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

Ph.D. in Agricultural Ecology
XXIV Cycle

# Definition and implementation of plant disease simulation models in interaction with crop models, aiming at forecasting the impact of climate change scenarios on crop production

Ph.D. Thesis

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A mio padre, l'uomo più buono,
sensibile e coraggioso che conosca

A mia madre, che amo infinitamente

**Simone BREGAGLIO**

# Definition and implementation of plant disease simulation models in interaction with crop models, aiming at forecasting the impact of climate change scenarios on crop production

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Titolo in Italiano: "Definizione e implementazione di modelli di simulazione di malattie delle piante in interazione con modelli di simulazione colturale, mirati a prevedere l'impatto di scenari di cambiamento climatico sulle produzioni agrarie"

Tesi di Dottorato in Ecologia Agraria

XXIV Ciclo, Anno Accademico 2011-2012

*Ringraziamenti*

Penso che se dovessi ringraziare il Dr. Marcello Donatelli per tutte le innumerevoli e fondamentali lezioni formative e per le occasioni che mi ha concesso, da quando mi ha dato la possibilità di cominciare a svolgere questa professione agli aiuti e incoraggiamenti degli ultimi giorni prima della consegna di questo lavoro, non basterebbero le 252 pagine di questa Tesi. Qundi mi limito a esprimergli la mia gratitudine per le lezioni extra lavorative che mi ha impartito in questi tre anni (e mezzo), da quando ci conosciamo. Forse la cosa più importante che mi ha insegnato e dimonstrato è che la correttezza e il serio impegno portano alla fiducia e al rispetto reciproci, i quali a loro volta portano all’amicizia sincera, senza dimenticare di non mischiare mai i rapporti lavorativi con quelli umani ☺.

Ringrazio il Dr. Roberto Confalonieri perché, oltre ad avermi trasmesso lo spirito con cui affrontare ogni giornata lavorativa e la maggior parte dei concetti che conosco riguardo alla modellizzazione dei sistemi colturali, da diversi anni mi concede l’onore di lavorare fianco a fianco, il che significa lottare, ridere, arrabbiarsi, sforzarsi, confidarsi, prendere decisioni ecc. cioè condividere non soltanto lo stesso mestiere ma la maggior parte della mia vita. Ci sono cose che non possono essere espresse con le parole, come il nostro rapporto che si è creato vivendo miriadi di situazioni di ogni tipo, senza mai sentirsi ad un punto morto e perdere la voglia di rilanciare, insieme.

Ringrazio il Prof. Marco Acutis perché, seppur non seguendo direttamente il mio lavoro, mi ha sempre comunicato fiducia, apprezzamento e rispetto, oltre a darmi consigli e spunti per migliorare diversi aspetti della mia ricerca.

Mi reputo una persona molto fortunata per aver incontrato queste persone, e spero di poter ripagare professionalmente e umanamente il debito di gratitudine che mi lega a loro.

Ringrazio il “neonato” gruppo di ricerca CASSANDRA, per sopportarmi ogni giorno.

Bregaglio, S., 2012. Definition and implementation of plant disease simulation models in interaction with crop models, aiming at forecasting the impact of climate change scenarios on crop production. Ph.D. Thesis, University of Milan, Italy.

English and Italian summaries.

*Reference to the contents of Chapters 2, 3, 4, 7, 8 and 9 should be made by citing the original publications*.

# ABSTRACT

The impacts of a changing climate on the social and economic development of humanity have been increasingly studied in the last decades. According to the Intergovernmental Panel on Climate Change (IPCC), the lack of implementation of effective and adequate measures for contrasting green house gases emissions will lead to increasingly severe and partially irreversible impacts on the environment, and consequently on the society. The estimate of possible impacts on food production, starting from agriculture, is essential to develop strategies to alleviate the consequences of climate change. In this context, the evaluation of the future dynamics of plant diseases plays a key role because they determine actual production levels for many crops in many areas, therefore deeply influencing food availability and security. In order to perform such analyses, process-based simulation modelling offers the capability to capture the high non-linearity characterizing the responses of biophysical processes to boundary conditions. However, such models have been marginally used to estimate scenarios of plant diseases impact on crop production, because of the limited availability of modelling approaches and tools. This work constitutes an attempt to respond to the need of developing a software framework for the simulation of a generic fungal plant airborne disease which can be easiliy coupled with a crop simulator in order to improve the estimation of the levels of crop productions under climate change scenarios.

The first section of the work deals with the evaluation of models for the estimation of meteorological data and for the simulation of leaf wetness, driving variable of the infection process of fungal plant pathogens. These assessments were justified by the need of feeding the disease models with high quality data, and by the scarce availability of hourly data in large area databases.

The second section presents the implementation and the calibration of the generic fungal plant epidemic framework, and its test via an extensive use of sensitivity analysis techniques.

The third section deals with the application of the developed modelling solutions, coupled with crop simulators, for the forecasting of the impact of climate change on crop production in Latin America.

In the last section, new criteria and metrics for biophysical model evaluation and analysis are presented, aimed at considering the models performance under heterogeneous climatic conditions such as those explored in climate change and large area application studies.

**Keywords:** Plant diseases, climate change, epidemic forecasting model, model evaluation.

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# INTRODUCTION

## 1.1. Climate change and plant diseases

According to the United Nations Framework Convention on Climate Change (UNFCCC), climate change can be defined as "a change of climate which is attributed directly or indirectly to human activities that alter the composition of the global atmosphere and which is in addition to natural climate variability observed over comparable time periods" (UNFCCC, 2006). These changes have already produced considerable impacts on various aspects related to human life: health, food security, social and economic development, hydrological resources and infrastructures. According to the Intergovernmental Panel on Climate Change (IPCC), if in the coming years humans will not adopt adequate and effective measures for contrasting climate change, its effects will be even more pronounced and severe (e.g., Bernard et al., 2001; Roessig et al., 2004; Tol, 2009). Climatologists agree in forecasting higher temperature regimes for the future climatic scenarios, coupled with modification in precipitation patterns and a rising frequency of extreme weather events (IPCC, 2007a,b). Agriculture is thus one of the sector of human activities that will be mostly subjected to climate change effects, since climatic variables are among the main forces driving crop growth and development (e.g., Rosenzweig et al., 2002; Tubiello, 2005, Lhomme et al., 2009). In this context, the evaluation of the impacts of a changing climate on plant diseases plays a key role because they determine actual production levels for many crops and in many areas. Oerke et al. (1994) and Oerke and Dehne (2004) stated that the damages caused by disease and insect pests are responsible for approximatively 40% of the losses for the eight most important food and cash crops.

Plant pathogens could react in a very heterogenous way to climate change. Many reviews focusing on the possible effects of biotic stresses on future crops productivity (e.g., Goudriaan and Zadocks, 1995; Garrett et al., 2006; Ghini et al., 2008) indicate that climate change could deeply modify the known patterns of plant diseases by means of altered spread of some species and introduction of new pathogens and vectors, leading to modified dynamics of current plant disease epidemics and shifts in their geographical distribution. In particular, most of the Authors agree on the fact that changes in temperature conduciveness and moisture availability are two of the main factors that could alter disease infection and severity not only in the short-term but even for a longer perspective in terms of evolutionary potential (Coakley et al., 1999; Garrett et al., 2006). Furthermore, climate change could modify the growing patterns and the development rates in the cycles of plant pathogens, other than influence the physiology and the degree of resistance of host plants (Chakraborty and Datta, 2003). This could lead to a potential enhancement of the number of the infection events and consequently the need of an increase in the application of fungicide treatments, with deep consequences for the environmental sustainability of cropping systems. Among the studies on the effects caused by climate change on pathosystems, Travers et al. (2010) observed lower expression of the genes associated with disease resistance in big bluestem in response to simulated precipitation change; Chakraborty and Datta (2003) have noticed an higher fecundity of *Colletotrichum gloeosporioides* under increased $CO_2$ regimes; Bergot et al. (2004) predicted an expansion of *Phytophthora cinnamomi* in Europe basing on General Circulation Models. Other studies point out that because plant disease pressure often increases following a compound interest model, a slight increase in the length of the growing season may have a very large impact on inoculum load.

## 1.2. Modelling plant diseases in climate change studies

The high non-linearity characterizing the responses of biophysical processes to boundary conditions makes their simulation via process-based models the only valid mean to explore conditions not experienced yet, in order to provide estimates of future dynamics related to crop-diseases interactions and pathogens expansion in new areas under different climate scenarios.
Several studies focusing on climate change impacts on crop productivity based either on experimental trials or on simulation models have been carried out in the last decades. There is a clear imbalance in the available literature between the investigation of the effects of climate change on crop growth and development (e.g., Rosenzweig and Parry, 1994; Tubiello et al., 2000; IPCC, 2001; Wolf and Van Oijen, 2003; Fischer et al., 2005, Challinor et al., 2010) and the assessment of scenarios of future spatial and temporal distribution of plant diseases (Chakraborty et al., 1999; Ghini et al., 2008). This situation is largely explained by the scarce availability of

process-based models for disease simulation, whereas crop growth models are much more widespread among the international modellers community. This has led, in practice, to consider acceptable a constanct impact of biotic stresses on crop production across the years, thus including the yield reductions due to plant diseases in the values of the parameters describing morphological and physiological crop traits. The consequences of this assumption are the degradation of the process-based logic behind the model, and the development of site-specific sets of crop parameters, thus depriving the model of its capability to be applied under conditions different (in space or time) compared to those used during the calibration process. These consequences may strongly decrease cropping systems models suitability for large-areas simulation or for evaluating the impact of climate change scenarios (Donatelli and Confalonieri, 2011). Furthermore, data on geographic distribution of diseases are still surprisingly difficult to collect, leading to a high degree of uncertainty in current and future geographical diseases patterns in the available studies.

Mathematical modelling of crop diseases moved its first steps with the work of Van der Plank (1960, 1963), who developed the first models of temporal development of epidemics, laying the basis for plant disease modelling (Campbell and Madden, 1990; McCartney, 1997). Further developments of this branch of pathology led to models able to estimate disease severity and yield losses as influenced by different factors such as weather, varietal resistance, and crop management practices (Luo et al., 1997; van Maanen and Xu, 2003). In the last decades, books and reviews on the broad range of approaches and models for simulating plant diseases and related crop yield losses have been proposed (e.g., Nutter, 1997, Savary et al., 2006; Madden et al., 2007; Sparks et al., 2008; Contreras-Medina et al., 2009). Common traits of such models are that (i) they were developed mostly for fungal pathogens and (ii) are often aimed at on-farm management (e.g., Spotts and Cervantes, 1991; Broome et al., 1995; Rossi et al., 1997).

The development of generic disease forecasting models, either suitable for simulating epidemics caused by different pathogens in different time frames or reusable within diverse software platforms is becoming a crucial issue agronomists and plant pathologist are facing with (Magarey and Sutton, 2007). This is proved by the flourishing in the last years of frameworks such as the Internet System for the Weather-Based Mapping of Plant Pathogens NAPPFAST (Magarey et al., 2007), implementing the potential infection model for foliar fungal pathogens developed by Magarey et al. (2005), or the Diseases framework developed within the FP6 APES (Agricultural Production and Externalities Simulator; Donatelli et al., 2010a), and tools as the generic biological model for the control of foliar plant diseases developed by Jeger et al. (2009), as well as the model for population dynamics of plant-parasite interactions developed by Gubbins et al. (2000), and the adaptation of the Kermack and McKendrick (1927) human epidemic model to spatial spread of plant disease made by Segarra et al. (2001). In order to manage the high complexity of the simulated biophysical processes, ranging from the relationships between meteorological variables and epidemic development to the physiological interactions between plants and pathogens, this modelling tendency should be supplied by the state-of-the-art of software engineering technology.

### 1.3. Sharing knowledge via software components

The term model has overloaded meanings: from a physical duplicate of a part of the real word to its abstraction, the latter often represented via mathematical equations which are meant to capture the traits of its behaviour with respect to a specific objective of analysis. The term model is also overloaded with respect to its specific structure: models range from very complex formalizations to a single equation, very often a model being a composition of many sub-models. Biophysical models in agriculture are not exceptions: what is commonly referred to as a cropping system simulation model is a set of interlinked mathematical representations of approaches which are abstractions of a single biological or physical process. They are called models, instead of the possibly more appropriate term modelling solutions, mostly because of the way they appear to the final user, who might even use them as black boxes driven by a graphical user interface. Also, when they originated at the end of the 80’, their implementation was monolithic, making often not obvious their discretization in several sub-models (Donatelli et al., 2011).

In the last decade, several Authors claimed the need for modularity and replaceability in biophysical models (e.g., Jones et al., 2001; David et al., 2002; Donatelli et al., 2004a, 2006a,b), aiming at improving the efficiency of use of resources and at fostering a higher quality of modelling units (Donatelli and Rizzoli, 2008). In order to fulfill this aims, the adoption of component-oriented programming is becoming not only an option, but even the unavoidable prerequisite for the development of agricultural and ecological models (Reynolds and Acock, 1997; Papajorgji et al., 2004; Donatelli et al., 2010b). The advantages deriving by this choice are unquestionable, and can be summarized by features as ease of maintenance of the code, granularity of the approaches implemented, reusability of the tools and cross platform capabilities (Meyer, 1997). In particular, model reusability is often a challenging task because of different architectural structures and binaries incompatibilities, thus often still forcing modellers to the conversion of the code from one programming language to another (Liu et al., 2002). According to the modular approach adopted in the software industry and which is at the base of component-oriented programming, the main concept is the encapsulation of the solution of a modelling problem in a discrete, replaceable, and interchangeable software unit, called component. A software component can be thus defined as a unit of composition with contractually specified interfaces and explicit context dependencies only (Szypersky et al., 2002), that can be deployed independently and is subject to composition by third parties. The isolation of modelling problems belonging to specific domains allows the development of submodels by specialists in the specific sectors, rather than having generalist modellers working on all details of complex integrated modelling systems. For these reasons, component-oriented designs represent the natural choice for building scalable and robust applications, and to maximize the ease of maintenance in a variety of domains. This concept has been applied to biophysical systems, leading to the development of several modelling frameworks (e.g., Simile, MODCOM, IMA, TIME, OpenMI, SME, OMS, as listed in Argent and Rizzoli, 2004), that use components both linking them directly, or via a simulation engine, if they expose their interface requesting a numerical integration service. One possible disadvantage of targeting model component design to match a specific interface requested by a modelling framework is the decrease of reusability. This could explain the scarce adoption of modelling frameworks by groups other than those that developed them (Rizzoli et al., 2008). Part of the solution for increasing component reusability is the adoption of a design targeting the interchangeability of model components across modelling platforms, allowing their implementation in a specific modelling framework via an application of the design pattern Adapter (Gamma et al., 1995), acting as bridge between the framework and the component interface. In order to achieve this aim, the guidelines to be followed are:

- the component must target the solution of a sufficiently widespread modelling problem;
- the published interface of the component must be well documented and it must be consistent;
- the configuration of the component should not require excessive pre-existing knowledge and help should be provided in the definition of model parameters;
- the model implemented in the component should be extensible autonomously by third parties,
- the dependencies on other components should be limited and explicit;
- the behaviour of the component should be robust, and degrade gracefully, raising appropriate exceptions;
- the component behaviour should be traceable and such a trace should be scalable (browseable at different debug levels);
- the component software implementation should be made using widely accepted and used technologies.

**1.4. Objectives and organisation of the research**

One of the key issues when developing and evaluating a plant epidemic model is represented by the quality of the data used as input and by their time resolution, which should respect the temporal scale of the biophysical processes simulated. Several processes involved with the different phases of a plant disease (i.e., infection, incubation, latency, outbreak of the symptoms and sporulation) can occur in a very short time, even few hours. An epidemic model aimed at the correct representation of these processes should adopt the same temporal resolution. However, the availability of hourly data is dependent on the presence of meteorological station with an advanced instrumentation, capable to measure hourly values of air temperature, air relative humidity, precipitation and wind speed. Although technically this is no longer a limit, in the vast majority of cases the additional storage and work required to perform a quality control is not counterbalanced by a strong demand by users. In fact, most crop/agrometeorological models used still require daily values, thus not making the availability of hourly values a priority. The limit above are even more pronounced when working on large areas and/or in climate change studies, where the data are often organized into grid cells, and are mainly the results of interpolation and downscaling procedures. One of the possible solutions to overcome this problem is the estimation of hourly variables starting from daily data, usually present in the available databases, via estimation and generation methods. For this reason, the first section of this thesis presents three studies focused on the evaluation and comparison of modelling tools for the generation of crucial variables driving plant disease models: air relative humidity, air temperature and leaf wetness duration.

The second section presents the framework for the simulation of a generic airborne fungal plant epidemic constituted by four software components implementing (i) a deterministic compartmental susceptible-infected-removed (SIR) model for host–pathogen dynamics simulating the response of a generic fungal pathogen to hourly meteorological variables; (ii) an approach for the estimation of initial conditions for the development of an epidemic, via the quantification of initial inoculum, (iii) different models for the consideration of the impacts of agricultural management practices on the epidemic development and (iv) models for the formalization of the interactions between the epidemic and crop growth and development, aimed at quantifying the disease impact on plants. This section includes also two sensitivity analysis assessments on different parts of the modelling solutions implemented by considering different host-pathogen couples.

The third section presents an application of the modelling solutions for plant-disease interaction in climate change scenarios, coupled with two crop simulators in order to forecast the future patterns of disease pressure on crops productivity in Latin America. The study was run also with the aim of addressing the problems which are encountered when moving from the use of very detailed data-sets to operational conditions.

In the last section, two studies on the development of new metrics for advanced evaluations of the performance of biophysical models are presented. The use of model compositions, integrating in an modelling solution a large number of modelling approaches, and their application in a variety of environmental conditions, requires a more articulated analysis of model performance than the ones usually performed based on single metrics, mostly related to model accuracy.

The general scheme of the organization of the 3-year research carried out during this doctorate is presented in Figure 1, and it will be reported in the first page of each Chapter.

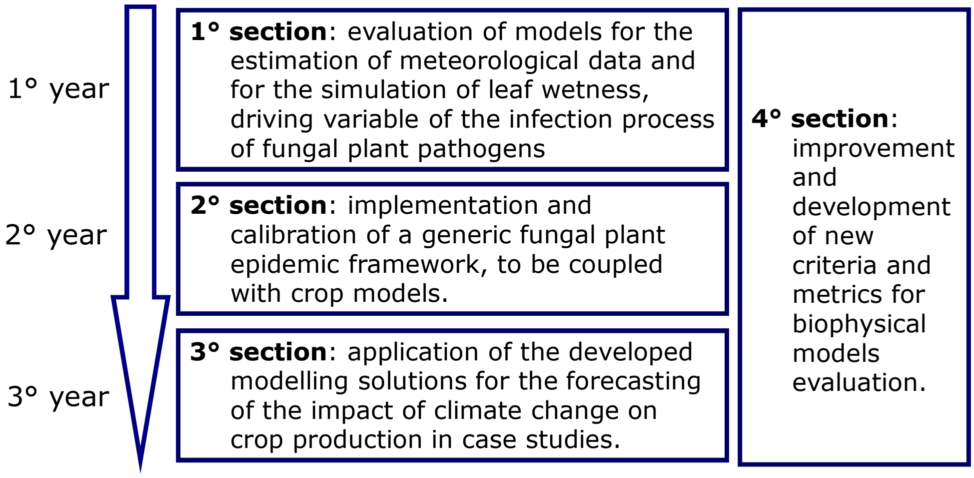



**Figure 1. Scheme of the organization of the research carried out during this thesis**

## 1.5. Synopsis

Chapter 2 presents a software component, *AirTemperature*, providing a collection of deterministic and stochastic approaches to generate atmospheric temperature data at daily and hourly time steps. Its software design allows for extension of the models implemented without re-compiling the component. *AirTemperature* can be considered a way to share knowledge, making it available in an operational tool. This is done via an architecture which decouples data from models, providing a semantically rich interface for framework-independent implementations, thus facilitating its reuse in custom applications, and the independent extensibility by third parties.

Chapter 3 presents a comparative evaluation of thirteen modelling solutions for the estimation of hourly values of air relative humidity. In this work, a synthethic indicator for model evaluation was developed, taking into account diverse aspects of simulation performances. This procedure allows a transparent traceability of the errors done in the generation process, making clear the steps of the modelling chain that need to be improved. The results of this work underline that (i) the presence of daily values of air relative humidity deeply improve the reliability of the estimation of hourly fluctuations of air relative humidity, and that (ii), when daily data are not available, the magnitude of the errors produced by the modelling solutions tested showed large differences, providing means to select the most suitable under specific contexts.

Chapter 4 presents a multi metric evaluation of six models for the simulation of leaf wetness duration, one of the main driving variables of epidemic models. The estimation of this variable is mandatory when working on large databases in which data are interpolated in grids starting from weather stations measurements. In this work, the behavior and reliability of six models is assessed by running them with inputs at different time resolutions aimed at large-area applications. The models were evaluated for their capability to estimate leaf wetness and for their impact on the simulation of the infection process for three pathogens via the use of a potential infection model. This study indicated that some of the empirical models tested are able to perform better than the physically based ones, given the availability of data considered. The classification and regression tree (CART) model showed the greatest robustness in most of the conditions explored.

Chapther 5 presents a sensitivity analysis assessment aimed at understanding the capability of a simple generic infection model (i) to differentiate its response in response to different parameterizations and (ii) to be sensitive to the variability of the data provided as inputs. Four pathogens were chosen, trying to maximize the variability in temperature and moisture requirements, and the model was run under diverse climatic conditions. The sensitivity of the model deeply changed according to the pathogen tested, and the relevance of its parameters in explaining model outputs was strongly related to the environmental conditions tested. The indications provided by this study strengthen the suitability of this model for pest risk assessment studies under both current conditions and climate change scenarios.

Chapter 6 presents the generic fungal epidemic framework, including four independent software components aimed at simulating a generic polycyclic fungal epidemic. These components can be easily extended by third parties and reusable within diverse modelling platforms. They provide options for simulating (i) the initial conditions for the development of an epidemic, (ii) the progress of the disease over time as driven by meteorological variables taking into account the effect of host resistance, (iii) the yield losses due to the interactions between plant and pathogen population via coupling with a crop growth model and (iv) the impact of agro management practices on disease progress. In the same chapter, the disease development component, i.e., the core of the framework, is analyzed via an extensive spatially distributed sensitivity analysis for two pathosystems, in order to gain an in-depth knowledge on model behaviour. Results indicate that the model is on one hand sensitive to diverse parameters according to the pathogen simulated whereas, on the other hand, the overall relevance of the model parameters is respected in both pathosystems tested.

Chapter 7 presents an assessment of the impacts of climate change on agricultural productivity in Latin America. Results indicate relevant impacts on crops production in the coming decades, underlying the need for a rigorous evaluation of response strategies and their costs, in order to devise effective policies facilitating successful adaptation by farmers. The Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment Report (AR4), published in 2007, stated that most of the impact models used in the assessment of climate change impacts have fell behind in the development and validation of key processes necessary to improve projections of crop yields in coming decades. The gaps include the representation of interannual climate variability and extreme events and the impacts of pests and diseases. Results indicates that, without adaptation, wheat, soybean and maize yields will be significantly affected by climate change, regardless of the emission scenario or GCM considered, whereas for rice the projections are less severe. The simulations carried out indicate that the implementation of adaptation strategies positively concurred to limit climate change damage to crop production. The impact of rust disease on soybean is projected not to increase with warming, with the exception of Colombia. This can be explained by the severity of the increase in temperature regimes in a warm environment, in turns leading to more favorable conditions for the pathogen. For wheat, the projected yield decrease due to diseases in 2020 and 2050 was significant. Frost damages were expected to affect wheat yields less seriously in Chile, where shortened cycles will reduce the crop exposure to pathogens, thus reducing also the pressure of wheat leaf rust on the crop. For maize, the simulations carried out indicate that the implementation of adaptation strategies positively concurred to limit climate change damage to crop production, even in the countries where the grey leaf spot resulted the most limiting factor. For rice in temperate areas, the blast disease pressure on the crop decreases, because of thermal and pluviometric conditions less favorable for the pathogen *Pyricularia grisea*. The implementation of adaptation strategies targeting crop features mainly related with crop cycle length led to indirect benefits in terms of pathogens pressure. This could suggest possible reduction of agrochemicals in the future in important rice producing countries, like Brazil, and to the uselessness of investing efforts in developing blast-resistant varieties.

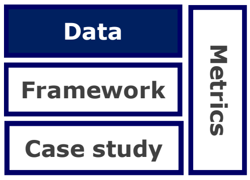
Chapter 8 proposes an approach for the quantification of model robustness based on the variability of errors to variability of explored conditions ratio. Model errors are quantified using the modelling efficiency and a normalized agrometeorological indicator based on cumulated rainfall and reference evapotranspiration is used to characterize the conditions of application. The indicator is tested for models estimating meteorological variables and crop state variables. The values assumed by the robustness tend to be worse when the number of simulated processes increase and, within the same typology of model, with the degree of overparameterization. The independence of the information provided by the robustness indicator from pure agreement metrics strongly support its inclusion in integrated systems for models evaluation.

Chapter 9 proposes an indicator of model plasticity, defined as the aptitude of a model to change the sensitivity to its parameters while changing the conditions of application. The concordance among the different sensitivity analysis results was related to the variability of a normalized agrometeorological indicator used to characterize the explored conditions. The plasticity indicator was tested using three different crop models (WARM, CropSyst, and WOFOST; rice was simulated), 10 European locations, and 10 years for each location. Results indicated WOFOST as the most plastic, both within location, year, and by using all the combinations location $\times$ year, whereas WARM showed to be the less plastic across the conditions explored. Previous studies carried out on the same models in Northern Italy seem to suggest a direct relationship between model complexity and plasticity, whereas model accuracy seems to be unrelated to these features. This underlines that different choices should be performed for different modelling studies, characterized by different aims and conditions of application.

Chapter 10 presents the general conclusions of this work, with regard to the development achieved and the realization of specific objectives, together with the drawing of future perspectives.

**Note**

Chapter 2 is published in SRX Computer science, and it is available at http://www.hindawi.com/archive/2010/812789/ref/. Chapter 3 is published in Theoretical and Applied Climatology. Chapter 4 is published in Agricultural and Forest Meteorology. Chapter 5 has been submitted to Ecological Modelling. Chapter 6 has been submitted to Environmental Modelling and Software. Chapter 7 is close to be published as an official World Bank report. Chapter 8 and 9 are published in Ecological Modelling. The reference lists from these individual papers have been amalgamated into one list at the end of this thesis. I would like to acknowledge the editorial boards of Theoretical and Applied Climatology, Agricultural and Forest Meteorology and Ecological Modelling, and the World Bank for their permission to include the papers and the report in this thesis.




# *AIRTEMPERATURE*, EXTENSIBLE SOFTWARE LIBRARY TO GENERATE METEOROLOGICAL DATA

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Published in: SRX Computer Science (2010) doi:10.3814/2010/812789

## 2.1. Abstract

The development of a set of reusable libraries to support custom applications has become a goal in biophysical modelling projects. This is true for weather modelling as well. *AirTemperature* is a software component providing a collection of deterministic and stochastic approaches to generate atmospheric temperature data on daily and hourly time steps. Data generated on a daily time step consists of maximum and minimum air temperature and dew point temperature. Hourly estimations include air and dew point temperatures. The software design allows for extension of the models implemented without re-compiling the component. The component, inclusive of hypertext help documentation files, is released as compiled .NET2 version, allowing application development in either programming environment. A sample client and a sample extension project using *AirTemperature* are provided as source code. A sample Web service and a Web application are also developed as examples of possible use of the component.

**Abbreviations***:* *AirTemperature*, air temperature (software component); $T_{max}$, maximum air temperature; $T_{min}$, minimum air temperature

## 2.2. Introduction

A large number of existing agricultural and ecological models have been implemented as software that cannot be well maintained or reused, except by their authors, and therefore cannot be easily transported to other platforms (e.g., Reynolds and Acock, 1997; Papajorgji et al., 2004). In order to possibly include legacy data sources into newly developed systems, object-oriented development has emerged steadily as a paradigm that focuses on granularity, productivity and low maintenance (Timothy, 1997). Several papers have been recently published in agro-ecological journals (Carlini et al., 2006; Donatelli et al. 2006a, b; Confalonieri et al., 2009a; Donatelli et al., 2009a, b; Holzworth et al., 2009) targeting at reusable dynamic link libraries either within the Microsoft .NET framework (http://www.microsoft.com/NET) or using the SUN Java platform (http://java.sun.com). Such solutions reflect a style of programming referred to as component-oriented programming that has become the leading methodology in developing systems in a variety of domains, including agro-ecological modelling (Papajorgji et al., 2004). Although different definitions of component do exist in the literature (Bernstein et al., 1999; Booch et al., 1999; Szypersky et al., 2002), a component is basically a discrete software unit which makes available specific functionalities, and it can be presented as a black box that provides access to its services through a defined interface. The component development paradigm is to make the construction of a software as plugging together independent components. In the context of the agricultural and environmental modelling community, alternative frameworks are available to support modular model development through provision of libraries of biophysical modelling modules, as well as reusable tools for data manipulation, analysis and visualization (Argent et al., 2006). Various object- and component-oriented solutions have approached the issue of agricultural and environmental modelling, such as maize irrigation scheduling (Bergez et al., 2001), multiple spatial scales ecosystems (Woodbury et al., 2002), greenhouse control systems (Aaslyng et al., 2003), households, landscape, and livestock integrated systems (Matthews, 2006). In the same perspective, we have approached the weather generation issue. Long records of weather data are in fact needed for evaluating agricultural management scenarios in natural resource models (e.g., Shenk and Franklin, 2001; Mavi, 2004). Weather inputs required by natural resource models include air temperature, precipitation, solar radiation, wind speed, and dew point temperature. Synthetic weather sequences are needed if long-term measured data are not available, measured data contain missing records, collection of actual data is cost or time prohibitive, or when necessary to simulate impacts of future climate scenarios. Weather simulation models (or weather generators) are commonly used to generate synthetic weather records for use in the study of crop growth and development, water availability, soil erosion, climate change, and other domains (e.g., WST, http://www.wcc.nrcs.usda.gov/climate/wst_fact.html). Several weather generators are available in the form of ready-to-use, user-oriented tools, implementing specific solutions to the basic problem of generating one or more weather elements. Such an approach is however ineffective for developers of custom applications, who have to re-implement the set of equations within modelling applications of various complexity. Moreover, because of either the empiricism or the alternative inputs required by different generation approaches, it may be desirable to compare different methods in case-specific applications in order to provide reliable weather data for case-specific applications. Reusability in weather generation can be efficiently achieved by capturing the domain knowledge currently available (i.e., weather models already developed and tested) and making it available in software components. This is the reason why component-oriented tools have been recently developed to fit this need, that is, ET for calculating evapotranspiration and related variables (Donatelli et al, 2006a), GSRad for estimating synthetic values of solar radiation (Donatelli et al, 2006b), Rain (Carlini et al., 2006) for generating precipitation data, and Wind (Donatelli et al., 2009b) for generating wind speed data. The components mentioned provide a set of alternate models to estimate variables specific for the domain targeted, and are implemented using a software architecture which promotes reusability (Donatelli and Rizzoli, 2008). The present study focuses on the modelling of air temperature that, to the best of the authors' knowledge, have not yet encapsulated into component-based solutions. Air temperature values are essential to plant growth and the development of organisms. One problem in simulating air temperature is that measured daily maximum and minimum air temperature are often slightly skewed and not normally distributed in each month. So, generating air temperature from the normal distribution may result in physically improbable values (especially extreme hot temperatures). Although the assumption of normality is often contradicted (Harmel et al., 2002), the normal distribution (variously interpreted and corrected) is the reference distribution of all the approaches currently used to generate air temperature data. Weather generators (including Cligen, Nicks and Gander, 1994; WGEN, Richardson and Wright, 1984; USCLIMATE, Johnson et al., 1996; LARS-WG, Semenov et al., 1998; ClimGen, Stöckle et al., 2001; and CLIMAK, Danuso, 2002) are commonly used to generate daily maximum and minimum air temperatures in agro-ecological projects. Generation of maximum and minimum air temperatures is also useful for modelling applications that require estimates of hourly temperature throughout a day. A best guess is made by assuming that minimum air temperatures normally occur close to sunup and maximum air temperatures a few hours after solar noon (e.g., Stöckle, 2002). Moreover, relationships between air relative humidity and air temperature can be rearranged as an association of the dew point temperature with the two daily extremes (e.g., Linacre, 1992). Disaggregation from daily to hourly records and estimation of dew point air temperatures are both largely based on empirical relationships. This paper illustrates how well-known air temperature generation approaches have been implemented into a software component (namely, AirTemperature). The procedures implemented in the component, the scientific background, some principles of usage, and source code are extensively documented in hypertext help files. The paper describes the implementation features that guided the development of AirTemperature, followed by a discussion on the main component features.

## 2.3. Background

The modelling background implemented in *AirTemperature*, fully documented in the online help file, is not reproduced hereafter. The main features are only briefly summarized. All these models are published in peer-reviewed journals; details about their development and the applications in case studies are reported in the referenced papers.

### 2.3.1. Daily generation of air temperature

The generation of daily maximum ($T_{max}$, °C) and minimum ($T_{min}$, °C) air temperatures is considered to be a continuous stochastic process, possibly conditioned by the precipitation status of the day. Three methods are implemented for generating daily values of $T_{max}$ and $T_{min}$. The multi-stage generation system is conditioned on the precipitation status with both approaches from Richardson (1981) and (Danuso, 2002). Residuals for $T_{max}$ and $T_{min}$ are computed first, then daily values are generated - independently (Richardson-type) or with dependence of $T_{max}$ on $T_{min}$ (Danuso-type). A third stage, that adds an annual trend calculated from the Fourier series, is included in Danuso-type generation. The Richardson-type approach accounts for air temperature- solar radiation correlation. A third approach (Remund and Page, 2002) generates $T_{max}$ and $T_{min}$ independently in two stages (daily mean air temperature generation first, $T_{max}$ and $T_{min}$ next), making use of an auto-regressive process from mean air temperatures and solar radiation parameters.

#### 2.3.2. Hourly generation of air temperature

Daily values of $T_{max}$ and $T_{min}$ are used to generate hourly air temperature values, according to alternative methods. Sinusoidal functions are largely used to represent the daily pattern of air temperature. Six approaches, by Campbell (1985), Goudriaan and Van Laar (1994), Ephrath et al. (1996), Porter et al. (2000), Stöckle (2002), and Gracia et al. (2003) are used to generate hourly values from daily maximum and minimum temperatures. A further approach, proposed by Dumortier (2002), derives hourly air temperatures from the daily solar radiation profile. Mean daily values of dew point air temperature are estimated via empirical relationships with $T_{max}$ and $T_{min}$ and other variables (Linacre, 1977; Iribarne and Godson, 1981; Linacre, 1992; Kimball et al., 1997; Allen et al., 1998; Hubbard et al., 2003). A diurnal pattern (hourly time step) of dew point air temperature is also modeled via two alternative methods (Ephrath et al., 1996; Meteotest, 2003).

### 2.4. Software features

#### 2.4.1. Input and outputs

The outputs produced by *AirTemperature* and the inputs (variables and parameters) required by the models implemented are listed in Table 1.

**Table 1. List of all the inputs and outputs of the models implemented into *AirTemperature* component. Outputs are arranged by an identification number (ID) assigned to input variables and parameters used to calculate each output**

| | Variables / parameters | Unit | Output ID |
|---|---|---|---|
| Output variables | $T_{d(hr)}$, hourly dew-point air temperature | °C | 1 |
| | $T_d$, daily dew-point air temperature | °C | 2 |
| | $T_{max}$, daily maximum air temperature | °C | 3 |
| | $T_{min}$, daily minimum air temperature | °C | 4 |
| | $T_T^k$ , yearly trend of daily maximum ($T$=$T_{max}$) and minimum ($T$=$T_{min}$) air temperatures on dry ($k$=0) or wet ($k$=1) days | °C | 5 |
| | $\chi_{(d)}^{k_0,k}(j)$, daily standardized residual of maximum ($j$=1) and minimum ($j$=2) air temperatures on dry ($k$=0) or wet ($k$=1) days | - | 6 |
| | $T_{hr}$, hourly air temperature | °C | 7 |
| Input variables | $RH_{max}$, daily maximum relative humidity | % | 2 |
| | $RH_{min}$, daily minimum relative humidity | % | 2 |
| | $dT$, day to day difference of mean air temperatures | °C | 3, 4 |
| | $dT_{sd}$, standard deviation of day to day difference of mean air temperatures | °C | 3, 4 |
| | $\overline{G}$ , monthly average of daily global solar radiation on a given surface | MJ $m^{-2}$ $d^{-1}$ | 3, 4, 6 |
| | $G_{x(d)}$, daily global solar radiation at ground level | MJ $m^{-2}$ $d^{-1}$ | 3, 4, 6 |
| | $z$, site elevation above sea level | m | 2 |
| | $T_m(c)$, mean air temperature of the coolest month | °C | 2 |
| | $T_m(d)$, mean air temperature of the warmest month | °C | 2 |
| | $G_{h(hr)}$, hourly global solar radiation on a horizontal surface | MJ $m^{-2}$ $d^{-1}$ | 7 |
| | $d$, day number into year | - | 3, 4, 5 |
| | $S_i$, precipitation occurrence of current day | - | 3, 4, 5, 6 |
| | $DL_{(d)}$, day length | h | 7 |
| | $sr_{(d)}$, time of sunrise | h | 1, 7 |
| | $T_{max}$, daily maximum air temperature | °C | 2, 7 |
| | $T_{min}$, daily minimum air temperature | °C | 2, 7 |
| | $\overline{T}_T^{k_0,k}$ , monthly average of daily maximum ($T$=$T_{max}$) and minimum ($T$=$T_{min}$) air temperature on dry ($k$=0) or wet | °C | 3, 4, 6 |

| | | | |
|---|---|---|---|
| | ($k$=1) days | | |
| | $\sigma_T^{k_0,k}$, monthly standard deviation of daily maximum ($T$=$T_{max}$) and minimum ($T$=$T_{min}$) air temperature on dry ($k$=0) or wet ($k$=1) days | °C | 3, 4, 6 |
| Input parameters | $A_T^k$, annual mean maximum ($T$=$T_{max}$) and minimum ($T$=$T_{min}$) air temperature on dry ($k$=0) or wet ($k$=1) days | °C | 3, 4, 5 |
| | $B_T^k$, semi-amplitude of the first harmonic for yearly trends of maximum ($T$=$T_{max}$) and minimum ($T$=$T_{min}$) air temperature on dry($k$=0) or wet ($k$=1) days | - | 3, 4, 5 |
| | $C_T^k$, phase shift of the first harmonic for yearly trends of maximum ($T$=$T_{max}$) and minimum ($T$=$T_{min}$) air temperature on dry ($k$=0) or wet ($k$=1) days | - | 3, 4, 5 |
| | $D_T^k$, semi-amplitude of the second harmonic for yearly trends of maximum ($T$=$T_{max}$) and minimum ($T$=$T_{min}$) air temperature on dry ($k$=0) or wet ($k$=1) days | - | 3, 4, 5 |
| | $E_T^k$, phase shift of the second harmonic for yearly trends of maximum ($T$=$T_{max}$) and minimum ($T$=$T_{min}$) air temperature on dry ($k$=0) or wet ($k$=1) days | - | 3, 4, 5 |
| | $RR_{nn}$, monthly autocorrelation coefficient for minimum air temperature residuals, with time lag of 1 day | - | 3, 4 |
| | $RR_{nx}$, monthly correlation coefficient between minimum and maximum air temperature residuals | - | 3, 4 |
| | $SR_T$, monthly standard deviation of the residuals from the trends of maximum ($T$=$T_{max}$) and minimum ($T$=$T_{min}$) both on dry and wet days | °C | 3, 4 |
| | $R_{1n}$, standardized residual of minimum air temperature of the previous day | - | 3, 4 |
| | $T_{max(d-1)}$, maximum air temperature of the previous day | °C | 3, 4, 7 |
| | $T_{min(d-1)}$, minimum air temperature of the previous day | °C | 3, 4, 7 |
| | $N$, number of days in a month | - | 3, 4 |
| | $N(d)$, number of dry days in a month | - | 3, 4 |
| | $N(w)$, number of wet days in a month | - | 3, 4 |
| | $b_T$, scaling factor | - | 3, 4 |
| | $k_0$, dry/wet days separation option | - | 3, 4, 6 |
| | $\boldsymbol{A}^{k}{}_{0}{}^{,k}$, 3x3 matrix function of the lag-0 serial- and cross-correlation coefficients of the residuals on dry ($k$=0) or wet ($k$=1) days | - | 3, 4, 6 |
| | $\boldsymbol{B}^{k}{}_{0}{}^{,k}$, 3x3 matrix function of the lag-1 serial- and cross-correlation coefficients of the residuals on dry ($k$=0) or wet ($k$=1) days | - | 3, 4, 6 |

| | | |
|---|---|---|
| $\chi_{(d-1)}^{k_0,k}(j)$, standardized residual of maximum (*j*=1), minimum (*j*=2) air temperatures and global solar radiation (*j*=3) on dry (*k*=0) or wet (*k*=1) days for the previous day | - | 3, 4 |
| $K_0$, daily dew point air temperature correction factor | °C | 2 |
| *a*, *b*, *c*, *d*, empirical parameters of model Hubbard for daily dew point air temperature | -, -, -, °C | 2 |
| *A*, *B*, *C*, *D*, *E*, *F*, *G*, empirical parameters of model Kimball et al. for daily dew point air temperature | -, -, -, -, -, -, °C | 2 |
| *EF*, evaporative demand | - | 2 |
| *A1*, *B1*, *C1*, *D1*, *E1*, empirical parameters of model Linacre 1 for daily dew point air temperature | $m^{-1}$, -, -, -, °C | 2 |
| *A2*, *B2*, *C2*, *D2*, empirical parameters of model Linacre 2 for daily dew point air temperature | -, $°C^{-1}$, -, | 2 |
| $hr_{dv}$, hour of the day for maximum air temperature to occur | H | 7 |
| $T_{min(d+1)}$, minimum air temperature of the next day | °C | 7 |
| $sr_{(d+1)}$, time of sunrise of the next day | h | 7 |
| $ss_{(d+1)}$, time of sunset of the next day | h | 7 |
| $T(ss_{(d-1)})$, air temperature at sunset of the previous day | °C | 7 |
| $a_{slp}$, slope coefficient | - | 7 |
| *LSH*, hour of maximum solar height | h | 7 |
| *p*, delay of the maximum air temperature | h | 7 |
| $T_k$, air temperature increment | °C | 7 |
| *TC*, nocturnal time coefficient | h | 7 |
| *k*, shift factor | - | 7 |
| $A_P$, $B_P$, $C_P$, empirical parameters of model Porter et al. for hourly air temperature | h, h, - | 7 |
| $A_S$, $B_S$, $C_S$, $D_S$, $E_S$, empirical parameters of model Stöckle for hourly air temperature | -, -, -, -, - | 7 |
| $T_{d(d+1)}$, dew-point air temperature of the next day | °C | 1 |
| $T_d(max)$, maximum dew-point air temperature | °C | 1 |

### 2.4.2. Design

The software design promotes reusability by limiting dependencies and providing a semantically rich, public interface. By allowing extensibility of approaches in a straightforward way, it also allows third parties to add new equations and the comparison of alternate air temperature models. This design (Donatelli and Rizzoli, 2008) combines architectural traits that maximize transparency, extensibility, scalability, traceability, and data quality control. The same design has been already used in the development of several components for agro-meteorology, agro-management, crop and soil water/nitrogen/chemicals simulation, model evaluation, and soil pedotransfer functions (http://www.apesimulator.org/help.aspx). The UML (Unified Modelling Language) component model of *AirTemperature* (Fig. 1) shows the discrete units and their dependencies.

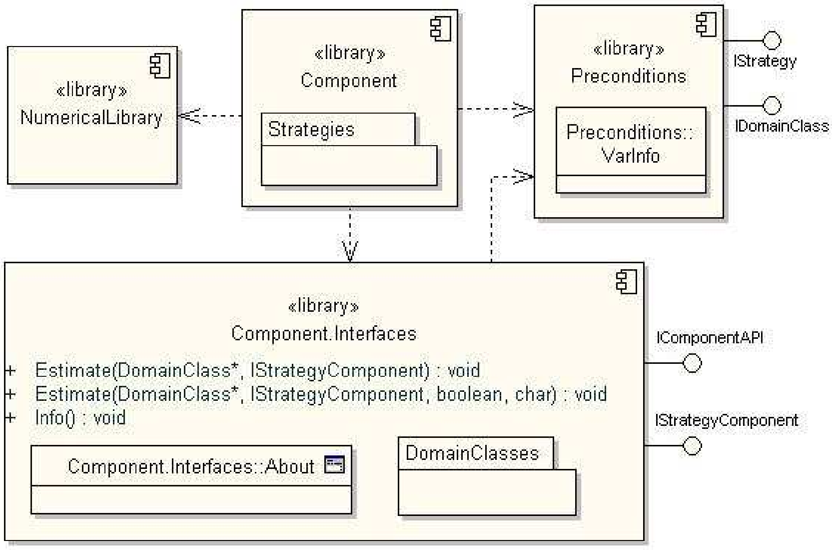



**Figure 1. Generic component model used for *AirTemperature*. The Preconditions component allows the implementation of the design-by-contract approach and provides the base classes to build and make accessible the component ontology. The separation of data-types (domain classes) and interfaces from models (strategies) in two discrete units allows the implementation in clients of the design pattern *Bridge*, which facilitates replacement of model components**

### 2.4.3. Architecture

*AirTemperature* architecture allows extending data-types, and adding new modelling solutions without the need of recompilation of the core component. The component implements *Strategies*, which are alternative implementation of air temperature models. Each model is computed via one of such discrete units, which encapsulates the algorithm, the test of pre- and post-conditions, and parameters declaration (if any). The component implements *Composite Strategies* (built using two or more strategies) and *Context Strategies*, that is, model units which implement logic to select among the strategies associated, e.g., based on the inputs available. Extension is made possible by the definition of the common interface `IAirTDataStrategy`, which must be implemented by all strategies. The UML class diagram (Fig. 2) shows the classes and interfaces which allow extending the component via the Composite and Strategy design patterns.

