition by third parties. The isolation of modelling problems belonging to specific domains allows the development of sub models by domain specialists, rather than having generalist modellers working on complex and integrated systems. The component-oriented design represents the natural choice for building scalable and robust applications, and to maximize the ease of maintenance in a variety of domains. Most advanced modelling frameworks (i.e., a group of interconnected models with infrastructure to support inter-model communications) embrace component-oriented programming as a common practice (e.g., BioMA, Donatelli et al., 2012; OMS, David et al., 2013; APSIM, Holzworth et al., 2014), fostering the development of modelling solutions that integrate single-disciplines approaches (Bregaglio and Donatelli, 2015). The strength of this approach is that it allows the collaboration of different parties around a common 'trusted' base, allowing cross-domain applications to be built on shared knowledge in the form of components (Holzworth et al., 2015). Nevertheless, many of current component realizations are designed to match a specific interface requested by a modelling framework, thus decreasing their reusability. This could explain the scarce adoption of modelling frameworks by groups other than those of developers (Rizzoli et al., 2008). A further step is then required for the modelling community, i.e. to increase the reusability of tools by adopting a design targeting the interchangeability of components across modelling frameworks.

1.4. Objectives and organisation of the research

The development of operational simulation tools able to support the management of agricultural systems is a key research topic in agriculture, and a variety of multi-approach software libraries is currently available for, e.g., weather data generation, crop growth and development, soil dynamics involved with water redistribution and runoff, plant-pathogens interaction. In this context a variety of approaches dealing with grain quality aspects of rice productions have been proposed, although in a non-systematic way and without being integrated in models for the simulation of rice-based cropping systems. This represents a clear gap of knowledge researchers are trying to fill, in light of the evidences of a climate change-driven decline in the nutritional properties of important food crops, with rice being particularly interested. For this reason, **the objective of the first section of this Thesis is to present a framework independent, extensible, multi-approach software library for the simulation of rice grain quality variables.** In order to promote the usability of the component, two typologies of users were identified: *beginners*, i.e., users without specific expertise in quality variables and models, and *experts*, represented by specialists in rice quality modelling.

One of the key issue in crop modeling is to evaluate model performances prior to apply it in large area applications. Available models targeting the simulation of grain quality are based on semi-empirical relationships developed in specific agrometeorological conditions (China, Japan and USA). In this perspective, **the second objective of this work is to perform a multi-site and multi-year comparative evaluation of alternate models targeting the simulation of rice grain quality, prior to apply them in spatially distributed simulations in the main European rice growing district**.

Crop yield forecasting systems (CYFS) based on simulation models are worldwide adopted to provide in season estimates of the production of staple food crops. Since the beginning, these systems focused on the simulation of potential and attainable yields, while progresses in the last decades would likely lead to the implementation of models to simulate actual productions, via the consideration of abiotic and biotic stresses. Available CYFS are thus increasing their ability in forecasting the annual yield variability, but they almost ignored the qualitative aspects of crop productions. A reliable forecast of pre-harvest grain quality is requested by stakeholders in rice sector, mainly to improve grain quality standards and to schedule the length of the milling season to maximize business profitability. **The third main objective of the present thesis is the development of a new forecasting system targeting the simulation of qualitative and quantitative rice productions in Northern Italy**. The quality variable chosen as a case study is the head rice yield, i.e., the percentage of entire rice grains after milling, representing the main determinant of rice market price at global level. The forecasting system is realized by coupling an available model for the estimation of head rice yield with the WARM rice crop model and is applied at field and province level.

The concerns about the climate change-driven decline for several cereal crops are pushing the demand for mid-term analyses of the economic and social sustainability of current production systems. Although giant reed is considered as a promising non-food and non-feed energy crop in temperate climates, no studies are available regarding its response under climate change scenarios. In this context, process-based biophysical models are the most suitable tools for estimating the potential impacts of climate change on the productivity of agricultural systems due to their ability in reproducing crop responses to meteorological and management conditions. In this perspective, **the fourth main objective of the Thesis is the definition of a systematic, generic and reproducible procedure to assess the climate change impacts via the spatially explicit application of process based models.** To illustrate the potentialities of the method developed, an exploratory evaluation of the climate change impact on giant reed productivity was carried out in the Lombardy plain (northern Italy), also evaluating the opportunity of changes in land use from corn to giant reed by analysing economic and environmental issues.

Crop quality is often neglected in available climate change impact studies, thus leading to the risk of possible underestimations of socio-economic and food security issues. Recent policies in European countries were implemented to safeguard the environment and to enhance the responsible use of resources, thus forcing farmers to improve the qualitative aspects of processes and products, besides merely increasing crop productivity. These aspects are of paramount importance in Italy, where national breeding programs to improve the milling and nutritive aspects of rice productions with the implementation of low impact agronomic practices were recently launched to support stakeholders of rice sector in identifying priorities for planning future investments. **The fifth main objective is then to support these programs by assessing the future trends of multiple aspects of Italian rice quality in the short (2030) and long (2070) term, via the spatially explicit application of process based models**. The analysis was conducted at 2 km spatial resolution on the main European rice district by integrating the state-of-the art of crop growth and quality models, IPCC climate change scenarios (2013) and remote sensing techniques for crop and sowing data detection.

1.5. Synopsis

Chapter 2 presents a framework-independent .NET software library, i.e., UNIMI.Cassandra.RiceQuality, implementing models to simulate various aspects of rice quality: amylose, protein, lipids and starch content, viscosity profile, chalkiness, cracking, pecky grains and head rice yield. All models reproduce the impact of meteorological conditions on grain quality during the ripening phase, with a final value for the quality variable reached at physiological maturity or dynamically simulated until the crop is harvested. Alternate approaches for the simulation of the same quality property are included, to allow users to select the most suitable for specific modelling studies. A case study is also presented where the library was linked to the WARM rice model and used to simulate head rice yield and the percentage incidence of cracked and milky white kernels (severely chalky) for two rice varieties in the main European rice district. The results achieved, showed the ability of the implemented models to differentiate their responses according to the meteorological and management conditions explored by the crop over the study area. The component, developed according to the state-of-the-art of component-oriented software development, is released with a Software Development Kit containing help and code documentation files, as well as sample applications showing how to use the library with different crop simulators.

Chapter 3 presents a multi-site, multi-year and multi-metric comparative evaluation of 26 of models for the simulation of rice milling quality and functional properties of grains, to understand the potential for application in the main European rice growing district. The analysis was performed using data collected during field experiments where cultivars Loto (*Japonica*, medium slender grain) and Gladio (*Indica*, long slender grain) were grown in 16 sites during the seasons 2011-2014. The study revealed that model accuracy increased with model complexity, reaching best results for functional properties referring to *Japonica*-type variety. Conversely, available approaches for the simulation of milling quality still require improvements to further reduce the uncertainty in model predictions, especially when applied to *Indica*-type cultivars. However the comparative analysis performed proved that the selection of most accurate approaches per quality variable allowed a proper simulation of the observed dynamics, thus being sufficiently accurate to be operatively applied either in forecasting activities or scenario analysis (e.g. climate change impact assessment).

Chapter 4 presents a new forecasting system – GLORIFY – targeting the simulation of quali-quantitative rice productions in Northern Italy. The quality variable considered is the head rice yield (HRY), representing the main determinant of rice market price at global level. An available HRY model was coupled to the WARM rice simulator and improved using field data referred to Loto and Gladio varieties collected in the Pavia province during the seasons 2006-2013. Simulations were carried out in three sites in the period 1994-2013. The simulated yield and HRY were used as independent variables to build multi-regression models to explain the variability of historical statistics (dependent variables). Results revealed that the GLORIFY system accurately performed at field and province scale, being capable to give reliable forecasts of the rice cropping system performances under different management and weather conditions. However model refinement are still required to enhance precision at provincial scale for Indica-type varieties, which represent an increasing segment of Italian and European rice demand.

Chapter 5 presents an exploratory analysis of the climate change impact on giant reed productivity in the Lombardy plain (northern Italy), an area that is currently characterized by intensive fodder corn-based cropping systems, but where corn is expected to be negatively affected by projected changes in thermal and pluviometric regimes. A dedicated simulation environment was developed, by coupling Arungro, a process-based model specific to giant reed, to a database including information on the presence of biogas plants, land use, crop management and distribution, in addition to weather scenarios for current climate and future projections. The baseline climate (1975-1994) was obtained from the European Commission MARS database; the Hadley3 and NCAR realizations of the IPCC AR4 emission scenarios A1B and B1 were used to generate 20-year climate projections centered on 2020 and 2050. Spatially distributed simulations were run at a sub-regional scale in areas selected according to their attractiveness for investments and low risk of competition between feed and no-feed crop destinations. The results indicate that an increased local suitability of giant reed in future climate projections is expected in terms of biomass production, and the economic and environmental sustainability of related cropping systems. Therefore, the obtained results could provide useful information to support multiple stakeholders in ensuring the resilience of the local corn sector and of related activities that strictly depend on it (i.e., livestock branch).

Chapter 6 presents an extensive evaluation of climate change impacts on multiple aspects involved with milling and technological suitability of rice productions in the main European rice growing district (Northern Italy). A modelling solution was developed by coupling a rice growth simulator to a collection of dynamic models of rice quality, using information on crop management and current and climate change scenarios as input data. An ensemble of four general circulation models (NOResm, MIROC-ESM, HadGEM2-ES and GISS-ES) and two representative concentration pathways (2.6 and 8.5) was used to generate 20-year future weather series centred on 2030 and 2070. Spatially distributed simulations were run at 2 × 2 km spatial resolution considering a *Japonica* (Loto , medium slender grain) and an *Indica* (Gladio, long slender grain) rice varieties. The results depicted an overall decline in milling quality, especially for cv. Loto in the warmest areas of the rice district. Conversely technological suitability was slightly affected by changes in thermal and pluviometric regimes, without displaying clear spatial patterns. The projected decays in milling suitability in 2030 and 2070 are expected to markedly reduce the revenues of both farmers and millers. Despite the assumptions behind this exploratory study, the results achieved allowed to provide plausible indications on rice cropping systems performances in the mid-long term, to be used by multiple stakeholders of the agricultural sector to preserve the sustainability of rice system.

Chapter 7 presents the general conclusions of this work, with regard to the development achieved and the realization of specific objectives, together with the drawing of future perspectives.

Appendix A presents the documentation of model algorithms implemented in the UNIMI.CASSANDRA.RiceQuality component, together with a detailed description of quality variables that can be simulated according to the effect on qualitative properties of rice grains.

Note

Chapter 2 is published in Computers and Electronics in Agriculture. Chapter 3 has been submitted to Field Crops Research. Chapter 4 has been submitted to European Journal of Agronomy. Chapter 5 is published in Biomass & Bioenergy. Chapter 6 has been submitted to Agronomy for Sustainable Development. The reference lists from these individual papers have been included into a list at the end of this thesis. I would like to acknowledge the editorial boards of Computers and Electronics in Biomass

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A SOFTWARE COMPONENT IMPLEMENTING A LIBRARY OF MODELS FOR THE SIMULATION OF PRE-HARVEST RICE GRAIN QUALITY

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2.1. Abstract

Despite the availability of a variety of models to simulate crop growth and development, few operational approaches have been developed to assess pre-harvest quality of agricultural productions as a function of the conditions actually explored by the crop during the season. This represents a clear gap of knowledge researchers are trying to fill, in light of the evidences of a climate change-driven decline in the nutritional properties of important food crops. Rice represents the staple food for half of the world's population, and this explains the noticeable interest in rice grain quality, because of the direct implications on the economic value of productions, on their market destination, and on food security issues. This paper presents a framework-independent .NET software library, i.e., UNIMI.CropQuality, implementing models to simulate various aspects of rice quality: amylose, protein, lipids and starch content, viscosity profile, chalkiness, cracking and head rice yield. Alternate approaches for the simulation of the same quality property are included, to allow users to select the most suitable for specific modelling studies. A case study is also presented where the library was linked to the WARM rice model and used to simulate head rice yield and the percentage incidence of cracked and milky white kernels (severely chalky) for two rice varieties in the main European rice district. RRMSE ranged between 4.33% and 6.47 % for head rice yield, 21.88% and 32.18% for cracking percentage, 35.92% and 55.01% for milky white chalkiness; modelling efficiency were always positive. The component, developed according to the state-of-the-art of component-oriented software development, is released with a Software Development Kit containing help and code documentation files, as well as sample applications showing how to use the library with different crop simulators.

Keywords: end-use value, food security, grain filling, milling quality, starch, WARM

Software availability:

Name of software: UNIMI.CropQuality

Available at: http://www.robertoconfalonieri.it/TMP/UNIMI.CropQuality_SDK.rar

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2.2. Introduction

Researchers started developing crop simulators in the late 1960s, providing process-based approaches for the estimation of crop growth and development under a variety of environmental and management conditions (Miglietta and Bindi, 1993). However, these models were focused on quantitative aspect of productions, and only in the last few years modellers started to formalize knowledge on pre-harvest quality dynamics (Porter and Semenov, 2005; Martre et al., 2011). This represents a crucial step towards the improvement of modelling tools, since crop quality plays a key role in determining the economic value and the final destination of agricultural products, thus being strongly related to the humans and animals health (Koubatros et al., 2004). Examples are provided by the occurrence of rice cracking, which usually halves the market value of head rice (Siebenmorgen et al., 2013) and can even prevent direct human consumption, redirecting products towards livestock feed or pet foods producers or brewer industry (Paranthaman et al., 2009). Another example concerns wheat and barley, the former requiring high grain protein content to enhance the quality of flour (Flagella et al., 2010), the latter needing low proteins to raise the quality of malt (Meyer-Aurich et al., 2010). In this context, special attention should be paid to the development of models to assess and improve the nutritional and processing value of rice productions, which feed more than 3.5 billion people worldwide and provide about half of the dietary calories consumed in many developing countries (GRiSP, 2010). These considerations are even more important under changing climate conditions, because of the expected decay in the quality of cereals (Porter and Semenov, 2005; White et al., 2011), with rice being particularly interested (Okada et al., 2011; Lannig et al., 2012). A recent simulation study reports that rice productions in the main districts of Latina America will not be quantitatively affected by 2050 climate projections, whereas a general decline of quality variables is expected, especially for Japonica ecotype in regions characterized by high thermal anomalies (Cappelli et al., 2012). Operational and effective models able to monitor and predict changes in rice grain quality would thus provide a strategic support to food security policies via the definition of specific adaptation measures.

Some of the available rice models (e.g., CERES-Rice, Ritchie et al., 1987; ORYZA 2000, Bouman et al., 2001) include grain quality approaches, although they are only focused on the simulation of grain nitrogen concentration, used as a proxy for protein content stored in the grains. In other cases, approaches dealing with other quality aspects of rice productions have been proposed (e.g., Yuan et al., 2008; Tsukaguchi et al., 2008; Lanning et al., 2012), although in a non-systematic way and without being integrated in models for the simulation of rice-based cropping systems.

The objective of this paper is to present a framework- and crop model-independent, extensible, multi-approach software library for the simulation of rice grain quality variables. A case study is also presented to demonstrate the capability of this software component to be operatively used to reproduce the occurrence of milky white (almost entirely opaque and chalky) kernels, head rice yield, and grain cracking for Loto and Thaibonnet cultivars in Northern Italy.

2.3. Quality variables and models

The UNIMI.CropQuality component implements a collection of approaches to estimate rice grain quality as a function of the meteorological conditions experienced by the crop during the ripening period. Most of the models implemented present parameters with a clear biological meaning, such as the optimal range of temperatures for the starch synthesis in the kernel (Okada et al., 2009; Chen et al., 2011). For each simulated variable, the component provides the final value reached at physiological maturity and in many cases its daily evolution in the field until the crop is harvested.

Table 1 reports all the models of rice grain quality implemented in the component, together with their input variables and parameters.

Table 1. List of all the inputs, outputs and parameters of the models implemented into UNIMI.CropQuality component. Outputs are grouped according to the effect on qualitative properties of rice grains. I = Indica; J = Japonica.

Variable	S	E	Input	Unit	Parameters	Unit
Effect on functional and sensory properties of rice grain						
Amylose (%)	1	I, J	latitude	°	Indica/Japonica-type	unitless
			T_{avg}, T_{max}, T_{min}	°C	Reference amylose content	% grain^{-1} (D.W.)
			Rad	MJ m^{-2} day^{-1}		
	2	I, J	$GDD_{Fl.}$	°C	Indica/Japonica-type	unitless
	3	J	$Hourly_{NT}$	°C	Indica/Japonica-type	unitless
	4	I, J	$Days_{Fl}$	Day	Indica/Japonica-type	unitless
Protein (%)	5	J	$Hourly_{NT}$	°C	Indica/Japonica-type	unitless
	6	I, J	latitude	°	Indica/Japonica-type	unitless
			T_{avg}, T_{max}, T_{min}	°C	Reference protein content	% grain^{-1} (D.W.)
			altitude	m		
Starch (14% humidity)			T_{avg}	°C	Potential sugar content of leaves	%
			AGB	kg ha^{-1} day^{-1}	Potential sugar content of stems	%
			LB	kg ha^{-1} day^{-1}	Post anthesis carb. remobilization beginning	°C day
			SB	kg ha^{-1} day^{-2}	Peculiar seed weight of selected cultivar	mg grain^{-1}
	2	I, J	GBr	kg ha^{-1} day^{-3}	Max rate of individual grain starch synthesis	mg grain^{-1} d^{-1}
					Lower temperature for opt. starch accumulation	°C
					Higher temperature for opt. starch accumulation	°C
					Lower temperature starch accumulation	°C
					Higher temperature starch accumulation	°C
Viscosity profile						
peak viscosity (RVU)	3	J	$Hourly_{NT}$	°C	Indica/Japonica-type	unitless
peak viscosity (Centipoise)	7	J	T_{avg}	°C	-	
breakdown viscosity (Centipoise)	8	I, J	T_{avg}	°C	Indica/Japonica-type	unitless
pasting temperature (°C)	7	J	T_{avg}	°C	-	
setback viscosity (RVU)	3	J	$Hourly_{NT}$	°C	Indica/Japonica-type	unitless
setback viscosity (Centipoise)	7	J	T_{avg}	°C	-	

gelatinization temperature (°C)	3	J	$Hourly_{NT}$	°C	Indica/Japonica-type	unitless
Lipid (%)	3	J	$Hourly_{NT}$	°C	Indica/Japonica-type	unitless
Effect on appearance and milling quality of rice grain						
Chalkiness						
degree (%)	5	J	$Hourly_{NT}$	°C	Indica/Japonica-type	unitless
milky white(%)	9	I, J	T_{avg}	°C	Damage threshold temperature	°C
					Sowing density effect	unitless
					Damage susceptibility duration	days
milky white kernels (%)	10	I, J	T_{min}	°C	Damage threshold temperature	°C
			Rad.	MJ m^{-2} day^{-1}	Damage susceptibility duration	days
milky white kernels (%)	11	I, J	T_{avg}	°C	Damage threshold temperature	°C
			GB	mg $grain^{-1}$	Average seed weight	mg $grain^{-1}$
			GBr	kg ha^{-1} day^{-1}		
white immature base (%)	12	I, J	T_{avg}	°C	Nitrogen stressed cultivar (Yes/No)	unitless
					Susceptible cultivar (Yes/No)	unitless
white immature base (%)	13	J	T_{avg}		Indica/Japonica-type	unitless
Cracking (%)	14	I, J	T_{max}	°C	Susceptible cultivar (Yes/No)	unitless
Effect on milling quality of rice grain						
Head rice yield (%)	5	J	$Hourly_{NT}$	°C	Indica/Japonica-type	unitless

References

1= Li et al. (2005b); 2= Chen et al. (2011); 3= Lanning et al. (2012); 4= Liu et al. (2013); 5= Lanning et al. (2011); 6= Li et al. (2005a); 7= Shen et al. (2007); 8= Yuan et al. (2008); 9= Nagahata et al. (2006); 10= Okada et al. (2009); 11= Tsukaguchi et al. (2008); 12= Kondo et al. (2006); 13= Morita et al. (2005); 14= Nagata et al. (2004).

Acronyms

S=Source; E=Ecotype; T_{avg}= average air daily temperature; T_{max}= maximum air daily temperature; T_{min}= minimum air daily temperature; Rad.= daily global solar radiation; GDD_{Fl}.= growing degree days after flowering; $Hourly_{NT}$= hourly night temperature; $Days_{Fl}$= days after flowering; AGB= aboveground biomass daily rate; LB= leaves biomass daily rate; SB= stems biomass daily rate; GBr= grain biomass daily rate; GB = grain biomass (cumulated).

Grain starch concentration represents the most important food energy source in the world (Pan et al., 2007). This carbohydrate is the main reserve compound of plants and consists of two types of molecules: amylose, ranging from 0 to 33%, and amylopectin, varying from 77 to 100% (Suwannaporn et al., 2007). The model available in the UNIMI.CropQuality component simulates the synthesis and accumulation of these molecules as affected by air temperature, nitrogen and water availability during the ripening period, and by photosynthetic activity and translocation processes.

From the functional standpoint, the amylose content of rice grain is among the most widely used chemical indicators of rice quality due to its importance in defining the eating value of rice in terms of texture and nutritional properties (Suwannaporn et al., 2007). Kernels with low amylose content appear to be sticky after cooking and suitable for pastry or sushi industries, whereas high amylose levels determine less soft kernels which become hard upon cooling, being more suitable for various rice dishes as timbales. The accumulation of this molecule during the ripening period is genetically controlled and, to a lesser extent, it is also influenced by both weather variables (Siebenmorgen et al., 2013) and agronomic practices, such as irrigation strategy or planting date (Cheng et al., 2003). However, this index – alone – is not enough for a comprehensive assessment of rice grain quality, since protein and lipid contents play a key role too. These two constituents of grain affect at the same time different nutritional properties by (i) providing calories and essential aminoacids (Juliano et al., 1985b), (ii) modulating the taste (Horne et al., 2002), (iii) favoring the ease of cooking of this cereal, and (iv) impairing the swelling of starch granules during the gelatinization process, the latter being the basis of starch digestibility (Suwannaporn et al., 2007). A model simulating the gelatinization temperature is available in the component, based on a widely used index – driven by nighttime air temperature during late ripening – to evaluate the cooking duration and the texture of boiled rice (Lanning et al., 2012; Siebenmorgen et al., 2013).

Other models simulating viscosity profile and behavior of starch during cooking are implemented in the component. In particular, the modelled indicators are: (i) pasting temperature, that is the temperature at which the starch viscosity starts to rise during the heating process (Liang et al., 2003), (ii) peak viscosity, that reflects the extent of granule swelling, representing the maximum value reached by viscosity during the heating phase (Liang et al., 2003), (iii) setback, that revealed the gelling ability or retrogradation tendency of the starch (Zaidul et al., 2007), (iv) breakdown viscosity, that is an extent of starch granules disruption and therefore a measure of paste stability (Zaidul et al., 2007).

In order to characterize rice grains appearance, the most common quality features analyzed to ensure the uniformity of productions are the occurrence of broken kernels and chalky grains, with the latter characterized by opaqueness and chalky texture because of the early interruption of final grain filling. Chalkiness is usually classified into distinct categories according to the position of the chalky area (i.e., white-cored, white-back, white-based and white-belly types). When chalky grains appear almost entirely opaque, they are defined as milky white (Ishimaru et al., 2009). Both these damages are genetically controlled, as well as being favored by high temperature stress during early ripening (Okada et al., 2009; Lanning et al., 2011), which causes weak kernels more susceptible to breakage during milling processes (Siebenmorgen et al., 2013). In order to simulate milling quality, a model of head rice yield (i.e., the relative weight presence of entire kernels after milling, Lanning et al., 2011) is implemented. This quality feature is a key determinant of rice price and it strongly depends both on weather conditions during the reproductive phase and grain moisture content at harvest.

All the models implemented in the component are described in detail in the component help file.

2.4. Component features

UNIMI.CropQuality is a .NET software library implementing multiple modelling approaches to the simulation of rice grain quality variables; the component is independent from both the framework and the crop simulator used. The architecture of the component (Donatelli and Rizzoli, 2008) promotes its extension by third parties via the implementation of alternative model realizations for variables already simulated, as well as via the inclusion of approaches for the simulation of new variables. The models available in the components can be accessed at different levels (Figure 1), thus allowing users to select just one of the approaches for peak viscosity, or to run all the models for assessing the viscosity profile.

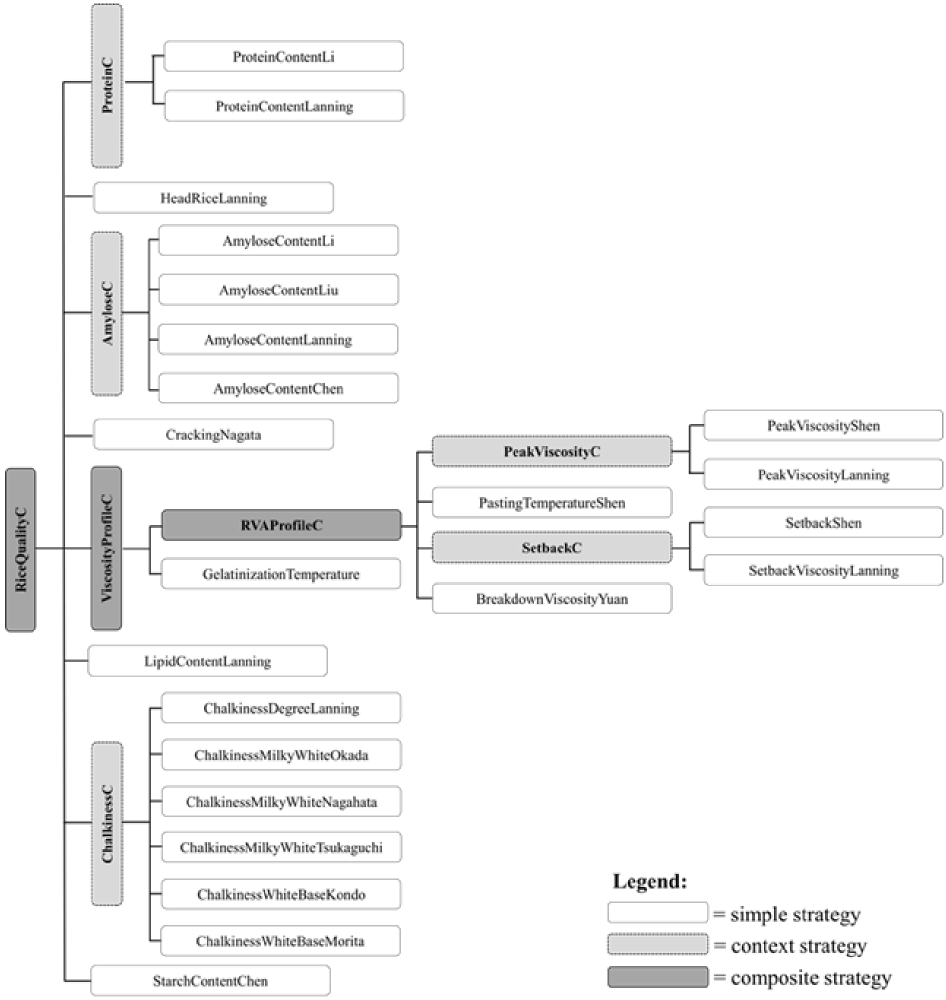

Figure 1. Strategy diagram of the UNIMI.CropQuality component. The suffix "C" indicates composite strategies.

In order to foster the usability of the component, two typologies of users were identified: (i) beginners, i.e., users without specific expertise in quality variables and models, and (ii) experts, represented by specialists in rice quality modelling. In case of beginners, the most suitable modelling approaches for the simulation of the different rice quality variables under specific contexts of, e.g., inputs availability, is automatically handled by the component; conversely, experts are allowed to select the approach they consider as the most appropriate for each of the quality variables, or to compare the performances of alternate approaches.

All these features derive from the implementation of quality models with a fine level of granularity and from the use of different design patters, like the strategy, the composite, the façade (Gamma et al., 1995), and the Create-Set-Call (Cwalina and Abrams, 2006) patterns. Each model implemented in the component (see the strategy diagram in Figure 1) encapsulates the parameter‘s ontology, and pre- and post-conditions tests, according to the design-by-contract approach (Meyer, 1997). The component, written in MS C# language under the MS .NET 4.0 framework, is released with a library of unit tests, contributing to the transparency of the modelling solutions.

The component Software Development Kit contains (i) the help file (documentation of all the algorithms implemented), (ii) the code documentation file (documentation of all the classes and their available public methods and properties) and (iii) two sample applications in which UNIMI.CropQuality is coupled with two rice crop simulators: WOFOST (Van Keulen and Wolf, 1986) and WARM (Confalonieri et al., 2009). Sample applications are VisualStudio .NET console projects explicitly designed to show in a transparent way how to use the component and to link it with simulators of crop phenology and biomass accumulation in the grains.

2.5. The case study

In order to illustrate the potentialities of UNIMI.CropQuality, a case study was carried out in the Italian rice district Lombardo-Piemontese, representing about half of the European rice harvested area (Confalonieri et al., 2009). Recent studies indicate that rice quality in this district will become the key factor to increase Italian rice competitiveness in a global market (e.g., Tesio et al. 2013). The occurrence of milky white grains (strategy ChalkinessMilkyWhiteOkada in Fig. 2), head rice yield (strategy HeadRiceLanning) and the percentage of cracked kernels (strategy CrackingNagata) were simulated for the cultivars Loto and Thaibonnet (Japonica and Tropical Japonica ecotypes, respectively), with the latter parameterized – like in previous modelling studies (e.g., Confalonieri et al., 2006) – as Indica–type based on the marked affinity in thermal requirements. Models calibration and validation were performed using data collected by Ente Nazionale Risi (ENR; www.enterisi.it) in Castello d’Agogna (latitude 45° 14’ N, longitude 8° 41’ E, altitude 106 m a.s.l.) and Vercelli (latitude 45° 19’ N, longitude 8° 25’ E, altitude 126 m a.s.l.) during the seasons 2004-2009. For all the experiments, rice was scatter-seeded and grown under flooded conditions and unlimiting nutrients supply; N was distributed as urea in two or three events (one pre-sowing, the others at panicle initiation and – when three applications were provided – at the beginning of tillering). Management allowed to keep fields weed and pest free. Data were equally, and randomly, divided in two datasets: one for calibration and the other for validation. Weather data – maximum and minimum daily air temperature, global solar radiation – were derived from the 25 km × 25 km spatial resolution MARS database (European Commission), available from 1975 to the last calendar year completed (http://mars.jrc.ec.europa.eu/mars/About-us/AGRI4CAST/Data-distribution/AGRI4CAST-Interpolated-Meteorological-Data). Hourly temperature data were derived from daily ones using the Campbell (1985) approach. The agreement between measured and simulated quality variables (Table 2) was expressed – for both the calibration and validation datasets – by using relative root mean square error (RRMSE; Jørgensen et al., 1986; minimum and optimum = 0); modelling efficiency (EF; Nash and Sutcliffe, 1970; from -∞ to 1, optimum = 1), coefficient of residual mass (CRM; Loague and Green, 1991; optimum = 0, if positive indicates model underestimation), and mean absolute error (MAE; Mayer and Butler, 1993; minimum and optimum = 0).

The values of the evaluation metrics (Table 2) are coherent with what is normally achieved when rice models are used. RRMSE values available in the literature for above ground biomass simulation range from about 10% for potential conditions to 30% for experiments carried out under insufficient water/nitrogen availability, whereas corresponding values for leaf area index are usually higher, often exceeding 50% (e.g., Bouman and van Laar, 2006; Confalonieri et al., 2009). The simulation of soil mineral nitrogen concentration is often reproduced with even less accuracy (Confalonieri et al., 2006). The results obtained here for head rice yield and percentage of fissured kernels (Table 2) should hence be considered as encouraging, given that (i) crop modellers started working on quality only recently, whereas approaches for crop growth simulation are continuously improved since the 1960s, and (ii) the quality models used here were mainly developed under agro-meteorological conditions (China, Japan and USA.) greatly different from those experienced by rice in northern Italy. The pattern of RRMSE and EF values for the different variables – e.g., percentage milky white kernels often achieving the best values of EF and the worst for RRMSE – are due to the relationship between the distribution of observations around their mean value. Indeed, RRMSE has the tendency to assume very low values when the mean of observations is large compared to the dispersion of the values. This, in turns, demonstrate the usefulness of using different metrics in model evaluation.

After models were tested at field level, they were applied at regional level (Lombardy rice district). Simulations were run with a 5×5 km spatial resolution by taking advantage of remote sensing-derived rice mask and management information (Manfron et al., 2013). Simulation results for 2003 and 2010 are summarized in Tables 3 for the cultivars Loto and Thaibonnet, together with average values of air temperature and global solar radiation experienced by rice crop in the two growing seasons. For both the cultivars, a reduced incidence of cracking (15%) and milky white kernels (7%) is shown under the conditions explored, with a higher incidence during the warmest season (2003), that also led to more marked differences between the cultivars. The same trend can be observed for head rice yield, which assumes values around 57% for both varieties in 2010. The warmest cropping season determined a decided decay of this quality feature, ranging from 36 % (cv. Thaibonnet) to 40% (cv. Loto).

Figure 2 presents the results of the application of the Okada approach to simulate the percentage incidence of milky white grains in the Italian rice district Lombardo-Piemontese. The two cultivars for which simulations were performed present a similar spatial pattern in both the seasons, with the Eastern part of the district more affected by these severe types of chalkiness. This is mainly due to the warmer conditions that characterize this area, frequently exceeding the threshold temperature (17.1°C and 17.3°C were used in this study for Japonica and Indica, respectively) beyond which the damage occurs in the early stages after heading (Okada et al., 2009). Larger differences between the two cultivars can be observed in 2003 (warmer than 2010 during the rice season, see Table 3), for which values lower than 4% were simulated for Thaibonnet in most of the simulation units (193 out of 216), whereas values ranging from 5.5% to 8.5% were simulated for Loto, because of the lower thermal requirements of that particular cultivar for starch synthesis and deposition (Chen et al., 2011; Xiong et al., 2011).

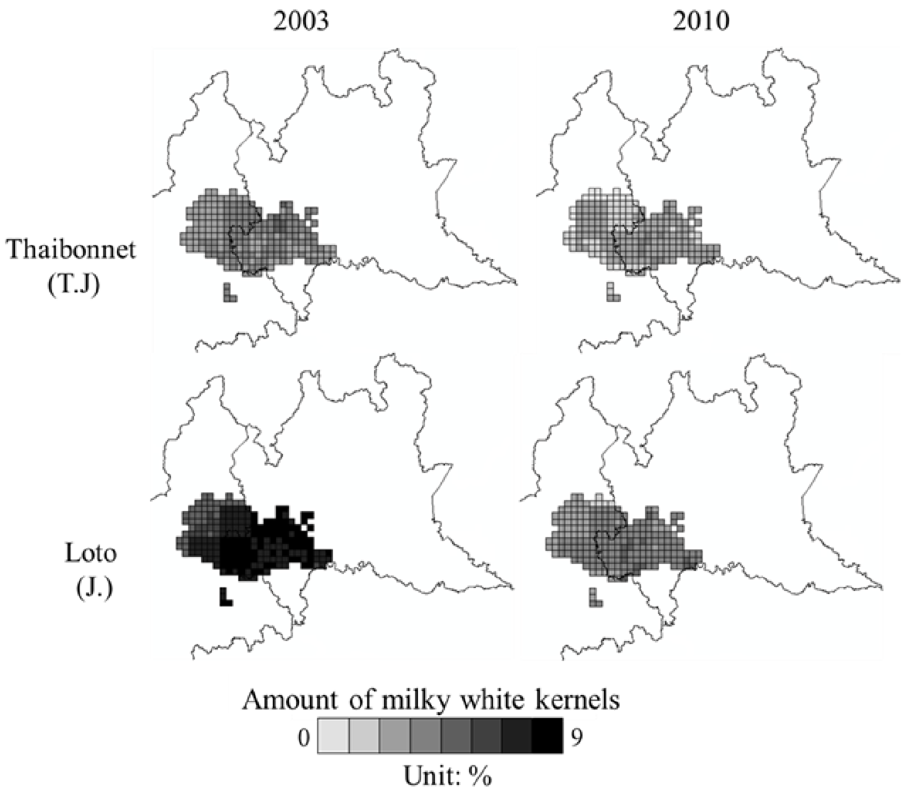

Figure 2. Results of the spatially distributed simulations of milky white grains occurrence in the Italian rice district Lombardo-Piemontese (model: Okada et al., 2009) for the Thaibonnet and Loto rice cultivars grown in 2003 and 2010. T.J. = Tropical Japonica, J.= Japonica.

2.6 Conclusions and remarks

The development of operational simulation tools able to support the management of agricultural systems is a key research topic in agriculture, and a variety of multi-approach software libraries is currently available for, e.g., weather data generation (e.g., Donatelli et al., 2009), crop suitability to environment (Confalonieri et al., 2013), crop growth and development (http://agsys.cra-cin.it/tools/cropml/help/), soil dynamics involved with water redistribution and runoff (e.g., Donatelli et al., 2014). Generic components for other sub-domains like, e.g., plant-pathogens interaction, impact of pests and crop-weed competition represent, instead, ideas that should catalyze the attention of the modellers community in the coming years. In this context, UNIMI.CropQuality represent one of the first attempts to start looking at crop modelling from the quality and market perspectives. The grain quality issue is indeed of great interest for stakeholders working at different levels in the agricultural sector: on one side to deal with the growing demand of high quality products (like in European countries), and on the other to face nutrition problems (like in some regions of Asia, Latin America and Africa). UNIMI.CropQuality represents a concrete attempt to address these issues in an integrated and systematic way, providing alternate approaches to reproduce the dynamics related with rice quality profile under different climatic and management conditions. The application of the component to the Italian rice district Lombardo-Piemontese showed the ability of the implemented models to differentiate their responses according to the meteorological and management conditions explored by the crop. The software package is fully documented and released with sample applications showing how to integrate the component with crop simulators.

ARE MODELS FOR CROP QUALITY SUITABLE FOR OPERATIONAL CONTEXTS? BOUNDARIES AND PERSPECTIVES FROM A MULTI-MODEL STUDY ON RICE IN NORTHERN ITALY.

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3.1. Abstract

Despite grain quality is increasingly recognized as crucial to meet market demand and preserve the sustainability of the European rice sector, the simulation of pre-harvest quality traits is still an open issue. In this context, the evaluation of available approaches is needed to explore their suitability in light of a potential use in operational contexts. This study presents a multi-site, multi-year and multi-metric comparative evaluation of 26 of models for the simulation of rice milling quality and functional properties of grains, focusing on the main European rice district (Northern Italy). The analysis was performed using data collected during field experiments where cultivars Loto and Gladio were grown in 16 sites during the seasons 2011-2014. Model performances denoted a good ability in reproducing the overall grain quality profile (average R^2 and RRMSE were in the range 0.38-0.63 and 10.92-13.36%, respectively). Best results were obtained for functional properties of Loto grains, as the models were able to explain, on average, 67% of the observed seasonal variability, with this value exceeding 80% for protein concentration and breakdown viscosity. Although improvements are needed to further reduce the uncertainty in model predictions, this study proved that the selection of most accurate approaches per quality variable allowed a proper simulation of the observed dynamics according to the variety-specific sensitivity to meteorological conditions during the ripening period.

Keywords: amylose, chalky grains, grain filling, milling quality, model comparison, starch viscosity

3.2. Introduction

Quality is a key determinant of the economic and nutritional value of agricultural products, since directly affecting their acceptability to buyers and consumers (Koutroubas et al., 2004). Indeed, the achievement of superior quality allows farmers to gain a competitive market advantage against countries exporting low price products (Griglione et al., 2015). Despite a variety of simulation tools were developed to simulate quantitative aspects of crop productions under a wide range of agro-meteorological conditions (e.g., Batchelor et al., 2002; Debaeke, 2004), modellers started focusing on product quality only recently (Zhang et al., 1993; Flénet et al., 2008).

In this context, the state of the art of quality models focused on a hierarchical mechanistic representation (i.e. from cell to organ) of biological processes regulating fruit size and composition. Examples are available for fruit (peach trees, Génard and Souty, 1996; vineyards, Dai et al. 2009) and industrial (tomato, Prudent et al., 2011) and cereal species (wheat, Porter et al., 1993; Martre et al., 2006) for which quality largely affect their processing and marketability value. However, most of these approaches are – to a certain extent – unsuitable in operational contexts since unlikely compatible with the level of abstraction used by the majority of crop models developed for scenario analysis and management support. In particular, for rice, the most refined quality models are involved with the simulation of grain nitrogen concentration, in turn used as a proxy for protein content (Ritchie et al., 1987; Bouman et al., 2001). Other examples are available for estimating the accumulation of starch/amylose in the grain as affected by environmental stressors (e.g. water, temperature stress; Chen et al., 2011). However, most of the few approaches available for rice are even less process-based, mainly relying on semi-empirical relationships between quality and weather variables (e.g. temperature, solar radiation) and on parameters, for the most part, with no clear biological meaning (Cappelli et al., 2014a). Despite the semi-empirical nature of rice quality models is expected to partly reduce their applicability outside the contexts they are calibrated for, related uncertainties remain largely unquantified. The few examples of studies targeting the evaluation of these models were often carried out using small datasets, where one or few varieties were grown in few sites and years. This prevents a clear understanding of the degree of suitability of the models for both research and operational contexts. Moreover, the use of different evaluation metrics in the different studies strongly hinders unambiguous comparisons of model performances to identify the most adequate approach to a given purpose (Bellocchi et al., 2009).

This study presents the first multi-site, multi-year and multi-metric comparative evaluation of alternative approaches targeting the simulation of rice grain quality, to understand the potential for application in the main European rice growing district.

3.3.Material and methods

3.3.1 Study area and field experiments

Due to its economic importance, the case study was focused on the Northern Italian Lombardo-Piemontese district (Figure 1), which accounts for about 50% of the European rice harvested area (Graglione et al., 2015).

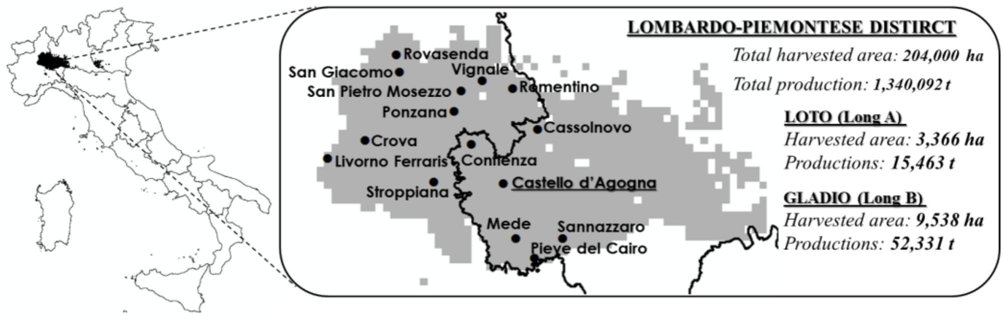

Figure 1. Geographic distribution of field experiments(black circles) within the study area and characterization of rice productions for Loto and Gladio varieties in 2014. The grey area represents the harvested area of Lombardo-Piemontese rice district.

The climate in the area is temperate humid, with high local heterogeneity of pedo-climatic conditions (Fumagalli et al., 2011). Average annual air temperature is about 13.5 °C, ranging from 0-4 °C in winter months, to peaks exceeding 30 °C in summer. Cumulated annual precipitations fluctuate around 750 mm, with two main rainy periods in autumn and spring, and a minimum from July to August. Dedicated multi-site field experiments were carried out by Ente Nazionale Risi (ENR) in the seasons 2011-2014 throughout the district, where Loto (Japonica, medium slender grain) and Gladio (Indica, long slender grain) varieties were grown under conditions unlimiting for water, nutrients, pest and weeds. Alternative irrigation strategies in the area were continuous flooding, or dry sowing with flooding at third-fourth leaf-stage. Nitrogen (140-180 kg N ha^{-1}) was distributed as urea in two or three events, one in pre-sowing and the others at beginning of tillering and/or at panicle initiation. While in-season phenological observations were performed at flowering (BBCH=65) and physiological maturity (BBCH=89), 40 samples of paddy grains per variety were collected for quality traits evaluation at maturity from plots with different combinations sowing dates × irrigation management. Weather data – daily minimum and maximum air temperatures (°C), rainfall (mm), wind speed (m s^{-1}) and reference evapotranspiration (mm) – were measured by the weather stations of the Regional Agency for Environmental Protection (ARPA). Global solar radiation (MJ m-2 d^{-1}) was generated according to Hargreaves equation (Hargreaves and Samani 1982).

