



Short Communication

Boundaries and perspectives from a multi-model study on rice grain quality in Northern Italy

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ABSTRACT

Grain quality is crucial to meeting market demand and preserve the sustainability of the European rice sector. However the relationships between agro-meteorological conditions and major features of pre-harvest quality are not well understood. The evaluation of available models is needed to assess their suitability for predicting grain quality for different environmental conditions. This study presents a multi-site and multi-year evaluation of 26 models for the simulation of rice grain composition, milling quality and cooking quality, in the main European rice district (Northern Italy). The analysis was performed using data from 16 sites where the cultivars Loto (*japonica*) and Gladio (*tropical japonica*) were grown in 2011–2014. Model performances denoted models' ability to reproduce grain quality variables, with increased modelling efficiencies (EF) from grain composition ($-0.78 < EF < 0.62$; median = 0.34) to cooking quality ($-0.09 < EF < 0.85$; median = 0.44). In general, models based on biological parameters ($0.18 < EF < 0.85$, median = 0.52) performed better than those that include empirical coefficients ($-0.78 < EF < 0.80$, median = 0.29), with the best results achieved for proteins, breakdown viscosity and pecky grains for Loto cultivar ($0.04 < EF < 0.85$, median = 0.65). The calibration of cultivar-specific coefficients, led the models based on empirical parameters to the best balance between goodness-of-fit and complexity, thus resulting as a possible alternative to models using biological parameters under the explored conditions.

1. Introduction

Crop quality is a key determinant of the economic and nutritional value of agricultural products, since it directly affects acceptability to buyers and consumers (Koutroubas et al., 2004). Indeed, the achievement of superior quality standards allows farmers to gain a competitive market advantage with respect to imported low price products (Griglione et al., 2015). A number of simulation models have been developed to simulate crop yield under a wide range of conditions (e.g., Batchelor et al., 2002), but it is only recently that modellers have begun to focus on product quality (Flénet et al., 2008).

Food quality models presents a hierarchical representation (i.e., from cell to organ) of biological processes that regulate organ size and composition. Examples are available for fruit (peach trees, Génard and Souty, 1996; vineyards, Dai et al., 2009), field crops (tomato, Prudent

et al., 2011) and cereals (wheat, Martre et al., 2006), with quality aspects affecting the processing and market value of the final products. However, the dynamic coupling between crop and food quality models is often hampered by technological bottlenecks, due to the lower level of abstraction used in modelling the physiochemical processes related to food quality. For rice, some models have been developed to simulate the grain nitrogen concentration as a proxy for protein content (Ritchie et al., 1987; Bouman and van Laar, 2006), and the accumulation of starch/amylose in the grain as affected by pedo-climatic conditions (e.g., soil water availability, temperature stress; Chen et al., 2011). Most of these models are based on the relationships between grain quality and weather variables (e.g., air temperature, solar radiation) and are driven by empirical parameters with low biological meaning (Cappelli et al., 2014). This reduces their applicability outside the conditions for which they are calibrated. Furthermore, studies on the

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evaluation of these models were carried out on datasets comprised of only a few cultivars and in a limited number of sites and years. This limits the understanding of the usefulness of these models for research and operational activities, dealing with scenario analyses (e.g. climate change impact studies), decision support systems (e.g. early warning systems) and crop monitoring and/or yield forecasting services (e.g., the Crop Growth Monitoring Systems of the European Commission, <https://ec.europa.eu/jrc/en/mars>). Moreover, the direct comparison of quality model performances is often prevented by the use of different evaluation metrics (Bellocchi et al., 2009). Systematic analyses comparing grain quality model performances across weather and management conditions are still generally lacking, except for few studies that focus on grain nitrogen/protein concentration in European crop rotations (Yin et al., 2017) or in wheat (Martre et al., 2015), maize (Bassu et al., 2014) and rice (Li et al., 2015).

Herein we present a multi-site and multi-year comparative evaluation of models to simulate rice grain quality, with the goal to improve understanding of model suitability when applied to the main European rice growing district.