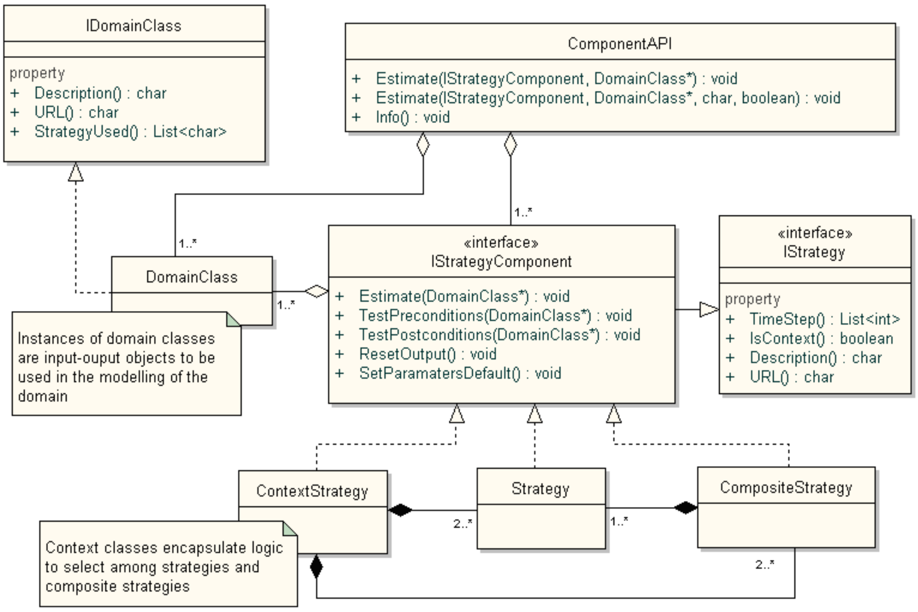



**Figure 2. Class diagram illustrating the specific implementation of the design patterns *Composite* and *Strategy***

The design-by-contract approach (Meyer, 1997) is used, requiring pre- and post-conditions (e.g., maximum daily air temperature > minimum daily air temperature) to be respected. Any application using *AirTemperature* can hence test inputs for a possible violation of pre-conditions, and it can check post-conditions (http://agsys.cra-cin.it/tools/preconditions/help). The *MCE* (Model Component Explorer, http://agsys.cra-cin.it/tools, page “Applications”, then “MCE”) is an application to discover parameters, inputs and outputs of each model, and to browse the component ontology by inspecting data-types (called *Domain Classes*) and the component interfaces. *AirTemperature* is one of the core components of the weather generator CLIMA (Donatelli et al., 2009a).

#### 2.4.4. Distribution

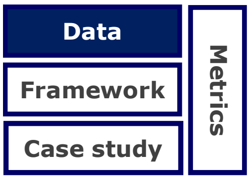
*AirTemperature* is distributed via a Software Development Kit that includes the source code of Visual Studio .NET projects demonstrating how to extend and re-use the component. Also, hypertext files are made available, documenting the models implemented (http://agsys.cra-cin.it/tools/airtemperature/help/) and the code of the software component (http://agsys.cra-cin.it/tools/airtemperature/codedoc/). The project source code of sample web services (http://agsys.cra-cin.it/webservices/airtemperature/) and web application (http://agsys.cra-cin.it/webapplications/airtemperature/) are also provided. The component requires the framework Microsoft .NET 2.0 (or newer) installed.

### 2.5. Remarks

It is widely accepted that research in agro-ecology must be supported by the state-of-the-art modelling. Model development and operational use require, however, the capability of quickly accessing knowledge in different domains, selecting and comparing alternate modelling options, and making use of such knowledge via computer based tools. The modelling system of *AirTemperature* can be considered a way to share knowledge, making it available in an operational tool. To date, although the use of software model frameworks has improved the maintainability of complex simulation systems, effective reuse of discrete units in the domain of biophysical models is still mostly a goal rather than an achievement. The architecture of *AirTemperature* decouples data from weather models, providing a semantically rich interface in framework-independent implementation, thus facilitating reuse and independent extensibility by third parties.

#### Acknowledgements

Laura Carlini is acknowledged for her contribution to the initial implementation.This publication has been funded under the SEAMLESS integrated project, EU 6th Framework Programme for Research, Technological Development and Demonstration, Priority 1.1.6.3. Global Change and Ecosystems (European Commission, DG Research, contract no. 010036-2).




# AN INTEGRATED EVALUATION OF THIRTEEN MODELLING SOLUTIONS FOR THE GENERATION OF HOURLY VALUES OF AIR RELATIVE HUMIDITY

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Published in: Theoretical and Applied Climatology (2010) 102, pp. 429-438.

### 3.1. Abstract

The availability of hourly air relative humidity (HARH) data is a key requirement for the estimation of epidemic dynamics of plant fungal pathogens, in particular for the simulation of both the germination of the spores and the infection process. Most of the existing epidemic forecasting models require these data as input directly or indirectly, in the latter case for the estimation of leaf wetness duration. In many cases, HARH must be generated because it is not available in historical series, and when there is the need to simulate epidemics either on a wide scale or with different climate scenarios. Thirteen modelling solutions (MS) for the generation of this variable were evaluated, with different inputs requirement and alternative approaches, on a large dataset including several sites and years. A composite index was developed using fuzzy logic to compare and to evaluate the performances of the models. The indicator consists of four modules: Accuracy, Correlation, Pattern, and Robustness.

Results showed that, when available, daily maximum and minimum air relative humidity data substantially improved the estimation of HARH. When such data are not available, the choice of the MS is crucial. given the difference in predicting skills obtained during the analysis, which allowed a clear detection of the best performing MS. This study represents the first step of the creation of a robust modelling chain coupling the MS for the generation of HARH and disease forecasting models, aiming at an improvement and an enhancement of their use through the systematic validation of each step of the simulation.


**Keywords**: Weather modelling, composite indicators, model evaluation, model comparison.

### 3.2. Introduction

The availability of weather data is one of the most serious factors limiting research in many applied sciences (Donatelli et al. 2004). In particular, the availability of hourly air relative humidity (HARH) data is crucial in the forecasting of plant epidemics, because of the role of this variable in driving the development and the propagation of various fungal pathogens (Sutton et al. 1984, Friesland and Schrödter 1988, Huber and Gillespie 1992; Laurence et al. 2002). HARH also plays a major role as input for almost all leaf wetness models (e.g., Kim et al. 2002; Wichink Kruit et al. 2004; Magarey et al. 2006; Sentelhas et al. 2006). Most of the existing epidemic forecasting models need as input HARH either explicitly (e.g., NegFry - Hansen et al. 1995; SimPhit - Gutsche and Kluge 1996; ProPhy - Nugtern 1997; Plant-Plus - Hadders 1997) or indirectly, for the estimation of leaf wetness duration (e.g., Magarey et al. 2005, Applescab - Arneson 2005). Whether air relative humidity, daily and even hourly, has become increasingly available in modern weather stations, such data are often neither available both in historical series of large database (e.g., MARS Database, Micale and Genovese 2004), nor in scenarios of climate change. For these reasons, aiming at using epidemic forecasting models on a wider scale or under different weather scenarios, the only available solution is the generation of HARH with meteorological models, starting from variables commonly measured. Weather generators (e.g., WGEN - Richardson and Wright 1984; Cligen - Nicks and Gander 1994; USCLIMATE - Johnson et al. 1996; ClimGen - Stöckle et al. 2001; CLIMAK - Danuso 2002) are collection of models to either estimate or generate meteorological variables; however, most do not implement models to estimate HARH. The CLIMA weather generator (Donatelli et al. 2009a) allows the user to select specific modelling options to generate meteorological variables including HARH, providing the capability to create alternate modelling solutions (MS); that is, discrete simulation engines where different models are selected and integrated in order to carry out simulations for a specific goal (Confalonieri 2009a). Whether different MS can be built, they must be tested against reference data and compared in specific contexts to select the most reliable ones.

According to Bellocchi et al. (2009), the accuracy of a model is determined on one hand by the appropriateness of the algorithms describing the processes of the real system, while on the other hand by the quality of both its input data and the data used to evaluate its outputs. Inaccuracies are common in both inputs and measured outputs. Being HARH an input to which epidemic forecasting models are very sensitive to, it is crucial to test the different generation methods available with measured data in different climatic conditions prior to operational use of relevant models.

Several statistical indices are available for quantifying how well models fit measurements. Many authors (e.g., Smith et al. 1997; Yang et al. 2000) advocate there is no single statistic that can be used to draw conclusions in model evaluation and, therefore, several metrics need to be used to give a comprehensive check (Donatelli et al. 2004; Bellocchi et al. 2009; Confalonieri et al. 2009b). When testing the performances of different models on a wide data-set, the evaluation of model performance cannot be limited to quantifying the agreement between model estimates and actual data. In fact, it is important to evaluate a) the correlation between estimated and measured values, b) the presence of anomalous behaviour in the residuals (Cook and Weisberg 1982; Draper and Smith 1998), and c) the ability of the models to maintain the same degree of accuracy among diverse conditions and years, in order to evaluate their reliability (in this paper, the last feature is called robustness).

The objectives of this work are: (i) to test 13 MS for the generation of HARH on a wide data-set (ii) to present a composite index for their evaluation.

## 3.3. Materials and methods

### 3.3.1. The models

The 13 MS tested are summarized in Table 1.

**Table 1. Summary of the 13 modelling solutions (MS) tested. See text for details**

| MS | Equations used | Notes |
|---|---|---|
| 1 | [1], [2], [3] | Hourly dew point temperature equal to generated daily dew point temperature. |
| 2 | [1], [2], [3], [4], [5] | Hourly dew point temperature generated. |
| 3 | [1], [2], [6] | Hourly dew point temperature equal to daily minimum air temperature. |
| 4 | [1], [2], [7] | Hourly dew point temperature equal to generated daily dew temperature. |
| 5 | [1], [2], [8] | Hourly dew point temperature equal to generated daily dew temperature. |
| 6 | [1], [2], [9], [10], [11] | Hourly dew point temperature generated. |
| 7 | [1], [12] | No generation of hourly dew point temperature. |
| 8_0, 8_1, 8_2, 8_3, 8_4, 8_5 | [1],[12],[13],[14], [15], [16], [17], [18] | No generation of hourly dew point temperature. Six calibration of $T_{dp\_hrmax}$ tested (from 0 to 5, step 1). |

All of them make use of sub-models implemented in the software components AirTemperature (http://agsys.cra-cin.it/tools/airtemperature/help; Donatelli et al. 2009b; for the generation of hourly air temperature) and EvapoTranspiration (http://agsys.cra-cin.it/tools/evapotranspiration/help; Donatelli et al. 2006; for the generation of dew point temperature and HARH), both included in CLIMA weather generator (http://agsys.cra-cin.it/tools/clima/help; Donatelli et al. 2009a). A detailed description of the MS for the generation of HARH follows. Variables of all the equations are described in Table 2.

**Table 2. Abbreviations used in the equations, in order of appearance**

| Abbreviaton | Meaning | Unit |
|---|---|---|
| $T_{\max}$ | Daily maximum air temperature | °C |
| $T_{\min}$ | Daily minimum air temperature | °C |
| $h$ | Hour of the day | Unitless |
| *TimeVar* | Hottest hour of the day | Unitless |
| $RH_{air\_hr}$ | Hourly air relative humidity | % |
| $e_a$ | Actual air vapor pressure | KPa |
| $e_s$ | Saturation air vapor pressure | KPa |
| $T_{dp\_day}$ | Daily dew point temperature | °C |
| $T_{dp\_hr}$ | Hourly dew point temperature | °C |
| $T_{dp\_\Delta}$ | Hourly fluctuations in dew point temperature within a day | °C |
| $K_r$ | Costant related to the average amount of monthly radiation | Unitless |
| $T_{avg}$ | Daily average air temperature | °C |
| $T_{dp\_hrmax}$ | Hourly maximum dew point temperature | °C |
| $T_{avmax}$ | Monthly average maximum air temperature | °C |
| $T_{avmin}$ | Monthly average minimum air temperature | °C |
| $R_{days}$ | Monthly days of rainfall | Unitless |
| $RH_{max}$ | Daily maximum air relative humidity | % |
| $RH_{min}$ | Daily minimum air relative humidity | % |
| *AF* | Correction factor for dew point temperature | °C |
| $e_{max}$ | Vapor pressure at daily maximum air temperature | KPa |
| $e_{min}$ | Vapor pressure at daily minimum air temperature | KPa |
| $e_{dew}$ | Vapor pressure at daily dew point temperature | KPa |

The generation of hourly values of air temperature is performed in all the MS tested using the method proposed by Campbell (1985) (Eq. 1), also used in other programs (e.g., SWAT 2000), which assumes that temperature variation is driven by solar irradiance, providing a smooth transition from minimum to maximum air daily temperature:

$$T_{air\_hr} = \left(\frac{T_{\max}+T_{\min}}{2}\right)+\left(\frac{T_{\max}-T_{\min}}{2}\right)\cdot\cos\left(0.2618\cdot\left(h-TimeVar\right)\right) \qquad [1]$$

The MS from 1 to 6 include: (i) the generation of hourly values of air and dew point temperature, (ii) the generation of hourly values of actual vapour pressure according to Allen et al. (1998) and (iii) of hourly values of saturation vapour pressure using the method proposed by ASAE (1998). At the last step (iv), HARH is calculated according to the following equation:

$$RH_{air\_hr} = \frac{e_a}{e_s} \cdot 100 \qquad [2]$$

The differences in MS 1 to 6 are represented by the model used for the generation of hourly values of dew point temperature. Dew point temperature is an important geophysical variable that indicates the temperature to which a given parcel of air must be cooled, at constant barometric pressure, for water vapour to condense into water. In some generation methods, the same value of daily dew point temperature is used for every hour in a day. This is done because several authors claimed that dew point temperature remains relatively constant during the day (Dyer and Brown 1977; Running et al. 1987; Glassy and Running 1994).

MS 1 utilizes a daily value of dew point temperature for every hour in a day, calculated with the linear relationship (Eq. 3) proposed by Bekele et al. (2007).

$$T_{dp\_day} = 0.9153 \cdot T_{\min} + 0.2021 \qquad [3]$$

MS 2 uses hourly values of dew point temperature, starting from daily values calculated using equation 3, with two additional assumptions: (i) dew point temperature varies linearly between consecutive days, and (ii) mean daily dew point temperature occurs at around sunrise (Bekele et al. 2007). The two following equations are then used:

$$T_{dp\_hr} = \left(T_{dp\_day}\right)_d + \frac{hr}{24} \cdot \left[\left(T_{dp\_day}\right)_d - \left(T_{dp\_day}\right)_{d+1}\right] + T_{dp\_\Delta} \qquad [4]$$

$$T_{dp\_\Delta} = 0.5 \cdot \sin\left[(hr+1) \cdot \frac{\pi}{K_r} - \frac{3 \cdot \pi}{4}\right] \qquad [5]$$

For average monthly radiation higher than 100 W $m^{-2}$ (equal to an average of 8.64 MJ $m^{-2}$ $d^{-1}$), $K_r$ = 6; else, $K_r$ = 12. We used $K_r$ = 6 for our analyses since average monthly radiations for all the months considered (from March to October) were higher than the 100 W $m^{-2}$ threshold in our study areas.

MS 3 utilizes the value of daily air minimum temperature as a proxy for the corresponding 24 hourly dew point temperature values. This method is used in the analysis because managerial and operational level decision-makers tend to use minimum air temperature as a surrogate for dew point temperature (Hubbard et al. 2003).

Also MS 4 and MS 5 make use of a single value of daily dew point temperature for each hour in a day, but calculate it according to Hubbard et al. (2003) (Eq. 6) and Linacre (1992) (Eq. 7), respectively.

$$T_{dp\_day} = -0.0360 \cdot T_{avg} + 0.9679 \cdot T_{\min} + 0.0072 \cdot (T_{\max} - T_{\min}) + 1.0019 \quad [6]$$

$$T_{dp\_day} = a \cdot T_{\max} + b \cdot T_{\max}{}^{2} + c \cdot T_{\min} + d \quad [7]$$

In Eq. 7, a (0.38), b (-0.018), c (1.4) and d (-5) are parameters.

MS 6 utilizes the method proposed by Ephrat et al. (1996), deriving hourly values of dew point temperature using Eq. 8.

$$T_{dp\_hr} = \min\left(T_{air\_hr}, T_{dp\_hr\,\max}\right) \quad [8]$$

The author of this method describes the parameter $T_{dp\_hrmax}$ as site specific. A simple regressive model was fit to calibrate the parameter using values from weather data collected on five sites from Sicily and Spain. The regressors chosen were: monthly average of air minimum temperature, monthly range of average air temperature, and monthly average of rainy days. Two different regressions were fit, one for the months of March, April and October (Eq. 9), and one for the months of May, June, July, August and September (Eq. 10). Splitting in two periods has allowed to get a better fit than using one regression for both. Although the relationships are valid likely for the environments considered, the methodology has allowed exploring the potential for calibrating the parameter without the availability of measured data. The results of these multiple regression analysis are shown in Table 3.

**Table 3. Summary of the multiple regression analysis performed for the calibration of maximum hourly dew point temperature in the months of April, March. October (3, 5) and May, June, July, August and September (4, 6)**

| Metric | April, March, October | May, June ,July, August, September |
|---|---|---|
| R-Squared | 0.96 | 0.92 |
| Adjusted R-Squared | 0.94 | 0.91 |
| Standard Error | 0.86 | 0.88 |
| Number of observations | 12 | 21 |

$$T_{dp\_hr\,\max} = -4.695 + 0.948 \cdot T_{av\min} + \left[0.406 \cdot \left(T_{av\max} - T_{av\min}\right)\right] + 0.225 \cdot R_{days} \quad [9]$$

$$T_{dp\_hr\,\max} = 1.510 + 0.83 \cdot T_{av\min} + 0.17 \cdot R_{days} \quad [10]$$

MS 7 uses as inputs daily maximum air temperature, daily minimum air temperature, daily maximum air relative humidity and daily minimum air relative humidity. HARH is calculated with equation 11, proposed by Waichler et al. (2003).

$$RH_{hr} = RH_{\max} + \frac{T_{air\_hr} - T_{\min}}{T_{\max} - T_{\min}}\left(RH_{\min} - RH_{\max}\right) \quad [11]$$

MS from 8_0 to 8_5 (differing for the value assigned to the parameter AF, ranging from 0 to 5, step 1; see also Table 2) (Allen et al. 1998) need as input daily maximum air temperature and daily minimum air temperature and calculate HARH through the generation of daily dew point temperature with the equation:

$$T_{dp\_day} = T_{\min} - AF \quad [12]$$

Then the following equations are used for the calculation of vapour pressure at daily minimum air temperature (Eq. 13), daily maximum air temperature (Eq. 14), and daily dew point temperature (Eq. 15):

$$e_{\max} = 0.6108 \cdot e^{\left(\frac{17.27 \cdot T_{\max}}{T_{\max} + 237.3}\right)} \quad [13]$$

$$e_{\min} = 0.6108 \cdot e^{\left(\frac{17.27 \cdot T_{\min}}{T_{\min} + 237.3}\right)} \quad [14]$$

$$e_{dew} = 0.6108 \cdot e^{\left(\frac{17.27 \cdot T_{dp\_day}}{T_{dp\_day} + 237.3}\right)} \quad [15]$$

Finally, maximum and minimum daily air relative humidity values are calculated using equations 16 and 17.

$$RH_{\max} = \frac{e_{dew}}{e_{\max}} \cdot 100 \quad [16]$$

$$RH_{\min} = \frac{e_{dew}}{e_{\min}} \cdot 100 \quad [17]$$

At the last step, equation 11 is used for the generation of HARH.

### 3.3.2. Study sites and years

The generation of HARH was performed on the sites and years listed in Table 4 in the period from March 1st to October 31st. Daily records with missing data were excluded from the analysis.

**Table 4. Sites and years used for the simulations**

| Site | Latitude | Longitude | Available year(s) |
|---|---|---|---|
| Almonte (SPA) | 37° 15’ | -6° 30’ | 2007 |
| Arezzo (IT) | 43° 28’ | 11° 51’ | 2007 |
| Campogalliano (IT) | 44° 41’ | 10° 50’ | 2007, 2008 |
| Caronia Buzza (IT) | 38° 02’ | 14° 28’ | 2003-2007 |
| Isla Cristina (SPA) | 37° 11’ | -7° 19’ | 2007 |
| Firenze (IT) | 43° 46’ | 11° 16’ | 2007 |
| Grosseto (IT) | 42° 45’ | 11° 07’ | 2007 |
| Javea (SPA) | 38° 47’ | 0° 09' | 2007 |
| Lagos (POR) | 37° 06’ | -8° 40’ | 2005 |
| La Palma (SPA) | 37° 41’ | 0° 56’ | 2007 |
| Lentini (IT) | 37° 17’ | 14° 59’ | 2004-2007 |
| Lucca (IT) | 43° 50’ | 10° 30’ | 2007 |
| Mineo (IT) | 37° 15’ | 14° 41’ | 2003-2007 |
| Mirandola (IT) | 44° 53’ | 11° 03’ | 2005 |
| Misilmeri (IT) | 38° 01’ | 13° 27’ | 2003-2007 |
| Paternò (IT) | 37° 34’ | 14° 53’ | 2003-2007 |
| Pistoia (IT) | 43° 57’ | 10° 53’ | 2007 |
| Ribera (IT) | 37° 30’ | 13° 15’ | 2003-2007 |
| Riposto (IT) | 37° 43’ | 15° 12’ | 2005-2007 |
| San Felice sul Panaro (IT) | 44° 50’ | 11° 08’ | 2007 |
| Varese (IT) | 45° 48’ | 8° 49’ | 2003, 2004 |
| Zola Predosa (IT) | 44° 29’ | 11° 13’ | 2005, 2006 |

### 3.3.3. Model evaluation

A fuzzy logic-based modular indicator ($I_{RH}$) was developed for the evaluation of the 13 MS. The indicator is based and extends the structure of the one proposed by Bellocchi et al. (2002). Aggregation of metrics is based on an expert weighting expression of the balance of importance of the individual metrics, used for the aggregation into modules. $I_{RH}$ is composed by 4 modules: Accuracy, Correlation, Pattern (Donatelli et al. 2004), and Robustness (Confalonieri and Bregaglio 2009). The modules chosen refer to different aspects of model evaluation and in particular: (i) the ability of the model to fit actual data (module “Accuracy”), (ii) the correlation between estimated and measured values (module “Correlation”), (iii) the presence of anomalous behaviour in the residuals (module “Pattern”), and (iv) the ability of the model to maintain a similar magnitude of the error among diverse conditions and years, in order to evaluate its reliability (module “Robustness”). The metrics used were (Table 5): root mean square error (*RMSE*), modelling efficiency (*EF*), the correlation coefficient of the estimates versus measurements (*R*), the pattern index of residuals versus hour of the day ($PI_{hour}$), the pattern index of residuals versus day of the year ($PI_{doy}$), the pattern index of residuals versus hourly air temperature ($PI_{temp}$), and the robustness index ($I_R$); all PI were computed considering three groups.

**Table 5. Multiple-metrics assessment method: modules and basic metrics**

| Module | Metric | Range of values and purpose |
|---|---|---|
| Accuracy (deviation between estimates and observations) | *EF*, modelling efficiency | 1 to negative infinity. Best performance given when *EF* = 1 |
| | *RMSE*, root mean square error | 0 to positive infinity. The closer values are to 1, the better the model |
| Correlation | *R*, Pearson's correlation coefficient of the estimates versus measurements | -1 (full negative correlation) to 1 (full positive correlation). The closer values are to 1, the better the model |
| Pattern | $PI_h$, p. i. hour $PI_{doy}$, p.i. day of the year $PI_{temp}$, p.i. hourly air temperature | 0 to positive infinity. The closer values are to 0, the better the model |
| Robustness | $I_R$, robustness index | 0 to positive infinity. The closer values are to 0, the better the model |

*E*: estimated value

*O*: observed value

*D*: difference between estimated and observed values (model residual)

$\overline{M}$ : mean of observed values

*l*, *m* : two groups being compared,

$q_l$, $q_m$ : number of residuals in the groups

$i_l$, $i_m$ : each value of residuals in the groups

$\sigma$ : standard deviation

*IV* : variability index, $IV = \frac{ET0 - Rain}{ET0 + Rain}$

ET0: is the reference evapotranspiration calculated according to DRETFAO56 (Priestley and Taylor, 1972) (mm)

Rain: is the cumulated rainfall in the same period (from March to October, mm)

For each data set, the above metrics were computed and then aggregated into the four modules. This allowed to derive a dimensionless value between 0 and 1 (0 = best model response, 1 = worst model response) for each module. In the process of defining the value of each module, the Sugeno method of fuzzy inference was adopted (Sugeno 1985). For each metric, two functions describing membership to the fuzzy subsets Favorable (F) and Unfavorable (U) were defined. As values in the fuzzy range are simultaneously F and U, two complementary S-shaped quadratic functions (Liao 2002) are used as transition probabilities in the range F to U (and vice versa). The full procedure is detailed in the paper from Bellocchi et al. (2002). A three-stage design inferring system of fuzzy-based rules is applied (Fig. 1): first, metrics are aggregated into their modules and then, using the same procedure, the modules Accuracy, Correlation and Pattern are aggregated in a second-level integrated measure, called Agreement module (again, ranging from 0 to 1). Then, the module Robustness is aggregated to the module Agreement into the third-level integrated measure ($I_{RH}$; again, ranging from 0 to 1). This further level of aggregation is needed because the metric belonging to Robustness module calculates a single value for each MS, while the other modules calculate a value for each combination MS $\times$ year $\times$ location.

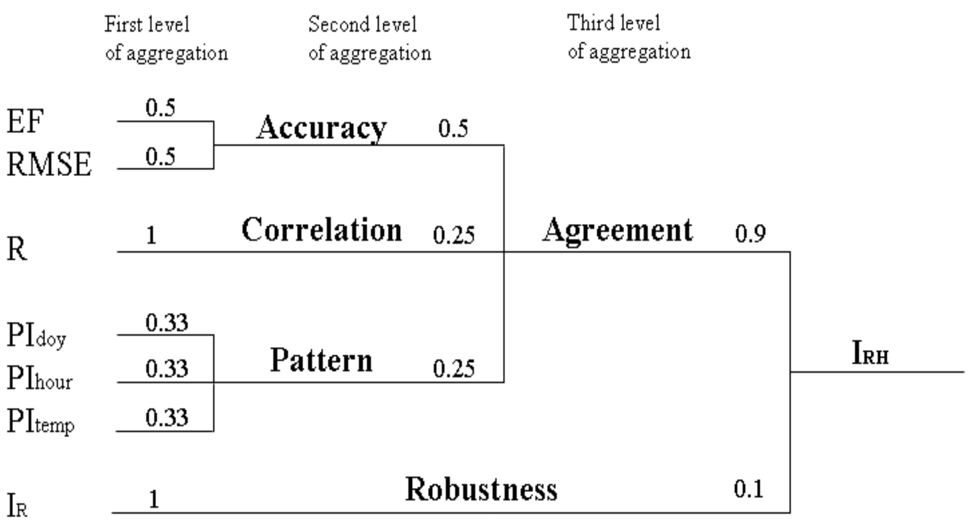



**Figure 1. Structure of the assessment method. $I_{RH}$: composite evaluation index for relative humidity models; *EF*: modelling efficiency; *RMSE*: root mean squared error; *R*: Pearson's correlation coefficient; $PI_h$, $PI_{doy}$, and $PI_{temp}$: pattern indices vs. hour, day of the year, and hourly air temperature, respectively; $I_R$, robustness index**

The logic of the expert reasoning follows (Table 6): if all input variables are F, the value of the module is 0; if all indices are U, the value of the module is 1, while for all the other combinations of input variables, the module assume intermediate values (from 0 to 1). The combinations of favourable and unfavourable metrics in a module and of favourable and unfavourable modules in $I_{RH}$ are set up according to a decision rule. Each decision rule is derived from the initial rules, i.e., the relative importance assigned to each metric, or module (e.g., Silvestri et al. 2006).

**Table 6. Summary of decision rules within the modules Accuracy, Correlation, Robustness, and Pattern; F: favourable threshold; U: unfavourable threshold**

| Aggregation | Module | Expert weight | Metrics | | |
|---|---|---|---|---|---|
| 2-metric | Accuracy | | Modelling Efficiency (EF) | Root mean square error (RMSE) | |
| | | 0.00 | F | F | |
| | | 0.50 | F | U | |
| | | 0.50 | U | F | |
| | | 1.00 | U | U | |
| No aggregation (single metrics) | Correlation | | Correlation coefficient (R) | | |
| | | 0.00 | F | | |
| | | 1.00 | U | | |
| | Robustness | | Robustness index ($I_R$) | | |
| | | 0.00 | F | | |
| | | 1.00 | U | | |
| 3-metric | Pattern | | Pattern index day of the year ($PI_{doy}$) | Pattern index hour of the day ($PI_{hour}$) | Pattern index hourly air temperature ($PI_{temp}$) |
| | | 0.00 | F | F | F |
| | | 0.33 | F | F | U |
| | | 0.33 | F | U | F |
| | | 0.33 | U | F | F |
| | | 0.66 | F | U | U |
| | | 0.66 | U | F | F |
| | | 0.66 | U | U | F |
| | | 1.00 | U | U | U |

The composition of the Accuracy module is based essentially on Yang et al. (2000). These authors found that a sound conclusion on model accuracy may be drawn using an index of the amount of residuals (e.g., *RMSE*) (Fox 1981) and a measure of modelling efficiency (*EF*) (Loague and Green 1991), The index *RMSE* may vary from 0 to positive infinity; the smaller the value, the better the model performance. The limit to the fuzzy subset F for this index was set equal to 12 (*RRMSE* ≤ 12 is F) while the limit to the subset U was established equal to 20 (*RRMSE* ≥ 20 is U). The index *EF* allows the immediate identification of inefficient models. It is upper-bounded by 1 and can assume negative values (lower-bounded at negative infinity). Negative values of *EF* indicate that the average of all measured values is a better predictor than the model used. When estimating HARH, the limit for the subset U, *EF* = 0.1, and the limit for the subset F, *EF* = 0.4 were chosen (*EF* ≤ 0.1 is U and *EF* ≥ 0.4 is F).

The value of the Correlation module depends on a single basic index, that is, the correlation coefficient *R* (Addiscott and Whitmore 1987), derived from the Pearson's simple linear correlation coefficient. The use of this index is questioned (e.g., Willmott 1982) because its value is not related to the accuracy of estimate. However, the index *R* is a universal measure with multiple interpretations. For instance, Cahan (1987) looks at *R* as a measure of identity between standardized values. Moreover, the value of *R* may help recognize the fluctuation of the estimates among *n* measurements (Kobayashi and Salam 2000). For these reasons, the index *R* is generally still regarded as a useful measure of model performance. The membership limits attributed here to the correlation coefficient are 0.5 and 0.8 (*R* ≤ 0 .5 is U, *R* ≥ 0.8 is F). Given that there is only one index in the module, the computation of correlation is simplified to two decision rules: If *R* is F then 0, and if *R* is U then 1.

The quantification of patterns in the residuals of model estimates versus other variables can be useful in both model evaluation and parameter calibration (Donatelli et al. 2004). For this reason, the module Pattern accounts for three relevant independent variables in HARH models, which are day of the year, hour of the day and hourly air temperature. For the computation of pattern indices (*PI*), the range of such independent variables is divided into three sub-ranges, thus producing three groups of residuals. Pattern indices are based on the pair wise differences between average residuals of each group, and are targeted at pointing out macro-patterns in the residuals. The *PI* values have the same units as the variable under study (in this case, %). The presence of patterns usually means that the residuals contain structure that is not accounted for in the model. When applied to different types of residual plots, *PI* may provide meaningful information on the adequacy of different aspects of the model, such as lack of inputs, poor parameterization, etc.; therefore, they should integrate difference- and correlation-based indices when evaluating model performance (Bellocchi et al. 2002). The limits attributed to *PI* reflect the authors' experience. Values of *PI* are considered F when < 7 % and U when

> 15%. The same weight was attributed to pattern index versus day of the year ($PI_{doy}$), pattern index versus hour of the day ($PI_{hour}$) and pattern index versus hourly air temperature ($PI_T$).

A single metric is used in the Robustness module, $I_R$ (Confalonieri and Bregaglio 2009). The limit to the fuzzy subset U for this index was set equal to 2 ($I_R \geq 2$ is U) while the limit for the subset F was fixed at 0.5 ($I_R \leq 0.5$ is F).

The relative incidence of each index on $I_{RH}$ can be deduced by combining the weights of the indices into their own module with the ones of the modules into the indicator (Fig. 1). For the evaluation of the performances of the MS, the software SOE was used (http://agsys.cra-cin.it/tools/soe/help).

### 3.4. Results and Discussion

Composite indicators allow a transparent top-down analysis of results, providing (i) a unique summary value for models comparison, and (ii) values at lower levels of aggregation to understand model behaviour with respect to specific metrics.

The values related to $I_{RH}$, to the second level of aggregation (modules Agreement and Robustness) and to the first (modules Accuracy, Correlation, Pattern), and the relevant simple metrics, are shown in Table 7, 8 and 9. The average values of $I_{RH}$, that represents the third level of aggregation and the final result of this analysis, showed that MS 7 obtained the best value ($I_{RH}$ = 0.025). This result was largely expected because this is the only MS that uses as inputs daily values of maximum and minimum air relative humidity, which may prove limiting in some contexts. When these inputs are not available, this study has pointed out that MS 5 provides the more reliable results ($I_{RH}$ = 0.340) than other MS. MS 2 and MS 1 were ranked third and fourth by $I_{RH}$, and they are very similar in the values of the metrics computed. In fact, they utilize the same algorithm (Eq. 3) for the calculation of daily dew point temperature. MS 2 contains a further option for estimating hourly values of dew point temperature, allowing a slight improvement. MS 6 ranks fifth for $I_{RH}$, but the results obtained by this MS should be considered exploratory, because the equation used for the computation of hourly maximum dew point temperature was calibrated only on a small data set. MS 3 obtained unsatisfactory results (11th value of $I_{RH}$).

**Table 7. Average values of each simple metric computed**

| **Modelling solution** | **Module** | | | | | | |
|---|---|---|---|---|---|---|---|
| | Accuracy | | Correlation | Pattern | | | Robustness |
| | *RMSE* | *EF* | *R* | $Pi_{doy}$ | $Pi_{hour}$ | $Pi_{temp}$ | $I_R$ |
| 1 | 16.524 | 0.201 | 0.705 | 7.244 | 9.755 | 7.211 | 0.979 |
| 2 | 16.253 | 0.204 | 0.719 | 7.247 | 9.736 | 7.128 | 1 |
| 3 | 19.013 | 0.02 | 0.663 | 8.298 | 11.405 | 17.354 | 1.67 |
| 4 | 17.929 | 0.14 | 0.706 | 7.202 | 9.618 | 7.951 | 1.233 |
| 5 | 16.767 | 0.319 | 0.725 | 5.654 | 5.94 | 7.384 | 0.805 |
| 6 | 18.134 | 0.139 | 0.698 | 7.121 | 6.566 | 6.783 | 1.637 |
| 7 | 11.253 | 0.705 | 0.858 | 3.722 | 3.271 | 6.776 | 0.398 |
| 8_0 | 19.748 | -0.067 | 0.693 | 7.585 | 11.795 | 8.606 | 1.683 |
| 8_1 | 17.56 | 0.064 | 0.689 | 8.335 | 12.034 | 7.255 | 1.355 |
| 8_2 | 16.611 | -0.071 | 0.686 | 9.229 | 12.403 | 6.553 | 1.203 |
| 8_3 | 16.795 | -0.063 | 0.684 | 10.342 | 12.697 | 6.343 | 1.458 |
| 8_4 | 17.914 | -0.366 | 0.681 | 11.537 | 12.952 | 6.446 | 2.217 |
| 8_5 | 19.697 | -0.863 | 0.678 | 12.75 | 13.187 | 6.813 | 3.446 |

**Table 8. Average values of Accuracy, Correlation and Pattern modules**

| **Modelling solution** | **Module** | | |
|---|---|---|---|
| | Accuracy | Correlation | Pattern |
| 1 | 0.541 | 0.269 | 0.192 |
| 2 | 0.500 | 0.226 | 0.196 |
| 3 | 0.682 | 0.456 | 0.435 |
| 4 | 0.642 | 0.268 | 0.199 |
| 5 | 0.477 | 0.196 | 0.088 |
| 6 | 0.631 | 0.335 | 0.118 |
| 7 | 0.017 | 0.041 | 0.046 |
| 8_0 | 0.798 | 0.321 | 0.268 |
| 8_1 | 0.683 | 0.330 | 0.272 |
| 8_2 | 0.646 | 0.340 | 0.280 |
| 8_3 | 0.730 | 0.351 | 0.300 |
| 8_4 | 0.837 | 0.362 | 0.333 |
| 8_5 | 0.923 | 0.375 | 0.351 |

**Table 9. Average values of Agreement and Robustness module and of $I_{RH}$ indicator**

| Modelling solution | Module | | |
|---|---|---|---|
| | Agreement | Robustness | $I_{RH}$ |
| 1 | 0.408 | 0.204 | 0.409 |
| 2 | 0.382 | 0.223 | 0.384 |
| 3 | 0.566 | 0.903 | 0.568 |
| 4 | 0.523 | 0.478 | 0.461 |
| 5 | 0.340 | 0.083 | 0.340 |
| 6 | 0.440 | 0.883 | 0.440 |
| 7 | 0.025 | 0.000 | 0.025 |
| 8_0 | 0.557 | 0.911 | 0.560 |
| 8_1 | 0.498 | 0.630 | 0.502 |
| 8_2 | 0.473 | 0.439 | 0.476 |
| 8_3 | 0.508 | 0.739 | 0.512 |
| 8_4 | 0.579 | 1.000 | 0.584 |
| 8_5 | 0.642 | 1.000 | 0.645 |

This is relevant because it points out that using minimum daily air temperature as a surrogate of hourly dew point temperature led to large errors in different aspects of the generation. MS from 8_0 to 8_5 obtained poor $I_{RH}$ values for all the calibrations tested.

The results obtained by the 13 MS in the Robustness module reflect those obtained for the second level of aggregation (Agreement module), with better value obtained again by MS 7 and worst value by MS 8_4 and MS 8_5. This means that there is a positive correlation between the capability of the MS tested of being precise and the tendency to maintain constant the magnitude of the errors among different conditions and years. With regards to the Accuracy, Correlation and Pattern modules, results (Table 8) show that MS 7 obtained the best values for all the data sets, hence resulting as the best one according to a wide range of evaluation criteria.

All the other MS performed worse, but with high variability. In particular, MS 5 obtained the second best average values in the modules Accuracy (0.477), Correlation (0.196), and Pattern (0.088). These result indicate that, when daily values of maximum and minimum air relative humidity are not available, this MS can be considered as the most reliable.

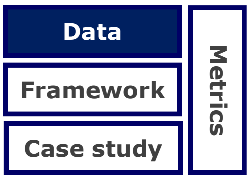
All of the other MS obtained values higher than or equal to 0.5 in the module Accuracy,, with the worst value calculated for MS 8_5 (0.923).

Considering simple metrics (Table 7), MS 7 obtained the best values of *RMSE* (11.253), while all the other MS obtained higher and quite similar values for this index (ranging from 16.253 to 19.748). MS 7 obtained the best values also for *EF*, with an average value of 0.705. MS 8_0, 8_3, 8_4, and 8_5 performed worse than the average of measured values, with *EF* values always negative, thus proving to be unable to predict HARH with acceptable accuracy. The results obtained for the *R* metric by the 13 MS were quite homogenous: MS 7 obtained again the best average value (0.858), while the worst value was obtained by MS 3 (0.663). This means that all the MS tested showed a good correlation between the observed and measured data. As in the other metrics, MS 7 obtained the best results for $PI_{doy}$ (3.722), followed by MS 5 (5.654). A similar situation was obtained for $PI_{hour}$, where the only difference was that MS 6 obtained the third best value (6.556). The values obtained by the 13 MS in $PI_{temp}$ were quite similar (from 6.343 to 7.951), exclusive of no. 3 which performed decidedly worse (17.357).

### 3.5. Conclusions

Before using estimated variables as input for impact models, it is mandatory to perform an evaluation of the methods used for their generation. This procedure allows a transparent traceability of the errors done in the generation process, making clear the steps of the modelling chain that need to be improved. The comparison among the 13 MS evaluated via the composite indicator IRH has allowed gaining an insight on models estimating capabilities and weaknesses. This kind of analysis can also be useful to guide the researchers in the choice of the model that obtained the best result in a particular area of interest. For example, in some situations it is preferable to have a model that is capable to maintain constant its performances even if it is less accurate as a whole than other ones. Analyses like the one performed here also provide indication on which model is preferable according to actual data availability.The results of the IRH indicator showed that, when present, daily maximum and minimum air relative humidity markedly improve the generation of HARH.

When such input values are not available, this analysis underlines that the errors made by the MS tested increase considerably, and that the choice of the particular MS is crucial. In fact, the analysis showed large differences in the magnitude of errors produced by the MS tested, providing means to select the most suitable in the context of interest. The structure of the indicator developed addresses model evaluation via multiple metrics. Hence, it can be re-used for evaluation of performance of different type of models simply by selecting relevant covariates for the Pattern Indices metrics.The next step will be the validation of the more precise MS through the use of generated and observed HARH values as input for epidemic forecasting models versus real data, aiming at using these tools on a wide scale and in different climate scenarios.




# MULTI METRIC EVALUATION OF LEAF WETNESS MODELS FOR LARGE AREA APPLICATION OF PANT DISEASE MODELS

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Published in: Agricultural and Forest Meteorology (2011) 151, pp. 1163-1172.

### 4.1. Abstract

Leaf wetness (LW) is one of the most important input variables of disease simulation models because of its fundamental role in the development of the infection process of many fungal pathogens. The low reliability of LW sensors and/or their rare use in standard weather stations has led to an increasing demand for reliable models that are able to estimate LW from other meteorological variables. When working on large databases in which data are interpolated in grids starting from weather stations, LW estimation is often penalized by the lack of hourly inputs (e.g., air relative humidity and air temperature), leading researchers to generate such variables from the daily values of the available weather data.

Although it is possible to find several papers about models for the estimation of LW, the behavior and reliability of these models were never assessed by running them with inputs at different time resolutions aiming at large-area applications. Furthermore, only a limited number of papers have assessed the suitability of different LW models when used to provide inputs to simulate the development of the infection process of fungal pathogens. In this paper, six LW models were compared using data collected at 12 sites across the U.S. and Italy between 2002 and 2008 using an integrated, multi metric and fuzzy-based expert system developed *ad hoc*. The models were evaluated for their capability to estimate LW and for their impact on the simulation of the infection process for three pathogens through the use of a potential infection model. This study indicated that some empirical LW models performed better than physically based LW models. The classification and regression tree (CART) model performed better than the other models in most of the conditions tested. Finally, the estimate of LW using hourly inputs from daily data led to a decline of the LW models performances, which should still be considered acceptable. However, this estimate may require further work in data collection and model evaluation for applications at finer spatial resolutions aimed at decision support systems.

**Keywords**: Fuzzy logic, composite metrics, disease potential infection, hourly values, weather variables

## 4.2. Introduction

Among the inputs required by fungal disease simulation models, leaf wetness (LW; as yes/no state) is widely recognized as a crucial input (Pedro, 1980; Huber and Gillespie, 1992; Gleason et al., 1994; Kim et al., 2002). In particular, the time free water remains on the surface of plant tissues, named leaf wetness duration (LWD; hours day$^{-1}$), is one of the most important driving variables for the forecasting of plant disease epidemics because of its considerable impact on processes, such as the start of the fungal pathogens active life cycle, their penetration into the leaves, primary infection occurrence and secondary infection occurrence. Carrying out reliable measurements of LWD is often challenging because of the physical complexity of the processes involved, i.e., its relationship with the structural and optical properties of the tissue surface and with micrometeorological aspects (Sentelhas et al., 2004). No standard for its measurement has yet been accepted (Dalla Marta et al., 2005). The sensors also require crop-specific calibrations (Giesler et al., 1996) and frequent maintenance, and the sensors need to be positioned on each individual farm (Dalla Marta et al., 2005). For these reasons, the simulation of LWD is widely suggested as a viable alternative to direct measurements (Pedro and Gillespie, 1982; Huber and Gillespie, 1992; and Wittich, 1997), especially for large area applications. The existing approaches for the generation of LW can be classified into two categories as follows: fully empirical (e.g., Gleason et al., 1994; Rao et al., 1998; Wichink Kruit et al., 2004) and process-based (e.g., Pedro and Gillespie, 1982; Luo and Goudriaan, 2000; Magarey et al., 2006; Sentelhas et al., 2006). Empirical models simulate LW using simple relationships between LW and a number of variables (e.g., air relative humidity, dew point temperature, rain occurrence and/or wind speed) derived in specific agrometeorological conditions. The process-based models consider physical principles of dew condensation, dew evaporation and/or rain evaporation through an energy balance approach. These models have demonstrated a good potential for applications even though the considerable effort required for model parameterization may be considered a limiting factor for operational use (Sentelhas et al., 2008). Although there are many reports about LW model development, there are only a few papers illustrating the comparison of the models under conditions exploring different sites, years and crops (Wichink Kruit et al., 2004; Sentelhas et al., 2008; Wichink Kruit et al., 2008). Also, LW models require hourly inputs that are not always available or reliable, especially in large area applications. When the goal of the analysis is to estimate the disease impact under scenarios of climate change, the downscaling from global circulation models does not include either the data needed to estimate LW or LW itself. In these cases, estimation of hourly values of weather variables is mandatory for using LW models. However, no assessment of LW models is available contrasting generated inputs and measured inputs. Furthermore, evaluation of the use of LW estimated from inputs at different time resolutions on impact models has yet to be performed.

Therefore, the objective of this paper was to evaluate models for the estimation of LW in large-area scenario analysis. Within this framework, the following specific objectives were carried out: i) comparison of six LW models; and ii) assessment of the impact of LW estimated data as input on an impact model.

## 4.3. Materials and Methods

### 4.3.1. Study sites and data sources

Data were collected at 12 sites across the U.S. and Italy between 2002 and 2008 using two different sensors (237 Leaf Wetness Sensor from Campbell Scientific, Inc., Utah, U.S.; and BF001 from Silimet s.r.l., Italy) and under different typologies of groundcover (Table 1).

