UNIVERSITÀ DEGLI STUDI DI MILANO
SCUOLA DI DOTTORATO
TERRA, AMBIENTE E BIODIVERSITÀ

PhD in Agricultural Ecology

XXIV Cycle

An integrated modelling framework for climate change impact assessment on rice production and evaluation of adaptation strategies. A case study in Mali

Ph.D. Thesis

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N°R08121

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Academic Year
2010-2011

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An integrated modelling framework for climate change impact assessment on rice production and evaluation of adaptation strategies. A case study in Mali

Ph. D. Thesis
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Titolo in Italiano: Framework di modellizzazione integrata per la vautazione dell'impatto del cambiamento climatico e delle strategie di adattamento sulla produzione di riso (Un caso studio in Mali)

Tesi di Dottorato in Ecologia Agraria

XXIV Ciclo, Anno Accademico 2010 – 2011

To my family

PhD in Agricultural Ecology – XXIV Cycle

Alexandra Stella Rosenmund

Rosenmund, A.S., 2012. An integrated modelling framework for climate change impact assessment on rice production and evaluation of adaptation strategies – A case study in Mali. Ph.D. Thesis, University of Milan, 153 pp.

The aim of this PhD research was to describe an assessment of the potential impacts of climate change as well as climate variability on rice production. It also discusses selected adaptation options within the context of the Malian agriculture. The research centers on an integrated modelling approach (BioMA) to compute current and future (2020, 2050) crop yields in the agricultural region of the Office du Niger (Mali).

BioMA – Biophysical Models Application – is a platform for running biophysical models on generic spatial units. The application is based on independent components which allow implementing modelling solutions targeted to specific modelling goals.

The collected data were used to (i) develop new modules (a model for simulating the height of the plant) (ii) implement the existing ones according to the peculiarities of the sub-Saharan environment (i.e. the Agromanagement module was extended in order to take into account the beginning of the rainy season) and to (iii) calibrate and validate the

modelling solution defined for the purpose. Although parameterization procedures were performed in critical conditions – being reference data from the area a limiting factor – a preliminary calibration of WARM, for tropical and subtropical conditions, could be performed aromatically on Chinese datasets. Indeed these results achieved from these modelling exercises showed that the model is robust and able to reproduce yield variability within years and locations which made it suitable for the impact assessment study in Mali.

The impact assessment on cropping systems was evaluated via a difference analysis with respect to the current conditions, focusing on changes in total biomass, final yield and transpiration demand. An overall reduction can be expected in 2050 (up to complete failure of the crop) whereas different results were obtained for 2020. The main season seem to be little affected by the increase of temperatures whereas the first cycle, which takes already place under extremely high temperatures, will face reductions up to 25%.

Based on the results obtained in the impact assessment changes in sowing dates were tested in order to detect the most suitable management techniques which allow alleviating the negative effect of climate changes. The results suggested that changes in the sowing may be very effective in mitigating the adverse effect of climate change as well as the use of new crop cultivars with longer vegetative cycles. In fact in both systems an increase of production can be expected at short-term whereas at medium-term the losses can be significantly reduced.

Credits Evaluation

Courses:

- Digital image analysis
- Geographic Information Systems
- Scientific Writing
- Programming with VB.NET and Object concept
- Training for occasional trainer
- AutoCAD 2D
- AutoCAD 3D

Attendance at international/national congress:

- 4th CGMS Expert meeting, Joint Research Centre, 18 – 19 March 2009, Ispra (VA), Italy.
- BECRA Workshop, Joint Research Centre, 30 November – 3 December 2009, Ispra (VA), Italy.
- Visit of the delegation from the Chinese Academy of Agricultural Sciences, Joint Research Centre, 8 – 9 September 2010, Ispra (VA), Italy.
- Workshop on agriculture and food security monitoring, Joint Research Centre, 16 – 17 September 2011, Ispra (VA), Italy.
- Visit of the Consortium Alps (Valle d'Aosta), Joint Research Centre, 25 October 2011, Ispra (VA), Italy.
- 5th CGMS Expert meeting, Joint Research Centre, 21 – 22 November 2011, Ispra (VA), Italy.

Oral presentation at international/national congress:

- B. Baruth, A. Klisch, I. Savin, **A.S. Rosenmund**. Forecasting rice yields in China and India - the role of low resolution data. 33rd International Symposium on Remote Sensing of Environment, 4 – 8 May 2009, Stresa (VB), Italy.
- M. Donatelli, M. Acutis, S. Bregaglio, **A.S. Rosenmund**. A Model Framework to simulate agro-management at field and farm level. Farming Systems Design 2009 an international symposium on methodologies for integrated Analysis of farm production Systems, 23 – 26 August 2009, Monterey, CA, USA.

Poster presentation at international/national congress:

- E. Chatzidaki, L. Nisini, **A.S. Rosenmund**, F. Micale. Statistical techniques for climate prediction at regional scale: Two possible approaches | [Tecniche statistiche per previsioni climatiche a scala regionale: Due possibili approcci]. 12° Convegno nazionale di Agrometeorologia - AIAM 2009, 15 – 17 June, 2009 – Sassari (SA), Italy.
- **A.S. Rosenmund**, M. Donatelli, B. Baruth. BECRA: research project on climate change and adaptation in Mali and Burkina Faso. Agro 2010, the XI ESA Congress, 29 August – 3 September 2010, Monpellier, France.

Publications:

- **A.S. Rosenmund**, M.E. Chiodini, M. Acutis, A. Perego, G.A. Sacchi, R. Confalonieri. Analysis and modelling of the combined effect of plant nitrogen concentration after fertilization and development stage on rice radiation use efficiency. Italian Journal of Agrometeorology, 5-6 (3) 2009

- R. Confalonieri, A. Perego, M.E. Chiodini, B. Scaglia, **A.S. Rosenmund**, M. Acutis. 2009. Analysis of sample size for variables related to plants, soil and microbial respiration in a paddy rice field. Field Crop Research, vol.113 (2009), pp.125 – 130
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- R. Confalonieri, S. Bregaglio, **A.S. Rosenmund**, M. Acutis, I. Savin. A model for simulating the heaight of rice plants. European Journal of Agronomy, vol. 34(1), (2011), pp.20 – 25

Training activity

- Agri4cast internal training, Joint Research Centre, 16 – 18 February 2011, Ispra (VA), Italy
- BECRA training, Centre Regional Agrhymet, 23 – 27 May 2011, Niamey, Niger.

JRC Scientific and technical reports:

- El Aydam M, Baruth B, Bettio M, Bussay A, Kasperska-Wolowicz W, Bojanowski J, Seguini L, Lopez Lozano R, Duveiller Bogdan G, **Rosenmund A**, authors Niemeyer S, El Aydam M, Baruth B, Bettio M, editors. MARS Bulletin Vol.19 No.16 - Agroweather, remote sensing and yield forecast. EUR 24736 EN. Luxembourg.
- El Aydam M, Baruth B, Bettio M, Bojanowski J, Bussay A, Duveiller Bogdan G, Kasperska-Wolowicz W, Lopez Lozano R,

Rosenmund A, Seguini L, Vassilev V. MARS Bulletin - Vol.19 No.11 - Agrometeorological analysis, remote sensing and yield forecast. EUR 24736 EN. Luxembourg (Luxembourg): Publications Office of the European Union; 2011. JRC66000.

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- **Rosenmund A**, Srivastava A, Vassilev V, Seguini L, authors El Aydam M, Niemeyer S, editors. MARS Bulletin 2011 Vol.19 No.12 - Rice monitoring in Europe. EUR 24736 EN. Luxembourg (Luxembourg): Publications Office of the European Union; 2011. JRC65990.
- **Rosenmund A**, El Aydam M, Bettio M, Baruth B, Duveiller Bogdan G, Lopez Lozano R, Bussay A, Bojanowski J, Kasperska-Wolowicz W, authors El Aydam M, Baruth B, Niemeyer S, editors. MARS Bulletin 2011 Vol.19 No.7. EUR 23298 EN. Luxembourg (Luxembourg): Publications Office of the European Union; 2011. JRC65349.
- Baruth B, Bojanowski J, Bussay A, Duveiller Bogdan G, El Aydam M, Lopez Lozano R, **Rosenmund A**, Seguini L, Bettio M, authors El Aydam M, Baruth B, Niemeyer S, editors. MARS Bulletin Vol.19 No.6 (2011) - Agrometeorological analysis, crop monitoring and yield forecast. EUR 23298 EN. Luxembourg (Luxembourg): Publications Office of the European Union; 2011. JRC64878.

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I wish to thank Prof. Marco Acutis for valuable professional assistance. I am deeply grateful to Dr. Bettina Baruth and Olivier Leo for the supervision and support in the Joint Research Centre, and to my dear colleagues for their big support.

Table of Content

Chapter 1

Introduction

1.1. Climate change impact assessment

The Framework Convention on Climate Change (UNFCC) defines climate change as 'a change of climate which is attributed directly or indirectly to human activity in addition to natural climate variability that alters the composition of the global atmosphere observed over comparable time periods'. According to Rosenzweig et al (2008), this anthropogenic climate change is having a significant impact on physical and biological systems at both the global and continental scale (although for some continents, there is not enough long-term observation data to provide a reliable conclusion). This has led to the emergence of a growing body of literature suggesting that climate change will result in a set of diverse and location-specific impacts on agricultural production. Due to the complexity governing the interactions between these processes and the uncertainty associated with modelling them, it is not presently possible to reliably quantify the aggregate impacts of climate change on global-scale agricultural productivity (Gornall et al., 2010).

Agricultural systems are managed ecosystems. Thus, the human response is critical to understanding and estimating the effects of climate change on production and food supply. Agricultural systems are also dynamic; producers and consumers are continuously responding to changes in crop and livestock yields, food prices, input prices, resource availability, and technological change. Accounting for these adaptations and adjustments is difficult but necessary in order to measure accurately climate change impacts. Failure to account for human adaptations, either in the form of short-term changes in consumption and production practices or long-term technological changes, will overestimate the potential damage from climate change and underestimate its potential benefits.

Climate change is a complex biophysical process. Even if it is not possible to predict precise future climate conditions the basis for assessing potential impacts of climate change is future climate predictions. To obtain such predictions, it is necessary to have a reliable model of the climatic system and to use it to estimate possible future outcomes. A clear distinction has to be done between these two concepts: models, which are based on physical laws, and scenarios, which are a coherent, internally consistent and plausible description of a possible future state of the world. Currently, the most advanced tools designed for studying climate processes and for projecting climate response to human-induced are coupled Atmosphere-Ocean General Circulation Models (commonly called GCM). GCMs have been developed to project future climates based on different greenhouse gas scenarios and complex earth atmosphere interactions. They are based on physical laws describing the dynamics of the atmosphere and oceans, incorporating numerical representations of the physical processes of radiation, turbulent transfer at the ground-atmosphere boundary and cloud formations (Barron, 1995).

The IPCC Fourth Assessment Report presented 23 general circulation models (GCMs) that by design span the globe. While some of these models are relevant to Africa and are reported at pixel resolutions of around 250 km^2, the underlying data used to generate this information are often so highly aggregated so as to undermine their utility at projecting regional climate. Some of the commonly used GCMs in the scientific literature are the HadCM3 model (Collins et al.,

2001) developed at the Hadley Centre in the United Kingdom, the ECHAM5 model (Roeckner et al., 2003) developed at the Max Planck Institute for Meteorology and the GFDL CM2 (Delworth et al., 2006) developed at the NOAA Geophysical Fluid Dynamics Laboratory in the United States. All three have been leading climate models used in the recent IPCC assessments. While the spatial resolution of GCMs is sufficient to simulate the averaged global climate, their output is often unsuitable when the scale of interest is refined. In fact whilst GCMs can more accurately project changes in average global temperature, these projections are often of little use to decision makers working on regional or local scales. Nevertheless, growing recognition of the need for climate information at finer scales is itself a driver of the volume of work aimed at downscaling climate model information for local and regional decision makers. At a finer scale or higher resolution, several factors complicate climate modelling, including local topography, land cover and land use features, the presence of atmospheric aerosols and other pollutants. To address climate modelling at regional scale several downscaling methods (e.g. Regional Climate models (RCMs) or stochastic weather generator) have been developed driven by initial and boundary conditions supplied by a GCM. Advances in climate change have improved the number, quality and availability of GCM scenarios, with a few of direct relevance to Africa. More important than the increased availability of GCM data, recent years have also seen an increase in downscaling efforts, both dynamic and empirical, providing information at a finer scale that, relative to the data produced by GCMs, is more relevant for research and policy making. This is because downscaled data, when analyzed appropriately, can provide station level responses from GCM patterns, improving the temporal and spatial resolution of available information. In Africa, however, the number of available downscaled datasets remains limited (especially when compared to those available for Europe and North America) and they are the product of an even more limited number of institutions and models

1.2. Climate variation and change in Africa

Observational data show that Africa has been warming through the 20th century at the rate of about 0.5°C per decade (Hulme et al., 2001). Although this trend seems to be consistent over the continent, the changes are not always uniform (Malhi and Wright, 2004; Kruger and Shongwe, 2004). Rainfall exhibits even more spatial variability and a notable temporal variability too. Interannual rainfall variability is large over most of Africa and, for some regions, multi-decadal variability is also substantial, e.g. in West Africa, a decline in annual rainfall has been observed since the end of the 1960s with a decrease of 20 to 40% (Dai et al., 2004). Model-based projections of climate change across Africa show considerable projected changes, based on the different input assumptions (e.g. greenhouse gas emission level) and model physical laws. In a comprehensive paper on climate change in Africa over the period 1900 2100, Hulme et al. (2001) show that climate change is not simply a phenomenon of the future, but one of the relatively recent past. Hulme et al. (2001) and IPCC suggest a future annual warming across Africa of between 0.2 and 0.5 °C per decade. This translates to a warming of between 2 and 6 °C by 2100, with the greatest warming over the interior semiarid tropical regions. Climate change projections realized by running GCMs (or RCMs) under different emission scenarios are intrinsically subject to a significant amount of uncertainty. While there is a general consistency in projected temperatures for Africa, precipitation projection are generally less consistent with large inter-models ranges for seasonal mean rainfall responses. Despite these uncertainties estimates of projected future rainfall has been undertaken. The projected rainfall changes for 2050 in IPCC (2001) is small (20% from baseline values) in most African areas. However, the results also show an increase in occurrence of extreme events in both rainfall (wet/dry years) and temperature. These changes are mostly likely to be more robust than changes in mean rainfall (Huntingford et al., 2005), and could have serious repercussions on crop production. Extreme events have long been recognized as being a key aspect of climate change and its impact (Burke et al., 2006).

1.3. Impacts on agricultural production: an integrated approach

As noted above the magnitude of the projected impacts of climate change on food crops in Africa varies widely among different studies and according to which GCM and/or crop model is used (Challinor et al., 2007 and Challinor et al., 2009). Most of them have assessed the effect of climate change on agricultural productivity using different climate models and emission scenarios (IPCC SRES) and have indicated that world agriculture, either in developed or developing countries remains very dependent on climate resources. Multiple model simulations are needed in order to sample the inherent uncertainties in the projection of climate and agricultural production. Uncertainty in climate change impacts assessments comes from a number of sources. Future emissions of greenhouse gases must be estimated and the responses of both the atmosphere and the impact in question have associated uncertainties (Challinor et al., 2005)

Recent assessments, combining global and regional-scale analyses, have also examined the impacts of climate variability and change on growing periods and agricultural systems (Jones and Thornton, 2003, Huntingford et al., 2005). Under different emission scenarios (i.e. A1F1, A2, B1 and B2) using the HadCM3 and ECHAM4 GCMs, Thornton et al. (2006) assessed areas of Sub- Saharan Africa under current and projected impacts of climate variability and change and showed that among other factors, the length of the growing period (LGP) was one of the elements that would be significantly affected by climate change. The study further concludes that by 2020 some losses in LGP greater than 20% will occur in highly marginal cropping areas. By 2050, areas that showed gains in LGP would have lost growing days as a result of the higher projected increases in temperature and projected changes in precipitation patterns and amount. Other studies indicate some of the additional impacts that may be experienced in a warmer world, which will increase challenges for food production and food security. Regarding water resources, by 2025 it is projected that 64 per cent of the world's population will live in water-stressed basins, compared with 38% today (Rosengrant et al., 2001). There are also likely to be substantial changes in land suitability for agriculture under future scenarios, by the end of the century, 15% of the land globally that is currently suitable for cultivation would become unsuitable, although this is more than balanced by an extra 20% of land that is currently too cold to support cultivation becoming suitable (Arnell 2009). But there is no balance in the situation for Africa. In East and southern

Africa, Arnell estimates that about 35% of current cropland will become unsuitable for cultivation. These stresses will add to the difficulties of adopting new varieties or increasing agricultural productivity, as water and land availability are key limiting factors (Thornton and Jones, 2011). On a more national scale, assessments have shown a range of impacts, Mohamed et al. (2002), using time series data of rainfall, crop production and other weather and agronomic data from Niger, argued that by 2025 climate change might reduce millet yields by 13% and groundnut yields by 11 to 25%. Downing (1992) argues that potential food production in Kenya will increase if increased temperatures are accompanied by high rainfall, while marginal zones will be adversely affected by decreased rainfall. This argument is supported by Makadho (1996), who argues that maize production in Zimbabwe is expected to fall as a result of increased temperatures and reduced rainfall. It appears evident therefore that African agriculture is very vulnerable to climate change. Although there are established concerns about climate change in Africa, little work has been carried out to show how seriously the problem will be in Sub Saharan Central Africa. Hence an integrated framework for assessing climate change impact on cropping systems in in specific districts of Mali and Burkina Faso was implemented in order to allow more detailed assessment of the impact on food production and security among the Sub-Saharan countries and the definition of suitable adaptation options

1.4. Adaptation strategies for agriculture and food security

The impacts described above in the 4◦C+ world hypothesized by Thornton and Jones (2011) will require quite radical shifts in agriculture systems, rural livelihood strategies and food security strategies and policies. Proactive adaptation will require much more concerted effort at all levels to manage quite radical shifts. In addition, when food security is considered as the outcome of food systems, which expand beyond agricultural production to include markets, trade and distribution networks, for example, the evaluation of successful adaptation becomes more difficult. For crops, changes in management practices and strengthening of seed systems are two key approaches to adapting agricultural systems in SSA (Challinor et al., 2007). While local seed systems can be resilient to climatic stresses (Sperling et al., 2004) the challenge for the future is to improve access to the varieties that will be needed as climate changes and to adapt farming systems to new climatic, land and water constraints.

Good practice in adaptation is constrained by a number of factors, and these will become much more critical in a 4◦C+ world. First, there are inherent limits to the predictability of both climate and its impacts; and there is variability in the methods and assumptions used by any single study to assess probable impacts. Thus, not only is our knowledge of the future necessarily imprecise, but also the degree of precision claimed by different studies varies considerably, making such studies not directly comparable.

The results achieved in research projects carried out in African and Asian conditions provide sufficient evidence that climate change will exhibit different impacts on crop yield depending on the climate change scenario investigated. Tingem et al., (2009) showed that the HadCM3 climate scenarios had the least severe impacts on crop yields whilst those of the GISS were the most detrimental, especially to maize and sorghum yields. However, the results provide useful insights for recommendations pertaining on future policies for adaptation in agriculture. For example, as an adaptation option, in order to alleviate the negative effect of higher temperatures on crops, research should be undertaken to create cultivars with higher optimal temperature requirements. Furthermore, the negative yield influence of year-to year variation of crop yields can be addressed by long range forecast of weather conditions. The findings presented in this chapter must not be seen as accurate predictions of future crop yields, but more as indicators of the possible impacts of climate change on Burkina Faso crop agriculture, which would be useful in designing appropriate adaptation options. Results of the climate change impact assessment showed that without adaptation, it will be problematic for agricultural production in Sub-Saharan Africa. However, several studies have suggested that detrimental climate impacts can be reduced and numerous opportunities can be created by the changing conditions (Thornton and Jones, 2011, Lobell et al., 2008, Brown and Funk, 2008). Extreme climate events will probably be the most challenging under future climate change (Rosenzweig et al., 2001). Farmers have traditionally used indigenous knowledge to mitigate climate hazards based upon observations and interpretation of natural phenomena and the currently adopted cropping calendars are largely based on that knowledge. However the foreseen changes of climate will probably be above the natural adaptation capacity of local population and it's very likely that most of these strategies need to be supported with national policies. Moreover climate change coupled with population growth pose serious challenges on future food security. These challenges emphasize the need to realign and adopt new policies that contribute to greater resilience of the agricultural sector. Previous research conducted in developing country settings indicates that, in principle, climate change impacts on agriculture can be reduced through human adaptations such as; adjusting sowing dates, changing cropping patterns (Winters et al., 1998), adopting higher yielding and heat resistant cultivars, and improved extension services (Butt et al., 2005).

1.5. The BioMA modelling framework

To quickly respond to demand of analysis of complex systems a model framework is needed to cover the different aspects which need to be taken into account. In fact, although biophysical models are already an effective tool for system analysis, a large effort still needs to be acted on to allow exploiting their full potential. This aiming at addressing the multiple and moving targets required by integrated analyses, in which bio-physical modeling plays the role of data provider to the following steps of the modeling chain. The work to be done can be identified as further improvement of models in terms of integration of modeling approaches and to building database of reference data to be used as benchmark for model evaluation (Donatelli, 2011).