For all the datasets, total nitrogen and amylose contents were determined respectively via Dumas combustion (LECO-FP 428 analyzer) and differential scanning calorimetry procedures (UV-VIS spectrophotometer Perkin Elmer), whereas pasting properties were measured in a Brabender Micro-ViscoAmyloGraph (Brabender OHG, Duisburg, Germany) according to Marti et al.(2010). The quantification of the chalky and broken kernel was carried out in agreement with Koutroubas et al. (2004), whereas pecky grains were derived as weight difference by spreading 100 g of grains on a white surface and excluding those showing any circular brown to black spot on grain surface.

3.3.2 Quality traits and models

The twenty-six models used in this study for the simulation of quality variables involved with functional/sensory properties and appearance/milling quality of rice grain are summarized in Table 1, together with their input variables, parameters and performance indices obtained in previous studies. All models reproduce the impact of meteorological conditions on grain quality during the ripening phase, with a final value for the quality variable reached at physiological maturity or dynamically simulated until the crop is harvested. Despite their conceptual similarities, quality models differ in the input weather variables considered, in the duration of sensitive period to weather conditions and in the biological meaning of parameters used. Detailed description of model algorithms is provided by Cappelli et al. (2014) and by documentation of the library available at www.cassandralab.com/components/10.

Model evaluation was carried out separately for each combination cultivar × quality variable (Figure 1). Data were split in two independent datasets. Model performances were evaluated using mean absolute error (MAE, 0÷∞, optimum = 0, Schaeffer, 1980), relative root mean square error (RRMSE, minimum and optimum = 0%; maximum = + ∞, Jørgensen et al. 1986), modelling efficiency (EF, -∞ ÷ 1, optimum =1, if positive, indicates that the model is a better predictor than the average of measured values, Nash and Sutcliffe, 1970) coefficient of residual mass (CRM, 0÷1, optimum = 0, if positive indicates model underestimation and vice versa, Loague and Green 1991) and coefficient of determination (R^2, 0÷1, optimum =1).

3.4. Results and discussion

An overview of model performances in reproducing grain quality variables for Gladio and Loto varieties is shown in Figure 2.

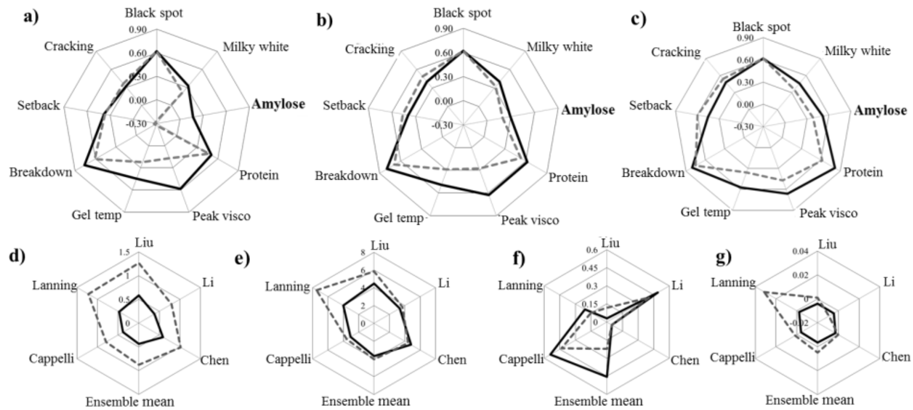

Figure 2: Model performances in reproducing all the grain quality variables (a-c) and grain amylose concentration (d-g) for Loto (black solid lines) and Gladio (grey dashed lines). a) mean EF calculated on the EF values achieved by the different models; b) EF values from the use of multi-models ensemble mean as predictor; c) EF values derived from the outputs of best model per variable; d) MAE, e) RRMSE, f) R^2, g) CRM.

Table 1. List of all the inputs, outputs and number of parameters (P) of the crop quality models tested in the study area. Country of model application and indices of performances achieved were also reported. Outputs are grouped according to the effect on qualitative properties of rice grains. Ref=model reference; n= number of pairs of simulated and measured quality variables.

Variable	Unit	Descritpion/properties	Ref	Inputs	P	Country	Metrics	Value	n
Functional and sensory properties of rice grain									
Amylose	% grain^{-1} *(D.W.)*	Determinant of grain texture and stickiness of boiled rice.	1	$GDD_{fl.}$, N_{stress}, DVS	1	China	R^2; RRMSE	0.88; 16.1%	12
			2	T_{night}, sunrise$_H$, sunset$_H$, DVS	2	U.S.A.	r	-0.62	7
			3	$T_{min.}$, $T_{avg.}$, $T_{max.}$, latitude, Rad, DVS	2	China	R^2, RMSE	0.96; 0.5%	20
			4	Days$_{ff.}$, DVS	1	China	R^2	0.93	6
			5	Tavg., solar radiation, wind speed, DVS	3	Italy	-	-	-
Protein	% grain^{-1} *(D.W.)*	Determinant of nutritional value, taste and cooking properties of rice.	6	T_{night}, sunrise hour, sunset hour, DVS	2	U.S.A.	r	-0.67	11
			7	$T_{min.}$, $T_{avg.}$, $T_{max.}$, latitude, DVS	2	China	R^2, RMSE	0.72; 0.25%	20
			8	T_{avg}, T_{night}, sunrise$_H$, sunset$_H$, days$_{ff.}$, DVS	9	Italy	-	-	-
Gelatinization temperature	°C	Mean thermal transition of the starch in presence of water and heat. Determinant of cooking duration and the texture	9	T_{night}, sunrise$_H$, sunset$_H$, DVS	2	U.S.A.	r	0.87	8
			10	$T_{avg.}$, DVS	1	China	R^2	0.80	16
			11	$T_{avg.}$, RH_{max}, DVS	8	Italy	-	-	-
Breakdown viscosity	BU	Starch granules disruption. Measure of paste stability	12	$T_{avg.}$, DVS	1	China	r	0.70	21
			13	$T_{avg.}$, DVS	3	Italy	-	-	-
Peak viscosity	BU	Maximum viscosity during the heating phase. Measure of granules swelling during gelatinization	14	T_{night}, sunrise$_H$, sunset$_H$, DVS	2	U.S.A.	r	0.68	14
			15	$T_{avg.}$, DVS	1	China	R^2	0.78	16
			16	$T_{min.}$, $T_{max.}$, DVS	5	Italy	-	-	-
Setback viscosity	BU	Retrogradation tendency of starch during cooling phase. Determinant of grain texture	17	T_{night}, sunrise$_H$, sunset$_H$, DVS	2	U.S.A.	r	-0.73	16
			18	$T_{avg.}$, DVS	1	China	R^2	0.78	16
			19	$T_{avg.}$, Days$_{ff}$, DVS	10	Italy	-	-	-
Appearance and milling quality of rice grain									
Cracking	%	Amount of fissured kernels.	20	$T_{max.}$, DVS	1	Japan	r	0.97	6
			21	$T_{min.}$, T_{max}, ET_0, RH_{min}, RH_{max}, rain$_D$, wind$_S$, DVS	6	Italy	-	-	-
Milky white	%	Grains almost entirely	22	$T_{avg.}$, DVS	4	Japan	r, RRMSE	0.85; 4%	16

grains		opaque with floury areas on the grain surface.	23	$T_{avg.}$, DVS	3	Japan	r	0.98	15
			24	$T_{min.}$, Rad, DVS	3	Japan	R^2, RMSE	0.47; 12.7%	92
			25	$RH_{min.}$, wind speed, DVS	3	Japan	R^2	0.72	18
Pecky grains	%	Grains with circular, brown to black spot.	26	$T_{min.}$, T_{max}, RH_{min}, RH_{max}, DVS	5	Italy	-	-	-

References: 1= Chen et al. (2011); 2, 6, 9, 14, 17= Lanning et al. (2012); 3= Li et al. (2005b); 4=Liu et al. (2013); 5, 8, 11, 13, 16, 19, 21, 26= UNIMI.RiceQuality component help file documentation; 7=Li et al. (2005a); 10, 15, 18=Shen et al. (2007); 19= Yuan et al. (2005); 20=. Nagata et al. (2004); 22= Masutomi et al. (2015); 23= Nagahata et al. (2006); 24=Okada et al. (2009); 25=Oya et al. (2008).

Acronyms: BU: Brabender Units, arbitrary unit of measuring the viscosity of a fluid; GDD_{fl}= growing degree days from flowering; N_{stress}=nitrogen stress factor; DVS=development stage code (1=emergence, 2=flowering, 2.5=full ripening, 3=physiological maturity); T_{night}=hourly night temperature; T_{avg}=average air daily temperature; T_{max}=maximum air daily temperature; T_{min}=minimum air daily temperature; $Days_{fl}$=days from flowering; ET0=potential evapotranspiration; RH_{min} =minimum air relative humidity; RH_{max} maximum air relative humidity; $sunrise_H$=sunrise hour; $sunset_H$=sunset hour; $rain_D$=daily rain; $wind_S$=daily wind speed; Rad=daily global solar radiation.

The overall simulation of variables involved with appearance and milling quality (AMQ) of rice grain showed slight differences among varieties (average EF of 0.42 for Loto; average EF of 0.4 for Gladio), whereas contrasting results were achieved in reproducing functional and sensory properties (FSP) for Loto (EF= 0.47) and Gladio (EF=0.25), with major differences in peak viscosity (EF of 0.59 vs 0.17, respectively) and amylose content (EF of 0.17 vs -0.34). Among ESP variables, best performances were always obtained for breakdown (average EF= 0.68) and protein (average EF= 0.49) variables, whereas blackspot model proved to be the most accurate in simulating AMQ traits for both varieties (average EF= 0.62).

The use of multi-models ensembles (statistics: mean of the outputs from different models) as predictor allowed to markedly improve the simulation of amylose content (EF = 0.29 and 0.2 for Loto and Gladio, respectively; Figure 2b). The same consideration is valid, in general, for FSP estimates (EF = 0.54 and 0.41 for Loto and Gladio; Figure 2b). The better performances in reproducing the whole grain quality profile were achieved by selecting the most accurate model per variable (EF = 0.60 and 0.52 for Loto and Gladio; Figure 2c). Although EF values achieved for ESP and AMQ exceeded in most cases 0.5 (6 variables out of 9) reaching peaks of 0.82 for Loto (Protein content; Figure2c) and 0.72 for Gladio (Breakdown; Figure 2c), the overall good of fitness was slightly penalized by the poor simulation of milky white grains and amylose content. The dominant role of genetic versus environmental factors in controlling these variables during the ripening period (Cappelli et al., 2014a) can explain the poor results achieved especially for Gladio variety, which further is less sensitive than Loto to meteorological drivers within the critical post-flowering period. However, the partial unsuitability of amylose models in reproducing time-trend of measured ($0.03<R^2<0.54$, Figure 2f) was partly counterbalanced by the accuracy in terms of average error (0.38%<MAE<1.3%, Figure 2d; 3%<RRMSE<7.5% , Figure 2e), which gradually increased with model complexity (number of input variables and parameters) (Table 1). While positive CRM values (Figure 2g) suggested the tendency of the model proposed by Lanning et al. (2012) to markedly underestimate amylose content for Gladio, no systematic bias was observed for others approaches for the same variable. Although R^2 values achieved in this study were less satisfactory than those achieved by model developers (Table 1), RRMSEs were comparable to what reported in previous studies carried out in China (Chen et al., 2011) and Northern Italy (Cappelli et al., 2014a).

As an example, the comparison among alternative models in reproducing AMP (i.e. pecky and milky white grains occurrence) and FSP (i.e. protein concentration, breakdown and setback viscosities) data is presented as scatterplot in Figure 3.

Regardless of the variety, original models revealed in most cases a flat distribution of simulated outputs, that led to marked over- and underestimations when measured values were low and high, respectively. Conversely, the new approaches allowed to increase R^2 values for FSP variables from 0.23-0.47 (Figure 3, a, d, e, g, h) up to 0.6-0.82 (Figure 3, b, f, i). Breakdown (Figure 3a, b, Gladio) and protein (Figure 3g, h and i, Loto) models were the most accurate in reproducing the variability of observations and showed good performances in terms of average error (21.82<MAE<35.45BU for breakdown; 0.27%<MAE< 0.49% for protein). As already mentioned for amylose content, the consideration of parameters with clear biological meaning (e.g. optimum temperature ranges for starch and proteins synthesis) allowed the two above-mentioned models to better reproduce the underlying system, thus allowing to achieve higher accuracy compared to approaches available in the literature. The same behavior was observed for the models involved with the simulation of setback viscosity, even if the new approach denoted moderate underestimation at high measured values (above 825 BU). On the other end, the performances achieved in simulating the occurrence of milky white grains were decidedly less satisfying, even though they largely depend on the model considered. While model developed by Okada (2009, Figure 3l) and Oya and Yoshida (2008, Figure 3m) failed to accurately reproduce chalkiness dynamics, approaches by Naghata et al. (2006, Figure 3n) and Masutomi et al. (2010, Figure 3o) allowed to obtain acceptable results, with R^2 and MAE ranging from 0.47 to 0.49 and from 0.83 to 0.84%, respectively. As reported by Martre et al. (2015) and Li et al. (2015) for wheat and rice yields, and as already discussed here for amylose content, the mean of multi-models ensembles confirmed to be a good predictor also for the incidence of milky white grains, with R^2 of 0.48 and MAE of 0.86%. However, despite the average errors were small in absolute terms, they increased when compared to the mean value of observation, suggesting to consider also RRMSE to make a more objective assessment.

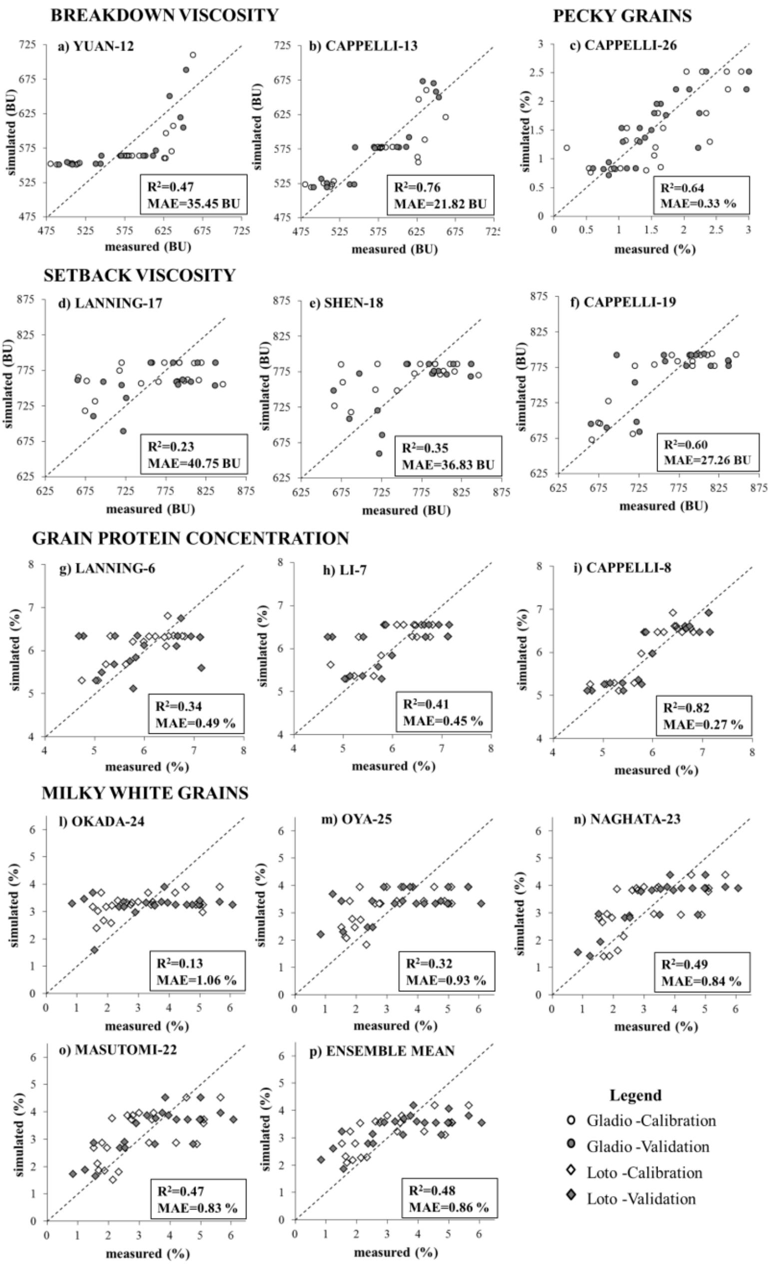

Figure 3: Multi-model comparison between measured and simulated quality variables for Loto (daimonds) and Gladio (circles) varieties; simulations were focused on breakdown viscosity(a,b), pecky grains (c), setback viscosity (d, e,f3), grain protein concentration (g, h, i) and milky white grains (l, m, n, o, p). Dashed lines represent the :1 line. MAE= mean absolute error. Numbers next to the name of model developers refer to the Ref column of Table1.

From an overall perspective, available models allowed to simulate the whole quality profile with contrasting performances, providing best results for Loto (Average RRMSE=13.36%; EF=0.46; R^2=0.5) compared to Gladio (Average RRMSE=12.17%; EF=0.3; R^2=0.38). The values of evaluation metrics were considerably improved when the best model estimates was used for each variable (Average RRMSE=12.04%; EF=0.6; R^2=0.63 for Loto; Average RRMSE=10.92%; EF=0.52; R^2=0.54 for Gladio). The values achieved for these metrics are coherent with what is normally achieved when rice biomass or yield is simulated (Bouman and van Laar, 2006; Confalonieri et al., 2010). This proved the ability of quality models in modulating the variety-specific response to the meteorological conditions perceived by the crop during the ripening phase.

3.5. Conclusions

Although crop quality is increasingly catalyzing the attention of the modelers community, the few simulations tools currently developed still present a rough level of detail in representing rice-based cropping systems, being mainly based on semi-empirical relations between quality and weather data within ripening period. Nevertheless, no studies are available in the literature regarding objective multimetric-evaluations of available alternative approaches under homogenous agro-climatic and management conditions, in order to understand their potential to be applied out of the context of development. In this context the present study represents the first attempt to address these concerns in a systematic way, exploring the performances of alternative approaches targeting the simulations of milling quality and functional properties of rice grain in the main European rice-growing district. Despite the selection of best models per variable allowed to accurately simulate the whole rice quality profile, single model performances were very heterogeneous according to the variety and quality feature considered. In general model ability in reproducing the reference values increased proportionally as the number of input variables and parameters of biological meaning grow, reaching best results for functional properties referring to Loto variety. Conversely, available approaches for the simulation of milling quality still requires model refinement to enhance precision, especially when applied to Indica-type varieties. Major improvement should involve the consideration of the interaction between genetic mechanism regulating the onset of damage in the kernel and agro-climatic factors. However in light of results achieved, models revealed to be sufficiently accurate to be operatively applied either in forecasting activities or scenario analysis (e.g. climate change impact assessment), to provide in advance plausible indications on rice cropping systems performances to be used by multiple stakeholders of agricultural sector.

Acknowledgements

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GLORIFY: A NEW FORECASTING SYSTEM FOR RICE GRAIN QUALITY IN NORTHERN ITALY

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4.1. Abstract

Reliable forecasts of pre-harvest grain quality are requested by stakeholders in rice sector, which is increasingly oriented to the achievement of superior grain quality standards to meet the market demand. Despite its economic importance, very few simulation models of rice quality as affected by meteorological conditions are available. This contribution presents a new forecasting system – GLORIFY – targeting the simulation of quali-quantitative rice productions in Northern Italy.

The quality variable considered is the head rice yield (HRY), representing the main determinant of rice market price at global level. An available HRY model was coupled to the WARM rice simulator and improved using field data referred to Loto and Gladio varieties collected in the Pavia province during the seasons 2006-2013. Simulations were carried out in three sites in the period 1994-2013. The simulated yield and HRY were used as independent variables to build multi-regression models to explain the variability of historical statistics (dependent variables). At field level, model performances denoted a good agreement between observed and simulated HRY (R2 and modelling efficiency, EF, always in the range 0.73 -0.93) and aboveground biomass values (R^2 and EF > 0.9). At province level, best results were obtained for Loto variety, as the regression model was able to explain 88% and 72% of the yield and HRY variability, respectively. Although improvements of the simulation environment are needed to reduce the uncertainty in Gladio forecasting, the present study allowed to realize a prototype system capable to give reliable forecasts of the rice cropping systems performance under different management and weather conditions.

Keywords: head rice yield, grain filling, milling quality, nighttime air temperature, WARM, crop yield

4.2. Introduction

Crop yield forecasting systems (CYFS) based on simulation models are worldwide adopted to provide in season estimates of the production of staple food crops (De Wit and van Diepen, 2007; Kogan et al. 2013; Bregaglio et al., 2015). Most of the existing CYFS rely on the outputs of crop models coupled with databases containing weather and soil data in the areas of interest (e.g., the Crop Growth Monitoring Systems of the European Commission, Supit et al., 2010; the Famine Early Warning System of the United States Agency for International Development, www.fews.net; the General Large-Area Model for annual crops, Challinor et al., 2004). Since the beginning, these systems focused on the simulation of potential and attainable yields (Van Ittersum and Rabbinge, 1997; Bezuidenhout and Singels 2007a, b), and progresses in the last decades would likely lead to the implementation of models to simulate actual productions, via the consideration of abiotic (e.g., spikelet sterility due to cold temperatures, Confalonieri et al., 2009a) and biotic stresses (e.g., the impact of fungal diseases, El Jarroudi et al., 2012; Bregaglio et al., 2015).

Available CYFS are thus increasing their ability in forecasting the annual yield variability, but they almost ignored the qualitative aspects of crop productions, which are affected by weather conditions and farmers management as well. This represents an urgent need, especially in most developed countries, where farmers are forced to reach superior quality standards both to meet the consumer preference and to respect the national and continental policies (Tesio et al., 2014). Also, grain buyers and millers are interested to have access to timely information before harvest, the former to purchase high-quality material at the best price, the latter to accurately schedule the length of the milling season to maximize business profitability (Bezuidenhout and Singels 2007a,b; Lee et al., 2013). Despite Italy is the first rice producer in EU-27 and the fourth-largest rice-exporting country at global level, its leading role is undermined by the recent decrease of CAP incentives to crop growers and by the increasing market competition with low-price exporting countries (Griglione et al., 2015). Furthermore the recent increase in the occurrence of weather extremes during rice growing season is threatening Italian productions, because of the severe decay in grain quality and consequent losses of market value (Cappelli et al., 2014a). National breeding programs targeting high quality productions were thus recently funded to improve Japonica – with large/short sized and soft cooking grain – rice varieties for the domestic market, and Indica varieties – with long, not sticky grain – for export. The traits Italian breeders are mainly working on are i) the improvement of milling quality, cooking properties and nutritive characteristics of rice productions (Russo and Callegarin 1997) and ii) the certification of the supply chain, considering the implementation of low impact agronomic practices (i.e., organic and Protected Geographical Indication rice varieties, Griglione et al., 2015). Although the economic importance of rice grain quality, an official classification of grain features, end-use destination and market price has not been yet defined, as in the case of other countries (i.e. Japan; Okada et al., 2011) or crops (i.e. bread wheat; Cocchi et al., 2005). Among the qualitative aspects of rice grain, head rice yield (HRY, the relative weight presence of entire kernels after milling), plays the major role in determining the global market price (Siebenmorgen et al., 2013). HRY is therefore recognized as the key indicator of milling quality, which depends both on weather conditions during the grain filling period and on grain moisture content at harvest.

Two main reasons limited so far the realization of a model-based rice qualitative forecasting system: (i) the lack of reference data, intended both as experimental observations to calibrate and evaluate grain quality models at field level and as time series of official statistics to validate the system on large area and (ii) the limited number of quality models (Jamieson et al., 1998; Bertin et al., 2010).

Despite the development of process-based simulation models to assess grain quality is recognized as a priority to improve current rice simulators (Porter and Semenov, 2005), most of the available models reproduce the impact of meteorological variables (e.g., air temperature, rainfall, wind speed and relative humidity) on grain composition (e.g., protein and starch content) via multiple regressions (Lee et al., 2013; Cappelli et al, 2014). This limits the applicability domain of these empirical approaches to the specific environmental datasets used to develop and evaluate these models.

This study presents a new CYFS, named Grain quaLity mOdel RIce Forecasting sYstem (GLORIFY), which aims at forecasting the quantity and quality of rice productions in Northern Italy.

4.3. Material and methods

4.3.1. Characterization of the study area

The simulation area of GLORIFY is the Northern Italian Lombardo-Piemontese district, which accounts for more than 50% of the total national production (Graglione et al., 2015). The semi-rural Pavia Province (latitude 45° 11’ N, longitude 9° 09’ E, altitude 258 m a.s.l.) contributing to the 35% and 18% of the Italian and European total rice area is selected as the case study. The climate in the area is temperate humid, with high local heterogeneity of pedo-climatic conditions (Fumagalli et al., 2011). Average annual air temperature is about 13.5 °C, ranging from 0-4 °C in winter months, to peaks over 30 °C in summer. Cumulative annual precipitations fluctuate around 750 mm, with two main rainy periods in autumn and spring, and a minimum from July to August. The utilized agricultural land (UAL) is mainly located in the plain area of the Po basin and extends for around 1800 km^2, with latitude ranging between 44° 44’ N and 45° 21’N and longitude ranging between 8° 31’E and 9° 30’ E (Figure 1).

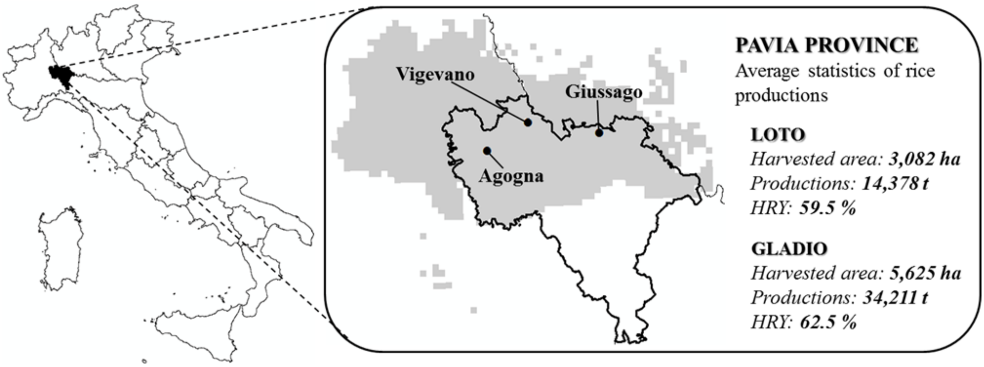

Figure 1: Geographic distribution of the study area and average statistics of rice productions within the Pavia province for Loto and Gladio varieties in the period 2000-2014. The grey area represents the Lombardo-Piemontese rice district; black circles correspond to the three municipalities where GLORIFY was applied.

The cultivation of paddy rice covers about 40 % of regional UAL, where farmers grow other cereals, forage and grapevine. The level of advancement of rice production systems in the area is supervised by the Ente Nazionale Risi (ENR – National Rice Authority) and by the Agricultural Research Council (CREA), which are in charge to collect official statistics on rice harvested area and productivity, to provide technical assistance to farmers and to certify the rice varieties entered in the Italian National

Register (197 rice cultivars in 2014). The University of Milan and the National Research Council also contribute to the research and development of rice sector via a downstream service to give real time support on crop status and risk alerts (EU-FP7 project, An Earth obseRvation Model based ricE smart information Service, Boschetti et al., 2014).

4.3.2. The data information layers

The GLORIFY forecasting system relies on a database with all the information needed to calibrate the crop and quality models at field level and to perform spatialized simulations in the study area (Figure 2).

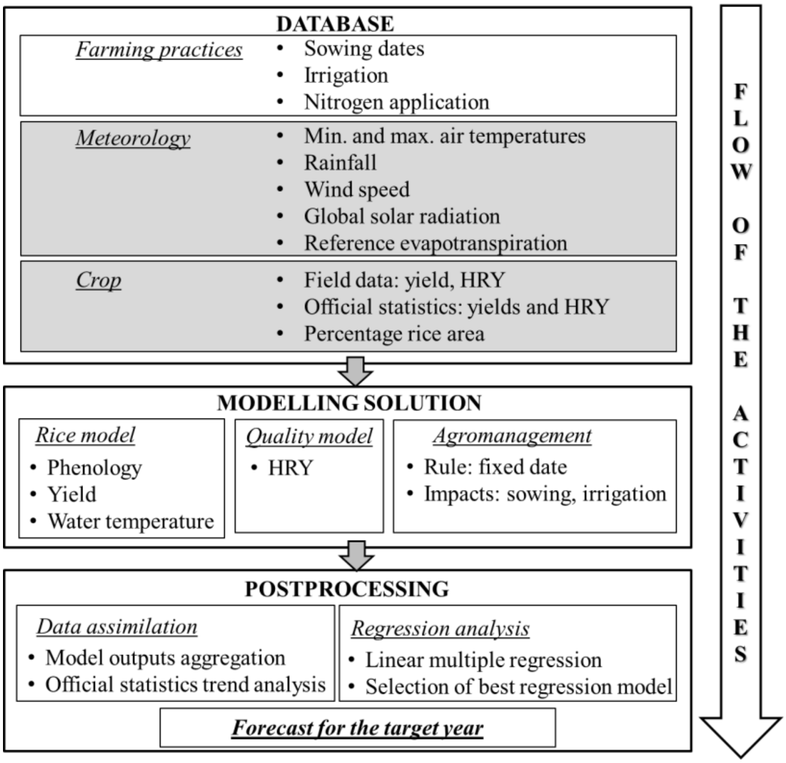

Figure 2: Schematic flow diagram of the GLORIFY crop yield forecasting systems. The database is structured in three layers, corresponding to farming practices, weather data and crop information at field and regional level; the modelling solution uses this information to perform spatially distributed simulations of the quantity and quality of rice productions with dedicated models; the post processing activities allow to correlate simulated productions with official statistics, and to provide forecasts for the ongoing growing season.

The database is structured in information layers and integrates data from different sources, allowing an ease coupling with biophysical models (section 2.3). The Crop layer contains experimental field data sampled to analyse rice crop development and growth dynamics. Available information are phenological observations (date of emergence, flowering and physiological maturity), the dynamic of aboveground biomass during the cropping season (kg ha^{-1}) and HRY profile, as percentage of entire kernels after milling. The data refer to the Italian cultivars Loto and Gladio, as representative of Japonica- and Indica-type varieties, respectively. The criteria for their selection were the high representativeness within the study area and the availability of long time series of statistics, i.e., official yields, percentage coverage and HRY data. Loto is a short cycle variety released in 1988, with medium slender grains suitable for parboiling and risotto preparation; Gladio is a medium cycle variety released in 1998 presenting long slender grains recommended for rice salads or side dishes cooking. The data of the experimental trials included in the Crop layer were collected by the University of Milan and the ENR in several sites of Po valley in the period 1990-2013 (Confalonieri et al., 2009b; Cappelli et al., 2015b). Official statistics of yields and HRY refer to 1994-2013 (21-years time series) and 1999-2013 (15-years time series) for Loto and Gladio varieties, respectively. The database is meant to be extended with new varieties.

The Meteorological layer contains daily minimum and maximum air temperatures (°C), rainfall (mm), wind speed (m s^{-1}) and reference evapotranspiration (mm) in the period 1990-2013 collected by the weather stations of the Regional Agency for Environmental Protection (ARPA). Global solar radiation (MJ m^{-2} d^{-1}) data were simulated according to Hargreaves formula (Hargreaves and Samani 1982), since not present in the stations data.

The Farming practices layer contains information related to the main agricultural management adopted by rice growers in the area, i.e., the sowing date, the irrigation water strategy and the timing, type and amount of the nitrogen application rates. Alternative irrigation strategies in the area are continuous flooding, or dry sowing with flooding at third-fourth leaf-stage, whereas nitrogen is mainly applied as urea in two or three events, one in pre-sowing and the others at beginning of tillering and/or at panicle initiation.

4.3.3. The GLORIFY modelling solution

The modelling solution is the simulation engine of the GLORIFY forecasting system. The core model is the WARM crop simulator (Confalonieri et al., 2009a, Cappelli et al., 2014a) which was extensively evaluated in the European rice growing conditions (Confalonieri et al. 2009b), and it is used by the European Community for rice yield forecasts in Europe, China and India, and in international projects dealing with food security (Crop monitoring as an E-agriculture tool in developing countries, E-Agri; Bio-Economic analysis of climate change impact and adaptation of Cotton and Rice based Agricultural production systems in Mali and Burkina Faso, BECRA), model improvement (The Agricultural Model Intercomparison and Improvement Project, AgMIP) and technology-development (i.e., FP7 ERMES and MODelling vegetation responses to EXTREMe Events, MODEXTREME). The simulation of crop development is performed at hourly time step considering a non-linear, upper-limited response to temperature (Yan and Hunt, 1999), and biomass accumulation rate is computed via a radiation use efficiency approach (Wilson, 1967). Photosynthates are partitioned to the plant organs according to development stage, and leaf area index increase is derived by the daily leaves biomass and a dynamic specific leaf area. Leaf senescence is simulated at daily time step as a function of the thermal time accumulation.

The floodwater effect is taken into account via a micrometeorological model estimating canopy layer and surface water temperatures at hourly time step based on the energy balance approach. The estimation of hourly values of the meteorological variables as inputs to the models is carried out via the CLIMA components and is performed on-the-fly during simulation runs.

4.3.3.1. Simulation of head rice yield

The model to simulate HRY is derived by Lanning et al. (2011), who formalized its dependency to hourly nighttime air temperature during the R8 reproductive stage (late maturity, 83-89 BBCH) (Equation 1).

$$HRY = a_i T_{95}^2 + b_i T_{95} + c_i \qquad [1]$$

where HRY (% of entire grains after milling) is the simulated HRY value; T95 (°C) is the 95-th percentiles of nighttime air temperature frequencies during the 83-89 BBCH ripening stages; a_i, b_i, c_i (unitless) are variety-specific coefficients. This model does not consider the impact of high windiness and low humidity at sub-optimal temperatures for the starch formation in the early ripening stages, which are known to markedly influence the final value of HRY (Oya et al., 2008; Ishimaru et al., 2009). This led to the definition of a new HRY model, able to modulate the susceptibility to breakage according to a simulated potential cultivar-specific HRY (Equation 2) modulated by the impact of rainfall, wind speed and temperature during the early ripening stages (BBCH 65 - 83) (Equation 3).

$$HRY_i = \begin{cases} a_i \cdot T_{\min}^2 + b_i \cdot T_{\min} + c_i & if \quad T_{95} \le T_{\min} \\ a_i \cdot T_{95}^2 + b_i \cdot T_{95} + c_i & if \quad T_{\min} < T_{95} \le Topt_{\min} \\ a_i \cdot Topt_{\min}^2 + b_i \cdot Topt_{\min} + c_i & if \quad Topt_{\min} < T_{95} \le Topt_{\max} \\ \left(d_i \cdot T_{95}^2 + e_i \cdot T_{95} + g_i\right) + \\ \left[\left(a_i \cdot Topt_{\min}^2 + b_i \cdot Topt_{\min} + c_i\right) - \left(d_i \cdot Topt_{\max}^2 + e_i \cdot Topt_{\max} + g_i\right)\right] & if \quad T_{95} > Topt_{\max} \end{cases} \qquad [2]$$

where Toptmin (°C) and Toptmax (°C) represent the lowest and highest optimal temperatures for the synthesis of starch in the rice grain; Tmin (°C) represents the minimum temperature for the starch synthesis; a_i, (0.6073 for Loto variety, -0.1791 for Gladio variety) b_i, (-27.848 for Loto variety, 8.5375 for Gladio variety) c_i (379.5568 for Loto variety, - 36.1533 for Gladio variety), d_i, (-0.39685 for Loto variety, -0.1791 for Gladio variety), e_i, (20.585 for Loto variety, 8.5374 for Gladio variety), g_i (-202.89 for Loto variety, -0.1791 for Gladio variety) are variety-specific coefficients (unitless).

The actual value of HRY (HRYc, Equation 3) is computed by decreasing the potential HRY (Equation 2) when rainfall (RainC), wind (WindTh) and temperature (T95em) exceed critical thresholds during the sensitive period after flowering (BBCH 65 - 83).

$$HRY_c = \begin{cases} HRY_i - e & if \; T95_{em} > Topt_{\max} \cap RainC < RainTh \cap WindyD > WindTh \\ HRY_i & else \end{cases} \qquad [3]$$

where HRY_c (%) is the corrected value of HRY, e (%) is a variety-specific
where HRY_c (%) is the corrected value of HRY, e (%) is a variety-specific
coefficient representing the HRY reduction due to critical humidity, wind and temperature conditions during the early ripening, experimentally determined for the study area; $T95_{em}$ (°C) is the 95th percentiles of nighttime air temperature during early maturity; RainC (mm) is the

cumulated precipitation in the early maturity period; RainTh (mm) is the minimum threshold of cumulated rainfall triggering HRY decrease; WindyD (day) is the number of days with average wind speed higher than a critical threshold, (WindyTh, m s^{-1}) to start HRY decrease.4.3.4. The calibration and evaluation activities

4.3.4.1 Field level calibration and evaluation

The field level evaluation of the WARM performances in reproducing quantitative aspects of rice productions was carried out on 18 datasets collected in rice experiments placed in municipalities of the Pavia province (Figure 1, Table 1). The calibration was performed via trial-and-error technique, with the minimum squared error between simulated and observed data as objective function. The calibration and evaluation of the new HRY model was carried out on 40 data per variety split in four independent datasets (Appendix A, Table A.1 for Loto and A.2 for Gladio). The model performances were evaluated using the mean absolute error (MAE, 0÷∞, Schaeffer, 1980), the relative root mean squared error (RRMSE, minimum and optimum = 0%; maximum = + ∞, Jørgensen et al. 1986), the modelling efficiency (EF, - ∞ ÷ 1, optimum =1, if positive, indicates that the model is a better predictor than the average of measured values, Nash and Sutcliffe, 1970) the coefficient of residual mass (CRM, 0÷1, optimum = 0, if positive indicates model underestimation, Loague and Green 1991) and the coefficient of determination (R^2, 0÷1, optimum =1).

4.3.4.2 .Simulation at provincial level

After model calibration and evaluation at field level, multiple year simulations were performed in three municipalities (Castello d’Agogna, Vigevano and Giussago) and the outputs were stored at a time resolution of ten days. The variables were then aggregated at provincial level according to the rice area in each municipality. A multi-regressive model was developed using aggregated outputs at maturity stage to explain the annual variability of official yields and HRY. The risk of collinearity among predictors was checked via the Variance Inflating Factor (VIF) and the tolerance index. Collinear regressors were then use separately in the model. Values of VIF > 15 and tolerance index <0.01 were assumed as thresholds for high-collinearity (Belsey and Welsch, 1980).

The presence of outliers in the historical series of yields and HRY was investigated via the Grubbs' test in case of normal data distribution (Grubbs, 1969) and via the non-parametric Hampel's test when the assumption of normality was not satisfied (Davies and Gather, 1993). Normality test was carried out at 95 % confidence interval through the Anderson-Darling (Anderson and Darling, 1952) and Shapiro-Wilk (Shapiro and Wilk, 1965) tests, the latter considered as very powerful with small samples sizes. The official statistics were analysed to identify any systematic time or technological trend via linear and quadratic regression. The slope of the regression line was analysed to understand whether the trend was increasing, constant or diminishing. Once a trend was detected, it was firstly extrapolated from the official yearly yield/HRY values and then added back to regression model outputs developed using simulated crop indicators against the de-trended yield/HRY values. Details concerning outliers detection procedure and the trend analysis are reported in the supplementary material (Appendix D, Figure D.1 and D2).

The multi regression model which obtained the highest correlation (R2 value) between simulated outputs and official data was used to predict yield and HRY in 2013 growing season, selected as the target year. The maximum number of model outputs (Table 2) included in the multiple regression models was four.

Table 2: Model outputs used as predictors to explain the annual variability of official yields and head rice yield (HRY). * Development Stage Code: 1 = emergence, 2 = flowering, 2.5 = full ripening 3 = physiological maturity.

Predictors of the regression model	Acron	Unit	Depende
Growth and development			
Aboveground biomass	AGB	kg	Yield
Storage organs	STO	kg	Yield
Leaf area index	LAI	m^2	Yield
DVS*	DVS	unit	Yield, HRI
Cycle length	CYCL	day	Yield, HRI
Length of the period from flowering to	RIPE	day	Yield, HRI
Grain quality			
Head Rice Yield	HRY	%	HRI
Meteorological variables influencing the HRY			
95-th percentiles of nighttime air	T95	°C	Yield, HRI
Cumulative rainfall	RAIN	mm	Yield, HRI
Windy days during ripening phase	WIND	day	Yield, HRI

4.4. Results

4.4.1. Model evaluation at field level

4.4.1.1. Simulation of crop growth and development

The simulation of crop development denotes the ability of the WARM model in reproducing the main phenological stages of Loto and Gladio varieties in the field experiments (Figure 3). Average errors in estimating flowering and maturity dates were four and ten days, respectively, with both varieties obtaining slightly better results in calibration than in the evaluation phase. The simulation of AGB values led to R2 values higher than 0.9, and highlights the correct reproduction of the growth patterns during the crop cycle.

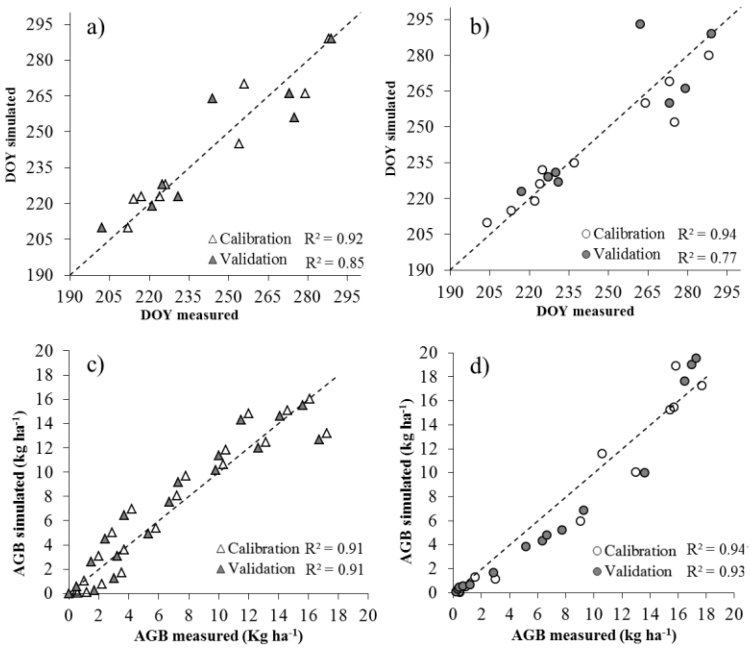

Figure 3: Comparison between measured and simulated phenological dates (a, b) and aboveground dry biomass (AGB) values (c, d) for Loto (triangles) and Gladio (circles) rice varieties in calibration and evaluation phase; the dashed lines represent the 1:1 line. DOY: Julian day of the year.

The model goodness of fit is confirmed by the values of the statistical indices presented in Table 3 for phenological development (average MAE <

7.5 days, RRMSE = 4%, EF = 0.86) and for in-season AGB dynamics (MAE < 1.5 t ha^{-1}, RRMSE < 25%, EF > 0.9), which are in line with literature values (Bouman and van Laar, 2006; Confalonieri et al., 2009a). Positive CRM values suggest the tendency of the WARM model to underestimate measured AGB data of Gladio variety in the early stages of the crop cycle, whereas no systematic bias can be observed in the simulation of phenological development of the Loto variety.

Table 3: Indices of agreement between observed and simulated i) phenological dates (flowering and maturity dates) and ii) aboveground biomass (AGB) values, computed for Loto and Gladio varieties. C: calibration; V: validation; MAE: mean absolute error (days, d; tons, t); RRMSE: relative root mean square error (%); EF: modelling efficiency (unitless); CRM: coefficient of residual mass (unitless); R^2: coefficient of determination (unitless).

Variable	Dataset	Variet	**MAE** (d; t)	**RRMSE** (%) **(%)**	EF	CRM	R^2
Phenology	C	Loto	6.30 d	3.18	0.9	0.00	0.92
	V		8.38 d	4.45	0.8	0.00	0.86
	Mean		7.34 d	3.82	0.8	0.00	0.89
	C	Gladio	6.10 d	3.53	0.9	0.01	0.94
	V		8.75 d	5.19	0.7	0.00	0.77
	Mean		7.43 d	4.36	0.8	0.01	0.86
	Mean		7.38 d	4.09	0.8	0.00	0.87
AGB	C	Loto	1.22 t ha	23.56	0.9	-0.03	0.92
	V		1.09 t	19.27	0.9	0.06	0.92
	Mean		1.16 t	21.42	0.9	0.02	0.92
	C	Gladio	1.44 t	25.43	0.9	0.00	0.95
	V		1.40 t	25.10	0.9	0.09	0.93
	Mean		1.42 t	25.27	0.9	0.05	0.94
	Mean		1.29 t	23.34	0.9	0.03	0.93

4.4.1.2. Simulation of head rice yield

The comparison of the outputs of the HRY models – the one by Lanning et al. (2011) and the new approach – with reference data is presented as scatterplot in Figure 4. Despite a very good agreement between observed and simulated data was obtained for Gladio cultivar, the original model (Figure 4a) failed in reproducing the HRY for Loto datasets, showing a flat distribution of simulated outputs with marked overestimation at low measured values (below 58%).