**Table 1. Sites and years used for the simulations**

| Site | Latitude N | Longitude E | Available years | Sensor* | Ground-cover |
|---|---|---|---|---|---|
| Brooking(US) | 32° 03′ | -124°17′ | 2003-2007 | 1 | Grass |
| Caronia-Buzza (IT) | 38° 02′ | 14° 28′ | 2002-2007 | 2 | Grass |
| Lentini (IT) | 37° 17′ | 14° 59′ | 2004-2007 | 2 | Grass |
| Linden (US) | 38°01′ | -121° 05′ | 2007 | 1 | Cherry |
| Lockeford (US) | 38° 10′ | -121° 12′ | 2002-2007 | 1 | Vineyard |
| Medford (US) | 42° 19′ | -122° 52′ | 2003-2008 | 1 | Vineyard |
| MiddleTown (US) | 38° 45′ | -122° 36′ | 2002-2006 | 1 | Vineyard |
| Mineo (IT) | 37° 15′ | 14° 41′ | 2003-2007 | 2 | Grass |
| Misilmeri (IT) | 38° 01′ | 13° 27′ | 2003-2007 | 2 | Grass |
| RedHills (US) | 38° 55′ | -122° 44′ | 2004-2008 | 1 | Vineyard |
| Vorden (US) | 38°19′ | 121° 32′ | 2007 | 1 | Alfalfa |
| Worden (US) | 42° 00′ | -121° 47′ | 2003-2008 | 1 | Grass |

* 1: 237 Leaf Wetness Sensor, Campbell Scientific, Inc., Utah, US; 2: BF001, Silimet s.r.l., Italy

The use of several sites and reference crops increased the heterogeneity of the data (e.g., errors or differences due to sensors) and increased the possible incoherence in parameterizations. However, our goal was to test LW models across a broad range of conditions for operational use in large-area applications or future climate scenarios. Consequently, the heterogeneity of the dataset used was a severe test for the LW models. The weather conditions at each site during the monitoring periods (summarized in Table 2 and partially presented according to Sentelhas et al., 2008) allowed consideration of the sites to be decidedly heterogeneous in the values of mean air temperature, air relative humidity (RH) and rainfall.

**Table 2. Average climatic conditions of the sites used in this study for the period 01/03-31/10**

| Site | Mean air temperature (°C) | Mean air relative humidity (%) | Total Rainfall (mm) | Rainy days (days) | Mean wind speed (m s$^{-1}$) |
|---|---|---|---|---|---|
| Brooking | 13.7 | 81.2 | 805.9 | 77.8 | 1.3 |
| Caronia Buzza | 20.6 | 66.7 | 392.6 | 58.2 | 2.2 |
| Lentini | 21.7 | 57.9 | 226.0 | 41.5 | 1.1 |
| Lockeford | 18.9 | 60.5 | 153.4 | 25.7 | 1.4 |
| Medford | 15.9 | 61.2 | 173.5 | 51.3 | 0.9 |
| MiddleTown | 16.9 | 58.2 | 383.9 | 33.0 | 1.4 |
| Mineo | 20.8 | 61.1 | 296.9 | 53.3 | 1.2 |
| Misilmeri | 20.7 | 63.4 | 368.5 | 54.7 | 2.6 |
| RedHills | 18.0 | 50.3 | 276.5 | 35.0 | 1.7 |
| Vorden | 18.4 | 75.1 | 61.3 | 15.0 | 2.2 |
| Worden | 12.0 | 66.7 | 236.3 | 57.8 | 1.7 |

The LW sensor and groundcover for the Sicilian sites (Caronia Buzza, Lentini, Mineo and Misilmeri) were different from the other sites, which led to systematically biased LW data at these locations compared to the other locations, that is, many hours were measured as wet while the RH was lower than 60%. Such data were used in the analysis for the following reasons: i) there was no absolute evidence to exclude the data from all of these stations, and ii) the results obtained by the LW models tested excluding these data from the evaluation procedure did not substantially change (data not presented).

### 4.3.2. The leaf wetness models

The six models evaluated, which are all implemented as alternate modelling solutions in the LeafWetness software component (freely downloadable with algorithms, code documentation and sample projects to illustrate its use at http://agsys.cra-cin.it/tools/leafwetness/help/), differed in the level of detail used to represent the phenomena ranging from process-based approaches to fully empirical models.

The surface wetness energy balance (SWEB; Magarey et al., 2006) model is a physical model based on the energy balance. The implementation of SWEB in the LeafWetness component presents five modules as follows: i) WindSpeed, which calculates wind speed at the air/canopy interface; ii) NetRadiation, which calculates the fraction of net radiation intercepted by the canopy; iii) WaterBudget, which considers the fraction of rain intercepted by the canopy, condensation of water as dew and their contribution to LW; iv) CanopyEvaporation, which simulates the latent heat flux density from the canopy (i.e., the negative term of the energy balance); and v) WaterBalance, which calculates the actual wet area of the canopy.

The leaf wetness reference (LWR) model (Sentelhas et al., 2006) implements a Penman-Monteith based approach for the calculation of LW. It assumes that the vertical thermal profile is linear from the height of the sensor to the air/canopy interface and that this air layer can be accounted for by the introduction of a resistance term into the model. LWR derives rain interception from the measured rainfall amount and maximal amount of water as rain reservoir (set to 0.6 mm). LWD is then estimated by adopting a two-step procedure similar to that recommended by FAO for estimating crop evapotranspiration (Allen et al., 1998) as follows:

$$W_c = W_r W \qquad [1]$$

where $W_c$ (hours) is the crop LWD (hours), $W_r$ (hours) is the reference LWD estimated using the Penman–Monteith approach for a sensor at a 30-cm height over turf grass and $W$ is the wetness coefficient (dimensionless) equal to the $W_c$ to $W_r$ ratio.

The dew parameterization (DP) model (Garratt and Segal, 1988) is based on earlier work by Monteith (1957) and estimates LW by considering the fluxes of water vapour from air to surface and from soil to canopy (dewfall and distillation, respectively) as driven by wind speed, absolute temperature, atmospheric stability, relative humidity, soil characteristics, and cloudiness.

The classification and regression tree (CART) (stepwise linear discriminant; Kim et al., 2002) model uses an empirical approach for the simulation of LW requiring hourly dew point depression (DPD), hourly wind speed (WS) and RH as input. CART classifies hours as dry or wet through the identification of four categories of conditions as follows: hours are considered dry if either DPD ≥ 3.7°C (category 1) or RH < 87.8% and WS ≥ 2.5 m s$^{-1}$ (category 4). The hours in categories 2 and 3 are classified as either dry or wet by a subsequent stepwise linear discriminant analysis. The model derives WS at the air/canopy interface from values measured by standard weather stations.

The extended threshold (ExT; Witchink Kruit et al., 2004) approach considers hours in which RH is higher than 87% as wet hours. For values of

RH between 70% and 87%, an hour is considered wet if RH is at least 3% higher than the RH of the hour before and dry if RH is at least 2% lower than the RH of the hour before. The hours in which RH is lower than 70% are considered dry. If these conditions are not satisfied, the hour is considered the same as the previous one. Note that our implementation of ExT simplified the model using an hourly time step instead of the 30-min time step proposed by Witchink Kruit et al. (2004). This solution did not affect the model coherence, and it extended its usability.

An additional model was added following the idea that RH is a suitable index for predicting LW occurrence (Sentelhas et al., 2008). The fixed threshold (FT) model was, therefore, derived by performing a logistic regression among all of the available values of LW and RH, which allowed for defining an RH threshold; above such threshold the hour was considered wet. The meteorological inputs required by the six LW models tested are listed in Table 3.

**Table 3. Hourly meteorological inputs required by leaf wetness models used in the study and references of the methods used to generate them**

| Input | Unit | CART | SWEB | DP | ExT | LWR | FT | References |
|---|---|---|---|---|---|---|---|---|
| Air temperature* | °C | × | × | | | | | Campbell, 1985 |
| Air dew point temperature | °C | × | | | | | | Murray, 1967 |
| Wind speed* | m $s^{-1}$ | × | × | | | × | | Mitchell et al., 2000 |
| Net radiation | MJ $m^{-2}$ $h^{-1}$ | | × | × | | × | | Allen et al., 1998 |
| Slope of vapor pressure curve | KPa $°C^{-1}$ | | × | × | | × | | Allen et al., 1998 |
| Latent heat of vaporization | MJ $Kg^{-1}$ | | × | × | | | | Harrison, 1963 |
| Rain* | mm | | × | | | × | | Meteotest, 2003 |
| Atmospheric density | Kg $m^{-3}$ | | × | × | | | | ASAE, 1998 |
| Air relative humidity* | % | × | × | | × | | × | Waichler and Wigmosta, 2003 |
| Saturation vapor pressure | KPa | | × | × | | × | | ASAE, 1998 |
| Specific heat of air | J $g^{-1}$ $C^{-1}$ | | × | × | | | | Not generated (0.286) |
| Aerodynamic resistance | s $m^{-1}$ | | | × | | × | | Allen et al., 1998 |
| Actual vapor pressure | KPa | | | × | | × | | Allen et al., 1998 |
| Psychrometric constant | KPa $°C^{-1}$ | | | × | | × | | Allen et al., 1998 |
| Soil heat flux | MJ $m^{-2}$ $h^{-1}$ | | | × | | | | Allen et al., 1998 |

*= measured values of these variables were available and they were used in the measured run (see the text for details)

For the process-based models (SWEB, DP and LWR), the default values of parameters were used as indicated by the authors of the models. The default values were needed because no precise information was available about the crops on which the sensors were placed. Moreover, the aim of this work was to evaluate the use of LW models for large area applications. Thus, the choice of not performing specific calibrations was consistent with the aim of this study.

### 4.3.3. The potential infection model

The six LW models were coupled with the simple generic potential infection model for foliar fungal pathogens developed by Magarey et al. (2005) to evaluate the impact of LW generation on the simulation of the infection process. The fungal potential infection model is a generic pathogen simulator in which different pathogens are represented by a set of parameters. It calculates the temperature response via the function developed by Yan and Hunt (1999) using an hourly time step. This model simplifies the one proposed by Yin et al. (1995) because it does not require a fully empirical shape parameter. The model is as follows:

$$f(t) = \left(\frac{T_{\max} - T}{T_{\max} - T_{opt}}\right)\left(\frac{T - T_{\min}}{T_{opt} - T_{\min}}\right)^{(T_{opt} - T_{\min})/(T_{\max} - T_{opt})} \quad [2]$$

where *f(t)* (0-1; dimensionless) is the temperature response function; $T$ (°C) is the mean air temperature during the wetness period; and $T_{\min}$, $T_{\max}$ and $T_{opt}$ (°C) are the minimal, maximal and optimal temperatures for infection, respectively. The effect of LW is taken into account by the following equation:

$$W(t) = \begin{cases} \dfrac{W_{\min}}{f(t)} & \dfrac{W_{\min}}{f(t)} \le W_{\max} \\ 0 & elsewhere \end{cases} \quad [3]$$

where *W(t)* (0-1; dimensionless) is the wetness response function, $W_{\min}$ (hours) is the minimal LWD for infection, *f(t)* (0-1; dimensionless) is the temperature response function (Eq. 2) and $W_{\max}$ (hours) is the optimal value of the LWD requirement. When the model is run with hourly data, it is necessary to know how many dry hours may interrupt a wet period without terminating the infection process. The additivity of two interrupted wet periods is determined by the critical dry period interruption value (*D50*), as indicated in the following equations:

$$W_{sum} = \begin{cases} W_1 + W_2 & D < D50 \\ \\ W_1 \quad or \quad W_2 & elsewhere \end{cases} \qquad [4]$$

where $W_{sum}$ is the sum of the surface wetting and $W_1$ and $W_2$ are wet periods separated by a dry period (*D*; hours). The *D*50 parameter (hours) is defined as the duration of a dry period that will result in a 50% reduction in disease compared with a continuous wetness period. The flow diagram of the model is presented in Fig. 1.

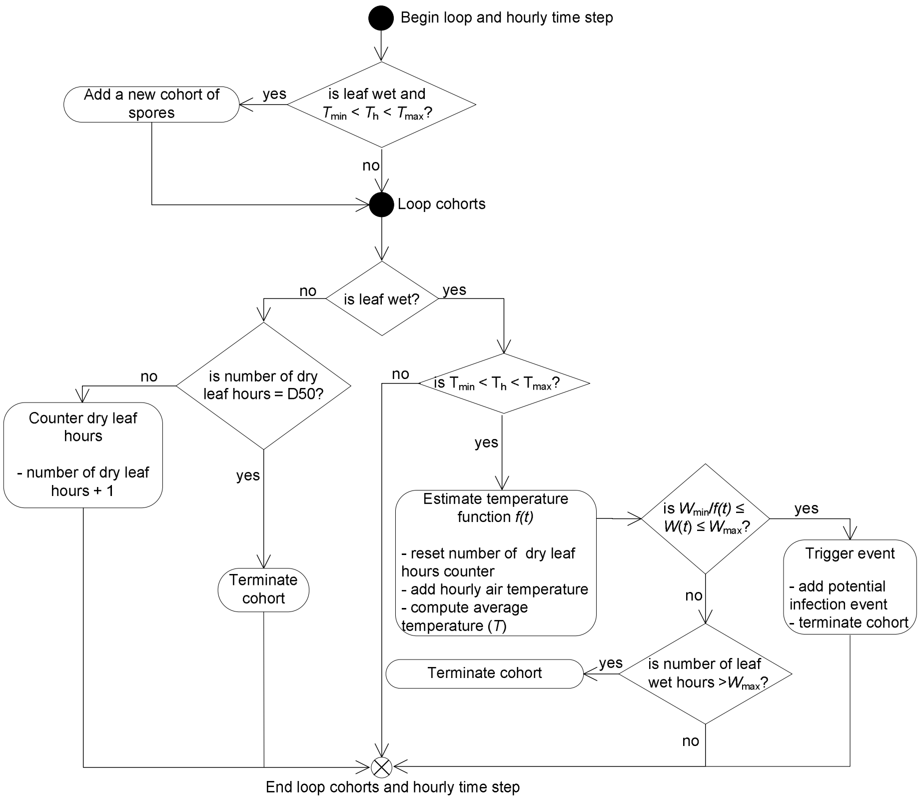



**Figure 1. Flow diagram of Magarey et al. (2005) for a simple generic infection model for foliar fungal plant pathogens. $T_h$ is hourly air temperature. The other symbols are explained in the text**

For this study, three foliar fungal pathogens were chosen for the evaluation of the LW models starting from measured and generated weather data. The three pathogens used were *Phytophthora infestans* (causal agent of late blight of potato), *Venturia inaequalis* (causal agent of apple scab) and *Puccinia striiformis* (causal agent of stripe rust of wheat). To emphasize the effect of LW simulation on the number of potential infections, the selection of the fungal foliar pathogens specifically tried to explore a great variability in response to temperature and/or wetness needs. The wetness requirements of pathogens at different temperatures used in this study are shown in Fig. 2. The parameters used in this study have been previously described by Magarey et al. (2005) and are listed in Table 4.

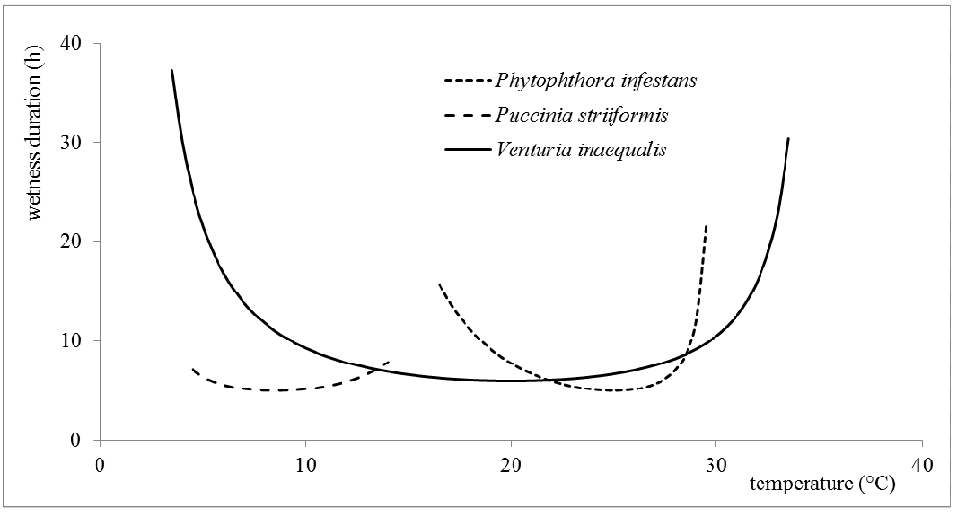



**Figure 2. Wetness duration requirements at different temperatures of the pathogens chosen for this study. Curves are plotted in the range of temperatures $T_{min} < T < T_{max}$ for each pathogen**

**Table 4. Parameters used for the fungal pathogen used in this study (source: Magarey et al., 2005). See the text for details**

| Pathogen | $T_{min}$ (°C) | $T_{opt}$ (°C) | $T_{max}$ (°C) | $W_{min}$ (hours) | $W_{max}$ (hours) | *D50* (hours) |
|---|---|---|---|---|---|---|
| *Phytophthora infestans* | 2.6 | 25 | 30 | 5 | 16 | 1 |
| *Venturia inaequalis* | 1 | 20 | 35 | 6 | 40 | 24 |
| *Puccinia striiformis* | 2.6 | 8.5 | 18 | 5 | 8 | 2 |

### 4.3.4. Generation of meteorological inputs

For each dataset, daily and hourly measured values of air temperature, RH, WS and precipitation were collected. The daily global solar radiation was estimated using the Bristow-Campbell model (Bristow and Campbell, 1984). For the generation of hourly meteorological inputs from daily inputs, the following software model components were used: AirTemperature (http://agsys.cra-cin.it/tools/AirTemperature/help/), Evapotranspiration (http://agsys.cra-cin.it/tools/EvapoTranspiration/help/; Donatelli et al., 2005), Rain (http://agsys.cra-cin.it/tools/Rain/help/; Carlini et al., 2006), Wind (http://agsys.cra-cin.it/tools/Wind/help/; Donatelli et al., 2009b) and SolarRadiation (http://agsys.cra-cin.it/tools/SolarRadiation/help/; Donatelli et al., 2006). The models used for hourly generation are listed in Table 3.

### 4.3.5. Simulation experiment design

For each dataset and pathogen considered, the six LW models coupled to the potential infection model were run twice. The first run used measured hourly inputs (measured run; MR), and the second run used hourly inputs generated from daily data (generated run; GR). At the same time, hourly measured data for the air temperature and LW were used as input for the same potential infection model (reference run; RR). The complete workflow of the simulation experiment is presented in Fig. 3.

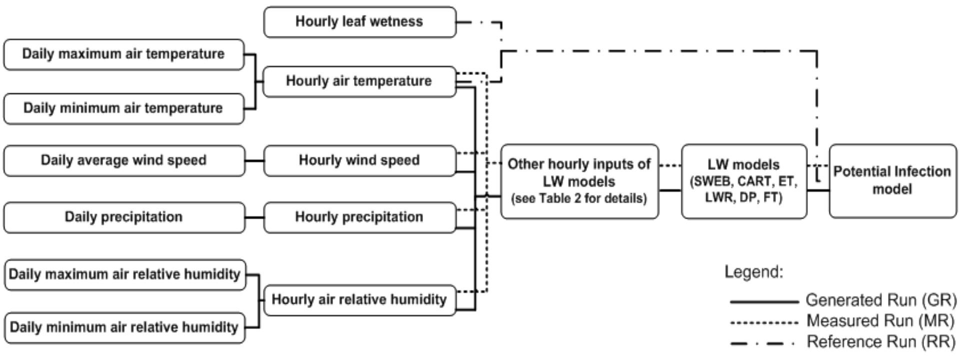



**Figure. 3 Workflow of the simulation processes of this study. LW is leaf wetness, SWEB, CART, ExT, DP, LWR, FT are the leaf wetness models used in the study**

### 4.3.6. Model output evaluation

The comprehensive assessment of the LW simulation models encompassed the following parameters: i) performance of the models in predicting LW in terms of accuracy and bias; ii) models' capability of reproducing potential infection events obtained with measured LW data; and iii) correlation between the number of potential infections coming from measured weather variables and estimated weather variables. This evaluation made use of composite indicators, which are measures that are able to summarize the performance of models by the integration of several metrics into modules that are hierarchically composed. Although the differences among their values cannot be tested for statistical significance, composite indicators are extremely useful in providing integrated, easily understandable and comparable measures of model performance (Bellocchi et al., 2010).

Two fuzzy-based modular indicators ($I_{lw}$ and $I_{inf}$) were built *ad hoc* for evaluating the performances of the six LW models via the following aspects: i) reproducing hourly values of LW and ii) providing inputs for the potential infection model (LWD). The structure of these indicators reflects and extends those proposed by Bellocchi et al. (2002), Donatelli et al. (2004), Confalonieri et al. (2009), Confalonieri et al. (2010) and Bregaglio et al. (2010).

$I_{lw}$ was composed of the Accuracy$_{lw}$ and Bias$_{lw}$ modules, whereas $I_{inf}$ was derived from the aggregation of the following four modules: Accuracy$_{inf}$, Bias$_{inf}$, Agreement$_{inf}$ and Correlation. Each module was composed of one or more simple metrics, as shown in Table 5.

**Table 5. Multiple-metrics assessment method: modules and basic metrics. F is Favourable threshold, U is Unfavourable thresholds (see the text for details)**

| Module | Metric(s) | Equation | Range of values and purpose | Threshold | |
|---|---|---|---|---|---|
| | | | | F | U |
| Accuracy$_{lw}$ Accuracy$_{inf}$ | $P_{od}$, Probability of detection | $P_{od} = \frac{a}{a+b}$ | 0 to 1. Best Performance when $P_{od}$ = 1 | 0.9 | 0.5 |
| | $P_{ne}$, probability of null event | $P_{ne} = \frac{c}{c+d}$ | 0 to 1. Best performance when $P_{ne}$ = 1 | 0.9 | 0.5 |
| Bias$_{lw}$ Bias$_{inf}$ | $B_{ias}$, balance of the models | $B_{ias} = \frac{a+c}{a+b}$ | 0 to positive infintive. Best performance when $B_{ias}$ = 1 | 1±0.2 | 1±0.7 |
| Correlation | $r$, Pearson's correlation coefficient | $r = \frac{\sum_{i=1}^{n}(E_i - \overline{R_{if}})(R_{if,i} - \overline{R_{if}})}{\sqrt{\sum_{i=1}^{n}(E_i - \overline{E})^2 \sum_{i=1}^{n}(R_{if,i} - \overline{R_{if}})^2}}$ | 0 to 1.Best value is$r$ = 1 and the worst is 0 | 0.3 | 0.8 |

lw=leaf wetness; inf= potential infection events; *a*= Hits; *b*= Misses; *c*= False Alarms; *d* = Correct Negatives (see Table 4); $E_i$= estimated value;$R_{if,i}$: reference value; $\overline{E}$ = mean of estimated values; $\overline{R_{if}}$ : mean of reference values;*i*= each of estimated/reference pairs; *n*= number of estimated/reference pairs

For each metric, two functions describing membership to the favorable (F) and unfavorable (U) fuzzy subsets were defined. As values in the fuzzy range were simultaneously F and U, two complementary S-shaped quadratic functions (Liao, 2002) were used as transition probabilities in the range F to U (and vice versa). This methodology has been fully described by Bellocchi et al. (2002).

The ability of the models to predict potential infection occurrence and LW data was evaluated using a dichotomous categorical verification (Wilks, 1995). In particular, the impact of LW models on the simulation of potential infection was evaluated by considering the days in which successful potential infections occurred (cohorts of spores that successfully completed their cycle according to the potential infection model; classified as 1) and the days in which no potential infections were simulated (classified as 0) during the period from March 1st to October 31st. A 2×2 contingency table (with four different categories) was obtained (Table 6) for potential infection and LW occurrence.

**Table 6. Contingency table used in the leaf wetness models evaluation. *Event* is a wet hour in case of leaf wetness simulation or a day in which potential infection occurs in case of potential infections simulation**

| | *Event* measured | No *Event* measured |
|---|---|---|
| *Event* generated | Hits (a) | Misses (b) |
| No *Event* generated | False Alarms (c) | Correct Negatives (d) |

The total number of potential infections per day in the same period of time was calculated to evaluate the impact of LW simulation on the infection process. All of the metrics used in this study are listed in Table 5. The composition of the accuracy modules ($Accuracy_{lw}$ and $Accuracy_{inf}$ for the simulation of LW and potential infections, respectively) accounted for two main features of model performance, consisting of the correct simulation of: i) an occurred event - probability of detection, $P_{od}$, and ii) a null event - probability of null event, $P_{ne}$.

The bias modules (Bias$_{lw}$ and Bias$_{inf}$ for the simulation of LW and potential infections, respectively) were composed of a single metric as follows: $B_{ias}$. These modules showed the tendency of the model to either underestimate or overestimate the simulated phenomenon. If $B_{ias}$ is greater than one, then the simulated events are more than the reference events. If $B_{ias}$ is less than one, then the simulated events are less than the reference events.

The correlation module was composed of a single basic metric, which is the Pearson's simple linear correlation coefficient $r$. The value of $r$ indicates the fluctuation of the estimates among $n$ measurements (Kobayashi and Salam, 2000) and is a useful measure of model performance. This metric was calculated using the numbers of potential infections obtained by the RR as reference values and the other numbers (from GR and MR) as estimated values.

For each dataset, the metrics explained above were computed and then aggregated into their modules according to the set of decision rules presented in Table 7.

**Table 7. Summary of decision rules within the modules Accuracy, Bias and Impact; F: favourable threshold; U: unfavourable threshold. Subscripts lw and inf stands for leaf wetness, and potential infection events, respectively**

| Aggregation | Modules | Expert weight | Metrics | |
|---|---|---|---|---|
| 2-metric | Accuracy$_{lw}$ Accuracy$_{inf}$ | | Probability of detection ($P_{od}$) | Probability of null event ($P_{ne}$) |
| | | 0.00 | F | F |
| | | 0.50 | F | U |
| | | 0.50 | U | F |
| | | 1.00 | U | U |
| No aggregation (single metric) | Bias$_{lw}$ Bias$_{inf}$ | | Balance of the model ($B_{ias}$) | |
| | | 0.00 | F | |
| | | 1.00 | U | |
| | Correlation | | $r$ | |
| | | 0.00 | F | |
| | | 1.00 | U | |

From these rules, a dimensionless value between zero and one was derived (0 = best model response; 1 = worst model response) for each module. For the definition of the value of each module, the Sugeno method of fuzzy inference was adopted (Sugeno, 1985). For the definition of the $I_{lw}$ composite indicator, a two-stage design inferring system was built (Fig. 4a) as follows: i) $P_{od}$ and $P_{ne}$ metrics were aggregated into their modules (Accuracy$_{lw}$), and the $B_{ias}$ metric was fuzzified into its module (Bias$_{lw}$); and ii) Bias$_{lw}$ and Accuracy$_{lw}$ modules were then aggregated into the second level integrated $I_{lw}$ metric. A three-stage design inferring system of fuzzy-based rules was applied for potential infection simulation (Fig. 4b) as follows: i) $P_{od}$ and $P_{ne}$ metrics were aggregated into their modules, thus, achieving the Accuracy$_{inf}$ module level, and the $B_{ias}$ metric and $r$ were fuzzified into their modules (Bias$_{inf}$ and Correlation, respectively); ii) the Bias$_{inf}$ module and Accuracy$_{inf}$ module were then aggregated into the Agreement$_{inf}$ module; and iii) the Agreement$_{inf}$ and Correlation modules were then aggregated into the third-level integrated measure, which is the final indicator ($I_{inf}$).

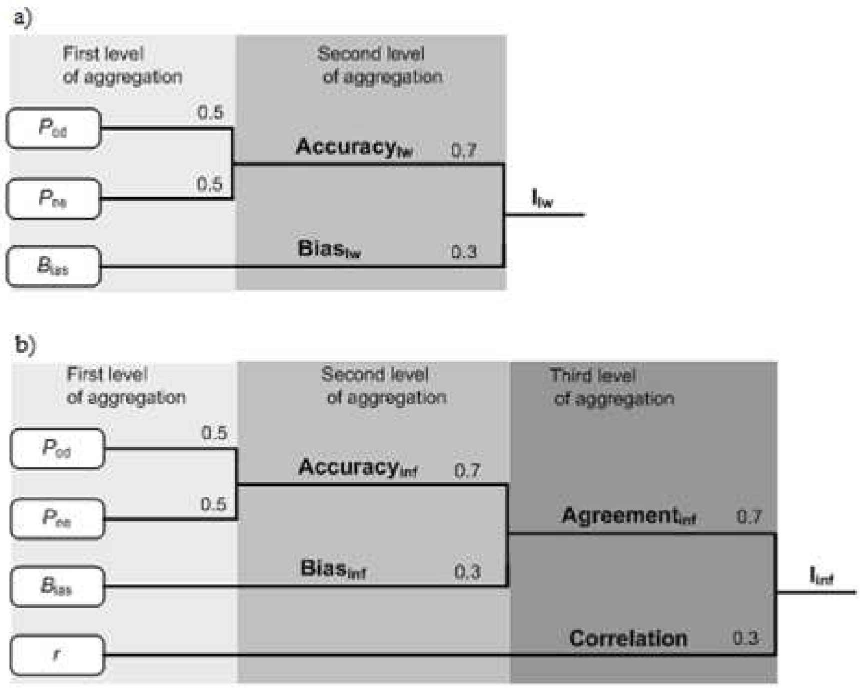



**Figure 4. Structure of the assessment method for leaf wetness simulation (a) and for potential infections simulation (b). $I_{lw}$: composite evaluation index for leaf wetness models; $I_{inf}$: composite evaluation index for potential infections simulation $P_{od}$: probability of detection; $P_{ne}$: probability of null event; $B_{ias}$: bias; $r$: Pearson's correlation coefficient; LW: leaf wetness**

## 4.4. Results and Discussion

Composite indicators allow a clear top-down analysis of results providing a unique summary value for model comparison and values at lower levels of aggregation to understand model behavior with respect to simple metrics. The average values of the $I_{inf}$ and $I_{lw}$ composite indicators are presented in Tables 8a, 8b, 9a and 9b, respectively.

**Table 8a. Performance statistic values used within multiple-metrics assessment method for the potential infections evaluation for the three pathogens tested (measured run). Grayed areas show the best result per metric for generated and measured runs. See the text for details**

| Pathogen | Indicator | Measured run (MR) | | | | | |
|---|---|---|---|---|---|---|---|
| | | physical models | | | empirical models | | |
| | | SWEB | LWR | DP | CART | ExT | FT |
| | $I_{inf}$ | 0.306 | 0.577 | 0.823 | 0.203 | 0.249 | 0.248 |
| | $Agreement_{inf}$ | 0.412 | 0.511 | 0.587 | 0.334 | 0.377 | 0.361 |
| | Correlation | 0.314 | 0.558 | 0.888 | 0.142 | 0.204 | 0.177 |
| | $Accuracy_{inf}$ | 0.404 | 0.448 | 0.500 | 0.296 | 0.324 | 0.322 |
| *P.i.* | $Bias_{inf}$ | 0.665 | 0.665 | 0.807 | 0.43 | 0.807 | 0.449 |
| | $r$ | 0.598 | 0.457 | 0.26 | 0.684 | 0.637 | 0.673 |
| | $P_{od}$ | 0.451 | 0.264 | 0.120 | 0.605 | 0.592 | 0.564 |
| | $P_{ne}$ | 0.927 | 0.945 | 0.956 | 0.905 | 0.883 | 0.925 |
| | $B_{ias}$ | 1.383 | 0.474 | 0.415 | 1.185 | 0.415 | 0.92 |
| | $I_{inf}$ | 0.426 | 0.607 | 0.763 | 0.287 | 0.343 | 0.314 |
| | $Agreement_{inf}$ | 0.411 | 0.514 | 0.585 | 0.334 | 0.380 | 0.362 |
| | Correlation | 0.391 | 0.647 | 0.929 | 0.200 | 0.264 | 0.231 |
| | $Accuracy_{inf}$ | 0.405 | 0.482 | 0.499 | 0.296 | 0.321 | 0.333 |
| *V. i.* | $Bias_{inf}$ | 0.433 | 0.614 | 0.807 | 0.43 | 0.533 | 0.449 |
| | $r$ | 0.553 | 0.396 | 0.148 | 0.649 | 0.608 | 0.64 |
| | $P_{od}$ | 0.441 | 0.225 | 0.074 | 0.592 | 0.569 | 0.535 |
| | $P_{ne}$ | 0.933 | 0.955 | 0.963 | 0.915 | 0.896 | 0.936 |
| | $B_{ias}$ | 0.901 | 0.662 | 0.415 | 1.185 | 1.453 | 0.92 |
| | $I_{inf}$ | 0.298 | 0.419 | 0.604 | 0.134 | 0.187 | 0.145 |
| | $Agreement_{inf}$ | 0.282 | 0.353 | 0.493 | 0.23 | 0.341 | 0.425 |
| | Correlation | 0.203 | 0.396 | 0.674 | 0.05 | 0.096 | 0.073 |
| | $Accuracy_{inf}$ | 0.387 | 0.472 | 0.499 | 0.233 | 0.266 | 0.251 |
| *P. s.* | $Bias_{inf}$ | 0.365 | 0.472 | 0.550 | 0.207 | 0.297 | 0.192 |
| | $r$ | 0.666 | 0.515 | 0.384 | 0.744 | 0.710 | 0.731 |
| | $P_{od}$ | 0.478 | 0.335 | 0.261 | 0.666 | 0.651 | 0.645 |
| | $P_{ne}$ | 0.940 | 0.922 | 0.921 | 0.912 | 0.89 | 0.926 |
| | $B_{ias}$ | 0.760 | 0.771 | 0.712 | 1.078 | 1.196 | 0.982 |

**Table 8b. Performance statistic values used within multiple-metrics assessment method for the potential infections evaluation for the three pathogens tested (measured run). Grayed areas show the best result per metric for generated and measured runs. See the text for details**

| Pathogen | Indicator | Generated run (GR) | | | | | |
|---|---|---|---|---|---|---|---|
| | | physical models | | | empirical models | | |
| | | SWEB | LWR | DP | CART | ExT | FT |
| | $I_{inf}$ | 0.617 | 0.849 | 0.893 | 0.599 | 0.699 | 0.593 |
| | $Agreement_{inf}$ | 0.414 | 0.548 | 0.580 | 0.373 | 0.419 | 0.379 |
| | Correlation | 0.697 | 0.919 | 0.943 | 0.646 | 0.718 | 0.658 |
| | $Accuracy_{inf}$ | 0.491 | 0.482 | 0.483 | 0.517 | 0.517 | 0.510 |
| *P.i.* | $Bias_{inf}$ | 0.655 | 0.655 | 0.655 | 0.472 | 0.721 | 0.454 |
| | $r$ | 0.358 | 0.217 | 0.150 | 0.394 | 0.361 | 0.383 |
| | $P_{od}$ | 0.306 | 0.225 | 0.249 | 0.288 | 0.283 | 0.284 |
| | $P_{ne}$ | 0.870 | 0.955 | 0.845 | 0.894 | 0.878 | 0.903 |
| | $B_{ias}$ | 2.089 | 2.089 | 0.538 | 0.909 | 1.654 | 0.783 |
| | $I_{inf}$ | 0.621 | 0.759 | 0.784 | 0.563 | 0.615 | 0.553 |
| | $Agreement_{inf}$ | 0.415 | 0.538 | 0.569 | 0.366 | 0.404 | 0.376 |
| | Correlation | 0.772 | 0.966 | 0.981 | 0.706 | 0.768 | 0.68 |
| | $Accuracy_{inf}$ | 0.497 | 0.551 | 0.526 | 0.515 | 0.524 | 0.523 |
| *V. i.* | $Bias_{inf}$ | 0.423 | 0.643 | 0.721 | 0.474 | 0.574 | 0.462 |
| | $r$ | 0.323 | 0.136 | 0.069 | 0.343 | 0.317 | 0.351 |
| | $P_{od}$ | 0.299 | 0.213 | 0.151 | 0.274 | 0.264 | 0.238 |
| | $P_{ne}$ | 0.866 | 0.831 | 0.863 | 0.888 | 0.876 | 0.898 |
| | $B_{ias}$ | 1.360 | 2.097 | 1.654 | 0.906 | 1.076 | 0.777 |
| | $I_{inf}$ | 0.479 | 0.672 | 0.696 | 0.511 | 0.546 | 0.516 |
| | $Agreement_{inf}$ | 0.418 | 0.555 | 0.554 | 0.483 | 0.484 | 0.473 |
| | Correlation | 0.537 | 0.762 | 0.810 | 0.532 | 0.597 | 0.538 |
| | $Accuracy_{inf}$ | 0.466 | 0.509 | 0.520 | 0.487 | 0.491 | 0.474 |
| *P. s.* | $Bias_{inf}$ | 0.302 | 0.666 | 0.644 | 0.487 | 0.464 | 0.444 |
| | $r$ | 0.437 | 0.357 | 0.332 | 0.450 | 0.437 | 0.445 |
| | $P_{od}$ | 0.362 | 0.291 | 0.299 | 0.293 | 0.327 | 0.311 |
| | $P_{ne}$ | 0.902 | 0.884 | 0.870 | 0.914 | 0.903 | 0.918 |
| | $B_{ias}$ | 0.839 | 0.871 | 1.018 | 0.670 | 0.763 | 0.673 |

**Table 9a. Performance statistic values used within multiple-metrics assessment method for the leaf wetness models evaluation (measured run). Grayed areas show the best result per metric for generated and measured runs. See the text for details**

| Pathogen | Indicator | Measured run (MR) | | | | | |
|---|---|---|---|---|---|---|---|
| | | physical models | | | empirical models | | |
| | | SWEB | LWR | DP | CART | ExT | FT |
| | $I_{lw}$ | 0.336 | 0.571 | 0.594 | 0.316 | 0.277 | 0.247 |
| | Accuracy$_{lw}$ | 0.361 | 0.575 | 0.668 | 0.253 | 0.142 | 0.174 |
| | Bias$_{lw}$ | 0.284 | 0.568 | 0.507 | 0.356 | 0.401 | 0.299 |
| | POD | 0.617 | 0.597 | 0.543 | 0.672 | 0.81 | 0.739 |
| | PNE | 0.799 | 0.606 | 0.564 | 0.892 | 0.845 | 0.911 |
| | BIAS | 1.175 | 1.919 | 1.812 | 1.086 | 1.318 | 0.997 |

**Table 9b. Performance statistic values used within multiple-metrics assessment method for the leaf wetness models evaluation (generated run). Grayed areas show the best result per metric for generated and measured runs. See the text for details**

| Pathogen | Indicator | Measured run (MR) | | | | | |
|---|---|---|---|---|---|---|---|
| | | physical models | | | empirical models | | |
| | | SWEB | LWR | DP | CART | ExT | FT |
| | $I_{lw}$ | 0.361 | 0.471 | 0.585 | 0.386 | 0.392 | 0.359 |
| | Accuracy$_{lw}$ | 0.429 | 0.516 | 0.572 | 0.459 | 0.442 | 0.469 |
| | Bias$_{lw}$ | 0.291 | 0.424 | 0.571 | 0.298 | 0.340 | 0.232 |
| | POD | 0.462 | 0.460 | 0.517 | 0.416 | 0.456 | 0.402 |
| | PNE | 0.845 | 0.745 | 0.669 | 0.851 | 0.824 | 0.848 |
| | BIAS | 1.038 | 1.561 | 2.278 | 0.921 | 1.161 | 0.960 |

Each Table contains the summary value, values of the intermediate modules and values of the simple metrics related to the six LW models tested. The values obtained by all of the LW models in the two composite indicators from GR were noticeably different from the values obtained from MR, which results from different sources of errors related to the generation of hourly values from daily values (e.g., air temperature and RH). However, it is interesting to note that there was a noticeable coherence between the rankings of the LW models (indicator $I_{lw}$) in the GR and MR runs. The results of the modelling solutions including the impact model (indicator $I_{inf}$) were similar but with some differences in the ranking. These results can be interpreted as an added value given by the use of the impact model in the evaluation of the LW models. Even if the evaluation results might be different when changing the impact model, it provides a first step in ranking LW models with respect to their operational use in the absence of a standard procedure to evaluate LW models via an impact model.

The performances of the LW models were different for the three pathogens, which can be explained by the variability of their thermal and wetness requirements (Fig. 1). In particular, all of the models showed better performances in reproducing potential infection occurrences of *Puccinia striiformis* using measured LW. In contrast, the worst results were obtained for *Venturia inaequalis*. The values of $I_{inf}$ showed that the CART model obtained the best value for all of the pathogens tested for MR (average $I_{inf}$ = 0.208). For GR, however, the CART model was classified second in all of the experiments (average $I_{inf}$ = 0.557). The CART model may be considered the most reliable when using input from either estimated daily data or hourly values. $I_{inf}$ values for the FT model were similar to those discussed for CART, with FT classifying second in all of the MR experiments (average $I_{inf}$ = 0.236) and first in the GR experiments (average $I_{inf}$ = 0.554). Similar considerations can be made for the ExT model, which was ranked third and fourth according to the MR (average $I_{inf}$ = 0.260) and GR (average $I_{inf}$ = 0.620) results, respectively. Both the ExT and CART models do not require calibration, and FT was fitted on the data used in the analysis: this may explain why they performed better than the process-based models (represented by SWEB, DP and LWR). When simulating LW on different crops and in a wide range of conditions, such as in the dataset used, accurate parameterization was not possible. Among the process-based models, SWEB was the most accurate in simulating potential infection occurrence, and SWEB ranked fourth (average $I_{inf}$ = 0.344) and third ($I_{inf}$ = 0.572) according to the MR and GR results, respectively (SWEB ranked even better than the ExT model under GR conditions). Worse values (higher) of $I_{inf}$ were obtained by the LWR and DP models for either the MR experiments (average $I_{inf}$ was 0.534 and 0.730, respectively) or GR experiments (average $I_{inf}$ was 0.760 and 0.791, respectively).

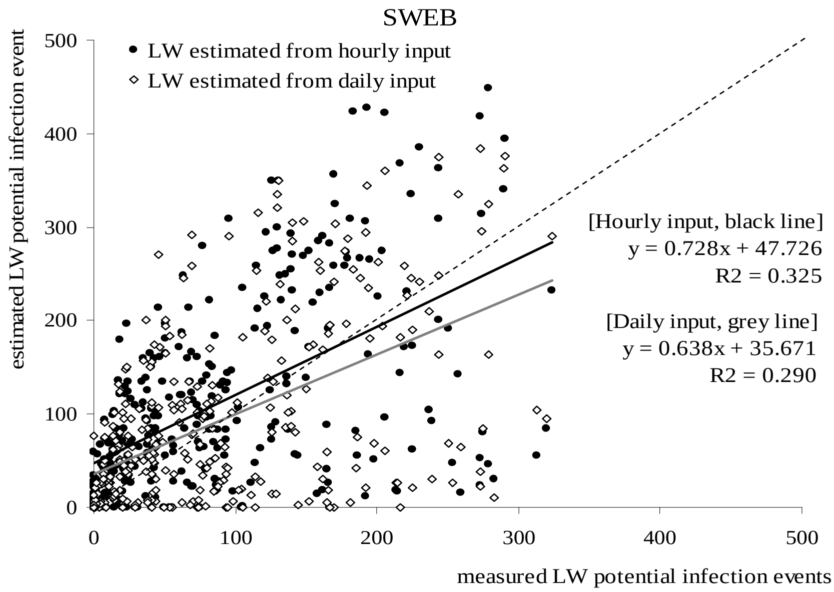
The $I_{lw}$ results obtained by the LW models, as detailed above, were quite different from the $I_{inf}$ results. In particular, the CART model was ranked second for MR (average $I_{lw}$ = 0.316) and third for GR (average $I_{lw}$ = 0.386), and it was preceded by ExT (average $I_{lw}$ = 0.277) for MR. The CART model was preceded by SWEB ($I_{lw}$ = 0.361) and ExT ($I_{lw}$ = 0.392) for GR. According to the values obtained for $I_{inf}$, the DP and LWR models classified next-to-last and last, respectively, in the values of $I_{lw}$.

Considering the specific modules and simple metrics, the ranking of the LW models in the Agreement$_{inf}$ and Correlation module values from MR and GR were consistent with the values obtained for $I_{inf}$, with the exception that model performances in the Agreement$_{inf}$ module were more heterogeneous than in the Correlation module. These results suggested that the ability of reproducing the days in which potential infections occur was shared by almost all of the LW models tested. Furthermore, the simulation of the number of potential infections per day was critical, and it was strongly influenced by the LW model chosen.

The average values of the accuracy modules (Accuracy$_{inf}$ and Accuracy$_{lw}$) and bias modules (Bias$_{inf}$ and Bias$_{lw}$) for MR underlined the highest reliability of the empirical models. When generated hourly inputs were used (GR), the differences in the performances of the LW models in these modules appeared decidedly less relevant. Finally, the values of $P_{od}$ were better for the estimation of LW when compared to the simulation of potential infection occurrence. The opposite situation occurred for $P_{ne}$.

Figure 5 presents the comparison between the monthly potential infection events of *Venturia inaequalis* simulated by CART (Fig. 5a) and SWEB (Fig. 5b) for GR and MR.