BioMA – Biophysical Models Application – is a platform for running biophysical models on generic spatial units. The application is based on independent components, for both the modelling solutions and the graphical user's interface. The component-based structure allows implementing in BioMA diverse modelling solutions targeted to specific modelling goals. The system allows also for adding new modelling solutions. Modeling frameworks represent a substantial step forward with respect to monolithic implementations of models describing environmental processes, especially in the light of integrated modeling efforts, where different perspectives and domains are to be considered. The separation of algorithms from data, the reusability of services such as I/O procedures and integration services, the target of isolating a modelling solution in a discrete unit brought a solid advantage in the development of software simulation systems in terms of flexibility and maintainability (Donatelli, 2011)

The key requirements of its design aim at maximizing (i) extensibility with new modelling solutions (ii) ease of customization in new environments (iii) ease of deployment and (iv) transparency of workflows. Moreover the implementation of modelling platforms allows enhancing simulation capabilities by adding crop-specific models under a flexible framework and further components to enrich the crop models (frost kill, pest and diseases, inundation) and simulate possible impacts on yields. It allows also running tailored modelling solutions targeted on the different goals. In fact a modelling solution is a discrete simulation engine where different models are selected and integrated in order to carry out simulations for a specific goal. Each modelling solution makes use of extensible components and allows adding simulation of relevant processes not considered in the core crop growth model and impacting on final yields.

1.6 The research framework: the BECRA project

Although general pattern of response are expected as a result of climate scenarios in the coming decades, several studies have shown that climate, agricultural system sustainability and resilience to adverse conditions may vary noticeably, both from a bio-physical and bio economical point of view, according to site. Consequently technical issues about production sustainability and production risk, applied to known and innovative production enterprises, interact with economic issues at micro and macro level. An integrated analysis is hence required for impact assessment and to develop adaptation scenarios for agricultural production.

The project BECRA (Bio-Economic analysis of climate change impact and adaptation of Cotton and Rice based Agricultural production systems in Mali and Burkina Faso) is an administrative arrangement between the European Commission Joint Research Centre (DG JRC) and the EuropeAid Co-operation Directorate- General of the European Commission (DG AIDCO), Contract n° 2008/170-047. The project has been carried out in cooperation with JRC-Food-Sec and the Institut Agronomique Méditerranéen de Montpellier (IAMM). In order to ensure expert knowledge and data collection cooperation with technical and higher education bodies in the regions of the case studies were envisioned. This cooperation was partially extended to government research bodies as a mean of having national governments endorse the results/methodology of the study, and therefore facilitate their use in policy dialogue on climate change. The main goal of the service agreement, carried out in two phases, is the development of a model framework for assessing climate change impact on cropping systems in specific districts of Mali and Burkina Faso, and defining adaptation strategies.

This project examined the effect of short and medium term climate variability and the change on rice production in Mali and cotton based rainfed cropping systems in Burkina Faso and identifies the adaptation options of the whole bio-economic systems using an integrated simulation analysis.

Within this context the research presented in the following paragraphs refers to the activities carried out in order to extend the modelling platform and to test the component on specific case studies referring particularly to the above mentioned BECRA project. In fact the project applies the methodology implemented within the research activity to specific case studies; therefore it represents a sort of pilot study showing the potentiality of integrated approaches to climate change impact assessment studies.

Within this context the specific objectives of this research were:

- Building a database of knowledge and reference data to be used in further climate change impact assessment studies;
- Collecting data in order to calibrate and validate existing modelling solutions used to run simulations under current conditions and future climate scenarios;
- Implementing new modelling component an approaches in order to improve the reliability of the simulation results;
- Simulating the effect of climate change impact on the cropping system of the case study and defining possible adaptation strategies.

1.7. Synopsis

In Chapter 2 (*Analysis of sample size for variables related to plant, soil, and soil microbial respiration in a paddy rice field*) the variability of different aspects of a paddy rice fields through sample size determinations for some of the plant and soil features of interest in agronomic field experiments was analyzed.

The objective was to underline the importance of carrying out pre-samplings in order to assure the reliability of collected data given that, as showed in the paper, the sample size varies according to the variable analyzed and according to the management conditions. In fact the quality of the input data used to describe the current conditions in a climate change impact assessment study can force a strong simplification process thus reducing the power of any innovative integrated approach.

Chapter 3 (*An improved model to simulate rice yield*) introduces the WARM model specific for the simulation of rice growth under flooded and unflooded conditions in China and Italy. The achieved results show that, once the most relevant model parameters were calibrated, the model was able to reproduce rice growth in temperate and tropical environments. The robustness and accuracy, combined with the low requirements in terms of input data make the model suitable for forecasting rice yields at regional, national and international scales and to be used in climate change impact assessment studies.

Chapter 4 (*A model for simulating the height of rice plants*) presents a new model for the simulation of plant height based on the integral of the percentage of biomass partitioned to stems. Although previous studies do not emphasize the importance of simulating correctly plant height a reliable approach for modelling this variable would allow the simulation of processes with a significant impact on rice yield e.g., lodging, floodwater effect on leaves temperature, crop-weeds competition for radiation interception, etc.

Chapter 5 (*Simulating climate change impact on rice production under extreme thermal regimes: a case study in Mali*) examines the effect of short and medium term climate variability and the change on rice production in Mali and identifies the adaptation options of the system using an integrated simulation analysis. Additionally the work focus on the changes required on the response functions to temperature in order to reproduce correctly the growth in environments characterized by extreme thermal regimes.

1.8. Notes

Chapter 2 has been published by Field Crop Research, vol.113 (2009), pp.125 – 130.

Chapter 3 has been published by Agronomy for Sustainable Development, vol. 29(3), (2009), pp.463 – 474

Chapter 4 has been published by European Journal of Agronomy, vol. 34(1), (2011), pp.20 – 25

Chapter 5 has to be submitted.

The reference lists from individual chapters have been combined into one list at the end of the thesis.

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Chapter 2

Analysis of sample size for variables related to plant, soil, and soil microbial respiration in a paddy rice field

Field Crop Research, 113 (2009), 125-130

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Keywords
Visual jackknife, resampling, pre-sampling, *Oryza sativa* L., SISSI.

2.1 Abstract

Pre-samplings for sample size determination are strongly recommended to assure the reliability of collected data. However, there is a certain dearth of references about sample size determination in field experiments. Seldom if ever, differences in sample size were identified under different management conditions, plant traits, varieties grown and crop age. In order to analyze any differences in sample size for some of the variables measurable in rice field experiments, the visual jackknife method was applied to pre-samples collected in a paddy rice field in Northern Italy, where a management typical for European rice was conducted. Sample sizes for 14 variables describing plant features (plant density, spikelet sterility, biomass, carbon and nitrogen concentration for the different plant organs and for the whole plant) and for 12 variables describing physical and chemical soil features (texture, pH, water holding capacity, soil organic matter, total carbon and nitrogen concentration, mineral nitrogen concentration) and soil microbial activity were estimated. The elementary unit of observation was a 3-plant sample and an aggregate sample of 4 125 cm3 sub-samples for soil. Sample sizes ranged between 15 and 27 for plant related variables and between 5 and 6 for soil variables. Relating to plant features, remarkable differences in sample size were observed in carbon concentration values of different plant organs, probably due to maintenance respiration. Homogeneity among sample sizes for soil variables could be explained by the capability of aggregate samples in capturing a big part of the total variance. This study underlines

importance of carrying out pre-samplings aiming at sample size determination for different variables describing the cropping system.

2.2 Introduction

Preliminary samplings aiming at determining sample size should be carried out before performing measurements to avoid the collection of data characterized by low reliability (Lapitan et al., 1979; Nath and Singh, 1989; Tsegaye and Hill, 1998; Ambrosio et al., 2004). However, sample size is often arbitrarily determined (Confalonieri et al., 2006a), increasing the probability of Type II errors if the sample size is smaller than needed or expending critical resources or funds if the sample size is larger than necessary (James-Pirri et al., 2007).

Although references about description of experiments where sample size was determined are not common, the effort invested in carrying out, describing and discussing results in the rare available examples demonstrates the importance of this practice.

According to the different situations, sample size determination is a process characterized by different degrees of complexity. Madhumita Das (2007) estimated sample size for saturated hydraulic conductivity of 129 topsoil samples (0.00-0.20 m depth) in India, founding values from 2 to 8 according to different levels of confidence and error percentage. Analyzing severity of Septoria leaf spot (caused by Septoria albopunctata) on blueberry plants, Ojiambo and Scherm (2006) identified 75 leaves (selected from 3 shoots per bush on 25 bushes) as the optimal sample size to determine disease severity as number of spots per leaf. A sample of 144 leaves (2 each sampled from 3 shoots per bush on 24 bushes) was required to detect disease severity as percent of necrotic leaf area. Araujo et al. (2004) identified 15% of total root mass of common bean plants as adequate to provide reliable root traits estimates. Lima e Silva et al. (2005) calculated sample size for 4 sorghum traits: plant height, dry matter without panicle, panicle length, and panicle dry matter, finding sample sizes of, respectively, 14, 11, 14, and 24 plants per plot concerning the 4 variables were adequate. A single sample size of 25 plants was found by the same authors for all the variables using the experimental coefficient of variation alone instead of a formula for sample size derived by Thompson (1992). The estimation of different sample sizes for different traits was carried out also by Storck et al. (2007), who estimated sample size for the following maize traits: ear length, ear and cob diameter, ear weight, weight of grains per ear, cob weight and the weight of 100 grains, the number of grain rows per ear, the number of grain per ear and the length of grains. Results showed that the weight-related ear features needed 21 ears for a precise (5%) determination; 8 and 13 ears were needed respectively for size- and number-related features. Confalonieri et al. (2006), analyzing paddy rice fields, estimated samples size values ranging from 15 to 33 plants under different management conditions (nitrogen fertilization, sowing techniques, sown variety) and development stages.

In these examples, different techniques to determine sample size were used and specific solutions were applied in the different conditions. Ojiambo and Scherm (2006) sampled plants at 3 hierarchical levels (leaf, shoot, bush) and related the sample size to the total time required for the determination (respectively 36 and 22 min in the two cases), thus taking into account the effort required in each case. Time required determining a variable was taken in account in sample size determination also by Araujo et al. (2004). Storck et al. (2007) estimated sample size according to the formula , following the approach proposed by Martin et al. (2005), where CV is the percent coefficient of variation of the sampling error, D is the percent half-amplitude of the confidence interval for the average and t is the critical value of the t distribution. The same authors estimated sample size for different variables/parameters by clustering them into classes (weight-, size-, and number-related traits). Confalonieri et al. (2006b) demonstrated how the sample size for rice aboveground biomass (AGB) determinations could vary according to management conditions using a resampling-based method, even when different managements affect plants growing in the same biophysical context.

The objective of this paper was to analyze the variability of different aspects of a paddy rice fields through sample size determinations for some of the plant and soil features of interest in agronomic field experiments. In Confalonieri et al. (2006b), differences in variability and in sample size were analyzed for aboveground biomass under different management conditions; in this study, the same objective was pursued in a standard rice field but concerning different variables related to soil, plant, and soil microbial activity.

2.3 Materials and methods

2.3.1 Experimental data

Data were collected in a field located in the southern part of Milano (Northern Italy, 45.47 °N, 9.18 °E, 120 m a.s.l.) during 2006. The soil was loam, acid, with soil organic matter content next to 2.5 %. Rice (Oryza sativa L., cv Libero, Indica type) was row seeded on April 12 and flooded at the third leaf stage (May 10; code 13 of the BBCH scale for rice; Lancashire et al., 1991). Rice received 140 kg N ha-1 split in 2 events: pre-sowing and top-dressed at the panicle initiation stage (June 29; code 34 of the BBCH scale for rice). 33.6 kg P2O5 ha-1 and 92.4 kg K2O ha-1 were distributed in pre-sowing. Field management allowed prevention of water and nutrient stresses and kept the field weed and pest free.

Plant related measured variables were aboveground biomass at physiological maturity (AGB; September 19; code 99 of the BBCH scale for rice), plant nitrogen concentration (PNC) and plant carbon concentration (PCC) at physiological maturity, spikelet sterility, and plant density. AGB, PNC and PCC were determined for leaves, stems and panicles separately. Measured soil variables were texture, mineral nitrogen concentration (N-NO3- and N-NH4+), total carbon and nitrogen concentrations (SCC and SNC), soil organic matter (SOM), water holding capacity (WHC), pH (KCl), and pH (H2O) in the soil layer 0.0-0.2 m. Microbial activity in the soil (SMA) was estimated using a respirometric approach.

2.3.2 The visual jackknife

The visual jackknife method (Confalonieri, 2004; Confalonieri et al., 2006a) was used in sample size determination. The standard jackknife (Tukey, 1958) is a re-sampling method based on the division of the original sample of N elements into groups of k elements, with k equal to 1 in case N is low. $\frac{N!}{(N-k)!k!}$ virtual samples (combinations without repetitions) of *N-k* elements are generated by eliminating $\frac{N!}{(N-k)!k!}$ times *k* different values from the original sample. In our case, the original sample is represented by the data coming from the pre-sampling. In the visual jackknife, different values of *k* are used. The process of generation of the $\frac{N!}{(N-k)!k!}$ virtual samples is repeated *N*-1 times with *k* assuming values from 1 to *N-2*, for a total of $\sum_{k=1}^{N-2}\frac{N!}{(N-k)!k!}$ different virtual samples. Mean and standard deviation are computed for all the generated samples and plotted on two charts, with the values of *N-k* on the X-axis and the means (or standard deviations) on the Y-axis, in order to get a visual representation of how the means and the standard deviations of the generated samples vary with increasing *N-k* values. Conceptually, the optimal sample size is considered equal to the *N-k* value for which the variability among the means does not really decrease anymore with increasing sample size. The algorithm used for the determination of the optimal sample size consists of selecting *(N-k)'* out of those N-k higher than 2 and lower than *N-2*. Four weighted linear regressions are performed over the generated means as follows: the first and the second run, respectively, over the highest and lowest values of the *N-k*<*(N-k)'*; the third and the fourth run over the highest and lowest values of the *N-k*>*(N-k)'*. A global index (SR^2) is computed by summing the coefficients of determination (R^2) of the four regressions. The reiteration of this procedure for all the possible *(N-k)'* allows the identification of the optimum sample size, that is the *(N-k)'* with the highest SR^2. The process stops when the next sample size does not produce SR^2 larger than 5% than the previous. A trimming process allows leaving extreme samples out of computation (for instance, the 5% most external means). This visual jackknife method overcomes the typical limitations of conventional methods (parametric statistics), requiring data-matching the statistical assumptions of normality and homoscedasticity.

The software SISSI 1.00 (Shortcut In Sample Size Identification; Confalonieri et al., 2007) was used to apply the visual jackknife. SISSI provides an easy access to the resampling-based computational procedures the visual jackknife is based on, and allows the user to easily customize the resampling settings. Numeric and visual outputs are displayed in the graphical user's interface, together with the sample size calculated with classical procedures based on Student's t. After the software has automatically applied the regression-based procedure to calculate the optimal sample size, the user is allowed to adjust manually the resampling-estimated sample size. This is meant to further reduce sample size if the variability achieved (expressed as % coefficient of variation) is expected to be low enough to fall within what is considered by the researcher to be acceptable.

The SISSI's installation package is available free of charge for non-commercial purposes at http://www.robertoconfalonieri.it/software_download.htm: The program is fully documented by the accompanying user's manual, which provides a detailed description of the scientific background and principles of usage.

2.3.3 Sample size determination

Plant related variables

AGB, PNC, PCC and spikelet sterility were determined considering a randomly-chosen 3-plant aggregate sample as basic unit of observation (Confalonieri et al., 2006b), with N equal to 27 (see section The visual jackknife). AGB (kg ha^{-1}) was determined by drying the plant samples in oven at 105 °C until constant weight to express them as dry matter. PNC (%) and PCC (%) were measured using an Elementary Analyzer (model NA 1500, series 2, Carlo Erba, Italy), after milling the plant samples at 0.5 mm. Plant density (plants m^{-2}) was determined adopting a value of N equal to 20 and as basic unit of observation the value $L / n \cdot R$, where L is a segment of row measuring 100 cm, n is the number of emerged plants in L, and R is the number of rows in a 100 cm segment crossing the rows.

Soil variables

SMA (mg CO_2 g DM^{-1} 25 day^{-1}), texture, N-NO^{3-} and N-NH^{4+} (respectively kg N-NO^{3-} ha^{-1} and kg N-NH^{4+} ha^{-1}), total carbon and nitrogen (%), SOM (%), WHC (%), pH (H_2O), and pH (KCl) (-) were determined assuming an aggregate sample (4 125 cm^3 sub-samples) as basic unit of observation, with N equal to 9. WHC was determined using the Stackman box method (Klute, 1986). SMA was measured as CO_2 release in a static system (ISO, 2002). Soil weights of 25 g (40% of the WHC) were incubated at 20°C in a closed vessel and the released CO_2 was adsorbed in a solution of sodium hydroxide (0.05 mol l^{-1}). The CO_2 absorbed was precipitated by adding $BaCl_2$. The unused NaOH was then titrated with HCl (0.1 mol l^{-1}). The respiration test was carried out for 25 days. Texture was evaluated using the gravimetric method according to USDA. $N\text{-}NO^{3-}$ and $N\text{-}NH^{4+}$ are measured with a continuous-flow analyzer (Flow Comp 1500, Carlo Erba, Italy). Total carbon and nitrogen concentration were determined using an Elementary Analyzer (model NA 1500, series 2, Carlo Erba, Italy).

Data pre-processing

Shapiro-Wilk (Shapiro and Wilk, 1965) and D'Agostino-Pearson (D'Agostino, 1970, 1986; D'Agostino et al., 1990) statistical tests were applied to test the assumption of the normality of the distributions of the data from the original *N*-element samples. Homoscedasticity for coherent variables (e.g., carbon concentration in the different plant organs) was verified with the Bartlett's test (Bartlett, 1937) and, in case of departures from normality, with the Levene test (Levene, 1960) which is less sensitive than Bartlett's to normality despite Bartlett's better performance (Snedecor and Cochran, 1967).

2.4 Materials and methods

Preliminary analysis

Panicles carbon concentration, plant density and SNC showed deviation from normality, whereas homoscedasticity was not verified for practically all the variables with a coherent meaning (e.g., total, leaves, stems, panicle biomass) (Tables 2.1.a and 2.1.b). Variances of total plant, leaves, stems and panicles carbon concentrations were considered homogeneous according to the Levene test.

Tab. 2.1.a: Features of the pre-samplings carried out for the different plant related variables. Shapiro-Wilk normality test was carried out for all the variables; Bartlett homoscedasticity test was carried out among the groups of coherent variables. Levene homoscedasticity test was carried out in case of deviation from normality.

Variable		Number of pre-sampling units *	Units	Mean	Standard deviation	Normality †	Homoscedasticity ‡
Biomass	Total (aboveground)	54	kg ha^{-1}	10250.36	2494.73		B-
	Leaves	54	kg ha^{-1}	858.94	269.61		
	Stems	54	kg ha^{-1}	6181.47	1509.92		
	Panicles	54	kg ha^{-1}	3209.95	799.20		
Nitrogen concentration	Total (aboveground)	54	%	0.72	0.09		B-
	Leaves	54	%	0.66	0.11		
	Stems	54	%	0.49	0.09		
	Panicles	54	%	1.16	0.14		
Carbon concentration	Total (aboveground)	54	%	42.02	0.37		B-, L+
	Leaves	54	%	40.67	0.50		
	Stems	54	%	40.99	0.51		
	Panicles	54	%	44.36	0.58	S- ($P < 0.10$)	
Spikelet sterility		54	%	14.78	7.01		-
Plant density		20	plants m^{-2}	478.00	114.00	S- ($P < 0.05$)	-

*: number of plants for variables describing plant features; number of determinations for plant density

†: S- indicates not normal according to the Shapiro-Wilk test; blanks indicate normality

‡: B- and L- indicate not homoscedastic respectively according to the Bartlett and Levene test. The latter is used in case of deviation from normality; L+ indicates homoscedastic according to the Levene test; - indicates that homoscedasticity tests were not performed since the variable was not belonging to a group of coherent variables

Tab. 2.1.b: Features of the pre-samplings carried out for the variables related to soil and soil microbial activity. Shapiro-Wilk normality test was carried out for all the variables; Bartlett homoscedasticity test was carried out among the groups of coherent variables. Levene homoscedasticity test was carried out in case of deviation from normality.