The consideration of the effect of rainfall and wind speed in the new model allowed to markedly improve HRY estimates for Loto variety (average R^2 = 0.81, Figure 4c), whereas similar performances were obtained for Gladio (average R2 = 0.93).

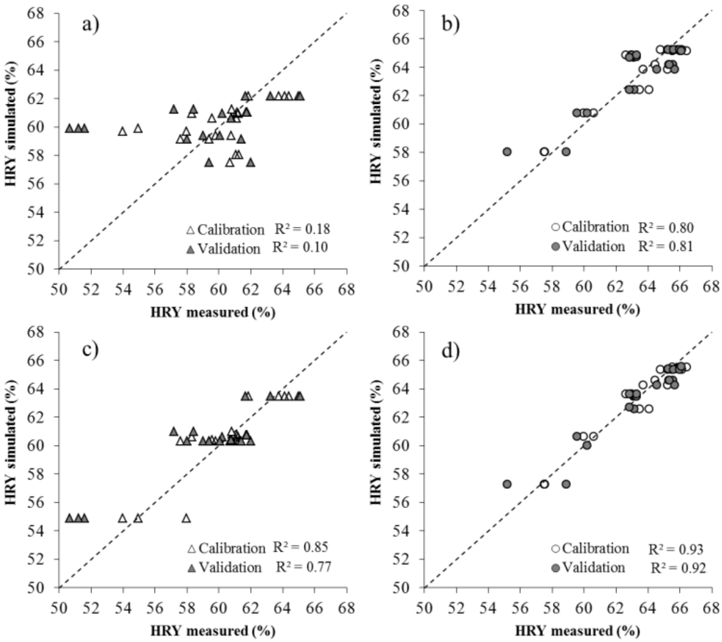

Figure 4: Comparison between measured and simulated head rice yield (HRY) values for Loto (triangles) and Gladio (circles) rice varieties; simulations were carried out using the Lanning (a, b) and the new (c, d) models. The dashed lines represent the 1:1 line.

The values of the evaluation metrics presented in Table 4 confirm the improved accuracy of the new model in reproducing the annual variability of HRY (average EF of 0.74), even increasing the accuracy in terms of average error (average RRMSE of 2.79 % for Loto; average RRMSE of 1.18 % for Gladio). The representation of variety-specific responses to the weather conditions experienced by the crop during the ripening phase also allowed to achieve average MAE values of 0.6 % (instead of 1%) for Gladio and 1.32 % (instead of 2.23%) for Loto cultivars. Regardless the statistical metric considered, the highest gains in accuracy were always achieved for Loto variety, which is more sensitive to temperature and humidity excursion within the critical period in post-flowering.

Table 4: Indices of agreement between observed and simulated head rice yield (HRY) values, computed for Loto and Gladio varieties. Performances of the original (Lanning) and new model were compared. C: calibration; V: validation; MAE: mean absolute error (%); RRMSE: relative root mean square error (%); EF: modelling efficiency (unitless); CRM: coefficient of residual mass (unitless); R^2: coefficient of determination (unitless).

Model	Dataset	Variety	MAE (%)	RRMSE (%)	EF	CRM	R^2
Lanning	C	Loto	1.76	3.88	0.18	0.00	0.19
	V		2.69	6.57	0.05	-0.02	0.11
	Mean		2.23	5.23	0.12	-0.01	0.15
	C	Gladio	0.94	1.78	0.81	0.00	0.81
	V		1.03	1.99	0.80	0.00	0.81
	Mean		0.99	1.89	0.81	0.00	0.81
	Average		1.61	3.56	0.47	-0.01	0.48
New Model	C	Loto	0.96	2.07	0.77	0.00	0.77
	V		1.68	3.50	0.73	-0.01	0.86
	Mean		1.32	2.79	0.75	0.00	0.81
	C	Gladio	0.56	1.05	0.93	0.00	0.93
	V		0.64	1.31	0.91	0.00	0.92
	Mean		0.60	1.18	0.92	0.00	0.93
	Average		0.80	1.54	0.87	0.00	0.87

A further model evaluation was performed via the Akaike Index (AIC, Information Criterion index, Akaike 1973, optimum =1), which is used to quantify the best trade-off between the accuracy of fit (explanatory power) and the complexity (number of parameters). The AIC values obtained by the new model ranged between 6.09 for Gladio (original model = 10.25) to 34.99 for Loto (original model = 45.43) and confirm the improvement of HRY simulation.

For all the processes simulated and for both varieties, calibrated parameters are presented in Appendix B, Table B.1 (growth and development) and B.2 (HRY).

4.4.2. Performances of the forecasting prototype at province level

4.4.2.1. Forecasting yield levels

The performances of GLORIFY in reproducing official yield statistics of Gladio and Loto varieties are shown in Figure 5. In-season forecasts were carried out in two moments of the crop cycle: around flowering (half of August) and at maturity (end of September).

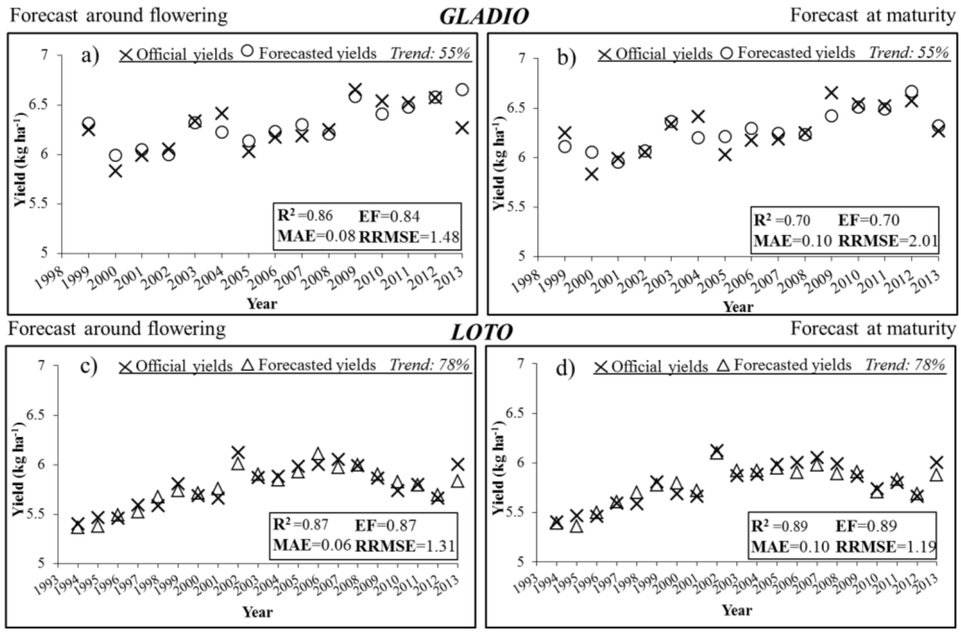

Figure 5: Comparison between official and estimated yields for Gladio (a, early forecast; b, late forecast) and Loto (c, early forecast; d late forecast) varieties at province level. R2: determination coefficient (unitless); EF: modelling efficiency (unitless); MAE: mean absolute error (t ha^{-1}); RRMSE: relative root mean square error (%).

GLORIFY accurately reproduced official statistics at provincial scale, and explained on average the 88 % and 78 % of the inter-annual yield variability for Loto and Gladio variety, respectively. No systematic bias can be observed in the regression models. Forecasts targeting Gladio variety were decidedly more accurate at flowering (R^2 = 0.86) than at maturity stage (R^2 = 0.70), whereas for Loto the accuracy of predictions remained constant (R^2 = 0.87 at flowering versus R^2 = 0.89 at maturity). The higher accuracy in reproducing the observed yields at flowering stage (e.g. 2000, 2005, 2009 and 2012) led to achieve overall best results for Gladio cultivar. Focusing on target year (i.e., 2013), the most accurate predictions were provided by the late forecasts, with slight deviations from the expected values for both varieties (underestimation of 50 kg ha^{-1} and 151 kg ha^{-1} for Gladio and Loto, respectively. The predictors selected in the regression model (Table 5) derived by crop model simulations (i.e. STO and RIPE for Loto, AGB and

CYCLE for Gladio) and by weather data (i.e., cumulative rainfall (RAIN) and windy days (WIND) in post flowering). For Loto variety, indicators were characterized by average SE of about 0.45 t ha^{-1} and 0.21 t ha^{-1} within early and late maturity forecasts respectively. For Gladio values of average SE were always higher than those computed for Loto and all T-values were not significant. However selected indicators increased the overall time trend explanatory power of about 12 % and 25 % for Loto and Gladio cultivars respectively, with the latter showing marked differences in terms of accuracy according to the forecasting period chosen.

Table 5: Results from best combinations of model indicators against the official rice yields and head rice yield (HRY) over the period 1994 - 1998, for Loto and Gladio varieties. T-values (T) in light grey are significant at confidence interval of 95%. SE: standard error (t ha^{-1} for yield, % for HRY); Tcrit.: Student's T critical value. Pr. represents the probability that computed T values are higher than the T critical value.

Variety	Variable	Decade	Indicators	SE	T	Pr. T> $\|T_{crit}\|$
Loto	yield	23	STO	0.228	4.041	0.001
			RAIN	0.536	0.926	0.369
			WIND	0.578	-1.829	0.087
Gladio	yield	23	AGB	0.257	0.543	0.600
			CYCLE	0.235	-1.666	0.130
			RAIN	0.709	0.282	0.785
			WIND	0.734	0.721	0.489
Loto	yield	29	STO	0.224	1.880	0.081
			RIPE	0.227	-1.302	0.214
			RAIN	0.186	3.168	0.007
			WIND	0.210	-2.311	0.037
Gladio	yield	29	AGB	0.399	1.252	0.242
			CYCLE	0.450	-2.095	0.066
			RAIN	0.345	0.997	0.345
			WIND	0.297	0.243	0.813
Loto	HRY	29	HRY	0.229	4.409	0.001
			T95	0.397	-2.767	0.016
			DVS	0.444	4.378	0.001
			CYCLE	0.389	3.187	0.007
Gladio	HRY	29	HRY	0.655	1.630	0.142
			T95	0.584	-1.656	0.136
			RAIN	0.289	-0.698	0.505
			WIND	0.367	1.984	0.082

4.4.2.2. Forecasting head rice yield

The ability of GLORIFY in reproducing official HRY statistics of Gladio and Loto cultivars are shown in Figure 6. Since the model developed to predict HRY do not provide dynamic simulation of this variable, forecasts were performed at maturity stage (end of September).

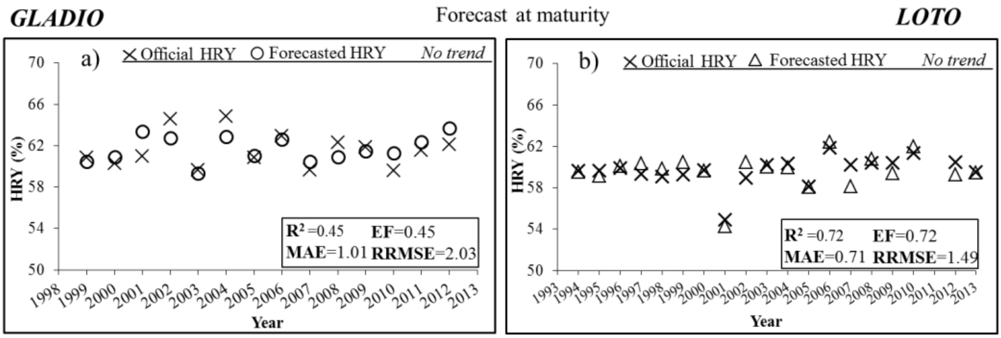

Figure 6: Comparison between official and estimated HRY for Gladio (a) and Loto (b) varieties at province level. R^2: determination coefficient (unitless); EF: modelling efficiency (unitless); MAE: mean absolute error (%); RRMSE: relative root mean square error (%).

GLORIFY performances in reproducing HRY were overall satisfactory, showing contrasting results according to the simulated variety (R^2 = 0.72 for Loto, R^2 = 0.45 for Gladio), with no trends in the historical series. For Loto cultivar, the regression model succeeded in reproducing the inter-annual variability of official statistics (MAE=0.71%, RRMSE=1.49%, EF=0.72), and predicted HRY in the target year with deviations lower than 1%. Despite the good performances shown by the HRY model at field level, unexpectedly results were less accurate for Gladio variety at province level (MAE=1.01%, RRMSE=2.03%, EF=0.45), mainly due to low accuracy in reproducing HRY in the period 2001-2004. Furthermore, the tendency to overestimate official HRY in the seasons 2011 (1.68 %) and 2012 (0.82 %), was confirmed in 2013 (target year), due to an error of about 1.6%. Best regression models included both HRY and T95 (Table 5), and indicators related to crop phenology for Loto (DVS and CYCLE) and meteorological conditions for Gladio (WIND and RAIN). For Loto variety, DVS and HRY predictors were significant at 99% confidence interval, with the latter proving to be very accurate (SE = 0.23 % instead of SE = 0.44%). Among the indicators selected for Gladio, similar accuracy was achieved by RAIN (SE = 0.29 %) and WIND

(SE=0.37 %), even though all the computed T-values were not significant at any confidence intervals considered.

4.5. Discussion

4.5.1. Field scale

The most relevant parameters of the WARM models involved with phenology, growth (i.e. AGB) and quality (i.e. HRY) were adjusted in calibration within the biophysical ranges of variations reported for Italian rice varieties (Confalonieri et al., 2009 b); all the other parameters were left to default. Compared with previous studies (Confalonieri and Bocchi 2005; Confalonieri et al., 2009b), minor changes involved cardinal temperatures for Gladio variety, whereas minimum and maximum temperatures thresholds triggering Loto growth and development were lowered of 1 °C (10 °C versus 11 °C) and 2.5 °C (39.5 ° versus 42 °C), according to the values proposed by Counce et al. (2000). These modifications allowed the model to reproduce the lower thermal requirements of this Japonica variety (Weng et al., 1987), and to increase the sensitivity to high temperatures during summer months. The maximum radiation use efficiency (RUE) was set to 2.35 and 2.47 g MJ^{-1} for Loto and Gladio cultivars, thus comparable to available studies in similar conditions (e.g. Kiniry et al., 1989; Confalonieri et al., 200b). The more productive attitude of Gladio variety was reproduced by setting a higher specific leaf area at tillering (SLA_{till}= 19 versus 15 m^2 kg^{-1}) and partitioning to leaves at emergence (RPL_0 = 0.625 versus 0.6, unitless). The largest errors in simulating the maturity date for Gladio variety slightly affect the accuracy of results, thus confirming the model ability in reproducing growth patterns of the two ecotypes under explored conditions. From the grain quality point of view, the development of a new model allowed to explicitly consider both i) the effects of meteorological conditions on the grain starch formation and deposition and ii) the cultivar-specific susceptibility to breakage through the valorization of parameters of clear biological meaning. According to previous studies (Yoshida 1981; Chen et al., 2011), optimal temperatures for starch synthesis of the two ecotypes were set in the range 25 – 27 °C, while the higher susceptibility to breakage of Loto grains was captured by increasing the slope of response function to temperature, lowering the critical cumulative rain threshold (RainC = 14 mm instead of 7 mm) and emphasizing the percentage reductions of HRY due to suboptimal meteorological conditions during early ripening (e = 5.4% instead of 1.7 %). The proper parametrization of the new developed HRY-WARM module allowed to markedly improve the simulation of HRY values compared to previous simulation works carried out in Northern Italy (Cappelli et al., 2014a) and United States (Lanning et al., 2011). While RRMSE, R^2 and MAE were in the same range of magnitude of literature values (RRMSE = 4 - 6.5 %; R^2 = 0.4 - 0.81; MAE =2 - 3 %), average EF was considerably enhanced for both varieties (EF = 0.92 versus 0.23 for Indica-type; EF = 0.75 versus 0.29 for japonica-type). Although the good performance of the original model for Gladio variety with high resolution weather data as input, it completely failed to reproduce HRY values for Loto variety. However, the changes made to the original formalization allowed to considerably improve HRY simulations especially for Loto variety, when small deviations from the optimum ranges of temperature and humidity occurred within the ripening period.

4.5.2. Provincial scale

In the study area seasonal rice yield varied in the range 5.4 – 6.1 t ha^{-1} for Loto (average 5.8 t ha^{-1}) and 5.8 – 6.7 t ha^{-1} Gladio varieties (average 6.3 t ha^{-1}) during the 1998 - 2013 growing seasons. While inter-annual variability of official yields did not show any correlation with seasonal weather trends (0.01 <R^2 < 0.16), significant downward quadratic and upward linear trends were observed for Loto (Appendix D, Figure 5b1) and Gladio (Appendix D, Figure 5b2) varieties. While Loto yields trend reflects the dynamic of the harvested area in the Pavia Province, Gladio yield levels are not correlated with the rice area. Higher productions in recent years are due to the progressive average temperature increases within the province (about 2 °C in the last two centuries, Brunetti et al., 2006), allowing Indica-type varieties to decrease cold stresses during crop establishment and flowering. The trend alone always proved to be a good yield predictor, being able to explain 78 % and 53 % of inter-annual variability of yields for Loto and Gladio varieties, with significant T-values. The GLORIFY system further increased the accuracy of yield forecasts, with different performances according to the phenological phase. For Loto variety, selected indicators at maturity and around flowering were able to explain the 89 % and 87 % of yield variations, and succeeded in predicting the yield in the target year. Among the predictors, STO and WIND increased the explanatory power of 3.5% and 5% respectively. Conversely selected indicators for Gladio variety increased the accuracy of 78%, with AGB and CYCLE providing the major contribution compared to RAIN and WIND. However, over and under yield estimates were exacerbated as time of forecast approached time of harvest, except for target year. The reason may be the lack of consideration of yield-limiting factors (e.g. cold sterility events, diseases) in the simulation. This can explained poor results in the seasons 2000, 2005, 2006 and 2012, when cold induced sterility and panicle blast attacks during ripening (ENR, annual technical reports, http://www.enterisi.it/) reduced Italian rice yields (Bregaglio et al., 2015; Titone et al., 2015). Conversely, the yield underestimates in 2004 and 2009 can be due to high temperatures during late summer (about +1.3 °C above the average), leading to a shorter simulated duration of the ripening period (about 7 days compared to the average) and reduced grain filling.

Also for HRY forecasts, best results were obtained for Loto variety, as the regression model explained 72% of the yield variability and matched HRY value in the target year. Indicators selected were always significant, and prove the capability of the model in seasons characterized by anomalous HRY values (i.e. 2001 and 2006). Marked HRY overestimations in 2002 (+2%) and 2004 (+2.4%) seasons may be partially explained by the marked humid meteorological conditions, as they accounted for the 45 % of total cumulative rainfall in the whole time series 1999-2013, and require further investigation. Compared to Loto results, HRY indicator showed a greater relative explanatory power (36% versus 19%), whereas crop models predictors were not included. The overestimation of HRY value of about 1.6% in the target year confirms the need of improving the quality of inputs information and the model formalization. The accuracy of GLORIFY yield forecasts were comparable to similar studies performed under a wide spectrum of agro-climatic conditions for sugarcane (Bezuidenhout and Singels, 2007b), wheat (El Jarroudy et al., 2012, Djaby et al., 2013; Kogan et al., 2013), maize (Mkhabela et al., 2005; Djaby et al., 2013; Wang et al., 2013) and rice (Manfron et al., 2013). At province/regional scale, these systems are usually able to explain about 55-60 % of inter-annual yields variability in the presence of technological/time trend, even reaching peak of 90-92 % when satellite-derived (de Wit et al., 2013) or simulated disease/water limited indicators (Pagani et al., 2013) are included in the regression models. For grain quality, the only two studies available in literature focus on wheat protein content, respectively using a statistical (Lee et al., 2013) and model-based (Toscano et al., 2014) approach. Best results were obtained by Toscano et al. (2014), who predicted wheat protein content in the major Italian supply basins with an average R^2 of 0.71.

4.6. Conclusions

The study presents a yield and grain quality forecasting system for Northern Italy, capable to give in-season indications on rice cropping systems performance to be used by agricultural stakeholders at different levels, from farmers to regional politicians. Although the GLORIFY system accurately performed at field and province scale, it still requires model refinement to enhance precision at regional scale especially for Indica-type varieties, which represent an increasing segment of Italian and European rice demand. Major improvement should involve the quality of data input and the models formalization, as the interactions between head rice yield and plant nutrients dynamics should be implemented. Furthermore, the GLORIFY system allows to be extended to forecast other qualitative variables influencing rice prices.

Acknowledgements

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Appendices

Appendix A

Table A1. Experimental data used to calibrate and validate the model for the estimation of head rice yield (HRY, %) of Loto variety. C: calibration datasets; V:validation datasets.

Year	Flooding	Sowing	Flowering	Maturity	HRY (%)	Dataset
2011	Continuo	144	226	273	63.8	C
2011	3rd leaf	137	226	273	64.1	
2012	3rd leaf	136	222	275	54.9	
2012	3rd leaf	136	223	275	58.0	
2013	Continuous	158	222	288	59.8	
2006	Continuo	144	226	268	58.3	
2006	Continuo	144	226	268	61.2	
2005	Continuo	152	233	284	61.6	
2009	Continuo	149	225	286	61.3	
2008	Continuo	152	227	277	61.1	
2011	Continuo	144	226	273	65.0	V
2011	3rd leaf	136	226	273	63.2	
2012	Continuo	149	221	275	51.6	
2012	3rd leaf	136	221	275	50.6	
2013	Continuo	158	230	288	59.0	
2006	Continuo	144	226	268	60.2	
2006	Continuo	144	225	267	58.4	
2005	Continuo	152	233	284	62.6	
2008	Continuo	152	227	276	61.8	
2008	Continuo	152	227	277	60.8	
2011	Continuo	144	226	273	64.4	C
2011	3rd leaf	136	226	273	61.9	
2012	Continuo	149	223	275	54.0	
2013	Continuo	158	230	288	60.8	
2013	3rd leaf	148	231	288	57.6	
2013	3rd leaf	148	231	288	59.4	
2006	Continuo	144	225	267	60.8	
2009	Continuo	149	225	287	61.1	
2008	Continuo	152	227	276	61.2	
2008	Continuo	152	227	276	61.7	
2011	Continuo	144	226	273	65.1	V

2011	3rd leaf	136	226	273	61.7
2012	Continuo	149	221	275	51.2
2013	Continuo	158	230	288	60.1
2013	3rd leaf	148	231	288	58.0
2013	3rd leaf	148	231	288	61.4
2006	Continuo	144	225	267	57.2
2005	Continuo	152	233	284	62.6
2008	Continuo	152	227	276	61.7
2008	Continuo	152	227	277	60.8

Table A2. Experimental data used to calibrate and validate the model for the estimation of head rice yield (HRY, %) of Gladio variety. C: calibration datasets; V:validation datasets.

Year	Flooding	Sowing	Flowering	Maturity	HRY	Dataset
2011	Continuous	144	227	273	65.5	
2011	3rd leaf	136	226	273	65.8	
2012	Continuous	149	222	275	62.6	
2012	3rd leaf	136	223	275	63.1	
2013	Continuous	158	230	288	64.4	**C**
2013	3rd leaf	148	234	288	63.7	
2008	Continuous	155	238	294	60.6	
2009	Continuous	139	218	273	65.5	
2010	Continuous	144	224	279	63.4	
2008	Continuous	169	248	302	57.5	
2013	3rd leaf	148	233	288	65.7	
2012	3rd leaf	136	225	275	63.3	
2013	Continuous	158	230	288	65.5	
2008	Continuous	155	239	294	59.5	
2009	Continuous	139	218	274	66	**V**
2010	Continuous	144	224	279	63.1	
2008	Continuous	170	248	302	58.9	
2011	Continuous	144	227	273	65.2	
2012	Continuous	149	222	275	63	
2011	3rd leaf	136	226	273	65.3	
2013	Continuous	158	230	288	65.3	
2009	Continuous	139	218	273	66.4	
2010	Continuous	144	224	279	64.1	**C**
2008	Continuous	170	250	302	57.5	
2011	Continuous	144	227	273	64.8	

2011	3rd leaf	136	227	273	66.1	
2012	3rd leaf	135	225	275	63.1	
2012	Continuous	148	222	275	62.9	
2008	Continuous	155	238	294	60	
2013	3rd leaf	148	233	288	65.2	
2011	Continuous	144	227	273	65.6	
2011	3rd leaf	136	227	273	65.9	
2012	Continuous	149	222	275	63.3	
2012	3rd leaf	136	223	275	62.8	
2013	Continuous	158	230	288	65.3	**V**
2013	3rd leaf	148	233	288	64.5	
2008	Continuous	155	239	294	60.2	
2009	Continuous	139	217	272	66.1	
2010	Continuous	144	224	278	62.8	
2008	Continuous	170	250	302	55.2	

Appendix B

Table B1. Calibrated values of WARM parameters involved with growth and development.

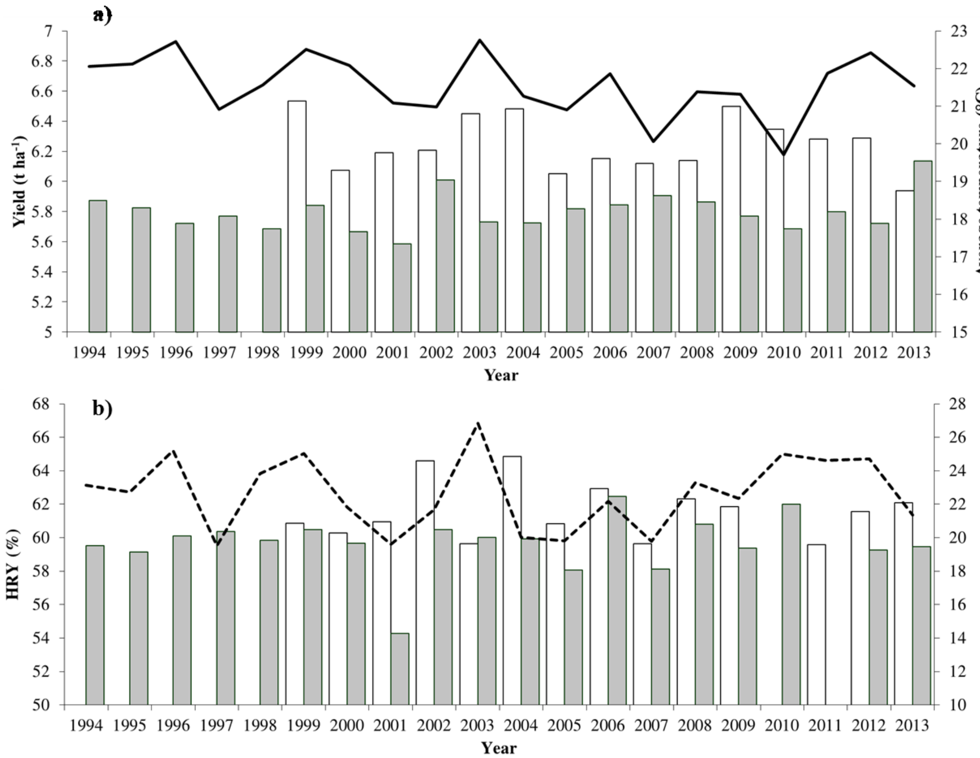
Parameters	Unit	Value	
		Japonica	***Indica***
Development			
Base temperature for development	°C	10	11.8
Optimum temperature for development	°C	30	31
Maximum temperature for development	°C	39.5	41.5
Degree days from sowing to emergence	°C day^{-1}	70	90
Degree days from emergence to flowering	°C day^{-1}	745	665
Degree days from flowering to maturity	°C day^{-1}	343.2	285
Growth			
Radiation-use efficiency	g MJ^{-1}	2.35	2.47
Extinction coefficient for solar radiation	-	0.48	0.48
Base temperature for growth	°C	11	12
Maximum T for growth	°C	39.5	41.5
Optimum T for growth	°C	30.5	31
Specific leaf area at emergence	m^2 kg^{-1}	33	29
Specific leaf area end tillering	m^2 kg^{-1}	15	19
Aboveground biomass partition to leaves at	-	0.6	0.62
Leaf duration	°C day^{-1}	600	580
Maximum panicle height	cm	100	80

Table B2. Calibrated values of parameters involved head rice yield simulation.

Parameters	Unit	Value	
		Japonica	***Indica***
Indica/Japonica-type	-	false	true
Grain lenght	-	medium	long
Higher night temperature for opt. starch synthesis	°C	26.5	26.8
Lower night temperature for opt. starch synthesis	°C	25.5	25.8
Minimum temperature for starch synthesis	°C	22.9	17
Windy days threshold for damage	day	10	
Wind speed threshold for damage	m s^{-1}	2	
Cumulated rain threshold for damage	mm	7	14
Average HRY underestimation	%	5.4	1.7

Appendix C

Figure C1. Comparison between inter-annual trend of official yield (detrended values) with the average air temperature within the crop cycle (a) in the study area. Official values of HRY were compared with the 95th percentile of nighttime temperature frequency in post flowering. Grey and white histograms respectively refer to Loto and Gladio official statistics.



Appendix D.

Table D1: Normality test of official yield and head rice yield (HRY) data distribution. Values of Shapiro-Wilk (W) and Anderson-Darling (A2) metrics are reported with the corresponding p-value calculated at 95 % confidence interval (α = 0.05).

Variety	Variable	W	p-value	A^2	p-value
Loto	Yeld	0.957	0.493	0.292	0.568
Gladio		0.971	0.875	0.199	0.859
Loto	HRY	0.632	< 0.0001	2.644	< 0.0001
Gladio		0.781	0.002	1.044	0.007

Figure D1: Outlier detection (black histogram) within yield (a, Grubbs' test) and HRY (b, Hampel test) official statistics for Loto (1) and Gladio (2) varieties. MADi = mean absolute deviation. Z-score represents the distance between score (e.g. observation or datum) and the population mean in units of the standard deviation.

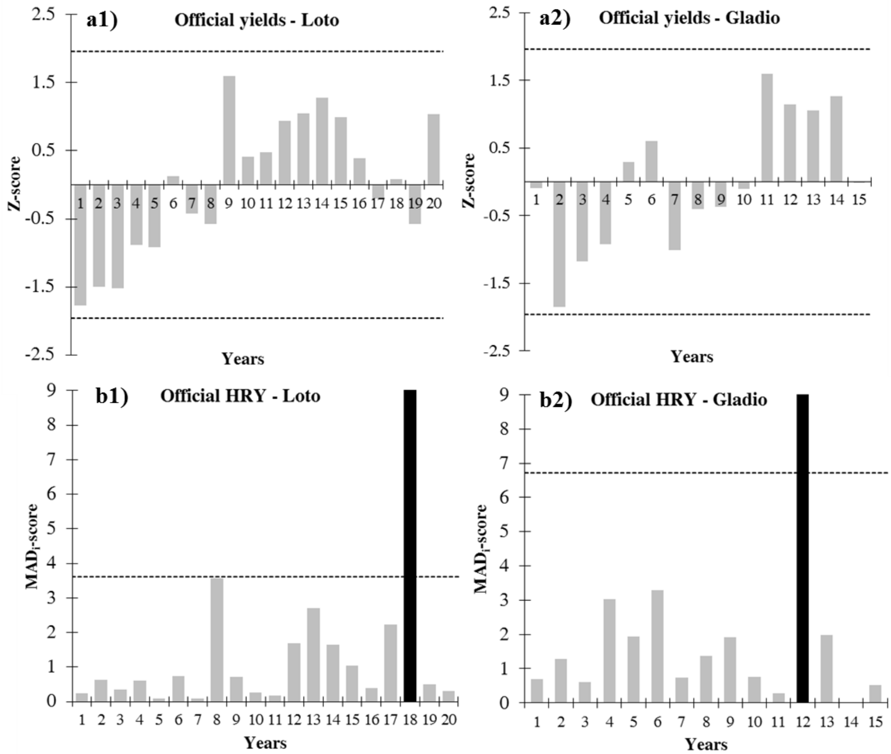


Figure D2: Time trend followed by rice official yields (1) and HRY (2) for Loto (a) and Gladio (b) varieties.

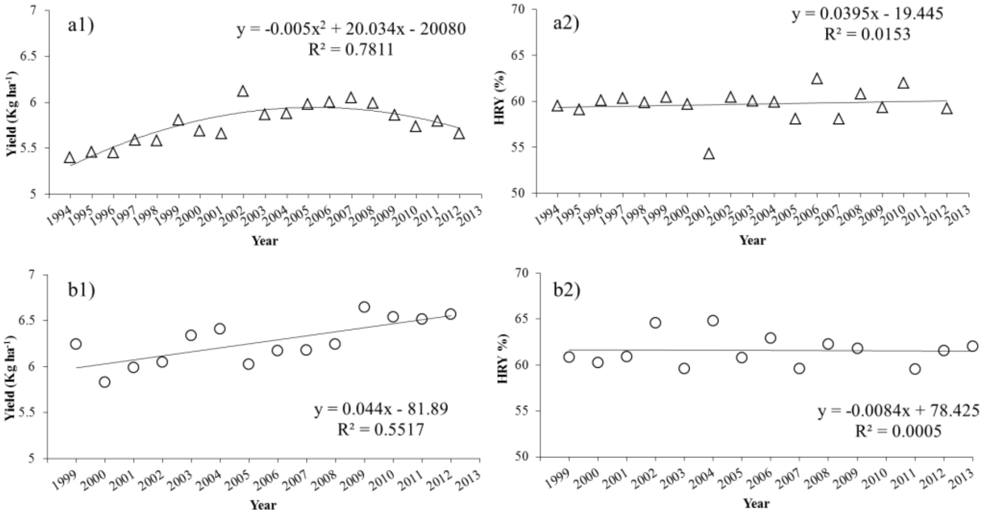
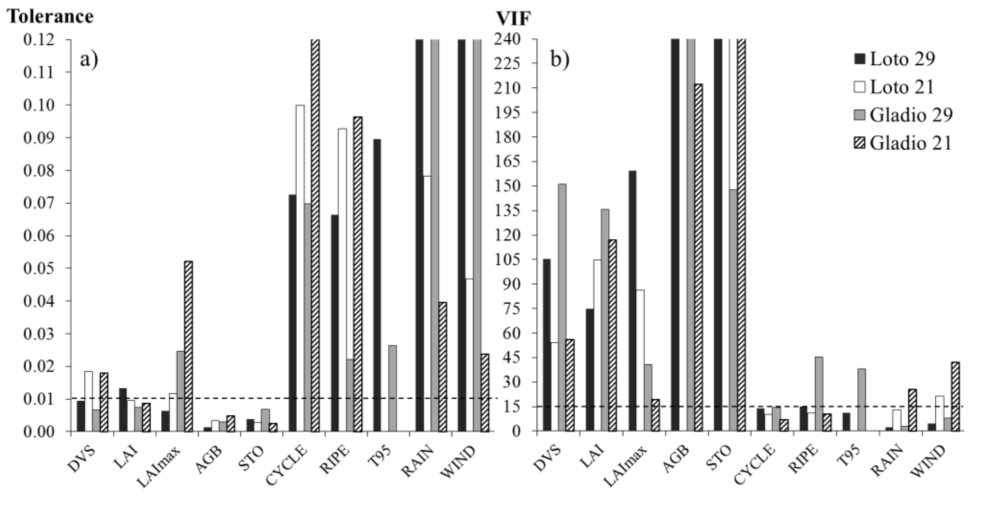


Figure D3: Collinearity detection among crop indicators simulated at 21th and 29th decade (1) and HRY (2) for Loto (a) and Gladio (b) varieties.



ARE ADVANTAGES FROM THE PARTIAL REPLACEMENT OF CORN WITH SECOND-GENERATION ENERGY CROPS UNDERMINED BY CLIMATE CHANGE? A CASE STUDY FOR GIANT REED IN NORTHERN ITALY.

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5.1. Abstract

Among non-food energy crops, giant reed (Arundo donax L.) represents a promising opportunity to reduce the fossil fuel dependency of Mediterranean countries. Nevertheless, the response of this crop to future climate projections is an open issue despite the crucial implications for mid-term planning policies. In this study, we present an exploratory analysis of the climate change impact on giant reed productivity in the Lombardy plain (northern Italy), an area that is currently characterized by intensive fodder corn-based cropping systems, but where corn is expected to be negatively affected by projected changes in thermal and pluviometric regimes. A dedicated simulation environment was developed, by coupling Arungro, a process-based model specific to giant reed, to a database including information on the presence of biogas plants, land use, crop management and distribution, in addition to weather scenarios for current climate and future projections. The baseline climate (1975-1994) was obtained from the European Commission MARS database; the Hadley3 and NCAR realizations of the IPCC AR4 emission scenarios A1B and B1 were used to generate 20-year climate projections centred on 2020 and 2050. Spatially distributed simulations were run at a sub-regional scale in areas selected according to their attractiveness for investments and low risk of competition between feed and no-feed crop destinations. The results indicate that an increased local suitability of giant reed in future climate projections is expected in terms of biomass production (+20% in 2020 for all scenarios and +30% in 2050 for Hadley-A1B) and the economic and environmental sustainability of related cropping systems.

Keywords: *Arundo donax* L., Arungro, biogas plant, crop model, renewable energy, *Zea mais* L.

5.2. Introduction

Climate change threatens agricultural production worldwide because of rising temperatures, unfavourable rainfall distribution and increasing frequency of extreme weather events (Porter and Semenov 2005; Kang et al., 2009) in many regions. Although the extent of changes in crop productivity is still an open issue (Lobell and Field 2007; Masutomi et al., 2009), corn is expected to be particularly affected in many regions (Jones and Thornton 2003; Fernandes et al., 2012; Supit et al., 2012). This crop is one of the most important in the Lombardy plain (northern Italy), an area that is characterized by intensive agriculture and livestock farming. Future projections for corn in the region indicate a decrease in productivity mainly because of shortening the grain filling phase (Supit et al., 2012) and because of unfavourable rainfall distribution (IPCC 2007; NIAER 2013). The latter would further reduce the extent of the few areas where corn is currently rainfed and, in general, would increase the frequency of irrigation events to avoid exposing the crop to water stress during crucial phenological phases (e.g., flowering and pollination) (Confalonieri and Bocchi 2005; Ercoli et al., 2008).

These projections are generating an increasing demand for mid-term analyses of the economic and social sustainability of current production systems; in this context, process-based biophysical models are the most suitable tools for estimating the potential impacts of climate change on the productivity of agricultural systems and to support local stakeholders and policy makers in defining effective and site-specific adaptation strategies (Fernandes et al., 2012; White et al., 2011).

Corn-based cropping systems will likely experience an increase in production costs, given the increased request of inputs, with water playing a key role (Kang et al., 2009; Bocchiola et al., 2013) because of the exacerbation of the competition between countryside and urban areas for water use during the summer months. From this perspective, some farmers are testing alternative business models with a special focus on the agrofuel sector. Indeed, as established in the Renewable Energy Directive (Directive 2009/28/EC), Italy should increase, by up to 17%, the share of primary energy produced by renewable energy sources by 2020. Giant reed (*Arundo donax* L.) has recently been included in the list of renewable energy sources that tare eligible for subsidies through the Ministerial

Decree of 6 July 2012 (Ministerial Decree of July 6, 2012). As a result, alternative giant reed-based supply chains and technologies have been studied and tested at a regional level, in particular, focusing on (i) biogas production via anaerobic digestion, (ii) combustion targeting the production of electric and thermal energy, and (iii) production of ethanol and biodiesel from anaerobic fermentation. Moreover, this crop demonstrated a high potential for the extraction of compounds of interest for the chemical and pharmaceutical industries (i.e., cellulose, alkaloids) and for phytoremediation because of its ability to absorb nitrates, phosphates and other pollutants. Giant reed is a perennial invasive grass that showed a tolerance to a broad spectrum of soil types (Perdue 1958) and exceptional biomass accumulation rates even with low agronomic inputs (Christou et al., 2000; Williams et al., 2009). These features make this species suitable for marginal areas where the cultivation of other species is not advantageous. Giant reed, therefore, can be considered to be a good solution to the ethical concerns dealing with competition for land between food (or feed) and energy crops. The evaluation of the potential productivity of giant reed in Italian environments (e.g., Angelini et al., 2009; Ceotto et al., 2013) indicated the possibility of achieving values of attainable energy per hectare higher than those obtained with corn [21]; this is leading some of the farmers who are already growing energy crops in Lombardy to convert portions of their land from corn to giant reed. Concerning biogas production, giant reed is commonly ensiled by adopting the same techniques that are used for corn, which represents the main energy crop for bio-methane production in the region. The crop is harvested by chopping the stalks when the average dry matter of the aboveground biomass is within a range of 30 to 38%, and it does not require any fermentation-based pre-treatment. The methane yield from giant reed anaerobic digestion ranges from 7170 to 11280 Nm^3 ha^{-1} $year^{-1}$, with double cutting leading to the highest biochemical methane potential and the most suitable digestion kinetics (Schievano et al., 2012; Ragaglini et al., 2014).

The aims of this study were (i) to estimate the impact of climate change on giant reed productivity in the Lombardy plain and (ii) to evaluate the opportunity of changes in land use from corn to giant reed by analysing related economic and environmental issues in the medium-long term.

5.3. Materials and methods

5.3.1. The study area

Lombardy is one of the most industrialised and intensively cultivated European regions, with a gross domestic product (GDP) equal to 21.1% of the Italian GDP and 2.6% of the European GDP. Agriculture plays a key role in the regional economy, and it is characterized by high productivity (a GDP/Work unit is 30% higher than the EU-27 average), technology and quality of productions; such productions are responsible for 11.4% of the national agricultural value (NIAER 2013). The regional utilized agricultural area (UAA) is mainly located in the watered Po plain (72,000 km^2 distributed between 44°50’N/8°40’E and 45°50’N/11°80’E) and is characterized by an overall temperate humid climate and by a pronounced heterogeneity in pedoclimatic conditions (Fumagalli et al., 2011). Most cropping systems target cereal and forage production (mainly corn, which covers approximately 30% of regional UAA, wheat, rice and alfalfa) to support the intensive livestock farming of pigs (4,639,000 heads), poultry (19,988,000 heads) and cattle (1,299,500 heads, of which 471,200 are dairy heads). In this context, livestock wastes represent the main substrate for bioenergy production in the region, which rely on 361 operating biogas plants accounting for 282 MW of total installed electric power. Fifty percent of the average digester diet is represented by liquid manure, whereas shares of 25%, 20% and 5% are a result of the use of (i) corn silage, (ii) industrial by-products (i.e., glycerine and vegetable oils) and organic urban waste and (iii) winter cereal silage, respectively (NIAER 2013). Ninety-six percent of the total regional plants are characterized by a nominal power class up to 0.999 MW, corresponding to the maximum threshold for obtaining public funding for electricity production from renewable sources (Cavinato et al., 2010). Given the strict European regulations for nitrogen loads, biogas plants also represent a solution for limiting the negative externalities from disposal of livestock manures, such as groundwater nitrate pollution (Scaglione et al., 2013). However, in addition to biogas production, the regional bioenergy sector also addresses biofuel (five operational processing plants for ethanol and biodiesel production) and the heat/electrical energy (12 district heating networks for public use) industries. The latter installations are supplied or co-supplied by wood biomass and are mainly concentrated in the upland areas, where the connections with the lowland intensive livestock-cereal farms are limited (NIAER 2013)

5.3.2. Definition of the elementary simulation unit and data used for the simulations

Based on the explorative nature of this study, the Agrarian Unit (AU, mean area = 26835 ha) was chosen as the elementary simulation unit. AUs result from the aggregation, within each province, of municipalities that are characterised by homogeneous pedoclimatic conditions and cropping/farming systems' structures. To identify the AUs of interest, three criteria were used (Fig. 1): (i) presence of operational biogas plants, (ii) future projections of fodder corn production, and (iii) livestock pressure.