**a)**




**b)**

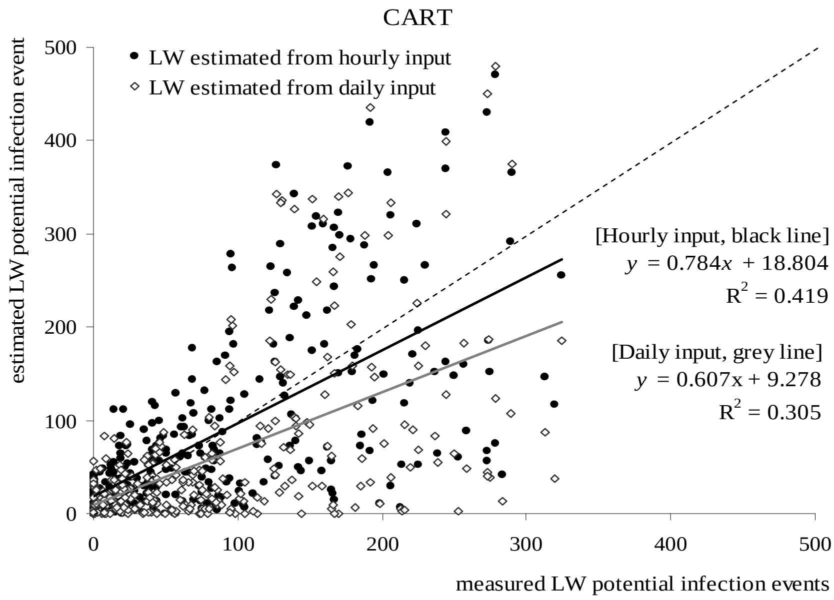



**Figure 5. Scatter plot, for two LW models, of the number of potential infection events of *Venturia inaequalis* per month (all years and all sites used in this analysis) obtained using LW estimated from hourly (black circles) and daily (white diamonds)**

**meteorological variables vs. potential infection events estimated using measured weather variables and LW. Linear regression lines and 1:1 lines are also shown**

Moreover, Fig. 5 shows the corresponding values obtained by the same models for RR. The two models were selected for their good performances (Tables 8 and 9) and because they were considered examples of fully empirical and process-based models. The charts present the specific matching of monthly events; the data should ideally fall on the 1:1 line. Both GR and MR values underestimated those simulated for RR, with the CART model explaining more of the RR value variability compared to the SWEB approach.

## 4.5. Conclusions

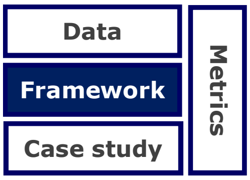
A reliable simulation of LW is an essential prerequisite for predicting the diffusion of plant pathogens and their impact on crop production under alternate climate change scenarios. The specific, multi metric methodology proposed allowed an articulated evaluation and comparison of models to estimate LW. The integrated assessment method developed in this study allowed a transparent traceability of the uncertainties and estimation errors that can characterize the generation process. This analysis showed that the magnitude of errors in the diverse steps of the modelling chain varied according to the LW model chosen and pathogen considered. Beyond the model evaluation presented in this paper for use in large-area applications, this study also suggests the need for evaluation and calibration of a LW model prior to its operational use in specific contexts to reduce the error of estimates. In fact, an optimization of the LW models parameters using reference data coming from a specific context could lead to a diverse ranking of the same LW models according to their performance, although without causing major changes. Furthermore, the proposed procedure takes into account the biological impact of LW simulation through the coupling of the models tested to a potential infection model. This analysis was important in considering that LW models are used in most applications as input for disease models. It allowed to discover that the rankings obtained by the LW models tested slightly vary when they are evaluated as coupled with the impact model chosen. This result can be due to the fact that the interactions between the temperature response function and the duration of the length of dry and wet periods could mask the ability of the LW models to reproduce the two discrete states of the output (LW; as yes/no state).

The generation of hourly meteorological variables from daily values generally led to a worsening of the estimation of both LW and potential infection events. Despite this limitation, large area studies where models are used to predict the impacts of climatic scenarios usually have to rely on daily input data. A site-specific calibration of models to generate hourly variables may improve the quality of LW estimates.

The modelling chain proposed can be used for scenario analysis and relative comparisons. As is, the proposed modelling chain is not suitable for in season support in decision-aided systems. The CART model achieved the best results for most of the metrics considered, especially for the potential infection assessment. Therefore, we conclude that although this model is not the most accurate in LW prediction, it guarantees the best performances when used to provide data for a potential infection model, such as the model used in this analysis. This result may be due to the ability of CART to reproduce the duration of alternate dry and wet periods, allowing a better reproduction of the wetness requirements of plant fungal pathogens.

**Acknowledgments**

The authors wish to thank Luigi Pasotti, Antonino Drago, Servizio Informativo Agrometeorologico Siciliano (SIAS), Regione Siciliana and Palermo (IT) for providing the meteorological data from the sites in Sicily. This work was partially funded by the Italian Ministry of Agricultural, Food and Forestry Policies under the AgroScenari project.




# EVALUATING THE SUITABILITY OF A GENERIC FUNGAL INFECTION MODEL FOR PEST RISK ASSESSMENT STUDIES

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Submitted to: Ecological Modelling (2011)

### 5.1. Abstract

Pest risk assessment studies are aimed at evaluating if weather conditions are suitable for the potential entry and establishment of an organism in a new environment. For fungal plant pathogens, the crucial aspect that has to be explored is the fulfillment of the infection process, that constitutes the first phase of the development of an epidemic as mainly driven by temperature and leaf wetness duration. This is valid in current weather conditions and even more in climate change scenarios, since the modified pattern of temperature and moisture regimes could completely alter the known distribution and severity of plant disease epidemics. Biophysical process-based models could effectively be used in such studies, since they are a tool for exploring conditions not experienced yet. One of the prerequisite of their adoption in operational contexts is a sensitivity analysis assessment aimed at understanding their ability (i) in differentiating the responses according to different parameterizations and (ii) to be sensitive to the variability of the data provided as input. In this study, a generic potential fungal infection model was analyzed in this way. Four pathogens were chosen, trying to maximize the variability in temperature and moisture requirements, and the model was run under diverse climatic conditions. The sensitivity of the model deeply changed according to the pathogen tested, and the relevance of its parameters in explaining model output was strongly linked to the environmental conditions tested. Therefore, these results suggest that this model is particularly suitable for pest risk assessment studies

**Keywords:** Potential infection, sensitivity analysis, leaf wetness, climate change.

## 5.2. Introduction

The damages potentially caused by the spatial changes in the diffusion of pests and diseases could concern several aspects: economy, ecology, and public health impacts (Andersen et al., 2004). In pest risk assessment studies, where the main goal is the evaluation of the potential entry and establishment of a fungal pathogen in a new environment, the crucial aspect that has to be explored is if the weather conditions are conducive for the fulfillment of the infection process, since it is the first phase of the establishment of an epidemic (Magarey et al., 2005). For this reason, the formalization of the infection process plays a key role in disease forecasting systems (Madden et al., 1988), via the inclusion of the main driving variables for foliar fungal plant pathogens into the infection sub-component, which are (i) air temperature and (ii) the duration of surface leaf wetness or high humidity periods. Many reviews focused on the possible effects of biotic stresses on crops in the future (e.g., Goudriaan and Zadocks, 1995; Garrett et al., 2006; Ghini et al., 2008) indicate that climate change could deeply modify the known patterns of plant diseases by means of altered spread of some species and introduction of new pathogens and vectors, leading to modified dynamics of current plant disease epidemics and shifts in their geographical distribution. In particular, most Authors agree with the fact that changes in temperature conduciveness and moisture availability are two of the main factors that could alter disease infection and severity not only in the short-term but even for a longer perspective in terms of evolutionary potential (Coakley et al., 1999; Garrett et al., 2006). In this context, process based models are the only valid tools able to explore conditions not experienced yet, as the ones driven by climate change, such as the estimation of crop-diseases interactions and expansion in new areas. In fact these biophysical processes show non-linear response to boundary conditions, hence results can be obtained only via the use of simulation models.

Nowadays, one of the crucial issues in plant disease modelling is that either agronomists or researchers in plant pathology ask for the development of generic disease forecasting models, within a reusable and compatible modelling framework suitable for simulating different plant diseases, as underlined by Magarey and Sutton (2007). The most important problem related to the development of such models is that they are created from either laboratory or field observations of resulting disease intensity at multiple combinations of temperature and leaf wetness. However, for many pathogens, especially those from overseas, such data sets may not exist. The main goal of sensitivity analysis (SA) is to determine how different sources of variations in parameters values affect the models outputs (Cariboni et al., 2007; Dresch et al., 2010), thus allowing users and developers to understand the degree of dependency of the model on the information given as input (Radiarta and Saitoh, 2009). One of the common outcome of SA studies is the determination of the parameters that have to be accurately measured, estimated or optimized, since they resulted to be the most relevant in affecting model outputs (e.g., Blower and Dowlatabady, 1994; Saltelli et al., 2005). The aim of this paper is an investigation about the suitability of a process-based generic fungal infection model to be effectively used in pest risk assessment studies. This evaluation was carried out via a sensitivity analysis exercise, aiming at evaluating the model response to (i) environmental input heterogeneity and (ii) under different parameterizations.

## 5.3. Materials and methods

### 5.3.1. The potential infection model

The generic potential infection model developed by Magarey et al. (2005) was used in the study. It takes into account both the impact of air temperature and leaf wetness duration by means of two diverse functions. It implements the hourly air temperature response function developed by Yan and Hunt (1999):

$$f(t) = \left( \frac{T_{\max,\inf} - T}{T_{\max,\inf} - T_{opt,\inf}} \right) \left( \frac{T - T_{\min,\inf}}{T_{opt,\inf} - T_{\min,\inf}} \right)^{(T_{opt,\inf} - T_{\min,\inf})/(T_{\max,\inf} - T_{opt,\inf})} \quad [1]$$

where *f(t)* (0-1; dimensionless) is the temperature response function; $T$ (°C) is the mean air temperature during the wetness period; $T_{\min,\inf}$, $T_{\max,\inf}$ and $T_{opt,\inf}$ (°C) are the minimal, maximal and optimal temperatures for infection, respectively. The leaf wetness impact on infection development is taken into account by the following equations:

$$W(t) = \begin{cases} \dfrac{WD_{\min}}{f(t)} & \dfrac{WD_{\min}}{f(t)} \le WD_{\max} \\ \\ 0 & elsewhere \end{cases} \qquad [2]$$

where *W(t)* (0-1; dimensionless) is the wetness response function, $WD_{\min}$ (hours) is the minimal leaf wetness duration for infection, *f(t)* (0-1; dimensionless) is the temperature response function (Eq. 1) and $WD_{\max}$ (hours) is the optimal value of leaf wetness duration requirement. The impact of a dry period on infection fulfillment is determined by the critical dry period interruption value (*D50*), as indicated in the following equations:

$$W_{sum} = \begin{cases} W_1 + W_2 & D < D50 \\ \\ W_1 \quad or \quad W_2 & elsewhere \end{cases} \qquad [3]$$

where $W_{sum}$ is the sum of the surface wetting and $W_1$ and $W_2$ are wet periods separated by a dry period (*D*; hours). The implementation of the model as used in this study is fully described in Bregaglio et al. (2011).

### 5.3.2. Pathogens tested

The model was parameterized for four pathogens characterized by marked heterogeneous temperature and moisture requirements, in order to analyse the model ability to differentiate its response to diverse parameters values.

The selected fungi were: (i) *Puccinia striiformis*, causal agent of stripe rust on wheat, that is a temperate pathogen characterized by low moisture requirements but very sensitive to dry periods; (ii) *Venturia inaequalis*, causal agent of apple scab, that is a temperate pathogen too, but insensitive to dry periods; (iii) *Bipolaris oryzae*, causal agent of brown spot on rice, that is a tropical pathogen characterized by medium requirements in terms of leaf wetness duration and moderate sensitivity to a dry-interruption event and (iv) *Cercospora carotae*, causal agent of leaf blight of carrot, which is a tropical pathogen showing a great wet hours requirement but insensitive to dry period. The statistical settings of the parameters distributions of the parameters for the SA study for the four pathogens are reported in Table 1, together with the reference sources.

**Table 1. Parameters of the generic potential infection model, statistical settings and sources of information for the pathogens analyzed in the study. For discrete distribution, the values tested are reported**

| Pathogen | $T_{min,inf}$ (°C) | $T_{max,inf}$ (°C) | $T_{opt,inf}$ (°C) | $WD_{min}$ (hours) | $WD_{max}$ (hours) | *D50* (hours) | Source |
|---|---|---|---|---|---|---|---|
| *Puccinia recondita* | *1.8* (1.23) | *20.5* (2.08) | *9.17* (1.61) | 3, 4 | 15, 16 | 1, 2 | 1, 2, 3, 4, 5, 6 |
| *Venturia inaequalis* | *1.75* (0.5) | *32* (4.62) | *22.5* (3.53) | 4, 5 | 40, 41 | 24, 25 | 1, 7, 8, 9, 10, 11, 12 |
| *Bipolaris oryzae* | *8* (0.4) | *35* (1.75) | *28.12* (2.39) | 8, 9 | 24, 25 | 4, 5 | 1, 13, 14, 15, 16 |
| *Cercospora carotae* | *11* (0.55) | *32* (1.6) | *24* (1.2) | 24,25 | 95, 96 | 12, 13 | 1, 17, 18, 19 |

1= Magarey et al., 2005; 2= Dennis, 1987; 3= Hogg et al., 1969; 4= Lemaire et al., 2002; 5= de Vallavieille-Pope et al, 2002; 6= Park, 2007; 7= Stensvand et al., 1997; 8= Schwabe, 1980 ; 9= Spotts and Cervantes, 1991; 10= Mills and Laplante, 1945; 11= Becker and Burr, 1994; 12= Villalta et al., 2000; 13= Percich et al., 1997; 14= Ou, 1985; 15= Ibiam and Arinze, 2007;16= Nyvall and Percich, 1999; 17= Carisse and Kushalappa, 1990; 18= Hooker, 1944; 19= Strandberg, 1968

### 5.3.3. Methodology for the sensitivity analysis

The SA method chosen for testing the model was the variance-based global sensitivity analysis method of Sobol’ (Sobol’, 1993) as improved by Saltelli (2002), considered a reference even if the most expensive in computational terms. It decomposes the output variance into terms of increasing dimension (i.e., partial variances), representing the contribution of single parameters, and of pair, triplets, … of parameters to the overall uncertainty of the model output. This method adopts Monte Carlo sampling in order to simultaneously explore the parameters hyperspace. It provides statistical estimators of partial variances in order to quantify the relevance of parameters and of groups of parameters via multi-dimensional integrals. For each parameter, a total sensitivity index (St) quantifying the overall effect of a parameter (i.e., including all the possible interactions) is also available. The output considered in this study was the number of successful potential infection events in an year.

### 5.3.4. Environmental conditions tested

The choice of the sites in which simulations were performed was driven by the need of exploring very heterogeneous meteorological conditions, ranging from very warm to very cold environments (Table 2).

**Table 2. Sites and years used for the sensitivity analyses**

| Country | Site | Years | Latitude | Longitude |
|---|---|---|---|---|
| Albania | Shkodra | 1996-2000 | 42° 04’ N | 19° 31’ E |
| England | Stornoway | 1996-2000 | 58° 12’ N | 06° 23’ W |
| France | Toulose | 1996-2000 | 43° 36’ N | 01° 26’ E |
| Israel | Tel Aviv | 1996-2000 | 32° 03’ N | 34° 46’ E |
| Italy | Reggio Emilia | 1996-2000 | 44° 42’ N | 10° 31’ E |
| Germany | Karlsruhe | 1996-2000 | 49° 01’ N | 08° 24’ E |
| Russia | Vladivostok | 1996-2000 | 43° 07’ N | 131° 55’ E |
| Spain | Zaragoza | 1996-2000 | 41° 39’ N | 00° 52’ W |

Daily maximum and minimum air temperature and rain were extracted from the European Climate Assessment & Dataset (ECA&D). For the estimation of hourly air temperature, the Campbell approach (1985) was adopted, whereas for the estimation of hourly air relative humidity the method proposed by Linacre (1992) was chosen since it gained the best results in previous studies (Bregaglio et al., 2010). Leaf wetness was estimated with the model developed by Kim et al (2002), the one providing the best performances according to Bregaglio et al. (2011).

## 5.4. Results and discussion

The average values of St by considering all the sites and the years tested for the four pathogens are graphically presented as box-plots in Figure 1, in order to give a summary of the overall impact of the diverse meteorological conditions on the relevance of the parameters, whereas the average values of St divided per location are presented in Table 3.

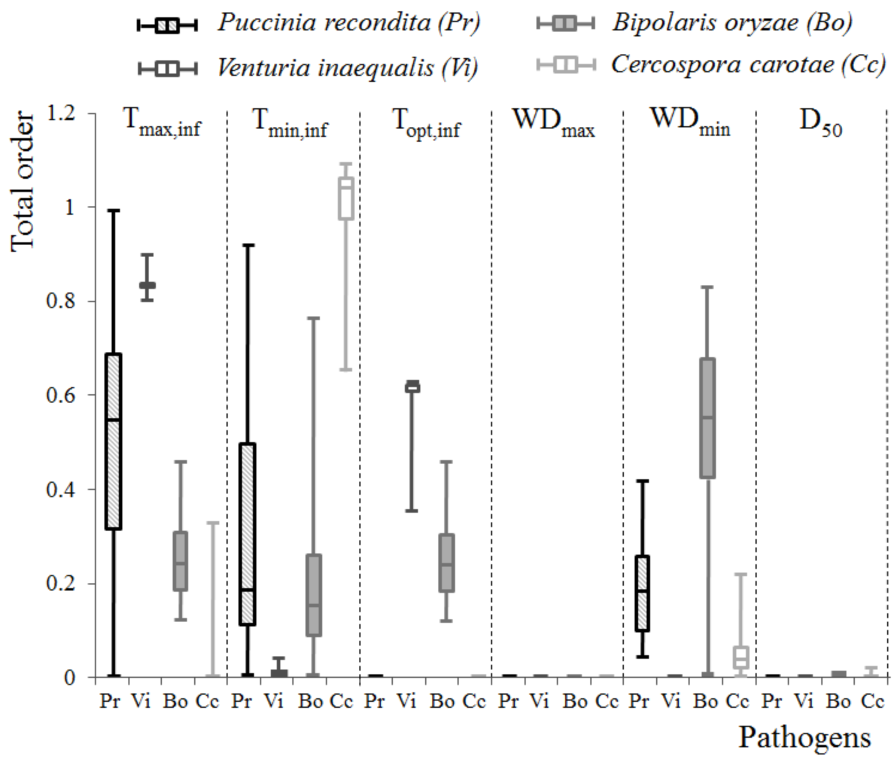



**Figure 1. Box-plots of Sobol' Total Order Indices for the four parameterizations of the potential infection model tested resulting from all the locations and years in which sensitivity analyses were carried out**

**Table 3. Average Sobol' total order effects obtained for the four pathogens tested in the years from 1996 to 2000 divided per site. Bold indicates the highest value within location**

| | | Site | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **Pathogen** | **Parameter** | **Karlsruhe** | **Reggio E.** | **Shkodra** | **Stornoway** | **Tel Aviv** | **Tolosa** | **Vladivostok** | **Zaragoza** |
| *Puccinia recondita* | $T_{max,inf}$ | 0.174 | **0.479** | **0.562** | 0.000 | **0.977** | 0.600 | **0.831** | **0.530** |
| | $T_{min,inf}$ | **0.484** | 0.337 | 0.178 | **0.887** | 0.000 | 0.164 | 0.118 | 0.157 |
| | $T_{opt,inf}$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | $WD_{max}$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | $WD_{min}$ | 0.177 | 0.186 | 0.262 | 0.126 | 0.059 | 0.237 | 0.061 | 0.311 |
| | D50 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| *Venturia inaequalis* | $T_{max,inf}$ | **0.817** | **0.820** | **0.831** | **0.829** | **0.883** | **0.832** | **0.829** | **0.831** |
| | $T_{min,inf}$ | 0.018 | 0.014 | 0.006 | 0.006 | 0.000 | 0.004 | 0.006 | 0.004 |
| | $T_{opt,inf}$ | 0.619 | 0.614 | 0.612 | 0.625 | 0.394 | 0.622 | 0.621 | 0.620 |
| | $WD_{max}$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | $WD_{min}$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | D50 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| *Bipolaris oryzae* | $T_{max,inf}$ | 0.211 | 0.190 | 0.185 | 0.260 | 0.380 | 0.258 | **0.428** | 0.135 |
| | $T_{min,inf}$ | 0.273 | 0.105 | 0.143 | **0.721** | 0.008 | 0.240 | 0.161 | 0.096 |
| | $T_{opt,inf}$ | 0.211 | 0.190 | 0.185 | 0.260 | 0.380 | 0.258 | **0.428** | 0.135 |
| | $WD_{max}$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | $WD_{min}$ | **0.513** | **0.688** | **0.658** | 0.008 | **0.595** | **0.486** | 0.406 | **0.753** |
| | D50 | 0.000 | 0.001 | 0.001 | 0.000 | 0.000 | 0.001 | 0.001 | 0.000 |
| *Cercospora carotae* | $T_{max,inf}$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.182 | 0.000 | 0.000 | 0.000 |
| | $T_{min,inf}$ | **1.017** | **0.974** | **1.026** | **1.071** | **0.826** | **1.018** | **1.049** | **1.028** |
| | $T_{opt,inf}$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | $WD_{max}$ | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 | 0.000 |
| | $WD_{min}$ | 0.412 | 0.111 | 0.066 | 0.000 | 0.046 | 0.053 | 0.011 | 0.072 |
| | D50 | 0.003 | 0.001 | 0.000 | 0.000 | 0.002 | 0.002 | 0.001 | 0.000 |

The model sensitivity resulted deeply affected by the diverse parameterizations. For *Puccinia recondita* (low moisture and temperature requests), the most relevant parameters resulted the minimum and maximum cardinal temperatures ($T_{min,inf}$ and $T_{max,inf}$), both characterized by a high variability across the conditions tested, whereas variations in optimum temperature for infection ($T_{opt,inf}$) did not affect the number of potential infection events. The importance of $T_{min,inf}$ and $T_{max,inf}$ strongly varied across the sites, ranging from 0 in Stornoway to 0.977 in Tel Aviv for the former and from 0 in Tel Aviv to 0.887 in Stornoway for the latter. This emphasizes the ability of the model to respond to environments characterized by diverse temperature regimes by shifting the relevance of the parameters according to warmer and colder conditions. The third most important parameter resulted $WD_{min}$ but with a low variability of St. The most relevant parameter for *Venturia inaequalis* (low temperature requirements, insensitive to dry periods) resulted $T_{max,inf}$ with a very low variability across the locations tested, followed by $T_{opt,inf}$. This could be partially explained by (i) the very large range of air temperature in which the pathogen could develop, thus being air temperature limiting only in very warm conditions and (ii) by the statistical settings derived from literature, in specific by the high standard deviation for both parameters (4.62 for $T_{max,inf}$ and 3.53 for $T_{opt,inf}$). As for *Puccinia recondita*, variations in the parameters related to leaf wetness did not affect the model outputs. For *Bipolaris oryzae* parameterization (high temperature and moderate moisture requests), $WD_{min}$ resulted the most important parameter, showing a high variability, from 0.008 in Stornoway, characterised by a very humid environment, to 0.753 in Zaragoza, in which weather conditions are decidedly more arid. For this pathogen, also the three cardinal temperatures resulted important in explaining the variability of the potential infection events simulated. For *Cercospora carotae* (high temperature and moisture requirements) the most important parameter resulted to be $T_{min,inf}$ with moderate variability, whereas the 2$^{nd}$ was $WD_{min}$ with the lowest St value in Stornoway (0), and the highest value in Karlsruhe (0.412). Throughout the parameterization tested, $WD_{max}$ parameter resulted always not relevant, whereas D50 showed to have a slight importance in explaining output variability only for *Bipolaris oryzae* and *Cercospora carotae*. A further analysis of the results is provided in Figure 2, in which the St normalized values of the parameter with the highest relevance for each pathogen are plotted in contour maps against the yearly average air temperature ($T_{avg,year}$) and air relative humidity ($RH_{avg,year}$). This graphical representation allowed to identify the pattern of variation of the most relevant parameters across the meteorological conditions tested.

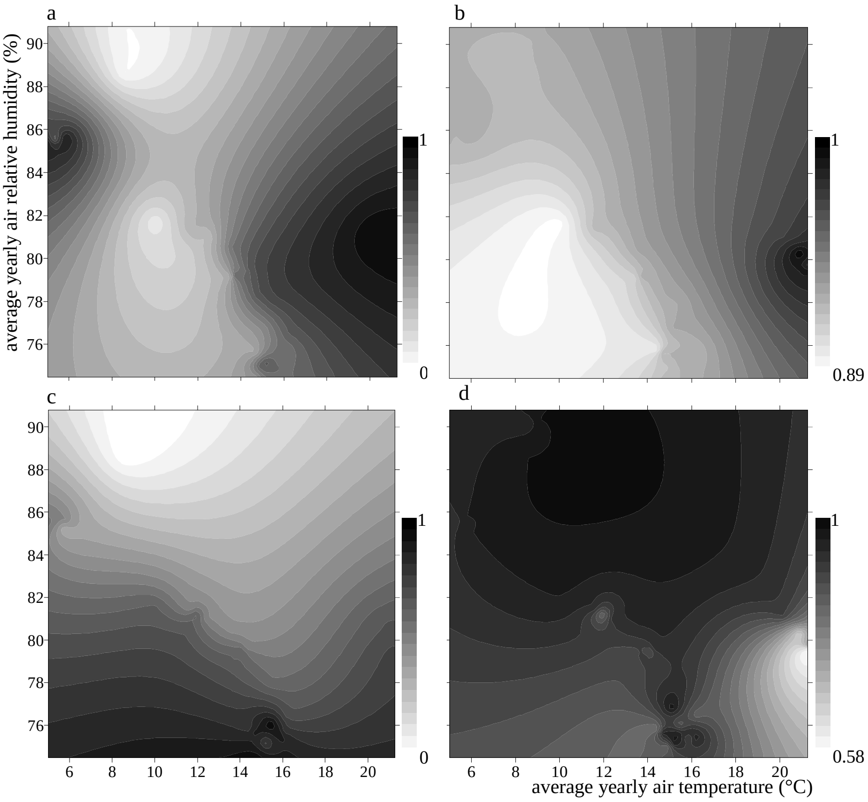
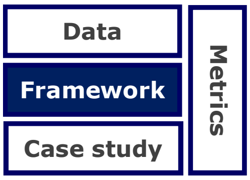



**Figure 2. Contour maps showing the pattern of variability of the parameters with the highest value of the normalized Sobol' Total Order Index for the four pathogen tested (a= $T_{max,inf}$ for *Puccinia recondita*; b= $T_{max,inf}$ for *Venturia inaequalis*; c= $WD_{min}$ for *Bipolaris oryzae*; d= $T_{min,inf}$ for *Cercospora carotae*) as a function of yearly average air relative humidity (y-axis) and air temperature (x-axis)**

For *Puccinia recondita* (Figure 2a), the St values of $T_{max,inf}$ reach the maximum with very low and very high $T_{avg,year}$, whereas variations in $RH_{avg,year}$ appeared to be not relevant. This behaviour could be explained by the fact that extreme temperature regimes emphasize the importance of this parameter. For *Venturia inaequalis* (Figure 2b) the pattern is quite the same as for *Puccinia recondita* but the increase in $T_{max,inf}$ is either uniform as $T_{avg,year}$ increases and the normalized value of St are always higher (bottom scale value is 0.89). The highest values of St are reached with $RH_{avg,year}$ around 80%. For *Bipolaris oryzae* (Figure 2c), there is a clear pattern in $WD_{min}$ indicating an increase in St values for decreasing $RH_{avg,year}$. This could be explained by the limiting moisture conditions for the development of the infection process of the pathogen. The relevance of this parameter seemed also to be affected by the increase in $T_{avg,year}$. For *Cercospora carotae* (Figure 2d), the relevance of $T_{min,inf}$ resulted affected both by $RH_{avg,year}$ and by $T_{avg,year}$, thus enhancing its relevance whilst the former increases and the latter decreases.

**5.5. Conclusions**

The need for developing effective generic biophysical process-based models that could be applied both in actual and future climate scenarios impact assessment is imperative. The SA carried out in this study highlights the ability of the potential infection model developed by Magarey et al. (2005) either (i) to deeply differentiate its sensitivity according to diverse parameterizations or (ii) to respond to the variability of the input data (hourly air temperature and leaf wetness) thus capturing the peculiarity of diverse meteorological conditions. The indications provided by this study are really encouraging and strengthen the suitability of this model to be used in pest risk assessment studies under both current conditions and climate change scenarios.




# A LIBRARY OF SOFTWARE COMPONENTS FOR PLANT AIRBORNE DISEASE SIMULATION

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Submitted to Environmental Modelling and Software (2011)

## 6.1. Abstract

The implementation of plant epidemic models into crop yield forecasting systems is becoming a crucial issue either for obtaining more realistic forecasts about actual production levels or for assessing the future impact of plant diseases in changing climate scenarios. In order to manage the increasing complexity of the biophysical processes simulated, e.g., the impact of plant diseases on leaf photosynthetic area and the interactions between pathogens and plant physiological processes, there is the need of developing modelling tools with the state of the art of software engineering technology. This paper presents four independent software libraries aimed at simulating a generic polycyclic fungal epidemic that can be easily extended by third parties and reusable under diverse modelling platforms. These components provide options for simulating (i) the initial conditions for the development of an epidemic, (ii) the progress of the disease over time as driven by meteorological variables taking into account the effect of host resistance, (iii) the yield losses due to the interactions between plant and pathogen population via coupling with a crop growth model and (iv) the impact of agro management practices on disease progress. The core component of this framework was analyzed via an extensive spatially distributed sensitivity analysis exercise with two pathosystems in order to gain an in-depth knowledge about model functioning and to obtain information about possible reduction or simplifications. The results of such analysis indicate that the model is on one hand sensitive to diverse parameters according to the pathogen simulated while on the other there is coherence about the relevance of parameters belonging to the same process (e.g., spore dispersal and catch) in the two pathosystem tested.

**Keywords**: Climate change, crop yield forecasting, scenario analysis, plant epidemic

## 6.2. Introduction

The development of generic disease forecasting models, either suitable for simulating epidemics caused by different pathogens or reusable within diverse software platforms is becoming a crucial issue agronomists or researchers in plant pathology are facing with (Magarey and Sutton, 2007). This is proved by the flourishing in the last years of frameworks such as the Internet System for the Weather-Based Mapping of Plant Pathogens NAPPFAST (Magarey et al., 2007), implementing the potential infection model for foliar fungal pathogens developed by Magarey et al. (2005), and tools as the generic biological model for the control of foliar plant diseases developed by Jeger et al. (2009), the population dynamics of plant-parasite interactions model developed by Gubbins et al. (2000) and the adaptation of the Kermack and McKendrick (1927) human epidemic model to spatial spread of plant disease made by Segarra et al. (2001). In order to manage the extreme complexity of the biophysical processes simulated, ranging from the relationships between meteorological variables and epidemic development to the physiological interactions between plants and pathogens, this modelling tendency should be supported by the state-of-the-art of software engineering technology. As a consequence, the adoption of component-oriented programming is becoming not only an option, but even the unavoidable prerequisite for the development of plant disease models and more in general of agricultural and ecological models (Reynolds and Acock, 1997; Papajorgji et al., 2004; Donatelli et al., 2010b). The advantages deriving by this choice are unquestionable, and can be summarized by features as ease of maintenance of the code, granularity of the approaches implemented, reusability of the tools and cross platform capabilities (Meyer, 1997). In particular, model reusability is often a challenging task because of different architectural structures and binaries incompatibilities, thus often forcing modellers to the conversion of the code from one programming language to another (Liu et al., 2002).

Mathematical modelling of crop diseases moves its first steps with the work of Van der Plank (1960; 1963), which developed the first models of the temporal development of epidemics and have since formed the basis for plant disease modelling (Campbell and Madden, 1990; McCartney, 1997). Further developments of this branch of pathology led to the development of models to estimate disease severity and yield losses affected by different factors such as weather, varietal resistance, and crop management practices (Van Maanen and Xu, 2003, Luo et al., 1997). In the last decades, many books and reviews focused on the broad range of approaches and models used for simulating plant diseases and crop yield losses were written (e.g., Nutter, 1997, Savary et al., 2006; Madden et al., 2007; Sparks et al., 2008; Contreras-Medina et al., 2009). Common traits of such models are that (i) they were developed mostly for fungal pathogens and (ii) are often aimed at on-farm management (e.g., Spotts and Cervantes, 1991; Broome et al., 1995; Rossi et al., 1997). Cropping systems simulation models are operationally used since the 1990s to forecast crop yields at different scales, through the estimation of the effects of weather conditions on crops' growth and development (Thornton et al., 1997; Challinor, 2004; De Wit, 2008). Most of the existing crop yield forecasting systems (CYFS) (e.g., the Crop Growth Monitoring Systems of the European Commission; the Famine Early Warning System of the United States Agency for International Development, www.fews.net; the General Large-Area Model for annual crops, Challinor et al., 2004) have been developed by coupling crop models with databases containing weather and soil data, without considering the impact of plant diseases on the year-to-year yield fluctuations, despite of their key role in determining actual production levels for many crops and in many areas. This is mainly due to the fact that even if weather-based forecasting systems have been developed for a number of plant diseases (Campbell and Madden, 1990), the coupling of disease forecasting models to crop growth models is not yet operational, although several approaches are available in literature (e.g., Boote et al., 1983; Bastiaans, 1991; Nemecek et al., 1996; Luo et al., 1997). For these reasons, it is crucial to deal with the implementation of models for the simulation of the dynamics of plant diseases and of the plant-pathogen interactions into CYFS, aiming at quantifying biotic yield losses.

Even having available a modelling solution coupling crop and disease models, model evaluation against reference data remains an insurmountable constraint when considering model use over large areas. Other techniques need to be applied to build confidence in model use. The main goal of sensitivity analysis (SA) is to determine how different sources of variations in parameters values affect the models outputs (Cariboni et al., 2007; Dresch et al., 2010), thus allowing users and developers to understand the degree of dependency of the model on the information given as input (Radiarta and Saitoh, 2009). Another emerging application of SA techniques is their introduction into the iterative process of model building in order to redefine step-by-step the model structure via the evaluation of the opportunity of reducing and simplifying the algorithms implemented, thus preventing the risk of over-parameterization (Tarantola and Saltelli, 2003; Refsgaard et al., 2005; Jakeman et al., 2006). Due to its crucial role, many Authors affirm that excluding SA assessment from model building procedure is therefore directly intellectually dishonest (Rabitz, 1989; Ratto et al., 2001; Saltelli, 2002a; Haydon and Deletic, 2007). These issues were formalized in the position paper by Jakeman (2006) which defined the steps to be followed while developing an environmental model, including SA assessments conceptually before the validation of the model against real data.

The objectives of this paper are therefore (i) to present four software components implementing a generic framework for large area simulation of plant fungal airborne disease epidemics and for the estimation of their impacts on plant growth and yield, via the consideration of the most important aspects related to the plant pathogens interaction; (ii) a spatially distributed, variance based SA exercise for evaluating model behaviour and supporting its development, made on a modelling solution in which two crop models are coupled to the software component for epidemic development simulation.

### 6.3. Software architecture

The Diseases components are four software libraries providing a generic frame to simulate disease development. They are: (i) DiseaseProgress, (ii) InoculumPressure, (iii) ImpactsOnPlants, and (iv) AgromanagementImpact. The structure of the components reflects the guidelines drawn by Donatelli and Rizzoli (2008). A component can be defined as an independent software unit making available specific functionalities and providing access to its services via a defined interface (Donatelli et al., 2010b). The components are stateless, they are released with a consistent documentation, and can be extended by third parties without requiring re-compilation. The Unified Modelling Language (UML) diagram of the Diseases components is presented in Figure 1.

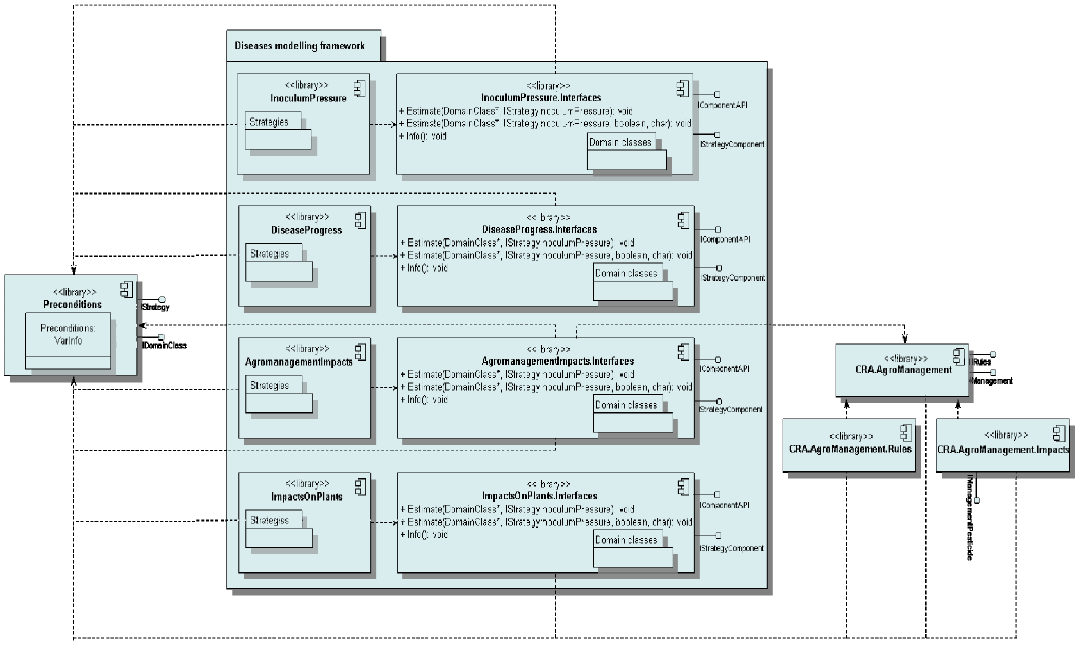



**Figure 1. Unified Modelling Language component diagram of the JRC.MARS.Diseases framework**

The components architecture adopts the Strategy design pattern in order to allow the plugging-in of alternative model formulations to generate the same outputs, since various models can be used for the same purpose. Great attention was paid in respecting the granularity of the modelling approaches implemented, thus aiming at enhancing their reusability for specific applications. The Composite Design Pattern is also used, in which simple strategies are composed into higher-level strategies to represent part-whole hierarchies, thus letting clients treat individual objects and compositions of objects uniformly (Gamma et al., 1995) because of the same interface exposed. Context strategies are implemented in the component, which contain logic to select among the simple or composite strategies associated. The inputs, outputs and the parameters are implemented by means of data structures called Domain Classes (Del Furia et al., 1995). Each attribute of such classes has, beside its value, a set of attributes such as minimum, maximum and default value, unit, description, and refers to a publicly available ontology via the attribute URL. The API (Application Programming Interface) of the components implements the pattern Create-Set-Call (Cwalina and Abrams, 2006), where firstly objects are created via a default constructor, then some attributes are set, and finally the model is called. The interface used for models is the same for all the strategies belonging to a component, implementing the Façade pattern to hide the complexity of each modelling solution preserving the articulated structure of its building components. This leads to have a unique signature for internal and extended models. The Design-by-contract approach implemented in the components establishes a clear contract between client and server, also allowing the development of a better targeted library of unit tests, and to set the domain of applicability of the models, contributing to the transparency of the modelling solutions. The technology used for the development of the components is based on the object oriented programming (OOP) paradigm via the MS .NET 3.5 framework.

**6.4. Models description**

The inputs (i.e., variables and parameters), the outputs, and the algorithms implemented in the four components with their relative reference sources are presented in the Appendices section to this paper. A complete documentation of the algorithms implemented in the components and of the code are available at http://agsys.cra-cin.it/tools/diseases/help/ and http://agsys.cra-cin.it/tools/diseases/codedoc/, respectively. The flow diagram of the Diseases components is shown in Figure 2, in order to underline their usability as stand alone in specific applications or linked together in a unique modelling solution.

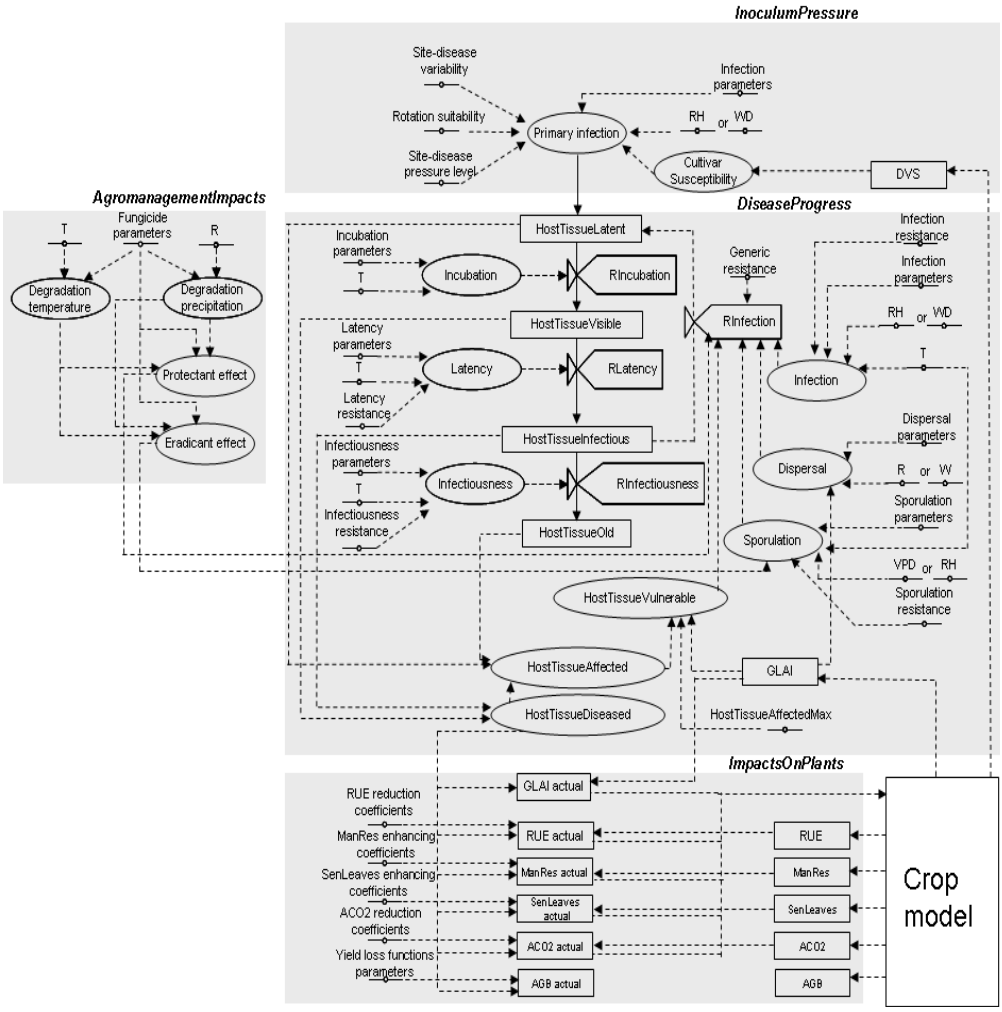



**Figure 2. Flow diagram of the JRC.MARS.Diseases modelling framework**

### 6.4.1. Disease progress

The DiseaseProgress component implements a deterministic compartmental susceptible-infected-removed (SIR) model for host–pathogen dynamics simulating the response of a generic fungal pathogen to hourly meteorological variables, considering the following components of the epidemic process: infection, incubation, latency, infectiousness, sporulation, and spore dispersal. This component is the evolution of the first realization (Salinari et al., 2008; Salinari et al., 2009) within the SEAMLESS projet. Each of them is simulated as function of meteorological variables and biological significant parameters, specific for each host-pathogen couple. Once the fungal spores have been deposited on the host tissue, which has not been affected yet and which is vulnerable ($HT_{vul}$), the model considers that infection occurs only if meteorological conditions are conducive. Infection efficiency mainly depends on temperature and on the availability of water in terms of relative humidity or leaf wetness, according to the pathogen considered. The component implements the potential infection model developed by Magarey et al. (2005) for both the moisture sources. Once the infection process has successfully taken place, a new cohort of host tissue affected ($HT_{aff}$) is created by the model. Each cohort of $HT_{aff}$ is classified in different states on the basis of the following disease stages: incubation, latency, infectiousness, and lesion senescence. The corresponding states of the host tissue will be, therefore: i) healthy ($HT_{heal}$), with no infections ii) latent ($HT_{lat}$), with latent infections not yet visible, iii) visible ($HT_{vis}$), with visible but no sporulating lesions, iv) infectious ($HT_{inf}$), with sporulating lesions, v) old ($HT_{old}$), with old and no longer sporulating lesions. States from ii) to v) represent the total proportion of $HT_{aff}$. More in details, $HT_{heal}$ becomes $HT_{lat}$ when infection occurs. Infected $HT_{lat}$ evolves to $HT_{vis}$ once the incubation period is over. The subsequent two states ($HT_{inf}$ and $HT_{old}$) occur when the latent and infectious periods are finished, respectively. Length of incubation, latent, and infectious periods are estimated as a function of hourly air temperature via the approach proposed by Blaise and Gessler (1992), in which the hourly response of each period varies according to the function developed by Yan and Hunt (1999). The portions of $HT_{heal}$ which become infected and therefore evolve to $HT_{lat}$ are estimated based on portion of $HT_{vul}$ and infection rate. The infection rate relative to each cohort depends on (i) sporulation, which is estimated as a function of temperature and/or vapor pressure deficit according to Analytis (1977) or air relative humidity and (ii) dispersal of spores transported and deposited on $HT_{vul}$, simulated as a function of either rainfall or wind speed, as described by Aylor (1982), Waggoner (1973), and Waggoner and Horsfall (1969). Once the spores are deposited on the surface of $HT_{vul}$, new infections can take place. For taking into account the impact of host resistance on the epidemic development, two approaches are implemented in the component, developed by White et al. (2004) and Savary et al. (2009). The former relates spore mortality to resistance of the specific cultivar, which is organized into discrete categories, from highly susceptible to highly resistant. The latter implements a partial resistance simulation, thus including the opportunity of linking cultivar resistance to QTLs and genes, as suggested by Ballini et al. (2008), by considering relative resistance to latency period, infectious period, infection efficiency and spores production.

#### 6.4.2. Inoculum pressure

As reported by Van Maanen and Xu (2003), without initial inoculum there is no epidemic. Its quantification is therefore crucial for the design of the forecasting scheme, since its source, density and type deeply influence the epidemic development. The InoculumPressure component implements an approach theoretically similar to the one developed by Audsley et al. (2005), in which inoculum is quantified via a combined stochastic and deterministic approach.