Variable		Number of pre-sampling units *	Units	Mean	Standard deviation	Normality †	Homoscedasticity ‡
Soil microbial activity		9	mg CO_2 g DM^{-1} 25 day^{-1}	22.49	4.23		-
N-NO_3 concentration		9	kg N-NO_3^- ha^{-1}	2.86	1.36		B-
N-NH_4 concentration		9	kg N-NH_4^+ ha^{-1}	3.53	0.94		
Total carbon concentration		9	%	1.42	0.12		B-, L-
Total nitrogen concentration		9	%	0.13	0.01	S- ($P < 0.10$)	
Soil organic matter		9	%	2.45	0.20		-
Water holding capacity		9	%	41.69	1.99		-
pH (H_2O)		9	-	5.69	0.12		B-
pH (KCl)		9	-	4.62	0.14		
Texture	Sand	9	%	39.46	5.97		B-
	Clay	9	%	17.18	0.97		
	Silt	9	%	43.36	5.48		

*: aggregated samples (four 125 cm^3 sub-samples)

†: S- indicates not normal according to the Shapiro-Wilk test; blanks indicate normality

‡: B- and L- indicate not homoscedastic respectively according to the Bartlett and Levene test. The latter is used in case of deviation from normality; L+ indicates homoscedastic according to the Levene test; - indicates that homoscedasticity tests were not performed since the variable was not belonging to a group of coherent variables

Plant-related variables

Higher sample sizes tended to be associated with carbon concentration variables; whereas, lower sample sizes were associated with plant density, spikelet sterility, and biomass variables. Among biomass-related variables, leaves presented the highest variability, probably due to senescence phenomena and loss of the oldest leaves in the last part of the crop cycle and during sampling procedures (Figure 2.1.a).

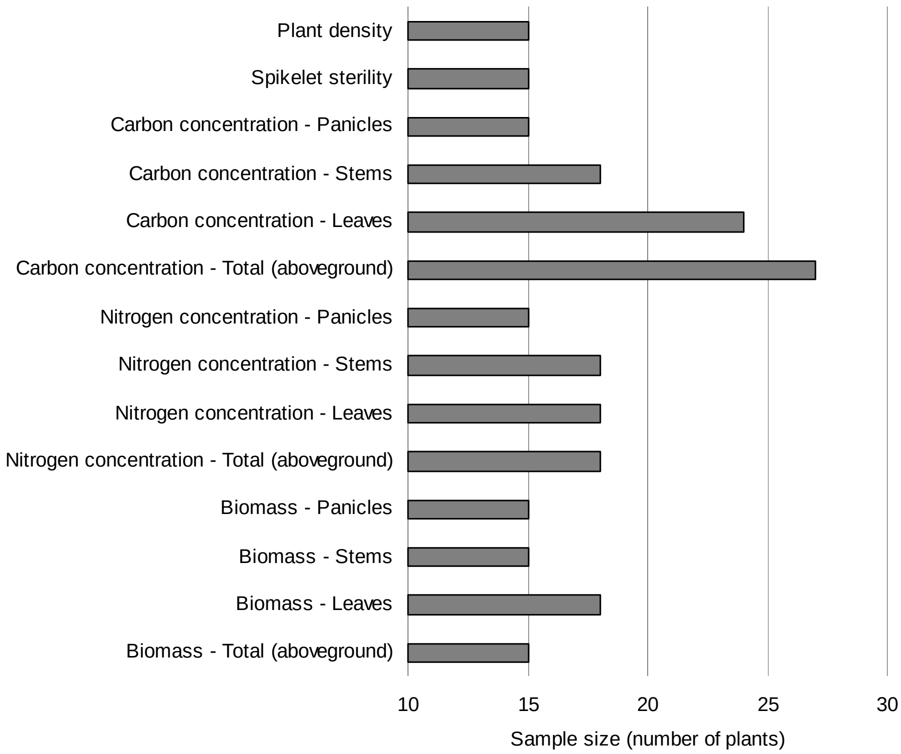

Fig. 2.1.a: Sample sizes obtained for the plant related variables.

This effect disappears when considering the variability of total biomass because of the low relative weight of leaves compared to the other plant organs (see Table 2.1.a). Lower sample size values for panicles nitrogen concentration with respect to the other plant organs is probably due to translocation during the grain filling and ripening phases. Nitrogen translocation processes are characterized by a single sink (grains) and by multiple sources, with leaf blades playing a major role, followed by stems and leaf sheaths (Mae and Ohira, 1981). Differences in nitrogen translocation efficiencies from different plant organs could be modulated according to nitrogen availability and uptake rates (driven by microscale phenomena) before anthesis, when most of the nitrogen uptake in rice plants occurs (Ntanos and Koutroubas, 2002), and to conditions experienced during the grain filling. According to this hypothesis, the variability in the sink nitrogen concentration at maturity would be lower than that of the sources.

The highest differences were observed in the sample sizes for the carbon concentration in the different plant organs. A possible explanation is related to their maintenance respiration rates. According to Van Diepen et al. (1988), relative maintenance respiration rates (kg CH_2O kg^{-1} day^{-1}) in leaves are about 30% higher than in stems and almost 7 times that of grains. For all these plant organs, respiration rate is strongly dependent on temperature. According to the morphology of the canopy and to the non-homogeneity of the plant density, leaves belonging to different plants can be exposed to different micrometeorological conditions (Uchijima, 1976). Even small differences in temperature exposure among plants can have an impact in modulating the high leaves' maintenance respiration rates, affecting the final variability in leaves carbon concentration. This effect can be even clearer when the field is not perfectly leveled, when water pools persist during drying events. Even a few centimeters of water can affect the vertical thermal profile (Confalonieri et al., 2005), generating variability between the plants growing in pools and those growing where the field is already dried.

Soil variables

The variability in sample size for soil related variables is lower than the one discussed for plant variables (Figure 2.1.b).

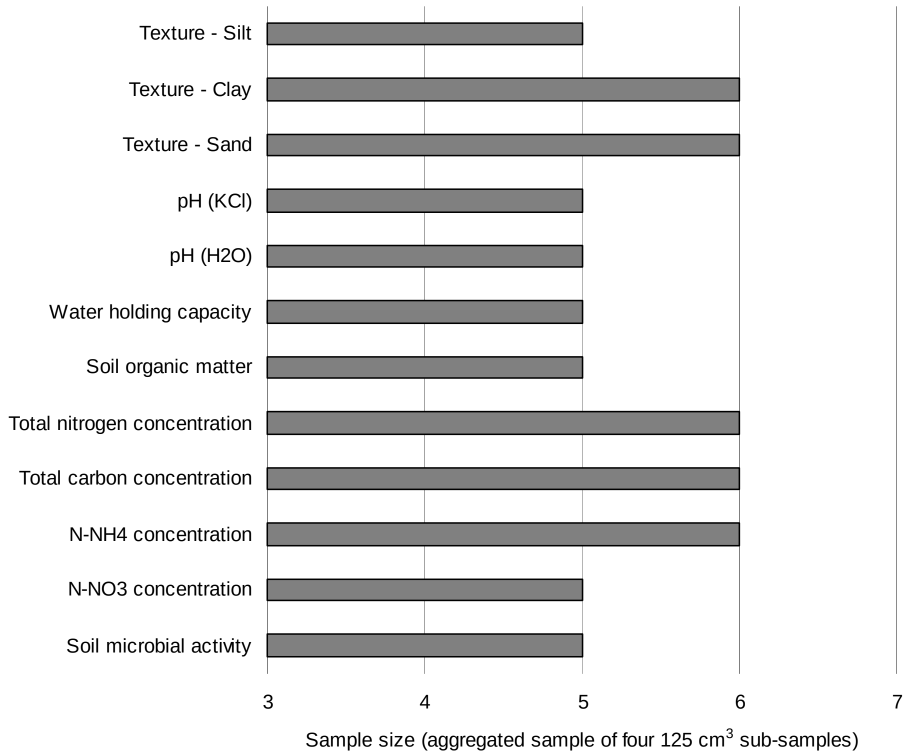

Fig. 2.1.b: Sample sizes obtained for the soil variables.

Sample size is 5 in 60% of the cases and 6 in the other ones. The definition of a sampling unit consisting in an aggregate sample of 4 sub-samples allowed surely capturing a significant amount of the total variance in the aggregate sample. The resulting low variability among aggregated soil samples is able to explain the low and homogeneous sample sizes obtained for soil variables.

Moreover the presence of floodwater for most of the crop cycle's days represents a kind of buffer for the physical and biochemical environment, thus reducing the spatial variability (e.g., the elements transformation rates).

2.5 Conclusions

Following a study where rice aboveground biomass sample size variability was discussed under different management conditions and different development stages (Confalonieri et al., 2006a), we analyzed here the sample size variability for different variables describing plant, soil and microbial activity under a standard rice management for European conditions.

In many cases, the statistical assumptions (normality and homoscedasticity) required by classic procedures in sample size determination based on t-distribution were not met. Moreover, the t-distribution methods require as input the maximum acceptable error (difference between sample and population means), which in many cases cannot be easily identified, since it varies according (i) to biophysical factors which could change from an experimental field (or situation) to another and (ii) to the resources for carrying out the experimentation (Confalonieri, 2004). Consequently, a re-sampling based method was used for sample size determination. In general, sample size values of plant features were higher than those estimated for soil related variables. Among plant variables, whose sample size ranges between 15 and 27 plants, sample size for carbon concentration in the different plant organs presented the highest variability. For soil, sample sizes are similar for variables describing biochemical and physical aspects and microbial activity.

This work confirmed the need of carrying out pre-samplings aiming at sample size determination to guarantee the representativeness of the measurements. In a previous study, Confalonieri et al. (2006b) underlined the importance of sample size determination for aboveground biomass under different management conditions, sown varieties, and development stages. Here, the importance of determining specific sample sizes also for the different variables describing a rice-based cropping system has been demonstrated. Besides these theoretical considerations, this paper could be used as support for identifying suitable sample sizes for the variables analyzed in case of lack of resources for extensive pre-sampling investigations.

Chapter 3

An improved model to simulate rice yield

Agronomy for Sustainable Development, 29(3), (2009),463 – 474

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Keywords
WARM, *Oryza sativa* L., simulation model, flooded conditions, micrometeorology, TRIS, yield forecast.

3.1 Abstract

Rice is the staple food for about one-half of the world population. Although global production has more than doubled in the last 40 years, food security problems still persist and need to be managed basing on early and reliable forecasting activities. The most advanced crop yield forecasting systems are based on simulation models. However, examples of operational systems implementing models which are suitable for reproducing the peculiarities of paddy rice, especially at small scales, are missing. The rice model WARM is used within the crop yield forecasting system of the European Commission. In this article we evaluated the WARM model for the simulation of rice growth under flooded and unflooded conditions in China and Italy. WARM model simulates crop growth and development, floodwater effect on vertical thermal profile, blast disease, cold-shock induced spikelet sterility during the pre-flowering period and hydrological peculiarities of paddy soils. We identified most relevant model parameters through sensitivity analyses carried out using the Sobol' method and then calibrated using the simplex algorithm. Data coming from 11 published experiments, covering 13 locations and 10 years are used. Two groups of rice varieties were identified for each country. Our results show that the model was able to reproduce rice growth in both the countries: average relative root mean square error calculated on aboveground biomass curves was 21.9 % for the calibration and 23.6 % for validation. The parameters of the linear regression equation between measured and simulated values were always satisfactory: intercept and slope were always close to their optima and R2 was always higher than 0.79. For some of the combinations of country and

simulated variable, the indices of agreement calculated for the validation datasets were better than the corresponding ones computed at the end of the calibration, indirectly proving the robustness of the modelling approach. The WARM robustness and accuracy, combined with the low requirements in terms of inputs and the implementation of modules for reproducing biophysical processes strongly influencing the year-to-year yield variation, make the model suitable for forecasting rice yields at regional, national and international scales.

3.2 Introduction

Rice is the most important food crop worldwide, representing the staple food for more than three billion people (Confalonieri and Bocchi, 2005). Since problems about food security still persist in many areas of the world where rice is one of the most important sources of dietary calories, robust and reliable tools for early forecasting rice yields are needed. This is especially true since the frequency of extreme weather events, able to decidedly affect final yield, are forecasted to increase (IPCC, 2007).

Crop models are increasingly used since the 70s to analyze the interactions between plants and factors driving their growth like weather, soil, and management practices. In the first years the activity was mainly focused in formalizing the knowledge on different physiological processes into integrated systems. This led to very detailed simulation models of physiological processes and did draw attention to gaps in understanding (Monteith, 1996). Examples of these models are those belonging to the SUCROS family of models, described and reviewed by Van Ittersum et al. (2003). Starting from the mid-80s, crop modellers focused their attention in developing management oriented models suitable for field decision-making, e.g. EPIC (Williams et al., 1984). In the last years, the technological development has favoured the small scale application of crop models, with the aim of monitoring crops conditions (Bezuidenhout and Singels, 2007) or evaluating the impact of different management practices or climatic scenarios (Olesen et al., 2007). In this context, one of the most important applications is the use of crop models for yield forecasting at regional, national and international scales (Bannayan and Crout, 1999).

The Joint Research Centre of the European Commission developed the MARS (Monitoring Agriculture with Remote Sensing) Crop Yield Forecasting System in the early nineties with the aim of providing timely, independent and objective yield estimates to support the Common Agricultural Policy (Genovese et al., 2001). The system is based on low-resolution satellite data, on historical series of statistics on yields and acreages, and on the Crop Growth Monitoring System (CGMS) which in turn is currently based on three crop models: WOFOST (Van Keulen and Wolf, 1986) as generic crop simulator, WARM (Confalonieri et al., 2006a) for rice and LINGRA (Rodriguez et al., 1999) for pastures. LINGRA and WARM were implemented to allow CGMS to take into account the peculiarities of pastures and flooded rice systems.

The WARM model (Confalonieri et al., 2006a) was developed in the last three years by an open group of researchers aiming at developing a coherent model for rice at mid-latitudes. Compared to the rice models already available (e.g. CERES-Rice, Singh et al., 1993a; ORYZA, Kropff et al., 1994), WARM takes into account some relevant processes influencing the final yield usually not considered (e.g. micrometeorological peculiarities of paddy fields, diseases) and adopts a consistent level of complexity in the reproduction of the biophysical processes involved. There are no processes modeled in a very detailed way and others which are reproduced using rough approaches acting on the same variables. Moreover, all parameters describing cultivars morphological and physiological features have a biophysical meaning and can be directly measured or derived from measured data. The peculiarity of rice-based cropping system had been analyzed and led to specific modules for the simulation of floodwater effect on vertical thermal profile (Confalonieri et al., 2005), the simulation of blast disease, the simulation of the typical hydrology of paddy soils and the simulation of the yield losses due to cold-shocks during the pre-flowering period. The model has proven to be suitable and robust for small scale simulations, where information for parameterizing and feeding models is characterized by a high degree of uncertainty (Wit et al., 2005). WARM was recently included in APES (Agricultural Production and Externalities Simulator – http://www.apesimulator.org), the modular, multi-model system being developed within the EU Sixth Framework Research Programme SEAMLESS (http://www.seamless-ip.org/).

With 218000 ha Italy is the largest European producer of rice, followed by Spain with less than half of the area (96000). Portugal, Greece and France have around 20000 ha each (EUROSTAT New Cronos database; http://ec.europa.eu/eurostat). Although these figures place European grown rice as a secondary crop for this continent, at world level it is the most important food crop (Solh, 2005).

We present the results of (i) a Monte Carlo based sensitivity analysis of WARM for China and Italy and (ii) the calibration and validation of two sets of model parameters (representing two groups of varieties) for each of the two countries.

3.3 Materials and methods

3.3.1 Experimental data

Data used for this study include 11 datasets collected in field experiments carried out between 1999 and 2002 in China and between 1989 and 2004 in Italy under flooded and under unflooded conditions (Table 3.1 and Figure 3.1).

*Tab. 3.1. Data sets used for model calibration and validation. *: aboveground biomass; **: leaf area index; §: flooded at the 3rd leaf stage*

Experiment no.	Country	Location	Latitude, Longitude	Years	Measured variables	Variety	Sowing date	Variety group	Calibration	Flooded
1	China	Changping	40° 02' N, 116° 10' E	2001	AGB*, LAI**	HD297	May 16	ChE		
						JD305	April 25	ChE	X	
				2002		HD297	May 15	ChE		
						JD305	April 20	ChE	X	
2	China	Jiangpu	32° 24' N, 118° 46' E	2001	AGB, LAI	Wuxiangjing9	May 15	ChL		X
				2002			May 11	ChL	X	X
3	China	Gaozhai	34° 02' N, 114° 51' E	2001	AGB, LAI	XD90247	May 9	ChE	X	X
4	China	Tuanlin	30° 52' N, 112° 11' E	1999	AGB	2You725	April 18	ChL		X
				2000	AGB, LAI		April 10	ChL	X	X
5	Italy	Opera	45° 22' N, 9° 12' E	2004	AGB, LAI	Gladio	May 24	ItI	X	X
6	Italy	Vignate	45° 29' N, 9° 22' E	2002	AGB, LAI	Sillaro	April 29	ItI	X	X
		Opera	45° 22' N, 9° 12' E	2002	AGB, LAI	Thaibonnet		ItI		X
7	Italy	Velezzo Lomellina	45° 9' N, 8° 44' E	1999	AGB	Thaibonnet	April 1	ItI		X §
8	Italy	Castello d'Agogna	45° 14' N, 8° 41' E	1996	AGB	Drago	May 8	ItJ		X
		Mortara	45° 14' N, 8° 41' E	1996			May 7	ItJ	X	X
9	Italy	Vercelli	45° 19' N, 8° 25' E	1989	AGB	Cripto	May 8	ItJ		X
				1990			May 10	ItJ	X	X
10	Italy	Gudo Visconti	45° 22' N, 9° 00' E	1990	AGB	Cripto	April 14	ItJ		X
11	Italy	Castello d'Agogna	45° 14' N, 8° 41' E	1994	AGB	Ariete	April 29	ItJ		X
				1995			May 10	ItJ	X	X

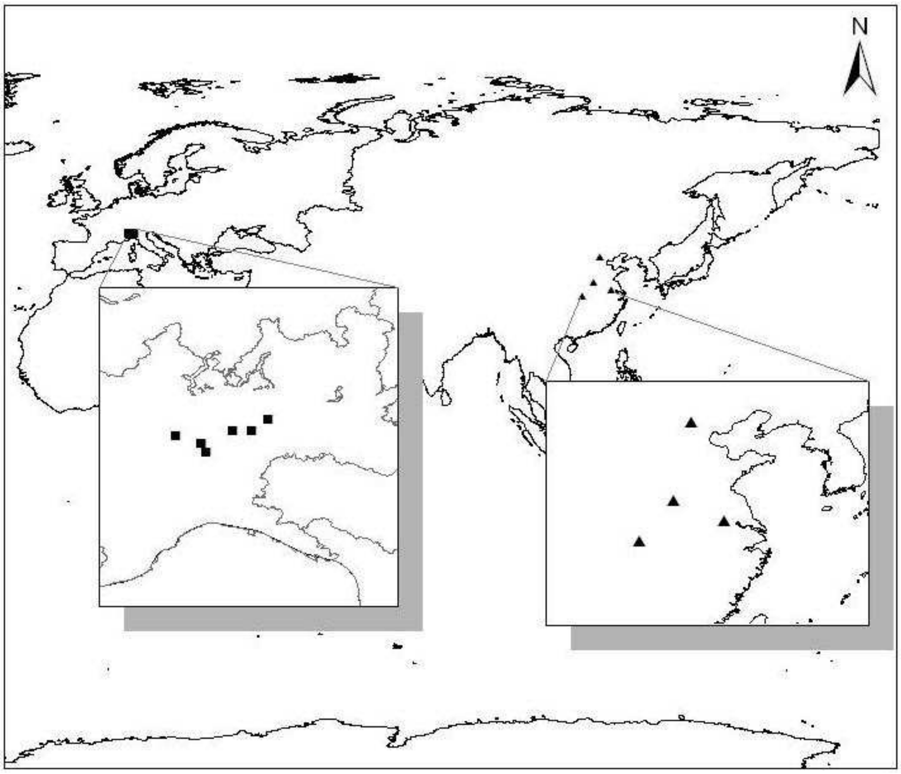

Fig. 3.1. Locations were experiments used for calibration and validation were carried out.

In any case, soil moisture was never limiting crop growth: the only biophysical effect in the absence of flooding was the absence of the floodwater effect on temperature. These conditions are suitable for evaluating a rice model looking at situations where water saving management could play a major role.

Experiment no. 1 was carried out in Changping (China, Beijing) and is described by Bouman et al. (2006). Two rice varieties were grown under aerobic conditions and five irrigation water treatments in order to assess their performance using a water saving management. During the Jiangpu experiment (no. 2; China, Nanjing; Jing et al., 2007), long cycle japonica rice varieties were grown under different nitrogen fertilization treatments to explore different options to combine high yields with high nitrogen use efficiencies in irrigated rice. Fields were submerged during the entire growing season. Experiment no. 3 was carried out in Gaozhai Village (China, Henan; Feng et al., 2007). Three water treatments were compared: continuous flooding in puddled soil, alternate wetting and drying in puddled soil and flush irrigation in non-puddled aerobic soil. All treatments received 180 kg N ha-1, applied in three events. The aim of Experiment no. 4, carried out in Tuanlin (China, Hubei), was to evaluate the effectiveness of alternate submerged-non submerged management in sub-tropical areas (Belder et al., 2004). Rice received 180 kg N ha-1. Experiment no. 5, 6, 7, and 8 were carried out in the Po Valley (Northern Italy) and are described by Confalonieri and Bocchi (2005) and Confalonieri et al. (2006b). During these experiments, rice was grown under flooded conditions and different levels of nitrogen fertilizer split in two or three events. During experiments no. 9, 10, and 11 (Confalonieri and Bocchi, 2005), different varieties were grown; Japonica type with different cycle lengths in experiments no. 9 and 10; Indica and Japonica type varieties in experiment no. 11. In the experiments where nitrogen was not one of the factors, the amount distributed was adequate to assure unlimited supply of this nutrient. Where different nitrogen amounts were applied, data from the treatment assuring non-limiting conditions were used. In case of unflooded conditions, only the treatments where water was not a limiting factor were used. The same was done in case different water treatments were compared. In any case, plots were kept free of weeds and received an optimal control against pests and diseases.