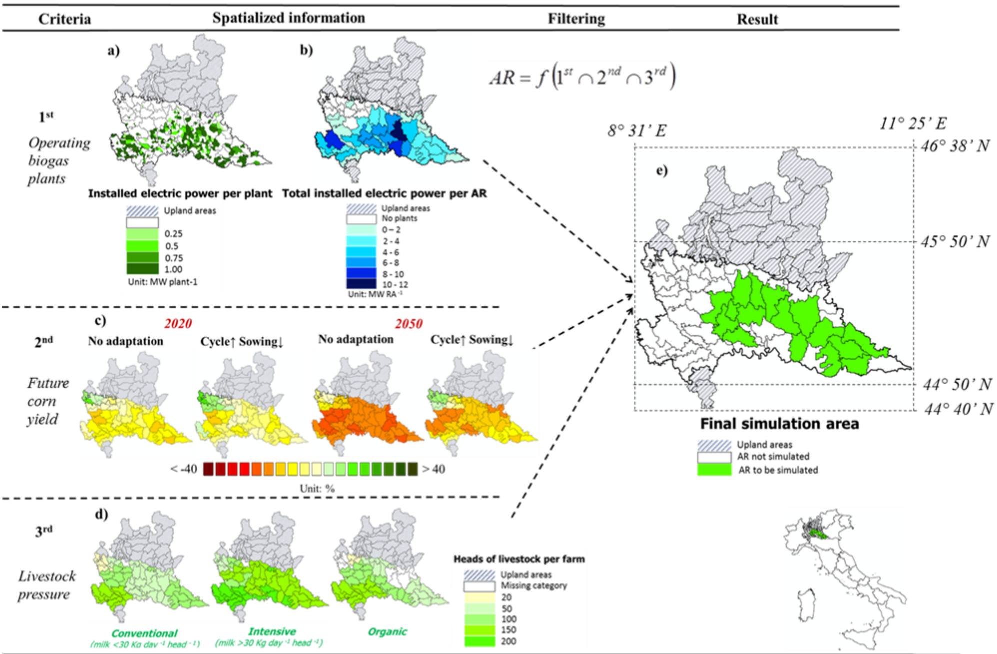

Figure 1. Criteria used to identify the eligible spatial units for giant reed simulation. 1a) Spatial distribution of biogas plants by electric power class (MW plant-1); 1b) aggregation of total nominal electric power per Agrarian Unit (AU) (MW); 1c) impact of climate change of fodder corn productivity in 2020 and 2050 for Hadley A1B (results are shown as percentage difference compared to the baseline); 1d) map of most represented categories of dairy cattle farming by class of livestock per farm; 1e) distribution of AUs selected for the simulation experiment.

For the first criterion, the spatial distribution of biogas plants at the municipality level (Fig. 1a) was used to derive the total nominal electric power per AU (Fig. 1b). The results were then used to sort AUs based on their theoretical demand for biomass (the greater the total power, the greater the demand). Given the scarce presence and/or the uneven distribution of district heating networks and biofuel installations in the study area, they were excluded from the present analysis. Indeed, the high transportation costs to cover the distance between the farm and the plant storage area would result in an unfruitful investment for farmers. The second criterion made use of data from a project (Cappelli et al., 2014b) funded by ERSAF-Regione Lombardia (ERSAF 2015) on the impact of climate change on agriculture in the region and on the identification of adaptation strategies based on the (i) anticipation of the sowing window, (ii) adoption of ideotypes with different crop cycle length and (iii) implementation of alternative irrigation techniques (e.g., drip irrigation). These data were produced at the AU level to properly test the feasibility of each technical solution in the different agro-climatic contexts characterizing the region. In particular, the areas where climate change is expected to have a more severe impact on fodder corn were identified (Fig. 1c). The third criterion was aimed at identifying the AUs characterized by the lowest load of dairy cattle heads, the diet of which is characterized by the highest inclusion of fodder corn. Indeed, partial abandonment of corn is supposed to have a negligible effect on the competition between feed and no-feed crops in those areas. For this purpose, the Italian National Institute of Statistics (ISTAT) database (ISTAT 2014) was investigated to identify the most widespread categories of cattle farming and related head consistency at the AU level (Fig. 1d).

For each criterion, a minimum threshold corresponding to the 50th percentile was used to define a compound filter to select the simulation units of interest. AUs were included in the simulation study in case the following conditions were simultaneously satisfied: total installed electric power > 2.5 MW, corn yield expected decrease > 12.5% in 2050 and head of livestock per farm < 140. The filtering procedure allowed for the consideration of 16 AR out of 54 as being eligible for the study (Fig. 1e).

The EC MARS database (Micale and Genovese 2004) was used to derive the 1975-1994 weather data for the baseline climate. Climate change scenarios were then derived for two contrasting IPCC AR4 emission scenarios, i.e., A1B (high impact) and B1 (low impact) (IPCC 2007). The uncertainty in the projections provided by global circulation models (GCMs) was managed using two different approaches: Hadley3 (Gordon et al., 2000) and NCAR (Collins et al., 2004). Temperature and rainfall anomalies were then used to generate 20-year weather series centred on 2020 and 2050 using a stochastic weather generator (CLIMAK; Danuso 2002).

5.3.3. Giant reed model and parameterization

The Arungro model (Stella et al., 2015) was used for the simulation of giant reed full productive stands, i.e., the juvenile phase characterizing the season of crop establishment was not taken into account. The model calculates daily biomass accumulation as a balance between gross photosynthesis and growth/maintenance respiration. The model implements a detailed description of leaf area index dynamics at the shoot and plant levels, accounting for leaf size heterogeneity on a single stem and among different stem cohorts. Evolution of the stem population was estimated on a thermal time basis, with the emission of new stems modulated as a function of rhizome biomass during sprouting. The model, specifically designed for giant reed, was derived from the sugarcane model Canegro (Inman-Bamber 1991) because of the morphological and physiological features shared by the two species. The moderate requirements for nutrients and the noticeable tolerance for drought of giant reed (Pilu et al., 2012) allowed, for this exploratory study, running the Arungro model under potential conditions for water and nutrients. Moreover, the low genetic variability of the species, derived from its agamic reproduction, allowed for running simulations using default values for parameters (Stella et al., 2015) and excluded the possibility of testing alternative genotypes as an adaptation strategy to the foreseen climate.

5.4. Results and discussion

5.4.1. Future climate scenarios

Figure 2 presents average daily thermal anomalies that were obtained as a difference between the climate change scenario and baseline data for all of the combinations' emission scenario × GCM × time frame.

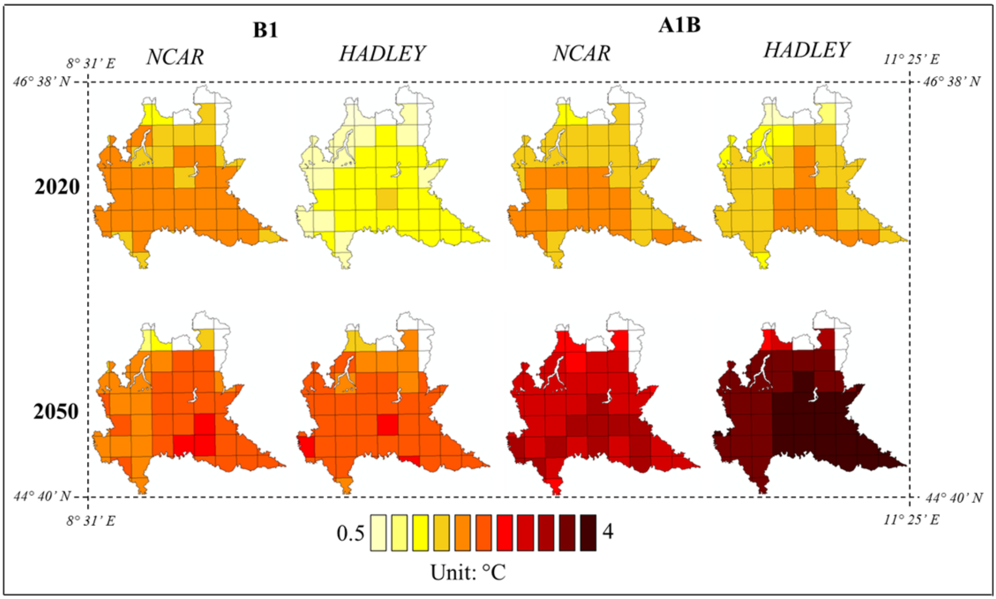

Figure 2. Average daily temperature anomalies expected in 2020 and 2050 obtained from two contrasting scenarios (A1B and B1) and two global circulation models (NCAR and Hadley). The results are shown as differences (°C) from the baseline.

In 2020, the A1B scenarios project a higher temperature compared to the B1 ones (approximately 1.7°C versus 1.5°C), with the latter more heterogeneous according to the GCM used (thermal anomalies range between 0.5°C and 1.9°C). Moving to the 2050 time horizon, B1 scenarios tend to be stationary (average temperature raise is stable approximately 2°C), with increases in thermal anomalies represented by the following order: NCAR-B1 ~ Hadley-B1 <NCAR-A1B <A1B-Hadley. For the latter, the temperature increases up to 3.7°C (± 0.24°C) following a north-east to south-west gradient. Because NCAR-B1 and Hadley-A1B represent the extremes of the four projections in the study area, they were selected for the spatially distributed simulations, allowing for an exploration of the widest range of climate scenarios. Although the scenarios used in this study have been recently superseded by the IPCC AR5 ones, our results maintain their usefulness in light of the marked similarity in thermal and pluviometric projections from Representative Concentration Pathways (RCPs; AR5; IPCC, 2014) and Special Report on Emission Scenarios (SRES; AR4; IPCC, 2000) when comparable scenarios are considered (IPCC 2013). Concerning the high-impact scenario used in this study (Hadley A1B), it is

highly consistent with Hadley RCP8.5 (radiative increase up to 8.5 W m^{-2} and CO_2 concentration up to 936 ppm in 2100), and the same can be argued for the low-impact scenario (Hadley B1) and Hadley RCP2.5 (radiative increase up to2.6 W m^{-2} and CO_2 concentration up to 420 ppm in 2100).

5.4.2. Giant reed yield projections for 2020 and 2050

The yields simulated under future climate projections were always higher than those obtained for the baseline (Fig. 3).

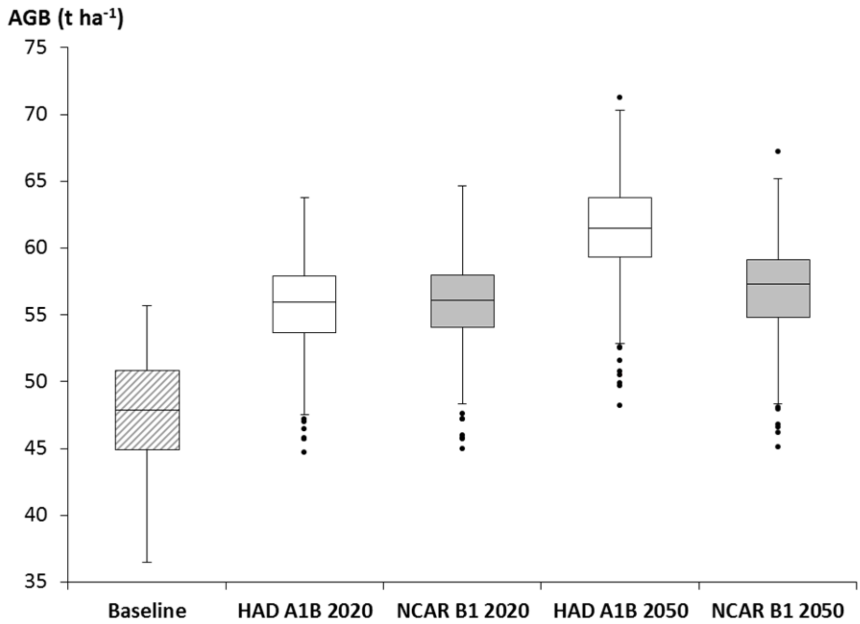

Figure 3. Boxplot of absolute aboveground biomass (AGB) values simulated for the baseline and climate change scenarios (Hadley A1B and NCAR B1). Each box is derived from the 320 values simulated for each combination year (20) × agrarian unit (16).

For the 2020 time horizon, average simulated yields were approximately 57 t ha^{-1} (42.8 t C ha^{-1} according to raw material composition of giant reed dry matter; Scordia et al., 2012) for both climate scenarios, with the differences among years and AUs overcoming those as a result of the considered GCM and emission scenarios. Instead, for 2050, the diverse thermal regimes projected for the two climate scenarios led to marked differences in model responses. Average yields that were simulated for

NCAR-B1 remained, indeed, practically unchanged compared to 2020, whereas those simulated for Hadley-A1B increased proportionally to the temperature increase with mean values for the 2050 time frame fluctuating approximately 63 t ha^{-1} (47.3 t C ha^{-1}) according to the AU and year.

These results can be explained by considering the high thermal requirements of giant reed, a macrothermal species that is well adapted to subtropical and warm temperate environments (Pilu et al., 2013). Indeed, with the baseline climate, production was slightly penalized by constraints to photosynthesis as a result of sub-optimal temperatures, whereas the faster rates of tiller and leaf emission simulated for the warmer scenarios led to more rapid leaf area expansion in the first part of the season that, in turn, anticipated the closed canopy stage. Moreover, increased temperatures reduced the limitation of carbon fixation associated with low temperatures. Instead, the absence of algorithms for limiting photosynthesis as a result of high temperatures did not affect Arungro simulations under the conditions explored because both current and projected temperatures rarely exceeded the optimal temperature range (i.e., 20-35°C) identified for giant reed (Barney and DiTommaso 2011). The assumption to consider water and nutrient availability as unlimited is consistent with the conditions explored by the crop in the study area. Indeed, giant reed is a species with a pronounced drought tolerance aptitude (Lewandowski et al., 2003; Barney and DiTommaso 2008) because of the deep and effective root system that makes the crop well suited to rainfed conditions in northern Italy in the current climate (Ceotto et al., 2015). According to the information available from experiments performed under semi-arid conditions (Lewandowski et al., 2003), the marked drought tolerance of giant reed is expected to prevent water limiting conditions in Northern Italy even for high-impact scenarios. In Lombardy, A1B is associated with projected decreases in rainfall up to 10% and 20% for the 2020 and 2050 time frames, respectively (Coppola and Giorgi 2010). In any case, the possible occurrence of light water stress under future scenarios would likely be counterbalanced by the positive effects of the increased atmospheric CO_2 concentration (Wand et al., 1999). These effects are currently not simulated by Arungro because extensive information about giant reed responses to different atmospheric CO_2 concentrations is still lacking. However, a recent exploratory study (Nackley et al., 2014) demonstrated that giant reed grown under enriched CO_2 environments markedly reduced transpiration rates, in turn, increasing the water use efficiency and enhancing drought tolerance. Concerning nutrient availability, the simulation of unlimited conditions under the explored conditions is likely to provide reliable estimates for both current and future scenarios. The high mobility of nutrients between below- and aboveground organs (especially nitrogen) sustains crop re-sprouting in the spring and prevents their removal from the field at harvest because of the autumn remobilization of N-rich compounds to rhizomes (Nassi o Di Nasso et al., 2013). Low fertilization rates are therefore enough to guarantee potential production levels. This allows crop demands to be met by applying animal slurries (Schievano et al., 2014), an abundant by-product of the intensive animal farming that characterizes the Lombardy region.

To investigate the spatial patterns in future biomass projections, disaggregated data were mapped as a percentage difference compared to the baseline (Fig. 4).

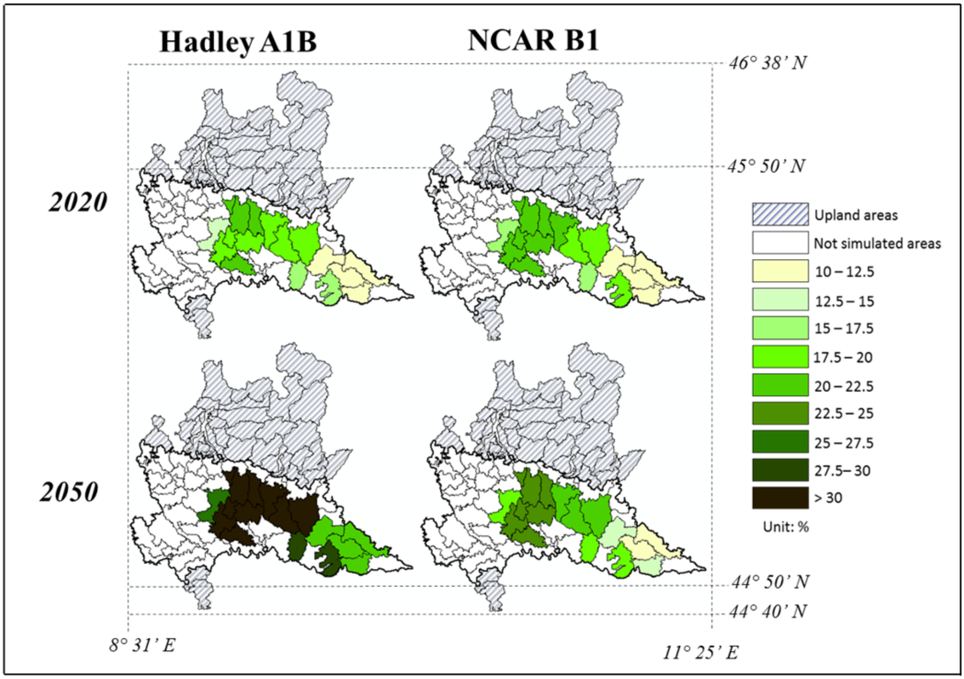

Figure 4. Projected impact of giant reed productivity in 2020 and 2050 for Hadley A1B and NCAR B1 scenarios. The results are shown for each agrarian unit as percentage difference compared to the baseline.

In general, the largest increase in productivity was simulated in the central part of the region, whereas in the eastern part, where thermal conditions for photosynthesis are already close to the optimum for the species, productivity was less affected by the positive effect of the projected temperature increase.

It is interesting to note that the highest production gains were obtained in the areas where the demand for biomass is assumed to be greater as a result of the high concentration of biogas plants, representing a favourable precondition for possible investments. Given that the cost for the cultivation of giant reed in a 15-year field lifetime is estimated in approximately 10,500 € ha^{-1} (Schievano et al., 2012; Pilu et al., 2013), the payback time for the investment could be reduced from 8.5 years (baseline scenario) to 6.4 years (Hadley-A1B, 2050) if a price of 26 € t^{-1} is applied; this value was derived (i) from the relative efficiency of giant reed in terms of potential biogas production compared to corn (m3 t^{-1} of dry matter; Schievano et al., 2012) and (ii) from the price that corn fodder is currently exchanged in the local agrofuel market (approximately 40 € t^{-1} on fresh weight basis). A comparison with alternative cropping systems currently tested in Lombardy for bioenergy production that was derived from the results produced within this study and from published data is given in Table 1 [48].

Table 1. Costs and productivity of giant reed and alternative pilot cropping systems targeted for biogas production in Lombardy (data modified from a previous study; Schievano et al., 2012 and 2014). Giant reed 2050 H and N derived from this study referring to Hadley A1B and NCAR B1 climate change scenarios, respectively. Gas volumes relate to the standard ambient temperature and pressure (288.15 K, 101.3 kPa).

Cropping system	**15-years costs** *(€ ha^{-1})*	**Biogas production rate** *(m^3 t^{-1};d.m.)*	**Payback time** *(years)*	**Potential biogas yield** *(m^3 ha^{-1} $year^{-1}$)*	**Potential biomethane yield** *(m^3 ha^{-1} $year^{-1}$)*
Giant reed			8.5	21,555	10,539
Giant reed 2050H	10,500	450	6.4	28,350	13,875
Giant reed 2050N			7.1	26,595	12,554
Corn 600	31,590	694	11.3	14,761	7,133
Rye-Corn	49,275	577	18.2	15,002	7,342
Triticale-Sorghum	43,545	540	9.0	16,740	8,193
Triticale-Corn	50,190	631	10.1	21,454	10,500
Grass-Corn	46,290	584	12.0	18,104	8,861

The costs presented in the table include all of the management operations that were needed to sustain the agricultural systems compared (e.g., soil tillage, harvest, transport and storage). Corn as a single crop (Corn 600 in Table 1) presents good performance in terms of both costs (second after giant reed) and potential biogas production per unit dry matter (the most efficient for this), leading to a very competitive payback time of 11.3 years. Crop successions allow for higher productions of total dry biomass to be achieved compared to corn in monoculture, with the best results obtained by the Triticale–Corn rotation, which allows for potential biogas yields very similar to the giant reed yields in the reference scenario to be achieved per year (approximately 21,500 sm^{3} ha^{-1} year^{-1}). Despite the higher relative abundance of lignin in stalk tissues compared with the composition of triticale-corn raw material used for anaerobic digestion (Pilu et al., 2013), giant reed was able to compensate for the lower biogas conversion efficiency through the markedly higher productivity of dry matter per unit area (57 t ha^{-1} vs. 34 t ha^{-1}). Therefore, both the giant reed and the double-crop systems are expected to increase the chances for biogas plants to operate close to their full capacity while reducing the land use demand for energy production. However, double-crop rotations are penalized by the higher costs that are estimated to be 1.5 and 5 times larger than those of corn 600 as a single crop and giant reed, respectively. As a consequence, the payback time for crop rotations is always less favourable than those reported for giant reed, ranging from nine years for triticale–sorghum to 18.2 years for rye–corn, preventing farmers from recovering their original capital investment. These considerations are enough to provide guarantees for the economic sustainability of giant reed for biogas production in the mid-term. Moreover, the aforesaid low-input (e.g., fuel, water, fertilizers) requirements compared to corn contribute to the positive picture and also highlight benefits in terms of the environmental impact. Indeed, based on the Nitrate Directive Directive (91/676/EEC), 15 out of the 16 AUs considered are identified as being vulnerable to nitrate leaching. Converting part of the land to giant reed would appear even more interesting in the extreme southeast of the Lombardy plain, where corn productivity is often constrained by insufficient water availability (NIAER 2013). To compensate for the projected yield reductions, corn could theoretically be imported from areas where production is expected to increase with climate change scenarios, such as

Northern or Central Europe (Olesen and Bindi 2012). However, from an economic standpoint, importing corn for feeding biogas plants may not be cost effective considering that (i) substrate costs markedly influence the profitability of biogas production and (ii) these costs are significantly affected by transportation distance (Walla and Schneeberger 2008; Strumer et al., 2011). Moreover, it should be considered that environmental costs to cover the distance between corn suppliers and target plant installations significantly affect the sustainability of biogas deployment, thus reducing the chance to receive public funding for green energy production. In a previous study, Poelsch et al. (2010) established, through LCA, that a maximum transportation distance of approximately 50 km allows for the maintenance of net environmental benefits in using corn silage for biogas production. If applied to the present study, this threshold would allow for the identification of alternative corn supplying farms in an area of Northern Italy that are exposed to the same temperature and rainfall anomalies as those used in this study (Coppola and Giorgi 2010), thus resulting in similar decreases in corn yields. Moreover, the demand for feeding purposes is expected to remain unchanged because it represents the main ingredient of pig and cattle diets in the region, with limited substitutability in terms of nutritional value, palatability and productivity (Battilani et al., 2008). The resulting imbalance in the local market between supply and demand of corn silage will likely lead to increasing prices, which are also favoured by the increased amount of inputs (especially water) required to grow the crop in the region. Instead, the projected increase in giant reed yields simulated for the medium-long term is expected to prevent any increase in prices because the increased offer of giant reed-based raw materials will likely satisfy the demand, which is driven by the stakeholders of the energy sector. Furthermore, the investment appears to be even more convenient in light of the production costs per unit surface, which are decidedly lower compared to those of corn.

5.5. Conclusions

Although Arundo donax L. is increasingly considered to be a promising non-food and non-feed energy crop in temperate climates, no studies are available in the literature regarding its response under climate change scenarios. The use of a dedicated process based-model that is able to reproduce the interactions between giant reed and environmental drivers allowed for an assessment of the feasibility of a partial shift to this species in case traditional corn-based cropping systems become no longer sustainable for biogas production in Lombardy. Despite the assumptions behind this exploratory study, i.e., nutrient and water shortage effects were not considered, the results of simulations carried out using climate change scenarios were decidedly encouraging, especially in the central part of the region. The projected giant reed productivity in 2020 and 2050 is expected to markedly reduce the payback time of the total investment compared to the current situation. Given the low requirements of giant reed for fuel, water and nitrogen, advantages are also expected in terms of environmental sustainability; the study area is almost entirely vulnerable to groundwater nitrogen pollution. Therefore, the obtained results could provide useful information to support multiple stakeholders in ensuring the resilience of the local corn sector and of related activities that strictly depend on it (i.e., livestock branch). This can be achieved via the preferential allocation of corn to food and feed destination while maintaining the potential for feeding biogas plants with cost-effective raw materials and preserving the income of farmers. This preliminary study can be extended to other corn districts at an optimal spatial resolution and may represent the basis for further studies accounting for key processes involved with greenhouse gas emissions and the combined effect of a water shortage and increased atmospheric CO^2 concentration. Moreover, the inclusion of modules for the simulation of qualitative aspects of production will allow for the use of simulation tools to support the identification of the optimal harvest time according to the biochemical characteristics of raw materials and their destination.

Acknowledgements

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IN SILICO EVALUATION OF CLIMATE CHANGE IMPACTS ON RICE GRAIN QUALITY IN THE MAIN EUROPEAN RICE-GROWING DISTRICT

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6.1. Abstract

Crop simulation models are widely used to forecast the impacts of climate change on agricultural systems and to test adaptation strategies. The qualitative aspect of crop productions is often neglected in available studies, in spite of its key importance in determining the economic and nutritional value of the final product. This study presents an extensive evaluation of the impacts of climate change on rice milling quality and technological suitability in the main European producing area, placed in Northern Italy. A modelling solution was developed by coupling a rice growth simulator to a collection of dynamic models of rice quality, using information on crop management and current and climate change scenarios as input data. An ensemble of four general circulation models (NOResm, MIROC-ESM, HadGEM2-ES and GISS-ES) and two representative concentration pathways (2.6 and 8.5) was used to generate 20-year future weather series centred on 2030 and 2070. Spatially distributed simulations were run at 2 × 2 km spatial resolution considering a Japonica (Loto , medium slender grain) and an Indica (Gladio, long slender grain) rice varieties.

The results depicted an overall decline in milling quality, especially for cv. Loto in the warmest areas of the rice district (-2% for GISS-ES-2.6 projections for all varieties; -12% for Gladio, -18.4 % for Loto under HadGEM2-ES-rcp8.5 projections in 2070). While the revenues of farmers and millers are expected to be reduced of approximately 38 € t ha^{-1} (Gladio) and 65 € t ha^{-1} (Loto) in the mid-long terms, only minor changes will affect physicochemical and functional properties behind texture and taste of boiled rice. Although improvements are needed to further reduce the uncertainty in the projections, this study allowed to provide plausible variety-specific indications on rice grain quality trends in the mid-long term, to be used by multiple stakeholders of the agricultural sector to preserve the sustainability of rice cropping system.

Keywords: amylose, chalky grains, global warming, milling quality, proteins, starch viscosity, technological suitability

6.2. Introduction

Crop quality has a key role in determining the economic and nutritional value of agricultural productions, as it determines their purchase by consumers and the acceptability to buyers (Koutroubas et al., 2004). The improvement of the qualitative aspect of crop production is then of paramount importance for farmers, in order to gain a competitive market advantage on low price/quality exporting countries (Griglione et al., 2015). Further, recent policies in European countries were implemented to safeguard the environment and to enhance the responsible use of resources, thus forcing farmers to improve the qualitative aspects of processes and products, besides merely increasing crop productivity.

Over the last 50 years, the crop yield has steadily increased due to genetic improvement and technological progress (Calderini and Slafer, 1998; Cassman, 1999), whereas the quality of productions has levelled off or even decreased for cereals (Oury et al., 2003), grain legumes (Graham and Vance, 2003), oilseeds (Triboi and Triboi-Blondel, 2002), fruits for processing (Grandillo et al., 1999) or fresh fruits (Causse et al., 2003). The available studies on the impacts of climate change on the quality of crop production indicate a progressive negative trend for many cereal crops (DaMatta et al., 2010), and especially for rice (Nagarajan et al., 2010; Sreenivasulu et al., 2015). The increased heat stress during ripening might be the main responsible for the alteration of sink strength and storage composition in rice grains, with an impact on the nutritional, rheological and milling attributes (Sreenivasulu et al., 2015). Many other physiological processes may contribute to decrease the quality of rice, such as the shortening of the grain filling period (Ishimaru et al., 2009), the reduced nitrogen translocation from the leaves to the panicles (Cheng et al., 2010), the predominance of the night-time respiration on photosynthesis (Sreenivasulu et al., 2015), the non-uniform moisture desorption from the grain surface before harvest (Lan et al., 1999) and the reduced biosynthesis of starch and its concurrent degradation via α-amylase (Yamakawa et al., 2007). Given the paramount importance of rice as a staple food for world's half population, with an increasing consumption even in non rice-eating countries (e.g. + 3 % year^{-1} in northern Europe and + 5 % year^{-1} in the U.S.A), research efforts are still needed to assess the future dynamics of qualitative aspects of productions.

Process based simulation models could represent effective research tools to address these questions, due to their capability to reproduce nonlinear responses to boundary agro-meteorological conditions at different spatial resolutions (Porter and Semenov 2005). Despite a variety of models have been developed to simulate pre-harvest grain quality (Martre et al., 2011; Cappelli et al., 2014a), very few attempts were made to assess future trends, e.g. of grain nitrogen concentration in wheat (Erda et al., 2005; Porter and Semenov 2005; Asseng et al., 2013) and of chalkiness in rice (Okada et al., 2011). Available studies indicate that appropriate adaptation strategies concerning the modulation of nitrogen fertilizations and the shift in sowing dates could partially counterbalance the quality decay of cereal crops.

We choose Italy, accounting for more than 50% of total rice production in EU-27, as a case study to evaluate the impacts of climate change on rice milling and technological suitability. National breeding programs to improve the milling and nutritive aspects of rice productions with the implementation of low impact agronomic practices (i.e., organic rice varieties, Griglione et al., 2015) were recently launched (Russo and Callegarin 1997) to support stakeholders of rice sector in identifying priorities for planning future investments. The objective of this study is to support these programs by assessing the future trends of multiple aspects of Italian rice quality in the short (2030) and long (2070) term, via the spatially explicit application of process based models.

6.3. Matherials and Methods

6.3.1. Study area

The Italian Lombardo-Piemontese district is chosen as the study area representing the leading rice district in Europe with 1,380,000 t produced on 216,000 ha in 2014 (Ente Nazionale Risi, ENR; www.enterisi.it) and an overall turnover of about one billion euros (National Institute of Agricultural Economics Research, INEA, 2014). The climate is temperate humid, with a high variability of pedo-climatic conditions (Fumagalli et al., 2011). Average annual air temperature is about 13.5 °C (0-4 °C in winter months, with peaks over 30 °C in summer), and annual precipitations amount is around 750 mm (minimum from July to August). Main limiting factors to rice productivity are low temperatures at sowing, cold induced sterility due to air irruptions at heading period, weeds infestation and blast disease attacks. The main irrigation strategies are continuous flooding of paddy fields, or dry sowing with delayed flooding at third-fourth leaf-stage; Nitrogen is mainly distributed as urea in two or three events, one in pre-sowing and the others at beginning of tillering and/or at panicle initiation. Among the rice varieties, 2/3 belong to the *Japonica* type (average yield of 6.5 t ha^{-1}) and 1/3 to *Indica* (average yield of 7 t ha^{-1}) with the length of the cycle ranging from short (120-140 days) to medium-long (140-170 days). Among *Japonica* cultivars, long rice with chalky grains and high amylose content is predominant, and bold and medium grains are mainly used for the parboiling process and the preparation of risotto dishes. The export of rice production is limited to chalky *Japonica* and *Indica* cultivars to both European and non-EU countries (above 60% of total milled rice), accounting for approximately € 500,000 in 2013 (INEA 2014). The sustainability and the innovation in rice sector are supervised by the Ente Nazionale Risi (ENR – National Rice Authority) and by the Agricultural Research Council (CREA), which cooperate on research programmes to achieve yield stability and superior grain quality by integrating agronomic management, genetic improvement and cultivar selection. Academic entities as the University of Milan and the National Research Council also contribute to the improvement of the rice system via a downstream service to give a real time support on crop status, risk alerts and grain quality (EU-FP7 project, An Earth obseRvation Model, http://www.ermes-fp7space.eu/).

6.3.2 Data used as input for the spatially distributed simulations

A georeferenced database including information on rice crop distribution (Figure 1a), sowing dates (Figure 1b) and current climate and future scenarios (Figure 1c, 1d) was built at 2 × 2 km spatial resolution to reproduce the spatial heterogeneity in the Lombardo-Piemontese district.

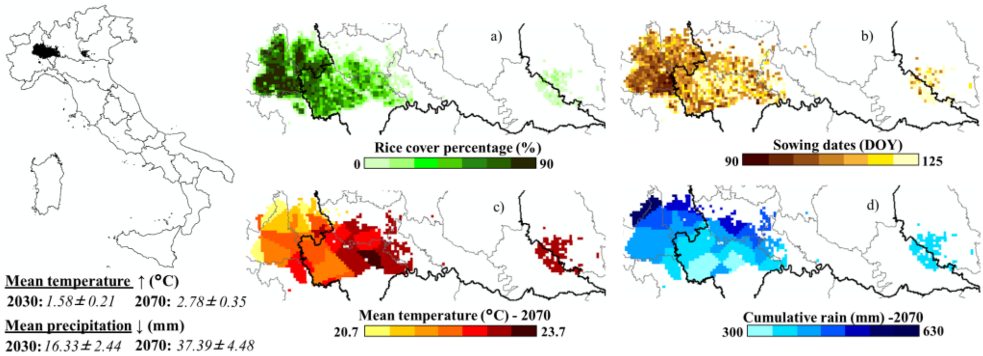

Figure 2: Input information used to perform spatially distributed simulation in the Lombardo-Piemontese district. a) rice distribution map, b) time windows of sowing dates, c)projected average temperature in 2070 and d) projected cumulative rain in 2070.

Daily maximum and minimum air temperature (°C), precipitation (mm), wind speed (m s^{-1}) and reference evapotranspiration (mm) in current conditions were retrieved from the database of Regional Agency for Environmental Protection (ARPA) in the period 2003-2014. Weather stations data were interpolated according to van der Goot (1998a). Daily global solar radiation (MJ m^{-2}) was estimated according to Hargreaves and Samani (1982), whereas daily minimum and maximum relative humidity (%) and hourly temperatures were estimated via the CLIMA software library (Donatelli et al., 2009). Climate change scenarios were generated by the stochastic weather generator CLIMAK (Danuso 2002), considering two contrasting Representative Concentration Pathways (RCPs) scenarios (AR5; IPCC, 2013), i.e., RCP 2.6 (low impact, with radiative increase up to 2.6 W m^{-2} and CO_2 concentration up to 420 ppm in 2100) and RCP 8.5 (high impact, with radiative increase up to 8.5 W m^{-2} and CO_2 concentration up to 936 ppm in 2100). Four general circulation models (GCMs) were used to take into account the uncertainty in future weather projections. They are the Norwegian Earth System Model (NOResm, Tjiputra et al., 2013), the Model for Interdisciplinary Research on Climate (MIROC-ESM, Watanabe et al., 2011), the Hadley Centre Global Environmental Model version 2 (HadGEM2-ES, Collins et al., 2011), and the GCM developed by the Goddard Institute for Space Studies (GISS-ES, Schmidt et al., 2006). For each combination of RCP × GCM × grid cell, the monthly temperature and precipitation anomalies (IPCC, 2013) were used to generate 20-year synthetic weather series centered on 2030 and 2070. Projected thermal increases (Figure 1c) and rainfall decreases (1d) followed a north-east to south-west gradient, in agreement with Cappelli et al. (2015), who assessed the future trends of maize and giant reed productivity in the same area. Information on rice crop distribution and farmers' sowing dates were derived via multi temporal analysis of MODIS composites images at 500 m spatial resolution (Boschetti et al., 2009).

6.3.3. Dynamic simulation of the rice cropping system

6.3.3.1. Crop development and grain quality simulation

The WARM rice model (Confalonieri et al., 2009) was used in this study, as it allows simulating the quantitative and qualitative aspects of rice productions (Cappelli et al., 2014a). Crop phenology is simulated based on hourly thermal time accumulation, considering a development stage code (DVS) ranging from 0 to 4, where 0 = sowing, 1 = emergence, 2 = flowering, 3 = maturity and 4 = harvest. The non-linear temperature response curve (Yan and Hunt, 1999) is driven by the minimum, optimum and maximum crop cardinal temperatures. The dynamic simulation of the different aspects of rice grain quality during ripening is performed via models driven by weather data, i.e. temperature, radiation, rainfall, wind speed and relative air humidity (Cappelli et al., 2014a, 2015b). The quality variables simulated here are the amylose (AC) and protein concentrations (PC), the indices describing the starch viscosity during cooking (i.e., the gelatinization temperature – GT, the breakdown – BDV, the setback – SV and the peak viscosity – PV), the percentage incidence of chalky (MWG), broken (BK) and pecky grains (PG) and the head rice yield (HRY).

All the rice quality models have parameters of clear biological meaning, allowing users to modulate the cultivar sensitivity to weather conditions, and the genetic ability and the optimal temperatures triggering the synthesis of chemical compounds, i.e., starch, amylose and protein.

Simulations were performed on current weather (baseline) and future climate projections, and model outputs were averaged and compared to the baseline as percentage differences (ΔB%). Quality variables were then aggregated according to their effect on milling (HRY, MWG, PG and BK) or technological suitability (i.e. AC, PC, SV, GT, BDV and PV) of rice grains, to give synthetic indications on the future trends of the qualitative aspects of rice productions.

6.3.3.2. Models parameterization

The Italian cultivars Gladio and Loto were selected as representative of *Indica* and *Japonica* type varieties due to the high representativeness in the study area (Cappelli et al., 2015b). Gladio is a short cycle variety released in 1998, presenting long slender grains recommended for rice salads or side dishes cooking with an average yield of 6.3 t ha^{-1}. Loto is a short cycle variety released in 1988, with medium slender grains suitable for parboiling and risotto preparation, with a slight lower yield than Gladio (5.8 t ha^{-1}). The features of the two cultivars in terms of technological and milling quality are summarized in Table 1.

Table 1. The quality characteristics of the Italian rice cultivars Loto and Gladio . The variables are grouped according to their effect on technological or milling suitability of rice grains.

Variable	Unit	Descritpion/properties	Average values	
			Loto	*Gladio*
		Technological suitability		
AC	% $grain^{-1}$	Determinant of grain texture and stickiness of boiled rice.	14-18.7	23.3-26.9
PC	% $grain^{-1}$	Determinant of nutritional value, taste and cooking properties.	4.9-7.5	5.0-7.6
GT	°C	Mean thermal transition of the starch in presence of water and heat. Determinant of cooking duration and the texture	65.5-71.3	73.4-79.4
BDV	BU	Starch granules disruption. Measure of paste stability	479-772.5	480.0-662.5
PV	BU	Maximum viscosity during the heating phase. Measure of granules swelling during gelatinization	1021-1257.0	934.0-1137.5
SV	BU	Starch retrogradation tendency during cooling phase. Determinant of grain texture	591-685.5	665.0-846.0
		Milling suitability		
BK	%	Amount of fissured kernels.	5.33-23.6	3.3-8.9
HRY	%	Relative weight presence of entire kernels after milling	47.6-70.8	62.6-68.6
MWG	%	Grains almost entirely opaque with floury areas on the grain surface.	0.8-6.1	0.2-1.6
PG	%	Grains with circular, brown to black spot.	0.8-7.6	0.2-3.0

Acronym: AC: amylose concentration; PC: protein concentration; GT: gelatinization temperature; BDV: breakdown viscosity; PV: peak viscosity; SC: setback viscosity; BK; broken kernels; HRY: head rice yield; MWK: milky white grains; PG: pecky grains; BU: Brabender Units.

The parameters driving the phenological development and the quality variables were calibrated via trial-and-error with data from field experiments collected in the growing seasons 2006-2014 (Cappelli et al., 2015a, 2015b). The R^2 between observed and simulated data was 0.88 for phenological dates and 0.61 for grain quality variables.

6.4. Results and discussion

Figure 2 presents the spatial and temporal variability of the values of some rice quality variables in 2030 and 2070. The mapped values are averages of projections from the eight combinations of RCPs × GCMs. The HRY (Figure 2a, b) and PC (Figure 2e, f) showed marked similarities in the pattern distribution, with a decreasing gradient from north-east to south-west in 2030. The simulations in 2070 further confirmed this trend, with minimum values (5.5 % for PC and 54 % for HRY) in the areas where highest thermal and pluviometric anomalies were projected.

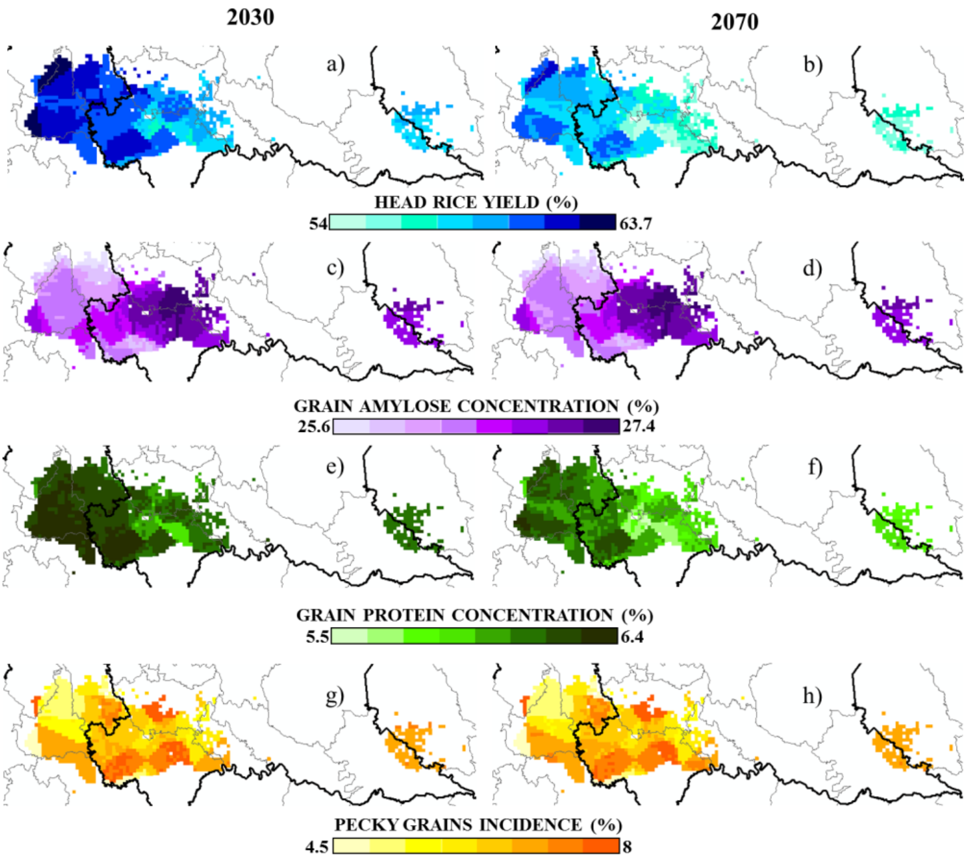

Figure 2: Projected climate change impacts on head rice yield (a, b, Loto), grain amylose (c, d, Gladio) and protein concentrations (e, f, Loto) and percentage incidence of pecky grains (g, h, Gladio) for 2030 and 2070. Results are presented as the average of all the combinations RCP × GCM

These results can be explained by the higher nighttime temperature and air humidity regimes, leading to the non-homogeneous packing of starch granules in the caryopsis, in turns favoring breakages during post-harvest processing. The elevated thermal regimes in post flowering led to the shortening of the grain filling period and to suboptimal temperatures for protein synthesis, thus reducing the N accumulation in grains and its conversion to protein compounds (Cheng et al., 2010; DaMatta et al., 2010). Conversely, the spatial representation of AC (Figure 2c,d) revealed an opposite pattern compared to PC and HRY, with lowest values in the eastern part of the district and highest AC in the central and western areas. The reason lies in the weather data needed as input by the three models: the AC model needs daily air temperature to compute the potential accumulation in the grain and decreases it in presence of low radiation values; the PC and HRY models consider variety-specific responses to hourly nighttime temperatures. While the higher increase in nighttime than daily maximum temperatures projected led to higher PC and HRY values in the sites where climate is currently less favorable for rice - i.e. eastern areas close to the mountainsides of Alps in the north and Apennines in the south - the smoothed amplitudes of daily mean temperatures variations and low radiation regimes perceived did not allow the crop to reduce meteorological constraints to actively synthesize AC during ripening.

The consideration of short (2030) and long term (2070) projections led to differences in model responses according to the simulated variables. The values of AC and PG remained unchanged in the two time frames, showing less variability compared with PC and HRY, which declined in agreement with temperature increase and rainfall decrease. For PG, the effects of thermal increases were counterbalanced by the decline in daily humidity ranges, which partially reduces the rates of moisture adsorption-desorption at the grain surface causing fissures in the kernels (Lan et al., 1999).