Being the components aimed at scenario analysis, the determination of initial inoculum quantity is obtained by considering the suitability of a site to a specific pathogen, obtained by multiple runs of the potential infection model developed by Magarey et al. (2005), e.g., on diverse grid cells of a database on an historical series. This allows deriving the parameters of the distribution of initial inoculum population in a specific site. Then, initial inoculum is random sampled from the inoculum distribution population. The inoculum distribution is characterized by a mean obtained from the multiplication of inoculum pressure and rotation suitability and a variance derived from inoculum variance level. Finally, the cultivar susceptibility to primary infection is considered in computing the daily value of inoculum produced by the pathogen in function of the crop phenology, as indicated by Magarey and Sutton (2007). In this case, primary infection susceptibility (ranging 0-1; with 1 total susceptibility) could be expressed either as a proportion in function of development stage code, or activated in correspondence to specific phenological stages, according to the simulated pathosystem. As for the other processes, new approaches can be easily added to the component for determining primary infection host susceptibility.

#### 6.4.3. Impacts on plants

Many authors claim that assessing yield losses is not only an aspect but even the *raison d'etre* of plant pathology (e.g., Nyvall, 1983; Fargette et al., 1988; Savary and Cooke, 2006). There are many available approaches for modelling crop losses, as reviewed by James and Teng (1979), Campbell and Madden (1990) and Madden and Nutter (1995), e.g., (i) single and multiple point models, in which disease intensity values at different time, together with other host characteristics are used in order to assess crop losses, (ii) integral models in which yield loss is related to the area under disease progress curve for accounting the time varying effect of disease severity on yield during the epidemic development; (iii) process based models, trying to reproduce the impact of a pathogen on a specific physiological process, or (iv) yield loss models that dynamically simulate healthy area duration and absorption. The component ImpactsOnPlants implements several approaches aiming at providing a broad range of options according to the user aims and specific applications. Being the component primarily aimed at scenario analysis via the linking with a dynamic crop growth model, it implements an approach originally developed by Waggoner and Berger (1987) for reducing leaf area index value within the same time step in function of $HT_{dis}$. This approach is suitable either for radiation use efficiency based crop growth models (e.g., CERES, Jones et al., 1984; CropSyst, Stockle et al., 2003; WARM, Confalonieri et al., 2006; STICS, Brisson et al., 2003) or for $CO_2$ assimilation based ones (e.g., SUCROS, Spitters et al., 1989; WOFOST, Van Keulen and Wolf, 1982; ORYZA, Kropff et al., 1994). In addition, functions for simulating the reduction of radiation use efficiency and gross assimilation and for the enhancing of leaves senescence and maintenance respiration in function of $HT_{dis}$ are implemented into the component, thus allowing the user to choose among different options.

### 6.4.4. Agro-management impacts on pathogen population

The goal of many agricultural modelling studies is to quantify the impact of agricultural management on production and system externalities. The impact of sprays application on the epidemic development and of the fungicide decay over time is therefore considered within the AgromanagementImpact component. This component has a dependency on the CRA.AgroManagement component (Donatelli et al., 2006c) that formalizes the decision making process via models called rules, and it formalizes the drivers of the implementation of the impact on the biophysical system via set of parameters encapsulated in data-types called impacts. A set of rules can be defined in function of the states of the system as outputs of the DiseaseProgress or ImpactsOnPlants components, e.g., the number of successful infection events in a day or the maximal percentage of yield loss accepted by the farmer. Following this logic, the impact of the commonly adopted agro-management practices (e.g., timing and number of treatments) can be compared to management scenarios driven by the models (rule-impact couples) implemented in the components. A treatment event is characterized by one or more fungicide, thus leading a chemical mixture, in which each active principle is characterized by an optimal dose, a protectant and an eradicant effect. The former reduces germination of spores landing on a leaf and thus reducing infection frequency but is ineffective against established infections (Manners 1993), while the latter slows down the rate of development of an infection, so that the development of symptoms is reduced or prevented (Bailey, 2000). For considering the decay of treatment efficiency, the component implements a generic approach originally developed for chlorothalonil on tomato foliage by Patterson and Nokes (2000), in which daily air temperature and rainfall causes a decline of the treatment efficiency via a degradation of the active principle according to its sensitiveness to those meteorological variables, as indicated by Bruhn and Fry (1982).

## 6.5. Sensitivity analysis

### 6.5.1. Study areas and weather data

For Europe, the standard 50 km $\times$ 50 km grid adopted by the European Commission for the crop monitoring and yield forecasting activities was used (Micale and Genovese, 2004). Wheat leaf brown rust (*Puccinia recondita*) simulations were run in the cells belonging to the wheat crop mask, according to the sowing dates stored in the MARS database (European Commission, Joint Research Centre; Micale and Genovese, 2004). For each cell, maximum and minimum air daily temperature, maximum and minimum air relative humidity, global solar radiation, and average wind speed were directly extracted from the MARS database. Hourly air temperature, hourly wind speed, and hourly air relative humidity were estimated according to Campbell (1985), Mitchell et al. (2000) and Bregaglio et al. (2010), respectively, with the latter based on Linacre (1992), Allen et al (1998) and ASAE (1998). Hourly leaf wetness was estimated from air temperature, dew point temperature, wind speed and relative humidity hourly values, using the approach proposed by Kim et al. (2002).

Rice blast (*Pyricularia oryzae*) simulations were performed in China, by adopting the database developed for the prototype system for rice monitoring and yield forecasts developed by the European Commission - Joint Research Centre (Confalonieri et al., 2008). In this case, daily maximum and minimum air temperature, global solar radiation and average wind speed were derived from the ECMWF (European Centre for Medium-Range Weather Forecast; http://www.ecmwf.int/) database. Data resolution is one degree latitude × one degree longitude. The archive is created using the ERA 40 data set. Four agroclimatic zones were identified according to the number of rice cycles in the same year, to the crop cycle length, and to the sowing period: central (mainly two cycles), south-eastern (late sowings), north-eastern and north-western (early sowings). Rice cropped cells were identified through the analysis of satellite images. For both China and Europe, since crop growth was simulated under potential conditions (without water and nutrients limitations), soil properties were not accounted for, and the elementary simulation unit was considered to coincide with the grid cell.

### 6.5.2. Sensitivity analysis methods

The high computational requirements due to the need of running spatially distributed SA, to the high number of model parameters, and to the hourly time step suggested to carry out the SA in two phases (e.g., Confalonieri, 2010). A parsimonious screening method (Morris, 1991) was used to identify the parameters with a negligible relevance on model output and the variance-based global SA method of Sobol’ (Sobol’, 1993) was used to analyze the relevance of the remaining ones. This two-step procedure allowed to get reliable results and to limit the computational time (the Sobol’ method is considered a reference in SA but is the most demanding in terms of model runs).

The Morris method calculates elementary effects due to each input factor (parameters in this study) by calculating an array of incremental ratios ($\Delta_{output}/\Delta_{parameter}$) in different points of the parameters hyperspace. Average (μ) and standard deviation (σ) of the incremental ratios distribution are then calculated, with μ representing the overall influence (total effect) of the parameter and σ identifying (when it assumes high values) nonlinearities in model response or interactions with other parameters. In this study, the evolution of the Morris method proposed by Campolongo et al. (2007) was used, allowing to get the absolute values of μ (μ*).

The method of Sobol' is based on the partitioning of the total output variance into terms of increasing dimension. These terms are called partial variances and quantify the role of single parameters (first order effect, no interactions among parameters is considered), and of the combined effect of pairs, triplets, ... of parameters in explaining the model output variance. In this study, we used the evolution of the Sobol' method deriving from the studies of Homma and Saltelli (1996) and Saltelli (2002), which introduced the concept of total sensitivity index (quantifying the overall effect of an input factor) and reduced the computational cost of the method.

### 6.5.3. Simulation of plant-pathogen interaction and sensitivity study

The DiseaseProgress component, that is the core of the Diseases modelling framework was coupled with two crop simulators: WARM (Confalonieri et al., 2009b,c) for rice and WOFOST (Van Keulen and Wolf, 1986) for wheat. WARM is used by the European Commission – Joint Research Centre for rice yield forecasts in Europe, China and India, whereas WOFOST is used for forecasting the yields of various herbaceous species in Europe and Northern Africa.

WARM simulates daily net photosynthesis by multiplying the absorbed photosynthetically active radiation (derived from global solar radiation and green leaf area index using the Lambert-Beer law) by the actual radiation use efficiency, the latter accounting for thermal limitation, saturation of the enzymatic chains, senescence processes, atmospheric $CO_2$ concentration. Assimilates are daily partitioned to the different plant organs by using a set of parabolic and beta functions, and daily increase in green leaf area index is derived by multiplying the biomass partitioned to leaves by a development-dependant specific leaf area. The partitioning pattern can be modified in case of spikelet sterility induced by cold shocks during the period between panicle initiation and heading. Leaves senescence is daily calculated by subtracting the dead leaf area to the total one. A micrometeorological model is used to simulate the floodwater effect on the vertical thermal profile, thus allowing WARM to reliably reproduce the processes involved with crop growth and development, leaves aging, and spikelet sterility.

WOFOST implements the photosynthesis approach to crop growth (Van Keulen et al., 1982), reproducing with a fine level of detail the processes related to gross $CO_2$ assimilation, maintenance and growth respiration, biomass partitioning and leaf area dynamics. Canopy is divided in three horizontal layers for the whole cycle length. Gross photosynthesis is derived on a daily basis with Gaussian integrations on the instantaneous $CO_2$ assimilation rates computed at three moments of the day and for three canopy layers. Maintenance and growth respirations are estimated by considering the different biochemical composition of leaves, stems, storage organs and roots. For the former, this implies that the various organs have different respiration to weight ratios. For the latter, the model reproduces the different energetic requirements for transforming generic photosynthates in constituents of the different organs. Processes related to growth respiration are associated with the partitioning dynamics, which are based on development-dependant coefficients. Leaf area is considered growing exponentially as a function of temperature in the post-emergence phase, whereas it is calculated from the daily partitioned leaves biomass and a development-dependant specific leaf area later on. Leaves death is estimated as a function of senescence and self-shading.

The parameters of the DiseaseProgress component and statistical settings used for SA are shown in Tables 1 (rice leaf blast, *Pyricularia grisea*) and 2 (wheat leaf brown rust, *Puccinia recondita*).

**Table 2. *Pyricularia grisea.* Parameters, statistical settings, and source of information**

| Parameter | Unit | Distribution [a] | Source [b] |
|---|---|---|---|
| Max. air temperature for infection ($T_{max}$inf) | °C | normal [32.33; 2.42; 0.01] | 1, 2, 3, 4, 5, 6 |
| Min. air temperature for infection ($T_{min}$inf) | °C | normal [13.75; 4.50; 0.01] | 2, 4, 5, 6 |
| Opt. air temperature for infection ($T_{opt}$inf) | °C | normal [24.95; 2.34; 0.01] | 1, 2, 4, 7, 8, 9, 11 |
| Min. wetness duration for infection (WDmin) | days | discrete uniform [4; 9] | 1, 5, 6, 12, 13 |
| Max. wetness duration for infection (WDmax) | days | discrete uniform [24; 40] | 6, 13 |
| Max. air temperature for incubation ($T_{max}$inc) | °C | normal [35.00; 1.75; 0.01 | 14 |
| Min. air temperature for incubation ($T_{min}$inc) | °C | normal [7.25; 3.18; 0.01] | 3, 14 |
| Opt. air temperature for incubation ($T_{opt}$inc) | °C | normal [26.83; 0.76; 0.01] | 3, 13, 14 |
| Min. incubation duration (MID) | days | normal [3.75; 1.06; 0.01] | 1, 13 |
| Max. air temperature for latency ($T_{max}$lat) | °C | normal [33.00; 1.65;0.01] [c] | 15 |
| Min. air temperature for latency ($T_{min}$lat) | °C | normal [10.00; 0.50; 0.01] | 15 |
| Opt. air temperature for latency ($T_{opt}$lat) | °C | normal [26.75; 0.35; 0.01] | 4, 10 |
| Min. latency duration (MLD) | days | normal [10.00; 7.78; 0.01] | 15 |
| Max. air temperature for infectiousness ($T_{max}$ness) | °C | normal [36.00; 1.82; 0.01] | 4, 16, 17 |
| Min. air temperature for infectiousness ($T_{min}$ness) | °C | normal [9.25; 2.50; 0.01] | 4, 16, 17, 18 |
| Opt. air temperature for infectiousness ($T_{opt}$ness) | °C | normal [26.36; 1.57; 0.01] | 3, 10, 11, 16, 18, 19 |
| Max. infectiousness duration (MSD) | days | normal [32.05;25.63;0.01] | 4, 20, 21 |
| Max. air temperature for sporulation ($T_{max}$spor) | °C | normal [36.00; 1.82; 0.01] | 4, 16, 17 |
| Min. air temperature for sporulation ($T_{min}$spor) | °C | normal [9.25; 2.50; 0.01] | 4, 16, 17, 18 |
| Opt. air temperature for sporulation ($T_{opt}$spor) | °C | normal [26.36; 1.57; 0.01] | 3, 10, 11, 16, 18, 19 |
| Min. rel. humidity for sporulation ($RH_{min}$spor) | % | normal [87.30; 6.61; 0.01] | 3, 4, 16 |
| Rain for 50% detachment (Rain50) | mmday$^{1}$ | normal [0.62; 0.03; 0.01] [c] | 4 |
| Maximum catch rain ($Rain_{max}$) | mmday$^{1}$ | normal [2.50; 0.12; 0.01] [c] | 23 |
| Minimum wind for detachment ($W_{min}$) | m s$^{-1}$ | normal [1.80; 0.09; 0.01] [c] | 4 |
| Wind for 50% detachment (W50) | m s$^{-1}$ | normal [3.50; 0.17; 0.01] [c] | 22 |
| Spores at max. wind for detachment ($W_{max}$spor) | % | normal [0.80; 0.04; 0.01] [c] | 23 |
| Maximum wind for detachment ($W_{max}$) | m s$^{-1}$ | normal [6.00; 0.30; 0.01] [c] | 23 |
| Wetness duration D50 (WD50) | days | discrete uniform [3; 5] | 23 |

a. Figures in brackets are: mean, standard deviation, truncation for normal distributions; minimum and maximum values for discrete uniform distributions.

b.

| | | |
|---|---|---|
| 1: Choi et al. (1987) | 9: Kim et al. (1990) | 17: Chinte (1965) |
| 2: Sharma and Kapoor (2003) | 10: UC IPM Guidelines | 18: Kato (1974) |
| 3: Biloni (2001) | 11: Castejon-Munoz (2008) | 19: Padmakar-Tripathi et al. (1998) |
| 4: Suzuki (1975) | 12:Greer and Webster(2001) | 20: Picco and Rodolfi (2002) |
| 5: Kim et al. (1988) | 13: Wastie (1980) | 21: Pinnschmidt et al. (1993) |
| 6: Cinara et al. (2008) | 14:Mossand Trevathan(1987) | 22: Calvero et al. (1996) |
| 7: Sang-Won (1994) | 15: Ding et al. (2002) | 23: Model default |
| 8: Huang et al. (1980) | 16: Awoderu et al. (1991) | |

c. A single value was available; for the sensitivity analysis, the standard deviation was set to 5% of the mean value (Tarantola, personal communication).

**Table 3. *Puccinia recondita*. Parameters, statistical settings, and source of information**

| Parameter | Unit | Distribution [a] | Source [b] |
|---|---|---|---|
| Max. air temperature for infection ($T_{max}$inf) | °C | normal [28.71; 3.86;0.01] | 1, 2, 3, 4, 5, 6, 7 |
| Min. air temperature for infection ($T_{min}$inf) | °C | normal [2.94; 1.01; 0.01] | 1, 2, 3, 4, 5, 7, 8 |
| Opt. air temperature for infection ($T_{opt}$inf) | °C | normal [20.42; 3.68;0.01] | 1, 3, 4, 5, 6, 7 |
| Min. wetness duration for infection (WDmin) | days | discrete uniform [3; 5] | 1, 2, 5, 7 |
| Max. wetness duration for infection (WDmax) | days | discrete uniform [14; 16 | 1, 2 |
| Max. air temperature for incubation ($T_{max}$inc) | °C | normal [33.60; 1.98;0.01] | 9, 10 |
| Min. air temperature for incubation ($T_{min}$inc) | °C | normal [11.40; 4.95;0.01] | 2, 3, 9, 11 |
| Opt. air temperature for incubation ($T_{opt}$inc) | °C | normal [23.36; 3.12;0.01] | 2, 3, 9, 10, 11 |
| Min. incubation duration (MID) | days | normal [7.86; 1.50; 0.01] | 2, 3, 9, 11, 12 |
| Max. air temperature for latency ($T_{max}$lat) | °C | normal [33.60; 1.98;0.01] | 9, 10 |
| Min. air temperature for latency ($T_{min}$lat) | °C | normal [11.40; 4.95;0.01] | 2, 3, 9, 11 |
| Opt. air temperature for latency ($T_{opt}$lat) | °C | normal [23.36; 3.12;0.01] | 2, 3, 9, 10, 11 |
| Min. latency duration (MLD) | days | normal [7.86; 1.50; 0.01] | 2, 3, 9, 11, 12 |
| Max. air temperature for infectiousness ($T_{max}$ness) | °C | normal [33.50; 1.91;0.01] | 2, 4, 5, 13 |
| Min. air temperature for infectiousness ($T_{min}$ness) | °C | normal [13.33; 5.77;0.01] | 2, 4, 14 |
| Opt. air temperature for infectiousness ($T_{opt}$ness) | °C | normal [25.25;0.35; 0.01] | 4, 14 |
| Max. infectiousness duration (MSD) | days | normal [65.5; 0.70; 0.01] | 11, 15 |
| Max. air temperature for sporulation ($T_{max}$spor) | °C | normal [33.5; 1.91; 0.01] | 2, 4, 5, 13 |
| Min. air temperature for sporulation ($T_{min}$spor) | °C | normal [13.33; 5.77;0.01] | 2, 4, 14 |
| Opt. air temperature for sporulation ($T_{opt}$spor) | °C | normal [25.25; 0.35;0.01] | 4, 14 |
| Min. rel. humidity for sporulation ($RH_{min}$spor) | % | normal [90.00; 4.50;0.01] | 16 |
| Rain for 50% detachment (Rain50) | mm day$^{1}$ | normal [3.70; 0.18; 0.01] | 17 |
| Maximum catch rain ($Rain_{max}$) | mm day$^{1}$ | normal [3.70; 0.18; 0.01] | 17 |
| Minimum wind for detachment ($W_{min}$) | m s$^{-1}$ | normal [1.15; 0.21; 0.01] | 17, 18 |
| Wind for 50% detachment (W50) | m s$^{-1}$ | normal [5.00; 0.25; 0.01] | 20 |
| Spores at max. wind for detachment ($W_{max}$spor) | % | normal [0.80; 0.04; 0.01] | 20 |
| Maximum wind for detachment ($W_{max}$) | m s$^{-1}$ | normal [6.00; 0.30; 0.01] | 20 |
| Wetness duration D50 (WD50) | days | discrete uniform [1; 2] | 1, 19 |

a.Figures in brackets are: mean, standard deviation, truncation for normal distributions; minimum and maximum values for discrete uniform distributions.

b. 1: Magarey et al. (2005)
2: Wójtowicz (2007)
3: Clifford and Harris (1981)
4: Singh et al. (2002)
5: NAPPFAST Pest record (2003)
6: Wiese and Ravenscroft (1979)
7: Vallavieille Pope et al. (1995)
8: Angus et al. (1981)
9: Eversmayer and Kramer (2000)
10: Roelsf et al. (1992)
11: Tomerlin et al. (1983)
12: Kovalenko et al. (2004)
13: Rapilly (1979)
14: Dick and Johnson (1983)
15: Mehta and Zadocks (1970)
16: ADAS (Agricultural Development and Advisory Service)
17: Sache (2000)
18: Geagea et al. (1997)
19: Stuckey and Zadocks (1989)
20: Model default

c. A single value was available; for the sensitivity analysis, the standard deviation was set to 5% of the mean value (Tarantola, personal communication).

The disease impact on crop is addressed by calculating the percentage of $HT_{aff}$, and by estimating (i) the effect on radiation use efficiency for WARM and (ii) the effects on maximum $CO_2$ assimilation, maintenance respiration, and senescence for WOFOST.

In this study, only the relevance of the parameters involved with the disease progress was analyzed. The outputs considered are the percentage of $HT_{aff}$ and the storage organs biomass simulated by both the models at physiological maturity.

### 6.5.4. Results

The analysis of $\mu$ of Morris values for the two tested pathosystems (Figure 3) shows that the DiseaseProgress component is sensitive to changes in a relatively small number of parameters.

In particular, according to the distributions derived from literature review, changes in the parameters related to wind and rain dispersion of the spores (Rain for 50% detachment, Rain50; Maximum catch rain, $Rain_{max}$; Minimum wind for detachment, $W_{min}$; Wind for 50% detachment, W50; Spores at max. wind for detachment, $W_{max}spor$; Maximum wind for detachment, $W_{max}$) have little or no relevance in explaining the variability of $HT_{dis}$. The rankings of the most important parameters in the two case studies are instead very different. In fact, the simulation of *Pyricularia oryzae* in China allowed to identify 6 out of 28 parameters with an high impact on $HT_{dis}$. The Sobol' method was applied on these parameters ($T_{min}inf$, minimum air temperature for infection; $WD_{min}$, minimum wetness duration; MLD, minimum duration of latency period, $RH_{min}spor$, minimum air relative humidity for sporulation; $T_{opt}spor$, optimum air temperature for sporulation; MSD, maximum duration of infectiousness period), in order to gain an in-depth knowledge about their relevance.

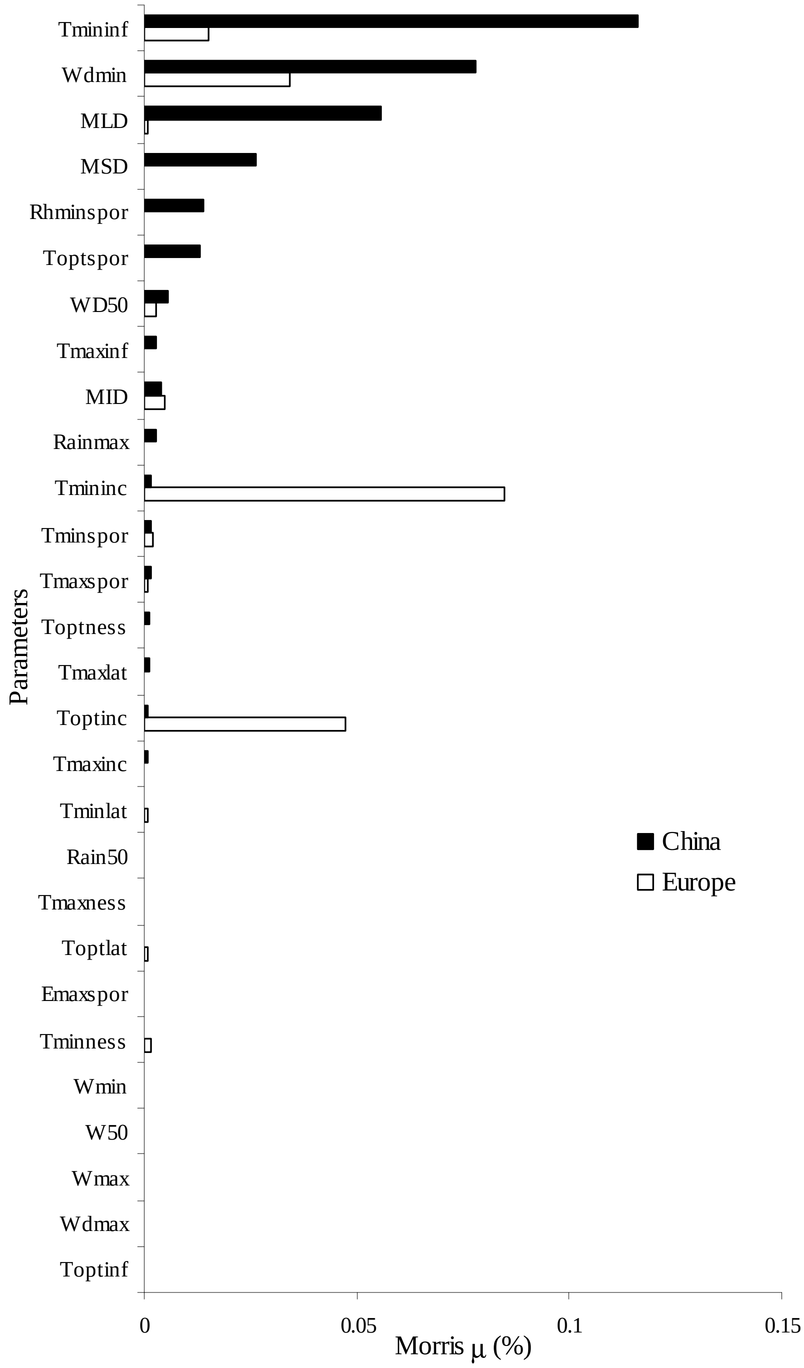
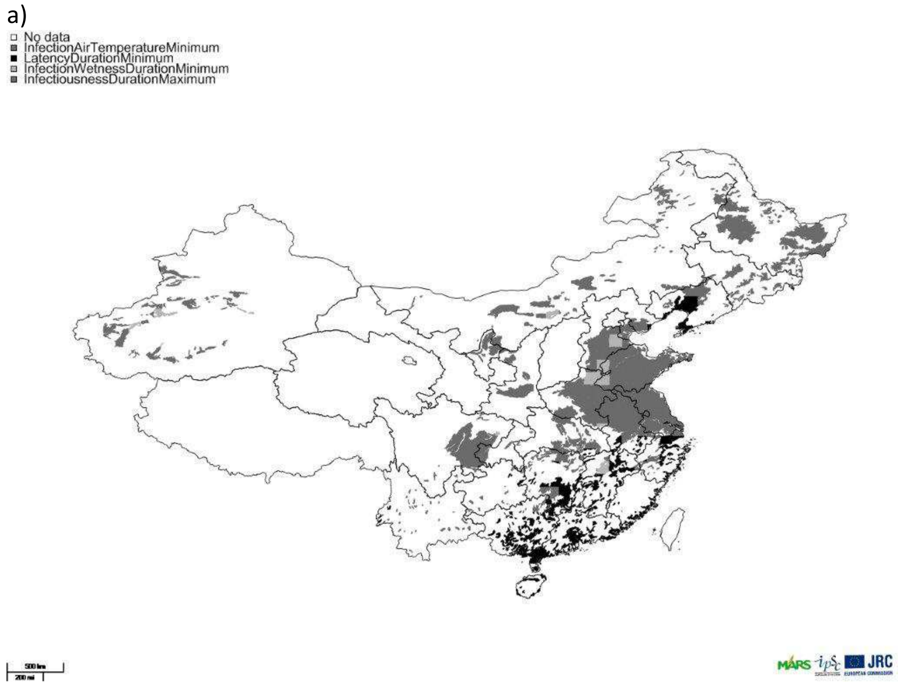



**Figure 3. Morris μ values for the parameters of the DiseaseProgress component for *Pyricularia oryzae* in China (black line) and for *Puccinia recondita* in Europe (white line).**

The main contributors map (Figure 4a) shows that $T_{min}$inf is the most important parameter in the North and in the Centre of China. Moving to the South, MLD becomes the most important one. This is due to the warmer temperature regimes of this area, that do not constitute a constraint for the infection phase of the epidemic (as in the Northern part of China), even if the pathogen is tropical with an high mean of the distribution of $T_{min}$inf (13.75 °C). In the South of China the progress of the simulated disease was more rapid (data not shown) and this is the reason why MLD resulted to be the main contributor parameter in this area. In fact, a shorter duration of the latent period speeds up the sporulation occurrence and thus the comparison of secondary infections and consequently of new $HT_{aff}$. Throughout China, there are some grids in which $WD_{min}$ resulted the main contributor parameter. Since it is related to the fulfilling of the infection process (as $T_{min}$inf), this strengthen the evidence that according to the model, this phase of the epidemic is the more relevant for *Pyricularia oryzae* in Chinese area.

The analysis of $\mu$ of Morris SA assessment for *Puccinia recondita* in Europe indicates that the parameters to which the model is sensitive are quite different with respect to the other pathosystem. In fact, even if $T_{min}$inf and $WD_{min}$ maintain their relevance ($3^{rd}$ and $4^{th}$ in terms of importance, respectively), the most important parameters in Europe resulted the minimum air temperature for incubation ($T_{min}$inc) and the optimum air temperature for incubation ($T_{opt}$inc). This is mainly due to the fact that the distribution adopted for $T_{min}$inc has a mean value strongly higher than $T_{min}$inf (11.4 versus 2.94) and so the temperature constraint to leaf rust development in Europe is mainly related to this phase of the epidemic process. As for China, moving from the Northern part to the South, according to warmer meteorological conditions, the sensitivity of the model changed, and $T_{opt}$inf becomes the main contributor parameter.

a)




b)

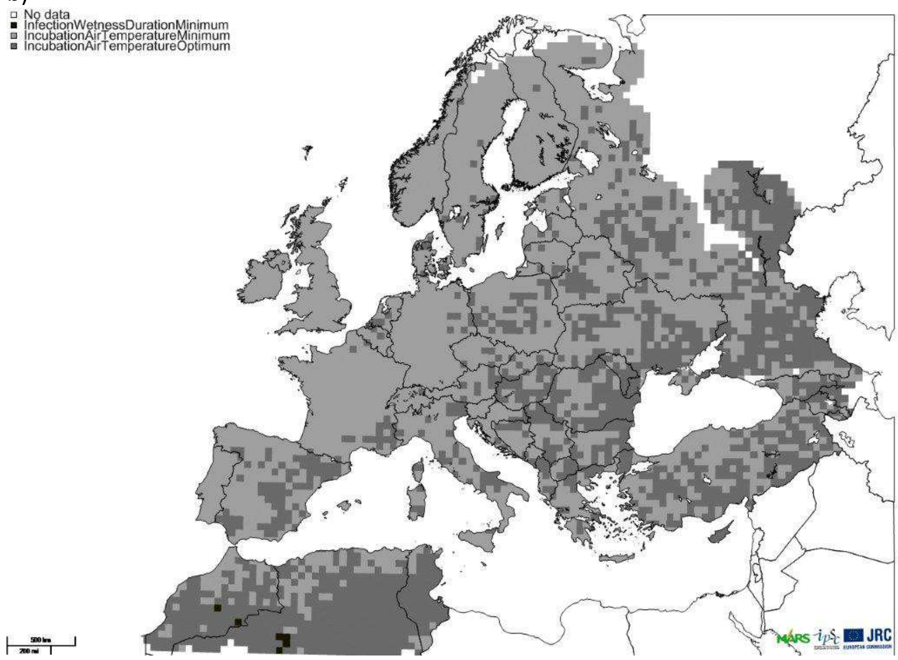



**Figure 4. Sobol' Total Order Index. *Pyricularia oryzae* on rice in China (a) and *Puccinia recondita* (b) on winter wheat in Europe. Main contributors maps showing the parameter that explain the largest variability of the output**

## 6.6. Conclusion and remarks

The implementation of epidemic models and biotic yield losses assessment tools into CYFS is a real claim for a representation of agricultural systems closer to the real world, especially when moving to climate scenarios in which the interactions between plants and pathogens are not experienced yet, thus leading to an high degree of uncertainty about the future impact of plant diseases. The framework-independent software architecture of the Diseases components, other than facilitating their reusability and extension by third parties according to specific aims and applications, provide a robust answer to this issue, because (i) they constitute a generic frame capable to simulate diverse fungal airborne pathogens by changing parameterization and (ii) they can be easily linked to a crop growth model. This study, other than presenting the architecture and the algorithms implemented in the components, highlights these two features via a SA exercise that allowed to discover that, according to the pathogen selected, the model is sensitive to changes in the values of diverse parameters, whereas there are parameters belonging to processes (spore dispersal and catch) that in the current implementation does not prominently affect model output. The introduction of SA techniques for supporting model building and development phase constitutes a good practice in agro ecological modelling and it is essential for providing an exhaustive documentation of model behaviour to the users.

## 6.7. Appendices

### 6.7.1. Appendix 1. Abbreviations used in the equations in alphabetic order

| Abbreviation | Meaning | Units |
|---|---|---|
| a, b | empirical coefficients | - |
| $ACO_{2act}$, $ACO_{2pot}$ | actual and potential $ACO_2$ | kg $ha^{-1}$ |
| $ACO_{2coeff}$ | parameters quantifying the impact on $ACO_2$ | - |
| $C_{\%}$ | fraction of active principle in the fungicide | % |
| $C_{max}$ | maximal percentage of spores caught by rain | % |
| $C_R$ | spores caught by rain | % |
| $C_w$ | spores caught by wind | % |
| D | fungicide actual dose | % |
| D50 | critical dry period interruption value | hours |
| $Deg_{rain}$ | fungicide degradation due to precipitation | % |
| $Deg_T$ | fungicide degradation due to air temperature | % |
| $Deg_{tot}$ | total fungicide degradation | % |
| $Dis_{var}$ | site specific disease variability | - |
| $Disp_{R,W}$ | total percentage of spores dispersed by rain or wind | % |
| $Dis_{pres}$ | site specific disease pressure level | - |
| DLAI | dead leaf area index | $m^2$ $m^{-2}$ |
| $D_{opt}$ | fungicide optimal dose | kg $ha^{-1}$ |
| $D_R$ | spore detached due to rain | % |
| $D_{tot}$ | fungicide amount | kg $ha^{-1}$ |
| $D_W$ | spores detached due to wind | % |
| E | chemical mixture eradicant effect | % |
| f(DVS) | function of development stage code of simulated crop (different options available) | - |
| f(t) | temperature response function | - |
| $f_{ACO2}$ | limiting factor on $CO_2$ assimilation | - |
| $f_{man}$ | maintenance respiration enhancing factor | - |
| $f_{RUE}$ | radiation use efficiency limiting factor (RUE) | - |
| $f_{sev}$ | leaves senescence enhancing factor | - |
| f1, f2, fn | fungicides present in the chemical mixture | - |
| GLAI | green leaf area index | $m^2$ $m^{-2}$ |
| $HT_{aff}$ | host tissue affected by the disease | % |
| $HT_{dis}$ | diseased host tissue | % |
| $HT_{inf}$ | infectious host tissue | % |
| $HT_{lat}$ | latent host tissue | % |
| $HT_{max}$ | maximum host tissue affected by the disease | % |
| $HT_{old}$ | dead host tissue | % |
| $HT_{vul}$ | vulnerable host tissue | % |
| $Inc_h$, $Inc_d$ | hourly and daily incubation rate | % |
| $Inc_{min}$ | minimal duration of the incubation period | days |

| | | |
|---|---|---|
| $Inf_{\%}$ | daily infection efficiency | - |
| $Inf_{events}$ | daily number of infection events | - |
| $Infs_{max}$ | maximum duration of the infectiousness period | days |
| $Infs_h$, $Infs_d$ | hourly and daily infectiousness rate | days |
| $Ino_{init}$ | initial inoculum infection efficiency | - |
| $Ino_{sample}$ | random sample from the initial inoculum normal distribution | - |
| L | yield losses | kg $ha^{-1}$ |
| LAI | leaf area index | $m^2$ $m^{-2}$ |
| $LAI_{act}$, $LAI_{dis}$, $LAI_{pot}$ | actual, diseased and potential leaf area index | $m^2$ $m^{-2}$ |
| $Lat_h$, $Lat_d$ | hourly and daily latency rate | % |
| Latmin | minimal duration of the latency period | days |
| $\mu_{ino}$ | mean of the initial inoculum normal distribution | - |
| $Man_{act}$, $Man_{pot}$ | actual and potential maintenance respiration | kg $ha^{-1}$ |
| $Man_{coeff}$ | parameters quantifying the impact on maintenance respiration | - |
| P | chemical mixture protectant effect | % |
| R | daily rainfall | mm $day^{-1}$ |
| R50 | precipitation for detaching of the 50% of the spores | mm |
| $R_{coeff}$ | cultivar resistance category | - |
| RH(t) | hourly air relative humidity response function | - |
| $RH_{d1}$, $RH_{d2}$ | moisture conducive periods separated by a dry period D | hours |
| $RH_{dmax}$, $RH_{dmin}$ | maximum and minimum period above minimum relative humidity for infection | hours |
| $RH_{dsum}$ | sum of the moisture conducive period | hours |
| $RH_h$ | hourly air relative humidity | hours |
| $RH_{min}$ | minimum air relative humidity for sporulation | % |
| $R_{inf}$ | infection resistant coefficient | - |
| $R_{infs}$ | infectiousness resistance coefficient | - |
| $R_{lat}$ | latency resistant coefficient | - |
| $Rot_{suit}$ | rotation suitability for disease development | - |
| $R_{spor}$ | sporulation resistance coefficient | - |
| $RUE_{coeff}$ | parameters quantifying the impact on RUE | - |
| $RUE_{act}$,$RUE_{pot}$ | actual and potential RUE | g $MJ^{-1}$ |
| S | cultivar susceptibility to primary infection | - |
| $\sigma_{ino}$ | Standard deviation of the initial inoculum normal distribution | - |
| $Sen_{act}$, $Sen_{pot}$ | actual and potential leaves death due to senescence | kg $ha^{-1}$ |
| $Sen_{coeff}$ | parameters quantifying the impact on leaves senescence | - |
| $Spor_h$, $Spor_d$ | hourly and daily sporulation efficiency | - |
| $Spor_{VPD}$ | hourly sporulation efficiency due to vapor pressure deficit | - |

| | | |
|---|---|---|
| $T$, $T_{avg}$ | hourly and daily average air temperature | °C |
| $T_{max}$, $T_{min}$, $T_{opt}$ | maximum, minimum and optimum temperature for the different epidemic phases | °C |
| $T_{th}$ | threshold temperature for fungicide degradation | °C |
| $VPD_{max}$,$VPD_{min}$ | Maximum and minimum vapor pressure deficit for sporulation | kPa |
| W | mean daily wind speed | m $s^{-1}$ |
| W50 | wind speed for detaching of the 50% of the spores | m $s^{-1}$ |
| W(t) | wetness response function | - |
| $WD_1$, $WD_2$ | wet periods separated by a dry period D | hours |
| $WD_{max}$, $WD_{min}$ | maximum and minimum leaf wetness duration for infection | hours |
| $WD_{sum}$ | sum of the surface wetting | hours |
| $W_{max}$, $W_{min}$ | maximum and minimum wind speed for spore detachment | m $s^{-1}$ |
| $y_{act}$ | actual yield | kg $ha^{-1}$ |
| $y_{pot}$ | potential yield | kg $ha^{-1}$ |

## 6.7.2. Appendix 2. DiseaseProgress equations

| Process | Equations | Source |
|---|---|---|
| Temp. response (common to different processes) | $f(t)=\left(\frac{T_{\max}-T}{T_{\max}-T_{opt}}\right)\left(\frac{T-T_{\min}}{T_{opt}-T_{\min}}\right)^{(Topt-T\min)/(T\max-Topt)}$ | Yin et al. (1995) |
| Infection WD | $W(t)=\begin{cases}\frac{WD_{\min}}{f(t)} & \frac{WD_{\min}}{f(t)}\le WD_{\max}\\ 0 & elsewhere\end{cases}$ <br> $WD_{sum}=\begin{cases}WD_1+WD_2 & D<D50\\ WD_1 \quad or \quad WD_2 & elsewhere\end{cases}$ | Magarey et al. (2005) |
| Infection RH | $RH(t)=\begin{cases}\frac{RH_{d\min}}{f(t)} & \frac{RH_{d\min}}{f(t)}\le RH_{d\max}\\ 0 & elsewhere\end{cases}$ <br> $RH_{dsum}=\begin{cases}RH_{d1}+RH_{d2} & D<D50\\ RH_{d1} \quad or \quad RH_{d2} & elsewhere\end{cases}$ <br> $Inf_{\%}=\frac{Inf_{events}}{24}$ | |

| | | |
|---|---|---|
| Sporulation RH | $Spor_h = \begin{cases} f(t) & RH_h > RH_{\min} \\ 0 & elsewhere \end{cases}$ | |
| Sporulation VPD | $Spor_{VPD} = \dfrac{1}{1 + \exp(-a + b \cdot VPD_h)}$<br>$a = -4.59512 \cdot \dfrac{\dfrac{VPD_{\min}}{VPD_{\max}} + 1}{\dfrac{VPD_{\min}}{VPD_{\max}} - 1}$<br>$b = \dfrac{1}{VPD_{\max}} \cdot (a + 4.59512)$<br>$Spor_h = f(t) \cdot Spor_{VPD}$<br>$Spor_d = \dfrac{\sum_{h=0}^{24} Spor_h}{24}$ | This study<br>Analytis (1977); Blaise and Gessler (1992) |
| Incubation | $Inc_h = \dfrac{Inc_{\min} \cdot 24}{f(t)}$<br>$Inc_d = \dfrac{\sum_{h=0}^{24} Inc_h}{24} \quad Inc_d = Inc_{d-1} + \dfrac{1}{Inc}$ | Blaise and Gessler (1992); Reed et al. (1976); Wadia and Butler (1994) |
| Latency | $Lat_h = \dfrac{Lat_{\min} \cdot 24}{f(t)}$<br>$Lat_d = \dfrac{\sum_{h=0}^{24} Lat_h}{24} \quad Lat_d = Lat_{d-1} + \dfrac{1}{Lat}$ | Analytis (1977); Blaise and Gessler (1992) |
| Infectiousness | $Infs_h = Infs_{\max} \cdot 24 \cdot f(t)$<br>$Infs_d = \dfrac{\sum_{h=0}^{24} Infs_h}{24} \quad Infs_d = Infs_{d-1} + \dfrac{1}{Infs}$ | Blaise and Gessler (1992), Reed et al. (1976); Wadia and Butler (1994) |
| Dispersal rain | $D_R = \dfrac{\dfrac{R}{LAI}}{R50 + LAI} \quad C_R = 0.9^{\left(\frac{1}{C\max}\right) \cdot R}$<br>$Disp_R = D_R \cdot C_R$ | Aylor(1982); Waggoner and Horsfall (1969); Waggoner (1973) |
| Dispersal wind | $c = \dfrac{1}{W_{\max} - W50} + \left[1 + \left(\dfrac{1}{W_{\max} - W50}\right) \cdot W50\right] \cdot W$<br>$C_W = 0.9$ | |

| | | |
|---|---|---|
| New host tissue affected | $HT_{aff} = HT_{\inf} \cdot Inf_{\%} \cdot Spor \cdot \max(Disp_{rain}, Disp_{wind})$ | |
| Host tissue vulnerable | $HT_{vul} = \begin{cases} \frac{GLAI}{LAI} - \left\{ \left[ \frac{(HT_{lat} + HT_{vis} + HT_{\inf} + HT_{old})}{HT_{\max}} \right] \cdot \frac{GLAI}{LAI} \right\} & DLAI > 0 \\ \frac{GLAI}{LAI} - \left[ \frac{(HT_{lat} + HT_{vis} + HT_{\inf} + HT_{old})}{HT_{\max}} \right] & \frac{(HT_{lat} + HT_{vis} + HT_{\inf} + HT_{old})}{HT_{\max}} < \\ 0 & \frac{(HT_{lat} + HT_{vis} + HT_{\inf} + HT_{old})}{HT_{\max}} > \end{cases}$ | This study |
| Resistance category | $HT_{aff} = HT_{aff} \cdot R_{cat}$ | White et al. (2004) |
| Resistance partial component | $Inf_{\%} = Inf_{\%} \cdot R_{\inf}$<br>$Spor = Spor \cdot R_{spor}$<br>$Lat = Lat \cdot R_{lat} \quad Infs = Infs \cdot R_{\inf s}$ | Savary et al. (2009) |

### 6.7.3. Appendix 3. Inoculum Pressure equations

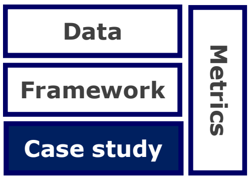
| Process | Equations | Source |
|---|---|---|
| Inoculum quantification | $\mu_{ino} = Dis_{pres} \cdot Rot_{suit}$<br>$\sigma_{ino} = Dis_{var}$ | Audsley et al. (2005); New approach developed |
| Susceptibility | $S = f(DVS)$ | Magarey et al. (2007) |

### 6.7.4. Appendix 4. Agromanagement impacts equations

| Process | Equation | Source |
|---|---|---|
| Fungicide degradation | $Deg_R = \exp\left(a \cdot R^{\frac{1}{3}}\right)$<br>$Deg_T = \exp(b \cdot (T_{avg} - T_{th}))$<br>$Deg_{tot} = Deg_T \cdot Deg_R$ | Nokes (2000) |
| Fungicide actual dose | $D = \left( \frac{D_{tot} \cdot C_{\%}}{D_{opt}} \right) \cdot Deg_{tot}$ | This study |
| Fungicide eradicant effect | $E = \max(D_{f1} \cdot E_{f1}, D_{f2} \cdot E_{f2}, ..., D_{fn} \cdot E_{fn})$<br>$Spor_d = Spor_d \cdot E$ | Bailey (2000) |
| Fungicide protectant effect | $P = \max(D_{f1} \cdot P_{f1}, D_{f2} \cdot P_{f2}, ..., D_{fn} \cdot P_{fn})$<br>$Inf_{\%} = Inf_{\%} \cdot P$ | Bailey (2000) |

## 6.7.5. Appendix 5. Impacts on Plants equations

| Process | Equations | Source |
|---|---|---|
| Yield loss (critical point models) | $L = a + b \cdot HT_{dis}$ | Madden and Nutter (1995) |
| Susceptibility | $L = a + b \cdot \ln HT_{dis}$ | Madden and Nutter (1995) |
| | $L = a + b \cdot HT_{dis}{}^{0.5}$ | Madden and Nutter (1995) |
| | $L = \frac{(1 - HT_{dis})}{[(1-a) + a(1 - HT_{dis})]^2}$ $y_{act} = y_{pot} - L$ | Hughes (1988) |
| Yield loss (critical point models) Light absorption damage Impacts on RUE | $L = \frac{a - (1-a)}{\left(1 + \frac{HT_{dis}}{b}\right)}$ | Wheeler et al. (1992) |
| | $L = \exp\left\{-\left[\frac{HT_{dis} - a}{b}\right]^c\right\}$ | Madden et al. (1981) |
| | $LAI_{dis} = LAI_{pot} \cdot HT_{dis}$ $LAI_{act} = LAI_{pot} - LAI_{dis}$ | Waggoner (1978); Bergamin Filho et al. (1997) |
| | Linear: $f_{RUE} = 1 - RUE_{coeff} \cdot HT_{dis}$ $RUE_{act} = RUE_{pot} \cdot f_{RUE}$ non linear: $f_{RUE} = 1 - HT_{dis}{}^{RUE_{coeff}}$ | Bastiaans (1991) |
| Impacts on $CO_2$ assimilation | Linear: $f_{ACO_2} = 1 - ACO_{2coeff} \cdot HT_{dis}$ Non linear: $f_{ACO_2} = 1 - HT_{dis}{}^{ACO_{2coeff}}$ | |
| Impacts on maintenance respiration | Linear: $f_{man} = 1 + Man_{coeff} \cdot HT_{dis}$ Non linear: $f_{man} = 1 + HT_{dis}{}^{Man_{coeff}}$ | Bastiaans (1993) |
| Impacts on senescence | Linear: $f_{sen} = 1 + Sen_{coeff} \cdot HT_{dis}$ Non linear: $f_{sen} = 1 + HT_{dis}{}^{Sen_{co}}$ | |




# ASSESSING THE IMPACTS OF CLIMATE CHANGE ON AGRICULTURAL PRODUCTIVITY AND TRADE IN LATIN AMERICA (2020 – 2050)

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Report World Bank, Service Contract Number 7157218.Regional Agroclimatic Study to Assess Climate Change Impacts on Land Use: Agroecological Zone Model Development

### 7.1. Executive Summary

The impacts of climate change on agriculture are projected to be significant in coming decades, so that response strategies and their costs need to be evaluated now, in regional detail, in order to devise effective policies facilitating successful adaptation by farmers. Models are routinely used to make such assessments, preferably by coupling biophysical models—to understand the likely impacts of agro-climatic factors on crop productivity— with economic models, to derive and evaluate a range of possible response paths as a function of monetary costs and benefits.