For experiments no. 1, 2, 3, 4, ECMWF (European Centre for Medium-Range Weather Forecast; http://www.ecmwf.int/) meteorological data were used. Data resolution is one degree latitude × one degree longitude. Weather data for experiments no. 5 and 6 were collected with a floating micrometeorological weather station placed inside the field (Confalonieri et al., 2005). For the simulations related to experiments no. 7, 8, 9, 10, 11, weather data were collected with standard automatic weather stations installed near the fields.

3.3.2 Simulation model

Temperature is one of the most important driving variables for the simulation of crop growth and development. In paddy rice systems, this meteorological variable is greatly influenced by the presence of floodwater. In WARM, the micrometeorological model TRIS proposed by Confalonieri et al. (2005) is adopted to take into account the floodwater effect on the vertical thermal profile. TRIS generates hourly and daily temperatures for both the water body and the air layers above the air-water interface (18 layers of 0.1 m each). In particular, the temperatures generated by TRIS at the meristematic apex height are used for simulating the processes related to plant development and spikelet sterility. Average canopy temperature is used for simulating thermal limitation to photosynthesis and leaves aging.

For crop development, the thermal time accumulated between a base temperature and a cut-off temperature is computed. The accumulated thermal time can be optionally corrected with a factor accounting for photoperiod. Base and cut-off temperatures can be set to different values for the periods sowing – emergence and emergence – physiological maturity. Similar to SUCROS-derived models, development stages are standardized by converting growing degrees days (GDDs) into a numerical code (DVS) from 0.00 to 2.00 (respectively, emergence and physiological maturity, with DVS=1.00 corresponding to flowering), useful for synchronizing the simulation of different processes. There variables are obtained as follows (Eqs. 1 and 2), respectively for the periods emergence-flowering and flowering-physiological maturity:

$$\mathrm{DVS} = \frac{(\mathrm{GDD_{cum}} - \mathrm{GDD_{em}})}{\mathrm{GDD_{flo}}} \tag{1}$$

$$\mathrm{DVS} = \frac{1 + (\mathrm{GDD_{cum}} - \mathrm{GDD_{em}} - \mathrm{GDD_{flo}})}{\mathrm{GDD_{mat}}} \tag{2}$$

where GDDcum (°C-day) are the cumulated GDDs, GDDem (°C-day) are the GDDs required to reach emergence, GDDflo (°C-day) are the GDDs required to reach flowering, and GDDmat (°C-day) are the GDDs required to reach physiological maturity.

The net photosynthesis rate is simulated using a radiation use efficiency (RUE)-based approach (Eq. 3):

$$AGB = RUE_{act} \cdot 0.5 \cdot Rad \cdot \left(1 - e^{-k \cdot LAI}\right) \tag{3}$$

where AGB (kg m^{-2} d^{-1}) is the daily accumulated aboveground biomass, RUE_{act} (kg MJ^{-1}) is the actual RUE, *Rad* (MJ m^{-2} d^{-1}) is the daily global solar radiation (with 0.5 *Rad* being an estimate for PAR), $(1\text{-}e^{-kLAI})$ is the fraction of PAR intercepted by the canopy, k is the extinction coefficient for PAR. RUE*act* is derived from potential RUE (RUE*max*, kg MJ^{-1}) crop parameter, using Eq. 4:

$$RUE_{act} = RUE_{\max} \cdot T_{\lim} \cdot Rad\_F \cdot DVS\_F \cdot CO2\_F \tag{4}$$

where *Tlim*, *Rad_F* and *DVS_F* are unitless factors in the range 0 (maximum limitation) – 1 (no limitation) accounting for temperature limitations, saturation of the enzymatic chains, and senescence phenomena, respectively. CO_2_F (unitless) accounts for the effect of atmospheric CO_2 concentration on *RUE* according to an approach derived by Stöckle et al. (1992). Other factors, accounting for nitrogen supply and occurrence of diseases, also play a role in affecting RUE in WARM. They will not be documented here because not of interest for this work, carried out at potential production level.

The factor accounting for thermal limitation to photosynthesis (T_{lim}) is calculated using a beta function (Eq. 5):

$$T_{\lim} = \left[\left(\frac{T_{avg} - T_b}{T_{opt} - T_b} \right) \cdot \left(\frac{T_{\max} - T_{avg}}{T_{\max} - T_{opt}} \right)^{\frac{T_{\max} - T_{opt}}{T_{opt} - T_{\min}}} \right]^C \tag{5}$$

where T_{avg} (°C) is the mean daily air temperature; T_b (°C), T_{opt} (°C) and T_{max} (°C) are respectively the minimum, optimum and maximum daily mean temperature for growth; C is an empiric parameter set to 1.8 to make the beta distribution function assume the value of 0.5 when T_{avg} is the average of T_b and T_{opt}. The factors accounting for saturation of the enzymatic chains involved with photosynthesis (*Rad_F*) and for the effect of senescence (*DVS_F*) are calculated using the following functions (Eqs. 6 and 7):

$$Rad\_F = \begin{cases} 1 & Rad < 25\ MJ\ m^{-2}\ d^{-1} \\ 2 - 0.04 \cdot Rad & Rad \geq 25\ MJ\ m^{-2}\ d^{-1} \end{cases} \quad (6)$$

$$DVS\_F = \begin{cases} 1 & DVS < 1 \\ 1.25 - 0.25 \cdot DVS & DVS \geq 1 \end{cases} \quad (7)$$

where *DVS* is the development stage numerical code.

AGB accumulated each day is assigned to leaves using a parabolic function (Eq. 8) which assumes the maximum value (input parameter *RipL0*) at emergence and zero at flowering:

$$LeavesAGB_{day} = \begin{cases} AGB_{day} \cdot \left(-RipL0 \cdot DVS^2 + RipL0\right) & DVS < 1 \\ 0 & DVS \geq 1 \end{cases}$$

(8)

where $LeavesAGB_{day}$ (kg m^{-2} d^{-1}) is the *AGB* partitioned daily to leaves and AGB_{day} (kg m^{-2} d^{-1}) is the *AGB* accumulated in the day.

AGB partitioning to panicles starts at the panicle initiation stage (*PI*) and is assumed as maximum at the beginning of the ripening phase, when all the daily accumulated *AGB* is partitioned to panicles. Like for the allocation of *AGB* to leaves, a parabolic function is used (Eq. 9):

$$PanicleAGB_{day} = \begin{cases} 0 & DVS < 0.6 \\ AGB_{day} \cdot \left(-1.9 \cdot DVS^2 + 5.4 \cdot DVS - 2.9\right) & 0.6 \leq DVS \leq 1.5 \\ 1 & DVS > 1.5 \end{cases} \quad (9)$$

where $PanicleAGB_{day}$ (kg m^{-2} d^{-1}) is the AGB partitioned daily to panicles. DVS=0.6 represents PI, DVS=1.5 is the beginning of the ripening phase.

Stems biomass is computed by subtracting panicles and leaves biomasses to total AGB.

A daily factor accounting for spikelet sterility due to cold shocks during the period between PI and heading is calculated using Eq. 10:

$$SterilityF = \begin{cases} \sum_{h=1}^{24} (T_{thresh} - T_h \cdot \left[\frac{1}{\gamma \cdot \sqrt{2 \cdot \pi}} \cdot e^{-\left(\frac{(DVS - DVS11)^2}{2 \cdot \gamma^2} \right)} \cdot \delta \right] & 0.6 \quad DVS < 0.9 \\ 0 & otherwise \end{cases} \quad (10)$$

where T_{thresh} (°C) is the threshold temperature below which cold-induced sterility damages are caused, T_h (°C) are the hourly temperatures (generated from the daily inputs according to Denison and Loomis, 1989), $DVS11$ is the DVS of the 11th day before heading

(*DVS*=0.8), γ and δ are coefficients used to discriminate between varieties sensitive for few or many days around the 11th before heading, which corresponds to the middle of the period *PI*–heading. The integral of *SterilityF* is used to reduce $PanicleAGB_{day}$.

Leaf area index (LAI, m2 m-2) is computed multiplying the leaves biomass by the specific leaf area (SLA, m2 kg-1), the latter varying according to the development stage (Eq. 11):

$$SLA = \begin{cases} \dfrac{SLA_{till} - SLA_{ini}}{0.35^2} \cdot DVS^2 + SLA_{ini} & DVS \leq 0.35 \\ \\ SLA_{till} & DVS > 0.35 \end{cases} \tag{11}$$

where SLA_{ini} and SLA_{till} (m^2 kg^{-1}) are input crop parameters identifying the SLA at emergence and mid-tillering stages (*DVS*=0.35).

Each day, leaf senescence is calculated by subtracting the dead *LAI* to the total one. Production of daily green leaf units starts at emergence and each leaf unit will cease to live once a threshold amount of degree-days (crop parameter *LeafLife*, °C-day) is accumulated. The crop phenology model is coupled to the simulation of leaf area units' life through a correspondence between degree-days and leaf units produced in each day after emergence.

3.3.3 Sensitivity analysis

Sensitivity analysis was carried out on the model parameters involved in crop growth. The analysis was based on the model output aboveground biomass at physiological maturity since it is a synthetic representation of the culmination of many biophysical processes and it is influenced by all crop parameters. The variation of aboveground biomass in response to changes in crop parameters values was investigated using the Sobol' method (Sobol', 1993) as made available in the SimLab library (http://simlab.jrc.ec.europa.eu/) via the tool integrated in the WARM modelling environment.

The method of Sobol' is a variance-based global sensitivity analysis method. This method assumes that the function $f(x_1, x_2, \ldots, x_k)$, i.e. the model, is assumed to be defined in the k-dimensional unit cube:

$$K^k = (X \mid 0 \le x_1 \le 1, 0 \le x_2 \le 1, \ldots 0 \le x_k \le 1) \tag{12}$$

where k is the number of factors.

According to Sobol' (1993), f can always be decomposed into summands of increasing dimension. The total variance D of $f(X)$ can be written as:

$$D = \int_{K^k} f^2(X)dX - f_0^2 \tag{13}$$

while each partial variance, corresponding to a generic term $f_{i1\ldots is}$ (all the $f_{i1\ldots is}$ are orthogonal) can be written as:

$$D_{i1\ldots is} = \int_0^1 \ldots \int_0^1 f_{i1\ldots is}^2(x_{i1}, \ldots, x_{is})dx_{i1}\ldots dx_{is} \tag{14}$$

where $1 \leq i1 < \ldots < is \leq k$ and $s = 1, \ldots, k$.

All the quantities f_0, D, $D_{i1\ldots is}$ can be computed by multidimensional Monte Carlo integration. Sensitivity estimates of the model parameters, which measure the main effect of each individual or group of inputs on the model output, as well as all higher-order effects that can be attributed to that parameter, are then defined as:

$$S_{i1...is} = \frac{D_{i1...is}}{D} \quad (15)$$

Total effects (S_{Ti}) are also computed for each parameter and are those used in this study.

The Sobol' method requires the distributions of the different factors in order to manage the a-priori knowledge about factors in a more effective way. Parameters distributions were retrieved from the literature (van Diepen et al., 1988; Kropff et al., 1994; Confalonieri and Bocchi, 2005; Boschetti et al., 2006), as described in detail by Confalonieri et al. (2006a). The Shapiro-Wilk test allowed to never rejecting the hypothesis of normality of the distributions. Average and standard deviation were: 3 and 0.5 for RUE_{max}; 0.5 and 0.04 for k; 12 and 0.6 for T_b; 28 and 2 for T_{opt}; 42 and 2 for T_{max}; 0.01 and 0.005 for LAI_{ini}; 27 and 2 for SLA_{ini}; 18 and 3 for SLA_{till}; 0.7 and 0.1 for *RipL0*; 700 and 80 for *LeafLife*; 100 and 20 for H_{max}.

For each location, the sample of parameters' combinations, and therefore the number of simulations run using average weather data, was 12288.

3.3.4 Model parameterization and validation

WARM version 1.9.6 (9 August 2007; download at: http://www.robertoconfalonieri.it/software_download.htm) was used.

Both for China and Italy, two sets of crop parameters were calibrated and validated: Chinese early and late varieties, respectively *ChE* and *ChL*, and Italian Indica and Japonica type varieties, respectively *ItI* and

ItJ. Table 3.1 shows the datasets used for calibrating and validating the four groups of varieties.

Parameters identified as the most relevant by the sensitivity analysis were calibrated; the others were left to their default values. For the groups *ChE*, *ItI* and *ItJ*, measured *RUE* values were available; measurements for the parameters SLA_{ini} and SLA_{till} were available for the groups *ItI* and *ItJ*. In these cases, measured values were used for the parameters. Information about parameters and their sources of information are shown in Table 3.2. Calibration was carried out using the automatic tool integrated in the WARM environment based on the evolutionary shuffled simplex (Duan et al., 1992). This evolution of the standard simplex method is based on (i) running several simplexes randomizing their starting points; (ii) eliminating a certain percentage of simplexes, with a probability inversely proportional to the value of the objective function; (iii) introducing a "mutation", substituting a new random vertex to a simplex vertex that tried to move outside a defined physical domain; (iv) combining the remaining simplexes using vertices from different simplexes, imposing that vertices with good objective function have a higher probability to be selected. The result is something similar to a genetic algorithm. The evolutionary shuffled simplex has been used since it demonstrated, also with the WARM model, to be effective in reaching the global minimum, avoiding the risk of finding local ones (Acutis and Confalonieri, 2006).

Table 3.2. Parameters values and sources of information (C: calibrated parameters; L: literature; E: local experience; M: measured; D: default). ChE and ChL represent the sets of parameters for, respectively, early and late Chinese varieties; ItI and ItJ the parameters for Indica- and Japonica-type varieties grown in Italy

Parameter	Units	Value				Description	Determination			
		ChE	ChL	ItI	ItJ		ChE	ChL	ItI	ItJ
Development										
TbaseDem	°C	11		12	11	base T for devel. before emergence	L	L	E, L	L
TmaxDem	°C	42				max. T for devel. before emergence	L			
GDDem	°C-days	75		100	120	GDDs from sowing to emergence	M			
TbaseD	°C	12				base T for devel. before emergence	L			
TmaxD	°C	42				max. T for devel. before emergence	L			
GDDem-fl	°C-days	1300	1495	800	850	GDDs from emergence to flowering	M			
GDDfl-mat	°C-days	380	555	430	500	GDDs from flowering to maturity	M			
Growth										
RUE_{max}	$g\ MJ^{-1}$	1.96	2.00	3.20	2.60	radiation use efficiency	M	C	M	M
k	-	0.50				extinction coeff. for solar radiation	D			
T_b	°C	12				base T for growth	D			
T_{opt}	°C	26		28	26	optimum T for growth	C	C	L, C	L, C
T_{max}	°C	35				maximum T for growth	L	L	E, L	E, L
LAI_{ini}	$m^2\ m^{-2}$	0.003		0.020	0.010	initial leaf area index	C			
SLA_{ini}	$m^2\ kg^{-1}$	28		29	28	specific leaf area at emergence	D	D	M	M
SLA_{till}	$m^2\ kg^{-1}$	18	20	19	18	specific leaf area end tillering	D	C	M	M
RipL0	-	0.7	0.8	0.6	0.7	AGB partition to leaves at emerg.	C	C	C	D
LeafLife	°C-days	900	1200	800	600	leaf duration	C			
ApexHeight	cm	100				maximum panicle height	D	D	E	E
kc	-	1.20				kc full canopy	L			

The agreement between measured and simulated values was quantified by using the following indices: relative root mean squared error (RRMSE, Eq. 16, minimum and optimum=0%; maximum +∞), the modelling efficiency (EF, Eq. 17, -∞ ÷ 1, optimum=1, if positive, indicates that the model is a better predictor than the average of measured values), the coefficient of residual mass (CRM, Eq. 18, 0-1, optimum=0, if positive indicates model underestimation) and the parameters of the linear regression equation between observed and predicted values.

$$RRMSE = 100 \cdot \frac{\sqrt{\frac{\sum_{i=1}^{n}(D_i)^2}{n}}}{\overline{M}} \tag{16}$$

$$EF = 1 - \frac{\sum_{i=1}^{n}(D_i)^2}{\sum_{i=1}^{n}\left(M_i - \overline{M}\right)^2} \tag{17}$$

$$CRM = \frac{\sum_{i=1}^{n} M_i - \sum_{i=1}^{n} S_i}{\sum_{i=1}^{n} M_i} \tag{18}$$

Di is the difference between S_i *and* M_i, with S_i *and* M_i being respectively the *i*th simulated and the *i*th measured values, *n* is the number of pairs S_i-M_i, $\overline{S}$ and $\overline{M}$ are the averages of simulated and measured values.

Within each group of varieties, the same values for the parameters involved in growing degree days accumulation and thermal limitation to photosynthesis were used both for flooded and unflooded experiments. In order to verify the presence of possible differences in model performances under flooded and unflooded conditions due to the simulation of the floodwater effect on temperatures, we compared the means of each index of agreement. For both the variables (aboveground biomass and leaf area index) and for each index, the two groups to compare were defined by including all the metrics calculated for calibration and validation: the factor was the type of irrigation. F-ratio and Student-t tests were performed to investigate if variances and means between groups were similar. When the F-test revealed significant differences ($p<0.05$), a Student-t test assuming unequal variances was performed, using the Welch-Satterthwaite equation (Satterthwaite, 1946; Welch, 1947) to calculate an approximation to the effective degrees of freedom. Otherwise, two-sided Student-t tests assuming equal variances were used to investigate if the differences between groups were significant.

3.4 Results and discussion

The aim of the study was to evaluate the adequacy of the WARM model for simulating rice in China and Italy. We used data coming from four field experiments carried out in China between 1999 and 2002 and seven experiments conducted in Italy between 1989 and 2004. The data used, collected under optimal conditions for water and nitrogen availability, were split in two independent datasets for the calibration and validation activities.

3.4.1 Sensitivity analysis

Figure 3.2 compares the sensitivity analysis results for North-Italian conditions to those obtained for the four Chinese locations under study. RUE_{max} is always ranked first. Averaging results for the four Chinese sites, the main difference between sensitivity indices computed for the two countries is that T_{opt} is ranked second in Italy whereas it appears less important than LAI_{ini} and *RipL0* in China. T_{opt} is considered more relevant with increasing latitude: within Chinese datasets, it is ranked fourth at latitudes between 30° 52′ N and 34° 02′ N, third at latitude of 40° 02′ N; it is ranked second in Italy, where latitudes is slightly higher than 45° N. The reason is related to the S-shaped function used for modelling the photosynthesis response to temperature (see Eq. 5): temperatures increase with decreasing latitude, thus getting closer to T_{opt} and leading T_{lim} to assume values which are in the region of the S-shaped function characterized by a plateau. This is translated in small variations in the output and therefore to decreasing relevance for decreasing latitude. Sensitivity analyses carried out for all the sites under study using the Sobol' method allowed to identify the parameters RUE_{max}, LAI_{ini}, T_{opt}, *RipL0*, and *k* as the most relevant. Therefore, these parameters were those on which we concentrated during the calibration.

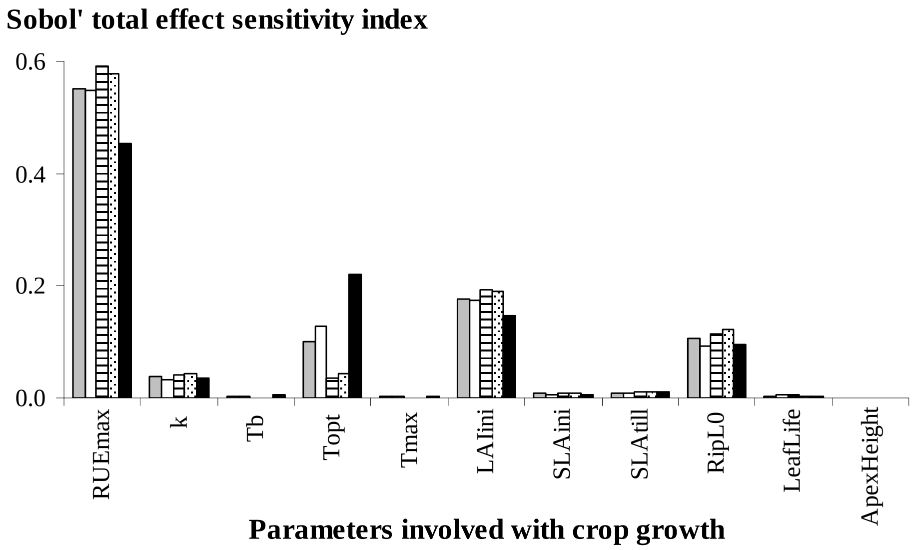

Figure 3.2. Results of the sensitivity analyses carried out using the Sobol' method: total order effects for the WARM parameters involved with crop growth. Grey, white, striped, dotted and black series refer, respectively, to Tuanlin, Changping, Gaozhai, Jiangpu and Italy. Most relevant parameters are those involved with radiation use efficiency and its thermal limitation (RUE_{max} *and* T_{opt}*), leaf area expansion at early stages (*LAI_{ini} *and RipL0) and light penetration into the canopy (k).* T_{opt} *decreases its relevance with decreasing latitude, because lower latitudes correspond to more suitable thermal conditions for the crop.*

3.4.2 Calibration of crop model parameters

Parameters values with source of information or after calibration are shown in Table 3.2. Base and optimum temperatures are in the range of those reported, respectively, by Sié et al. (1998) and Casanova et al. (1998). Maximum temperatures are coherent with those used by Mall and Aggarwal (2002) for the Ceres-rice and Oryza1 models. Similar values were also used by Confalonieri and Bocchi (2005) for the CropSyst model. Measured values of RUE_{max} were derived from Bouman et al. (2006) for the group of varieties *ChE* and by Boschetti et al. (2006) for *ItI* and *ItJ*. Although the values measured by these authors could appear quite spread, they fall within the range of those published (e.g. Kiniry et al., 2001; Campbell et al., 2001). The value of 0.5 for k is consistent with what reported by other authors (e.g. Dingkuhn et al., 1999). The values of SLA_{ini} and SLA_{till} are within the range of those measured by Dingkuhn et al. (1998) and by Boschetti et al. (2006). Although not identified as relevant by the sensitivity analysis, SLA_{till} and *LeafLife* were calibrated to allow the model reproducing measured leaf area index curves.