Figure 3 reports the comparison between the grain quality variables simulated in 2030 and 2070 for Gladio and Loto varieties. The results are depicted as average percentage differences compared to the baseline.

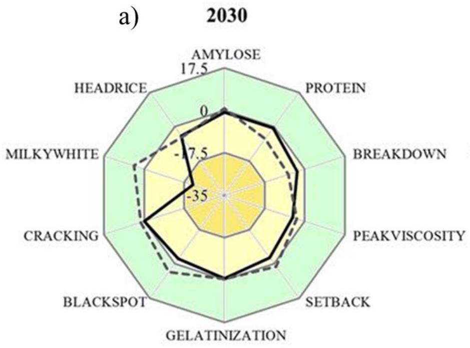

Figure 3: Results of the simulation of grain quality variables in 2030 (a) and 2070 (b) for Loto (black solid line) and Gladio (grey dashed lines) varieties. Results are presented as the average of the projections from the eight combinations RCP × GCMs.

The simulations revealed a higher decline in the qualitative aspects of Loto in 2030, whereas Gladio obtained similar values than in current conditions. In 2070, the differences between the two varieties enlarged, with Loto being more sensitive than Gladio to high temperatures and humidity in the post-flowering period. Indeed, the temperature increases in 2070 led to unfavorable conditions for starch and protein biosynthesis and an increment of grain fissuring. The longer duration of the critical period in post flowering and the higher susceptibility to temperature did not allow Loto to benefit from low thermal and humidity excursion during ripening. The PC values decreased in 2070, with average values around -4% for Loto and -10% for Gladio, in line with literature data (Yang et al., 2007; Cheng et al., 2010; Da Matta et al., 2010). Conversely, AC values remained unchanged, due to the dominant role of genetic factors in controlling this trait (Cappelli et al., 2014a). The changes in the storage composition due to raising temperatures will lead to less favorable pasting properties of rice flours, by increasing PV, BDV and GT in a range between 0.42 % and 8.32 %. These results suggest that, behind amylose reduction, some modifications of starch structure occurred in the caryopsis influencing viscoelastic and rheological properties of this molecule. Indeed recent studies showed that the exposure to elevated thermal regimes during reproductive growth markedly decreased the frequencies in amylopectin branching (Lanning et al., 2012), also favoring the formation of links protein-amylose (Hamaker and Griffin 1990) and lipid-amylose (Liang et al., 2002) as well as pre-gelatinization of starch due to increased activity of α-amylase enzyme (Yamakawa et al., 2007). In any case, above changes in physiochemical characteristics of grain resulted in greater GT, PV, BV and lower SV, thus reducing texture and sensory attributes and increasing temperature requirements to gelatinize starch.

To investigate the overall range of variability of grain quality variables under climate change projections, results obtained from different combinations of GCMs × emission scenarios were summarized in Table 1. In general, the climate projections from the GISS GCM and the RCP 2.6 emission scenario led to lowest quality declines in most of the combinations variety × quality attribute × time frame, whereas the most pronounced ones were usually obtained within the combination HADGEM × rcp 8.5. This is explained by considering the critical temperatures triggering the onset of quality decay and the temperature rises in the climate change projections.

Under the conditions explored, indeed, the climate generated coupling HADGEM GCM and the rcp 8.5 emission scenario is characterized by higher thermal increases, in turn generating conditions less favorable for grain filling, with temperatures frequently exceeding the optimum for storage biosynthesis and packing of starch granules. In general, largest decreases in quality variables were projected for MWG and HRY among variables involved with milling yield, and for PC between those targeting the technological properties of rice grain. While the incidence of MWG in Gladio was slightly reduced under future climate conditions regardless of the time horizon considered (average -4.5%), it reached percentage increases between 14% and 60% for Loto, which are slightly higher than results from previous simulation works carried out in Japan using comparable scenarios from AR4 IPPC SRES (Okada et al., 2011). In the same way the magnitude of protein (-0.24%--14.50% for Loto, -4.35%--20.20% for Gladio) and HRY (-1.83%--20.00% for Loto, -2.71%--15.22% for Gladio) decreases were coherent with findings from experiments carried out under FACE conditions (Yang et al., 2007; Taub et al., 2008; DaMatta et al., 2010) revealing an average decline up to 15% and 23.5% respectively in PC and HRY.

Table 1. Projected impacts of climate change on grain quality variables involved with technological and milling suitability of rice. V: variety; SD: standard deviation. Results are presented as percentage difference compared to the current scenario (baseline).

			GENERAL CIRCULATION MODEL																			
VAR	Unit	V	GISS		NORESM		MIROC		HADGEM				GISS		NORESM		MIROC		HADGEM			
			2.6	*8.5*	*2.6*	*8.5*	*2.6*	*8.5*	*2.6*	*8.5*	*Mean*	*SD*	*2.6*	*8.5*	*2.6*	*8.5*	*2.6*	*8.5*	*2.6*	*8.5*	*Mean*	*SD*
MY						***2030***										***2070***						
BK	%	L	0.29	0.37	0.62	0.30	0.18	0.02	-0.01	-0.26	***0.19***	***2.70***	0.81	0.04	0.36	-0.324	0.20	-0.70	0.00	-0.35	***0.00***	***2.77***
		G	-1.39	-1.51	-1.50	-1.44	-1.55	-1.44	-1.42	-1.65	***-1.49***	***2.07***	-1.53	-1.59	-1.54	-1.96	-1.61	-2.13	-1.62	-2.22	***-1.77***	***2.12***
HRY	%	L	-3.20	-3.95	-3.22	-4.16	-4.27	-5.54	-6.51	-6.55	***-4.68***	***2.74***	-1.83	-8.69	-3.96	-10.67	-5.20	-14.13	-7.41	-20.02	***-8.99***	***3.19***
		G	-3.97	-4.63	-4.06	-4.81	-4.89	-5.81	-6.45	-6.54	***-5.15***	***1.37***	-2.71	-7.96	-4.72	-9.31	-5.58	-11.58	-7.10	-15.22	***-8.02***	***1.55***
MWG	%	L	15.98	18.97	16.8	19.81	20.04	24.32	26.87	27.23	***21.25***	***6.18***	13.82	33.99	19.4	38.85	23.77	47.31	31.68	62.16	***33.87***	***7.65***
		G	-3.59	-4.01	-4.04	-4.15	-4.05	-4.86	-5.45	-5.64	***-4.48***	***8.60***	-2.62	-5.46	-4.09	-5.31	-4.73	-3.58	-5.36	-4.518	***-4.46***	***8.89***
PG	%	L	2.84	2.74	2.92	3.05	2.99	2.07	2.50	1.71	***2.60***	***11.71***	2.98	2.51	3.34	1.19	2.10	0.55	2.834	0.71	***2.03***	***12.15***
		G	-4.39	-4.39	-4.39	-3.99	-4.09	-4.30	-4.13	-3.91	***-4.20***	***7.25***	-4.31	-3.90	-3.82	-4.32	-4.31	-4.21	-4.01	-3.94	***-4.10***	***7.51***
MS	%	*L*	***-3.39***	***-4.12***	***-3.50***	***-4.33***	***-4.40***	***-5.53***	***-6.41***	***-6.39***	***-4.76***	***2.17***	***-2.31***	***-8.44***	-4.17	***-10.09***	***-5.26***	***-13.09***	***-7.35***	***-18.40***	***-8.64***	***2.36***
		G	***-2.80***	***-3.33***	***-2.86***	***-3.52***	***-3.57***	***-4.32***	***-4.86***	***-4.94***	***-3.78***	***1.12***	***-1.75***	***-6.13***	-3.45	***-7.19***	***-4.11***	***-9.09***	***-5.40***	***-12.12***	***-6.16***	***1.25***
TY						***2030***										***2070***						
AC*	%	L	-0.67	-0.67	-0.75	-0.78	-0.83	-0.90	-1.08	-1.03	***-0.84***	***2.76***	-0.91	-0.91	-0.77	-1.21	-0.92	-1.13	-0.82	-1.14	***-0.97***	***2.82***
		G	0.81	0.78	0.81	0.82	0.82	0.84	0.84	0.87	***0.82***	***0.98***	0.81	0.04	0.36	-0.324	0.20	-0.70	0.00	-0.35	***0.00***	***0.96***
PC*	%	L	-0.24	-0.42	-0.31	-0.53	-0.58	-0.83	-1.41	-1.29	***-0.70***	***3.01***	-0.67	-2.62	-0.35	-4.18	-0.81	-7.27	-2.20	-14.47	***-4.07***	***4.06***
		G	-5.18	-5.80	-5.34	-5.94	-6.13	-6.94	-7.73	-7.79	***-6.36***	***1.58***	-4.35	-9.38	-5.85	-11.28	-6.88	-14.49	-8.61	-20.16	***-10.12***	***3.20***
GT	°C	L	0.48	0.55	0.50	0.57	0.58	0.67	0.72	0.72	***0.60***	***0.16***	0.38	0.85	0.57	0.95	0.65	1.10	0.792	1.34	***0.83***	***0.17***
		G	0.34	0.38	0.35	0.40	0.40	0.46	0.50	0.50	***0.42***	***0.19***	0.26	0.58	0.39	0.65	0.45	0.75	0.54	0.89	***0.57***	***0.28***
BDV	BU	L	2.72	3.06	2.81	3.17	3.20	3.63	3.90	3.92	***3.30***	***2.67***	2.17	4.53	3.14	5.03	3.56	5.80	4.254	7.01	***4.44***	***2.73***
		G	5.47	8.52	7.06	9.05	7.57	9.76	8.25	10.86	***8.32***	***3.33***	5.47	8.52	7.06	9.05	7.57	9.76	8.248	10.859	***8.32***	***3.44***
PV	BU	L	3.98	4.74	4.22	4.99	5.04	5.99	6.58	6.59	***5.27***	***1.52***	3.13	7.94	4.93	8.88	5.844	10.25	7.451	12.071	***7.56***	***1.73***
		G	2.91	3.25	3.01	3.39	3.40	3.75	4.04	4.02	***3.47***	***1.04***	2.38	4.70	3.30	5.31	3.68	6.43	4.39	8.50	***4.84***	***1.19***
SV	BU	L	-2.12	-2.74	-2.25	-2.85	-2.90	-3.74	-4.29	-4.30	***-3.15***	***1.47***	-1.45	-5.57	-2.82	-6.71	-3.62	-8.29	-5.02	-10.48	***-5.49***	***1.75***
		G	1.11	1.27	1.14	1.31	1.34	1.46	1.50	1.50	***1.3***	***2.88***	0.81	1.44	1.36	1.48	1.45	1.09	1.493	-0.062	***1.13***	***1.85***
TS	%	*L*	***-0.11***	***-0.13***	***-0.13***	***-0.16***	***-0.18***	***-0.23***	***-0.35***	***-0.32***	***-0.20***	***0.36***	***-0.22***	***-0.52***	***-0.13***	***-0.82***	***-0.23***	***-1.32***	***-0.43***	***-2.51***	***-0.77***	***0.40***
		G	***-0.25***	***-0.28***	***-0.25***	***-0.28***	***-0.31***	***-0.36***	***-0.43***	***-0.41***	***-0.32***	***0.30***	***-0.18***	***-0.70***	***-0.36***	***-0.91***	***-0.47***	***-1.24***	***-0.64***	***-1.65***	***-0.77***	***0.29***

Acronyms: MS: milling suitability; TS: technological suitability; MY: milling yield, TY: technological yield; BK: broken kernels; HRY: head rice yield; MWG: milky white grains; PG: pecky grains; AC: amylose concentration; PC: protein concentration; GT: gelatinization temperature; BDV: breakdown viscosity; PV: peak viscosity; SV: setback viscosity; BU: Brabender Units, arbitrary unit of measuring the viscosity of a fluid; SD: standard deviation.
Notes*: amylose and protein contents are expressed as percentage of grain dry matter.

To better understand the possible effects of grain quality decay on milling (MS) and technological suitability (TS) for European commercial processing and marketability, percentage difference from single variables were grouped and mapped over the whole district (Figure 4).

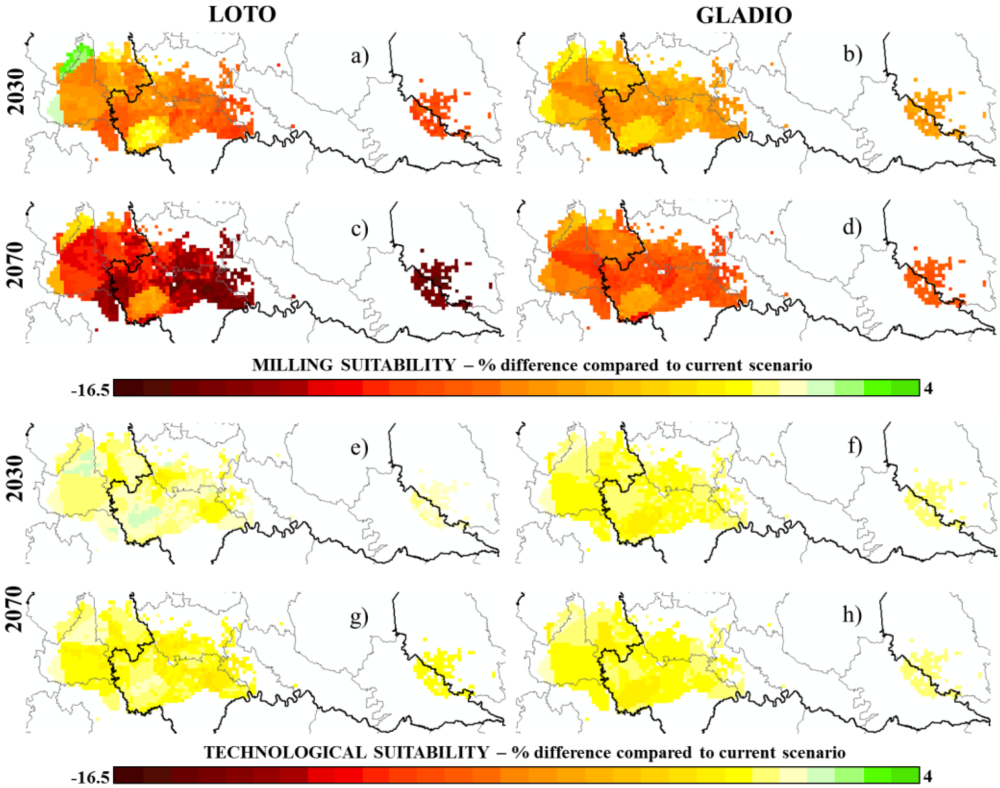

Figure 4: Projected climate change impact on milling (a, c, Loto; b, d, Gladio), and technological suitability (e, g, Loto; f, h, Gladio) for 2030 and 2070. Results are presented as average of all the combination emission scenario x GCM as percentage difference compared to the baseline.

While future projections revealed a marked in-district heterogeneity in the decline of simulated MS according to the variety and time horizon considered, TS was slightly affected by thermal and pluviometric anomalies, without showing significant differences among varieties. As already noticed for many single variables, MS of Loto cultivar progressively reduced along the North-East-South-West gradient proportionally to the thermal increases (with peaks up to -15%), whereas results achieved for Gladio did not show clear patterns along the study area. For the latter variety the expected decreases in HRY will be partially counterbalanced by the less favourable meteorological conditions triggering the onset of BK, MWG and BG occurrence, while Loto cultivar was largely penalized by the noticeable increase in the occurrence of MWG and, to a lesser extent, in PG.

These findings are expected to have critical impacts on the profitability of the farmers, millers and buyer businesses, by influencing quality, quantity and prices of rice productions, as severely damaged grains are usually redirected towards livestock feed or pet foods producers (Paranthaman et al., 2009). By considering the price that milled rice is currently exchanged in the local market (approximately 680 € t ha^{-1} for Gladio, 740 € t ha^{-1} for Loto, www.enterisi.it, updated 2015 December 1), above milling losses could reduce the millers revenues of about 82 € t ha^{-1} and 136 € t ha^{-1} respectively for Gladio and Loto varieties. In the same way, farmers income will be reduced of approximately 38 € t ha^{-1} and 65 € t ha^{-1} for Indica- and Japonica-type cultivars, since the price of the paddy rice is nearly the half of the milled one. These considerations are enough to call the attention on the economic sustainability of the rice sector in the mid-term. Compared to the trends noticed for MS, the spatial representation of TS denoted most encouraging results, with major declines in a range between -0.11%--0.32% for Loto and -0.25%--0.32% for Gladio varieties in 2030. The exacerbation of the thermal regimes projected for 2070 and the reduced rainfall amounts will lead to slight decrease in TS, especially in the areas along the boundaries between Piedmont and Lombardy regions, although not exceeding -3%.

Despite some declines in variables composing the TS were relatively high in absolute terms (e.g. PV and BDV), they markedly reduced when normalized against the sum of amylose and protein concentration, which are the main storage components involved with the variability of pasting properties. The negative effects due to projected decrease in PC for Gladio were noticeably smoothed by the high AC peculiar of this variety (almost double than Loto).

6.4. Conclusions

In spite of the projected decline in the nutritional properties of cereal crops, very few studies are available in the literature targeting the simulation of grain quality under climate change scenarios. This study represents the first attempt to assess multiple aspects involved with rice milling and technological suitability under different climate change projections. The development of a simulation environment based on simulation models to reproduce the interactions between milling/functional attributes of rice and environmental drivers and linked to a spatial explicit database with information on agronomic practices and current/climate change scenarios, allowed to identify potential trends in rice quality in the main European rice-growing district.

This preliminary study lays the basis to test adaptation strategies to alleviate the decline in rice quality, by implementing alternate agronomic practices and/or improved varieties for quality variables (e.g. rate of amylose accumulation, sensitivity to temperature stresses within starch, protein, amylose and chalky grains formation). From the modeling side, major improvements should be focused on the simulation of milling quality, by considering the interaction between genetic mechanism regulating the onset of damage in the kernel and agro-climatic factors.

Despite the assumptions behind this exploratory study, the results achieved allowed to provide plausible indications on rice cropping systems performances in the short and ong term, to be used by multiple stakeholders of the agricultural sector to preserve the sustainability of rice system.

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GENERAL DISCUSSION AND PERSPECTIVES

7.1. The development achieved

The plan of this doctorate was to target specifically the development of a reliable simulation environment able to forecast multiple aspects of rice grain quality under current and future climate conditions, in order to provide useful information to support multiple stakeholders in ensuring the resilience of the rice sector in the main European rice growing-district. A set of reference quality crop models and software architecture were identified as suitable to develop a modelling framework targeting the simulation of rice grainquality; it provided from the very beginning of this doctorate the infrastructure to organize modelling knowledge and make it operational. However, it became soon evident that the assessement of climate change impact on grain quality via spatially explicit application of semi empirical models had to be integrated by several other actions, in order to develop model tools that could be used operationally.

Firstly, the problem of finding reliable multi-site series of measured data to evaluate goodness of model responses out of the context they were developed, which is crucial especially when semi-empirical approaches have to be applied at a large scale. In this contex another problem was to retrieve consistent weather data needed to feed both crop simulators and quality models, as they are the main drivers influencing their responses and thus their reliability in reproducing the system under study. In addiction, in order to use the most suitable time resolution for the biophysical processes involved, there is the need to use hourly data. Such data are often unavailable when working on large areas and/or in climate change studies, thus forcing their estimation starting from daily values. Furthermore when operating at large scale it is of paramount importance adopt different sowing dates representing the heterogeneity of the cropping system to be represented, since they leads to shifts in crop phenology and, thus, in the time windows when the crop is susceptible to weather variables. Another key issue when dealing with spatially explicit forecasting activities or scenario analysis is to retrieve input information layers (e.g. crop and land use masks, weather data) having the same spatial resolution or even full format compatibility.The problem of input data can consequently be summarized as a detrimental lack of integration in research between scientists operating in different branches of agricultural domain.

Secondly, the aspects of model evaluation, which are not only related to grain quality models, but more in general to the bio-physical modelling. Despite the semi-empirical nature of rice quality models is expected to partly reduce their applicability outside the contexts they are calibrated for, related uncertainties remain largely unquantified. The few examples of studies targeting the evaluation of these models are often carried out using small datasets, where one or few varieties were grown in few sites and years. This prevents a clear understanding of the degree of suitability of the models for both research and operational contexts. Moreover, the use of different evaluation metrics in the different studies strongly hinders unambiguous comparisons of model performances to identify the most adequate approach to a given purpose. The usefulness of considering a broad range of metrics in model evaluation, although not providing statistical significance, allows getting an in-dept insight on model behavior. The multivariate nature of the issue is explicitly stated, the rules are easy to read, and the numerical scores easy to tune to match expert opinions. Consequently, part of the activities of this doctorate have targeted the multiple metrics model evaluation.

As third, the need to define the most suitable procedure to achieve plausible projections of future climate, handling the state of-the-art of climate change scenarios currently available. In the most frequent cases, climate change impact studies are carried out by adjusting historical daily data with outputs of the circulation models or generic effects. The generation of synthetic weather series via stochastic weather generator, by perturbing its parameters with deltas from IPPC, is currently the most powerful procedure to provide synthetic sets of daily data intended to be statistically representative of future climates. Furthermore the baseline - current scenario - should correspond to a time frame roughly contemporaneous with time of the research and with the time horizon at which precipitation and temperature anomalies from IPCC refer. In this context a minimum of 20 years is deemed enough to parameterize weather generators, since allowing to capture the most part of the less frequent climate events. In this perspective, part of the work of this doctorate focused on development of a systematic procedure to generate climate chnge scenarios for the study area, coherent with the IPCC projections.

The current state of development of the framework to model grain quality certainly has not reached its final stage. However, it meet the goal of modelling grain quality responses to weather dirivers in scenario analysis, and makes available a substantial set of model tools and utilities to foster its usability by third parties and which make possible performing studies at the level of abstraction presented in the case studies of this doctoral thesis.

7.2. Specific objectives

The specific objectives of this doctorate were:

1. The implementation of the state-of-the-art models targeting the estimation of multiple aspects of rice grain quality in a framework independent software component, to be easily used in specific modelling studies exploring different climatic and management conditions;
2. The comparative evaluation of models for the simulation of rice milling quality and functional properties of grains aimed at assessing their potential in being operatively applied either in forecasting activities or scenario analysis;
3. The development of a modular modelling solution, coupling quality models to a crop model specific for rice, targeting quali-quantitative yield forecasts at field and province scale;
4. The development of a systematic and reproducible procedure to assess, at an optimal spatial resolution, the climate change impacts on different sub-domains of cropping systems via spatially explicit application of process based models;
5. The development of a customized modeling solution targeting an extensive evaluation of the impacts of climate change on rice milling quality and technological suitability at a very fine spatial resolution.

The main concept at the base of the realization of the entire work is that, in order to manage the complexity of the biophysical processes simulated, mainly relying on the relationships between grain quality, crop and environment, the adoption of the state-of-the-art of software technology and crop modeling, together with high quality input data, is an unavoidable precondition. Furthermore, although a fine level of granularity is an acknowledged objective of the modelling community since many years, actually model reuse is still an open issue. This is the reason why the models targeting the simulation of milling and technological suitability of rice grain were implemented following the component-oriented design, which encapsulates model representations of specific domain into reusable, discrete, replaceable software units (i.e., the components).

According to this concept, after the identification of approaches for rice grain quality simulation compatible with the level of abstraction used by the majority of crop models developed for scenario analysis, I co-developed and programmed a software component (i.e., *RiceQuality*, presented in Chapter 2) for the estimation of such variables. This component mainly implement collection of models already published in literature and represent a concrete base to compare, extend or replace the approaches implemented according to the specific aims or of the model user.

The fulfillment of the first objective resulted crucial for the progress of the work because the availability of libraries of approaches for the simulation of grain quality variables foster the evaluation of the goodness of the diverse estimation methods before couple them to crop models, thus limiting the uncertainty of results.

The multi-model approach implemented in these component favored the achievement of second general objective, which relied on the comparison of the performances of the alternative models implemented in the compomnent, with the aim of identifying the best performing model per quality variable in the specific conditions of analysis (Chapter 3). To reach the goal, a multi-metric, multi-site and multi year calibration procedure was adopted to have an in-depth complete overview of model behavior under the conditions explored.

The third general objective was achieved by developing a dedicated simulation environment linking models for quality estimation to a crop simulator specific for rice, to be applied in a forecasting study at different spatial scale (Chapter 4). This realization meet the demand of multiple stakeholder of rice sector, that ask for the development of quali-quantitative yield forecasting systems, to reduce the uncertainty under which they have to take their own choices. The modular approach adopted to build the forecasting prototype, allows to extend it to other varieties and contexts, or even to add new quality variables to be forecasted. The fourth objective focused on the definition of systematic and reproducible procedure targeting the extent of climate change impacts on different sub-domains of cropping systems, via spatially explicit application of all the best quality models identified within the previous activities (Chapter 5).

The procedure developed allowed to customize a modelling solution specific for the evaluation of climate change impact on the productivity of a promising second-generation energy crop, as well ad the economic and environmental sustainability of related cropping systems in the mid long-term, by considering only the potential production level. The simulations carried out under future climate projections revealed a marked reduction in the payback time of the total investment compared to the current situation. This can be achieved via the preferential allocation of corn to food and feed destination, while maintaining the potential for feeding biogas plants with cost effective raw materials and preserving the income of farmers.

The systhematic procedure developed to perform climate change impacts was then followed to build a high resolution modeling solution targeting an extensive evaluation of the impacts of climate change on rice milling quality and technological suitability over the main European rice growing-district. To the aim, the state of the art of crop and quality models, last generation climate change scenarios and remote sensing techniques to derive information about crop distributions and agronomic practices were adopted. The results depicted an overall decline in milling quality, in the warmest areas of the rice district. While the revenues of farmers and millers are expected to be reduced in the mid-long terms, only minor changes will affect physicochemical and functional properties behind texture and taste of boiled rice. Despite the assumptions behind this exploratory study, the results achieved allowed to provide plausible indications on rice cropping systems performances in the short and long term, to be used by multiple stakeholders of the agricultural sector to preserve the sustainability of rice system.

7.3. Future perspectives

The work carried out within the doctorate foster and facilitates new developments.

Firstly, the architecture of the component promotes its extension by third parties via the implementation of alternative model realizations for variables already simulated, as well as via the inclusion of approaches for the simulation of new variables. To foster model reuse, two typologies of users were identified: (i) beginners and (ii) experts. In case of beginners, the most suitable modelling approaches for the simulation of the different rice quality variables under specific contexts of, e.g., inputs availability, is automatically handled by the component; conversely, experts are allowed to select the approach they consider as the most appropriate for each of the quality variables. The software components can be thus considered means to foster knowledge sharing with multiple uses as discussed in the chapters of this thesis.

New developments can be grouped in two types of activity: 1) Increasing the robustness of the simulation of varieties already parameterized, and adding new sets of parameters, and 2) Adding new simulation capabilities and/or uses of the framework.

7.3.1. Consolidating the framework

The robustness of the modelling solutions developed could be improved via a better definition of model parameters values via dedicated experimental trials and by a more precise characterization of the degree of genetic response to weather stresses of group of varieties with similar charachteristics.

The development of possibly shared transparent database of reference data and set of parameters could markedly facilitate the effective testing and calibration of models, with respect to the variety-specific peculiarities to be simimulated.

7.3.2. Extending framework use

Due to the dominant role of genetic versus environmental factors in controlling variables involved with milling quality, major improvements of simulation capabilities should involve the consideration of the interaction between genetic mechanism regulating the onset of grain defects and agro-climatic factors.

In the context of climate change impact studies, a further extension could involve the implementation of adaptation strategies to alleviate the expected effects of changing climate on grain quality features. In this context it would be really interesting to carry out an explorative investigation of possible responses to climate change of improved variety for traits related to quality variables (e.g. the rate of amylose accumulation, intensity and duration of sensitivity to temperature within starch, protein, amylose and chalky grains formation). In the same way it would of paramount interest to apply the developed framework to other rice district, where the crop is even more exposed to seasonal weather variability and/or extreme weather events.

Another foremost improvement should target the implementation of specific algorithms to represent the effect of nitrogen fertilization and water management on grain quality, in light of their pivotal role in influencing the nutritional properties of rice, as well as the susceptibility to grain damage occurrence.

Even if the original development of the component is targeted to be applied on rice, it could be extended and adapted for the simulation of other important crop species for which quality largely affect their processing and marketability value.

Although knowledge to be abstracted to models could be a limiting factor, the simulation of the pathogen pressure on quality features could be a further extension to better represent plausible trends of the real system under future scenarios of climate and agro-management.

Another aspect that could be developed is related to knowledge sharing also with respect to teaching purposes. In the same way a crop simulation model can be used to learn about the generalities of crop response to agricultural management, an *ad hoc* software could be used to teach and learn about interactions among crop, grain quality, weather drivers and agromanagement via simulation.

7.4. Concluding remarks

Although the importance of modelling pre harvest grain quality in cropping systems was set decades ago, modellers started focusing on product quality only recently. As for other aspects representing the behavior of crop performances and agricultural management, semi empirical approaches have been developed. Such models, crop specific, are expected to partly reduce their applicability outside the contexts they are calibrated for, without an extensive validation against reliable measured data representing environments and climatic conditions to be explored. The growing concerns about the projected climate change-driven decline for several cereal crops, are increasing demand for mid-term analyses of the economic and social sustainability of current production systems in the coming years. These objectives require the definition of systematic and reproducible procedure targeting the climate change impacts on different sub-domains of cropping systems via spatially explicit application of reliable models, at an optimal spatial resolution.

The work of this thesis is in that direction and can be considered as a shift of paradigm in addressing the problem of developing model tools for the grain quality, crop and environment interactions. The fine spatial resolution and quality of input data used, together with the rigorous approach followed to integrate the state-of-the art of i) crop growth and quality models, ii) IPCC climate change scenarios (2013) and iii) remote sensing derived information, allowed to reproduce the high heterogeneity which characterize the rice cropping systems under study. A case study was carried out to explore the responses to climate change of a promising energy crop by evaluating the economic and environmental sustainability of related cropping systems. This proved the effectiveness of the modular structure adopted in fostering the reuse in customized applications targeting climate change impact studies at an optimal spatial scale. The work has allowed highlighting knowledge gaps, and may suggest research actions to allow developing quantitative methods more strongly linked to the biological system, possibly providing researchers new incentives in defining their projects.

The framework developed, even if it needs further development, has allowed to move a step beyond the actual knowledge in performing analysis in climate change scenarios.

PUBLICATIONS DURING THE DOCTORAL WORK

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APPENDIX A. UNIMI.CASSANDRA.RICEQUALITY DOCUMENTATION

Abstract

The UNIMI.Cassandra.RiceQuality component is a library of semi-empirical modelling approaches aimed at estimate rice grain quality as a function of the meteorological conditions experienced by the crop during the ripening period.

Quality variables considered are: amylose, protein, total lipids and starch content, some indices of starch viscosity profile, chalkiness, cracking and head rice yield and the percentage of grains affected by black spot defect. Alternate approaches for the simulation of the same quality variable are available, in order to favour the immediate comparison among available models. Most of the models implemented present parameters with a clear biological meaning, allowing to characterize different degree and duration of grain susceptibility to damages such as the genetic ability and the optimal range of temperatures for the starch synthesis in the kernel (Okada et al., 2009; Chen et al., 2011). For each simulated variable, the component provides the final value reached at physiological maturity and its daily evolution in the field, from crop physiological maturity to harvest. RiceQuality component is/was used within national ("Climate change in Lombardy" project, funded by ERSAF-Regione Lombardia) and international projects (e.g., EU-FP7 ERMES and FIRST SCENARICE, funded by Cariplo Foundation). The component, extensible by third parties, is released as .NET DLL, thus targeting the development of .NET clients.

The component implements the test of pre-conditions and post-conditions, allowing an input to screen, TXT or XML file, and to .NET listeners. Custom output drivers can also be developed. Moreover, data sets used to perform unit tests is also provided as part of this documentation.

The component can be freely used and distributed by modelers and developers in their own applications. The component design allows for extensions by the users without requiring the re-compilation of UNIMI.RiceQuality. Sample clients are provided inclusive of source code to demonstrate how to add models, and to build a Win .NET application.

Getting Started

UNIMI.Cassandra.RiceQuality is a software component, hence it can be used by applications, or more in general by clients in a client-server architecture.

Being a component, a start on component use can be given by working on the sample projects provided in the software development kit (SDK).

The code documentation provided allows developers to access all the information needed to make full use of the component in custom developed applications.

Quality attributes and models

The UNIMI.Cassandra.RiceQuality component implements a collection of approaches with a different degree of empiricism to estimate rice grain quality as a function of the meteorological conditions experienced by the crop during the ripening period. Most of the models implemented present parameters with a clear biological meaning, allowing to characterize different degree and duration of grain susceptibility to damages such as the genetic ability and the optimal range of temperatures for the starch synthesis in the kernel (Okada et al., 2009; Chen et al., 2011). For each simulated variable, the component provides the final value reached at physiological maturity and its daily evolution in the field, from crop physiological maturity to harvest.

Quality variables are grouped according to the main effect on qualitative properties of rice grains, as shown below:

- Variables with effect on functional and sensory properties
- Variables with effect on appearance and milling quality
- Variables with effect on milling yield and quality

Variables with effect on functional and sensory properties

The quality variables affecting the functional and sensory properties of rice grain are:

- Grain starch concentration
- Grain protein content
- Grain amylose content
- Total lipid content
- Starch viscosity profile

Grain starch concentration

Grain starch concentration represents the most important food energy source in the world (Pan et al., 2007). This carbohydrate is the main reserve compound of plants and it consists of two type of molecules: amylose, ranging from 0 to 33%, and amylopectin, varying from 77 to 100% (Suwannaporn et al., 2007).

The model available in the UNIMI.CropQuality component simulates the synthesis and accumulation of this molecule as affected by air temperature, nitrogen and water availability during the ripening period, other than as a function of the photosynthetic activity and translocation phenomena. The flowchart of all the processes involved in the model given by Chen (2011) is showed in Figure 1.

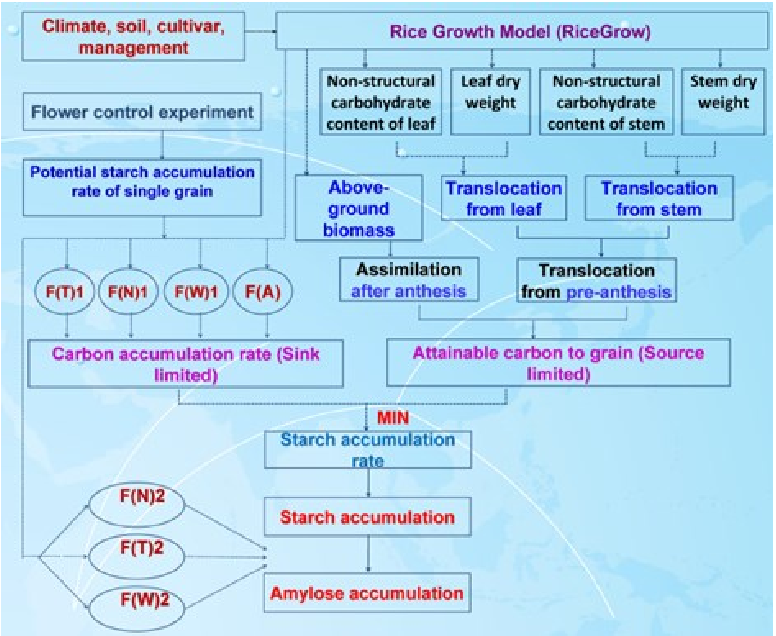


Figure 1. Theoretical flowchart of rice grain starch accumulation model.

In particular the relative starch content of individual grain is daily calculated as follow:

$$GCC_{(i)} = \frac{GSTA_{(i)}}{GDW_{(i)}} \cdot 100$$

Where:

$GCC_{(i)}$ is the relative starch content of individual brown rice grain;

$GSTA_{(i)}$ is the individual grain starch accumulated (mg grain^{-1}) on day i after flowering;

$GDW_{(i)}$ is the individual grain dry weight (mg grain^{-1}).

The individual grain starch $GSTA_{(i)}$ is derived through the daily integration of individual grain starch accumulation rate restricted by source or by or by sink, which is calculated as follow:

$$GSTAR_{(i)} = MIN\left(GCA_{(i)}, GSTARR_{(i)}\right)$$

Where:

$GSTAR_{(i)}$ (mg grain^{-1} day^{-1}) is the daily rate of individual grain starch accumulation;

$GCA_{(i)}$ (mg grain^{-1} day^{-1}) is the daily rate of available carbon restricted by source;

$GSTARR_{(i)}$ (mg grain^{-1} day^{-1}) is the daily rate of available carbon restricted by sink.

The individual grain carbon accumulation rate **sink limited** is simulated considering possible genetic, meteorological and environmental limitations factors, according to the next equation:

$$GSTARR_{(i)} = GSTAR_m \cdot MIN\left[F(A_i), F(T_i), F(W_i), F(N_i)\right]$$

Where:

$GSTAR_{(m)}$ (mg grain^{-1} day^{-1}) is a parameter, specific for the simulated variety, describing the maximum daily rate of individual grain starch accumulation;

$FA_{(i)}$, $FT_{(i)}$, $FW_{(i)}$, $FN_{(i)}$ (unitless) are limiting facors ranging from 0 (higher impact) to 1 (no impact): they are related respectively to i) genetic ability for starch synthesis, ii) average air temperature after the flowering date, iii) water stress status and iv) nitrogen stress status of crop.

In the current version of UNIMI.RiceQuality component the water and nitrogen stress status come as external rates variables from the crop models linked to the starch model, whereas the starch ability and air temperature factors are calculated consistently with the next two equations:

$$FA_{(i)} = \begin{cases} 0.032 \cdot e^{0.007 GDDi} & GDDi < 410 \\ 2 \cdot 10^{-5} (GDDi)^2 - 0.02 (GDDi) + 6.206 & GDDi \geq 410 \end{cases}$$

Where: $FA_{(i)}$ (unitless) is the factor describing the ability of simulated crop for the starch synthesis;

$GDD_{(i)}$ (°C day^{-1}) are the growing degree days accumulated after flowering date;

410 (°C day^{-1}) is the threshold of growing degree days, identified by developers, at which the rate of grain filling reach the max value.

$$FT_{(i)} = \begin{cases} \sin\left(\dfrac{Ti - Tb}{Tol - Tb} \cdot \dfrac{\pi}{2}\right) & Tb \leq Ti < Tol \\ 1 & Tol \leq Ti < Toh \\ \sin\left(\dfrac{Tm - Ti}{Tm - Toh} \cdot \dfrac{\pi}{2}\right) & Toh \leq Ti \leq Tm \\ 0 & Tm < Ti \ or \ Ti < Tb \end{cases}$$

Where:

$FT_{(i)}$, (unitless) is the factor describing the effect of air temperature on starch synthesis during ripening period;

$T_{(b)}$ $T_{(m)}$ (°C) are the minimum and maximum temperature bounds for starch synthesis;

$T_{(ol)}$ $T_{(oh)}$ (°C) are the lower and higher temperature thresholds for optimal starch synthesis;

$T_{(i)}$ (°C) is the average daily temperature.

Instead the individual grain carbon accumulation rate **source limited** is simulated via the following algorithm:

$$GCA_{(i)} = \frac{GCP_{(i)} + GCT_{(i)}}{GN_{(i)}}$$

Where:

$GCP_{(i)}$ (g m^{-2}) is the daily carbon assimilation in the grains due to photosynthetic activity on day i after flowering;

$GCT_{(i)}$ (g m^{-2}) is the daily carbon remobilization from vegetative organs on day i after flowering;

$GN_{(i)}$ (grain m^{-2}) is the number of grains per square meter.

The $GCP_{(i)}$ is an external rate variable from the crop model linked with the starch module, whereas the grain numbers is calculated as function of $GCP_{(i)}$ and the single grain weight.

Then the total carbon daily remobilized from vegetative organs ($GCT_{(i)}$) is calculated through the following equation:

$$GCT_{(i)} = \begin{cases} 0 & i < GDD_m \\ CTL_{(i)} + CTS_{(i)} & i \geq GDD_m \end{cases}$$

Where:

$GDD_{(m)}$ (GDD day) is a parameter describing the growing degree days after flowering at which the remobilization of stored assimilates begins;

$CTL_{(i)}$ (g m^{-2}) is the total carbon remobilized after anthesis from leaves;

$CTS_{(i)}$ (g m^{-2}) is the total carbon remobilized after anthesis from stems.

Both $CTL_{(i)}$ and $CTS_{(i)}$ are derived daily by multiplying the leaves and stems biomass by its relative fraction of solubles sugars. These fractions of carbohydrates are calculated respectively through a linear and a quadratic function of growing degree days accumulated from sowing date.

Grain protein content

Protein concentration of rice normally accounts for 5-9% of grain dry weight, and is a key index to reflect grain quality properties (Zhu et al., 2009). This constituent of rice kernel affects at the same time i) the nutritional value of rice, providing essential aminoacid (Juliano et al., 1985b), (ii) the taste and iii) the ease of cooking of this cereal. Furthermore the ability of proteins to form complex protein-protein and to absorb water, can lead to impair the swelling of starch granules during the gelatinization process, the latter being the basis of starch digestibility (Hamaker et al., 1990; Suwannaporn et al., 2007).

Currently the amylose content of rice grain is simulated via two alternative modeling approaches, given respectively by:

- Li (2005a)
- Lanning (2012)
- Cappelli (2015)

Li model (2005a)

This model calculates the protein fraction accumulated in the rice grain during the ripening phase, in response to two environmental factors: temperature and latitude. Each of these factors multiplies a reference protein content, peculiar of the tested varieties, increasing or decreasing its value, with a specific effect. The impact factors are adimensional and they can assume values ranging from 0 (maximum impact) and 1 (no impact).

The model was developed by considering a potential production level and two ecotypes, *Japonica* and *Indica*, characterized by different parameterizations.

The protein content is therefore calculated via the following equation (Li et al., 2005a):

$$PC = PPC \cdot \left(p_a \cdot LF + p_c \cdot T_{avg}F + p_i \cdot T_{\min}F + p_l \cdot T_{\max}F\right)$$

Where:

PC (%) is the protein content of rice kernel as percentage of grain dry weight (D.W.);

PPC (%) is the peculiar protein content (D.W.) of the simulated rice variety;

LF (unitless) is the latitude factor;

$T_{avg}F$ (unitless) is the factor related to average air temperature;

$T_{max}F$ (unitless) is the factor related to maximum air temperature;

$T_{min}F$ (unitless) is the factor related to minimum air temperature;

p_a, p_c, p_i, p_l (unitless) are the relative weights of the above mentioned factors.

All the above mentioned environmental factors are derived using a quadratic function of corresponding input experienced by the rice crop during the entire ripening phase (e.g. minimum air temperature to calculate minimum temperature factor) as shown in Figure 2.

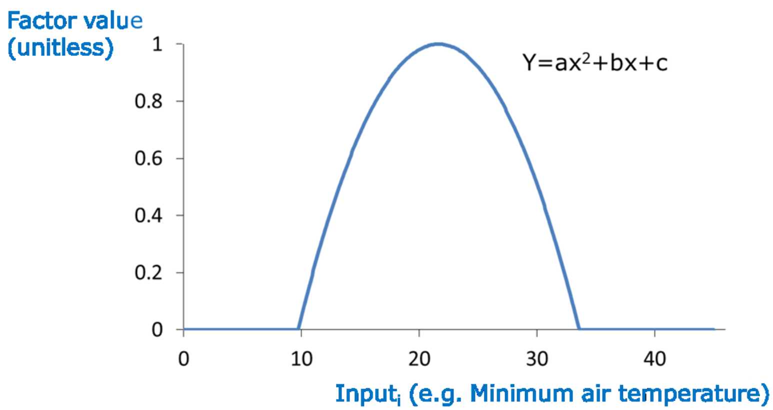


Figure 2. Generic quadratic function used to determine the impact of minimum air temperature on rice protein content.

The relative weights of considered factors are derived using the following equation:

$$p_i = \frac{R_i^2}{\sum_{i=1}^{n}\left(R_1^2 + R_2^2 + \dots\dots + R_n^2\right)}$$

Where:

R_i^2 is the value of regression coefficient between the i-th input taken into account and the protein content from field campaign data.

This model was evaluated in different sites of China, Japan and Thailand, reporting values of RMSE equal to 0.4% and 0.5% for Indica and Japonica varieties respectively.

Lanning model (2012)

This modelling approach simulates the protein content of rice as function of air temperature observed during the R8 stage of the ripening period (Counce et al., 2009), when the main culm turns to brown (Lanning et al., 2011).

In particular the protein concentration is determined using a linear regression on the 95-th percentile of nighttime air temperature values observed during the above mentioned phenological phase.