In evaluating how crop models were being used around the world for climate change applications, the International Panel of Climate Change (IPCC) Fourth Assessment Report (AR4) published in 2007, noted that most of the models had fallen behind in development and validation of key processes necessary to improve projections of crop yields in coming decades. The gaps include representation of interannual climate variability and extreme events and the impacts of pest and disease. Assessments of the effects of elevated $CO_2$ concentration under typical field management conditions need to also be improved. Importantly, the same IPCC report concluded that existing crop modelling platforms, including those coupling of biophysics and economics, should be made more transparent and accessible to end users, so that their assumptions and applications could be tested more extensively and so that their utilization base could be enriched with contributions of researchers and practitioners from around the world.

This report details the components of a new modelling platform for crop impact studies, the AZS-ENVISAGE model, capable of evaluating the dynamic interactions of agro-climatic and field management factors impacting on crop growth and development, and capable of interacting with a general equilibrium model in order to include the constraints of realistic socio-economic factors on actual production levels, trade and welfare outcomes.

Although several such platforms exist, the current work represents progress on a number of current bottlenecks, following recommendations made in IPCC AR4:

1. The basic datasets and biophysical models are fully transparent, both in terms of their validation and availability of components, including remote accessibility to interested users. These key features imply that stakeholders around the world can access the platform, evaluate it, test

it, and wherever possible, improve it by adding or refining datasets, oreven by modifying or substituting component code, as appropriate for specific areas of study or particular problems.

2. The platform is extensible to any region of the world, and is independent of spatial scale, so that the latter can be also modified by users as the availability of more refined dataset for specific regions arise.
3. The model allows for explicit, albeit simplified, adaptation of agro-management, including a crop suitability assessment module, in order to test and evaluate adaptation strategies aimed at limiting risk under climate change scenarios.
4. The linkages between biophysical and economic models are explicit, and allow in principle for two-way interactions, with the ability to evaluate economically specific agro-management solutions identified by the crop models, so that the latter could further test specific solutions and then feedback the information for new updated modelling runs.

This report details (a) model components, (b) the application of the modelling platform to evaluating the impacts of climate change on key crops in the Latin America and Caribbean region (LCR), and (c) the economic implications of the projected agronomic impacts in 2020 and 2050. Section 1 presents a literature review of climate change impacts in Latin America, and then details the characteristics of the modelling platform proposed for further analysis, including the advantages and limitations compared to existing tools. Section 2 describes the basic datasets used as inputs for the simulations, including climate (current and future climate change scenarios), soils, agro-management, current and projected and socio-economic variables. Sections 3 and 4 present and discuss simulation results of both biophysical and coupled simulations, with and without adaptation responses. Two SRES emission scenarios, A1b and B1, are chosen to represent respectively a “high” (business as usual) and low (near $CO_2$ stabilization at 550 ppm) scenario, detailing realistic boundaries to the envelope of likely impacts. In addition, two time horizons, 2020 and 2050, are chosen to investigate risk to production under, respectively, a short-term (little time for adaptation) and medium term outlooks.

Results of this study confirm and extend previous findings, indicating that the impacts of climate change on agriculture in LCR are expected to be significant, with severe risk to crop production in most countries, and the potential to alter regional production and welfare distribution compared to present.

**For Wheat**, without adaptation, wheat yields were significantly affected by climate change, regardless of the emission scenario or Global Climate Model (GCM) considered. Percentage yield decreases were more pronounced in Mexico, in the Caribbean region, and in the North-eastern parts of the continent (Colombia and Brazil). Projected water-limited productions for 2020 and 2050 were always lower than in the baseline, with Southern and Western countries less affected. Yield reductions were due to the shortening of the crop cycle due to higher thermal time accumulation, leading to fewer days available to fill grains. The projected yield decrease due to diseases in 2020 and 2050 was significant. Frost damages were expected to affect wheat yields less seriously in Chile, where shortened cycles will also reduce the crop exposure to pathogens, thus reducing also the pressure of wheat leaf rust on the crop. With few exceptions (e.g., Chile), insufficient water availability affected wheat productivity more than other factors, thus suggesting the development of varieties with characteristics able to assure higher resistance to water shortages, e.g., more capability to deepen the soil portion explored by roots.

With adaptation strategies, projected impacts were decidedly less pronounced for all the production levels and scenarios considered. Impact on water limited yields was still significant however, with water availability playing a key role in limiting wheat productivity: the use of genotypes with longer cycles compensated for the climate change effect in reducing the grain filling period, but increased transpiration demands. Except for Chile, disease pressure decreased everywhere, although no adaptation strategies specific for leaf rust were applied. The highest indirect benefits of adaptation on disease-limited productions were simulated for Brazil, Uruguay, and for Central America and Caribbean countries. Insufficient water availability played a major role in Brazil and Chile, whereas disease pressure affected productions especially in Argentina.

**For Soybean**, without adaptation yields were affected by climate change in 2020 and increasingly in 2050, although with different magnitudes throughout Latin America. Yield losses were larger in Brazil and in the Northern part of the continent (>-30% with respect to baseline), whereas in Argentina, Uruguay, Bolivia and Colombia yield decreases were less pronounced. By considering projected water-limited production level, yield losses were reduced in Argentina and Uruguay, whereas in Brazil, Central America and Caribbean regions they suffered reductions. This could be explained by the greater impact of climate change in Brazil, where the reduction of crop cycle length is more pronounced than in other parts of Latin America, markedly shortening the soybean grain-filling period. The impact of rust disease did not increase with warming, with the exception of Colombia, in which it increased for all combinations GCM emission scenario. This can be explained by the severity of the increase in temperature regimes in a warm environment such as the Colombian one, in turn leading to more favorable conditions for the pathogens.

With Adaptation strategies reduced the magnitude of impacts across all scenarios and time windows considered. For example, considering the potential production level, there were situations with positive impacts of climate change with adaptation (Ecuador and Uruguay). The most affected country was Brazil, with a maximum percentage of yield losses still close to -25% (Hadley-A1B). In certain countries, percentage yield decreases were similar regardless of water management status (i.e., Brazil, Colombia, Uruguay, Central America and Caribbean); in others, the climate change impact was larger under water limited conditions (Ecuador). In Argentina, the use of varieties with longer cycle effectively compensated the climate change negative effects tending to shorten crop cycles.

**For Maize**, without adaptation climate change negatively affected the yields of maize throughout Latin America, regardless to the emission scenario or GCM is used. This was mainly due to the reduction in the grain filling period under the higher thermal time accumulation rates, not compensated for by the increase in daily biomass accumulation rates and by the carbon dioxide fertilization effect (lower in C4 species like maize compared to C3 species like soybean). The countries most affected were Brazil, Ecuador, Mexico and Caribbean countries, where maize is one of the main crops Generally, the Hadley GCM led to the highest losses except for Brazil and Ecuador (and for the latter, only for the B1 scenario). Abiotic factors did not significantly affected maize productions, with the only exceptions are represented by a slight yield decrease in Mexico, Central America, and Caribbean. Considering the heterogeneity of the responses in the area, country-level adaptations strategies will be critical to mitigate productivity declines.

With adaptation, especially in the 2020 time frame, significantly reduced climate change impacts on grain maize yields in most of LCR, although yield decrease was still significant in major maize producing countries, like Mexico. Higher percentage decreases were simulated for the Hadley GCM compared to the NCAR, with the A1B emission scenario usually leading to the most severe declines. Adaptation strategies positively contributed to limit climate change damage to maize production, even in the countries where grey leaf spot disease was the most limiting factor.

**For Rice**, the simulations show that, on average, productivity increases. The fact that rice is a wetland/irrigated crop contributes significantly to the production outlook even in the face of climate change.

The economic impacts of implementing the climate-induced agricultural productivity shocks projected by the AZS Climate Change-Crop Impact models are generally negative—consistent with the yield shocks. At the aggregate level, in other words, the impacts on GDP, the magnitude of the shock will reflect the overall level of the crop-specific shock, the relative importance of the crop in total production, and general equilibrium feedback effects—both domestically and global. For example, a loss in export revenues typically leads to a real depreciation as exports of other goods must rise to compensate for the ex ante change in the trade balance—assumed to be fixed across scenarios.

The aggregate impact on LAC GDP could be as high as 1.7 percent in 2050 under the A1B emission scenario and using the results of the Hadley GCM. Though the climate signal is strong, even taking into account the strong climate signal, this seems a fairly large decline in regional GDP, considering that the four affected crops would only represent about 1.3 percent of total LAC GDP in 2050 under the baseline scenario. From this it can be inferred that the GE and multiplier effects are significant. In general, negative impacts tend to accelerate between 2020 and 2050, they are larger for the Hadley model than the NCAR model, and they tend to be higher for the A1B emission scenario than the B1 emission scenario. The impacts on global output are negligible.

The countries that are the most impacted across all scenarios and GCMs are Argentina and Brazil, which are also two of the largest agricultural producers. Uruguay would be the only country that would see positive gains in most of the scenarios—though under the A1B scenario using the Hadley model, even Uruguay would lose and by a relatively significant 2.3

percent. Amongst the least impacted are Chile, Ecuador and Peru. Chile's agricultural sector as a share of the total economy is small in the base year and declines over time—particularly for the four affected crops. Ecuador and Peru have relatively low production shares in the affected crops. It is useful to re-iterate that the other sectors of the economy are not impacted by climate change in this scenario—thus crops such as tropical fruits, coffee and sugar are not affected directly.

As a significant agricultural producer, changes in LAC's ability to produce will have impacts on global agricultural prices. The most impacted crop is oil seeds where prices would rise between 11 and 17 percent in 2050—relative to a no climate-change scenario depending on emission scenario and GCM with HAD A1B producing the highest relative rise. Other grains (essentially maize) would see the next largest impact—at around 5 percent with little variation across scenarios and GCMs. Wheat prices would rise only by about 2 percent, again with little variation. Rice is an exception. As on average, productivity would increase for rice, prices would drop (slightly)—as much as 0.7 percent in the more optimistic climate scenario (NCAR B1). These price changes would clearly be exacerbated if the other regions in the world exhibited similar productivity shocks.

The within country distribution between agricultural and the rest of the economy would tend to worsen in all countries and regions in LAC. In Argentina, agricultural value added could drop by 7 percent in 2020 in the best case and by 32 percent in 2050 in the worst case. The loss in agricultural value added is significantly lower in Brazil than in Argentina in 2050, even as the 2020 impacts are similar. There are some countries/regions that may see a rise in agricultural value added, obviously Uruguay, but the rest of South America as well (under all scenarios). The farmers in the rest of the world would benefit—albeit in this partial framework.

As significant net exporters, climate change induced damage would generate a large drop in agricultural exports from the LAC region albeit relative to a situation where the rest of the world is unaffected by climate change (estimating crop damage functions for other regions was beyond the scope of and resources available to this study). In aggregate, agricultural exports would decline between 25 and 33 percent in 2050 compared to the no-damage baseline. Argentina would suffer the largest loss in percentage terms—varying between 46 and 67 percent in 2050. The export decline in Brazil, though significant, would be much lower than in the case of Argentina. For most of the other countries regions, the impacts on exports are mildly positive and even potentially significantly positive for Mexico. Agricultural exports from Uruguay could potentially be volatile with a decline of nearly 50 percent in 2050 in the worst scenario, to a sharp rise of 60 percent in 2050 in the more optimistic scenario.

## 7.2. Introduction

The Latin American and Caribbean region (LAC) is a big region with heterogeneous climate, ecosystems, population and cultures. The IPCC AR4 (2007) notes that climate change in LAC will affect a number of ecosystems and sectors over the coming decades, with specific impacts on agro-ecosystems including: Decreasing plant and animal species diversity; changes in ecosystems composition, biome boundaries and area distribution shifts; reduction in the quantity and quality of irrigation water; increasing aridity and desertification; and increasing incidence and impacts of crop pests and disease.

Agriculture is likely to suffer the largest and most direct impact of climate change among economic sectors in LAC (de la Torre et al., 2009). Total economic damage estimated for 2100 ranges from $35 billion (Mendelsohn and Williams, 2004) to over $100 billion by 2100 (0.56% of GDP). These projected losses could be substantial already by 2050 under pronounced warming scenarios (de la Torre et al., 2009). For cropping systems, Cline (2007), based on an average of four different climate models, projected significant yield losses in Latin America, aggregating declines as follows: -19% for higher-income food exporting countries; -13.5% for higher-income food importing countries; and -17% in middle- and low-income countries. The recent IPCC AR4 report indicated for LAC significant crop yield losses, including -30% and -15% for rainfed maize in Central America and Brazil, respectively.

Based on the projected yield impacts, Seo and Mendelsohn (2008) estimated average potential revenue losses to farming households from climate change in 2100 of 12% for a mild climate change scenario to 50% for a more severe scenario, after adaptive reaction by farmers. Mendelsohn et al. (2008) predicted changes in land value as a proxy for the decline in land productivity. In a country like Mexico, expected to suffer severe effects of climate change, the predicted decrease in values was greater than the value of the land itself for 30-85% of all farms, depending on the model and severity of warming.

In addition to the impacts of climate change through changes in mean climatic variables, projected increases in the frequency and severity of extreme events pose serious threats to agricultural production systems. Rosenzweig et al. (2002) found significant additional impacts of climate change on US maize production, once effects of excessive soil moisture were included in simulations. Raddatz (2009) computed that climatic disasters reduce per capita GDP by 0.6% on average, and that drought and extreme temperatures are major drivers of such impacts (windstorms and hurricanes having significant effects in Central America and the Caribbean region). These data suggest that agriculture is a major channel through which the effects of climate change are transmitted to the economy at large (de la Torre et al., 2009b). If the trends of the past four decades continue, disasters could result in a permanent GDP reduction of 2% over a decade.

In a study that utilized the inputs of local stakeholders and local experts in diverse agroecological zones in Latin America to develop regional climate change action plans based on the identification and prioritization of improved adaptation strategies to anticipated climate changes (Lee et al. 2009), a key finding included the need for local communities to have access to information and decision support systems such as early warning systems (for climate forecasts, extreme weather events, pests and disease outbreaks), climate risk maps, and geographic information systems.

In the face of projected changes in climate and impacts on land use systems, the long-term sustainability of agro-ecosystems and associated livelihoods is therefore unattainable without the development of adaptation strategies. These strategies will need to incorporate not only changes to existing cropping systems but also point to the identification of alternative production systems and environmental services, and a reorganization of production landscapes for enhanced environmental, social, and economic resilience. In particular, the following questions relevant to decision-makers in coming decades will revolve around monitoring, planning and implementation issues:

- What are the specific changes in climate expected over time, and what will be their regional distribution?

- Which adaptation land and water management practices can best minimize expected impacts, and how can resources be mobilized regionally to implement them?
- What are the expected effects of the anticipated sectoral impacts at the macro-economic level, on trade, employment and poverty and inequality within a certain country and across countries in the region?

To develop effective adaptation strategies, robust and quantitative assessment tools that are able to estimate climate change risks and vulnerabilities for land use systems, especially within a portfolio of development projects, are a necessary step towards providing answers to the questions above. Once developed, the tools can then be used to identify and assess opportunities, risks, and vulnerabilities and to prioritize and coordinate a range of adaptation actions. The tools and outputs provide a platform for data sharing and regional action in Latin America. This report summarizes results of a methodological approach for developing and testing appropriate agro-climatic tools that can be used to guide policy and decision makers in Latin America and the Caribbean on the four issues highlighted above.

### 7.2.1. Goal and Objectives of this study

The goal of the study is to enhance regional knowledge and capacity for understanding, simulating, and assessing the impact of climate change on agro-ecological zones and component land uses.

The Objectives of the study include:

1. The development of a climate change-crop productivity impact modelling platform (Agro-Ecozone Simulator (AZS)) that is open-access and transparent with respect to model components and data.
2. The testing of the modelling platform to derive crop impact estimates for 2020 and 2050.
3. The coupling of the crop impact estimates to the World Bank's Environmental Impacts and Sustainability Applied General Equilibrium model (ENVISAGE) to help guide adaptation responses and related policy options through a quantification of costs and benefits related to the projected crop impacts

The formulation of a user-friendly and accessible AZS modelling platform provides for data and model sharing among all interested member countries in Latin America and the Caribbean—and can be extended to other regions of the world. AZS facilitates analysis of impacts and adaptation responses, including:

- Selected agricultural production systems with defined input and management relationships, and crop-specific environmental requirements and adaptability characteristics;
- Geo-referenced climate, soil, and terrain data, combined into a land resources database;
- Procedures for calculating the potential agronomically attainable yield and for matching crop environmental and management requirements with the respective environmental characteristics contained in the land resources database, by grid cell;
- Procedures for computing water limited, biotic factors limited, abiotic factors limited, and actual crop yields, by grid cell;
- Assessment of crop suitability and land productivity of cropping systems.
- Analysis of socioeconomic factors of land resource use for sustainable agricultural development

The output of this effort is a robust AZS model platform, capable of collecting necessary agro-climatology datasets and providing equations for data manipulation by the user, including generic crop suitability and water balance calculations and mapping. The modelling platform facilitates the evaluation of changes in cropping patterns and growing seasons as a function of projected changes in temperature, precipitation and evaporative demands, including investigations of adaptation potentials by means of available or improved varieties.

Specifically, this study chose two time windows into the future, 2020 and 2050 respectively, to investigate immediate and medium-term impacts on LA agriculture. At the same time, two possible “storylines” of plausible socio-economic development were chosen among the four IPCC SRES families (IPCC, 2000):

1. So-called “business as usual” development (**A1b**), associated with significant GHG emissions through the 21st century; and
2. A more concerted effort to achieve development while reducing regional impacts (**B1**), leading to GHG emissions that decrease through time and a near stabilization of atmospheric CO2 to about 550 ppm.

Comparing impacts of climate change between the two scenarios provides insight into the benefits of serious mitigation efforts, compared to business as usual[1] (Tubiello and Fischer, 2007). Finally, two different climatic realizations of these two scenarios were used by means of GCM outputs, representing changes in mean weather variables between future and current climate regimes and relevant to the crop model.

While all technical components of model inputs and modules will be discussed in following sections, Fig. 1 below provides a conceptual framework of the various components involved in this work.

[1] It is noted that although stabilization at 550 ppm represents a serious challenge (current $CO_2$ concentration is 392 ppm) current mitigation targets set in Copenhagen and Cancun for post-2012 climate agreements indicate stabilization at 450ppm as necessary to keep global warming to below 2C, seen as the threshold of “dangerous anthropogenic interference” with the climate system. No stabilization scenarios at this level were available in IPCC AR4.

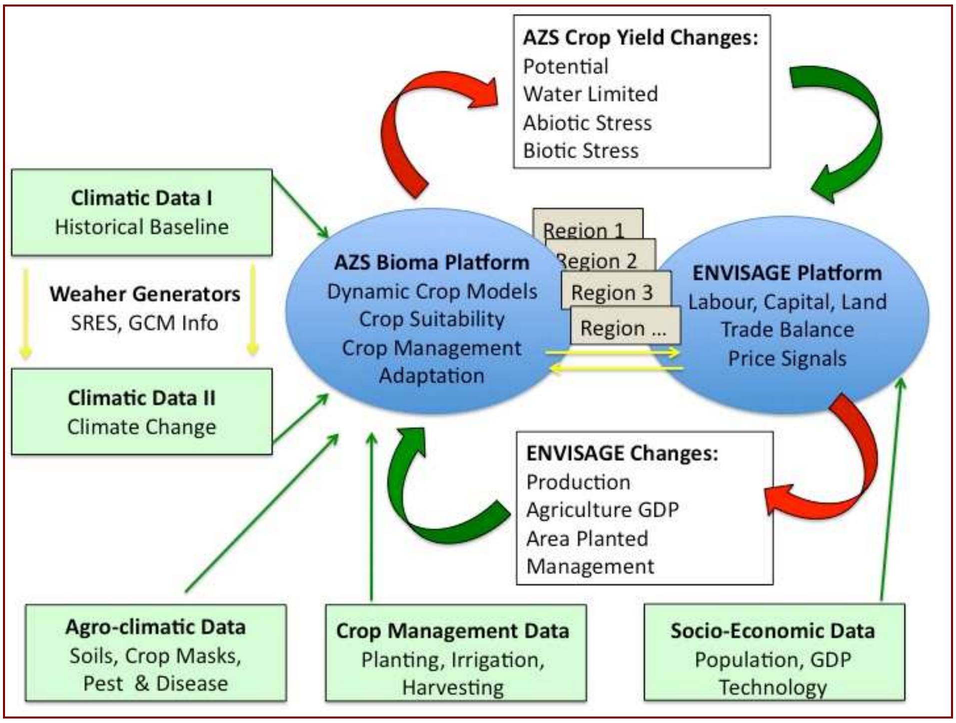



**Figure 1. Schematic representation of the flow of information (green=inputs; red=outputs) linking biophysical and economic simulations through agro-climatic input factors, climate scenario generation, and yield assessment**

## 7.3. The Agro-Ecozone Simulator (AZS-BioMA) and Applications

At the core of this effort are two modelling platforms:

1. AZS-BioMA, providing the biophysical representation of crop development and growth, as a function of agro-climatology and management; and
2. ENVISAGE, the World Bank's own general equilibrium economic model, providing a representation of economic costs and value of production, as a function of socio-economic inputs and scenarios.

The crop models compute, at each point over a 25 km grid for Latin America, the development, growth and productivity of selected crops (wheat, maize, soybean, rice) as a function of daily weather variables, including min and max temperature, precipitation and solar radiation. Each of the grid level-results can be easily aggregated at any scale of interest. For this study, and in order to provide meaningful inputs into ENVISAGE, yield simulation results were aggregated at national level. Two climate regimes are considered: the baseline climate, representing the average observed weather over the last thirty years; and climate change climate, representing projected future weather conditions that would be realized under a number of assumptions.

### 7.3.1. Inputs

#### 7.3.1.1. Climate Data and Generation

The climate database was developed by pursuing the following steps:

- Identification of a suitable and reliable historical climate database covering the study area;
- Selection of IPCC AR4 emission scenarios (A1B and B1) as input for two GCMs (Hadley and NCAR);
- Generation of the baseline and of the climate change scenarios (using GCMs outputs) via a weather generator.

The historical climate data are those produced by the European Centre for Medium-Range Weather Forecasts (ECMWF), an intergovernmental organization supported by thirty-two countries. Among the main activities carried out by ECMWF, the re-analysis of multi-decadal series of past observations plays a major role.

Data used within this project come from the ECMWF ERA-Interim, which is a global reanalysis of the data-rich period since 1989 (http://www.ecmwf.int/research/era/do/get/era-interim). The ERA-Interim reanalysis starts in January 1989 and provides meteorological data until present. The ERA-Interim data are, for our purposes, re-sampled to 0.25 degree grid cells (25 km at the horizon) in order to be consistent with other real time data like outputs of the ECMWF global circulation model.

Variables available in the ECMWF ERA-Interim database are average surface air temperature, maximum and minimum surface air temperature, precipitation, evapotranspiration (over water, bare soil, and based on the Penman-Monteith method), global solar radiation, snow depth, average wind speed, and water vapour pressure. Other variables, including hourly values, are derived using the CLIMA libraries (Donatelli et al., 2005 and 2009; Bregaglio et al., 2011).

Two IPCC AR4 scenarios (A1B and B1; IPCC, 2000) were selected as input for two different GCMs: Hadley3 (Gordon et al., 2000) and NCAR (Collins et al., 2004). The GCM are realizations of the emission scenario chosen. The choice of the Hadley3, maintained and run by the European Meteorological

Office, was because it is a de facto standard, whereas the NCAR model was chosen because of the extensive evaluations in the Americas. The time span of the analysis are centered on 2020 and 2050.

The A1B scenario considers rapid economic growth, a global population peak in 2050 with a rapid introduction of new and more efficient technologies (i.e., the A1 business as usual storyline) combined with a balanced input between fossil and non-fossil energy sources to support the technological changes envisaged (resulting in the A1B scenario). The B1 scenario is based on the same storyline as in the A1, but foresees rapid changes in the economic structure that reduces material and carbon intensity, introducing clean and resource-efficient technologies.

Without being the most extreme, the two emission scenarios selected represent most of the range of projected increase of temperate in the coming decades. It must also be pointed out that for a given emission scenario, the realizations done by the more than 10 GCM available show a variability on estimates with noticeably overlaps with the one of other emission scenarios. Further, even considering the average of estimates, emission scenarios differ at the end of the century, much less at 2050, and very little at 2020, the latter two being the time span of interest for this study. This is shown in Figure 2 below.

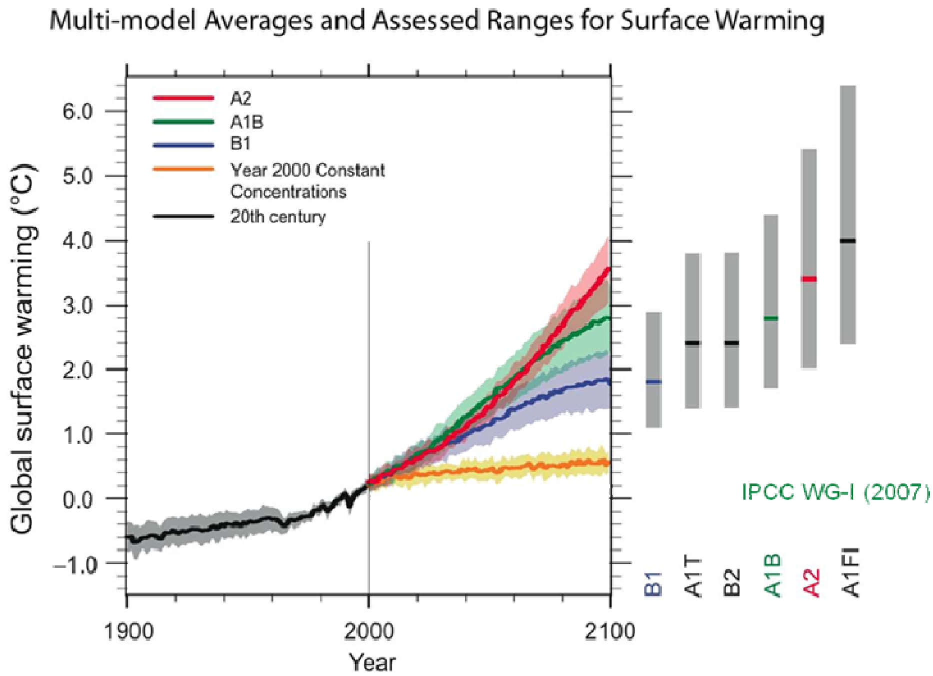



**Figure 2. Projected mean surface temperature change as a function of IPCC SRES scenario, indicating mean projected values (solid colors) from a range of GCM simulations. Corresponding to each family of GHG emission scenario (grey bars)**

The uncertainty in GCM predictions and the time span of the analysis make us consider that the choice of the emission scenarios for the analysis, once it explores the range from IPCC scenarios as in this project, cannot be considered critical.

In order to generate spatially distributed weather data to be used for feeding biophysical models, the Climak weather generator (Danuso, 2002) was used. Climak was chosen has its performance resulted equivalent to other weather generators as ClimGen and WGEN in a previous study, and because its implementation as a tool in the BioMA framework represented an advantage. According to Climak, the occurrence of rain events is estimated stochastically by using a first order Markov chain with month-specific parameterization. Precipitation amount is generated by sampling values from a 2-parameter (month-specific) gamma distribution. Maximum and minimum air daily temperatures are estimated separately, using different parameters for rainy and dry days. Sinusoidal trends are calculated using a second-order Fourier series for average daily minimum and maximum temperatures for the dry and rainy days. Once temperature trends are calculated, random residuals (sampled from bivariate normal distributions) are calculated on a monthly basis and added to the trends. Daily global solar radiation is derived from the ratio between daily and maximum (astronomical) radiation, with the ratio derived from the daily thermal excursion using a beta probability density function. Daily reference evapotranspiration is obtained as a linear function of daily solar radiation and is then adjusted by additive residuals, sampled from a normal distribution with mean equal to 0 and standard deviation calculated with a linear function of photoperiod.

A first phase involved the use of the weather generator to estimate parameters describing the features of the climate for each cell, e.g., monthly and annual trends, level of continentality, thermal excursion, rainfall distribution, etc. Once these parameters were estimated, they were used to generate the baseline climate (without applying any GCM-derived information to the parameters) and the climate scenarios (applying results from GCM to specific parameters).

- The baseline – a series of climate data with the same feature of the historical ones was re-generated to allow the most unbiased comparisons between the results of biophysical models based on baseline and climate change scenarios (in both cases derived from a generation process).
- Regional Climate Models (RCM) were not applied, as intermediate step between the GCM outputs and the parameters of the weather generator, because we could not assess, in the time frame of the project, if an homogenous set of models was available to cover the Central and Latin America. A heterogeneous set of RCMs, even assuming their ready availability, would have likely introduced a bias in the comparison of different countries.
- The years generated were 10, instead of a larger number such as 50, due to the time and resource constraints imposed by the project.

Figure 3 presents summer average daily thermal anomalies (°C; difference between climate change scenario and baseline data) for Hadley-A1B for the two time frame considered.

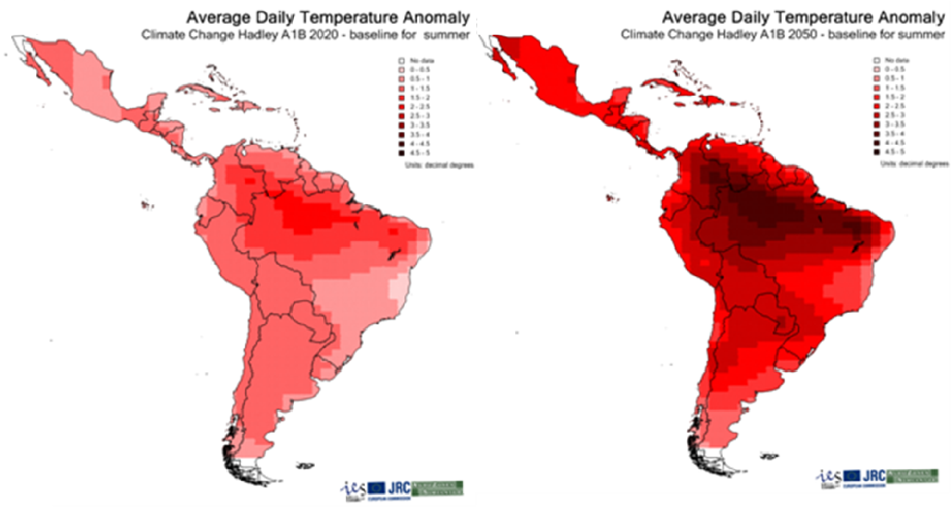



**Figure 3. Summer (December, January, February) temperature anomalies obtained by generating A1B scenarios (2020 on the left, 2050 on the right) with the Hadley GCM**

#### 7.3.1.2. Soils

The soil data set (Hoogenboom et al., 2009) is derived from the updated version of the "World Inventory of Soil Emission Potentials" (WISE version 1.1, Batjes, 2002).

WISE 1.1 database was created to provide a basic set of uniform soil data for a wide range of global and regional environmental studies (e.g., agro-ecological zoning and assessments of crop production). The profiles collected in the database derive from five main sources: (i) ISIS 4.0, the Soil Information System (Van Waveren and Bos, 1988) of the ISRIC (International Soil Reference and Information Centre); (ii) SDB, the FAO Soil Database System (FAO, 1989); (iii) a digital soil data set compiled by the Natural Resources Conservation Service (NRCS) of the United States of America (Soil Survey Staff, 1996); (iv) international data gathering activity coordinated by WISE project staff, in which national soil survey organizations were asked to supply descriptions and analysis of profiles representative of the units of the Soil Map of the World (FAO-Unesco, 1974); (v) suitable profiles obtained from a survey and stored in the ISRIC library.

It must be pointed out that the simulations limited to soil water (not considering nitrogen) are sensitive to basic soil parameters derived from texture, and soil depth, as they determine the hydraulic characteristics. In other terms, while a more detailed database that would better represent actual soil depths and % of presence in a given cell could improve the representativeness of simulations for that cell, the differences in the output would not differ markedly except for extremely shallow soils.

Figure 4 provides examples of soil properties stored in the soil data set.

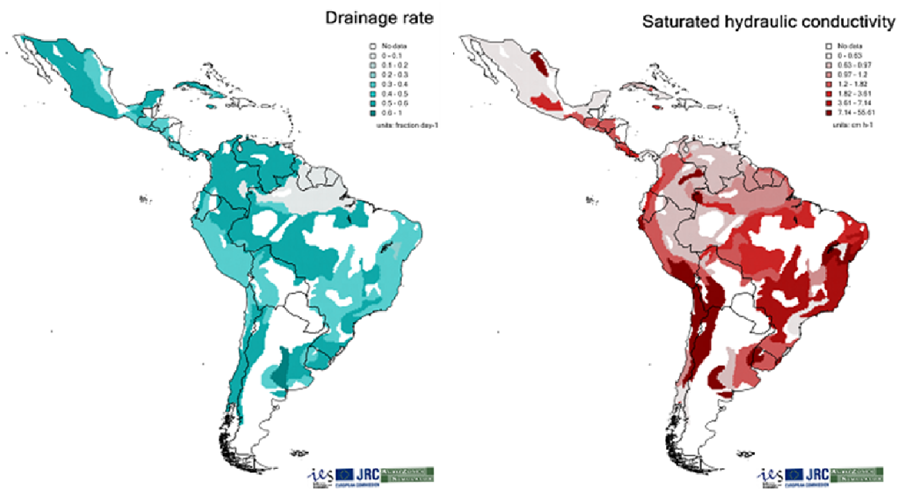



**Figure 4. Drainage rate (whole profile) and saturated hydraulic conductivity (top soil)**

### 7.3.1.3. Crops, Masks and Calendars

The crops considered within the study are maize, wheat, soybean and rice. According to 2008 FAO statistics (http://faostat.fao.org), the crop produced with the most tonnage in Latin America is sugarcane (Mt in Table 1), even if it is second to soybean in terms of economic relevance. The 2nd crop in terms of production is soybean. Rice and maize are the 3rd and 4th ranked crops in terms of economic production (thousand $ in Table 1), whereas in terms of production their ranks are inverted. Wheat comes in at 8th and 6th for economic production and tonnage, respectively.

**Table 1. Tonnage and economic productivity for the four crops analyzed during the project**

| | Crop production (Bt) | | | | Economic production (M$) | | | |
|---|---|---|---|---|---|---|---|---|
| **Country** | Maize | Rice | Soybean | Wheat | Maize | Rice | Soybean | Wheat |
| Argentina | 22017 | 1246 | 46238 | 8508 | 2042 | 258 | 9859 | 1234 |
| Bolivia | 1002 | 338 | 1260 | 200 | 60 | 68 | 246 | 29 |
| Brazil | 58933 | 12061 | 59242 | 6027 | 1925 | 2523 | 12361 | 877 |
| Chile | | | | 1238 | | | | 163 |
| Colombia | | 2792 | | | | 577 | | |
| Costa Rica | | 248 | | | | 52 | | |
| Ecuador | 804 | 1442 | | | 26 | 299 | | |
| Guyana | | 507 | | | | 105 | | |
| Guyana (Fr) | | 9 | | | | 2 | | |
| Honduras | 536 | 49 | | | 21 | 10 | | |
| Nicaragua | 424 | 322 | | | 45 | 67 | | |
| Panama | | 301 | | | | 63 | | |
| Paraguay | 2472 | 150 | 6312 | 799 | 158 | 31 | 1309 | 104 |
| Peru | | 2776 | | | | 585 | | |
| Suriname | | 183 | | | | 34 | | |
| Trinidad and Tobago | | 2 | | | | | | |
| Uruguay | | 1330 | 880 | 1288 | | 278 | 180 | 187 |
| Venezuela | 2996 | 1361 | | | 187 | 189 | | |
| TOTAL | 89184 | 25117 | 113932 | 18060 | 4464 | 5143 | 23954 | 2595 |
| Rank within LCR | 3 | 4 | 2 | 6 | 4 | 3 | 1 | 8 |

Crop masks for maize, wheat, soybean and rice (Figure 5) were derived from the SAGE Center for Sustainability and the Global Environment – Nelson Institute of Environmental Studies, University of Wisconsin-Madison (SAGE, http://www.sage.wisc.edu/index.html).

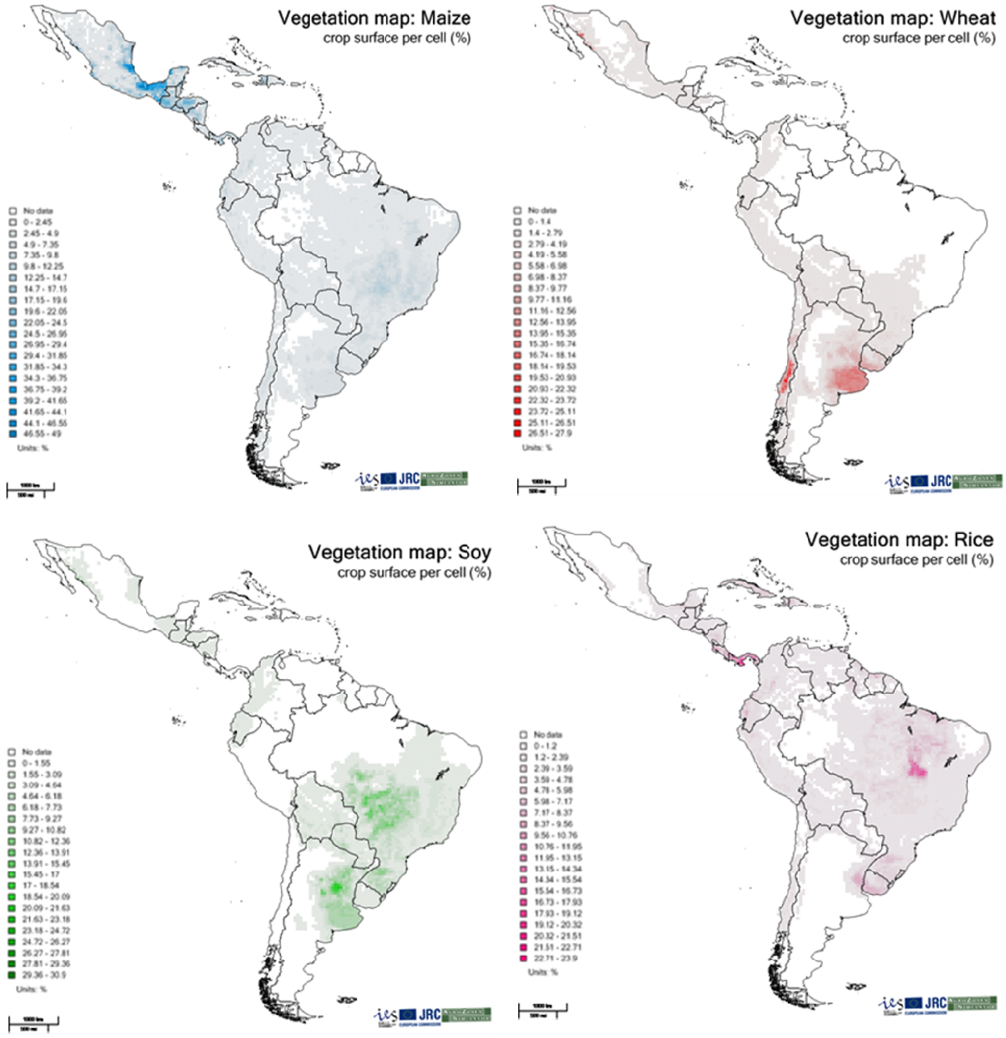



**Figure 5. Crop masks used within the project**

Crop calendars for LCR were downloaded from the SAGE Center for Sustainability and the Global Environment databse (http://www.sage.wisc.edu/download/sacks/crop_calendar.html).

### 7.3.2. Modelling Platform

#### 7.3.2.1 Crop Development and Growth

The modelling platform designed for this study to assess the impact of climate change on agricultural productivity includes uses a range of approaches to model crop development and growth. For example, the approaches currently being implemented are:

1. ***CropML-CropSyst*** (Stöckle et al., 1992, 2003) is a cropping system model including generic crop simulator which allows for simulating both determined and perennial species. This component implements the plant related part of the original CropSyst model, version 3.X
2. ***CropML-WARM*** (Water Accounting Rice Model, (Confalonieri et al., 2009b,c) is a daily time step model for the simulation of growth and development of paddy rice crops. The model accounts for all the main processes which characterize this peculiar system.
3. ***CropML-WOFOST*** (Van Keulen and Wolf, 1986; Boogaard et al., 1998) is a member of the family of crop growth models developed in Wageningen by the school of C.T. de Wit. It follows the hierarchical distinction between potential and limited production and shares similar crop growth submodels, with light interception and $CO_2$ assimilation as growth driving processes and crop phenological development as growth controlling process.

The modelling platform represents a paradigm shift with respect to current modelling approaches for three reasons:

1. The concept of multiple options for simulation is made available and can be further extended, adding modelling approaches as, for instance, the ones implemented in DSSAT models; and
2. Because of the fine resolution used to implement models, users can implement variants of modelling approaches. In particular, given the goal of simulating crop growth under extreme weather conditions, a curvilinear response to hourly temperature of phenology (plant development phases) and growth, with a decline beyond optimal temperature, is implemented (hourly temperatures are derived with good accuracy from daily maximum and minimum temperature data). For example, this approach estimates sub-optimal rates at high temperatures, reproducing biologically-known patterns of response to temperature, and leading to estimates of development and growth that are diversified with respect to the known accumulation of growing degree days and the plateau response to temperature.

3. The software architecture allows users to easily simulate various production levels (e.g., potential, water limited, nitrogen-limited limited, and disease limited productivity) thereby allowing deeper analysis and insight of the production system simulated.

BioMA, through its full implementation of these three models, is the platform currently used at the EU-JRC to investigate the impacts of climate change on crops in the EU-27, as well as in key production regions of the world, including Russia and the CIS, Latin America, China, India, and a few countries in sub-Saharan Africa.

CropSyst (Stöckle et al., 1992, 2003) is a cropping system model including generic crop simulator that allows for simulating both annual and perennial species. This component implements the plant related part of the original CropSyst model, version 3.02.23. WARM (Water Accounting Rice Model, (Confalonieri et al., 2009c) is a model explicitly developed for the simulation of growth and development of paddy rice crops. WOFOST is a member of the family of crop growth models developed in Wageningen (Van Keulen and Wolf, 1986), which has been used historically at the JRC for crop forecasting.

All three models, which are established platforms of crop models alongside others, such as EPIC or DSSAT (e.g., Tubiello and Ewert, 2002), follow the hierarchical distinction between potential and limited production; crop growth is computed via light interception and CO2 assimilation; growth driving processes depend and are driven by crop phenological development stages, mainly via degree day accumulation.

During the project, CropSyst was used for maize, wheat and soybean, whereas WARM was used for rice. The two models were selected because of their accuracy and robustness (Confalonieri et al., 2010).

**7.3.2.2. Soil Water**

SoilW is a software component implementing a wide range of alternative methods to simulate water dynamics into the soil profile, covering all those already in use in major crop modelling platforms worldwide. The component allows for the simulation of the following processes:

1) Water redistribution among soil layers;
2) Effective plant transpiration (several options available);
3) Soil evaporation (several options available);
4) Drained water if pipe drains are present (under development).

5) Effects of soil tillage and subsequent settling of hydrological properties of the soil (field capacity, wilting point, retention functions, conductivity functions, bulk density).

For each of these processes, several approaches are implemented, allowing SoilW to reproduce the behavior of all the most diffused cropping systems models. As an example, for water redistribution, three approaches are implemented. The first is based on a numerical solution of the Richards' equation (Richards, 1931), based on the physical concept that water flux between two points is driven by the pressure gradient between the points themselves, and it is function of the hydraulic conductivity. In this approach, water retention curves and hydraulic conductivity as a function of soil water content and/or water pressure are needed. This approach is used in several well-known models, like CropSyst, SWAP (Van Dam et al., 1997) and MACRO (Jarvis, 1994). The second approach, i.e., cascading (also known as 'tipping bucket'), is the less demanding in terms of data needs, and assumes that water can move only downward through the soil profile, filling up the layers until field capacity is reached, with the fraction of water exceeding this threshold moving to the deeper layer (Jones and Ritchie, 1990). This approach is adopted in most of the DSSAT models. The third approach is a modification of the cascading one, in which water movements are reduced by soil hydraulic conductivity, thus allowing water contents to be higher than field capacity. This approach is adopted in various simulation models (e.g., SWAT, Neitsch et al., 2002; WARM, Confalonieri et al., 2009b).