The agreement between observed and simulated aboveground biomass values after calibration is shown in Figure 3.3 and Table 3.3. In general WARM presents a reasonable accuracy in simulating aboveground biomass accumulation. It is possible to notice, for some of the Chinese datasets, the tendency in slightly overestimating biomass values, especially in the early varieties (Changping 2001 and Gaozhai 2000 datasets). This is confirmed by the fitting indices, shown in Table 3.3, where coefficient of residual mass is negative for the two datasets. Whereas the relative root mean square error values obtained for the late varieties are below 20%, the others, though presenting satisfying results, are lightly higher. The same considerations are valid for the modelling efficiency. In general the regression parameters are satisfactory: slope values are close to one for all simulations. Simulated values of aboveground biomass for the Italian datasets present a good agreement with measured ones in almost all the situations, with the modelling efficiency constantly above 0.9. The agreement between observed and simulated leaf area index values is usually lower. This is probably due both to the difficulty of simulating the balance between emission and death of green leaf area index units before flowering and to the higher errors in leaf area index measurements compared to aboveground biomass ones. Although daily aboveground biomass accumulation rate depends on absorbed radiation and therefore on green leaf area index state, the not completely satisfactory simulation of green leaf area index before flowering does not significantly affect aboveground biomass accumulation because in this phase the canopy is practically closed and the interception of radiation can be considered complete. Calibrated values for the parameters are within the range of values found in the literature and allowed the model to reproduce measured data in a satisfactory way, especially the aboveground biomass curves.

*Table 3.3. Indices of agreement between measured and simulated aboveground biomass (AGB; t ha-1) and leaf area index (LAI; m2 m-2) values. *: flooded at the 3rd leaf stage.*

Dataset				Variable	Flooded	RRMSE	EF	CRM	Slope	Intercept	R2
Country	Activity	Location	Year			(%)				(t ha-1)	
China	Calibration	Changping	2001	AGB		28.6	0.79	0.04	0.96	0.76	0.79
		Changping	2002			35.6	0.77	-0.24	0.93	-1.17	0.88
		Gaozhai	2001		X	20.8	0.91	-0.11	0.99	-0.77	0.93
		Jiangpu	2002		X	17.1	0.95	0.03	1.26	-1.95	0.99
		Tuanlin	2000			15.4	0.96	-0.02	1.01	-0.31	0.96
		Changping	2001	LAI		34.0	0.57	0.14	1.08	0.38	0.64
		Changping	2002			39.7	0.59	-0.15	0.78	0.36	0.70
		Gaozhai	2001		X	37.6	0.52	0.24	0.87	1.19	0.73
		Jiangpu	2002		X	40.1	0.31	0.24	0.95	1.18	0.56
		Tuanlin	2000			28.2	0.87	-0.17	1.28	-2.30	0.97
	Validation	Changping	2001	AGB		28.9	0.69	0.18	0.85	2.77	0.84
		Changping	2002			25.7	0.87	-0.03	0.88	0.62	0.88
		Gaozhai	2001			15.0	0.95	-0.10	1.02	-0.99	0.97
		Jiangpu	2001		X	25.1	0.89	-0.18	0.86	-0.12	0.97
		Tuanlin	1999			10.4	0.99	-0.01	1.05	-0.48	0.99
		Changping	2001	LAI		59.9	0.12	0.26	0.71	2.37	0.34
		Changping	2002			45.7	0.46	0.00	0.76	0.83	0.51
		Gaozhai	2001			33.8	0.66	0.21	0.93	0.88	0.79
		Jiangpu	2001		X	24.4	0.79	-0.03	0.78	0.62	0.86
Italy	Calibration	Opera	2004	AGB	X	23.7	0.93	0.07	0.88	0.83	0.96
		Vignate	2002		X	17.3	0.92	0.12	1.08	0.46	0.96
		Castello d'Agogna	1995		X	19.6	0.95	-0.04	0.90	0.34	0.96
		Mortara	1996		X	13.3	0.98	0.06	1.13	-0.53	0.99
		Vercelli	1990		X	27.9	0.91	-0.14	0.80	0.57	1.00
		Opera	2004	LAI	X	22.8	0.91	-0.13	0.96	-0.31	0.94
		Vignate	2002		X	47.5	0.81	0.01	1.31	-0.88	0.86
	Validation	Castello d'Agogna	1996	AGB	X	23.1	0.93	0.08	1.22	-0.96	0.98
		Gudo Visconti	1990		X	43.1	0.73	-0.33	0.77	-0.09	0.98
		Vercelli	1989		X	14.3	0.97	-0.05	0.88	0.59	0.99
		Opera	2002		X	14.0	0.96	-0.08	0.88	0.43	0.99
		Castello d'Agogna	1994		X	31.7	0.89	-0.24	0.86	-0.30	0.98
		Velezzo Lomellina	1999		X*	32.0	0.94	-0.17	0.83	0.12	1.00
		Opera	2002	LAI	X	56.8	0.68	-0.04	1.17	-0.63	0.70

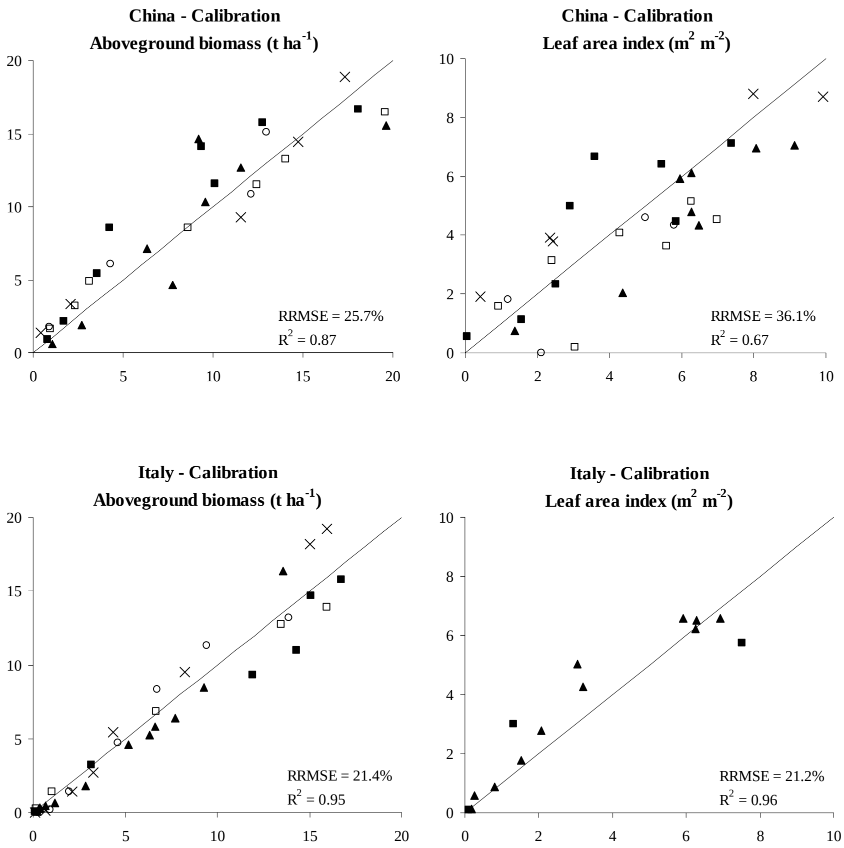

Figure 3.3. Measured (X-axis) and simulated (Y-axis) aboveground biomass and leaf area index values after calibration. For the Chinese datasets: black triangle, black square, white circle, white square, and black cross refer, respectively, to Changping 2001, Changping 2002, Gaozhai 2001 (flooded), Jiangpu 2002, and Tuanlin 2000. For Italian datasets: the same symbols refer to Opera 2004, Vignate 2002, Castello d'Agogna 1995, Mortara 1996, and Vercelli 1990.

3.4.3 Validation of crop model parameters

Figure 3.4 and Table 3.3 show the results of crop parameters test. Despite a general slight overestimation, both for China and Italy, WARM simulates accurately aboveground biomass values also during the validation. For China, as already discussed for the calibration phase, the best values of fitting indices were calculated for the late varieties.

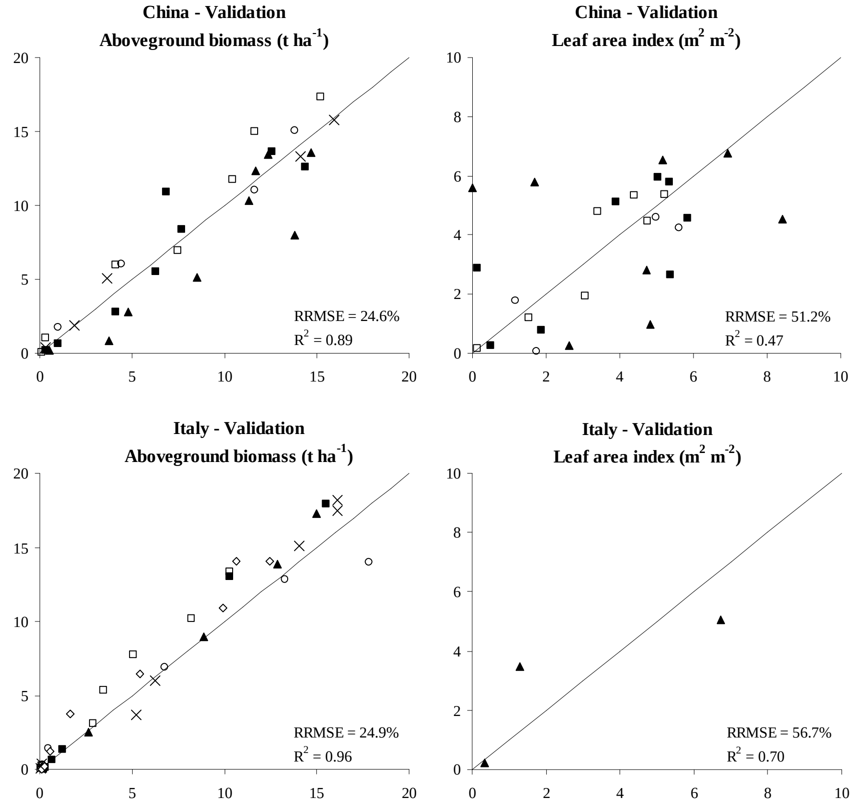

Figure 4.3. Measured (X-axis) and simulated (Y-axis) aboveground biomass and leaf area index values after validation. For the Chinese datasets: black triangle, black square, white circle, white square, and black cross refer, respectively, to Changping 2001, Changping 2002, Gaozhai 2001 (unflooded), Jiangpu 2001, and Tuanlin 1999. For Italian datasets: the same symbols refer to Opera 2002, Velezzo 1999, Castello d'Agogna 1996, Gudo Visconti 1990, and Vercelli 1989; the white rhombus refer to Castello d'Agogna 1994.

In general, results obtained for leaf area index simulation reflect the problems discussed for the calibration datasets, nonetheless in some cases (Gaozhai 2001 and Jiangpu 2001) fitting indices can be considered satisfactory also for this variable. Also for the Italian datasets, measured aboveground biomass values are accurately reproduced by the model. In all cases R^2 is higher than 0.98. Although the model validation for the simulation of leaf area index for Italian varieties cannot be considered exhaustive because of the poor dataset available, the modelling efficiency reached a value of 0.68 and the R^2 was equal to 0.70. It is important to underline that, for China, WARM performances in validation are better than the calibration ones: average values of relative root mean square error, modelling efficiency, coefficient of residual mass and R^2 for the validation datasets are closer to their optimum whereas for Italy the agreement in validation is generally only slightly lower, although average values of R^2 and intercept are better. In some cases, the best values for the indices of agreement were calculated for validation datasets (e.g. Gaozhai 2001, Tuanlin 1999, Vercelli 1989, Opera 2002). This can be considered as an indirect, preliminary proof of the model robustness. No patterns in model performances related to the presence of floodwater and therefore to the micrometeorological simulation of the effect of floodwater on temperatures were noticed. The means of the indices of agreement calculated for flooded and unflooded experiments resulted always not statistically different. For aboveground biomass *p(t)* ranged between 0.21 and 0.76, obtained respectively for R^2 and relative root mean square error. For leaf area index, the intercept of the linear regression between measured and simulated values presented the lowest *p(t)* (0.37), whereas the highest (0.98) was obtained for modelling efficiency. During the validation, the model presented the same level of accuracy discussed for the calibration data set.

3.5 Conclusions

We calibrated and validated the WARM model for rice simulation in China and Italy using data from 11 published field experiments, after having identified most relevant model parameters with a Monte Carlo based sensitivity analysis. Average relative root mean square error and R^2 are 23.0% and 0.95 for the simulation of aboveground biomass and 39.2% and 0.72 for leaf area index. Modelling efficiency is always positive and no systematic over- or under-estimations are evidenced. Model performances in calibration and validation are very similar and the simulation of floodwater effect on temperature did not lead to incoherent model behaviors. These results show that the model is robust and able to reproduce yield variability within years and locations.

This is the first time a model explicitly accounting for the micrometeorological peculiarities of paddy rice is evaluated and, given the importance of this biophysical aspect in affecting crop growth and development through the smoothing of daily thermal extremes, the proposed approach can be considered suitable for investigating the interactions between weather and crop productivity in a changing climate. The coherence between the WARM needs in terms of input requirements and the information stored in the available agro-meteorological databases makes the model suitable for spatialized simulations. This is a crucial pre-requisite, together with the model robustness, for carrying out operational rice yield forecasts at regional, national and international scales, aiming at managing food security problems.

Chapter 4

A model for simulating the height of rice plants

European Journal of Agronomy, 34(1), (2011),20 – 25

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Keywords
Oryza sativa L., biomass partitioning, allocation pattern, model robustness, Akaike's information criterion, WARM.

4.1 Abstract

A reliable approach for modelling rice plant height would allow the simulation of processes with a significant impact on rice yield, e.g., lodging, floodwater effect on leaves temperature, crop-weeds competition for radiation interception, etc. In this paper we present a new model for the simulation of plant height based on the integral of the percentage of biomass partitioned to stems. The model was compared with four alternative approaches using data collected during eight experiments carried out in Russia, Japan and USA between 1991 and 2000, proving to be the most accurate in reproducing plant height during the whole crop cycle. RRMSE ranged between 8.02% and 20.87%, modelling efficiency was always close to one and the absolute value of coefficient of residual mass never exceeded 0.16. The model demonstrated to be also the most robust and the less complex (according to the Akaike's Information Criterion) among those compared. The model presents a lower level of empiricism with respect to the other approaches found in literature, deriving plant height from the allocation of biomass to stems, the plant organs which play a major role in determining the height of the canopy. This makes the model a suitable base for further developments aiming at including the effect of management (e.g., fluctuating water depth) and environmental factor (e.g., competition for radiation interception). Moreover, the low requirements in terms of data needs make the model suitable for its inclusion also in operational cropping systems models.

4.2 Introduction

Traditionally, the most common crop growth models simulate light interception assuming two kinds of canopy architecture. The first simply represents the canopy as a photosynthetic monolayer. Examples of models implementing this approach are CropSyst (Stöckle et al., 2003) and the models belonging to the CERES family (Jones and Kiniry, 1986). The second category arbitrarily divides the canopy in n layers (typically three or five), with n constant for the whole crop cycle length. This approach is implemented by the SUCROS family of models (Van Keulen et al., 1982). In both cases, plant height simulation is not needed and this could be the reason why plant height models did not flourished in the last decades. Anyway, some simple approaches have been proposed. A simple sigmoidal model for maize plant height as a function of final plant height and development stage was described by Lizaso et al. (2005). Kotera and Nawata (2007) presented a model for rice plant height needing as inputs average daily temperature, plant height of the day before, and maximum plant height. A very simple and empirical model used by Confalonieri et al. (2005) derives rice plant height multiplying leaf area index (*LAI*) by 15. Another approach based on *LAI* is implemented in the CropSyst model (Bechini and Stöckle, 2007).

Despite the small effort invested by crop modellers for developing reliable approaches for plant height simulation, this variable is decidedly important in determining plant behavior and yield potential (Yang et al., 2006). As an example, plant height is one of the main driving variables for modelling yield losses due to lodging (Berry et al., 2003; Sterling et al., 2003). According to the mechanistic lodging model proposed by Baker et al. (1998), the height of the plant centre of gravity (function of plant height) is one of the key variables for determining lodging risk, because of its influence on the stem base bending moment. The same Authors calculated that lodging risk moves from 0.039 to 0.704 in the range of variation of wheat centre of gravity height. A reliable simulation of plant height is also important for implementing three-dimensional approaches for canopy architecture (Pronk et al., 2003), in case of intercropping simulations and for modelling crop-weeds interaction, since it is one of the main factor influencing the plant capability to compete for light interception (Kropff and Van Laar, 1993). Plant height is also crucial for modelling the profile of meteorological variables inside the canopy (e.g., Uchijima, 1976), and this is particularly important in complex micrometeorological environments like those characterizing paddy rice. Confalonieri et al. (2005) proposed the TRIS model for the simulation of the floodwater effect on vertical thermal profile, needing plant height as input. Coupling TRIS with a rice crop model simulating plant height would provide the routines involved with aboveground biomass (*AGB*) accumulation with temperatures correctly affected by floodwater, increasing the suitability of the model in reproducing the real system. The relevance of the relationship between floodwater and temperature along the rice canopy profile (function of plant height) has been underlined in many studies (e.g., Nishiyama, 1995; Dingkuhn et al., 1995). Moreover, analysis of field experimental data demonstrated good correlations between plant height and productivity: Khomiakov (1989) used plant height as an indicator within a crop yield prediction system based on simple regression models. The relevance of plant height in cropping systems analysis emerges also from the Russian agro-meteorological crop monitoring system: according to their recommendations (Methodical recommendations, 1988), plant height should be measured 5-10 times during crop growing season.

The objectives of this study were the development of a robust, process-based model for the simulation of rice plant height, and its evaluation in a comparative study with four alternative models.

4.3 Materials and methods

4.3.1 Experimental data

Data were collected in eight experiments carried out between 1991 and 2000 in Russia, Japan, and Texas (US) (Table 4.1).

Table 4.1. Data sets used for model parameterization and validation.

Exp. no.	Site		Latitude	Longitude	Year	Sowing date	SAM [a]	Reference
1	Beaumont	Texas, USA	29° 57' N	94° 30' W	1991	May 2	0.066	Sass et al. (1992)
2	Slaviansk	Russia	45° 17' N	38° 06' E	1997	May 7	-0.106	
3	Novoselskoe	Russia	44° 47' N	132° 41' E	1997	May 11	-0.201	
4	Novoselskoe	Russia	44° 47' N	132° 41' E	1998	May 13	-0.090	
5	Volnoe	Russia	47° 06' N	47° 36' E	1999	May 7	-0.642	
6	Slaviansk	Russia	45° 17' N	38° 06' E	1999	April 28	-0.426	
7	Volnoe	Russia	47° 06' N	47° 36' E	2000	May 26	-0.718	
8	Hiroshima	Japan	34° 50' N	133° 38' E	2000	May 8	0.181	Oguro et al. (2001)

[a] Synthetic AgroMeteorological indicator (-; Confalonieri et al., 2010): $SAM = (Rain - ET0)/(Rain + ET0)$, with *Rain* and *ET0* being cumulated rainfall and reference evapotranspiration in the period March 1st – October 31st.