The general equation developed for *Japonica* varieties (Lanning et al., 2012) is given below:

$$PC_i = -a_i \cdot Tn_{95th} + b_i$$

Where:

PC (%) is the crude protein content of rice kernel as percentage of grain dry weight (D.W.);

Tn_{95th} (°C) is the 95th percentiles of nighttime air temperature frequencies that occurred during the R8 phase of rice ripening;

a_i, b_i (unitless) are the coefficients of the equation, specific for medium and long grain *Japonica* varieties.

Basically, once a DVS equal to 2.5 is reached, the model for the simulation of HRY begins to receive as input the hourly values of air temperature. Thus, each day, the HRY model populate a list object by using the hourly temperature data included between Sunset and Sunrise hour. These latter are exogenous variables that vary depending on the latitude of the site where simulations are performed. At last, when physiological maturity stage (DVS = 3) is achieved, the values stored in the above mentioned list object are used to calculate the 95-th percentile of nighttime air temperature, which represents the input of the equation listed above.

Cappelli model (2015)

The model provides a dynamic simulation of the protein content in the rice grain considering the peculiar effect of temperature and irrigation management on its daily accumulation in post flowering. The model also considers both the intensity and the duration of the varietal sensitivity to suboptimal thermal regimes for the synthesis of protein compounds.

The grain protein content accumulated at day "i" is simulated using the following equation (Figure3):

$$GPC_i = \begin{cases} \left[\dfrac{GP_{avg}}{1+\exp\left(a_j \cdot DFF_i + b_j\right)^{c_j}} - \sum_{1}^{i} LT_i \right] \cdot IF & \text{if } NT_{avg} \geq NTT \\ \dfrac{GP_{avg}}{1+\exp\left(a_j \cdot DFF_i + b_j\right)^{c_j}} - \sum_{1}^{i} LT_i & \text{else} \end{cases}$$

Where:

GPC_i (%) is the protein content of rice kernel simulated in the i-th day after flowering (D.W.);

GP_{avg} (%) is the average grain protein content expected at the end of the season for the simulated rice variety;

DFF_i (d) are the days from flowering date;

LT_i (%) represents the percentage of protein losses simulated in the i-th day after flowering and due to suboptimal temperatures during the ripening phase;

IF (unitless) is a parameter accounting for the effect of irrigation management used to grow the rice variety on cracking occurrence;

NT_{avg} (°C) is the average nighttime temperature perceived by the rice crop during the R8 phase of ripening (between DVS 2.5 and 3);

NTT (24.09 for Loto variety, 25.2 for Gladio variety; °C) is the nighttime temperature threshold above which the irrigation management adopted to grow the rice crop affect the grain protein content of the grain;

a_j (-0.6924 for Loto variety, -0.5 for Gladio variety; unitless),b_j (7.6016 for Loto variety, 12 for Gladio variety; unitless) and c_j (1.0104 for Loto variety, 1.0499 for Gladio variety; unitless) are coefficients of the equation.

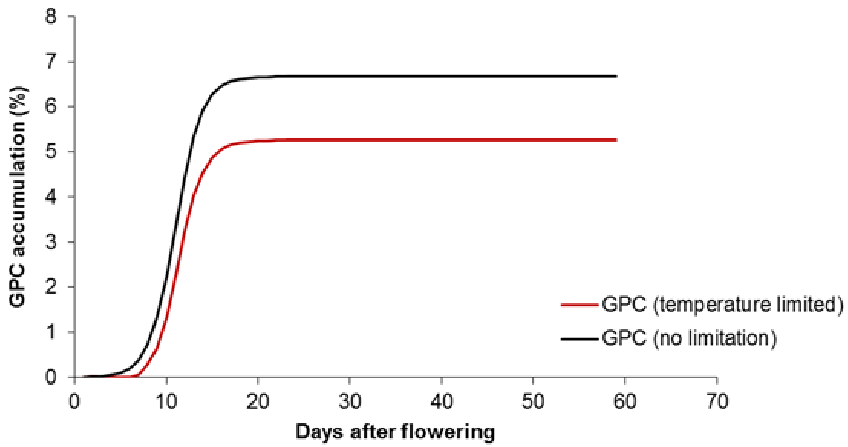


Figure 3. Grain protein accumulation (GPC, %) along the ripening period. The black line represents the potential grain protein concentration that can be achieved under optimum temperature conditions, whereas the red one indicates the actual grain protein concentration due the effect of suboptimal thermal regimes.

The Irrigation factor, varies depending on the irrigation management used to grow the rice crop. In Northern-Italian conditions, the default values are:

- continuous flooding (FLD): 1 (Loto) and 0.774 (Gladio);
- dry sowing and postponed flooding at three/fourth leaf stage (DRY): 1.074 (Loto) and 1.108 (Gladio);
- dry sowing and time-scheduled (IRR): 0.78 (Loto) and 1.057 (Gladio).

The daily thermal limitation to protein accumulation due to suboptimal temperatures is calculated as follow:

$$LT_i = \begin{cases} 1 - TF_i & \text{if } DFF_i \leq SDSTT \\ 1 & \text{else} \end{cases}$$

Where:

TF_i (unitless) is the temperature factor (1 no limitation, 0 maximum limitation) accounting for the temperature effect on protein synthesis;

SDSTT (d) is a parameter representing the duration of the impact of suboptimal temperatures on protein synthesis after flowering.

The factor accounting for the temperature effect on protein synthesis is calculated using the following equation:

$$TF_i = \begin{cases} VSST & \text{if } T_i \leq T_{\min} \text{ or } Ti \geq T_{\max} \\ (\alpha \cdot T_i + \beta) & \text{if } T_{\min} \leq T_i \leq T_{optL} \\ 1 & \text{if } T_{optL} \leq T_i \leq T_{optM} \\ (\gamma \cdot T_i + \delta) & \text{if } T_{optL} \leq T_i \leq T_{\max} \end{cases}$$

Where:

VSST (unitless) is a parameter representing the varietal sensitivity (0 maximum sensitivity, 1 no sensitivity) to suboptimal thermal regimes during the protein synthesis;

T_i (°C) is the average daily temperature of the day i;

T_{min} (°C) is a parameter representing the minimum temperature threshold for the grain protein synthesis;

T_{max} (°C) is a parameter representing the maximum temperature threshold for the grain protein synthesis;

T_{optL} (°C) is a parameter representing the lower optimum temperature threshold for the grain protein synthesis;

T_{optM} (°C) is a parameter representing the higher optimum temperature threshold for the grain protein synthesis;

α, β, γ,δ (unitless) are coefficients of the equation.

α is calculated as:

$$\alpha = \frac{1 - VSST}{T_{optL} - T_{\min}}$$

β is calculated as:

$$\beta = \frac{VSST - (1 - VSST)}{(T_{optL} - T_{\min}) \cdot T_{\min}}$$

γ is calculated as:

$$\gamma = \frac{1 - VSST}{T_{\max} - T_{optM}}$$

δ is calculated as:

$$\delta = \frac{VSST + (1 - VSST)}{(T_{\max} - T_{optM}) \cdot T_{\max}}$$

Grain amylose content

From the functional standpoint, the amylose content of rice grain is among the most widely used chemical indicators of rice quality due to its importance in determining the eating value of rice in terms of texture and nutritional value (Suwannaporn et al., 2007). Kernels with low amylose content appear to be sticky after cooking and suitable for pastry industry or sushi, whereas high amylose levels determine less soft kernels which become hard upon cooling, being more suitable for various rice dishes as timbales. The accumulation of this molecule during the ripening period is genetically controlled (Cheng et al., 2005) and, to a lesser extent, it is also influenced both by climatic variables (Siebenmorgen et al., 2013) and agronomic practices, such as irrigation strategy or planting date (Cheng et al., 2003)

Currently the amylose content of rice grain is simualted via four alternative modelling approaches, given respectively by:

- Chen (2011)
- Lanning (2012)
- Li (2005b)
- Liu (2013)
- Cappelli (2015)

Chen model (2011)

This modelling approach simulates the amylose content of rice grain as function of growing degree days accumulated from flowering date, using a logarithmic equation. The amylose content computed at maturity is then multiplied by the average nitrogen stress factor observed during the ripening period, that can decrease its potential value.

The general equation for *Indica* and *Japonica* ecotypes (Chen et al., 2011) is given below:

$$AC = (a_i \cdot LN(GDD_{Fl}) - b_i) \cdot N_{stress} \cdot 100$$

Where:

AC (%) is the amylose content of rice kernel as percentage of grain dry weight (D.W.);

GDD_{Fl} (C° day^{-1}) are the growing degree days accumulated from flowering date;

N_{stress} (unitless) is the average nitrogen stress factor computed during ripening period of rice crop;

a_i, b_i, (unitless) are the coefficients of the equation, specific for Japonica and Indica varieties.

Lanning model (2012)

This modelling approach simulates the amylose content of rice as function of air temperature observed during the R8 stage of the ripening period (Counce et al., 2009), when the main culm turns to brown (Lanning et al., 2011).

In particular the amylose concentration is determined using a linear regression on the 95-th percentile of nighttime air temperature values observed during the above mentioned phenological phase.

The general equation developed for *Japonica* varieties (Lanning et al., 2012) is given below:

$$AC = -a_i \cdot Tn_{95th} + b_i$$

Where:

AC (%) is the amylose content of rice kernel as percentage of grain dry weight (D.W.);

Tn_{95th} (°C) is the 95th percentiles of nighttime air temperature frequencies that occurred during the R8 phase of rice ripening;

a_i, b_i (unitless) are the coefficients of the equation, specific for medium and long grain japonica varieties.

Basically, once a DVS equal to 2.5 is reached, the model for the simulation of HRY begins to receive as input the hourly values of air temperature. Thus, each day, the HRY model populate a list object by using the hourly temperature data included between Sunset and Sunrise hour. These latter are exogenous variables that vary depending on the latitude of the site where simulations are performed. At last, when physiological maturity stage (DVS = 3) is achieved, the values stored in the above mentioned list object are used to calculate the 95-th percentile of nighttime air temperature, which represents the input of the equation listed above.

Li model (2005b)

This model calculates the amylose fraction accumulated in the rice caryopsis during the ripening phase, in response to three environmental factors: temperature, global radiation and latitude. Each of these factors multiplies a reference amylose content, peculiar of the tested varieties, increasing or decreasing its value, with a specific effect. The impact factors are a-dimensional and they can assume values ranging from 0 (maximum impact) and 1 (no impact).

The model was developed by considering a potential production level and two ecotypes, *Japonica* and *Indica*, characterized by different parameterizations.

The amylose content is therefore calculated via the following equation (Li et al., 2005b):

$$AC = PAC \cdot \left(p_f \cdot LF + p_g \cdot RF + p_h \cdot T_{avg}F + p_i \cdot T_{\min}F + p_l \cdot T_{\max}F\right)$$

Where:

AC (%) is the amylose content of rice kernel as percentage of grain dry weight (D.W.);

PAC (%) is the peculiar amylose content (D.W.) of the simulated rice variety;

LF (unitless) is the latitude factor;

RF (unitless) is the factor related to global solar radiation;

$T_{avg}F$ (unitless) is the factor related to average air temperature;

$T_{max}F$ (unitless) is the factor related to maximum air temperature;

$T_{min}F$ (unitless) is the factor related to minimum air temperature;

p_f, p_g, p_h, p_i, p_l (unitless) are the relative weights of the above mentioned factors.

All the above mentioned environmental factors are derived using a quadratic function of corresponding input experienced by the rice crop during the entire ripening phase (e.g. minimum air temperature to calculate minimum temperature factor) as shown in Figure 4.

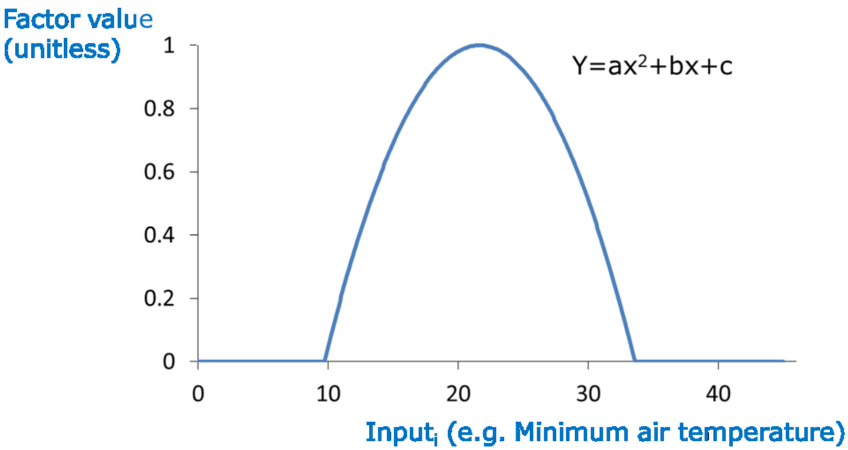


Figure 4. Generic quadratic function used to determine the impact of minimum air temperature on rice protein content.

The relative weights of considered factors are derived using the following equation:

$$p_i = \frac{R_i^2}{\sum_{i=1}^{n}\left(R_1^2 + R_2^2 + \ldots\ldots + R_n^2\right)}$$

Where:

R_i^2 is the value of regression coefficient between the i-th input taken into account and the amylose content from field campaign data.

This model was evaluated in different sites of China, Japan and Thailand, reporting values of RMSE ranging from 0.14% to 0.41% for both *Indica* and *Japonica* varieties.

Liu model (2013)

This modelling approach simulates the amylose content of rice grain as function of days elapsed after flowering date using a quadratic relationship.

The general equation for *Indica* and *Japonica* ecotypes (Liu et al., 2013)is given below:

$$AC = -a_i \cdot days_{Fl}^2 + b_i \cdot days_{Fl} + c_i$$

Where:

AC (%) is the amylose content of rice kernel as percentage of grain dry weight (D.W.);

$days_{Fl}$ (days) are the days accumulated starting from flowering date;

a_i, b_i, c_i (unitless) are the coefficients of the equation, specific for *Japonica* and *Indica* varieties.

Cappelli model (2015)

This model calculates the amylose content of rice kernels as a function of average temperature experienced by the crop during the whole ripening period. The amylose estimation is then corrected by an adimensional factor which account for the effect of average global solar radiation and wind speed perceived by the crop during the first ten days after flowering.

The general equations for *Indica* and *Japonica* ecotypes are given below:

$$AC = \begin{cases} a_i \cdot T_{avg}^2 + b_i \cdot T_{avg} + c_i & \text{if } T_{avg} \leq T_{th} \\ \left(a_i \cdot T_{th}^2 + b_i \cdot T_{th} + c_i\right) - RadWindF & \text{else} \end{cases}$$

Where:

AC (%) is the amylose content of rice kernel as percentage of grain dry weight (D.W.);

T_{avg} (°C) is the average air temperature within the whole ripening period;

RadWindF (MJ s m^{-4} d^{-1}) is a factor triggering the AC variations due to the impact of solar radiation and wind during the first ten days of ripening;

a_i (0.1384 for Loto, 0.1693 for Gladio; unitless), b_i (- 6.1338 for Loto, -7.0109 for Gladio; unitless), c_i (83.9114 for Loto, 97.0356 for Gladio; unitless), are coefficients of the equation, specific for *Japonica* and *Indica* varieties.

The RadWindF is calculated using the following equation:

$$RadWindF = \begin{cases} d_i \cdot \left(\dfrac{Rad_{10}}{Wind_{10}}\right)^2 + e_i \cdot \left(\dfrac{Rad_{10}}{Wind_{10}}\right) + g_i & \text{if } \dfrac{Rad_{10}}{Wind_{10}} \leq A \\ o_i \cdot \left(\dfrac{Rad_{10}}{Wind_{10}}\right) + p_i & \text{if } A \leq \dfrac{Rad_{10}}{Wind_{10}} \leq B \\ q_i & \text{if } \dfrac{Rad_{10}}{Wind_{10}} \geq B \end{cases}$$

Where:

Rad_{10} (MJ m^{-2} d^{-1}) is the average global solar radiation experienced by the rice crop during the first ten days of ripening;

$Wind_{10}$ (m^2 s^{-1}) is the average wind speed experienced by the rice crop during the first ten days of ripening;

d_i (0 for Loto, 0.0007 for Gladio; unitless), e_i (-0.0607 for Loto, -0.198 for Gladio; unitless), g_i (2.5 for Loto, 1.9363 for Gladio; unitless), o_i (-2.0093 for Loto, -0.0328 for

Gladio; unitless), p_i (40.302 for Loto, -1.1819 for Gladio; unitless), q_i (-2.5005 for Loto and Gladio; unitless), are coefficients of the equation, specific for *Japonica* and *Indica* varieties;

A (19.4 for Loto, 20.7 for Gladio), B (40.2 for both varieties), (m^2 s^{-1}) are thresholds triggering the points of discontinuity of the RadWindF function.

Total lipid content

Lipids in rice are found predominantly in the aleurone layer of the bran but are also present in the endosperm, cross-linked with starch. These molecules, present in milled rice, seem to influence the viscoelastic properties of starch by forming complexes with the helical structures of amylose, which affects the swelling ability of starch granules. This grain constituents affects also the nutritional value of rice providing calories and the aroma.

The available modelling approach simulates the total lipid content of brown rice as function of air temperature observed during the R8 stage of the ripening period (Counce et al., 2009), when the main culm turns to brown (Lanning et al., 2011).

In particular the lipid concentration is determined using a linear regression on the 95-th percentile of nighttime air temperature values observed during the above mentioned phenological phase.

The general equation developed for *Japonica* varieties (Lanning et al., 2012) is given below:

$$TLC = a_i \cdot Tn_{95th} + b_i$$

Where:

TLC (%) is the total lipid content of brown rice kernel as percentage of grain dry weight (D.W.);

Tn_{95th} (°C) is the 95th percentiles of nighttime air temperature frequencies that occurred during the R8 phase of rice ripening;

a_i, b_i (unitless) are the coefficients of the equation, specific for medium and long grain *Japonica* varieties.

Starch viscosity profile

The viscosity profile is a set of indices describing the cooked viscous properties of starch in terms of gelatinization and retrogradation tendency, being both the basis of starch digestibility (Hamaker et al., 1990; Suwannaporn et al., 2007).

Gelatinization is a process that breaks down the intermolecular bonds of starch, in the presence of water and heat (Liang et al., 2003).

Thus the crystalline starch becomes amorphous and hygroscopic and the granules start to swell, depending on temperature, water, protein, lipid, solutes content and amylose:amylopectine ratio. Therefore amylose and amylopectin chains result more exposed to hydrolytic digestive enzymes than raw starch (Figure 5).

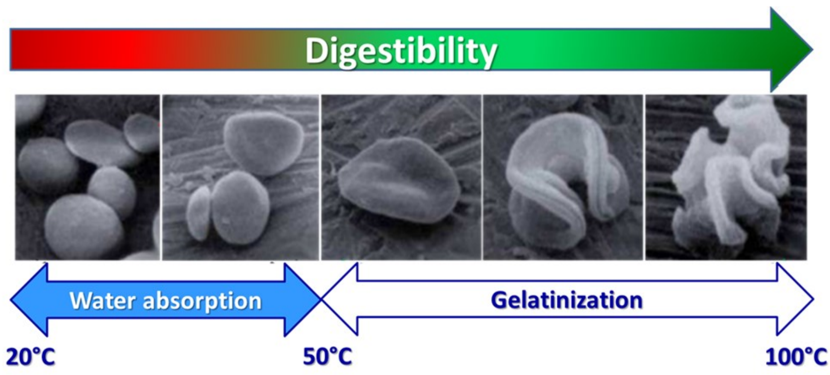


Figure 5. Structural modifications of starch granules during the gelatinization process.
This variable is composed by:

- *Gelatinization temperature*
- Pasting temperature
- Peak viscosity
- *Breakdown viscosity*
- Setback viscosity

With the exception of the gelatinization temperature, all this indices are commonly quantified by the Rapid Visco Anlyzer (RVA) instrument: in fact, the changes in viscosity provide a characteristic curve (Figure 6) depending on chemical-physical characteristics of the starch analyzed.

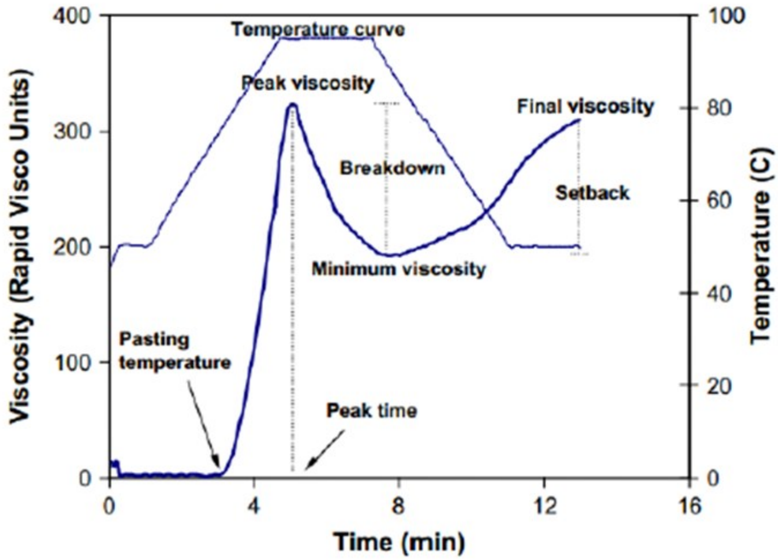


Figure 6. Peculiar RVA profile of rice starch (Source:Copeland et al., 2009).

Pasting temperature

Pasting temperature is a RVA profile index, representing the temperature at which the starch viscosity starts to rise during heating process (Liang et al., 2003). Usually its value is higher than the gelatinization temperature, meaning the starch granules are completely gelatinized before the viscosity begins to rise.

The available modelling approach simulates the pasting temperature of rice as function of air temperature observed during the whole ripening period of rice. In particular this index is derived using a linear regression on the mean value of average air temperature occurring during the above mentioned phenological phase.

The general equation developed for *Japonica* varieties (Shen et al., 2007) is given below:

$$PT = a_i \cdot T_{avg} + b_i$$

Where:

PT (°C) is the pasting temperature of rice starch;

T_{avg} (°C) is the average air temperature that occurs during the entire ripening of rice;

a_i, b_i (unitless) are the coefficients of the equation, specific for medium and long grain *Japonica* varieties.

Peak viscosity

Peak viscosity is a RVA profile index representing the maximum value reached by viscosity during the heating phase. It is a commonly used extent of granules swelling during the gelatinization phase (Liang et al., 2003).

The available approaches to calculate this output variable are:

- Lanning model (2012)
- Shen model (2007)
- Shen-Cappelli (2015)

Lanning model (2012)

This model simulates the peak viscosity of rice as function of air temperature observed during the R8 stage of the ripening period (Counce et al., 2009), when the main culm turns to brown (Lanning et al., 2011). In particular this viscoamilographic index is determined using a linear regression on the 95-th percentile of nighttime air temperature values observed during the above mentioned phenological phase.

The general equation developed for *Japonica* varieties (Lanning et al., 2012) is given below:

$$PV = a_i \cdot Tn_{95th} + b_i$$

Where:

PV (Rapid Visco Unit) is the peak viscosity of starch;

Tn_{95th} (°C) is the 95th percentiles of nighttime air temperature frequencies that occurred during the R8 phase of rice ripening;

a_i, b_i (unitless) are the coefficients of the equation, specific for medium and long grain *Japonica* varieties.

Basically, once a DVS equal to 2.5 is reached, the model for the simulation of HRY begins to receive as input the hourly values of air temperature. Thus, each day, the HRY model populate a list object by using the hourly temperature data included between Sunset and Sunrise hour. These latter are exogenous variables that vary depending on the latitude of the site where simulations are performed. At last, when physiological maturity stage (DVS = 3) is achieved, the values stored in the above mentioned list object are used to calculate the 95-th percentile of nighttime air temperature, which represents the input of the equation listed above.

Shen model (2007)

This modelling approach simulates the peak viscosity of rice as function of air temperature observed during the whole ripening period of rice. In particular this index is derived using a linear regression on the mean value of average air temperature occurring during the above mentioned phenological phase.

The general equation developed for *Japonica* varieties (Shen et al., 2007) is given below:

$$PV = a_i \cdot T_{avg} + b_i$$

Where:

PV (Centipoise) is the peak viscosity of rice starch;

T_{avg} (°C) is the mean value of average air temperature that occurs during the entire ripening of rice;

a_i, b_i (unitless) are the coefficients of the equation, specific for medium and long grain *Japonica* varieties.

Shen-Cappelli (2015)

This model calculates the Peak viscosity (PV) of rice starch as a function of the average air temperature experienced by the crop during the whole ripening period. The final value of PV is then corrected by a factor accounting for the effect of maximum air temperature experienced by the crop in the first 20 days after flowering.

The PV value (BU) at maturity (DVS = 3) is calculated as follow:

$$PV = PV_{Tavg} - FT_{\max}$$

Where:

PV_{Tavg} (BU) is the Peak viscosity of rice starch calculated as function of average temperature perceived by the crop during the whole ripening period;

FT_{max} (BU) represents the effect of average maximum air temperature experienced by the crop during the first 20 days after flowering on starch viscosity.

The PV_{Tavg} value (BU) is calculated as:

$$PV_{Tavg} = \begin{cases} a_i \cdot T_{avg} + b_i & \text{if } T_{avg} < T_{\min} \\ c_i \cdot T_{avg}^2 + d_i \cdot T_{avg} + e_i & \text{if } T_{\min} \leq T_{avg} \leq T_{\max} \\ g_i \cdot \log\left(T_{avg}\right) - m_i & \text{if } T_i > T_{\max} \end{cases}$$

Where:

T_{avg} (°C) is the average temperature experienced by the crop during the whole ripening period;

T_{min} (°C) is the temperature threshold below which the PV response to temperature is linear;

T_{max} (°C) is the temperature threshold beyond which the PV response to temperature restarts to decrease;

a_i (22.082 for Loto variety, 17.505 for Gladio variety; unitless), b_i (650 for Loto variety, 750 for Gladio variety; unitless), c_i (11.8199 for Loto variety, 13.7658 for Gladio variety; unitless), d_i (464.1795 for Loto variety, 607.3935 for Gladio variety; unitless), e_i (5622.0032 for Loto variety, 7701.0670 for Gladio variety; unitless), g_i (434.85 for Loto variety, 846.6 for Gladio variety; unitless), m_i (-164.87 for Loto variety, -1641.6 for Gladio variety; unitless), are coefficients of the equations.

The effect of average maximum air temperature experienced by the crop during the first 20 days after flowering on starch viscosity is computed as follow:

$$FT_{\max} = \begin{cases} n_i \cdot T_{\max}^2 + o_i \cdot T_{\max} + p_i & \text{if } T_{\max\,\min} \leq T_{\max} \leq T_{\max\,\max} \\ q_i & \text{else} \end{cases}$$

Where:

T_{max} (°C) is the average maximum temperature experienced by the crop during the first 20 days after flowering;

$Tmax_{min}$ (°C) is the maximum temperature threshold below which the PV response to temperature is linear;

$Tmax_{max}$ (°C) is the maximum temperature threshold beyond which the PV response to temperature restarts to decrease;

n_i (-4.8869 for Loto variety, 4.523 for Gladio variety; unitless), o_i (279.49 for Loto variety, -257.52 for Gladio variety; unitless), p_i (-3944.2 for Loto variety, 3616.5 for Gladio variety; unitless), q_i (-51.294 for Loto variety, 43.887 for Gladio variety; unitless).

Breakdown viscosity

Breakdown viscosity is a RVA index representing the starch granules disruption and it is commonly used as a measure of paste stability (Zaidul et al., 2007).

The available approaches to calculate this output variable are:

- *Yuan model (2008)*
- *Cappelli model (2015)*

Yuan model (2008)

The available modelling approach simulates this indicator as function of air temperature experienced by the rice crop during the whole ripening period. In particular this index is derived using a linear regression on the mean value of average air temperature occurring during the above mentioned phenological phase.

The general equation developed for both *Indica* and *Japonica* varieties (Yuan et al., 2008) is given below:

$$BV = a_i \cdot T_{avg} + b_i$$

Where:

BV (Centipoise) is the breakdown viscosity of rice starch;

T_{avg} (°C) is the mean value of average air temperature that occurs during the whole ripening period;

a_i, b_i (unitless) are the coefficients of the equation, specific for medium and long grain *Japonica* varieties.

Cappelli model (2015)

This model calculates the Breakdown viscosity (BV) of rice starch as a function of the average air temperature experienced by the crop during the whole ripening period.

The BV value (BU) at maturity (DVS = 3) is calculated as follow (Figure 7):

$$BV = \begin{cases} a_i \cdot T_{avg} + b_i & \text{if } T_{avg} < T_{\min} \\ BV_{avg} + c_i + \cos(2\pi \cdot d_i \cdot T_{avg}) + e_i \cdot \sin(2\pi \cdot d_i \cdot T_{avg}) & \text{if } T_{\min} \le T_{avg} \le T_{\max} \\ g_i \cdot \log(T_{avg}) - m_i & \text{if } T_i > T_{\max} \end{cases}$$

Where:

BV (BU) is the breakdown viscosity of rice starch at maturity;

BV_{avg} (BU) is a parameter representing the average breakdown viscosity of rice starch for the simulated variety;

T_{avg} (°C) is the average temperature experienced by the crop during the whole ripening period;

T_{min} (°C) is the temperature threshold below which the BV response to temperature is linear;

T_{max} (°C) is the temperature threshold beyond which the BV response to temperature restarts to decrease;

a_i (5.0261 for Loto variety, 12.94 for Gladio variety; unitless), b_i (340 for Loto variety, 300 for Gladio variety; unitless), c_i (-123.1532 for Loto variety, 4.6759 for Gladio variety; unitless), d_i (-0.1992 for Loto variety, -0.2026 for Gladio variety; unitless), e_i (0.0002 for Loto variety, 21.655 for Gladio variety; unitless), g_i (276.94 for Loto variety, 226.55 for Gladio variety; unitless), m_i (-147.98 for Loto variety, -57.307 for Gladio variety; unitless), are coefficients of the equations.

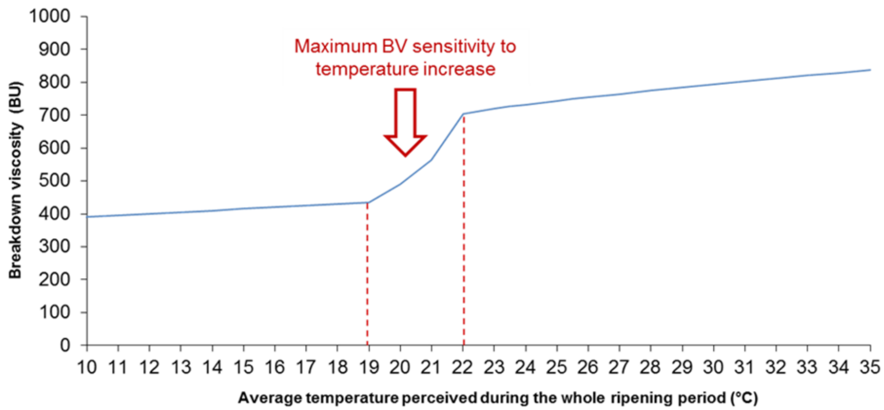


Figure 7. Breakdown viscosity (y-axis; BU) at maturity as function of the average temperature experienced by the rice crop during the whole ripening period (x-axis). The area between the red dotted lines represents the range of maximum viscosity increase due to temperature.

Setback viscosity

Setback viscosity is a RVA profile index, revealing the gelling ability or the retrogradation tendency of starch during cooling phase (Zaidul et al., 2007). In general higher amylose content determines higher seatback viscosity values.

The modelling approaches currently available are:

- Lanning model (2012)
- Shen model (2007)
- Cappelli (2015)

Lanning model (2012)

This modelling approach simulates the setback viscosity of rice as function of air temperature observed during the R8 stage of the ripening period (Counce et al., 2009), when the main culm turns to brown (Lanning et al., 2011) . In particular this viscoamilographic index is differently determined for medium and long grain varieties, using respectively a linear and quadratic function of the 95-th percentile of nighttime air temperature values observed during the abovementioned phenological phase.

The general equation developed for *Japonica* varieties (Lanning et al., 2012) are given below:

$$SV_{long} = a_i \cdot Tn^2_{95th} + b_i \cdot Tn_{95th} + c_i$$

Where:

SV_{long} (Rapid Visco Unit) is the setback viscosity of long grain rice starch;

Tn_{95th} (°C) is the 95th percentiles of nighttime air temperature frequencies that occurred during the R8 phase of rice ripening;

a_i, b_i, c_i(unitless) are the coefficients of the equation, specific for long grain *Japonica* varieties.

$$SV_{medium} = a_i \cdot Tn_{95th} + b_i$$

Where:

SV_{medium} (Rapid Visco Unit) is the setback viscosity of medium grain rice starch;

Tn_{95th} (°C) is the 95th percentiles of nighttime air temperature frequencies that occurred during the R8 phase of rice ripening;

a_i, b_i (unitless) are the coefficients of the equation, specific for medium grain *Japonica* varieties.

Basically, once a DVS equal to 2.5 is reached, the model for the simulation of HRY begins to receive as input the hourly values of air temperature. Thus, each day, the HRY model populate a list object by using the hourly temperature data included between Sunset and Sunrise hour. These latter are exogenous variables that vary depending on the latitude of the site where simulations are performed. At last, when physiological maturity stage (DVS = 3) is achieved, the values stored in the above mentioned list object are used to calculate the 95-th percentile of nighttime air temperature, which represents the input of the equation listed above.

Shen model (2007)

This modelling approach simulates the setback viscosity of rice as function of air temperature observed during the whole ripening period of rice. In particular this index is derived using a linear regression on the mean value of average air temperature occurring during the above mentioned phenological phase.

The general equation developed for *Japonica* varieties (Shen et al., 2007) is given below:

$$SV = a_i \cdot T_{avg} + b_i$$

Where:

SV (Rapid Visco Unit) is the setback viscosity of rice starch;

T_{avg} (°C) is the mean value of average air temperature that occurs during the entire ripening of rice;

a_i, b_i (unitless) are the coefficients of the equation, specific for medium and long grain *Japonica* varieties.

Cappelli model (2015)

This model calculates the setback of rice starch as a function of amylose accumulation and average air temperature perceived by the crop along the ripening period. Intensity and duration of varietal sensitivity to temperature effect on amylose synthesis are both considered.

The setback value at the day "i" is simulated using the following equation (Figure 8):

$$S_i = \sum_{1}^{i} SR$$

Where:

S_i (BU) is the setback viscosity of rice starch at the day i;

SR (BU) is the daily accumulation rate of setback viscosity of rice starch.

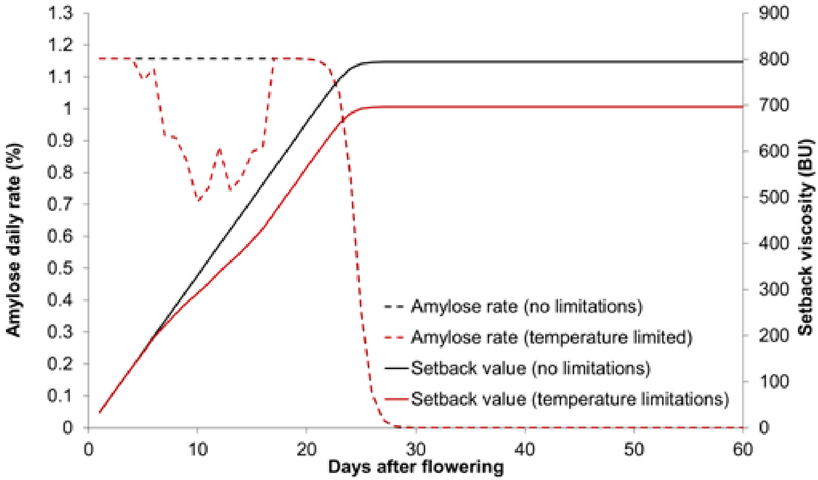


Figure 8. Amylose daily rate (left-y-axis; %) and setback viscosity accumulation (right y-axis; BU) along the ripening period. The dotted black line represents the maximum daily rate of amylose accumulation that can be reached under optimum temperature conditions, whereas the dotted red one indicates the actual amylose rate due the effect of suboptimal thermal regimes.The filled black line represents the potential setback viscosity that can be achieved under optimum temperature conditions, whereas the filled red one indicates the actual setback viscosity due the effect of suboptimal thermal regimes.

The daily accumulation rate of setback viscosity is calculated as follow:

$$SR_i = \frac{AR_{max}}{a} - \frac{\frac{AR_{max}}{a}}{1+\exp(b - c \cdot DFF_i)} \cdot TF_i$$

Where:

AR_{max} (%) is the maximum amylose accumulation rate of the rice variety selected for the simulation;

DFF_i (d) are the days since flowering date;

TF_i (unitless) is a temperature factor (1 no limitation, 0 maximum limitation) accounting for the temperature effect on amylose synthesis;

a (0.025 for Loto, 0.035 for Gladio; unitless), b (16.8813 for Loto, 37.0865 for Gladio; unitless), c (0.5644 for Loto, 1.5141 for Gladio; unitless),are coefficients of the equation.

The daily thermal limitation to amylose accumulation due to suboptimal temperatures is calculated as follow:

$$TL_i = \begin{cases} TF_i & if\ SSTT_{start} \leq DFF_i \leq SSTT_{end} \\ 1 & else \end{cases}$$

Where:

TF_i (unitless) is the temperature factor (1 no limitation, 0 maximum limitation) accounting for the temperature effect on amylose accumulation;

$SSTT_{start}$ (d) is a varietal parameter representing the doy after flowering at which the amylose accumulation start to be sensitive to suboptimal thermal regimes;

$SSTT_{end}$ (d) is a varietal parameter representing the doy after flowering at which the amylose accumulation ceases to be sensitive to suboptimal thermal regimes;

The factor accounting for the temperature effect on protein synthesis is calculated using the following equation:

$$TF_i = \begin{cases} VSST & \text{if } T_i \leq T_{\min} \text{ or } Ti \geq T_{\max} \\ (\alpha \cdot T_i + \beta) & \text{if } T_{\min} \leq T_i \leq T_{optL} \\ 1 & \text{if } T_{optL} \leq T_i \leq T_{optM} \\ (\gamma \cdot T_i + \delta) & \text{if } T_{optL} \leq T_i \leq T_{\max} \end{cases}$$

Where:

VSST (unitless) is a parameter representing the varietal sensitivity (0 maximum sensitivity, 1 no sensitivity) to suboptimal thermal regimes during the amylose synthesis;

T_i (°C) is the average daily temperature of the day i;

T_{min} (°C) is a parameter representing the minimum temperature threshold for the grain amylose synthesis;

T_{max} (°C) is a parameter representing the maximum temperature threshold for the grain amylose synthesis;

T_{optL} (°C) is a parameter representing the lower optimum temperature threshold for the grain amylose synthesis;

T_{optM} (°C) is a parameter representing the higher optimum temperature threshold for the grain amylose synthesis;

α, β, γ, δ (unitless) are coefficients of the equation.

α is calculated as:

$$\alpha = \frac{1 - VSST}{T_{optL} - T_{\min}}$$

β is calculated as:

$$\beta = \frac{VSST - (1 - VSST)}{(T_{optL} - T_{\min}) \cdot T_{\min}}$$

γ is calculated as:

$$\gamma = \frac{1 - VSST}{T_{\max} - T_{optM}}$$

δ is calculated as:

$$\delta = \frac{VSST + (1 - VSST)}{(T_{max} - T_{optM}) \cdot T_{max}}$$

Gelatinization temperature

Gelatinization temperature is a widely used index to evaluate the cooking duration and the texture of boiled rice (Lanning et al., 2012). Its value is strongly influenced by the physico-chemical properties of starch, but also by climatic factors (Siebenmorgen et al., 2013), such as air temperature during the ripening period of rice.

The available approaches to calculate this output variable are:

- Lanning model (2012)
- Shen-Cappelli model (2015)

Lanning model (2012)

The model simulates the gelatinization temperature of rice as function of air temperature observed during the R8 stage of the ripening period (Counce et al., 2009), when the main culm turns to brown (Lanning et al., 2011). In particular this viscoamilographic index is determined using a linear regression on the 95-th percentile of nighttime air temperature values observed during the above mentioned phenological phase.

The general equation developed for *Japonica* varieties (Lanning et al., 2012) is given below:

$$GT = a_i \cdot Tn_{95th} + b_i$$

Where:

GT (°C) is the gelatinization temperature of rice starch;

Tn_{95th} (°C) is the 95th percentiles of nighttime air temperature frequencies that occurred during the R8 phase of rice ripening;

a_i, b_i (unitless) are the coefficients of the equation, specific for medium and long grain japonica varieties.

Basically, once a DVS equal to 2.5 is reached, the model for the simulation of HRY begins to receive as input the hourly values of air temperature. Thus, each day, the HRY model populate a list object by using the hourly temperature data included between Sunset and Sunrise hour. These latter are exogenous variables that vary depending on the latitude of the site where simulations are performed. At last, when physiological maturity stage (DVS = 3) is achieved, the values stored in the above mentioned list object are used to calculate the 95-th percentile of nighttime air temperature, which represents the input of the equation listed above.

Shen-Cappelli model (2007)

This model calculates the Gelatinization temperature (GT) of rice starch as a function of the average air temperature experienced by the crop during the whole ripening period. The value of GT is then corrected by a factor accounting for the effect of maximum relative air humidity perceived by the crop in the field during the first 20 days after flowering.

The GT value (°C) at maturity (DVS = 3) is calculated as follow (Figure 9):

$$GT = GT_{Tavg} - FRH_{\max}$$

Where:

GT_{Tavg} (°C) is the Gelatinization temperature of rice starch calculated as function of average temperature perceived by the crop during the whole ripening period;

FRH_{max} (°C) represents the effect of average maximum relative air humidity experienced by the crop during the first 20 days after flowering on starch viscosity.

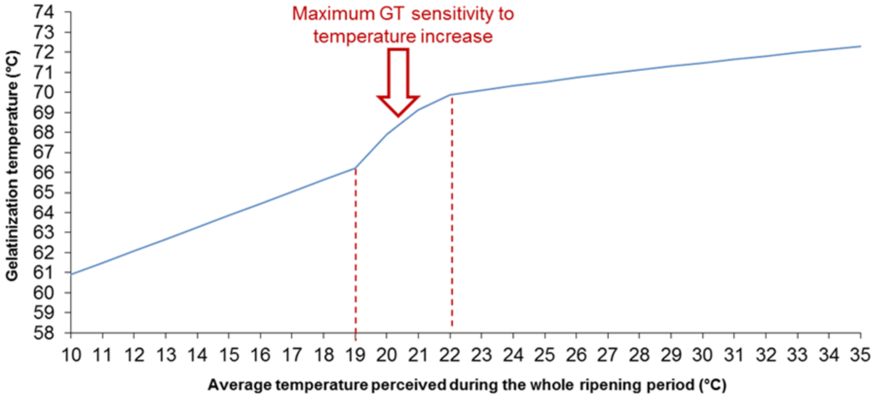


Figure 9. Gelatinization temperature (y-axis; °C) at maturity as function of the average temperature experienced by the rice crop during the whole ripening period (x-axis). The area between the red dotted lines represents the range of maximum gelatinization temperature relative increase due to temperature.

The GT_{Tavg} value (°C) is calculated as:

$$GT_{Tavg} = \begin{cases} a_i \cdot T_{avg} + b_i & \text{if } T_{avg} < T_{\min} \\ c_i \cdot T_{avg}^2 + d_i \cdot T_{avg} + e_i & \text{if } T_{\min} \le T_{avg} \le T_{\max} \\ g_i \cdot T_{avg}^{m_i} & \text{if } T_i > T_{\max} \end{cases}$$

Where:

T_{avg} (°C) is the average temperature experienced by the crop during the whole ripening period;

T_{min} (°C) is the temperature threshold below which the GT response to temperature is linear;

T_{max} (°C) is the temperature threshold beyond which the GT response to temperature restarts to decrease;

a_i (0.5906 for Loto variety, 0.5666 for Gladio variety; unitless), b_i (55 for Loto variety, 62 for Gladio variety; unitless), c_i (-0.244 for Loto variety, -0.3345 for Gladio variety; unitless), d_i (11.2193 for Loto variety, 15.0361 for Gladio variety; unitless), e_i (-58.8454 for Loto variety, -92.1536 for Gladio variety; unitless), g_i (55.705 for Loto variety, 62.608 for Gladio variety; unitless), m_i (0.0733 for Loto variety, 0.0648 for Gladio variety; unitless), are coefficients of the equations.