Rainfall and irrigation water actually infiltrating the soil (after possible runoff and plant/mulch interception) is simulated with a library of models implemented in the SoilRE component. Also in this case, a variety of approaches are available for sub-process, involved in runoff volume, water interception by vegetation and mulch, actually infiltrating water. As an example, for runoff, approaches implementing the curve number and the kinematic wave methods are available.

Management events (see section 2.2.5 'Crop Management') involved with soil dynamics like, e.g., irrigation, are processed by the SoilRE component.

During the project, the cascading approach for simulating soil water redistribution was used, given the constraint of lack of detail in the data available, which had to be homogeneous for the whole area considered.

#### 7.3.2.3. Diseases and abiotic factors affecting productions

In almost the totality of the climate change impact studies, cropping systems modelers have been used to consider only temperature, radiation, rainfall, atmospheric $CO_2$ concentration and – in some cases – irrigation as forces driving crops productivity. Biotic (e.g., diseases) and abiotic (e.g., ozone concentration, frost events) factors were traditionally considered as having a constant impact on the crops under a changing climate. This assumption is false, since weather variables have a crucial effect, e.g., in modulating plant-pathogens interactions, in turns leading climate to alter the magnitude of the gaps in crops productivity due to diseases. This consideration is valid also for damages caused by abiotic factors (e.g., frost), in most of the cases driven by extreme weather events, in some cases forecasted to increase by global climate models.

In this project, we considered the impact of diseases (Disease component) and abiotic damages induced by extreme temperatures (Abiotic Damage) on crops productions.

Disease is a component simulating the progress of the epidemics of fungal pathogens by explicitly considering the processes of infection, incubation, latency, infectiousness, sporulation, and spore dispersal, all driven by weather conditions and by interactions with the host plant. The impact on the host is simulated mainly via lesions to the photosynthetic tissues. Host resistance (different varieties can greatly differ in terms of susceptibility to a specific disease) is accounted for in the component, and it is based on a generic classification of resistance levels. Figure 6 shows the distribution – within Latin America – of the pathogens simulated during the project (the most relevant ones for each of the considered crops).

Damages due to extreme temperature events, e.g., frost, cold-shock induced sterility, were simulated using the Abiotic Damage component, implementing a approaches for a variety of abiotic damages affecting crops, over and above those in use in most other crop modelling platforms in use worldwide. The models currently implemented belong to six categories: lodging, frost, cold-induced spikelet sterility, heat-induced spikelet sterility, ozone and salinity.

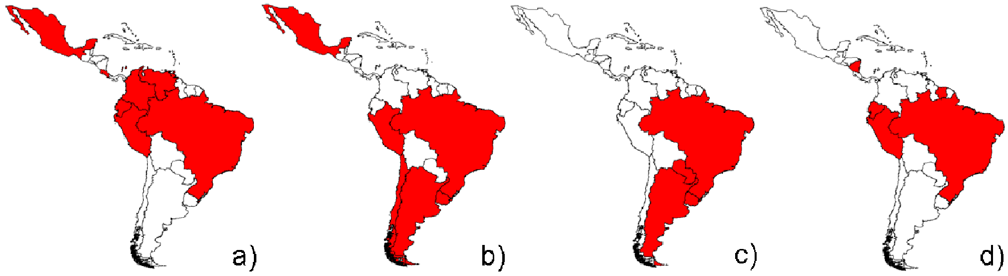



**Figure 6. Geographical distribution of: a) maize Gray leaf spots (Cercospora zeae-maydis), b) wheat leaf rust (Puccinia recondita), c) soybean rust (Phakopsora pachyrizi), d) rice blast disease (Pyricularia oryzae)**

### 7.3.2.4. Crop Management

Dates of irrigation events and the amount of water needed by the crop under current or future climate conditions were simulated via rule-based models. This is based on the state of the system, mimicking farmers' behavior with respect to management decisions related to resources availability and on the physical characteristics of the system. A proper set of rules were implemented in the AgroManagement component.

Irrigation was used for maize and soybean, whereas wheat was simulated under rainfed conditions. Water limited production was not simulated for rice, since the crop is grown in the study region under paddy conditions.

Irrigation events were simulated for both maize and soybean (i) when soil water content fell below 50% of the plant available water, (ii) by limiting the total amount of irrigation water in a season to a maximum of 300 mm, and (iii) by setting the maximum amount of water to 40 mm for each event. This parameterization of irrigation rule allowed reproducing standard typology of irrigation practices, leading to a medium satisfaction of crop water requirements during a season.

### 7.3.2.5. Crop Suitability

Assessing crop suitability is an important component of assessment studies, including changes to crops geographic distribution under climate change in coming decades. On the one hand, it is well known that crops will respond to specific changes in temperature and precipitation at the locations where they are currently grown; on the other, it is also expected that not all crops and cultivars will remain suitable within their current geographical ranges, with tendencies to migrate towards higher latitudes and a push out of production in areas already at the margin of production. Yet most crop modelling platforms available today present fixed grid simulations of crops, i.e., they do not allow for dynamical movements of ideal crop ranges, and thus tend to underestimate likely adaptation responses by farmers. These will doubtlessly attempt to switch where possible to cultivars and crops better adapted to changing conditions. By the same token, those model platforms that have excelled in computing suitability have much less crop modelling detail than available under the proposed platform.

The Suitability component included in AZS-BioMA implements a variety of approaches for suitability estimation based on single-cell (e.g., threshold based approaches) or multi-cell (i.e., based on multiple regressions) computations. Among the approaches implemented, some are retrieved from the literature, and based on soil and/or weather inputs, e.g., FAO EcoCrop (http://ecocrop.fao.org), Less Favorable Areas (Eliasson et al., 2010). Others, developed during the project, derive a suitability index from simulated variables, like yields, completion of crop cycle, yield gaps due to biotic and abiotic factors affecting productions.

Our implementation of all the methods allow the user to select the methods themselves (i) in their original configuration, and (ii) with options allowing to exclude categories of variables or parameters from the computation. Another criterion implemented during the project (District criterion) is based on the assumption that crop choices by farmers tend to aggregate in production districts. This approach cannot be used alone and the Suitability component gives the user the possibility of coupling it to all the other methods implemented.

The user can run the AZS-BioMA suitability component by deciding exactly which method to use or by leaving the component itself to selecting the most appropriate method, in light of the actual data availability or the particular exercise that needs to be run.

### 7.3.3. The simulation platform

The use of biophysical models has broadened to multi-objective analysis in the area of agriculture, ecology and environment. For one, stakeholders increasingly require greater level of integration in system analysis. Additionally, there is an increasing number of biophysical processes to be considered, requiring model extension, comparison, and multi-team work to address the impact at large scales of context specific problems.

The analysis of climate change impact on agriculture, its possible adaptation and the mitigation service that adapted system may perform, represent a moving target under the fast dynamics of markets in the global economy. Simulation tools must be flexible and capable of incorporating existing knowledge to rapidly address stakeholder needs.

The development of modelling tools in the context above goes beyond the pure domain-specific knowledge of the problem being addressed, requiring state of the art infrastructure to match the challenge. A software architecture based on modular components facilitates such processes.

Although the goal of building modular simulations systems has been long accepted, the emphasis so far has been on building modelling framework-centered software solutions. This has likely been an obstacle to the diffusion of such frameworks beyond the groups developing them. Reusability of components has also been very modest, if any. Instead, a software solution based on the component-oriented paradigm has its focus on reusable components, and does not target a unique software framework and framework-specific components.

In the following section we illustrate the innovations introduced with the simulation platform, whereas the concrete products of this project (limited in time and resources) show the level of advance of its realization. The goal of this realization can be anticipated and summarized as providing an effective tool for use *now*, but having the capability of adding new layers of data, and of extending solutions to modelling problems, also in time periods compatible for an effective response to customers.

**7.3.3.1. Component-oriented development**

In systems analysis, it is common to deal with the complexity of an entire system by considering it to consist of interrelated sub-systems. This leads to think of models as made of sub-models. Such a (conceptual) model can be implemented as a computer model composed of a number of connected component models. A software component can be defined as "*a unit of composition with contractually specified interfaces and explicit context dependencies only. A software component can be deployed independently and is subject by composition by third parties*".

Thinking of models in modular terms is a needed shift of paradigm with respect to monolithic, unchangeable models; a modular conceptualization of models allows:

- An easier transfer of research results to operational tools

- The comparison of different approaches
- A greater transparency
- More rapid application development
- Re-use of models of known quality
- Independent extensibility by third parties
- Avoiding duplication

An implementation based on component models has at least three major advantages:

- New models can be constructed by connecting existing component models of known and guaranteed quality together with new component models
- The predictive capabilities of two different component models can be compared, as opposed to compare whole simulation systems as the only option
- Common and frequently used functionalities, such as visualization and statistical ex-post analysis tools, can be implemented as generic tools and developed once for all and easily shared by model developers

The component-centered approach of this platform from one side provides advanced features both to components and to the whole system (Donatelli and Rizzoli, 2008), from the other it allows an easier extension by third parties which do not develop *for* the platform, instead, they develop independent components with high quality features which can be reused by third parties, one of which is the platform presented. In other terms, they do not have to “subscribe” to this platform; rather, they can have this platform as one of their customers. Further, they can use either the platform and its tools, or just single components of the platform, which are also independently reusable.

#### 7.3.3.2. AZS-BioMA features

The Agro-ecological Zones Simulator is a realization based on the BioMA (Biophysical Model Applications) platform. BioMA is an extensible platform for running biophysical models on generic spatial units. It is based on discrete conceptual units codified in software components (both for simulation engines and user's interface). The guidelines followed during its development aim at maximizing:

- Expansion and adaptation with new modelling solutions
- Ease of customization in new environments
- Ease of deployment (at national and local research and academic facilities)

Simulations are carried out via modelling solutions, which are discrete simulation engines 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. BioMA can be extended autonomously by third parties by adding new modelling solutions, making use of components already used by the application or using new ones.

The current version of BioMA includes heterogeneous modelling solutions:

- WARM-BlastDisease-Sterility
- CropSyst-Water Limited
- WOFOST-Water Limited
- Agricultural Production and Externalities Simulator - APES
- PotentialDiseaseInfection
- Diseases (linked to crops)
- ClimIndices

BioMA is developed at JRC (project leader: M.Donatelli) in close cooperation with the University of Milan and the Italian Agricultural Research Council. Additional collaboration is being established with the INRA, France.

**7.3.3.3. AZS use at different scales**

This is a key feature of the platform that allows building configurations which access data-layer at different spatial resolution. The current setting use a grid 25 x 25 km, but, say 1 x 1 km DB can be used allowing detailed analysis for instance of a region in a country. The added value is that the same tools and methodology can be used, creating possibly figures from a region or a country based on less abstract both production systems and technical adaptation strategies. This sets a concrete and consistent basis also for effective and transparent communication between regional offices and runners of large area analysis (see also last paragraph).

#### 7.3.3.4. Model extension

New modelling solutions can be added to the system. The process is straightforward although it requires assistance from IT personnel. One a model box is made available for BioMA (hence for AZS), it can use all the tools in the platform. As an example, a possible modelling solution could be about grape vine phenology and quality (preliminarily developed for Europe). The following diagram shows the macro-components of the BioMA deployment for Europe.

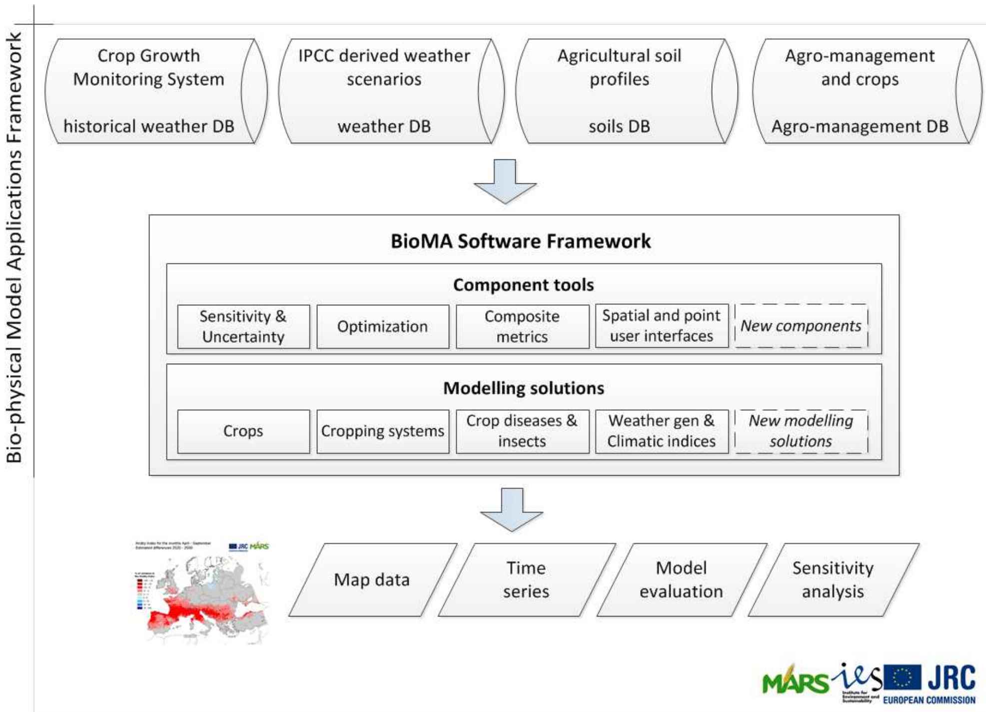



**Figure 7. Macro-components of the BioMA deployment for Europe**

#### 7.3.3.5. Data access as input to analysis external to the AZS platform

Data will be accessible read-only via dedicated web services (cross platform) to authorized users. This allows building applications or utilities that will be able to query data and use them in local applications. A target use of biophysical simulation output is the link to agro-economic models. The linking and the workflow to develop adaptation strategies is shown in the following figure. The workflow may include either agricultural sector models (as in the current project) or farm models. If the economic model is a farm model, this allows accounting for technological and resource driven constraints, allowing a detail analysis of production systems that are more context specific. The dashed line connector suggests possible iterations between a bio-economic farm model and biophysical models to further improve the definition of adaptation scenarios.

In this project, scenarios are not set to interact with economic models, and the adaptation strategies, as described in section 1.1, represent basic technical options. The study of further options could be driven by agricultural sector models needed to investigate, for instance, a specific crop, or specific constraints in resources.

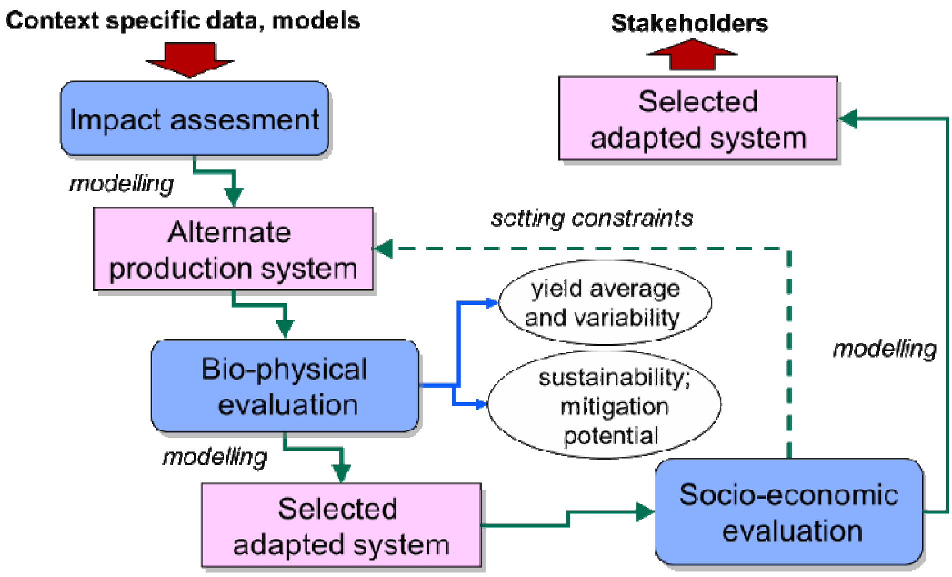



**Figure 8. Possible use of environmental outputs for selecting specific production systems**

In more general terms, the outputs of biophysical analysis (which includes also static indicators based on climate) could be used to build integrated indices to estimate, for instance, land use changes based on bio-physical indicators, hence using the outputs as proxies for semi-qualitative estimates of climate change impact. The figure highlights also a possible use of outputs of environmental interest for selecting among possible alternate production systems.

#### 7.3.3.6. Calibration and model evaluation

Calibration and model evaluation must be considered separately for current weather conditions and for conditions of climate change, as in the following paragraphs.

Process-based, deterministic models like the ones use for simulation in this project, are evaluated against referenced data. This activity, often referred as model “validation”, for crop/cropping system models is done by simulating the same conditions where the reference data were collected (weather, soil, agricultural management) and comparing simulation results to data collected from the real system (e.g., biomass produced, yield, soil water content). Prior to actually performing model evaluation the model is calibrated, a process that consists in adjusting the value of some model parameters in order to minimize the difference between simulated and reference data. This is a very delicate process when performed with process based models, where parameters have a bio-physical meaning; in no case the result of calibration may lead to parameter values which are out of the range known for the process they refer to. Once model parameters are calibrated, model evaluation is run as described above against an independent dataset.

In all cases, model evaluation is run against articulated dataset, in which not only the context is described in detail to allow simulating it, but also the measurements on the state of system regard both different variables and time series. In fact, yield, which is very often the variable of major interest, is the final result of the simulation of several processes. As such, (dataset always being limited in number because very costly), a calibration based only on yield has often multiple solutions, often resulting in unpredictable model performance under changing bio-physical contexts. Model outputs such as crop progression through different development stages (phenology) is typically driven by a much smaller number of factors than yield.

Models are simplified representations of the real system, and they must include the essential processes (as sources of variability of responses) with respect to the goal of the analysis planned. Some processes can be omitted, in this case adding to the assumptions made for the simulation exercise. Although acceptable, this has implication also on the data which can be used for model calibration and evaluation: for instance, if a model not simulating water limitation is used, reference data based on systems where water limitation occurs cannot properly be used either for calibration or evaluation.

The implications on which dataset can be used for evaluating a crop/cropping system model are important. In fact, whether models tend to simulate crop development and growth as limited by few factors, actual agricultural production systems, especially in developing countries, show a wide range of production constraints that may impact on production non-linearly. Unfortunately, yield statistics are presented as values, rather than ranges; should ranges be available, the upper limit could be used for calibration and model evaluation, allowing deletion from reference data of cases that cannot be represented by models, because they include processes, or technical mismanagement, which increase the yield gap. Furthermore, the technological gap of production system can be different across regions and countries; when combined to environmental factors; it may lead to a different resiliency with respect to adverse weather. The impact is again on the usability of yield statistics to calibrate and/or evaluate process based models, because it introduces a further bias as result of the year-by-year variability.

The models used in this project are well known and peer reviewed, which implies that they have been evaluated across a broad range of environmental conditions. The analyses carried out in this project thus are based on such evaluation, and rely on data from the scientific literature for model calibration. It must be pointed out that this study uses crop production as a level of abstraction for production system, hence aiming at representing yield changes (at various production levels) in response to scenarios via a 25 x 25 km grid. Even if yields are considered at the various production levels mentioned above, yield estimates are potential, and can have different realizations in specific production system if analyzed within more specific context constraints. This suggests that this type of analysis, using the very same tools which allow for different spatial resolutions, could benefit from a more detailed calibration in specific countries or regions. Yet this level of detail in the analysis was beyond this project goals and resources; future applications involving local knowledge and expertise will be necessary to refine simulation results.

A different aspect of model evaluation to be considered relates to model use in scenarios of climate change. This refers to unexplored conditions where there is no data, site specific, which may represent the performance of production system. Being relationships among biophysical processes in the real system non-linear, system performance cannot be estimated using trends and statistical models. Likewise, it cannot be used by relying on empirical parameters whose empiricism is at the same level of the one of the estimate. The relationships used in process-based models also have some empiricism, but that empiricism will be one or more levels below the level of the prediction, as shown in Figure 9.

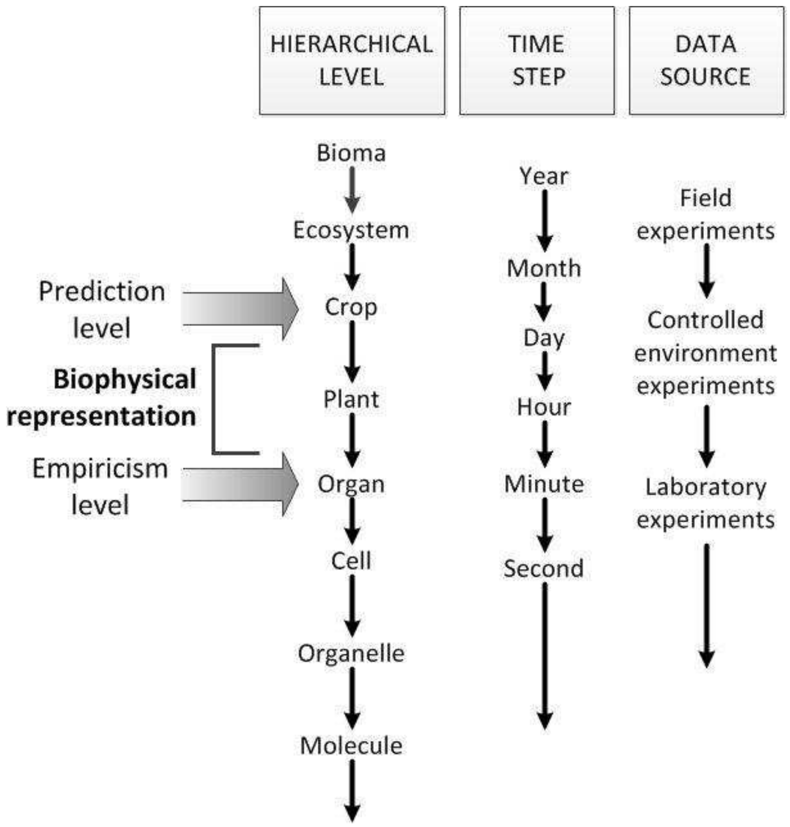



**Figure 9. Level of prediction and level of empiricism in process-based models (redrawn from Acock and Acock, 1991)**

The goals in defining new models are using relationships known from physics or chemistry, and parameters that have either a biological or a physical meaning. A process-based model can, in principle, be used to extrapolate to conditions outside the ones used to develop it. By contrast, a fully empirical model, as any statistical model, can be considered usable only for the context that originated the data used to build it.

Given that no evaluation against data can be done for scenarios of climate change impacting on crop development and growth, to accept their use in such condition a system analysis must be done confirming model adequacy under the new conditions. This has been done for the models used in this project, leading to changes in curves of response to temperature. The original models had a plateau of response to daily maximum air temperature, perfectly adequate in conditions such as the one of temperate climates, in which temperature rarely reaches levels above the optimum. Hence making the plateau approximation is acceptable. It is however known that rates of development and growth start decreasing above optimum temperature. For instance, a plateau model will estimate an overall increase of temperature-driven rates in the linear part of the response, and same response in the plateau region, when temperature increases as in climate change scenarios. By contrast, a curvilinear model will estimate a decrease of rates of development and growth at higher temperatures. The latter is the case in scenarios of climate change where the steep raise of temperature does not allow for accepting the hypothesis of good adaptation of crops to environmental conditions, as built in decades of agriculture under variable weather, but under no steep trend toward higher temperature. This is why the models used include curvilinear responses to temperature, which do not show any difference of estimates, compared to the original ones, under current weather, but start estimating differences at higher temperatures.

Another aspect that impacts on the adequacy of model structure, if the assumption of crop adaptation cannot be accepted, is the response to extreme meteorological events. We can consider extreme events for a crop the values of environmental variables which are beyond the capability of providing a physiological response by the crop, and which may lead either to a permanent damage or to death of the crop. Referring to air temperature as discussed above, a crop will respond with a given rate to temperature, but if temperature reaches levels beyond maximum temperature for growth, or below minim temperature for growth, permanent damages occur. These aspects were generally ignored in commonly used modelling solutions, and are now implemented representing one of the production levels simulated.

To summarize, the development and implementation of the identified temperature responses, and the models of impact of extreme events, allows the use of models originally developed for temperate climates, under the assumption of good crop adaptation, in scenarios of climate change.

### 7.4. Climate Change-Crop Impact Simulation Results and Discussion

Simulations of crop development, growth and yield were carried out using the AZS-BioMA models for the following production levels:

- Potential Yield (no stress);
- Water limited Yield[2] (rainfed or under limited irrigation regimes);
- Disease-affected Yield (soybean rust and maize grey leaf spots);
- Abiotic damaged Yield (e.g., thermal shocks);
- Actual Yield (All limitations simulated together, including their non-linear interactions).

For each scenario considered, data are presented in the form of percentage differences with respect to results under the baseline climate.

Eight climate change scenarios were considered from combinations of time horizon, SRES pathway and GCM, as discussed in previous sections. In addition, two sets of simulations were run for each of these eight combinations: without and with adaptation, making a total of sixteen scenarios considered. Adaptation strategies were based on:

- Genotypes with different crop cycle lengths (± 5% of growing degree days to reach each phenological stage, targeting average 10-day variations of crop cycles);
- Sowing dates (± 20 days);
- Irrigation via automatic application rules (with context-specific constraints, i.e., no more than 300 mm/season of irrigation; no more than 3 irrigation events).

Important to note that simulations were not performed on grid cells where crops are not shown to be present in the assembled crop distribution masks.

[2] As per local practices, rainfed soybean in Colombia; moderately irrigated maize in Ecuador.

#### 7.4.1. Climate Change Simulations

This section analyzes simulation results in terms of percentage yield decrease due to climate change without and with adaptation strategies for the 2020 and 2050 time frames.

Figures included in this section present the simulation results (percentage variation compared to the baseline) for water (a) and disease (b) limited yields. Results refer to the climate change scenario Hadley-A1B. Full simulation results are given in Appendix 1.

##### 7.4.1.1 Production levels simulated and adaptation strategies

The general definition of adaptation tested via simulation in this project is given by changes in agricultural management that farmers may implement to alleviate negative impacts of the weather scenarios evaluated. Adaptation by farmers will occur, to some extent, regardless of any action to support or steer it from government or local authorities. Consequently, although simulating impact assessment for "unchanged systems" is a prerequisite to get insight of system behavior with the target of developing adaptation strategies, its results should not be consider as one of the possible "future scenarios for agriculture".

Adaptation tests are run considering three factors:

- Genotype: the duration of the crop cycle evaluated is medium for the analysis of the baseline, whereas early and late maturity genotypes are also evaluated in the simulation of weather scenarios.
- Planting time is explored by testing the anticipation of planting dates.
- Water supply is implemented using the same rule-based model used for the baseline simulation, parameterized in order to provide a medium level of water availability as detailed in the technical annexes.

Water supply was always active in simulations for irrigated/potentially irrigated crops (maize and soybean in this study), while all combinations related to genotype and planting time were explored.

Crops were simulated in cells where their relative occupancy resulted 1% or greater of the agricultural area. The modelling capabilities of the platform allow simulating, for each crop, adaptation strategies, weather scenarios, and different abstractions of production systems identified as *production levels*:

- Potential production (P: crop growth solar radiation and temperature driven);
- Water limited (WL: all factors of P and water limitation);
- Abiotic stresses limited (AL: P and effects due to temperature stresses of extreme events for crops);
- Disease limited (DL: P and impact from one crop-specific disease);
- Multiple-factors limited (MFL: P, WL, AL, and DL limited).

The simulation of potential production, as defined above, is useful to test responses not constrained by either resources - as quantities, or technology (or both). Consequently, estimating a multiple factors limited production allows estimating the technological gap (e.g., we do not use a pivot system to irrigate weekly, hence no more than 4 irrigations per season via sprinkler) and resource limited production (e.g., no more than 300 mm /season of water available). Noticeably, the levels potential production and abiotic stress limited production can be counteracted as adaptation measures either via planting different genotypes and changing timing of sowing (same crop - we test both in this project), or changing crops (we provide only scenarios of land suitability for crops in this project).

When water limited production was simulated, a rule-based agro-management model to supply water to crops was used i.e., adaptation with respect to water use is included (adaptation not constrained by water availability beyond the setting of rules, and not constrained by technology). The picture provided by WL simulations estimates a possible technical adaptation, whereas context specific constraints (e.g., no more than 300 mm/season of irrigation; no more than 3 irrigations) can either be considered ex-post evaluating the adaptation scenarios provided, or may lead to another run of simulations.

The simulation of diseases limited production does not include agro-management to alleviate the impact of a possible increased pressure by plant pathogens due to climate change. These simulations can be of direct use if no chemical can be used in a given context; otherwise simulation results would overestimate the impact of climate change neglecting possible adaptation (see opening paragraph). In the latter case, economists could use the quantitative estimates of diseases-limited production could be used in a semi-qualitative fashion. From the above, the assumption made using scenarios of water-limited production is that diseases, if affecting the crop, will be either chemically or genetically controlled.

As concluding note related to the choices of production systems and adaptation in this project, basic food commodities-based production systems abstracted at the level of "crops", and basic adaptation strategies, are evaluated. However, it must be pointed out that the simulation of impacts of extreme events and of the system crop-disease is completely innovative. Also, the platform is suitable for more detailed analysis as scale and/or context specificity.

**7.4.1.2. Assumptions of data and modelling solutions**

Several assumptions were made while using data and selecting specific modelling solutions, and by designing the simulation experiments presented herein. Such assumptions set the limit of use of the results of this analysis. They should be carefully evaluated, to avoid introducing conceptual errors in the final results of this analysis. The latter are the result of an integrated modelling chain, of which the crop biophysical simulations are an input. Such assumptions are discussed below.

*Weather data*

Weather data refer to the ERA-Interim interpolation and run as described in the relevant paragraph. The time series representing each 25 x 25 km grid cell refers to a flat land at the predominant elevation above sea lea level. This makes the time series more representative of real systems, which are also more uniform, in flat land areas, whereas the representativeness in more critical for areas where slopes and aspect (i.e., the orientation of the slope) change within cell. In these cases a more detailed analysis using digital elevation models and a smaller spatial scale would articulate more system performance. However, given the target of the study, which focuses on the entire Central and Latin America, the approximation can be considered acceptable.

Furthermore, GCMs provide estimates primarily of mean temperature, rainfall, and solar radiation. Given model requirements as inputs, the patter of variability of other variables (e.g., wind, air relative humidity) must also be used, and was kept unchanged in data layers of scenarios of climate change in these simulations. In addition, GCM outputs typically lack detailed and quantified indications of realistic changes in frequency of extreme events. For this reason, climate variability, i.e., the shape of higher-order moments was kept at present values. The specific distributions, based on thresholds, such as the number of temperature or water-related stress events, were modified in our time series. Yet one could imagine developing climatic "sub-scenarios," where the variability of specific climate variables could be changed in a sensitivity approach—using the features of the weather generator in the platform.

*Model calibration*

Model calibration, was based on literature resources, which generally make available reference data for large areas. As for weather data, an analysis at finer spatial scale is needed using local expertise would yield more articulate results per target areas.

*Soils*

As assumed for weather data, soils were distributed on a flat surface, i.e., terrain. This may alter significantly the soil water balance in areas with steep terrain. Also, in areas where soils are differentiated, ranging from high to low water holding capacity, simulation results will represent only a limited portion of actual results, although they capture the predominant features of the system.

*Production systems*

Production systems were abstracted at the level of "crop", ignoring possible structures typologies of cropping systems. If cropping systems were analyzed instead, crop performance in a given cell would result from its performance in different rotations and under different inputs of resources. Also as a consequence of weather data resolution, model calibration, and soils, simulation results were an abstraction of production systems for the area, and should be compared to actual, point data, with caution. However, the goal of the analysis aims at estimating basic impact dynamics and adaptation strategies for the large areas considered.

*Adaptation strategies*

The adaptation strategies considered basic technical options, likely available to farmers today. This implies that alleviation to the impact of climate change was estimated on the basis of the same abstraction of production system evaluated in the baseline simulations (i.e., referred to current conditions).

There was no consideration of agent-based feedback to the building of adaptation strategies—neither from agricultural sector models nor from farm models—capable of identifying further option for production systems (e.g., new crops), and setting constraints due to technology, resource limitations, or both. Also, given the time span of the analysis, no innovation (e.g., new genotypes) was tested. This hypothesis can be considered mostly adequate for 2020, but is probably quite conservative for 2050, when even the adapted systems tested would not be very effective at all sites in alleviating the consequences of climate change. In the latter case, complete changes in the typology of production systems should be tested, rather than simple changes in agro-management and resource use evaluated in this study.

#### 7.4.1.3 Biophysical Results

**Wheat**

Without adaptation, wheat yields were significantly affected by climate change, regardless of the emission scenario or GCM considered (Tables 10, 14, Appendix 1). Percentage yield decreases were more pronounced in Mexico, in the Caribbean region, and in the Northeastern parts of the continent (Colombia and Brazil). Projected water-limited productions for 2020 and 2050 were always lower than in the baseline, with Southern and Western countries less affected. Yield reductions were due to the shortening of the crop cycle due to higher thermal time accumulation, leading to lesser days available to fill grains. The projected yield decrease due to diseases in 2020 and 2050 was significant. Frost damages were expected to affect wheat yields less seriously in Chile, where shortened cycles will reduce the crop exposure to pathogens, thus reducing also the pressure of wheat leaf rust on the crop. With few exceptions (e.g., Chile), insufficient water availability affected wheat productivity more than other factors, thus suggesting the development of varieties with characteristics able to assure higher resistance to water shortages, e.g., more capability to deepen the soil portion explored by roots, more favorable leaf angle distribution.

Compared to the simulations carried out without the implementation of adaptation strategies, projected impacts were decidedly less pronounced for all the production levels and scenarios considered (Tables 18, 22, Appendix 1). Impact on water limited yields was still significant however, with water availability playing a key role in limiting wheat productivity: the use of genotypes with longer cycles compensated for the climate change effect in reducing the grain filling period, but increased transpiration demands. Except for Chile, disease pressure decreased everywhere, although no adaptation strategies specific for leaf rust were applied. The highest indirect benefits of adaptation on disease-limited productions were simulated for Brazil, Uruguay, and for Central America and Caribbean countries. Insufficient water availability played a major role in Brazil and Chile, whereas disease pressure affected productions especially in Argentina.

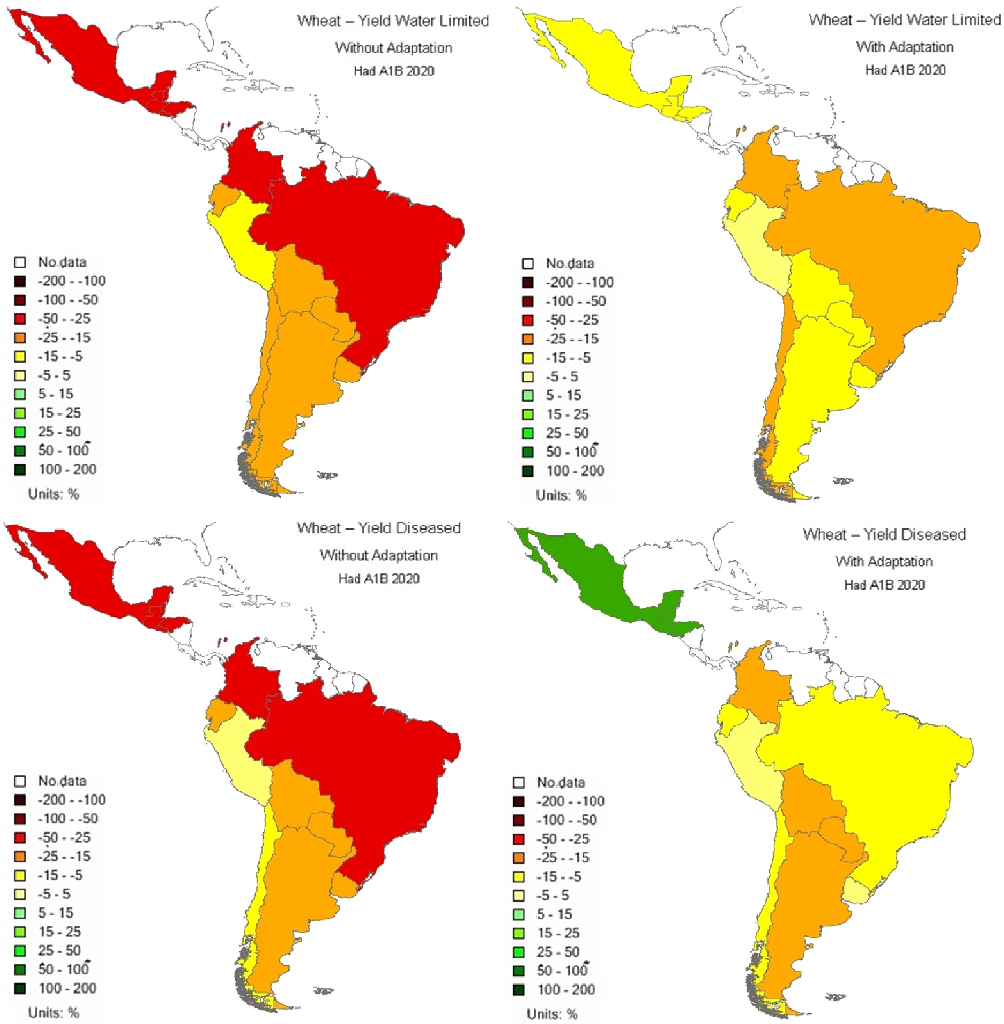



**Figure 10. Wheat Productivity Shocks (Hadley A1B) to 2020**

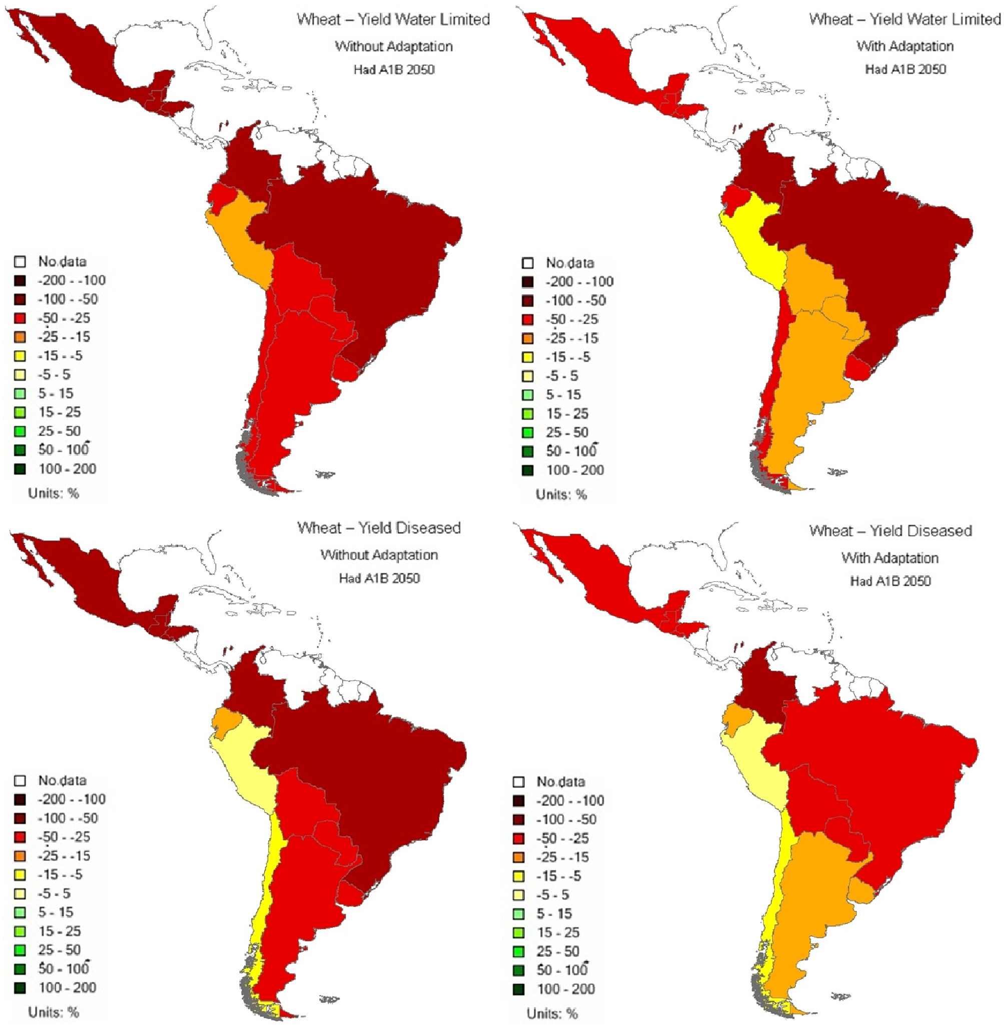



**Figure 11. Wheat Productivity Shocks (Hadley A1B) to 2050**

**Soybean**

Without adaptation strategies, soybean yields were affected by climate change in 2020 and increasingly in 2050, although with different magnitudes throughout Latin America (Tables 12, 16 Appendix 1). Yield losses were larger in Brazil and in the Northern part of the continent (>-30% with respect to baseline), whereas in Argentina, Uruguay, Bolivia and Colombia yield decreases were less pronounced. By considering projected water-limited production level, yield losses were reduced in Argentina and Uruguay, whereas in Brazil, Central America and Caribbean regions they suffered reductions. This could be explained by the greater impact of climate change in Brazil (see D2 for further details), where the reduction of crop cycle length is more pronounced than in other parts of Latin America, markedly shortening the soybean grain-filling period. The impact of rust disease did not increase with warming, with the exception of Colombia, in which it increased for all combinations GCM $\times$ emission scenario. This can be explained by the severity of the increase in temperature regimes in a warm environment such as the Colombian one, in turns leading to more favorable conditions for the pathogen.

Adaptation strategies (Tables 20, 24) reduced the magnitude of impacts across all scenarios and time windows considered. For example, considering the potential production level, there were situations with positive impacts of climate change with adaptation (Ecuador and Uruguay). The most affected country was Brazil, with a maximum percentage of yield losses still close to -25% (Hadley-A1B). In certain countries, percentage yield decreases were similar regardless of water management status (i.e., Brazil, Colombia, Uruguay, Central America and Caribbean); in others, the climate change impact was larger under water-limited conditions (Ecuador). In Argentina, the use of varieties with longer cycle effectively compensated the climate change negative effects tending to shorten crop cycles.

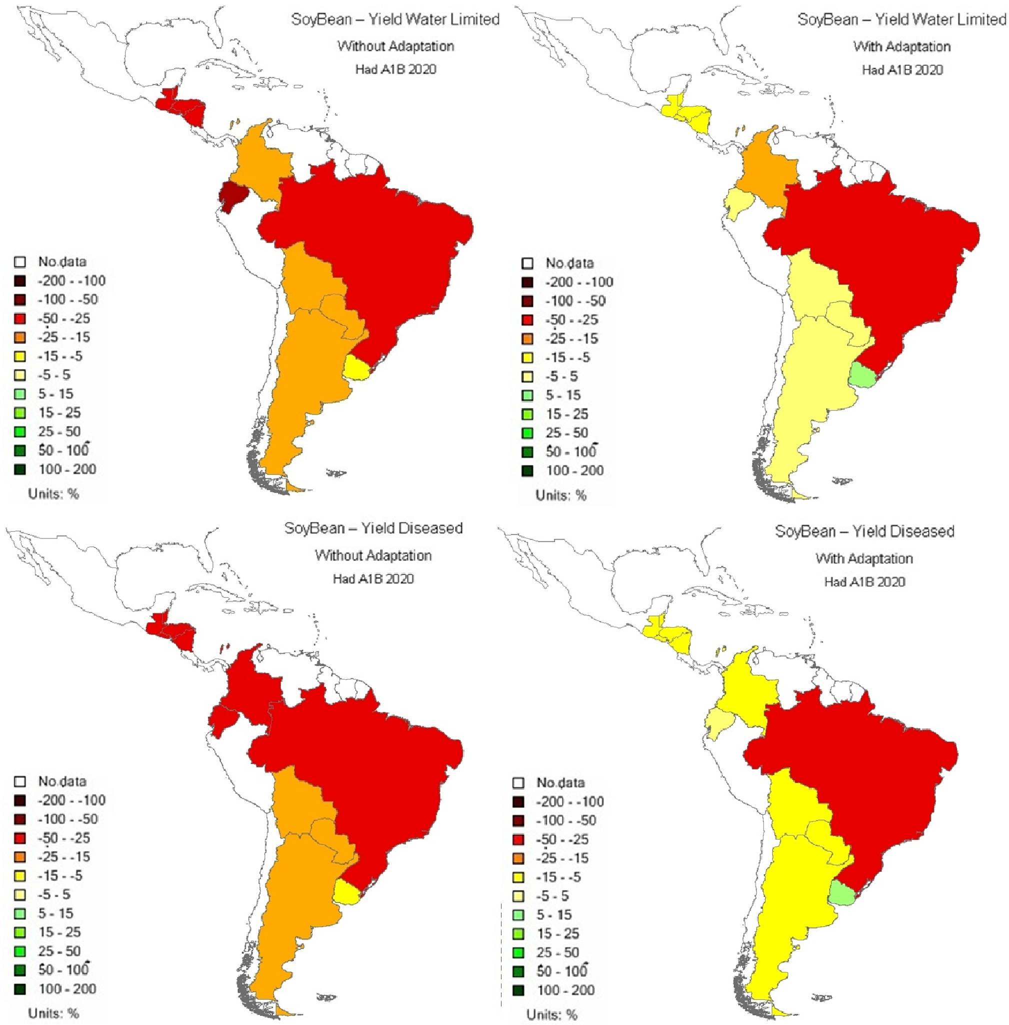



**Figure 12. Soybean productivity shocks (Hadley A1B) to 2020**

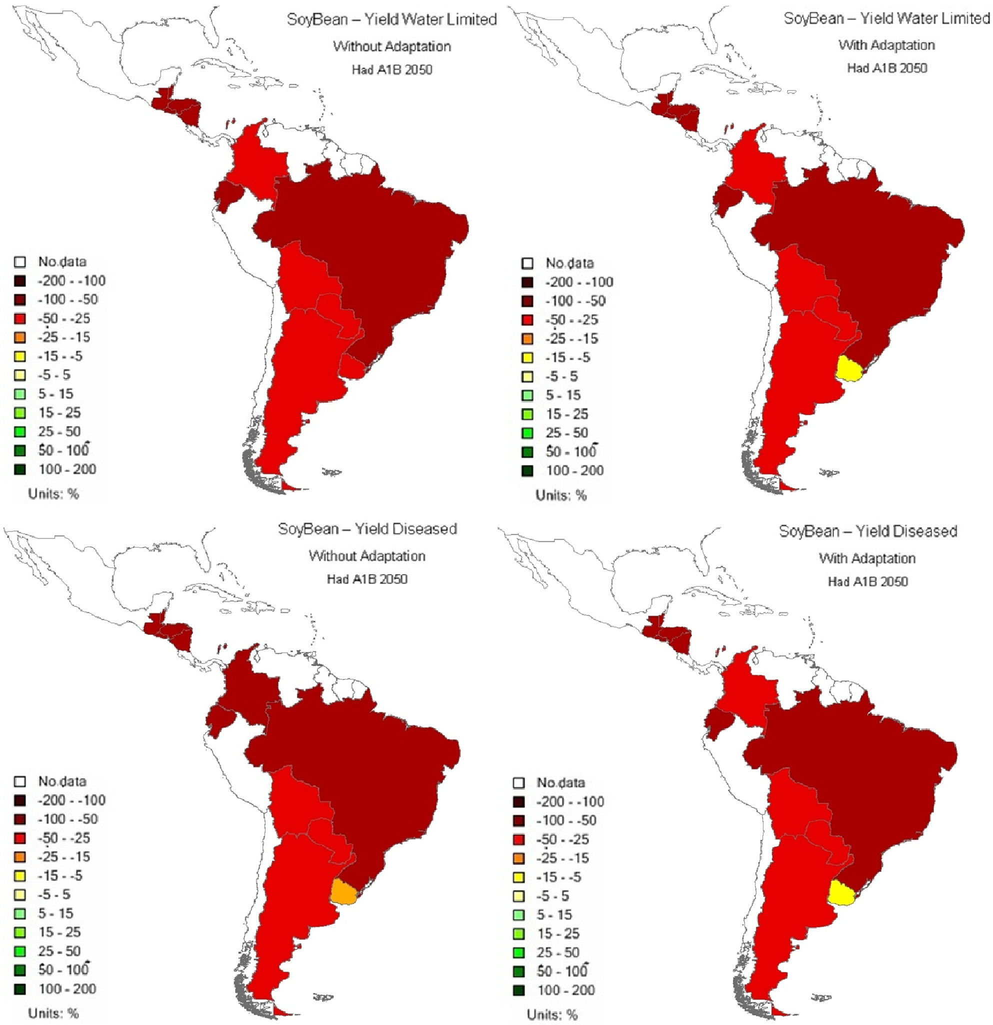



**Figure 13. Soybean productivity shocks (Hadley A1B) to 2050**

## Maize

Climate change negatively affected the yields of maize throughout Latin America, regardless to the emission scenario or GCM is used (Tables 11, 15, Appendix 1). This was mainly due to the reduction in the grain filling period under the higher thermal time accumulation rates, not compensated for by the increase in daily biomass accumulation rates and by the carbon dioxide fertilization effect (lower in C4 species like maize). The countries most affected were Brazil, Ecuador, Mexico and Caribbean countries, where maize is one of the main crops Generally, the Hadley GCM led to the highest losses except for Brazil and Ecuador (for the latter, only for the B1 scenario). Abiotic factors did not significantly affected maize productions, with the only exceptions are represented by a slight yield decrease in Mexico, Central America, and Caribbean. Considering the heterogeneity of the responses in the area, it is evident the need for adaptations strategies developed at country level.