2. Materials and methods

2.1. Study workflow

This study articulates in a five-step workflow (Fig. 1), envisaging the comparison of available models to simulate the milling quality, the cooking properties and the nutritive characteristics of rice grain productions in Northern Italy. We collected site-specific data related to weather conditions, phenological observations and grain quality measurements, as well as crop management information (i.e., sowing and irrigation practices, *first step*). Missing weather variables needed as inputs by the quality models (i.e. global solar radiation, hourly nighttime temperatures) were then generated (*second step*). The available models were clustered according to the input variables and parameters used (*third step*), and then calibrated/validated with reference grain quality data (*fourth step*). A statistical analysis of model results was then

performed to assess the accuracy, the complexity and the uncertainty in reproducing field observations (*fifth step*).

We focused on the traits defining the quality of rice productions according to the standards of the Ente Nazionale Risi (Italian Rice Authority, http://www.enterisi.it/servizi/notizie/notizie_homepage.aspx), in order to support the selection of models to be used in forecasting activities and climate change applications in the study area. Details on data and methods used are discussed in the next subparagraphs of the material and methods section.

2.2. Study area and field experiments

The area of study is the Northern Italian Lombardo-Piemontese district (Fig. 2), which accounts for about 50% of the European rice area (Griglione et al., 2015).

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 to 4 °C in winter months, with peaks temperature exceeding 30 °C in the summer. Cumulated annual precipitations fluctuate around 750 mm, with two main rainy periods in autumn and spring, and a smaller rainy period from July to August. Field experiments were carried out by Ente Nazionale Risi (ENR) in 2011–2014, where rice was grown under non-limiting conditions for water, nutrients, pests and weeds. For the first three years, the experiments were carried out in Castello d'Agogna (lat. 45° 14' N, long. 8° 41' E, alt. 106 m a.s.l.) in a split-plot design, with irrigation as a main factor (three levels arranged in six 20 × 80 m plots, with two replicates for each irrigation treatment) and cultivar (two levels) and sowing date (four levels) as secondary factors (Miniotti et al., 2016). The Italian rice cultivars Gladio and Loto were respectively selected as representative of *tropical japonica* and *japonica* types grown in the study area and of the different end-use destination. Gladio is an early long B (EU standards) cultivar with crystalline grains recommended for rice salads or side dishes cooking (average yield = 6.3 t ha⁻¹). Loto is a short cycle long A (EU standards) cultivar with vitreous kernels suitable for parboiling and risotto preparation

Objectives	Data and methods
<p>STEP 1 Measured data collection</p> <ul style="list-style-type: none"> ○ 2011–2013 (Agogna) ○ 2014 (15 fields in the rice district) 	<ul style="list-style-type: none"> • Weather: daily min and max air temperature, rainfall, wind speed, min and max relative air humidity and reference evapotranspiration. • Rice crop (44 independent cultivar-specific measurements for Loto and Gladio cultivars): <ul style="list-style-type: none"> ○ phenology: flowering and maturity dates; ○ grain quality (9 variables): <ul style="list-style-type: none"> ▪ grain composition: amylose and protein concentration; ▪ milling quality: broken, pecky and milky white grains; ▪ cooking quality: gel. temp., peak, setback and breakdown viscosity. • Farming practices: sowing dates and irrigation.
<p>STEP 2 Generation of missing weather data</p>	<ul style="list-style-type: none"> • hourly temperature, • sunrise and sunset hours, • daily global solar radiation. <p style="text-align: right;">} hourly nighttime temperatures</p>
<p>STEP 3 Models selection and classification</p>	<p>26 rice quality models classified into four groups based on</p> <ul style="list-style-type: none"> • input weather variables (temperature vs. temperature + other variables), • parameters (biological vs. empirical).
<p>STEP 4 Models calibration and validation</p>	<p>For each combination of cultivar × quality trait:</p> <ul style="list-style-type: none"> • random split of 44 measures in 2 sets of 22 data each for cal. and val., • cal. of models via trial-and-error using modeling efficiency (EF).
<p>STEP 5 Statistical analysis of results</p>	<ul style="list-style-type: none"> • Accuracy: EF and relative root mean square error (RRMSE); • Complexity (variables + parameters): Akaike Information Criterion (AIC); • Uncertainty: boxplots with variability of EF and AIC.

Fig. 1. Workflow of methods and data used in this study. Gel temp. = gelatinization temperature; cal. = calibration; val. = validation; EF = modelling efficiency; RRMSE = Relative root mean square error; AIC = Akaike Information Criterion index.

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