The effect of average maximum air relative humidity experienced by the crop during the first 20 days after flowering on starch viscosity is computed as follow:

$$FRH_{max} = \begin{cases} n_i \cdot RH_{max}^2 + o_i \cdot RH_{max} + p_i & if\ RH_{max\,min} \leq RH_{max} \leq RH_{max\,max} \\ q_i & else \end{cases}$$

Where:

RH_{max} (%) is the average maximum relative air humidity experienced by the crop during the first 20 days after flowering;

$RHmax_{min}$ (%) is the maximum relative air humidity threshold below which the GT response to temperature is linear;

$RHmax_{max}$ (%) is the maximum relative air humidity threshold beyond which the GT response to temperature becomes exponential;

n_i (0.0048 for Loto variety, -0.1127 for Gladio variety; unitless), o_i (-0.8449 for Loto variety, 22.146 for Gladio variety; unitless), p_i (36.795 for Loto variety, -1086.9 for Gladio variety; unitless), q_i (0.3074 for Loto variety, -1.522 for Gladio variety; unitless).

Variables with effect on appearance and milling quality

The quality variables affecting the appearance and milling quality of rice grain are:

- *Rice cracking*
- Grain chalkiness
- Black spot

Rice cracking

The rice cracking is a grain damage which usually halves the market value of head rice on an equal weight basis (Siebenmorgen et al., 2013). Furthermore, damaged productions cease to be suitable for direct human consumption, and they are often exploited by brewers industry and by the producers of livestock feed or pet foods (Paranthaman et al., 2009). The rice grain pericarp is hygroscopic and it adsorbs moisture in a humid environment while it desorbs moisture in a relatively dry environment (depending on vapor pressure difference between kernel surface and the surrounding air).The resulting stresses may cause fissures in rice kernels when the stresses exceed the failure strength of the grain (Lan et al., 1999).

The available approaches to calculate this output variable are:

- Nagata model (2004; 2006),
- Cappelli model (2015)

Nagata model (2004; 2006)

This model simulates the percentage occurrence of rice cracking as function of the average maximum temperature experienced by the crop during the first ten days after heading date. The model (Nagata et al., 2004 and 2006) provides two different parameterization to mimic both low and moderate susceptibility to cracking damage.

The general algorithm is the following:

$$Cracked_i = \alpha_i \cdot T\max_{Avg} - \beta_i$$

Where:

$Cracked_i$ (%) is the percentage occurrence of broken kernels;

$Tmax_{Avg}$ (°C) is the mean maximum temperature occurred in the first ten days after heading date;

α_i, β_i (unitless) are the coefficients of the equation, specific for both the considered degree of susceptibility to cracking.

Cappelli model (2015)

This model calculates the percentage of fissured rice kernels as function of a meteorological indicator composed by i) potential evapotranspiration, ii) average thermal and humidity excursion, iii) windy days, iv) consecutive and total dry days, v) total rainy days and vi) total amount of rainfall during the first ten days after heading.

The general equation is given below:

$$Cracked = a_i \cdot MI + AC \cdot (b_i \cdot IF)^{c_i}$$

Where:

Cracked (%) is is the percentage occurrence of rice broken kernels;

MI (unitless) is an agro-meteorological indicator accounting for several meteorological variables which can induce the rice grain to adsorb and desorb moisture in the field;

AC (%) is the average percentage of fissured kernels expected at the end of the season for the simulated rice variety;

IF (unitless) is a parameter accounting for the effect of irrigation management used to grow the rice variety on cracking occurrence;

ai (0.4599 for Loto, 0.2072 for Gladio; unitless), bi (3.161 for Loto, 0.653 for Gladio; unitless), ci (0.1116 for Loto, 0.2821 for Gladio; unitless), are coefficients of the equation, specific for *Japonica* and *Indica* varieties.

The agro-meteorological indicator (MI) is calculated using the following equation:

$$MI = \frac{\dfrac{\Delta T_{10} \cdot ET0_{avg10} \cdot WD_{10} \cdot DD_{10} \cdot CDD_{10}}{DHH_{10} \cdot (RD_{10} \cdot TR_{10} + 0.25)}}{1000}$$

Where:

ΔT (°C) is thermal excursion experienced by the rice crop during the first ten days after the heading date;

$ET0_{avg10}$ (mm d^{-1}) represents the average value of the reference evapotranspiration within the first ten days after heading date;

WD_{10} (d) is the number of days characterized by wind speed higher than a critical threshold (default value equal to 1.7 m s^{-1}) during the first ten days after heading;

DD_{10} (d) is the number of dry days (complete absence of rain) within the first ten days after heading;

CDD_{10} (d) represent the number of consecutive dry days in the period considered;

DHH_{10} (d) are the days with high air humidity, i.e. the number of days characterized by daily humidity excursion lower than a critical threshold (default value equal to 50%) during the first ten days after heading;

TR_{10} (mm) is the total amount of rain fallen during the first ten days after heading.

It is important to note that in the above equation the divisor is automatically corrected

i) with the default value of 0.5 when it is equal to 0;

ii) with the default value of 10 when the the nominator and the divisor are respectively higher than 100 and lower than 10.

The Irrigation factor, varies depending on the irrigation management used to grow the rice crop. In Northern-Italian conditions, the default values are:

- continuous flooding (FLD): 1 (Loto) and 1.029 (Gladio);
- dry sowing and postponed flooding at three/fourth leaf stage (DRY): 1.030 (Loto) and 1 (Gladio);
- dry sowing and time-scheduled (IRR): 1.133 (loto) and 1.15 (Gladio).

Once valorized the string parameter "IrrigationManagement" in the parameter file ("FLD", "DRY" and "IRR" choices are currently possible), the corresponding IF will be automatically calculated.

Grain chalkiness

The grains affected by chalkiness are characterized by opaqueness and chalky texture because of the interruption of final grain filling. This kind of damage is genetically controlled, other than being favored by high temperature stress during early ripening (Ishimaru et al., 2009; Okada et al., 2009; Lanning et al., 2011), which cause weak kernels, more susceptible to breakage during milling processes (Siebenmorgen et al., 2013).

Chalkiness can be classified in four types based on the grain area affected by the damage as shown in Figure 10.

Figure 10. Types of rice grain chalkiness.

Milky White kernels: this condition is when the rice is entirely opaque due to poorly developed starch granules in the center of the endosperm (Figure 11). In general, this rice is slender with non-uniform shape. It is treated as screenings.

White Core kernels: starch granules in the central cells of the endosperm develop poorly. Although undesirable for table rice, this characteristic is often considered favorable for brewer’s rice (i.e. sake).

White Belly kernels: this is rice with white, opaque areas on the belly or ventral side of the grain. The white area is a result of poorly developed starch granules in the peripheral layers of the endosperm. It is caused by insufficient transport of carbohydrates to the rice grain during ripening. White belly generally does not degrade the quality of the rice.

White Base kernels: the kernels are characterized by an immature and chalky area in the basal region of the endosperm.

White Back kernels: the kernels have a chalky area at the dorsal part of the endosperm

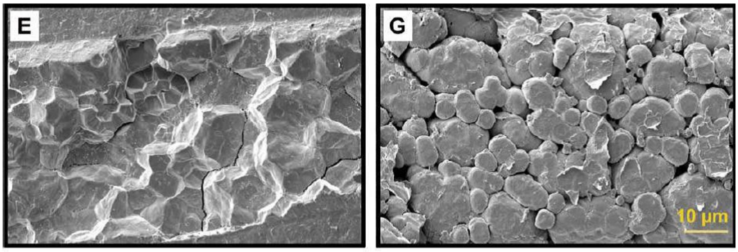


Figure 11. Scanning electron micrographs of amyloplasts in the center part of rice grain. E: control, G: sample exposed to high temperature (Ishimaru et al., 2009).

Currently in the UNIMI.CropQuality component implements models simulating:

- Milky white chalkiness
- White base chalkiness

Furthermore a model considering the chalkiness degree of rice productions is available.

Milky white chalkiness

The approaches currently available for the milky white chalkiness are:

- Nagahata model (2006)
- Okada model (2009)
- Tsukaguchi model (2008)
- Oya (2008)

Nagahata model (2006)

This model simulates the percentage occurrence of milky white grains on the total dry mass of rice kernels as function of average air temperature occurring in the whole ripening period.

Furthermore the model via two specific parameters takes into account that i) the susceptibility to damage decreases with the progress of the ripening and ii) low seeding density increase the incidence of chalkiness.

The general equation (Naghata et al. 2006) is:

$$MW = k \cdot \left(\delta - a_j\right)$$

Where:

MW (%) is the percentage incidence of milky white grains on the dry mass of kernels;

k (0.0513 for Loto, 0.0085 for Gladio; unitless) is a coefficient of the equation;

δ (°C) represents the effective temperature daily accumulated over a fixed damage threshold temperature;

a_i (11.9867, for Loto, 11.0376 for Gladio; unitless) is a parameter describing the effect of sowing density on chalky incidence: the higher the planting density the lower chalkiness incidence.

In particular the effective temperature (δ) is calculated as follow:

$$\delta = \sum f_i \cdot (T_i - T_b)$$

Where:

f_i (unitless) is a parameter decreasing the grain susceptibility to chalkiness during the ripening progress. Its values derives from field campaign experiments;

t_b (°C) is the average temperature threshold beyond which the damage to grain begins to occurs;

t_i (°C) is daily average air temperature occurring during the ripening period of rice.

In the Northern-Italian conditions *fi* can be valorized using the following default values:

Loto variey:

- fi =1: days from heading ≤ 2;
- fi = 0.5: 2 > days from heading ≤ 8;
- fi = 0.397: 8 > days from heading ≤ 25;
- fi = 0: days from heading >25.

Gladio variety:

- fi = 0.5926: days from heading ≤ 11;
- fi = 0.2977: 11 > days from heading ≤ 29;
- fi = 0: days from heading > 29.

Okada model (2009)

This model calculates the incidence of chalky grains as regression on temperature and solar radiation occurred during the whole ripening phase as shown in the following equation (Okada et al., 2009):

$$Q = 100 - (\alpha \cdot \delta + \beta \cdot SR + \gamma)$$

Where:

Q (%) is the percentage incidence of milky white grains on the dry mass of kernels;

δ (°C) represents the effective temperature daily accumulated over a fixed damage threshold temperature;

SR (MJ m^{-2}) is the accumulated global solar radiation during the ripening period;

α, β, γ (unitless) are the coefficients of linear regression.

In particular the temperature factor (δ) is calculated as follow:

$$\delta = \sum_{i=0}^{m} f_i \cdot (T_i - T_b)$$

Where:

f_i (unitless) is a daily factor modulating the grain susceptibility to chalkiness during the ripening progress.;

t_b (°C) is the average temperature threshold beyond which the damage to grain begins to occurs;

t_i (°C) is daily minimum air temperature occurring during the ripening period of rice.

Contrary to the model developed by Nagahata that assumes four fixed values of f_i factor during the ripening progress, in this case f_i is daily calculated using the following equation:

$$f_i = 1 - \frac{1}{1+\exp(b-i)}$$

Where:

b (unitless) is a parameter regulating the duration of maximum grain.

Tsukaguchi model (2008)

This model simulates the percentage occurrence of milky white grains on the total dry mass of rice kernels considering the assimilates supply to single grain characterizing the whole ripening period. In particular the relationship formalized by developers (Tsukaguchi et al. 2008) is an equilateral hyperbola which assumes two different parameterizations based on mean value of average temperature experienced from the crop during the ripening phase.

The general equation is:

$$MW = \begin{cases} \dfrac{10.19}{AS} & if \quad T_{avg} \le T_b \\ \dfrac{24.63}{AS} & if \quad T_{avg} > T_b \end{cases}$$

Where:

MW (%) is the percentage incidence of milky white grains on the dry mass of kernels;

AS (mg grain^{-1} day^{-1}) is the single grain carbon assimilates supply that occurs during the ripening period;

t_b (°C) is the threshold of average temperature beyond which the damage to grain begins to occurs;

t_i (°C) is daily average air temperature occurring during the ripening period of rice.

Oya (2008)

This model calculates the occurrence of milky white chalkiness on the total rice kernels dry mass, considering the peculiar effects of minimum air humidity and maximum wind speed in the period between six and 25 days after heading. In Northern-Italian conditions this period corresponds to the period between seven and 25 days for Gladio and 5 30 days for Loto varieties.

The general equation (Oya et al. 2008) is:

$$MW = k_i \cdot [(100 - H_{\min}) \cdot WS_{\max}]$$

Where:

MW (%) is the percentage incidence of milky white grains on the dry mass of kernels;

K_i (0.01196 for Loto, 0.0034 for Gladio; unitless) is an empirical coefficient of the equation;

H_{min} (%) corresponds to the minimum value of relative air humidity perceived by the crop within the period under study;

WS_{max} (m s^{-1}) is the maximum value of average daily wind speed experienced by the crop within the period under study.

White immature base chalkiness

The approaches currently available for the white immature base chalkiness are:

- Kondo model (2006)
- Morita model (2005)

Kondo model (2006)

This model simulates the percentage of kernels characterized by immature base chalkiness as function of the average air temperature experienced by rice crop during the first twenty days after the heading. The algorithm proposed by developer (Kondo et al., 2006) was implemented considering four different parameterization based on two levels of grain susceptibility in both potential and nitrogen limiting conditions.

The general equation is:

$$WB = a_i \cdot T_{avg}^{b_i}$$

Where:

WB (%) is the percentage incidence of white immature base grains on the dry mass of kernels;

t_{avg} (°C) is the mean value of average air temperature occurring during the ripening period of rice;

$a_{i,}$ b_i (unitless) are the coefficients of equation, assuming different values according to susceptibility and production level considered during simulations.

Morita model (2005)

This model simulates the percentage of kernels characterized by immature base chalkiness as function of the average air temperature experienced by rice crop during the first twenty days after the heading.

The general polynomial function proposed by developer (Morita 2005) for *Japonica* ecotypes is given below:

$$WB = a_i \cdot T_{avg}^2 + b_i \cdot T_{avg} + c$$

Where:

WB (%) is the percentage incidence of white immature base grains on the dry mass of kernels;

t_{avg} (°C) is the mean value of average air temperature occurring during the ripening period of rice;

$a_{i,}$ $b_{i,}$ c_i (unitless) are the coefficients of equation.

Chalkiness degree

Chalkiness degree (C.D.) is a commonly used indicator aimed at evaluating the appearance and the quality of milling of rice grains. This index in a sample is determined as the ratio of the total chalky area (pixels) of the 100-kernel set to the total area of the kernels, multiplied by 100 (Figure 12).

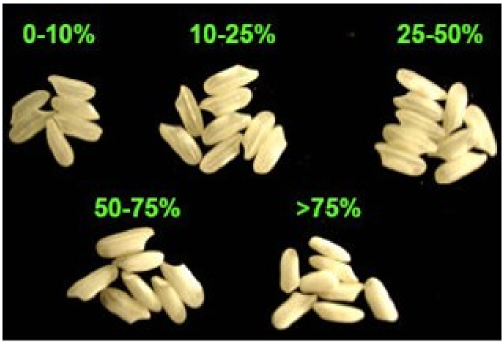


Figure 12. Kernels characterized by different chalkiness degree (Source: International Rice Research Institute - IRRI).

This modelling approach simulates the C.D. of rice as function of air temperature observed during the R8 stage of the ripening period (Counce et al., 2009), when the main culm turns to brown (Lanning et al., 2011). In particular this HRY index is calculated using a quadratic function of the 95-th percentile of nighttime air temperature values observed during the above mentioned phenological phase.

The general equation developed for *Japonica* varieties (Lanning et al., 2011) is given below:

$$CD = a_i \cdot Tn_{95th}^2 + b_i \cdot Tn_{95th} + c_i$$

Where:

CD (%) is the simulated chalkiness degree value;

Tn_{95th} (°C) is the 95th percentiles of nighttime air temperature frequencies that occurred during the R8 phase of rice ripening.

a_i, b_i, c_i (unitless) are the coefficients of the equation, specific for medium grain *Japonica* varieties.

Basically, once a DVS equal to 2.5 is reached, the model for the simulation of HRY begins to receive as input the hourly values of air temperature. Thus, each day, the HRY model populate a list object by using the hourly temperature data included between Sunset and Sunrise hour. These latter are exogenous variables that vary depending on the latitude of the site where simulations are performed. At last, when physiological maturity stage (DVS = 3) is achieved, the values stored in the above mentioned list object are used to calculate the 95-th percentile of nighttime air temperature, which represents the input of the equation listed above.

Black spot

In rice, black spot damage (or pecky rice; Fig.13) is one of the most important quality factors for grading, marketing, and end-use value (Wang et al., 2002). The pecky rice rice is characterized as a roughly circular lesion, which in some cases appears as a shrunken area. In general, this kind of defect is accompanied by a brown to black grain discoloration of the whole kernel or portion of the kernel. This complex disorder involves many fungi, the white-tip nematode and insect damage. High winds at the early heading stage may cause similar symptoms. Heading applications of stink bug insecticides and fungicides targeted at other more important diseases will reduce the peck rice occurrence. Black spot causes both yield and quality losses that affect rice end-use. Pecky grains weigh substantially less than normal grains since they are not fully developed or are damaged by fungus which results in a yield loss.

Figure 13. Rice grains affected by black spot damage

The new developed model calculates the percentage of rice kernels affected by black spot damage as a function of average temperature and relative humidity excursion during the first 20 days after heading. In particular the output is achieved by multiplying the maximum percentage of pecky grains expected at the end of the season for the simulated rice variety for three factors, related to temperature and relative air humidity perceived by the crop during the ripening period.

The main equation is given below:

$$BS = BS_{avg} \cdot DT_{20} \cdot DHH_{20} \cdot DHTE_{20}$$

Where:

BS (%) is the percentage of rice grains affected by black spot damage;

DT_{20} (unitless) is the factor referring to the average daily thermal excursion perceived by the crop during the first twenty days after heading;

DHH_{20} (d) is the factor referring to the number of days with high air humidity during the first 20 days after heading;

$DHTE_{20}$ (mm) is the factor related to the number of days with high daily thermal excursion during the first 20 days after heading;

BS_{avg} (%) is the maximum percentage of pecky grains expected at the end of the season for the simulated rice variety.

The three agro-meteorological factors are computed as follow:

$$DT_{20} = \frac{a_i \cdot \Delta T_{20}^2 + b_i \cdot \Delta T_{20} + c_i}{BS_{avg}}$$

Where:

ΔT_{20} (°C) represents the average daily thermal excursion perceived by the crop during the first twenty days after heading;

a_i (0.1823 for Loto, 0.1096 for Gladio; unitless), b_i (-5.0672 for Loto, -3.7312 for Gladio; unitless), c_i (43.7063 for Loto, 32.8166 for Gladio; unitless) are coefficients of the equation.

$$DHH_{20} = \frac{d_i \cdot dH^2_{20} + e_i \cdot dH_{20} + g_i}{BS_{avg}}$$

Where:

dH_{20} (d) are the days with high air humidity, i.e. the number of days characterized by daily humidity excursion lower than a critical threshold (default value equal to 50%) during the first 20 days after heading;

a_i (0.0433 for Loto, 0.0135 for Gladio; unitless), b_i (-1.006 for Loto, -0.2914 for Gladio; unitless), c_i (9.0008 for Loto, 4.5034 for Gladio; unitless) are coefficients of the equation.

$$DHTE_{20} = \frac{h_i \cdot H\Delta T^2_{20} + l_i \cdot H\Delta T_{20} + m_i}{BS_{avg}}$$

Where:

$H\Delta T_{20}$ (°C) are the days with high daily thermal excursion, i.e. the number of days characterized by daily thermal excursion higher than a critical threshold (default value equal to 10 °C) during the first 20 days after heading;

h_i (0.0079 for Loto, 0.0165 for Gladio; unitless), l_i (-0.0002 for Loto, -0.0044 for Gladio; unitless), m_i (3.9419 for Loto, 2.2072 for Gladio; unitless) are coefficients of the equation.

Variables with effect on milling yield and quality

The only variable with impact on milling yield and quality currently implemented in UNIMI.Cassandra.RiceQuality component is the Head rice yield (HRY).

Head rice yield

Head rice yield (HRY) is a widely accepted indicator of milling quality, defined as the mass percentage of rough rice kernels that are at least three-fourths of their original kernel length after milling (USDA, 1997).This quality feature is a key determinant of rice price and it strongly depends both on weather conditions occurring during the reproductive phase, and on grain moisture content at harvest.

The modelling approach developed by Lanning and colleagues (Lanning et al., 2011) simulates the HRYof rice as function of air temperature observed during the R8 stage of the ripening period (Counce et al., 2009), when the main culm turns to brown. In particular this HRY index is calculated using a quadratic function of the 95^{-th} percentile of nighttime air temperature values observed during the abovementioned phenological phase.

The general equation developed for *Japonica* varieties is given below:

$$HRY = a_i \cdot Tn^2_{95th} + b_i \cdot Tn_{95th} + c_i$$

Where:

HRY (%) is the simulated HRY value;

Tn_{95th} (°C) is the 95th percentiles of nighttime air temperature frequencies that occurred during the R8 phase of rice ripening;

a_i, b_i, c_i (unitless) are the coefficients of the equation, specific for medium and long grain *Japonica* varieties.

In particular.

- a_i is equal to: -0.5942 for Lagrue variety,-0.4411 for the Wells variety; -0.4154 for Cypress variety; -0.4089 for Jupiter variety; -0.3848 for Bengal variety;-0.3968 for a generic medium slender *Japonica* variety and -0.4836 for a long slender *Japonica* cultivar.
- b_i is equal to: 28.563 for Lagrue variety 20.913 for the Wells variety; 20.378 for Cypress variety; 21.122 for Jupiter variety; 20.048 for Bengal variety; 20.585 for a generic medium slender *Japonica* variety and 23.2847 for a long slender *Japonica* cultivar.
- c_i is equal to: -282.41 for Lagrue variety -186.37 for the Wells variety; -186.31 for Cypress variety; -208.14 for Jupiter variety; -197.64 for Bengal variety; -202.89 for a generic medium slender *Japonica* variety and -218.3633 for a long slender *Japonica* cultivar.

Basically, once a DVS equal to 2.5 is reached, the model for the simulation of HRY begins to receive as input the hourly values of air temperature. Thus, each day, the HRY model populate a list object by using the hourly temperature data included between Sunset and Sunrise hour. These latter are exogenous variables that vary depending on the latitude of the site where simulations are performed. At last, when physiological maturity stage (DVS = 3) is achieved, the values stored in the above mentioned list object are used to calculate the 95-th percentile of nighttime air temperature, which represents the input of the equation listed above.

Furthermore, the UNIMI.Cassandra.RiceQuality component implements an improved version of Lanning's approach which consider several limiting factors to the starch deposition process, such as the impact of high windiness and low humidity at sub-optimal thermal regimes.

In detail, the model was modified according to the following phases (*Figure 14*):

a) characterization of the original quadratic function by introducing thresholds for minimum (T_{min}) and optimum temperatures ($Topt_{min}$ and $Topt_{max}$) for the synthesis of starch in the rice grain;

b) change of the slope of the curve in the range of suboptimal thermal regimes (Temperature below $Topt_{min}$), in order to mimic the cultivar-specific susceptibility to breakage;

c) definition of specific rules to reproduce the dependency of HRY to low humidity and high windiness in conjunction with suboptimal temperatures for the starch synthesis. These unfavorable conditions could lead to the formation of weak areas in the grain that are more likely to break in the subsequent processing steps.

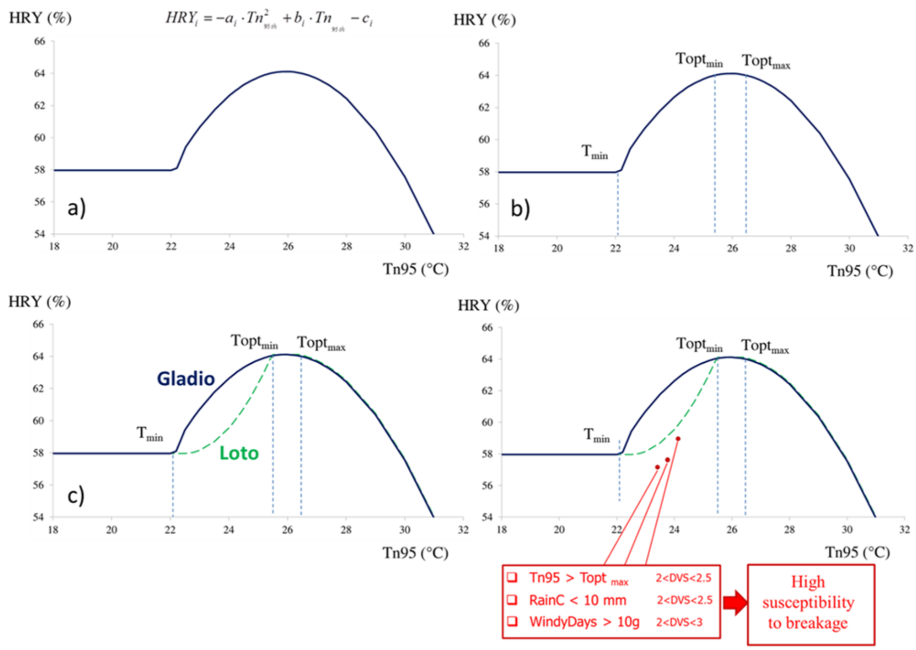


Figure 14. Changes in the HRY response function to temperature developed by Lanning a). The process involved the following phases: b) introduction of thresholds for minimum (T_{min}) and optimum temperatures ($Topt_{min}$ and $Topt_{max}$) for the synthesis of starch in the rice grain, d) definition of specific rules aimed at reproducing the impact on HRY of unfavorable weather conditions for the starch synthesis. Tn95 represents the 95-th percentile of nighttime air temperature within the range DVS 2.5 e DVS 3.

Indeed the new developed version of the model was then formalized using the two equations below:

$$HRY_i = \begin{cases} a_i \cdot T^2_{\min} + b_i \cdot T_{\min} + c_i & \text{If } \; T_{95} < T\min \\ a_i \cdot T^2_{95} + b_i \cdot T_{95} + c_i & \text{else if } \; T\min < Tn_{95} < Topt\min \\ a_i \cdot Topt^2_{\min} + b_i \cdot Topt_{\min} + c_i & \text{else if } \; Topt\min < T_{95} < Topt\max \\ \left(d_i \cdot T^2_{95} + e_i \cdot T_{95} + g_i\right) + \left[\left(a_i \cdot Topt^2_{\min} + b_i \cdot Topt_{\min} + c_i\right) - \left(d_i \cdot Topt^2_{\max} + e_i \cdot Topt_{\max} + g_i\right)\right] & \text{else } \; T_{95} > Topt\max \end{cases}$$

Where:

HRY*i* (%) is the simulated HRY value;

Tn_{95th} (°C) is the 95th percentiles of nighttime air temperature frequencies that occurred during the R8 phase of rice ripening;

$Topt_{min}$ (°C) and $Topt_{max}$ (°C) respectively represent the minimum and optimum temperatures for the synthesis of starch in the rice grain;

T_{min} (°C) represents the minimum temperature threshold for the starch synthesis.

a_i, (0.6073 for Loto variety, -0.1791 for Gladio variety; unitless) b_i, (-27.848 for Loto variety, 8.5375 for Gladio variety; unitless) c_i (379.5568 for Loto variety, - 36.1533 for Gladio variety; unitless) are variety-specific coefficients of the equation;

d_i, (-0.39685 for Loto variety, -0.1791 for Gladio variety; unitless), e_i, (20.585 for Loto variety, 8.5374 for Gladio variety; unitless), g_i (-202.89 for Loto variety, -0.1791 for Gladio variety; unitless) are variety-specific

In particular the actual HRY (HRYc) is computed by subtracting from the potential value of HRY the variety-specific reduction in HRY experimentally determined for the study area (parameter e, %) when rainfall (RainC), wind (WindTh) and temperature (T95em) regimes simultaneously exceed specific critical thresholds within the sensitive period after flowering:

$$HRY_c = \begin{cases} HRY_i - e & \text{if } T95_{em} > Topt_{\max} \cap RainC < RainTh \cap WindyD > WindTh \\ HRY_i & \text{else} \end{cases}$$

Where:

HRY*c* (%) is the actual value of HRY;

e (%) (%) is a variety-specific coefficient representing the HRY reduction due to critical humidity, wind and temperature conditions with respect to the average values of HRY for the simulated variety;

Tn_{95thp} (°C) is the 95th percentiles of nighttime air temperature frequencies that occurred during the early maturity (2<DVS<2.5);

RainC (mm) is the minimum threshold of cumulated rainfall triggering HRY decrease;

WindyDays (day) is the number of days with average wind speed higher than a critical threshold,(WindyTh, m s^{-1}) to start HRY decrease.

The new approach has been developed and parameterized for Loto (*Japonica*) and Gladio (*Indica*) Italian rice varieties, using field data collected by the National Rice Authority (ENR; www.enterisi.it) in the Lombardo-Piemontese district (Major European rice district - northern Italy) during the seasons 2006–2013.

Design and Use

Project documentation

Model diagram

UNIMI.Cassandra.RiceQuality is a .NET software library implementing multiple modelling approaches to the simulation of rice grain quality variables; the component is independent from both the framework and the crop simulator used. The architecture of the component (Donatelli and Rizzoli, 2008) promotes its extension by third parties via the implementation of alternative model realizations for variables already simulated, as well as via the inclusion of approaches for the simulation of new variables. The models available in the components can be accessed at different levels, thus allowing users to select just one of the approaches for peak viscosity, or to run all the models for assessing the viscosity profile. In order to foster the usability of the component, two typologies of users were identified: (i) beginners, i.e., users without specific expertise in quality variables and models, and (ii) experts, represented by specialists in rice quality modelling The diagram that displays the strategies that UNIMI.CropQuality component makes available is showed below (Figure 15).

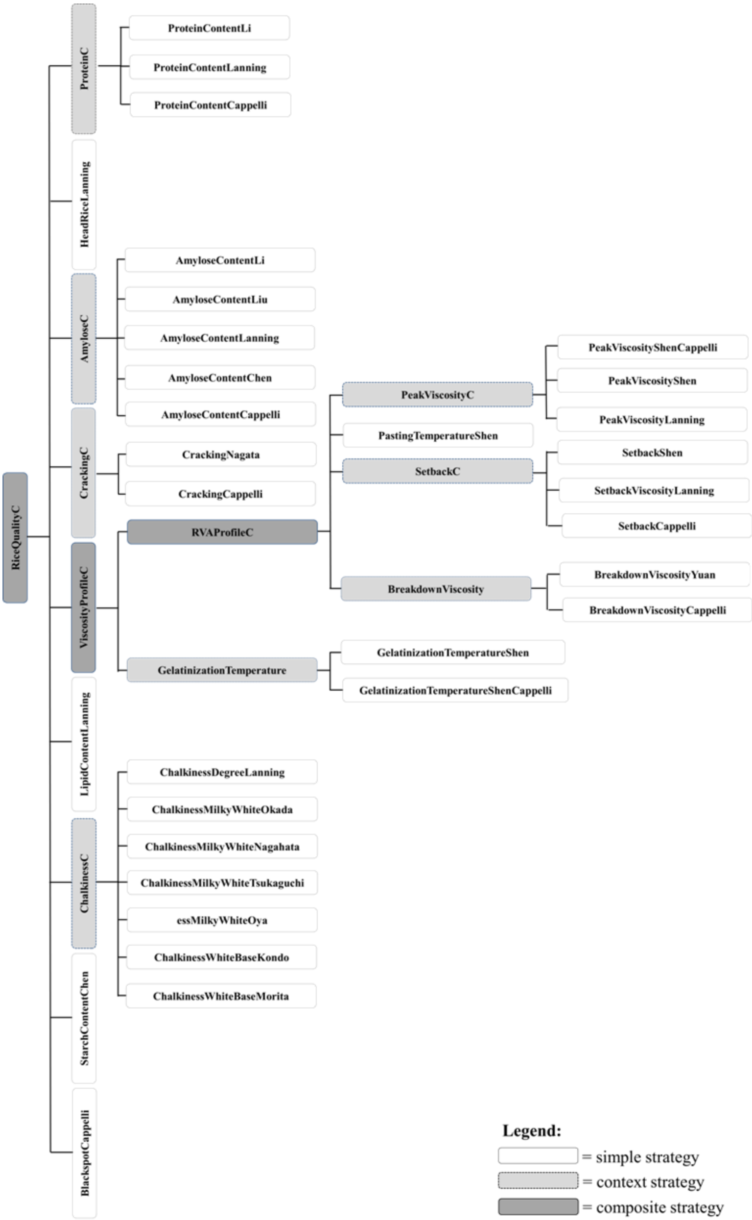


Figure 15. Strategy diagram of UNIMI.RiceQuality component.

Furthermore a customized composite strategy (*Figure 16*) is now available to assess the quality profile of rice grain in the Lombardo-Piemontese district, the main rice area in Europe. This strategy allows the user to simulate at the same time the following ten variables: protein and amylose concentration, head rice yield, the percentage incidence of broken, chalky and black spotted grains, peak viscosity, breakdown viscosity, setback viscosity and gelatinization temperature. The included models are currently calibrated for Loto and Gladio rice varieties, two of the most representative cultivars of Northern Italy.

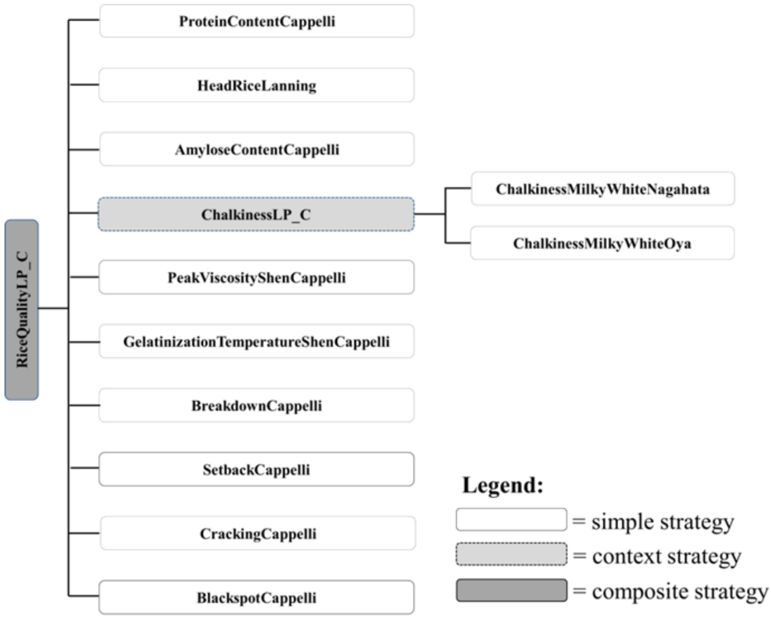


Figure 16. Strategy diagram of UNIMI.RiceQuality component customized for the Lombardo-Piemontese district.

Design by contract

The component implements a design by-contract approach (Meyer, 1997). This approach uses assertions as pre-conditions, post-conditions of methods, and class invariants, that is a class can be viewed as having a contract with its clients whereby the class guarantees to provide certain results (post-conditions of its methods) provided that the clients agree to satisfy certain requirements (pre-conditions of the class methods).

The design-by-contract approach implementation in UNIMI.Cassandra.RiceQuality includes an option for testing pre-conditions and post-conditions via a dedicated component. The Estimate public method in the UNIMI.Cassandra.RiceQuality classes has two overloads, one of which allows testing pre-conditions and post-conditions. The test of pre-conditions is also always made (in both overloads) if an exception occurs, and the test result is shown in the error message box which is shown. If the pre-conditions are not respected, an exception may occur and an error message is shown, allowing continuing the client run.

Domain classes

These are the domain classes of UNIMI.Cassandra.RiceQuality component:

- Exogenous
- External State
- Rates

- External Rates
- States
- Auxiliary

Exogenous

Name	MinValue	MaxValue	DefaultValue	Units	Type	Description
AirTemperatureMax	-30	50	20	°C	double	Maximum air daily temperature
AirTemperatureMin	-40	40	10	°C	double	Minimum air daily temperature
Altitude	-100	8000	0	m	double	Altitude of site above sea level
DailyRain	0	300	20	mm	double	Daily precipitation
DailyWindSpeed	0	500	1	m s-1	double	Average daily wind speed
GlobalRadiation	0.05	42	25	MJ m-2 d-1	double	Daily global solar radiation
Hour	0	24	0	h	int	Hour of the day
HourlyTemperature	-40	50	20	°C	double[24]	Hourly temperature
Latitude	-90	90	0	°	double	Latitude of site
PotentialEvapotranspiration	0	15	6	mm d-1	double	Potential Evapotranspiration
RelativeHumidityMax	0	100	90	%	double	Maximum air relative humidity
RelativeHumidityMin	0	100	60	%	double	Minimum air relative humidity
SunriseHour	0	24	6	h	double	Time (hour) of sunrise
SunsetHour	0	24	18	h	double	Time (hour) of sunset

External States

Name	MinValue	MaxValue	DefaultValue	Units	Type	Description
DevelopmentStageCode	0	4	0	unitless	double	DevelopmentStageCodeaboveground biomass daily rate accumulation after anthesis
GrowingDegreeDays	0	10000	400	°C d-1	double	GrowingDegreeDays
StemsDryWeight	0	20000	10000	Kg ha-1	double	Stems dry weight on day i
LeavesDryWeight	0	15000	4000	Kg ha-1	double	Leaves dry weight on day i
TotalAbovegroundBiomass	0	50000	15000	Kg ha-1	double	Aboveground biomass dry weight on day i
GrainDryWeight	0	20000	6000	Kg ha-1	double	Grain dry weight on day i

Rates

Name	MinValue	MaxValue	DefaultValue	Units	Type	Description
AmyloseAccumulationRate	0	3	1	% d-1	double	Daily rate of amylose accumulated in the grain during the ripening period
DevelopmentStageCodeRate	0	1	0	°C d -1	double	Rate of development stage code
GrowingDegreeDaysRate	0	50	20	°C d-1	double	Rate of growing degree days
IndividualAssimilateSupply	0	10	2	mg grain-1 d-1	double	Rate of assimilate supply of carbohidrates per grain
IndividualGrainCarbonRateRestricted	-10	10	0.8	mg grain-1 d-1	double	Individual grain starch accumulation rate restricted by source or sink on day i
IndividualStarchRateSinkRestricted	-10	10	0.8	mg grain-1 d-1	double	Individual grain starch accumulation rate restricted by sink on day i
IndividualStarchRateSourceRestricted	-10	10	0.8	mg grain-1 d-1	double	Individual grain carbon rate available on day i from source
TotalGrainCarbonAvailableRate	-10000	10000	0	g m-2 d-1	double	Daily rate of total grain carbon available on day i from source

External Rates

Name	MinValue	MaxValue	DefaultValue	Units	Type	Description
AbovegroundBiomassDailyRate	-500	5000	300	Kg ha-1 d-1	double	Total aboveground biomass daily rate accumulation after anthesis
LeavesWeightDailyRate	-500	2000	50	Kg ha-1 d-1	double	Total leaves weight daily rate accumulation after anthesis
StemsWeightDailyRate	-500	3000	150	Kg ha-1 d-1	double	Total stems weight daily rate accumulation after anthesis
WaterStressFactor	0	1	1	unitless	double	Impact of water stress status on grain starch accumulation rate
GrainBiomassRate	0	5000	50	Kg ha-1 d-1	double	Total grain weight daily rate accumulation after anthesis
NitrogenStressFactor	0	1	1	unitless	double	Impact of nitrogen stress status on grain starch accumulation rate

States

Name	MinValue	MaxValue	DefaultValue	Units	Type	Description
BlackSpotGrainPercentageStatic	0	100	0	%	double	Percentage of rice kerr
BreakdownViscosityDynamic	0	5000	1800	centipoise	double	Index representing the
BreakdownViscosityStatic	0	5000	1800	centipoise	double	Index representing the
ChalkinessDegreeDynamic	0	100	0	%	double	Chalkiness degree, as
ChalkinessDegreeStatic	0	100	0	%	double	Chalkiness degree, as
ChalkyGrainPercentageImmatureBaseDynamic	0	100	0	%	double	Percentage of rice kerr
ChalkyGrainPercentageImmatureBaseStatic	0	100	0	%	double	Percentage of rice kerr
CrackedGrainPercentageDynamic	0	100	0	%	double	Percentage of fissured
CrackedGrainPercentageStatic	0	100	0	%	double	Percentage of fissured
GelatinizationTemperatureDynamic	0	100	72	°C	double	The temperature at whi
GelatinizationTemperatureStatic	0	100	72	°C	double	The temperature at whi
GrainAmyloseContent	0	40	20	% grain-1	double	Amylose content as a p
GrainProteinContent	0	15	7	% grain-1	double	Protein content as a pe
HeadRiceYieldDynamic	0	100	100	%	double	Mass percentage of rou
HeadRiceYieldStatic	0	100	100	%	double	Mass percentage of rou
IndividualGrainStarchAccumulated	0	1000	20	mg g-1	double	Individual grain starch
MilkyWhiteChalkyGrainPercentageDynamic	0	100	0	%	double	Percentage of rice kerr
MilkyWhiteChalkyGrainPercentageStatic	0	100	0	%	double	Percentage of rice kerr
NitrogenStressRipening	0	1	1	unitless	double	Stress factor due to nit
PastingTemperatureDynamic	40	100	75	°C	double	The temperature at wh
PastingTemperatureStatic	40	100	75	°C	double	Pasting Temperature is
PeakViscosityDynamic	0	5000	2500	centipoise	double	Maximum value of satr
PeakViscosityRVUStatic	0	1000	250	RVU	double	Maximum value of satr
PeakViscosityStatic	0	5000	2500	centipoise	double	Maximum value of satr
RelativeDailySolubleSugarLeaves	0	10	7	% grain-1	double	Relative soluble sugar
RelativeDailySolubleSugarStems	0	20	10	% grain-1	double	Relative soluble sugar
RelativeGrainStarchContent	0	84	78	% grain-1	double	Individual grain starch
SetbackDynamic	-800	5000	300	centipoise	double	Setback represent the
SetbackStatic	-800	5000	300	centipoise	double	Index representing the
SetbackViscosityRVUStatic	-1000	1000	50	RVU	double	Index representing the
TotalCarbonAssimilationPhotosyntheticOrgans	0	10000	5000	g m-2	double	Carbon assimilation fr
TotalGrainCarbonAvailable	0	80000	30000	g m-2	double	Total grain carbon avai
TotalLipidContentDynamic	0	5	2	% grain -1	double	Total lipid content of rc
TotalLipidContentStatic	0	5	2	% grain -1	double	Total lipid content of rc
TotalSolubleSugarDailyLeaves	0	1400	600	g m-2	double	Total soluble sugar cor
TotalSolubleSugarDailyStems	0	1400	700	g m-2	double	Total soluble sugar cor
TotalSolubleSugarDailyVegetativeOrgans	0	2800	1300	g m-2	double	Total soluble sugar cor

Auxiliary

Name	MinValue	MaxValue	DefaultValue	Units	Type	Description
AccumulatedRainfallFromFlowering	0	1000000	200	mm	double	Value of accumulated precipita
AccumulatedRainfallFromHeading	0	1000000	200	mm	double	Value of accumulated precipita
AmyloseAverageTemperatureFactor	0	100	1	unitless	double	Lowering effect of average dail
AmyloseLatitudeFactor	0	100	1	unitless	double	Lowering effect of latitude on g
AmyloseMaximumTemperatureFactor	0	100	1	unitless	double	Lowering effect of maximum da
AmyloseMinimumTemperatureFactor	0	100	1	unitless	double	Lowering effect of minimum dai
AmyloseRadiationFactor	0	100	1	unitless	double	Lowering effect of daily photosy
AverageET0AfterHeading	0	15	6	mm d-1	double	Average values of potential eva
AverageGlobalRadiationFromFlowering	0	45	25	MJ m-2 d-1	double	Average values of global solar
AverageIndividualAssimilateSupplyRipening	0	10	2	mg grain-1	double	Average value of assimilate car
AverageMaximumAirHumidityFromFlowering	0	100	90	%	double	Average value of maximum air
AverageMaxTempAfterFlowering	0	50	25	°C	double	Average maximum temperature
AverageMaxTempAfterHeading	-10	50	20	°C	double	Average maximum temperature
AverageTempAfterFlowering	-10	40	15	°C	double	Average temperature during ri
AverageTempAfterHeading	-10	40	15	°C	double	Average temperature after Hea
AverageTemperatureSum	0	10000000	100	°C	double	Average air temperature sum
AverageThermalExcursionAfterHeading	0	60	10	°C	double	Average values of daily temper
AverageWindSpeedAfterFlowering	0	50	2	m s-1	double	Average wind speed after flowe
AverageWindSpeedSumAfterFlowering	0	10000	0	m s-1	double	Average wind speed sum after
ConsecutiveDryDaysAfterHeading	0	100	0	d	int	Number of consecutive non-rai
Cultivar	0	15000	1	unitless	string	cultivar key for parameter file
DailyHumidityDifference	0	100	30	%	double	Daily difference between maxin
DailyThermalExcursion	0	40	10	°C	double	Daily temperatures excursion a
DaysFromFlowering	0	100	1	d	int	Accumulated days from flowerir
DaysFromHeading	0	100	1	d	int	Accumulated days from heading
DaysWithHighHumiditySum	0	100	0	d	int	Number of days after heading w
DaysWithHighThermalExcursionSum	0	100	0	d	int	Number of days after heading w
DryDaysAfterHeading	0	100	0	d	int	Number of non-rainy days after
EffectiveWeightedTempMWDamSum	0	5000	100	°C	double	Accumulated effective weighted
ET0AfterHeadingSum	0	10000	100	mm	double	Sum of potential evapotranspira
GrainsNumber	0	80000	38000	grain m-2	double	Grain number of rice plant
GrowingDegreeDaysAtFlowering	0	500000	10	°C d-1	double	growing degree days at floweri
IndividualAssimilateSupplySum	0	10000	1000	mg grain-1	double	Sum of daily assimilate carboh
IndividualGrainWeight	0	100	25	mg grain -1	double	Individual grain dry weight on d
MaximumAirHumiditySumAfterFlowering	0	1000000	100	%	double	Sum of values of maximum air
MAximumConsecutiveDryDays	0	1000	0	d	int	Number of maximum consecuti
MaximumTemperatureSum	0	10000000	100	°C	double	Maximum air temperature sum
MaximumWindSpeedAfterHeading	0	50	2	m s-1	double	Maximum wind speed observe
MinimumAirHumidityOfYesterday	0	100	60	%	double	Value of minimum air humidity
MinimumHumidityAfterHeading	0	100	50	%	double	Minimum value of air humidity
MinimumHumiditySumFromHeading	0	1000000	0	%	double	Sum of daily values of minimum
MinimumTemperatureList	0	10000	20	unitless	List<double>	List of minimum temperature v
MinimumTemperatureSum	-100	40000000000	200	days	double	Sum of minimum air temperatu
NightTemperatureList	-50	55	10	°C	List<double>	List of night temperature during
NightTemperatureListProtein	-50	55	10	°C	List<double>	List of night temperature during
NitrogenStressSum	9	10000	100	unitless	double	Sum of nitrogen stress rates du
PreviousConsecutiveDryDaysSeries	0	1000	0	d	int	Number of maximum consecuti
ProteinAltitudeFactor	0	100	1	unitless	double	Lowering effect of altitude abo
ProteinAverageTemperatureFactor	0	100	1	unitless	double	Lowering effect of average dail
ProteinEcologicalHeightFactor	0	100	1	unitless	double	Lowering effect of ecological h
ProteinLatitudeFactor	0	100	1	unitless	double	Lowering effect of latitude on g
ProteinLimitationDueToTemperatureSum	0	10	0	%	double	Percentage of protein losses d
ProteinMaximumTemperatureFactor	0	100	1	unitless	double	Lowering effect of maximum da
ProteinMinimumTemperatureFactor	0	100	1	unitless	double	Lowering effect of minimum dai
RainOfYesterday	0	250	10	mm	double	Daily prcipitation of the day be
RainyDaysAfterHeading	0	100	0	d	int	Number of rainy days after hea
SetbackLimitationDueToTemperatureSum	0	500	0	BU	double	Setback reduction due to subo
SolarRadiationSum	0	10000000	650	MJ m-2 d-1	double	Accumulated global solar radia
StarchSynthesisAbility	0	1	1	unitless	double	Ability for starch synthesis in g
StrategyUsed	0	0	0	unitless	List<string>	Strategy selected
TemperatureFactorAmylose	0	1	1	unitless	double	Temperature impact factor on a
TemperatureFactorProtein	0	1	1	unitless	double	Temperature impact factor on
TemperatureFactorStarch	0	1	1	unitless	double	Temperature impact factor on s
TemperatureSumFromHeading	0	1000000	20	°C	double	Temperature sum from heading
ThermalExcursionSumAfterHeading	0	100000	500	°C	double	Sum of daily temperatures exc
Tnight95th	-40	40	15	°C	double	95th percentiles of nighttime air
TotalVegetativeWeight	0	40000	10000	Kg ha-1	double	Total weight of vegetative orga
TotalVegetativeWeightYesterdays	0	40000	10000	Kg ha-1	double	Total weight of vegetative orga
WindSpeedOfYesterday	0	50	2	m s-1	double	Value of average daily wind sp
WindyDaysAfterFlowering	0	10000	0	d	int	Number of days after flowering
WindyDaysAfterHeading	0	10000	0	d	int	Number of days after heading w

Unit tests

RiceQualityLP_C

Inputs variables to carried out the test are summarized in the following table, where i) maximum and minimum air temperature (°C), ii) daily wind speed (m s^{-1}), iii) global solar radiation (MJ m^{-2} d^{-1}), iv) minimum and maximum relative air humidity (%), v) reference evapotranspiration (mm d^{-1}) are given for the first 50 days after flowering. Conversely hourly air temperature (°C), sunrise and sunset hour (h) are given as fixed input data.