During the Russian experiments, plant height and phenological stages – among other variables – were determined. Plant height was measured from the soil surface to the upper leaf edge before heading and to the top of the panicle later on. Data were collected within the activities of the Russian agro-meteorological crop monitoring system, carried out to estimate yields under growing conditions representative of the main Russian rice districts, located in the regions Krasnodar, Primorsky, and Astrakhan. These districts are sited in areas suitable for rice, although temperatures are usually lower than in West European districts, and rice fields are often located on saline soils. Water availability allows adopting flood irrigation. Local, well-adapted varieties were grown, able to assure satisfying production levels (around 6 t ha^{-1}), with a cycle length decreasing with longitude. Experimental data from Japan and Texas were derived from Oguro et al. (2001) and Sass et al. (1992), respectively. The former refers to the investigation of the relationships between satellite vegetation indices and biophysical rice plant features (e.g., plant height, *LAI*), whereas the latter is about the assessment of the influence of management practices on methane emission from paddy rice fields. For all the experiments, management practices allowed to prevent water and nutrients stresses and to keep the fields weed and pest free. ECMWF ERA 40 (European Centre for Medium-Range Weather Forecast; http://www.ecmwf.int/) meteorological data were used for all the simulations.

4.3.2 Models for plant height

Table 4.2 presents the compared approaches for simulating plant height. Two out of five (Confalonieri et al., 2005; Bechini and Stöckle, 2007) need *LAI* as driving variable, whereas the Lizaso et al. (2005) model needs a decimal phenological code. Five out of six models require maximum plant height as input parameter. The model proposed by Kotera and Nawata (2007) is the only one which calculates the daily increase in crop height, therefore needing the state of the day before to derive the value of the current day.

Table 4.2. Models for the simulation of plant height compared in this study.

Equation	Input variables	Parameters	Reference
$H = \dfrac{H_{\max} \sum_{i=Eday}^{today} P_{STEMS}}{10 \cdot SSA}$	P_{STEMS}	H_{max} SSA	This study
$H = \dfrac{LAI \cdot H_{\max}}{LAI_{\max}}$	LAI	H_{max} LAI_{max}	Bechini and Stöckle (2007)
$H = \dfrac{H_{\max}}{1 + e^{-12 \cdot (PA - 0.5)}}$	PA	H_{max}	Lizaso et al. (2005)
$H = LAI \cdot 15$	LAI	-	Confalonieri et al. (2005)
$\Delta H = \dfrac{H_y \cdot v \cdot T \cdot (H_{\max} - H_y)}{H_{\max}}$	H_y T	H_{max} v	Kotera and Nawata (2007)

H (cm): plant height (state).
H_{max} (cm): maximum plant height.
$Eday$ (-): emergence day.
P_{STEMS} (%): partitioning factor to stems.
SSA (m^2 kg): specific stem area.
LAI (m^2 m^{-2}): leaf area index.
LAI_{max} (m^2 m^{-2}): maximum leaf area index.
PA (-): relative phenological age (0: emergence, 1: silking, 2: physiological maturity).
ΔH (cm day-1): rate of plant height increase.
T (°C): average daily air temperature.
v (-): coefficient of the temperature effect on plant height increment.
H_y (cm): plant height of yesterday.

The model proposed in this study simulates plant height as the result of the competition for assimilates between stems and the other plant organs. It needs as input the percentage of *AGB* partitioned to stems, which is available for all the crop models implementing a daily partitioning of assimilates, e.g., all the models belonging to the SUCROS and CERES families. In case any daily partitioning of assimilates is explicitly simulated, like in CropSyst (Stöckle et al., 2003), the simple approach of the WARM rice model (Confalonieri et al., 2009a, b) can be used. According to this approach, the percentage of AGB partitioned to leaves (P_{LEAVES}; 0.0-1.0) is calculated using Eq. 1:

$$P_{LEAVES} = \begin{cases} -RipL0 \cdot DVS^2 + RipL0 & 0.0 \le DVS \le 1.0 \\ 0 & 1.0 < DVS < 2.0 \end{cases} \quad (1)$$

where *DVS* is a development stage code assuming the values of 0.0, 1.0, and 2.0 respectively at emergence, flowering, and physiological maturity; *RipL0* (0.0-1.0) is the *AGB* partitioned to leaves at emergence. Like in SUCROS-derived models, *DVS* is obtained by normalizing the thermal time accumulated before and after flowering. The percentage of *AGB* partitioned to panicles ($P_{PANICLES}$; 0.00-1.00) results from Eq. 2:

$$P_{PANICLES} = \begin{cases} 0 & 0 \le DVS < 0.6 \\ -1.9 \cdot DVS^2 + 5.4 \cdot DVS - 2.9 & 0.6 \le DVS \le 1.5 \\ 1 & 1.5 < DVS \le 2.0 \end{cases} \quad (2)$$

The percentage of *AGB* partitioned to stems (P_{STEMS}; 0.00-1.00) is derived by subtracting P_{LEAVES} and $P_{PANICLE}$ to one.

Among the models implementing a daily partitioning, we used WARM because of the simplicity of the approach used to simulate the processes involved in assimilates allocation to plant organs, driven by a single variable (*DVS*) and a single parameter (*RipL0*). However, in spite of its low complexity, the model proved its reliability under a variety of conditions in Europe (e.g., Delmotte et al., 2010) and Asia (Confalonieri et al., 2009a), and also in comparative studies with other worldwide diffused models (Confalonieri et al., 2009b). WARM is the model used by the European Commission for rice yield forecasts in Europe, China and India (http://mars.jrc.it/mars/Bulletins-Publications/MARS-Bulletin-Europe-Rice-bulletin-03-08-2010-Vol.6-No.1).

4.2.3 Models parameterization and evaluation

For all the models, the parameter H_{max} was set to 60 cm for the datasets collected in Volnoe, 70 cm for those collected in Novoselskoe, 100 cm for the datasets of Slaviansk and Hiroshima, and 120 cm for the Beaumont experiment. The value of ν (Table 2) for the Kotera and Nawata model (2007) was set to the value of 0.002, the same used by the authors. The Bechini and Stöckle (2007) parameter LAImax was set to 7.5 m2 m-2 (Confalonieri et al., 2009a). For the model proposed in this study, (see also Eqs. 1 and 2), the value of *RipL0* was set to 0.7 (Confalonieri et al., 2009b), whereas the value for the parameter SSA (Table 4.2) was the one provided by Van Diepen et al. (1988). For the two models needing *LAI* as input, the time course of this variable was simulated using the WARM model.

Models were compared by evaluating their accuracy, complexity and robustness. Accuracy was evaluated using the Relative Root Mean Square Error (RRMSE, %, 0 to +℠, optimum = 0), the Modelling Efficiency (EF, -, -℠ to 1, optimum = 1; if negative indicates that the average of observations is a better predictor than the model), and the Coefficient of Residual Mass (CRM, -, -℠ to +℠, optimum = 0; if positive indicates model underestimation and vice versa) (Loague and Green, 1991). Model complexity and robustness were quantified using the Akaike's Information Criterion (*AIC*, -, -℠ to +℠, optimum = -℠; Akaike, 1974) and the Robustness Indicator (*IR*, -, 0 to +℠, optimum = 0; Confalonieri et al., 2010), respectively. *AIC* and *IR* are calculated according to Eqs. 3 and 4:

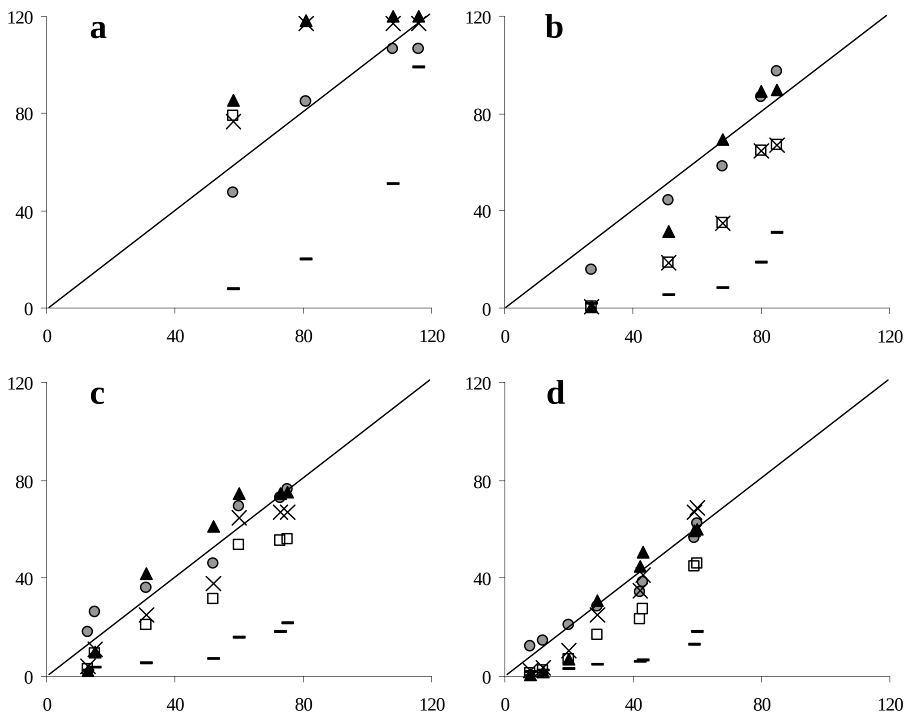
$$AIC = n \cdot \log(MSE) + 2 \cdot T \qquad (3)$$

$$I_R = \frac{\sigma_{EF}}{\sigma_{SAM}} \tag{4}$$

where n is the number of observed/simulated pairs, *MSE* is the mean square error, T is the number of inputs in the model, σ_{EF} and σ_{SAM} are the population standard deviations of EF and of the synthetic agro-meteorological indicator (see Table 4.1).

4.4 Results and discussion

Figure 4.1 shows that the proposed model (grey circles) was able to reliably reproduce the time course of plant height for most of the datasets, without systematic patterns related to specific locations, years, phenological phases or cultivar size.



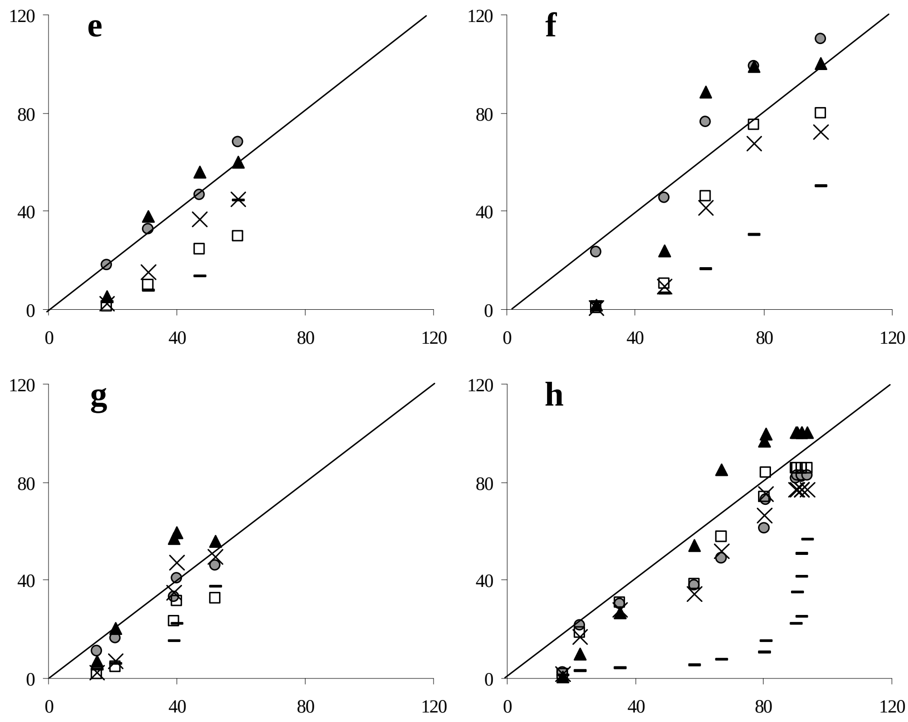


Figure 4.1. Measured (X-axis) and simulated (Y-axis) plant height values: a. Beaumont – 1991; b. Slaviansk – 1997; c. Novoselskoe – 1997; d. Novoselskoe – 1998; e. Volnoe – 1999; f. Slaviansk – 1999; g. Volnoe – 2000; h. Hiroshima – 2000. ●: model proposed in this study; □: Bechini and Stöckle (2007); ▲: Lizaso et al. (2005); ×: Confalonieri et al. (2005); –: Kotera and Nawata (2007).

A slight overestimation affected model predictions in the last part of the cycle for the Slaviansk – 1999 dataset, whereas an opposite behaviour can be observed for the data collected in Hiroshima. On the contrary, the model proposed by Kotera and Nawata (2007) strongly underestimated observations in all the datasets, especially in the central part of the cycle (black dashes). In some cases, the accumulated gap was partially recovered during the ripening phase. The model from Lizaso et al. (2005) demonstrated to be sufficiently accurate in most of the situations (white triangles), whereas the other approaches always showed a marked underestimating tendency. It is interesting to notice the satisfying behaviour demonstrated by the two models requiring less input (variables and parameters), i.e., the Confalonieri et al. (2005) and Lizaso et al. (2005) approaches. The accuracy indices (RRMSE, EF, CRM) shown in Table 4.3 confirm these considerations.

Table4.3. Performance statistic values used to compare the five plant height models. Greyed areas show the best result per metric.

Model	Dataset	RRMSE (%) [a]	EF [b]	CRM [c]	AIC [d]	I_R [e]
This study	Beaumont - 1991	8.02	0.90	0.05	101.89	0.315
	Slaviansk - 1997	18.37	0.71	0.00		
	Novoselskoe - 1997	14.40	0.93	-0.08		
	Novoselskoe - 1998	11.16	0.96	0.02		
	Volnoe - 1999	14.34	0.87	-0.09		
	Slaviansk - 1999	20.87	0.70	-0.12		
	Volnoe - 2000	11.01	0.93	-0.02		
	Hiroshima - 2000	17.60	0.79	0.16		
Bechini and Stöckle (2003)	Beaumont - 1991	25.58	-0.02	-0.21	130.45	2.057
	Slaviansk - 1997	41.89	-0.52	0.40		
	Novoselskoe - 1997	30.64	0.67	0.28		
	Novoselskoe - 1998	39.49	0.49	0.38		
	Volnoe - 1999	58.88	-1.15	0.58		
	Slaviansk - 1999	37.64	0.02	0.32		
	Volnoe - 2000	45.10	-0.24	0.44		
	Hiroshima - 2000	12.76	0.89	0.10		
Lizaso et al. (2005)	Beaumont - 1991	26.35	-0.09	-0.22	118.81	1.163
	Slaviansk - 1997	25.03	0.46	0.10		
	Novoselskoe - 1997	19.54	0.86	-0.06		
	Novoselskoe - 1998	20.81	0.86	0.07		
	Volnoe - 1999	22.11	0.70	-0.03		
	Slaviansk - 1999	35.47	0.13	0.00		
	Volnoe - 2000	37.34	0.15	-0.20		
	Hiroshima - 2000	17.14	0.80	-0.07		
Confalonieri et al. (2005)	Beaumont - 1991	23.16	0.16	-0.18	123.43	1.593
	Slaviansk - 1997	41.89	-0.52	0.40		
	Novoselskoe - 1997	17.86	0.89	0.14		
	Novoselskoe - 1998	20.79	0.86	0.07		
	Volnoe - 1999	37.07	0.15	0.37		
	Slaviansk - 1999	42.05	-0.23	0.39		
	Volnoe - 2000	27.78	0.53	0.16		
	Hiroshima - 2000	20.34	0.72	0.19		
Kotera and Nawata (2007)	Beaumont - 1991	54.68	-3.68	0.51	170.50	4.254
	Slaviansk - 1997	81.87	-4.80	0.79		
	Novoselskoe - 1997	84.77	-1.56	0.76		
	Novoselskoe - 1998	90.45	-1.70	0.80		
	Volnoe - 1999	59.45	-1.19	0.56		
	Slaviansk - 1999	67.62	-2.17	0.66		
	Volnoe - 2000	51.44	-0.62	0.50		
	Hiroshima - 2000	73.99	-2.71	0.70		

[a] Relative Root Mean Square Error (%, 0 to +∞, optimum = 0)
[b] Modelling Efficiency (-, -∞ to 1, optimum = 1)
[c] Coefficient of Residual Mass (-, -∞ to 1, optimum = 0)
[d] Akaike's Information Criterion (the lower the better)
[e] Robustness Indicator (-, 0 to +∞, optimum = 0)

The model proposed in this study obtained the best values of RRMSE (mean RRMSE = 13.87%, ranging from 8.02% to 20.87%) and EF (mean EF = 0.86, ranging between 0.70 and 0.96) in seven out of eight datasets and the best CRM values in half of them. CRM is negative in half of the cases, demonstrating the absence of any over- or underestimating behavior. The model from Lizaso et al. (2005) achieved the best CRM for the remaining datasets, and was ranked second in four out of eight cases according to RRMSE and EF. Despite its simplified formulation, the approach from Confalonieri et al. (2005) was ranked second in four cases (three Russian datasets and the one from US) according to both RRMSE and EF. The approach proposed by Kotera and Nawata (2007) was always the worst, with EF values negative for all the datasets.

The values of the indices of agreement obtained by the proposed approach are consistent with those reported for models simulating other processes of rice-based cropping systems. Shimono et al. (2005) obtained RRMSE values ranging from 9.6% to 33.4% for a rice spikelet sterility model. Confalonieri et al. (2006a) calculated average RRMSE and CRM values of 62% and 0.03 respectively while simulating soil N-NH_4 and N-NO_3 content in rice fields. RRMSE values ranging from 10.4% to 35.6% and from 22.8% to 59.9% were found by Confalonieri et al. (2009a) while simulating rice AGB and LAI, respectively. The same authors calculated EF ranging from 0.69 to 0.99 and from 0.12 to 0.91 for the same variables. RRMSE values ranging between 11% and 13% were obtained by Bouman and Van Laar (2006) while simulating rice yield.

Although model accuracy is often not correlated with model robustness (Confalonieri et al., 2010) and complexity (Confalonieri et al., 2009b), the approach we propose in this paper achieved the best scores for both the IR and AIC indices, demonstrating to be the most robust and the *less complex* one. Note that AIC assigns a good score (low value) to a model able to guarantee good performances using few inputs. Its results should be therefore considered in the light of the Occam's razor. This is why the simplest model in this comparison (H = LAI·15; Confalonieri et al., 2005) did not achieved the best value for AIC. Both IR and AIC ranked as second and third the Lizaso et al. (2005) and the Confalonieri et al. (2005) models, respectively. These ranks reflect those suggested by the accuracy indices considered. The performances of the Bechini and Stöckle (2007) approach were probably affected by the uncertainty in the estimation of the parameter LAI_{max}, hard to be determined without a deep knowledge of the grown cultivars.

4.5 Conclusions

Despite plant height is a variable influencing many processes in real systems it is difficult to find in the literature reliable process-based approaches to model it. During this study we developed a new model for rice plant height based on the partitioning of biomass to stems. The model proved to be accurate in the explored conditions, reproducing correctly the behaviour of plants grown in the eight experiments carried out in Russia, Japan and USA between 1991 and 2000. Averaging the values obtained in the parameterization and validation datasets, we obtained values of 14.47% and 0.85 respectively for RRMSE and modelling efficiency. The coefficient of residual mass did not identify relevant under- or overestimating behaviours. The proposed model demonstrated to be more accurate and robust than the other four models previously compared, and the relationship between its performances and the number of inputs required allows considering it the most efficient among those.

Although rice plant height is influenced by genetic and management factors (e.g., dwarfing genes, plant density, fluctuating water depth, rate and timing of nitrogen supply) for them the proposed model does not account for, its level of empiricism is lower with respect to the existing approaches. In fact, the idea of simulating plant height as the results of the competition for assimilates between stems and the other plant organs represents a robust base for further modelling studies accounting for other key factors modulating plant height increase.

Chapter 5

Simulating climate change impact on rice production under extreme thermal regimes: a case study in Mali.

To be submitted

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Keywords

Oryza sativa L., WARM, thermal response function, climate change impact..

5.1 Abstract

Agriculture remains the main engine for economic growth for most Sub-Saharan African (SSA) countries, with an added value around 30-40% of GDP, and serves as the main base for food security in this region (World Bank and FAO reports). Despite its economic importance, however, the agricultural sector in SSA has performed poorly relative to other developing countries. The causes highlighted in literature are several, mainly due to poor policies and institutional failures, but there is another important factor to consider, the particular sensitivity of agricultural production to climatic changes (Barris et al., 2008).

Although general patterns of response are expected as a result of climate change scenarios in the coming dekades, several studies have shown that climate, agricultural system sustainability and resilience to adverse conditions may vary noticeably. It appeared also evident that moving from temperate areas (the one usually used to test most of the commonly adopted crop models) to conditions characterized by extreme thermal regimes the effect of the climate change on crop development and growth vary substantially according to the implemented patterns of response to temperature.

As plant development rate is not a linear function of temperature and for the simulation of the effect of biotic and abiotic stress a realistic simulation of development phases is required a curvilinear response characterized by minimum, optimal, and maximum temperature for development was implemented on an hourly basis.

The main objective of this work is therefore the development of a model framework for climate change impact assessment and the development of adaptation strategies suitable for environments characterized by extreme thermal conditions made even worse in climate change scenarios and to compare them with the standard version of the model

5.2 Introduction

Climate and agriculture have an intimate and intricate relationship that is continuously subject to change. Crop and climate models are abstractions of this real-world complexity, as is the case generally with models (Müller, 2011). Quantification of complex crop-climate-soil interaction is essential for supporting agricultural management strategies and policy decisions at multiple scales, from the farm to the continent; unfortunately our modelling approaches are not always up to the task. Many of our current models do not incorporate the latest knowledge about how crops respond to a changing climate and may not properly represent modern crop varieties and management practices (Rötter et al., 2011). In fact the majority models that are applied to assess the potential impacts of anthropogenic climate change on crop productivity were developed two decades ago. Though they have been recalibrated over time they urgently need to be updated to reflect new research in crop physiology, agronomy and soil science. For example, more recent field experiments have shown that when temperatures go above thresholds of about 30-36°C during flowering, rice, but also other staple crop as maize and wheat, experience a sharp decline in grain set and yield. A suppressant effect of average high temperatures has been found also on biomass accumulation independently from a particular development stage. Most process-based models do not account for this, and so tend to overestimate future yields in regions experiencing more frequent hot days during the growing season, i.e. Sub-Saharan Africa. Especially for rice air temperature is one of the major factors affecting production; rice plants are cultivated widely from tropical through temperate climates nevertheless optimal temperature ranges exist for their growth and development (Nishiyama, 1976).

Observational data show that Africa has been warming through the 20th century at the rate of about 0.5°C per decade (Hulme et al., 2001). Although this trend seems to be consistent over the continent, the changes are not always uniform (Malhi and Wright, 2004; Kruger and Shongwe, 2004). A comprehensive paper on climate change in Africa over the period 1900-2100, Hulme et al. (2001) show that climate change is not simply a phenomenon of the future, but one of the relatively recent past. Hulme et al. (2001) and IPCC suggest a future annual warming across Africa of between 0.2 and 0.5 °C per decade. This translates to a warming of between 2 and 6 °C by 2100, with the greatest warming over the interior semiarid tropical regions.

As noted above the magnitude of the projected impacts of climate change on food crops in Africa varies widely among different studies and according to which GCM and/or crop model is used (Challinor et al., 2007 and Challinor et al., 2009). Climate change projections realized by running GCMs (or RCMs) under different emission scenarios are intrinsically subject to a significant amount of uncertainty. While there is a general consistency in projected temperatures for Africa, precipitation projection are generally less consistent with large inter-models ranges for seasonal mean rainfall responses. Despite these uncertainties estimates of projected future rainfall has been undertaken. Multiple model simulations are needed in order to sample the inherent uncertainties in the projection of climate and agricultural production (Thornton et al., 2011).

Under different emission scenarios (i.e. A1F1, A2, B1 and B2) using the HadCM3 and ECHAM4 GCMs, Thornton et al. (2006) assessed areas of Sub- Saharan Africa under current and projected impacts of climate variability and change and showed that among other factors, the length of the growing period (LGP) was one of the elements that would be significantly affected by climate change.

It appears evident therefore that African agriculture is very vulnerable to climate change. Although there are established concerns about climate change in Africa, little work has been carried out to show how seriously the problem will be in Sub-Saharan Central Africa.

In fact few studies have been conducted to assess the impact of climate change on agriculture in developing countries and to our knowledge, a detailed assessment study considering all the involved processes has not been undertaken yet.

The impacts described above in the 4◦C+ world hypothesized by Thornton (2011) will require quite radical shifts in agriculture systems and this proactive adaptation will require much more concerted effort at all levels to manage quite radical shifts.

The objective of this work, which is part of a research project aimed developing a model framework for assessing climate change impact on cropping systems in specific districts of Mali and Burkina Faso, examines the effect of short and medium term climate variability and the change on rice production in Mali and identifies the adaptation options of the system using an integrated simulation analysis.

5.3 Materials and methods

5.3.1 Test site

With its 80,000 ha of irrigated land, the Office du Niger is one of the largest irrigation schemes of West Africa. It is situated in the Ségou region in Mali in the semi-arid western Sahel zone at the Delta Mort of the Niger River was set up in 1932 to aid in improving cotton and rice production (Fig.5.1).

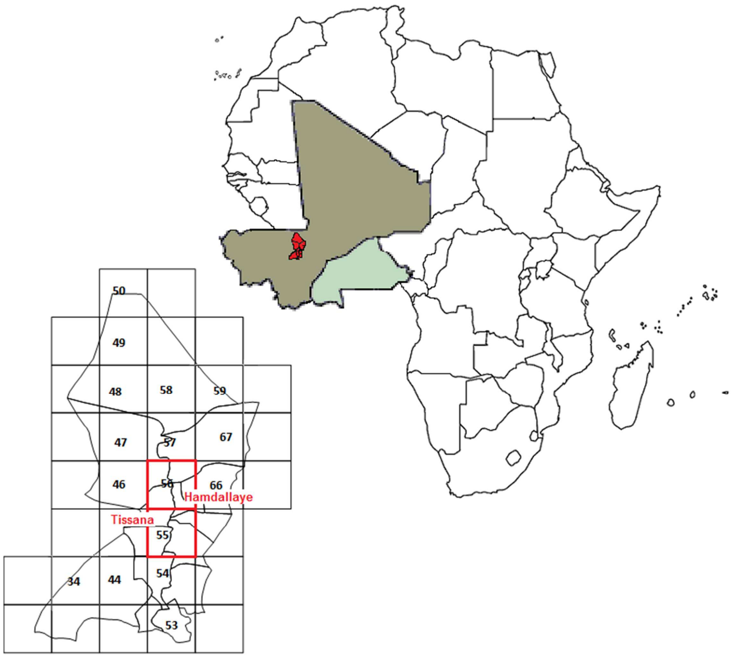

Figure 5.1. Administrative boundaries of the irrigated perimeter of the Office du Niger and representation of the simulation grid. Highlighted the two grids referring to the villages where the data were collected.

At present, it is of vital importance for national food security in Mali, providing approximately 465,000 tons of paddy each year or 40 % of the national production. As such, the Office du Niger contributes significantly to the self-sufficiency of the country in rice, which is currently at about 90 % (Chohin-Kuper et al., 2002).

The zone of the Office du Niger (14°18'N 5°59'W) has a semi-arid climate. Yearly rainfall varies from 300 to 600 mm and is concentrated in the months from July to September. Reference evapotranspiration amounts to about 2,500 mm a year and exceeds rainfall in all months except August (Hendrickx et al., 1986). Yearly rainfall increases from north to south in the study area (Boeckx, 2004). Soils are predominantly *Fluvisols* and *Vertic Cambisols* with a clayey texture (Haefele et al., 2003).

5.3.2 Experimental data

Agromanagement and yield data

Data were collected in two surveys carried out by the Institute d'Economie Rurale (IER) in the villages of Hamdallaye (14°26'18.74"N, 6° 7'0.82"W) and Tissana (14°13'12.01"N, 5°58'48.01"W) between 1995 and 1998 and in 2010. As shown in figure 5.1 the two villages are located in the central part of the irrigated perimeter and fall into two different simulation units.

During the field surveys, data concerning the main agro-management practices and the final yield were determined. Dates of sowing, transplanting and harvest were available as well as the adopted variety among the short cycle cultivar BG 90-2 and the long cycle cultivar KOGONI 91-1 and the average length of the growing cycle.

According to the collected data yields vary strongly among the different exploitations and from a preliminary analysis the only existing significant correlation is between yield and the total amount of nitrogen. The spatial variability detected in the older dataset is extremely wide counting values between 1.2 t/ha and 6.9 t/ha for BG 90-2 and between 1.3 t/ha and 7.2n t/ha for KOGONI 91-1 whereas the more recent data show less intra-annual differences and vary between 3 t/ha and 5.3 t/ha during the wet season and between 2.6 t/ha and 4.9 during the dry season. Although the yields are similar both in Hamdallaye and Tissana slightly better conditions were observed in the latter village and more in general in the southern part. According to the available field data it was possible to define three ideal subgroups characterized by theoretical, optimal and suboptimal management conditions. The literature reports average potential yields between 5 t/ha and 8 t/ha for sub-Saharan varieties with better performances during the wet season. However according to the data collected in the surveys, under well managed actual condition it is possible to expect a yield potential varying between 2.2 t/ha and 4.0 t/ha during the dry season and between 3 t/ha and 5 t/ha during the wet season. Under suboptimal conditions yields are below these ranges mentioned above and in some cases close to complete crop failure.

Meteorological data

Given the sparseness of ground-based observations available, the Era-Interim (reprocessed in order to get a grid of 25×25 km) dataset from the European Centre for medium-range Weather Forecasting (ECMWF) was used both for describing current climate conditions and to build future climate scenarios. Meteorological Synoptic weather observation datasets were used to assess the performance of the estimates. Future scenarios were built using libraries of the LARS-WG stochastic weather generator (Racsko et al, 1991; Semenov et al, 1998; Semenov & Brooks, 1999). The use of stochastic weather generators allows deriving statistically robust weather series from otherwise coarse GCM output, i.e., series with temporal and spatial properties for use by crop models. Hence we generate a climatic baseline, representing the variability of the actual conditions and then produced multiple-year climate change scenarios at daily time scales, incorporating changes in both mean climate and variability applying the "delta method" (Ramirez and Jarvis, 2010). The method, basically, produces a smoothed (interpolated) surface of changes in climates (deltas or anomalies) and then applies this interpolated surface to the baseline climate.

Rainfall distribution, and other weather variables, where kept unchanged. Historical series (1982-2008) were used to generate a climatic baseline, as well as climate scenarios (2020 and 2050), using the A1B and B1 HADCM3 (Hadley Centre Coupled Model, version 3) projections via the delta method mentioned above. The variation of CO2 concentration for the considered storylines is calculated according to the Bern-CC model (Joos et al., 1999). CO2 abundance is set for the baseline at 355 ppm and in 2020 at 418 ppm and 410 ppm respectively for the A1B and B1 IPCC storylines, and at 522 ppm and 482 ppm in 2050.

5.3.3 Simulation model

WARM (Confalonieri et al., 2009a,b) simulates rice growth using the concept of radiation use efficiency (RUE) proposed by Monteith (1977), but compared to the already available rice models, like CERES-Rice (Singh et al., 1993a) or ORYZA (Kropff et al., 1994), it takes into account some relevant processes influencing the final yield usually not considered. In fact WARM simulates rice growth taking into account micrometeorological peculiarities of paddy fields, diseases, hydrology of paddy soils, temperature-shock induced spikelet sterility and reproduces these biophysical processes with a consistent level of complexity.

The effect of temperature on rice production is very divergent and complex and in in paddy fields it is strongly influenced by floodwater. In WARM the micrometeorological model TRIS proposed by Confalonieri et al., (2005) is adopted to take into account the floodwater effect on the vertical profile.

Crop development is based on the thermal time accumulated between a base temperature (Tb, °C) and a cut-off temperature (Tc, °C), optionally modulated by a photoperiodic factor. Base and cut-off temperatures can be different for the period sowing-emergence and emergence harvest.

Aboveground biomass rate is calculated on a daily time step as shown in eq.1.

$$AGB = RUE_{act} \cdot 0.5 \cdot Rad \cdot \left(1 - e^{-k \cdot LAI}\right) \qquad (1)$$

where Rad MJ m^{-2} d^{-1} is daily global solar radiation (converted to par using the 0.5 factor), $1\text{-}e^{-kLAI}$ is the fraction of PAR absorbed by the canopy, k is light extinction coefficient, LAI (m^2 m^{-2}) is green leaf area index (total leaf area index is used to compute the fraction of PAR intercepted by the canopy), RUE_{act} (g MJ^{-1}) is actual photosynthetically active radiation (PAR=0.5×Rad, MJ m^{-2} d^{-1}) use efficiency, which varies from the unlimited RUE_{max} according to irradiance level, CO_2 concentration, development stage, diseases, nitrogen concentration and thermal limitations.

A typical biological response to temperature from the base temperature (T_b) to the optimal temperature (T_o) follows a logistic curve. The response increases slowly as temperature increases from T_b, it then increases in a linear fashion in an intermediate range of temperature, and then the rate of increase in the response decreases as temperature approaches T_o, at which the response is maximal. At temperatures above T_o, the response decreases in a nonlinear fashion and eventually ceases at T_m (Shaykewich 1995).

In *WARM-Standard* the response to temperature was modelled using a broken-linear response function (Hammer et al. 1993) with plateau for the high temperatures. In fact this function describes the response to temperature well in temperate regions where the mean daily temperatures fall always in the part of the function between T_b and T_o. However moving to regions characterized by thermal regimes which are far from these boundaries, an implementation of a non-linear response function capable to capture the thermal limitation to growth and development above T_o is required.

The beta function proposed by Yin el al. (2003) was therefore implemented in the sub-models for development and biomass assimilation. Because plant development rate is not a linear function of temperature, averaging the daily maximum and minimum temperatures to estimate development will result in error (Shaykewich 1995). Thus an accurate modelling approach requires consideration of the temperature variation throughout the day. This can be done by separating the day into 1-h segments, calculating development rates over 24-h periods and summing these rates to obtain the appropriate mean daily rate. The hourly generation of daily temperatures is done by the CLIMA component (http://agsys.cra-cin.it/tools/clima/help/) according to the method proposed by Campbell, 1985. The resulting improvement of the model is therefore a new version of WARM (WARM-Hourly) simulating the response function to temperature according to Yin et al., (2003) on an hourly basis. The two response functions are shown in figure 5.2

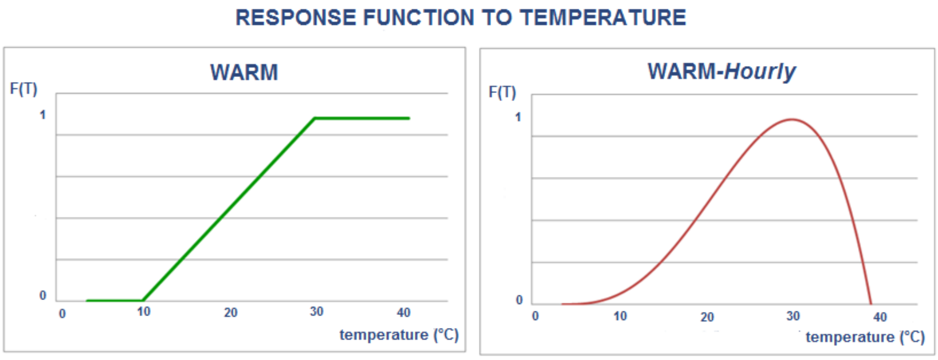

Figure 5.2. Thermal response functions for simulating crop development and growth according to the standard version of WARM (left) and the new WARM-Hourly implementation (right)

5.3.4 Model parameterization and evaluation

Starting from the calibration proposed in Confalonieri et al. (2009a) for Chinese conditions, two sets of crop parameters were calibrated trying to reproduce the behavior of the two typical varieties grown in the Office du Niger: the short cycle cultivar BG 90-2 and the long cycle cultivar KOGONI 91-1. The model was then run for each grid cell over the whole perimeter of the Office du Niger under current weather conditions and future climate scenarios. Results are therefore shown as maps in order to present the total spatial variability or as figures referring to the two grid cells where field data come from.

In *WARM-Standard* the cardinals of temperatures adopted in the simulations are 12°C as base temperature, 28°C as optimal and 42°C as a cut-off temperature, equal for both varieties. New parameters, with a stronger biological meaning, were then used in the new version of the response function to temperature. Base temperature and optimal temperatures were derived from Dingkhun and Miezan (1995) while the maximum temperature was calibrated on the base of the review of Nishiyama (1976). The chosen values are 6.7 °C and 40°C respectively as base temperature and maximum temperature for both varieties and 29°C and 31 °C as optimum temperature respectively for BG 90-2 and KOGONI 91-1. According to this difference the thermal sum for the different development stages differ among the two simulation approaches. Concerning nitrogen limitation we'll define a second set of simulations with a decreased radiation use efficiency coefficient –we assume a constant suboptimal N availability during the whole crop cycle – in order to be able to mimic at least partially the impact on states variables

In order to describe the actual conditions different management options were described on a rule based approach characterized by different levels of optimization. In fact one set of options was calibrated in order to define potential conditions whereas two additional sets of simulations were derived in order to mimic, at least partially, the impact on state variables due to suboptimal management conditions (i.e. lack of nutrients, poor soils, weeds). In order to do this the radiation use efficiency coefficient was reduced with respect to the potential conditions. The management options differ by the sequence adopted (BG 90-2 + KOGONI 91-1, or twice KOGONI 91-1) and by the rule used to simulate the sowing date in the wet season. In one option both crops are sown at fixed dates in the other the second crop is sown after a certain period after the previous one has reached maturity. This rule based approach is meant to be capable to simulate the effect of anticipating or postponing the second cycle according to changes in crop cycle length due to thermal limitations.

Due to the lack of complete series (biomass and leaf area index) and detailed data the calibration of the system was mainly aimed at reaching a plausible representation of the length of the crop cycles and of the expected yield using biologically robust parameters. Moreover, in order to overcome the limitations due to the insufficient information required to capture the entire variability results will be shown as absolute values but also as difference of the expected yield under the future scenarios and the actual conditions. As a consequence of the lack of consistent datasets for biomass and leaf area index, the improvement of the *WARM-Hourly* model with respect to the standard version could not be performed adopting the currently used indices and evaluation strategies, proposed e.g. by Loague and Green (1991) or more recently by Confalonieri et al. (2009b) but has to be discussed using a qualitative and more application-oriented approach.

5.3.5 Definition of adaptation strategies

Previous research conducted in developing country settings indicates that, in principle, climate change impacts on agriculture can be reduced through human adaptations such as adjusting sowing dates and changing cropping patterns (Winters et al., 1998). Obviously in order to define the management strategies capable to offset the negative climate change impacts on cropping systems the simulation tools adopted to evaluate them needs to be robust in the sense of having a strong biological meaning. In fact given that optimizing the period of growth so that the crops do not suffer thermal limitations appears to be crucial, the shape and parameterization of the functions describing the response to temperature determines strongly the direction of investigation of the possible adaptation options. This means that if the responses function has a biophysical reason it will lead to the identification of the best period for growing the crops under changing climate. Therefore the second objective is to show the different results which were achieved by using a function characterized by a plateau for high temperatures and by using the new implemented beta function. The first step in defining adaptation strategies was to run simulations moving the sowing dates within different time windows, hence exploring the best management practice. The exercise was done using both variety adopted in the current conditions. Sowing dates of both rice cultivars were shifted by either bringing forward the first cycle or delaying sowings of the second within the interval (D_{1-50}, D_{1-40}, D_{1-30}, D_{1-20}, D_{2+20}, D_{2+40}, D_{2+60}, D_{2+80} days) with respect to the baseline case, $D_{1/2}$ being the normal sowing date and testing the efficiency of both varieties. During the dry season simulations were run using only the short cycle variety whereas during the wet season both varieties were tested in order to get twelve different combinations. However the yield potential of each option was evaluated separately for each season given that no effects were observed due to the combinations of the two seasons. The adaptation strategies explored by moving the sowing date are listed in table 5.1.

Table 5.1. List of the adaptation strategies explored by moving the sowing date of both crop cycles (dry season and wet season.

Variety	sowing date shift (dry season)	sowing date shift (wet season)
BG 90-2	D_{1-50}	D_{2+20}
BG 90-2	D_{1-40}	D_{2+40}
BG 90-2	D_{1-30}	D_{2+60}
BG 90-2	D_{1-20}	D_{2+80}
KOGONI 91-1	D_{1-50}	D_{2+20}
KOGONI 91-1	D_{1-40}	D_{2+40}
KOGONI 91-1	D_{1-30}	D_{2+60}
KOGONI 91-1	D_{1-20}	D_{2+80}

The parameters describing the two crop varieties were the same as in the current conditions in order to enhance the effect of the management practice in adapting to climate change and reducing the impact.

Considering the extreme temperatures characterizing part of the season already under current conditions the strategies which allow the crop to complete the most sensitive development stages (i.e. grain filling) during more favorable thermal regimes appear to be the most suitable for adapting to climate change. Then, once these strategies, capable to reduce the negative effect of the high temperatures on the final yield, were identified, they were run under the future scenarios in order to evaluate the impact of climate change on this management options.

5.4 Results and discussion

5.4.1 Weather conditions

Changes between the actual conditions and the future scenarios were evaluated preliminarily via the analysis of difference maps for the main driving variables (minimum and maximum temperature, rainfall, evapotranspiration) and for some of the most common climatic indices (i.e. the aridity index). This allowed quantifying the increase/decrease of the variables and analyzing their spatial variability.

The increase in temperatures, already evident in 2020, becomes significant in 2050 mainly for the daily maximum temperature (Table 5.2) and the spatial variability becomes high especially in the dry season. The differences maps on cumulated temperatures, which can be considered as a proxy of changes in thermal sums, confirm the increased pattern observed for the average values.

Table 5.2. Monthly average maximum temperature and standard deviation for the baseline and the Hadley A1B 2020 and 2050 scenarios for the villages of Hamdallaye and Tissana.