DAF	TMAX	TMIN	WIND	RADIATION	RHmax	RHmin	Rain	ET0	Fixed Input variables
1	31.8	19.8	1.4	27.46	91.5	45.8	0.0	8.00	Sunrise Hour
2	31.05	19.05	1.4	26.67	93.7	46.5	0.0	7.62	8
3	29.6	18.6	1.6	23.60	96.0	58.3	0.0	6.65	Sunset Hour
4	25.55	21.55	2.5	26.40	96.0	35.5	0.2	7.26	20
5	26.2	22.2	2.4	27.64	93.8	39.3	0.0	7.74	Hourly Temperature
6	26.8	22.8	1.8	26.21	94.5	44.8	0.0	7.44	22.28
7	27.2	23.2	1.9	23.32	93.2	41.8	0.0	6.66	
8	27.5	23.5	1.5	25.55	88.5	36.2	15.0	7.37	
9	25.25	21.25	2	21.01	92.8	55.3	0.0	5.70	
10	26.1	22.1	4.3	22.30	94.8	49.0	0.0	6.19	
11	25.4	25.4	1.8	22.17	93.2	51.0	0.0	6.36	
12	26.1	26.1	1.4	24.02	93.5	51.7	0.0	7.02	
13	24.9	24.9	1.3	23.68	92.0	46.3	0.0	6.72	
14	27.3	27.3	1.7	23.34	89.5	45.8	0.0	7.02	
15	27.3	27.3	2.1	24.67	94.5	40.5	0.0	7.43	
16	28.15	28.15	2.3	25.46	93.0	40.7	0.0	7.83	
17	28.3	28.3	1.5	25.72	94.7	42.5	0.0	7.94	
18	28.5	28.5	1.5	24.35	95.7	38.5	0.0	7.54	
19	28.55	28.55	1.6	24.61	96.7	50.5	0.0	7.63	
20	26.85	26.85	2.1	23.23	94.2	49.3	0.0	6.91	
21	27.1	27.1	1.7	23.15	95.7	46.3	0.0	6.93	
22	26.45	26.45	2.2	23.07	95.2	23.5	0.0	6.80	
23	24.4	24.4	1.4	22.47	89.3	32.0	0.0	6.29	
24	21	21	1.6	23.81	88.0	37.8	0.0	6.10	
25	21.6	21.6	1.7	22.81	94.5	36.2	0.0	5.93	
26	22.9	22.9	4.3	24.70	96.0	48.0	0.0	6.67	
27	20.3	20.3	1.8	15.88	97.0	59.8	6.6	3.93	
28	18.85	18.85	1.4	16.09	94.8	57.5	2.4	3.83	
29	17.35	17.35	1.3	17.26	94.3	57.5	26.8	3.93	
30	19.25	19.25	1.7	19.43	96.0	57.5	0.0	4.71	
31	18.75	18.75	2.1	11.33	96.7	57.5	6.2	2.64	
32	20.15	20.15	2.3	14.43	95.0	57.5	14.6	3.54	
33	22.6	22.6	1.5	19.72	94.5	57.5	4.0	5.25	
34	23.2	23.2	1.5	22.08	96.8	57.5	0.0	5.99	
35	22.7	22.7	1.6	21.88	95.5	57.5	0.0	5.86	
36	23.1	23.1	2.1	21.09	96.2	57.5	0.0	5.70	
37	22.7	22.7	1.7	21.34	96.3	57.5	0.0	5.71	
38	22.55	22.55	2.2	22.75	73.3	57.5	0.0	6.07	
39	22.45	22.45	1.4	21.99	86.0	57.5	0.0	5.85	
40	19.6	19.6	1.6	20.46	92.8	57.5	0.0	5.02	
41	16.9	16.9	1.7	19.39	94.5	57.5	0.0	4.38	
42	16.5	16.5	1.7	22.84	93.5	57.5	0.0	5.13	
43	16.7	16.7	1.7	21.99	95.0	57.5	0.0	4.96	
44	18.6	18.6	1.7	20.74	92.0	60.0	0.0	4.94	
45	18.95	18.95	1.7	20.34	87.5	60.0	0.0	4.89	
46	19	19	1.7	20.06	92.2	60.0	0.0	4.83	
47	21.6	21.6	1.7	15.18	86.3	60.0	0.0	3.89	
48	17.25	17.25	1.7	17.56	96.0	60.0	0.0	3.99	
49	15.7	15.7	1.7	17.99	95.0	60.0	0.0	3.90	
50	18.25	18.25	1.7	15.57	94.0	60.0	0.0	3.63	

The set of parameters values used to simulate the Gladio variety (*Indica* type) within the unit test were:

```
IsIndicaCultivar = true;
GrainLength = "Gladio";
TemperatureThresholdForAmylose = 23;
HumidityThreshold = 50;
AverageCracking = 6.01557643909629;
WindSpeedThresholdCracking = 1.7;
IrrigationManagement = "IRR";
AverageBlackSpot = 3.40680440771435;
ThermalExcursionThreshold = 10;
ReferenceGrainProteinContent = 5.77188213923176;
MinimumTemperatureProteinAccumulation = 18.5242765550973;
LowerTemperatureOptimalProteinAccumulation = 23.5939856861738;
MaximumTemperatureProteinAccumulation = 35;
HigherTemperatureOptimalProteinAccumulation = 28.9486210298357;
VarietySensitivitySuboptimaltemperatureProteinSynthesis = 0.691066654696866;
DurationSensitivitySuboptimaltemperatureProteinSynthesis = 15.5327258121946;
WindSpeedThreshold = 2;
CumulatedRainTreshold = 14;
WindyDaysNumberThreshold = 10;
MinimumNighttimeTemperatureStarchAccumulation = 17;
LowerNighttimeTemperatureOptimalStarchAccumulation = 25.8;
HigherNighttimeTemperatureOptimalStarchAccumulation = 26.5;
AverageHryUnderestimation = 1.7;
DamageTresholdTemperatureAvg = 14.200954;
SowingDensityEffect = 11.0376789;
ReferenceBreakdown = 597.504932847037;
ReferenceMaximumAmyloseAccumulationRate = 1.158488128;
MinimumTemperatureAmyloseAccumulation = 16.3587823217269;
LowerTemperatureOptimalAmyloseAccumulation = 25;
MaximumTemperatureAmyloseAccumulation = 37.3767462150776;
HigherTemperatureOptimalAmyloseAccumulation = 28.7416944512054;
VarietySensitivitySuboptimaltemperatureAmyloseSynthesis = 0.478651070312374;
StartSensitivitySuboptimaltemperatureAmyloseSynthesis = 4.53750632038129;
EndSensitivitySuboptimaltemperatureAmyloseSynthesis = 16.4796235165887;
```

The expected outputs are given instead in the following table, where i) grain amylose content (%), ii) percentage of cracked grains (%), iii) incidence of black spot damage (%), iv) grain protein content (%), v) Head Rice Yield (%), vi) occurrence of chalky grains (%), vii) peak viscosity (BU), viii) breakdown viscosity (BU), ix) setback viscosity (BU), x) gelatinization temperature (°C) are given at maturity (DVS =3).

```
Days from Flowering = 50
DVS = 3.00450000000001
GrainAmyloseContent = 25.1178329176121
CrackedGrainPercentageStatic = 5.55477987812199
BlackSpotGrainPercentageStatic = 13.1803813241522
Protein = 6.27669166623542
HeadRice = 65.1719716457225
Chalky grains = 1.1231556957
Peak Viscosity = 1050.10529571747
Breakdown Viscosity = 547.229218658437
Setback Viscosity = 786.728300694234
Gelatinization Temperature = 78.1933552284423
```

The set of parameters values used to simulate the Loto variety (*Japonica* type) within the unit test were:

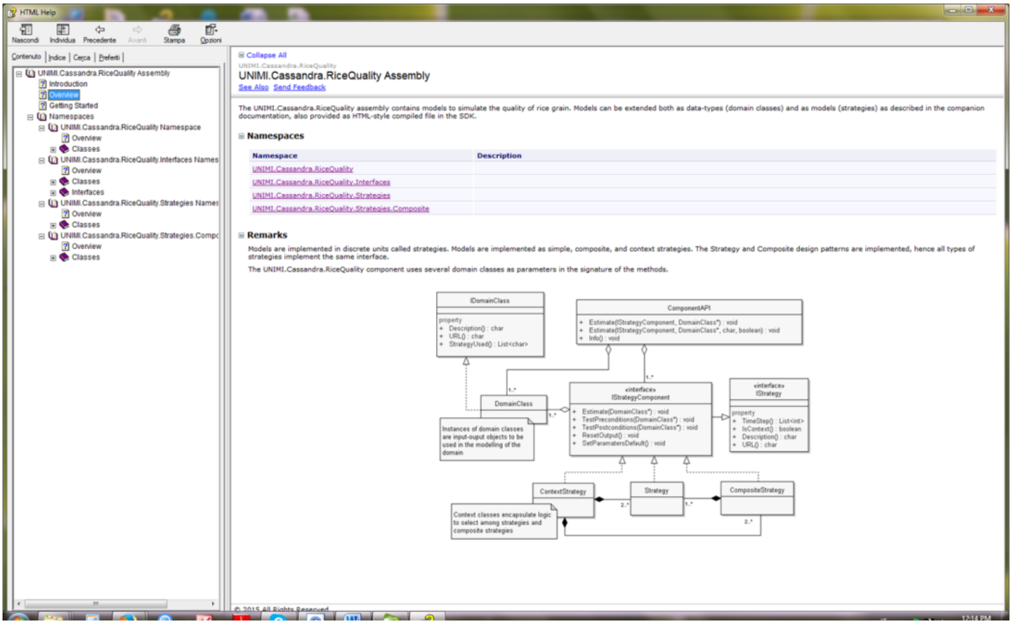
```
IsIndicaCultivar = false;
GrainLength = "Loto";
TemperatureThresholdForAmylose = 22.9717497841304;
HumidityThreshold = 50;
AverageCracking = 8.91180063002711;
WindSpeedThresholdCracking = 1.7;
IrrigationManagement = "DRY";
AverageBlackSpot = 8.16650693388185;
ThermalExcursionThreshold = 10;
ReferenceGrainProteinContent = 6.53847952542544;
MinimumTemperatureProteinAccumulation = 17.530114592667;
LowerTemperatureOptimalProteinAccumulation = 23.85924227;
MaximumTemperatureProteinAccumulation = 35.0927340805981;
HigherTemperatureOptimalProteinAccumulation = 27.74381295;
VarietySensitivitySuboptimaltemperatureProteinSynthesis = 0.543719249743645;
DurationSensitivitySuboptimaltemperatureProteinSynthesis = 15.1536625416685;
WindSpeedThreshold = 2;
CumulatedRainTreshold = 7;
WindyDaysNumberThreshold = 10;
MinimumNighttimeTemperatureStarchAccumulation = 23;
LowerNighttimeTemperatureOptimalStarchAccumulation = 25.8;
HigherNighttimeTemperatureOptimalStarchAccumulation = 26.5;
AverageHryUnderestimation = 5.4;
DamageTresholdTemperatureAvg = 17.16838379;
SowingDensityEffect = 11.98675003;
ReferenceBreakdown = 613.174883321541;
ReferenceMaximumAmyloseAccumulationRate = 0.55205677;
MinimumTemperatureAmyloseAccumulation = 16.3361686272317;
LowerTemperatureOptimalAmyloseAccumulation = 21.6002138938109;
MaximumTemperatureAmyloseAccumulation = 39.9836731299432;
HigherTemperatureOptimalAmyloseAccumulation = 26.1802720609144;
VarietySensitivitySuboptimaltemperatureAmyloseSynthesis = 0.546532734525182;
StartSensitivitySuboptimaltemperatureAmyloseSynthesis = 15.3475624278453;
EndSensitivitySuboptimaltemperatureAmyloseSynthesis = 33.8336118672914;
```

The expected outputs are given instead in the following table, where i) grain amylose content (%), ii) percentage of cracked grains (%), iii) incidence of black spot damage (%), iv) grain protein content (%), v) Head Rice Yield (%), vi) occurrence of chalky grains (%), vii) peak viscosity (BU), viii) breakdown viscosity (BU), ix) setback viscosity (BU), x) gelatinization temperature (°C) are given at maturity (DVS =3).

```
Days from Flowering = 50
DVS = 3.00450000000001
GrainAmyloseContent = 15.99170476766
CrackedGrainPercentageStatic = 10.1845980277958
BlackSpotGrainPercentageStatic = 5.63103590339377
Protein = 6.60144936926494
HeadRice = 60.3264339208969
Chalky grains = 4.37354436819465
Peak Viscosity = 1128.24486925094
Breakdown Viscosity = 735.734766039573
Setback Viscosity = 624.911153707072
Gelatinization Temperature = 70.30897270084
```

Code documentation

Code is documented via a compiled HTML-style file, as shown in the image below.



Preconditions

Abstract

The UNIMI.Cassandra.RiceQuality component uses CRA.Core.Preconditions assembly (.NET), a component developed to make numeric tests of pre-conditions and post-conditions in clients of different types. This component was developed having as main target software components implementing agro-ecological models. In fact, pre-conditions and post-conditions are not only useful, when tested, to get all the advantages of the design-by-contract approach, but they are also an essential part of model documentation. Furthermore, the clear definition of pre-conditions and post-conditions is of great help during the development of agro-ecological model components; in fact, it allows the modeller to more easily define unit tests by narrowing the ranges of inputs and outputs to be tested. A top requirement for the design of this component was to make its use in clients as simple as possible. As a side effect, the information passed from the client to the component might be, in some cases, slightly redundant, but we believe this is widely compensated by its ease of use. The component provides some output options for showing/storing tests results (screen, txt file, XML file), but its design also allows clients to easily define custom outputs.

The VarInfo data-type

The VarInfo data-type is used to make available information about each public variable / parameter in components. By defining an attribute as a VarInfo type, the attributes description, Name, MaxValue, MinValue, DefaultValue, CurrentValue, Units, and URL become available as set / get methods.

Properties of the VarInfo type Copy Code

```
/// <summary>Variable name </summary>
string Name { get; set; }
/// <summary>Variable description </summary>
string Description { get; set; }
/// <summary>Maximum value allowed</summary>
double MaxValue { get; set; }
/// <summary>Minimum value allowed</summary>
double MinValue { get; set; }
/// <summary>Default value</summary>
double DefaultValue { get; set; }
/// <summary>Current value</summary>
object CurrentValue { get; set; }
/// <summary>Units, not used for pre and post-conditions tests </summary>
string Units { get; set; }
/// <summary>Variable description URL</summary>
string URL { get; set; }
```

Developing an output driver

A custom driver is a class implementing the ITestsOutput interface. It must be developed in the domain of a client, without any need to recompile CRA.Core.Preconditions.dll and using the same calls. As an example, lets look at the code of the TestsOutputDefault class:

Parameters

Parameters (properties) of this output driver Copy Code

```
#region Parameters

private static string localLogFileName = "PrePostConditionsLog.txt";
```

```
/// <summary>
/// Name of the txt file to output pre and post conditions test results.
/// The default name is PrePostConditionsLog.txt, saved on the same directory where
/// the CRA.Core.Preconditions component is saved; a path can be specified.
/// </summary>
public static string LogFileName
{
get { return localLogFileName; }
set { localLogFileName = value; }
}

#endregion
```

Here the output destination is defined as a file name. Other parameters might be added.

ITestOutput members

Text output driver Copy Code

```
#region ITestsOutput Members

/// <summary>
/// This methods allows saving on file the tests results.
/// </summary>
/// <param name="result">a string containing all tests results</param>
/// <param name="saveLog">false=on screen, true=on file</param>
/// <param name="componentName">the name of the component</param>
public void TestsOut(string result, bool saveLog, string componentName)
{
if (saveLog == false)
{
//display on screen
System.Windows.Forms.MessageBox.Show(result, componentName + " - Violation of pre/post-
conditions");
}
else
{
//save on file localLogFileName
DateTime dt = DateTime.Now;
FileStream file = new FileStream(localLogFileName,
FileMode.Append,
FileAccess.Write);
StreamWriter sw = new StreamWriter(file);
sw.WriteLine(componentName + " - " + dt + "\r\n" + result);
sw.Close();
file.Close();

#endregion
```

Strategies

Design summary

The following is an excerpt from the paper Donatelli and Rizzoli 2007 referenced in the [references page](#) which summarizes requirements identified to build re-usable components, and which are matched by the design proposed and implemented.

The design

The re-usability of software components can be enhanced by addressing the following requirements: 1. The component must target the solution of a sufficiently widespread modeling problem; 2. The published interface of the component must be well documented and it must be consistent, 3. The configuration of the component should not require excessive pre-existing knowledge and help should be provided in the definition of the model parameters 4. the model implemented in the component should be extensible by third parties, 5. The dependencies on other components should be limited and explicit, 6. The behavior of the component should be robust, and degrade gracefully, raising appropriate exceptions, 7. The component behavior should be traceable and such a trace should be scalable (browsable at different debug levels), and 8. The component software implementation should be made using technologies with a widespread adoption. There are a number of solutions to address these requirements and we present the choices made for the design we have used in some components we have developed.

1. Targeting an explicit common modeling problem is associated with the granularity of the modeling approach. Fine grained components are more likely to be reused for specific computations, in the context of larger modeling problems. Simple model units can either be used in isolation or they can be composed to develop other modeling units. An example are the CLIMA components (Donatelli et al. 2006a; Carlini et al., 2006) which implement fine-grained models that generate synthetic weather variables. The component architecture adopts the Strategy design pattern in order to allow for the plugging-in of alternative model formulations to generate the model output, since various models can be used for the same purpose. The components referenced above match such requirements. A large coarse-grained component that simulates groundwater transport of a contaminant over a region might require a very complex configuration. This does not mean that large components are not reusable, but the effort to reuse them is bigger.

2. Components depend on the data they access (inputs, parameters, states etc.). Such data can be described and implemented by means of data structures called Domain Classes (Del Furia et al., 1995). Each attribute of such classes will also have, beside its value, a set of attributes such as minimum, maximum, and default value; units; description, and may refer to a publicly available ontology via the attribute URL. Reflection can be used on such types thus allowing access to their ontology. The values of domain classes goes beyond their meaning as software implementation items, in fact they describe the domain of interest. The use of domain classes is equally valid for static and dynamic components (e.g., Acutis et al., 2007; Trevisan et al., 2007). If domain classes and interfaces are implemented in a separate discrete unit from models, the model unit can be replaced without affecting the client using the components (this is the Bridge design pattern). A component implementing domain classes and interfaces and another implementing models are a *unit of reuse*; the model component alone can be defined as a *unit of interchangeability*.

3. The API of the component must implement a pattern like the Create-Set-Call; objects are created via a default constructor, some attributes are set, and finally the model is

called. The interface used for models should be the same for all modeling solutions in the component, implementing the Façade pattern to hide the complexity of each model solution. This leads to having a unique signature for internal and (see below) extended models. Such unique signature (its first overload in its simplest form), can be like: Update(DomainClass d, IStrategy s);being dan input-output object. Components should be stateless, to simplify their use in different systems. Sample clients, inclusive of code, must be made available.

4. The component must expose public interfaces to allow extensibility by third parties without requiring the re-compilation of the component, and to allow freedom of implementation. Components can be extended inheriting also from domain classes to extend them,

5. While dependencies should be kept at a minimum, we found necessary and particularly useful to introduce a dependency to another component, available both in .NET and Java (http://www.apesimulator.it/help/utilities/preconditions) which implements the Design-by-contract approach (see next point), and provides a type (*VarInfo*) to set the attributes of each variable. Moreover, it provides other base interfaces for models (strategies) and domain classes. Other dependencies to specific libraries (e.g. for numerical calculus) can be included, but no dependency to specific frameworks is implemented.

6. The robustness of the component is ensured by the implementation of the Design-by-contract approach, thus a clear contract between client and server is established. This allows not only developing a better targeted library of unit tests, but it also sets the domain of applicability of the models, contributing to the transparency of the modeling solution. If an unhandled exception occurs, an informative message describes the error and model and component source of the exception, allowing for continuing execution of the client according to a user choice.

7. The traceability of component behavior is implemented in the .NET versions using the TraceSource class, in one implementation that allows setting the listeners by the client. Various levels of tracing can be hence pooled in one or more listeners with all traces from other components and from the client. In Java component this is obtained using a logger.

8. The technology used is based on the object oriented programming (OOP) paradigm via the MS .NET 2.0 framework. However, the object model of .NET allows easy migration to the Sun Java platform. Such migration has been realized for some of the components referenced.

Design patterns used

The architecture of components is based on four different software design pattern in order to implement the desirable features extensibility and modularity. Three of the used patterns are structural, and one is behavioral (Bishop, 2008).

The keystone pattern used is the **Composite** pattern. Different types of model units, i.e. simple strategies and composite strategies, implement the same interface, IStrategyComponent, as shown in the diagram below. This means that composite strategies are associated with simple strategies and they implement the same operations (i.e. a composite strategy calls the methods specified in the interface also for associated strategies). Thanks to this, composite and simple strategies are treated in the same way and can be accessed through the same API method.

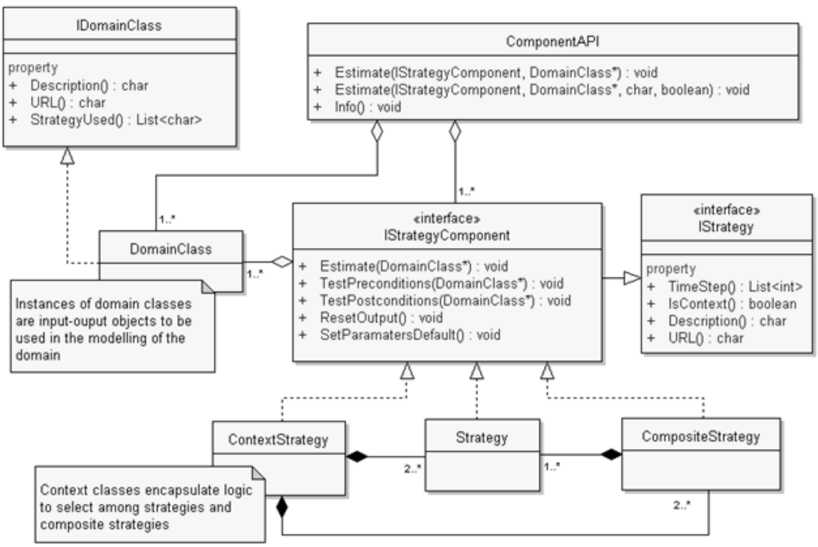
From the modelling point of view, the software design can be seen as an implementation of the **Transparent Façade** pattern; composite strategies offer a unique entrance to layers of modelling, hiding the complexity behind them but preserving a robust, modular structure. Simple strategies are still accessible.

A third type of model unit, the context class, is defined by imposing the implementation of the same IStrategyComponent interface. Context classes are defined in the behavioral pattern **Strategy**; in a context class decisions on the strategies to be used at run-time (simple or composite) are taken based on a specific model, responding to the context of operation. A typical use of such context classes is the selection of the appropriate strategy based on the inputs available in the instance of the domain class (classes).

Finally, by keeping interfaces, domain classes, and the component API class in one single component, and all model units (simple and composite strategies, contexts) in a different one, the **Bridge** pattern is implemented. This pattern de-couples the abstraction (data structures, methods declaration) from the implementation (models). In fact, a client will have a dependency on the data and interface component, and no dependency on the model component. This allows both easy replaceability of the latter, and the extensibility to multiple model components without the need of recompiling the client.

Referring to the class diagram below, the subdivision to meet the architecture described subdivides classes in the following components:

- interfaces IDomainClass and IStrategy belong to a core component used by all components using this design;
- ComponentAPI, IStrategyComponent, and DomainClass are implemented as data and interfaces component;
- Strategies, Composite strategies, and Contexts are the model component.



Proofs of concept

Components implementing the solutions above have been made available for public use and other are being developed (examples are referenced below). The design has been tested on static and dynamic biophysical models, on agro-management models, and on statistical indices. Use of components has been done on applications and via frameworks such as TIME and Modcom.

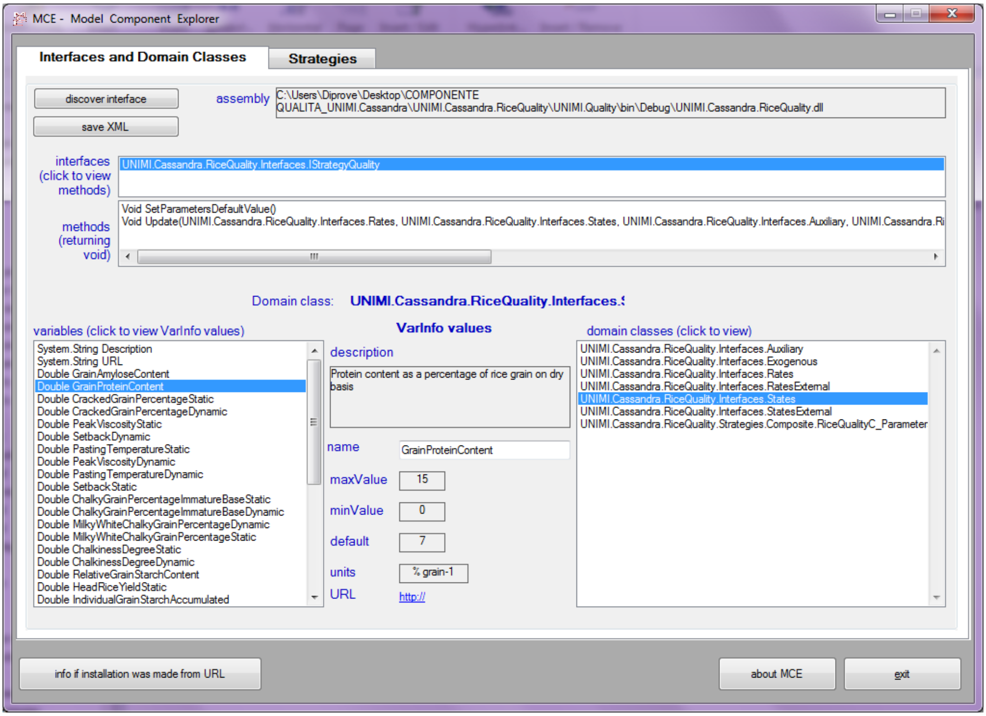
What are strategies

Design patterns (see relevant paragraph in the page Design summary)are elegant and effective solutions to common programming problems; they describe how objects communicate without knowing each other's data and methods. The design patterns strategy allows offering to the user of the component different models (one or more algorithms) by encapsulating each of them in a class. Different algorithms, which are alternate options to do the same thing, are called strategies. When building a biophysical model component this allows in principle to offer alternate options to estimate a variable or, more in general, to model a process. This often needed feature in the implementation of biophysical models, if implemented using the design pattern Strategy, comes with two very welcomed effects from the software side: 1) it allows an easier maintenance of the component, by facilitating adding other algorithms, 2) it allows to add easily further algorithms from the client side, without the need of recompiling the component, but keeping the same interface and the same call.

A class implementing the interface inheriting from the IStrategy is a strategy of the UNIMI.Cassandra.RiceQuality component. Many of such classes are implemented in the component, but a client of the component may extend the modelling capabilities by adding models which use as inputs and outputs the ones in the Domain Classes (which can also be extended).

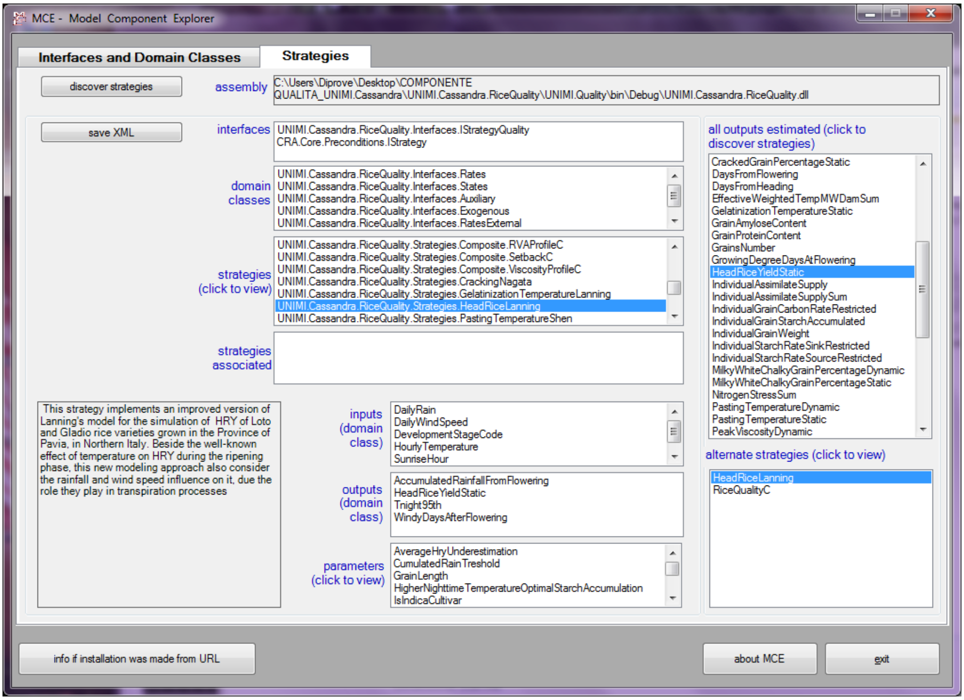
MCE: Model Component Explorer

The Model Components Explorer (MCE) is a GUI application to discover interfaces and domain classes in the interfaces assemblies, and strategies in model components. Each property of domain classes and strategies can be viewed according to the VarInfo type. The screen image below shows the main form of MCE.



The first tab allows discovering the strategy interface, and the domain classes. By clicking on a domain class, all the properties of the class are shown.

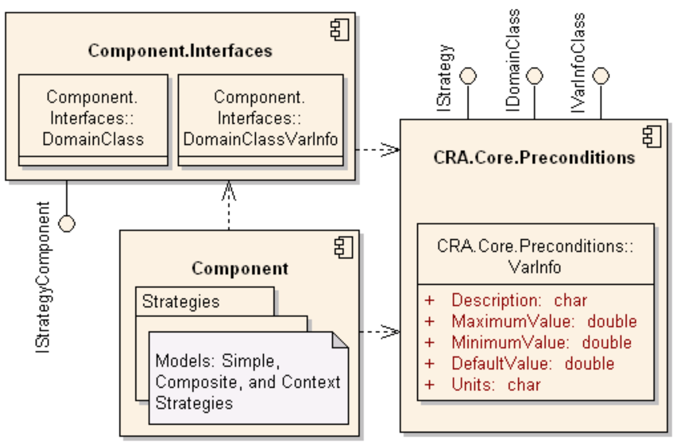
The second tab allows discovering strategies implemented. Clicking on parameters allows browsing the relevant VarInfo type. Finally, by clicking on an output in the right box, all the strategies are shown in the list in the lowest-right corner list box.



UML diagram

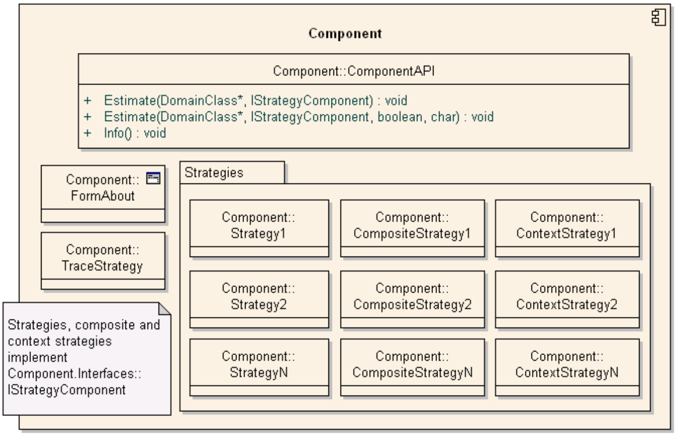
Component diagram

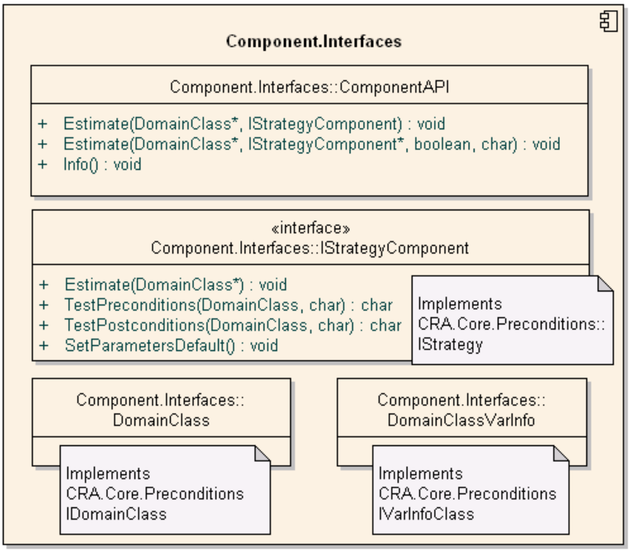
Data-types (domain classes) and models (strategies) in UNIMI.Cassandra.RiceQuality are implemented in two units (*UNIMI.Cassandra.RiceQuality.Interfaces* and *UNIMI.Cassandra.RiceQuality.Strategies*); The component has a dependency to the CRA.Core.Preconditions.dll assembly, to implement the test of pre- and post-conditions, and to implement the interfaces exposed.



The namespace interfaces include the interface that the model component API must implement, and the IStrategy interface which allows using the same signature for any strategy. These interfaces are at the base of the extensibility of the component.

It also includes the application public interface (ComponentAPI).





UNIMI.Cassandra.RiceQuality SDK

Sample applications

Sample projects (C# .NET v. 4 code) are provided as examples of use of the component. Each sample application provided in the Software Development Kit contains a Console Application project with an example of use of the component UNIMI.Cassandra.RiceQuality.

In particular two sample applications were developed, in which UNIMI.Cassandra.RiceQuality is coupled with two different rice crop simulators (Figure 17 and 18): WOFOST (Van Keulen and Wolf, 1986) and WARM (Confalonieri et al., 2009). Sample applications are VisualStudio .NET console application projects explicitly designed to show in the clearest way how to use the component, and to link it with crop simulators providing UNIMI.Cassandra.RiceQuality with crop phenological development and biomass accumulation in the grains.

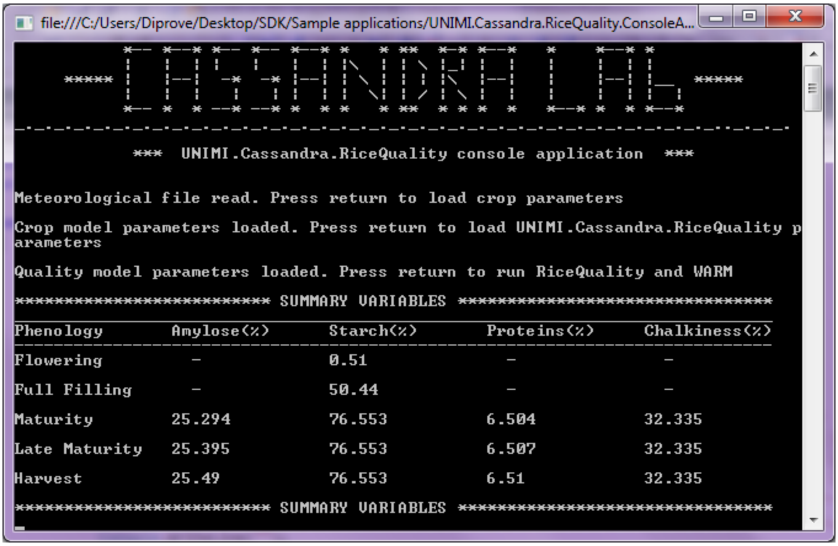


Figure 11. Sample application with WARM model.

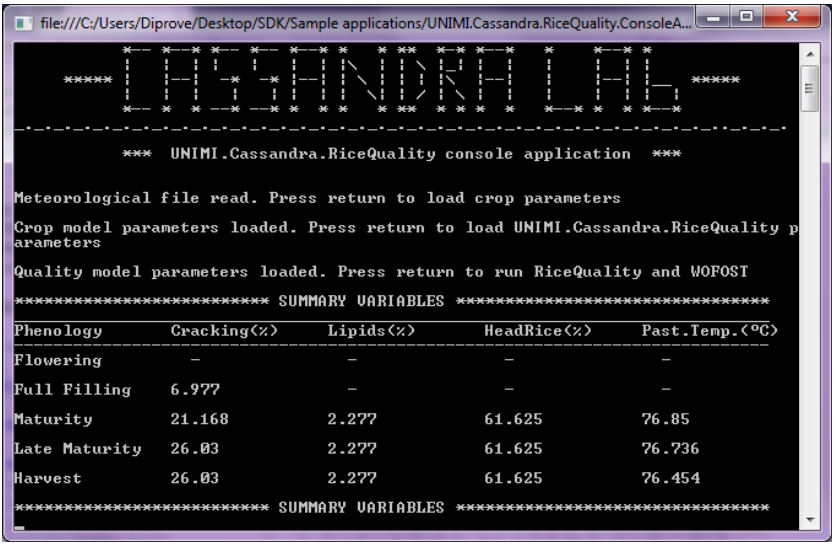


Figure 12. Sample application with WOFOST model.

Deployment package

Each compressed file provided contains:

- sample application (.NET 4 C# project)
- library UNIMI.Cassandra.RiceQualityQuality
- UNIMI.Cassandra.RiceQuality help file
- UNIMI.Cassandra.RiceQuality code documentation

About

The current version of UNIMI.Cassandra.RiceQuality was developed by Università di Milano.

Development: Giovanni Cappelli, Roberto Confalonieri, Simone Bregaglio. Programming:Giovanni Cappelli, Roberto Confalonieri, Simone Bregaglio.

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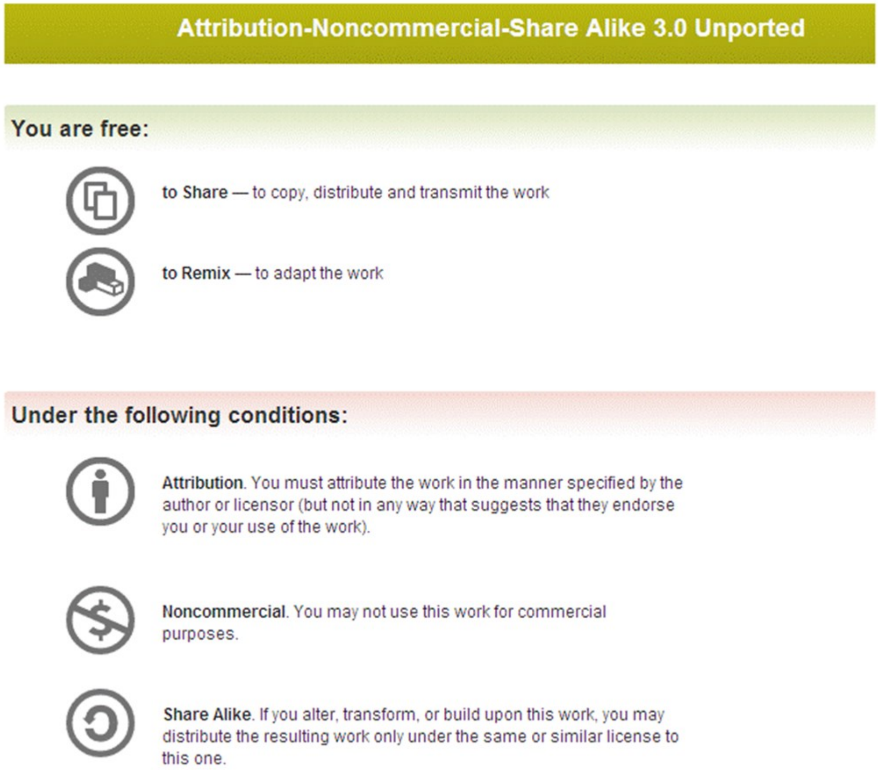

Web resources

Support:
mailto://giovanni.cappelli@unimi.it;
mailto://cassandra.lab@unimi.it
Info:
mailto://giovanni.cappelli@unimi.it
MCE - Model Component Explorer page:
http://agsys.cra-cin.it/tools/mce