		Baseline		**Hadley A1B 2020**		**Hadley A1B 2050**	
		Average	*Standard Deviation*	*Average*	*Standard Deviation*	*Average*	*Standard Deviation*
Hamdallaye	Jan	31.3	2.2	32.0	2.0	33.3	2.0
Hamdallaye	Feb	34.1	2.7	34.9	2.4	36.0	2.3
Hamdallaye	Mar	38.2	2.4	38.6	2.3	40.1	2.3
Hamdallaye	Apr	41.1	1.8	41.7	1.6	43.3	1.5
Hamdallaye	May	41.5	1.7	42.4	1.5	44.0	1.5
Hamdallaye	Jun	40.0	1.8	40.8	1.7	42.8	1.8
Hamdallaye	Jul	36.7	2.3	37.2	2.3	38.9	2.4
Hamdallaye	Aug	34.4	1.7	34.8	1.7	36.0	1.7
Hamdallaye	Sep	36.0	1.9	36.3	1.8	37.8	1.9
Hamdallaye	Oct	38.0	1.6	38.8	1.6	40.2	1.6
Hamdallaye	Nov	35.5	1.7	36.3	1.7	37.8	1.7
Hamdallaye	Dec	32.2	2.1	33.1	1.9	34.5	1.8
Tissana	Jan	31.9	2.2	32.6	1.9	33.9	1.9
Tissana	Feb	34.9	2.5	35.5	2.2	36.5	2.3
Tissana	Mar	38.8	2.2	39.1	2.0	40.4	2.1
Tissana	Apr	41.3	1.5	41.8	1.5	43.4	1.5
Tissana	May	41.2	1.7	42.1	1.5	43.7	1.6
Tissana	Jun	39.6	1.8	40.3	1.9	42.2	1.8
Tissana	Jul	36.2	2.2	36.4	2.2	38.1	2.3
Tissana	Aug	33.8	1.7	34.4	1.7	35.6	1.7
Tissana	Sep	35.2	1.9	35.8	1.9	37.3	1.9
Tissana	Oct	37.7	1.6	38.5	1.7	40.0	1.7
Tissana	Nov	36.0	1.6	36.8	1.7	38.3	1.6
Tissana	Dec	32.9	2.1	33.6	1.9	35.2	1.9

Changes in rainfall variability, similar for 2020 and 2050, appear to be higher in the dry season between March and May (between -20% and +40%) than in the wet month between June and August (between -15% and +20%). This means that the interannual variability in the beginning of the rainy season will be further enhanced.

The calculated evapotranspiration values stay close to these calculated for the baseline in 2020 whereas in 2050 as a direct consequence of the high increase in temperature the evapotranspiration demand seems to rise up to 5%. Nevertheless, given that the total precipitation is foreseen to increase, the climatic water balance does not seem to worsen in the 2020 and 2050 weather scenarios. This has been confirmed by calculating the trend of the aridity index which does not show any relevant change in the three time windows and the difference between the scenarios and the baseline does not show as well any significant worsening (Fig.5.3)

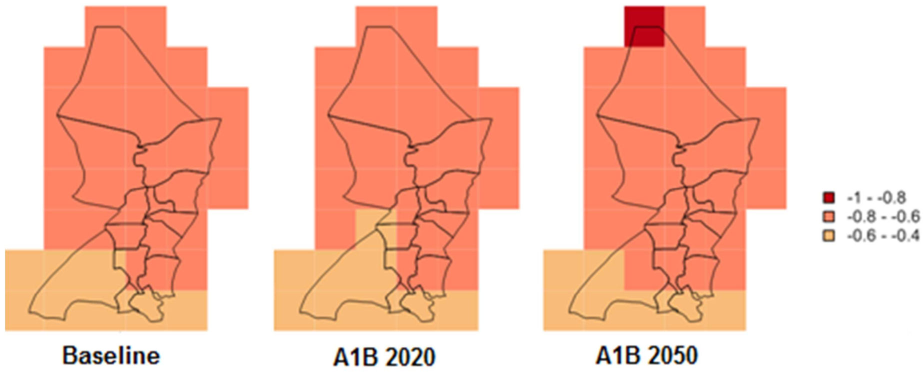

Figure 5.3. Values of calculated the aridity index (AI) for the baseline, the A1B 2020 and the A1B 2050 during the wet season (June-August).

These results even if they allow some preliminary conclusions about plausible changes in climatic conditions, at least of single variables, cannot be considered exhaustive for the analysis of the climate change impact on cropping systems. It appears evident that the scenarios need to be tested against crop simulations including an analysis of a crop-based water balance and the impact of abiotic stresses (i.e. high daily maxima).

5.4.2 Models evaluation: climate change impact assessment

The simulation of the crop cycles under current conditions and future climate scenarios (2020 and 2050 projections) aimed at analyzing the crop behavior in response to climate change. Simulation results are presented and discussed as average values at maturity referring to the sample cells corresponding to these from which field data were collected. Simulations results refer to actual conditions under optimal management.

WARM-Standard showed a relative good accuracy in reproducing the actually adopted crop calendar under the current conditions. The average yields simulated for Hamdallaye and Tissana in the baseline are coherent with the data collected in the field surveys (close to 2.9 t/ha during the dry season and around 3.3 t/ha in the wet season).

Relatively to the simulations run under future scenarios the average yield reaches in average 3.1 t/ha (dry season) and 3.4 t/ha (wet season) in 2020 and among 3.2 t/ha (both for the dry and the wet season) in 2050.

The difference maps presented in figure 5.4 confirms that an increase in productivity occurs in the dry season in the 2020 scenario and only slight losses appear in northern areas during the wet season, whereas the situation changes consistently in 2050. In fact in the long term scenarios a strong increase in biomass production and yield is depicted for the dry season but the losses in the wet season become more significant (up to -15% for larger areas). This seems to depend from the shortening of the crop growth period. It is caused, according to the response function to temperature characterized by a plateau for the high temperatures, by a significant increase in temperatures leading to a suboptimal development of the canopy and grain filling. This seems to be confirmed by the pattern describing the leaf area expansion which decreases progressively from the baseline to the long term projections.

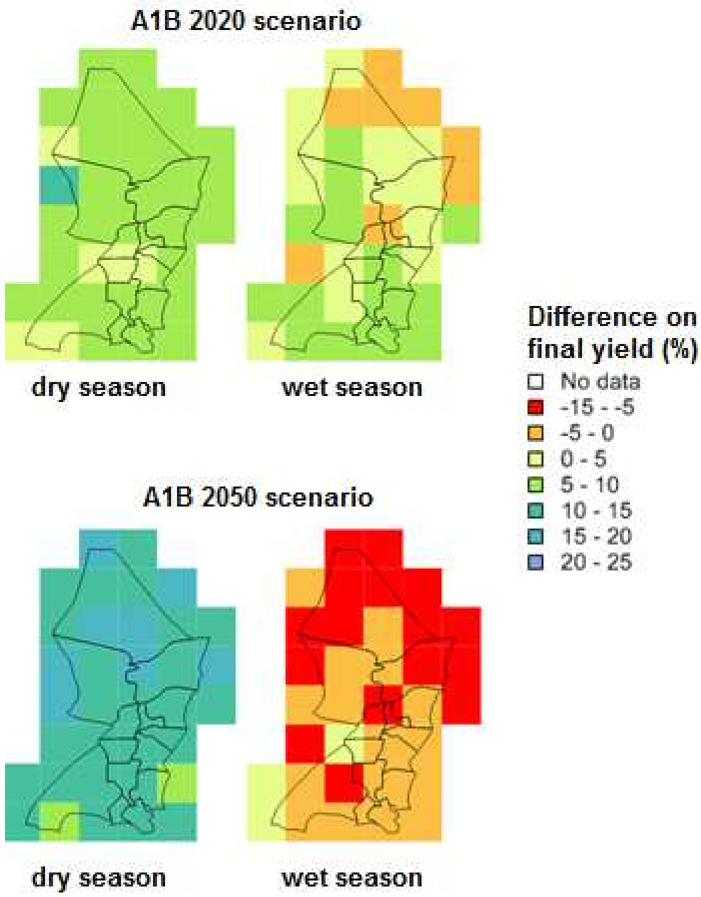

Figure 5.4. Percentage difference maps on average values of average final yield for the scenarios A1B 2020 and A1B 2050 with respect to the baseline. Differences are shown for the dry season and for the wet season.

Analyzing the simulation results obtained using the broken linear function of response to temperature they show pattern of response which cannot be considered reliable with respect to the thermal regime. Given that limitation due to high temperatures where not taken into account an increase in grain accumulation was depicted in 2020 for both cycles and for the dry one in 2050. The decrease in productivity shown for the second cycle in 2050 is only due to a shortening of the vegetative cycle which leads to a decrease of the time available for the crop to develop the canopy and perform the grain filling. In particular the effects (i.e. decline in yields) expected in the temperature increasing 2050 scenario did not emerge as a mayor outcome and the response to management strategies was minimal.

Running the simulation using WARM-Hourly allowed a better detection of the different yield potential among the two growing periods. The final yield was 2.27 t/ha and 2.47 t/ha for the dry respectively for the grid of Hamdallaye and Tissana and 4.37 t/ha and 4.17 t/ha during the wet season. This difference is not only explained by the different yield potential of the varieties but is directly dependent from the thermal conditions of the growing cycles.

The graph shown in figure 5.5 represents the average decadal maximum temperatures for the village of Hamdallye for the baseline and the Hadley A1B 2020 and 2050 scenario; it is possible to notice how already under the current conditions temperature between the end of March and the end of June are above the maximum temperature for crop growth. Moving to the future scenarios the time intervals characterized by thermal regimes above the threshold becomes wider.

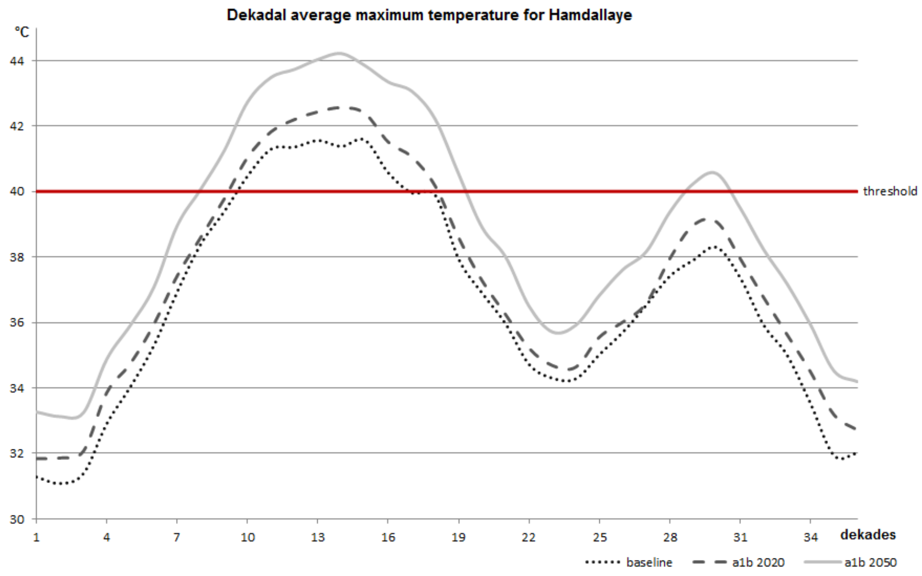

Figure 5.5. Decadal average maximum temperature trend for the baseline, the Hadley A1B 2020 and 2050 scenario for the Hamdallaye village.

Considering that the dry season takes place largely in this period it appears evident that the final yield is reduced by these unfavorable conditions. The negative effect of the thermal regime is confirmed by analyzing the spatial variability of the final yield which shows a north-south gradient. In fact it is possible to observe that in the northern part the threshold of the 40°C is reached later than in the south and this allows a better development of the canopy. A more homogeneous situation is depicted for the wet season because the thermal regime stays below the maximum values of temperature during almost the whole growing period. The use of *WARM-Hourly* depicted completely different results in the climate change impact assessment.

In the 2020 scenario an overall reduction of total biomass (between 5-10%) was depicted for the dry season, whereas a slight increase (up to10%) is observed for the wet season (especially in the southern part of the Office du Niger). The final grain yield appears to be significantly more affected by the increase of temperatures therefore reduction between 10-25% characterize the dry season and between 0-10% the wet one. At the same time a slight increase (>5%) of cumulated transpiration values is shown for both seasons as a consequence of the prolongation of the first crop cycle due to a delayed development because of the high temperatures and as a consequence of the increase of biomass in the second cycle.

In the 2050 scenario the reduction in total biomass and grain becomes definitively more significant and in several cases the crop does not reach maturity in the given time frame. This is due to the temperatures exceeding the threshold already in March at the very first stages of crop's growth, with two-three decades of advance with respect to the baseline. The reduction of final yield is stronger (up to -50%) than the reduction of potential biomass (large areas between -10% and -25%) and again the effect is stronger during the dry season. A detailed description of the results of the simulations, run with *WARM-Hourly*, among the different management options considered is presented in table 5.3.

Table 5.3. Simulated final yield differences between the baseline and the future scenarios for the five management options considered, both for the dry and wet season.

Yield reduction (%)	**A1B 2020**		**A1B 2050**	
	Dry	*Wet*	*Dry*	*Wet*
management 1	-19.14	0.48	-56.8	-21
management 2	-19.14	3.96	-56.8	-21.8
management 3	-18.31	-5.3	-45.8	-17.7
management 4		8.33		-17.5
management 5		3.21		-17.4

It is possible to see that the trend reflects the one described above for the most commonly adopted practice (option one) with the exception of management option three which represents a non-suitable practice. In that case, indeed, the worsening with respect to the baseline occurs also for the wet season in 2020 due to the bad timing of the sowing activities. This further confirms the capacity of *WARM-Hourly* to catch the effects of the thermal regimes properly.

5.4.2 Models evaluation: adaptation strategies assessment

The achieved results showed that not only figures related to the climate change impact assessment are drastically different if simulations are run using *WARM-Standard* or *WARM-Hourly*. In fact also the adaptation strategies considered suitable to offset the negative influence of changing climate change substantially in one case or the other.

Considering *WARM-Standard* version the effects of higher temperature is causing a reduced periods for green canopy development and grain filling therefore these negative conditions have to be offset adopting late and/or long-cycle varieties; on the other hand, running the simulations with *WARM-Hourly* the negative impact of increasing temperatures, which slow down the crop development and reduce biomass accumulation, needs to be overcome adopting opposite management options. It is in fact necessary to shorten the cycles or advancing the sowing period in order to escape the period where temperature are exceeding the maximum threshold for plant growth in order to avoid the failure of the crop.

With respect to the results obtained considering the limitation on crop development and biomass accumulation due to high temperatures it seems that the adaptation strategies showing a better response to future climatic conditions are the ones anticipating the sowings during the dry season by 30 days and delaying the same practice by 30-60 days during the wet season. Simply shifting sowing dates allows grown crops to develop under more favorable thermal conditions improving the grain filling period and hence the crop grain yield. In all cases, due to the delay in development as a consequence of the extreme temperatures, the best performances were shown by short cycle varieties which are capable to reach high productive levels in shorter time. This is especially valid if we consider the first cycle which is more sensitive to high temperatures. The losses in final yield for the rice grown in the dry season pass from -19.1% to -6.2% in the 2020 scenario and from -56.8% to -28.4% in the 2050 scenario. On the contrary considering the wet season the shift in the sowing dates reduced only slightly the expected losses.

5.5 Conclusions

Differences in crop yield under each of the scenarios reflect a complex interplay between temperature increase, projected changes in precipitation change, and increase in atmospheric CO_2 concentrations. Higher temperatures does not translate always into faster crop development and earlier maturation which results into lower crop yields because the crop intercepts less cumulative solar radiation before it reaches maturity and harvest because above a certain threshold the effect on crop growth is opposite determining even worse effect on the final yield expectation. In fact if the threshold effect is respected in simulating biomass accumulation and crop development the impact of climate change on the cropping system vary according to the season because grown under different thermal regimes. Yield losses during the wet season are limited and in some cases it is possible to expect a slight increase whereas the dry season, characterized by very high temperatures, will face strong losses already in the 2020 scenario. Moving to 2050, the increase in temperatures is expected to be so high that even in the wet season the final yield will be strongly reduced, and in some cases it is very likely that keeping the actual crop calendar crops will not reach maturity in time due to the above optimal temperature for growth temperatures. The water use increases especially in 2020 scenarios where the crop cycle is longer and the canopy expansion satisfactory, on the contrary the simulated transpiration values decrease under 2050 scenarios; even if the evapotranspirative demand becomes higher the reduced leaf expansion causes a decreased water demand. Equally if we consider the definition of adaptation strategies' taking into account the threshold effect or not gives a completely different picture of the most suitable options. In fact, as highlighted by impact assessment, it is crucial to detect the most suitable time window for growth in order to optimize the thermal regime and the results suggested that sowing dates may be very effective in mitigating the adverse effects of climate change. However how to shift it is completely dependent from the effect of the high temperatures on crop development and biomass accumulation.

Finally it appears clear that in regions characterized by extreme thermal regimes it is necessary to consider the effect of the high temperatures on crop growth already under current conditions, all the more if the purpose is the climate change impact assessment and/or the definition of adaptation strategies.

The use of WARM-Hourly simulation model represented an effective tool for testing the effect of climatic and technological changes and management advances at field level; however the efficiency of system was limited by the limited amount of information which could be collected.

As a consequence the modelling exercise could not reproduce completely the effect of the most critical limiting factors, forcing to make some simplifications, thus reducing the power of the modelling tools available. These issues, due mainly to a lack of overall information on the system, are not new in studies in contexts like the one analyzed, and remain the limiting factor to whatever type of analysis can be run. In the frame of further development of other actions with similar goals, an improvement is needed in the quantity of available data (e.g. through rigorous field data collection) which could enhance the ability to assess the impacts of future climate scenarios on cropping systems dynamics.

Chapter 6

Conclusions

The future food security conditions in many developing countries will be heavily influenced by climate change and variability. While the effects of climate change and variability are seriously disruptive for crop production, the new technologies, and adaptations to climate change and variability may attenuate their negative effects, hence helping to preserve food security conditions. It is imperative to perform an integrated assessment of climate change impacts on these countries.

This research examined the effects of short and medium-term climate variability and changes on rice production in Mali and identified the adaptation options of the systems using an integrated modelling framework.

The study shows that most crop yields are likely to be different in the future under the effects of increased atmospheric CO_2 and the resulting climatic changes, as expressed by the four future climate scenarios. For the future climates, crop yields are projected to increase in some case in the near future but to decrease decidedly in the midterm.

The differences in crop yield under each of the scenarios reflect a complex interplay between temperature increase, projected changes in precipitation change, and increase in atmospheric CO_2 concentrations. Higher temperatures translate into faster crop development and earlier maturation which results in lower crop yields because the crop intercepts less cumulative solar radiation before it reaches maturity and harvest (Young et al., 2000, Brassard and Singh, 2007). This relationship is confirmed by the results presented in chapter 5. Growing periods are shorter under A1B scenarios than under B1. This is because the projected temperatures under B1 scenarios were moderate, so less change in development period occurred as the climate changed. The increased rainfall in the scenarios is able to accommodate the increasing growth due to enhanced photosynthesis that occurred under elevated CO_2 conditions. Using regression analysis, Rosenzweig (1993) found that daily maximum temperatures >30°C during the growing season were negatively correlated with maize yield in the US Maize Belt. The future climate scenarios used had maximum daily temperatures >30 °C on several days during the growing season.

Even if the positive effects of elevated CO_2 concentrations on biomass production and grain yield are higher at increased temperatures for C3 species, our results indicate that the negative effect of increased temperatures on development will not be sufficiently counterbalanced by the fertilizer effect of higher CO_2 concentrations. Climate change will also have complex interactions with the timing and severity of diseases, pests and weeds (Fuhrer, 2003), but their combined effects on the yields presented here were assumed to be controlled.

In order to cope most of the processes involved this research also focused on the development of an integrated framework that could aid impact assessment, policy analysis and decision making in the agriculture sector.

The use of the BioMA-BECRA crop growth simulation platform represented an effective tool for testing the effect of climatic and technological changes and management advances at field level;

however the efficiency of system was limited by the limited amount of information which could be collected. In fact, one point that must be addressed about this study is the difficulty in establishing an effective cooperation with local stakeholders at every level, to provide the needed information to be used to set the conditions for the simulation study. As a consequence the modelling exercise could not reproduce completely the effect of the most critical limiting factors, forcing to make some simplifications, thus reducing the power of the modelling tools available. These issues, due mainly to a lack of overall information on the system, are not new in studies in contexts like the one analyzed, and remain the limiting factor to whatever type of analysis can be run. Despite the lack in accuracy several indicatives results were obtained and, even more important, tools and knowledge, that could be used to produce analysis having a more concrete set of inputs, were developed and deployed to local researches, during a dedicated training.

In the frame of further development of this research or of other actions with similar goals, an improvement is needed in the quantity of available data (e.g. through rigorous field data collection) which could enhance the ability to assess the impacts of future climate scenarios on cropping systems dynamics.

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Curriculum Vitae

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In January 2009 she started her Ph.D. in Agricultural Ecology detached at. the Agri4cast Action (IES, EC-JRC, Ispra). During this period she was in charge of a research project aiming the development of integrated methodologies for climate change impact assessment on cropping systems and the definition of adaptation strategies in developing countries. The project has been founded by DG-EuropeAid and has been carried out in cooperation with the IAMM of Montpellier. Meanwhile she was involved in the operational activities of crop yield forecasts and other projects carried out by the team.