For the 2020 time frame, and to a much lower extent in 2050, adaptation strategies significantly reduced climate change impacts on grain maize yields in most of the regions of interest (Tables 19, 23, Appendix 1), although yield decrease was still relevant in major maize producing countries, like Mexico.

Higher percentage decreases were simulated for the Hadley GCM compared to the NCAR one, with A1B emission scenario usually leading to the most severe situations. Adaptation strategies positively concurred to limit climate change damage to maize production, even in the countries where the grey leaf spot resulted the most limiting factor.

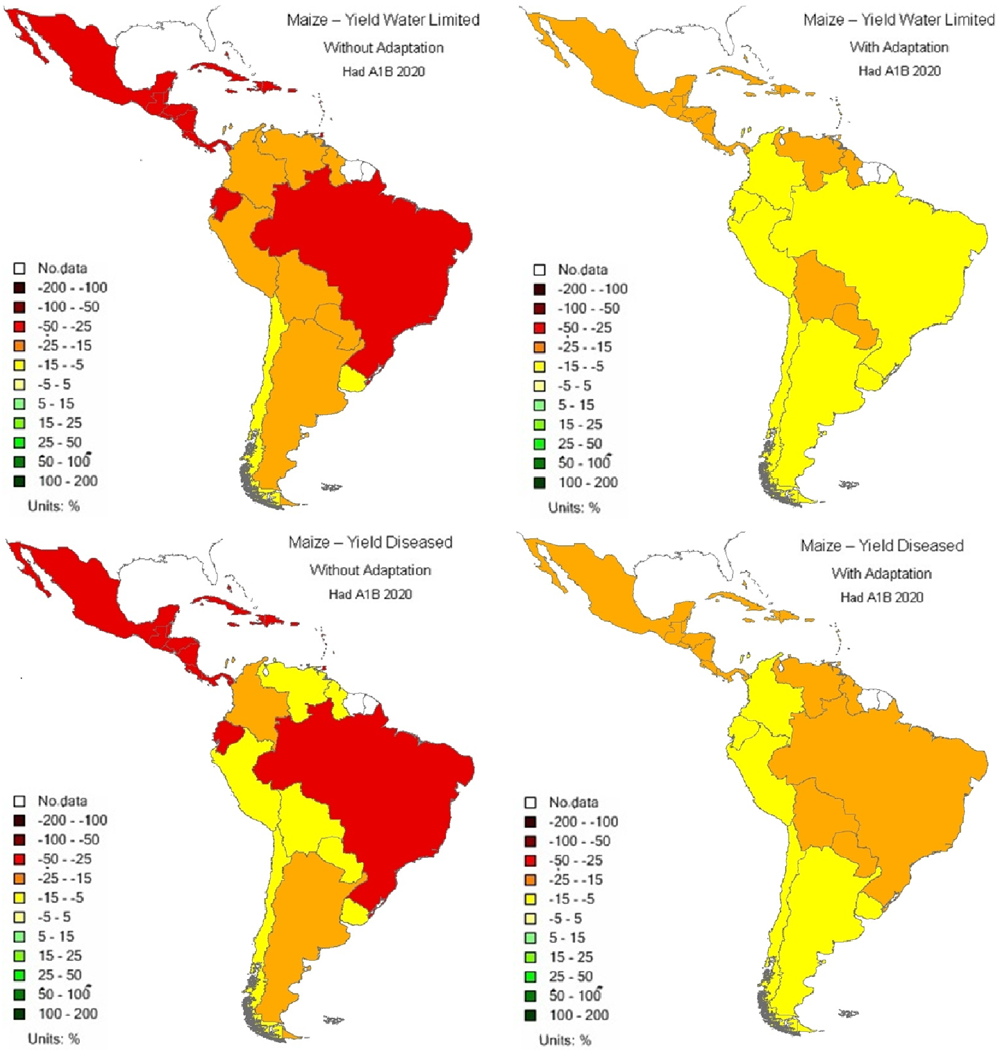



**Figure 14. Maize Productivity Shocks (Hadley A1B) to 2020**

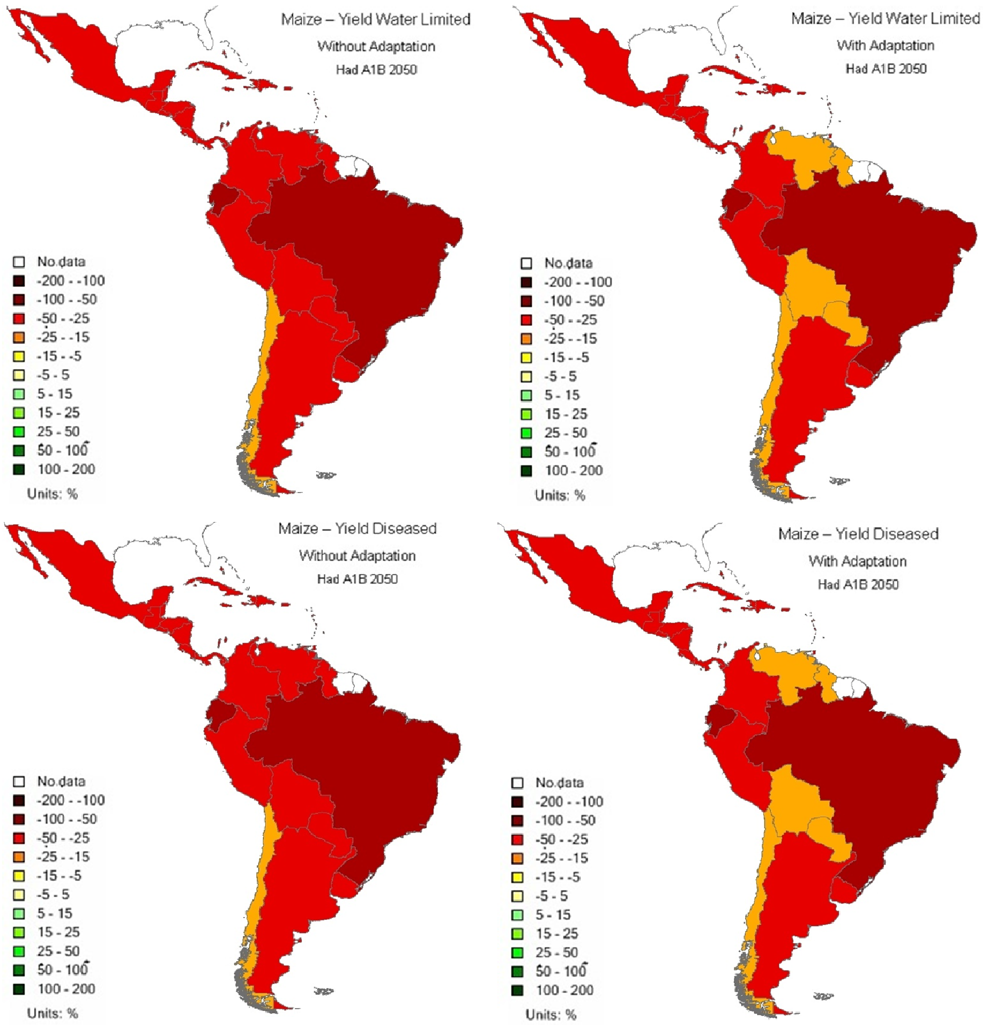



**Figure 15. Maize Productivity Shocks (Hadley A1B) to 2050**

**Rice**

Except for Brazil, Mexico, and Caribbean, 2020 and 2050 projections are encouraging, with percentage variations positive in most of the cases (Tables 13, 17, Appendix 1). This is due to the high thermal requirements of rice (a macrothermal of tropical origin). Under the *current* climate (i.e., the baseline), productions are slightly penalized by limitations to photosynthesis due to sub-optimal temperatures. Under warmer conditions, the negative effect due to the shorter grain filling period due to the higher thermal time accumulation rates is counterbalanced by higher biomass accumulation rates because of the most favorable conditions for photosynthesis. The net result of these two opposite effects is a generalize increase in productivity, except in countries already experiencing warm climates (where thermal conditions for photosynthesis are already close to optimal levels and the reduced grain filling period leads to a decrease in final yields). In temperate areas (especially in Uruguay) climate change leads to a decrease in the incidence of pre-flowering cold shocks inducing sterility. Except for Brazil and Caribbean, the blast disease pressure on the crop decreases, because of thermal and pluviometric conditions less favorable for the pathogen *Pyricularia grisea*.

Adaptation strategies – based on the use of different genotypes and of different sowing dates – were applied only for the countries where a decrease in production levels was observed (Tables 21, 25, Appendix 1): Brazil, Ecuador, Mexico and Caribbean. The rational behind the adaptation was mainly related to the use of genotypes with a longer cycle to compensate the climate change effect in shortening the grain filling period. Sowing dates were also changed. Results indicate that future conditions will be decidedly favorable for rice. The use of long-cycle genotypes allowed to get long grain filling periods and high daily biomass accumulation rate, because of negligible thermal limitation to photosynthesis and of the carbon dioxide fertilization effect, higher for the C3 species than for the C4 ones (e.g., maize). As discussed for wheat, the implementation of adaptation strategies targeting crop features mainly related with crop cycle length led to indirect benefits in terms of pathogens pressure (Fig. 12.b). This could suggest possible reduction of agrochemicals in the future in important rice producing countries, like Brazil, and to the uselessness of investing efforts in developing blast-resistant varieties.

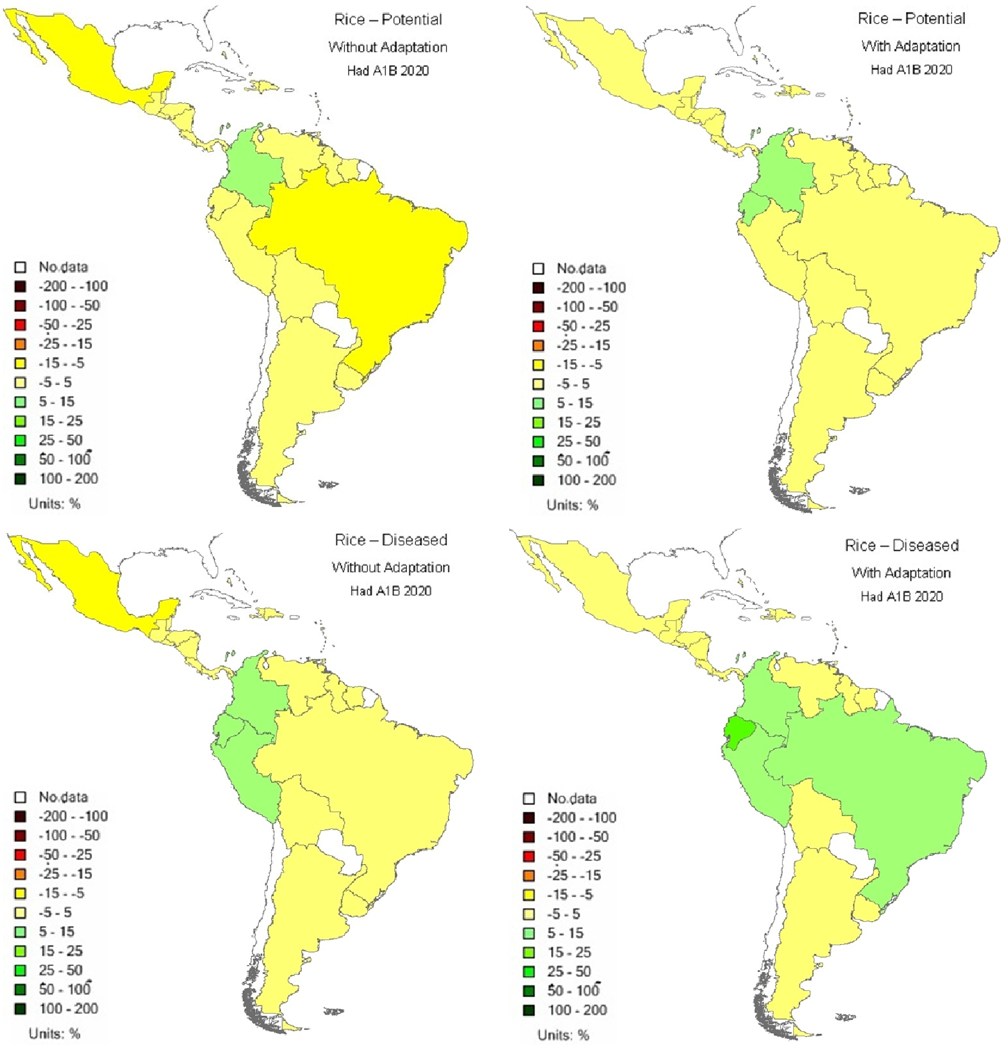



**Figure 16. Rice Productivity Impacts (Hadley A1B) to 2020**

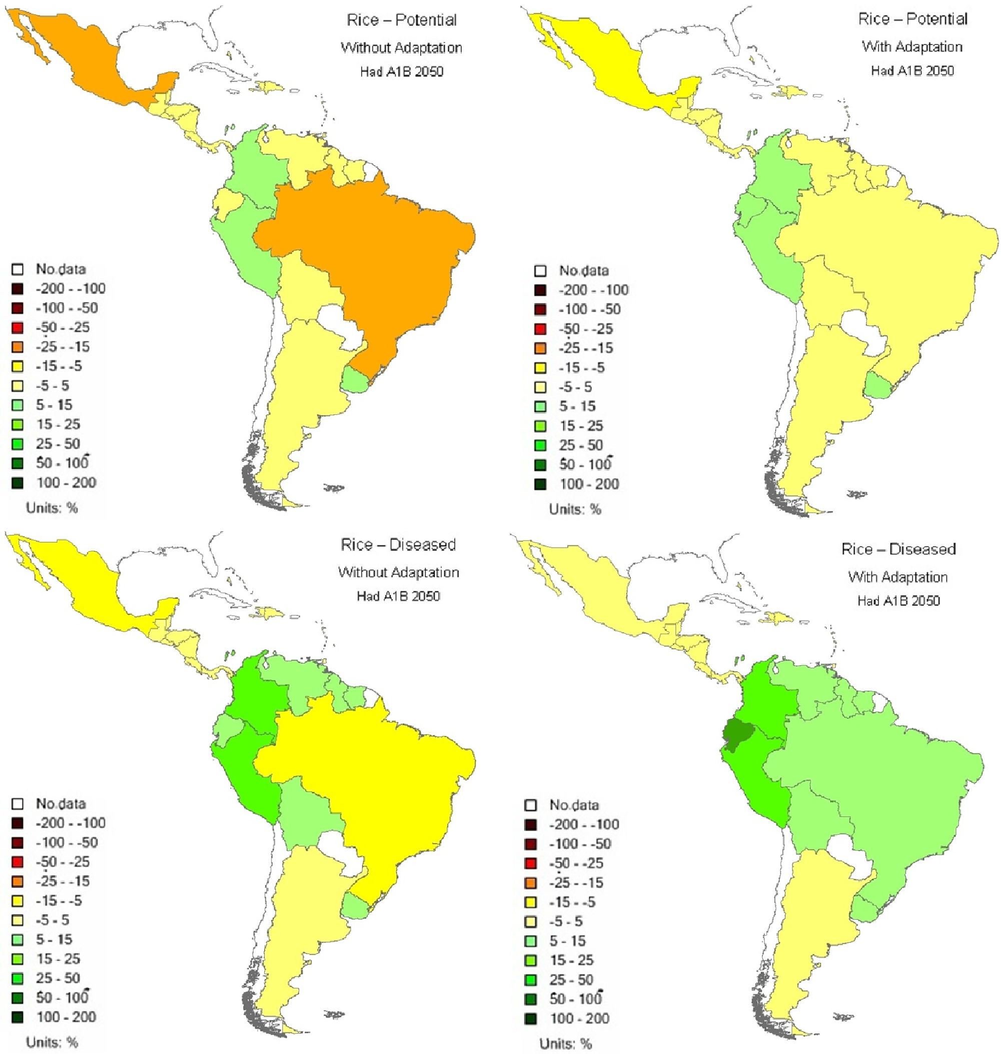



**Figure 17. Rice Productivity Impacts (Hadley A1B) to 2050**

### 7.4.1.4 Agro-management Adaptation

At sub-national scales, specific simulations and analyses were carried out to resolve irrigation solutions under climate change regimes necessary to limit, at each simulated grid, the otherwise negative impacts under the no adaptation scenarios.

## Maize

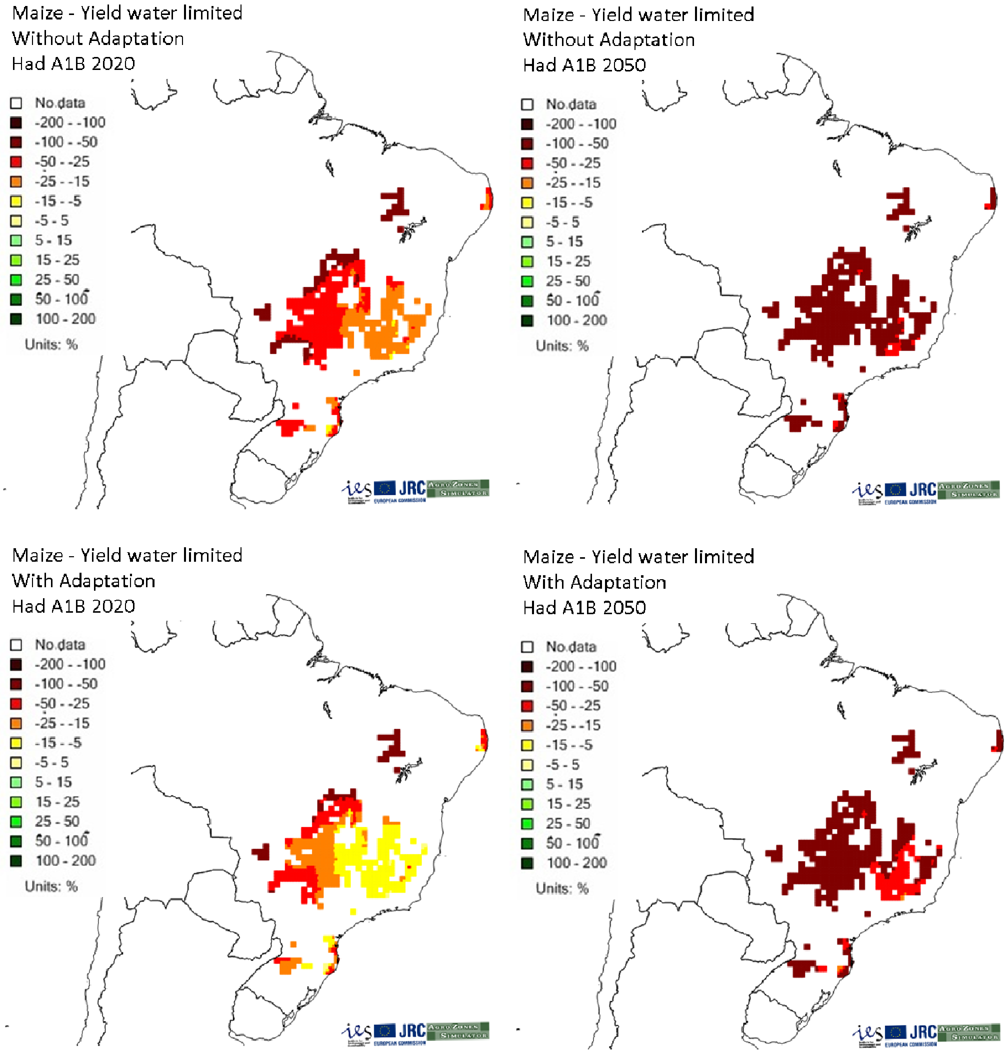



**Figure 18. Maize Productivity Impacts (Hadley A1B) 2020-2050**

## Soybean

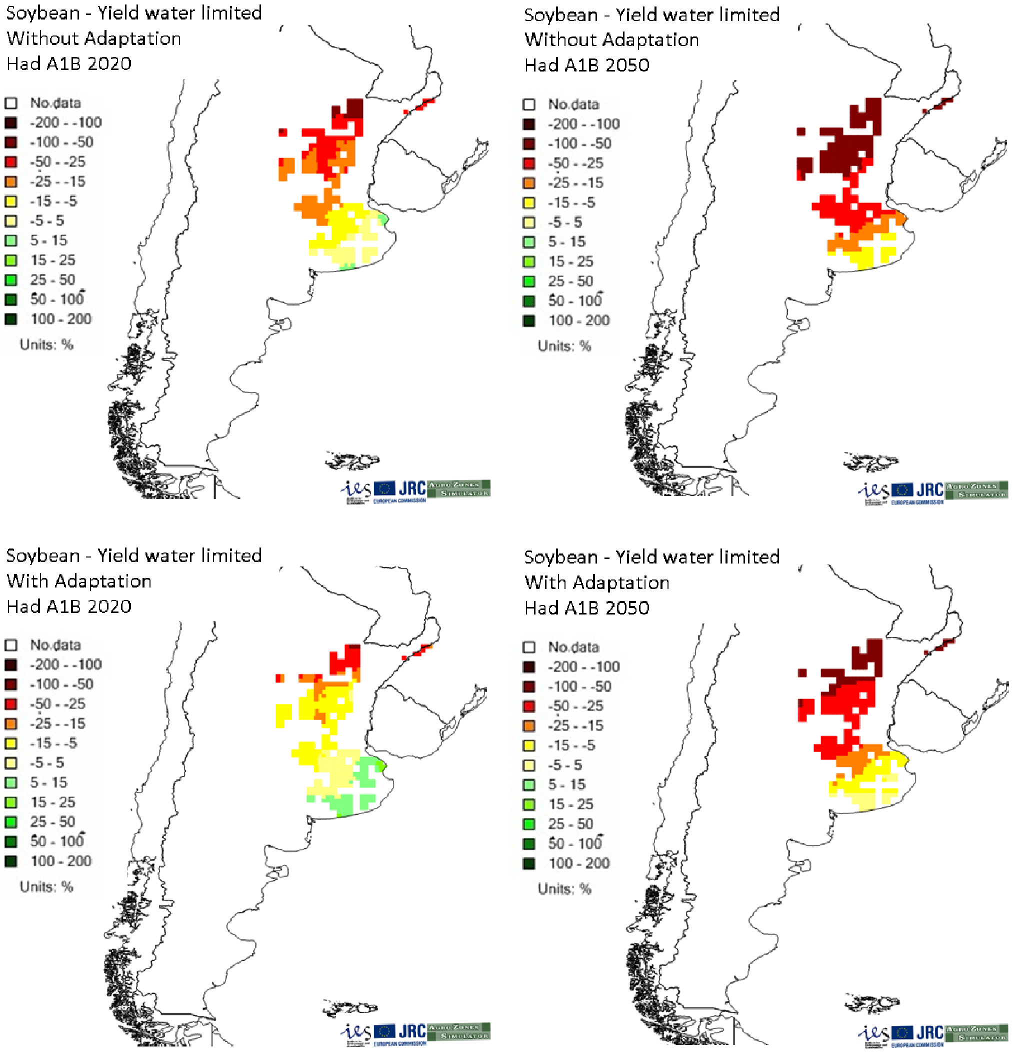



**Figure 19. Soybean Productivity Impacts (Hadley A1B) 2020-2050**

### 7.5. Conclusions

This report detailed the components of a new modelling platform for crop impact studies, the AZS-ENVISAGE model, capable of evaluating the dynamic interactions of agro-climatic and field management factors impacting on crop growth and development, while interacting with a detailed general equilibrium model in order to include the constraints of realistic socio-economic factors on actual production levels, trade and welfare outcomes.

Although several such platforms exist, the current work represents progress on a number of current bottlenecks, following recommendations made in IPCC AR4. First, its basic datasets and biophysical models are fully transparent, both in terms of their validation and availability of components, including remote accessibility to interested users. These key features imply that stakeholders around the world can access the platform, evaluate it, test it, and wherever possible, improve it by adding or refining datasets, or even by modifying or substituting component code, as appropriate for specific areas of study or particular problems. Second, the platform is extensible to any region of the world, and is independent of spatial scale, so that the latter can be also modified by users as the availability of more refined dataset for specific regions arise. Third, it allows for explicit, albeit simplified, adaptation of agro-management, including a crop suitability assessment module, in order to test and evaluate adaptation strategies aimed at limiting risk under climate change scenarios. Finally, the linkages between biophysical and economic models are explicit, and allow in principle for two-way interactions, with the ability to evaluate economically specific agro-management solutions identified by the crop models, so that the latter could further test specific solutions and then feed back the information for new updated modelling runs.

This report documented in details model components, and then focused on the application of the modelling platform to evaluating the impacts of climate change on key crops in Latin America.

Results of this study confirmed and extended previous findings, indicating that the impacts of climate change on agriculture in Latin America are expected to be significant, with severe risk to crop production in most countries, and the potential to alter regional production and welfare distribution compared to present. Next steps will include evaluation of the platform regionally, via interactions with stakeholders and extension of regional dataset addressing specific problems, and the extension of the platform to allowed more dynamic interactions between biophysical and economic computations.

Data
Framework
Case study
Metrics

# A PROPOSAL OF AN INDICATOR FOR QUANTIFYING MODEL ROBUSTNESS BASED ON THE RELATIONSHIP BETWEEN VARIABILITY OF ERRORS AND OF EXPLORED CONDITIONS

Roberto Confalonieri, Simone Bregaglio, Marco Acutis

Published in: Ecological Modelling (2011) 221, pp. 960-964

### 8.1. Abstract

The evaluation of biophysical models is usually carried out by estimating the agreement between measured and simulated data and, more rarely, by using indices for other aspects, like model complexity and overparameterization. In spite of the importance of model robustness, especially for large area applications, no proposals for its quantification are available. In this paper, we would like to open a discussion on this issue, proposing a first approach for a quantification of robustness based on the variability of model error to variability of explored conditions ratio. We used modelling efficiency (*EF*) for quantifying error in model predictions and a normalized agrometeorological index (*SAM*) based on cumulated rainfall and reference evapotranspiration to characterize the conditions of application. Population standard deviations of *EF* and *SAM* were used to quantify their variability. The indicator was tested for models estimating meteorological variables and crop state variables. The values provided by the robustness indicator ($I_R$) were discussed according to the models' features and to the typology and number of processes simulated. $I_R$ increased with the number of processes simulated and, within the same typology of model, with the degree of overparameterization. No correlation were found between $I_R$ and two of the most used indices of model error (*RRMSE*, *EF*). This supports its inclusion in integrated systems for model evaluation.


**Keywords**: Model evaluation, air relative humidity, modelling efficiency, WARM, CropSyst.

## 8.2. Introduction

Simulation models are increasingly used in large area agro-environmental applications to support decision making. In this context, real-time monitoring of crop conditions, estimating the environmental impact of cropping systems, and evaluating the effects of alternate management and climate change scenarios are some of the crucial challenges modellers are facing with (Bannayan and Crout, 1999). For these kinds of application, like for all the others where simulation models are used, it is necessary to clearly identify the objectives and conditions of application (e.g., scale, availability of data) in order to derive a criterion to evaluate the models according to their suitability. This will allow to identify the *best model* among those available to simulate the biophysical processes of interest in the specific conditions which characterize each specific modelling study.

Model evaluation - as an autonomous discipline - is one of the issues which mostly catalyzed the attention of the modellers community in the last years (e.g., Mayer and Butler, 1993; Rykiel Jr., 1996; Bellocchi et al., 2009). Many indices for quantifying the agreement between measured and simulated data were proposed (e.g., Loague and Green, 1991), together with indices for assessing model complexity (e.g., Akaike, 1974) and relevance (Confalonieri et al., 2009c). The need of defining evaluation criteria accounting for different aspects of models behaviour led to the use of fuzzy-based procedures for aggregating different indices (Bellocchi et al., 2002) in order to allow multi-metric model evaluations (e.g., Confalonieri et al., 2009c).

Robustness is one of the model features users are more interested in, especially in case of large area applications, when users have to trust the model in conditions far from those in which the model itself was calibrated and tested. Although no expressions for its quantification have been proposed, it can be defined as a measure of models reliability under different sets of experimental conditions. Lack of robustness can be explained (i) by incoherence in some of the mathematical relationships used to formalize the knowledge, (ii) by gaps in the knowledge itself, or (iii) by the inclusion of the effects of a specific location, season, or management practice in the model's parameters, which instead should only describe the features of the biophysical system modelled, regardless to the conditions of application. Bellocchi et al. (2009) suggested that a sound test of model robustness is obtained when a validation is carried out by comparing the seasonal evolution of different simulated variables with observations collected in a large number of experiments under a broad range of conditions, covering different locations and management practices. Although these criteria appear suitable for testing models robustness and instinctively reasonable, they do not provide any quantification for this important aspect, thus avoiding the use of this concept in integrated multi-metric systems for model evaluation. Confalonieri et al. (2009a) proposed a quantification of model robustness based on the comparison of model performances during calibration and validation, suggesting that a model is robust if its performances at the end of the calibration process are not significantly better than those shown on an independent validation dataset. The same authors observed that this method has the limit of being drastically influenced by the selection of the data used for calibration and validation, therefore suggesting multiple calibration tests against independent datasets (i.e., every possible combinations of calibration and validation datasets). This method appears hard to perform, even in case tools for automatic calibration are available.

The objectives of this study were (i) to propose an indicator for quantifying model robustness, (ii) to test it on two typologies of models, and (iii) to discuss it in terms of relationships with other aspects of model evaluation.

## 8.3. Materials and methods

### 8.3.1. A new indicator of model robustness (*$I_R$*)

The indicator of model robustness ($I_R$) is calculated using Eq. 1:

$$I_R = \sigma_{EF} / \sigma_{SAM} \qquad [1]$$

where $\sigma_{EF}$ (Eq. 2) is the standard deviation of the modelling efficiencies (*EF*; Nash and Sutcliffe, 1970; -∞ ÷ +1; optimum = 1; if positive indicates that the model is a better predictor than the average of observations) calculated for different datasets:

$$EF = 1 - \sum_{i=1}^{n} (D_i)^2 \Big/ \sum_{i=1}^{n} \left(M_i - \overline{M}\right)^2 \qquad [2]$$

where $D_i$ is the difference between $S_i$ and $M_i$, with $S_i$ and $M_i$ being the *i*th simulated and the *i*th measured values, respectively; $n$ is the number of couples $S_i$-$M_i$; $\overline{M}$ is the mean of measured values.

$\sigma_{SAM}$ is the standard deviation of the values of a Synthetic AgroMeteorological indicator (SAM; -1 ÷ +1; Eq. 3) calculated for the same datasets used to calculate $\sigma_{EF}$.

$$SAM = (Rain - ET0)/(Rain + ET0) \qquad [3]$$

where *ET0* (mm) is the reference evapotranspiration calculated for the period March 1st – October 31st and *Rain* (mm) is the cumulated rainfall in the same period. In case of other typologies of biophysical models, *SAM* must be substituted with another indicator describing the variability among datasets. In order to calculate both *EF* and *SAM* standard deviations, the available datasets are assumed to coincide with their population, therefore the sum of the squared deviations is divided by the number of datasets.

$I_R$ assumes values between 0 and +∞, with optimum = 0.

### 8.3.2. Models and datasets used

$I_R$ was tested using published data from papers in which two categories of models were tested (Table 1): meteorological and crop growth and development.

The papers were selected according to the following criteria: (i) availability of data from different sites/years/variables; (ii) presence of *EF* values. Abraha and Savage (2008) tested six models for the estimation of daily global solar radiation from air temperature using data collected in seven sites spread through four continents. Bregaglio et al. (2009) evaluated 13 modelling solutions for the estimation of hourly air relative humidity using data collected in 22 European sites. Confalonieri et al. (2009a) compared three crop models for the simulation of rice aboveground biomass (AGB) in Northern Italy. Among these crop models, WARM was also evaluated against rice AGB and leaf area index (LAI) data collected in China by Confalonieri et al. (2009b), whereas CropSyst was used by Bechini et al. (2006) for simulating wheat growth.

**Table 1. Data used for this study. Details on models used can be found in the text**

| Type of model* | Datasets: Site name | Latitude | Longitude | Years | Models used** | Variables simulated*** | References |
|---|---|---|---|---|---|---|---|
| 1 | Davis, USA | 38° 32' N | 121° 47' W | 1985-2005 | BC, CD, DB, Hgvs, HKS, MH | Rad | Abraha and Savage, 2008 |
| | Cortez, USA | 37° 14' N | 108° 41' W | 1992-2005 | | | |
| | Griffith, Australia | 34° 17' S | 146° 3' E | 1986-2005 | | | |
| | Padova, Italy | 44° 58' N | 12° 11' E | 1990-2003 | | | |
| | Pretoria, South Africa | 25° 45' S | 28° 11' E | 1993-2003 | | | |
| | Rothamsted, UK | 51° 48' N | 0° 24' E | 1980-2000 | | | |
| | Wageningen, The Netherlands | 51° 58' N | 5° 38' E | 1985-2005 | | | |
| | Almonte, Spain | 37° 2' N | 6° 31' W | 2007 | RH 1, RH 2, RH 3, RH 4, RH 5, RH 6, RH 7, RH 8_0, RH 8_1, RH 8_2, RH 8_3, RH 8_4, RH 8_5 | HARH | Bregaglio et al., 2009 |
| | Arezzo, Italy | 43° 3' N | 11° 5' E | 2007 | | | |
| | Campogalliano, Italy | 44° 4' N | 10° 5' E | 2007, 2008 | | | |
| | Caronia Buzza, Italy | 38° 0' N | 14° 3' E | 2003-2007 | | | |
| | Isla Cristina, Spain | 37° 1' N | 7° 3' W | 2007 | | | |
| | Firenze, Italy | 43° 5' N | 11° 6' E | 2007 | | | |
| | Grosseto, Italy | 42° 5' N | 11° 1' E | 2007 | | | |
| | Javea, Spain | 38° 5' N | 0° 1' E | 2007 | | | |
| | Lagos, Portugal | 37° 0' N | 8° 4' W | 2005 | | | |
| | La Palma, Spain | 37° 4' N | 0° 6' W | 2007 | | | |
| | Lentini, Italy | 37° 2' N | 15° 0' E | 2004-2007 | | | |
| | Lucca, Italy | 43° 5' N | 10° 3' E | 2007 | | | |
| | Mineo, Italy | 37° 2' N | 14° 4' E | 2003-2007 | | | |
| | Mirandola, Italy | 44° 5' N | 11° 0' E | 2005 | | | |
| | Misilmeri, Italy | 38° 0' N | 13° 3' E | 2003-2007 | | | |
| | Paternò, Italy | 37° 4' N | 14° 5' E | 2003-2007 | | | |
| | Pistoia, Italy | 43° 6' N | 10° 6' E | 2007 | | | |
| | Ribera, Italy | 37° 3' N | 13° 2' E | 2003-2007 | | | |
| | Riposto, Italy | 37° 4' N | 15° 1' E | 2005-2007 | | | |
| | San Felice sul Panaro, Italy | 44° 5' N | 11° 1' E | 2007 | | | |
| | Varese, Italy | 45° 5' N | 8° 5' E | 2003, 2004 | | | |
| | Zola Pedrosa, Italy | 44° 3' N | 11° 1' E | 2005, 2006 | | | |
| 2 | Castello d'Agogna, Italy | 45° 14' N | 8° 41' E | 1994-1996 | WARM, CropSyst, WOFOST | AGB (rice) | Confalonieri et al., 2009a, b |
| | Gudo Visconti, Italy | 45° 22' N | 9° 0' E | 1990 | | | |
| | Mortara, Italy | 45° 15' N | 8° 45' E | 1996 | | | |
| | Opera, Italy | 45° 22' N | 9° 12' E | 2002, 2004 | | | |
| | Velezzo Lomellina. Italy | 45° 9' N | 8° 44' E | 1999 | | | |
| | Vercelli, Italy | 45° 19' N | 8° 25' E | 1989, 1990 | | AGB, LAI (rice) | |
| | Vignate, Italy | 45° 29' N | 9° 22' E | 2002 | | | |
| | Changping, China | 40° 02' N | 116° 10' E | 2001, 2002 | WARM | AGB, LAI (rice) | Confalonieri et al., 2009b |
| | Gaozhai, China | 34° 02' N | 114° 51' E | 2001 | | | |
| | Jiangpu, China | 32° 24' N | 118° 46' E | 2001, 2002 | | | |
| | Tuanlin, China | 30° 52' N | 112° 11' E | 1999, 2000 | | | |
| | Sant'Angelo Lodigiano, Italy | 45° 15' N | 9° 22' E | 1986-1990, 2001 | CropSyst | AGB, PNC, UPTK | Bechini et al., 2006 |
| | Lodi, Italy | 45° 19' N | 9° 28' E | 1996 | | | |

* 1: meteorological; 2: crop growth and development

** BC: Bristow and Campbell (1984); CD: Donatelli and Campbell (1998); DB: Donatelli and Bellocchi (2001); Hgvs: Hargreaves et al. (1985); Hunt et al. (1998); Mahmood and Hubbard (2002); RH 1, 2: Bekele et al. (2007); RH 3, 4: Hubbard et al. (2003); RH 5: Linacre (1992); RH 6: Ephrat et al. (1996); RH 7: Waichler et al. (2003): RH 8_X: Allen et al. (1998)

*** Rad: global solar radiation (MJ $m^{-2}$ $d^{-1}$); HARH: hourly air relative humidity (%); AGB: aboveground biomass (t $ha^{-1}$); LAI: leaf area index ($m^2$ $m^{-2}$); PNC: plant N content (%): UPTK: N uptake (kg $ha^{-1}$); N-$NO_3^-$, N-$NH_4^+$: 10 cm soil content (kg $ha^{-1}$)

## 8.4. Results and Discussion

Table 2 shows the values of $I_R$ calculated for the different models belonging to the two typologies analyzed, together with the population standard deviations of *EF* and *SAM* – used for its computation – and the average values of *RRMSE* and *EF*.

**Table 2. Average and population standard deviation of relative root mean square error (*RRMSE*, %), modelling efficiency (*EF*), population standard deviation of the synthetic agrometeorological indicator (*SAM*), and Indicator of model robustness ($I_R$) for the models under study. Greyed areas show the best result per metric**

| Type of model* | Variables simulated** | Model used | $\mu_{RRMSE}$ (%) | $\mu_{EF}$ | $\sigma_{EF}$ | $\sigma_{SAM}$ | $I_R$ |
|---|---|---|---|---|---|---|---|
| 1 | Rad | BC | 23.16 | 0.8186 | 0.0488 | 0.2269 | 0.2151 |
| | | CD | 22.88 | 0.8200 | 0.0501 | | 0.2208 |
| | | DB | 23.34 | 0.8114 | 0.0520 | | 0.2292 |
| | | Hgvs | 23.74 | 0.8071 | 0.0592 | | 0.2610 |
| | | HKS | 23.33 | 0.8143 | 0.0602 | | 0.2654 |
| | | MH | 25.84 | 0.7743 | 0.0414 | | 0.1823 |
| | HARH | RH 1 | 25.69 | 0.2329 | 0.2069 | 0.2074 | 0.9975 |
| | | RH 2 | 25.15 | 0.2440 | 0.2113 | | 1.0189 |
| | | RH 3 | 28.77 | 0.0747 | 0.3527 | | 1.7007 |
| | | RH 4 | 27.21 | 0.1845 | 0.2605 | | 1.2562 |
| | | RH 5 | 27.03 | 0.3171 | 0.1700 | | 0.8196 |
| | | RH 6 | 27.66 | 0.1631 | 0.3458 | | 1.6674 |
| | | RH 7 | 17.56 | 0.7004 | 0.0841 | | 0.4056 |
| | | RH 8_0 | 29.55 | -0.0082 | 0.3554 | | 1.7138 |
| | | RH 8_1 | 26.89 | 0.1057 | 0.2862 | | 1.3802 |
| | | RH 8_2 | 25.98 | 0.1015 | 0.2541 | | 1.2250 |
| | | RH 8_3 | 26.87 | -0.0419 | 0.3080 | | 1.4853 |
| | | RH 8_4 | 29.29 | -0.3510 | 0.4683 | | 2.2580 |
| | | RH 8_5 | 32.85 | -0.8486 | 0.7278 | | 3.5092 |
| 2 | AGB (rice) | CropSyst | 24.04 | 0.9012 | 0.0645 | 0.1914 | 0.3370 |
| | | WARM § | 23.78 | 0.9316 | 0.0312 | | 0.1632 |
| | | WOFOST | 25.34 | 0.9333 | 0.0712 | | 0.3719 |
| | AGB (rice; China) | WARM § | 22.98 | 0.8990 | 0.0820 | 0.2220 §§ | 0.3693 |
| | LAI (rice; China) | WARM | 39.21 | 0.6075 | 0.2236 | 0.1978 §§ | 1.1304 |
| | AGB (wheat) | CropSyst | 22.00 | 0.7170 | 0.1556 | 0.1200 | 1.2964 |
| | PNC (wheat) | CropSyst | 18.67 | -0.2500 | 2.6368 | 0.1027 | 25.6701 |
| | UPTK (wheat) | CropSyst | 17.22 | 0.5078 | 0.3542 | 0.1027 | 3.4483 |

* 1: meteorological; 2: crop growth and development

** Rad: global solar radiation (MJ $m^{-2}$ $d^{-1}$); HARH: hourly air relative humidity (%); AGB: aboveground biomass (t $ha^{-1}$); LAI: leaf area index ($m^2$ $m^{-2}$); PNC: plant N content (%): UPTK: N uptake (kg $ha^{-1}$)

§ different values for all the metrics were calculated for the Chinese dataset, to allow the comparison among $I_R$ values calculated for the three models used by Confalonieri et al. (2009a) under North Italian conditions

§§ not all the datasets from the same source (reference) contained all the variables. This explains the different values of $\sigma_{SAM}$

Among the models for the estimation of daily global solar radiation from air temperature data, MH (Mahmood and Hubbard, 2002) appears to be the most robust, although it presents the worst values for *RRMSE* and *EF*. This leads to conclude that, in the explored conditions, MH – 'the worst' – has a more stable behaviour than the other models across different sites and years, therefore providing the highest warrantees to avoid bad surprises when used under unexplored conditions (e.g., large area applications). RH 7 (Waichler and Wigmosta, 2003), the modelling solution providing the best agreement with measured data (best values for both *RRMSE* and *EF*), is also decidedly the most robust one. This can be explained by the fact that RH 7 is the only modelling solution using as inputs daily values of maximum and minimum air relative humidity. Among the models for crop growth and development compared by Confalonieri et al. (2009a), WARM demonstrated to be the most robust, although it is not the most accurate according to all the agreement metrics (best value for *RRMSE*, second for *EF*). It is interesting to notice that WOFOST (van Keulen and Wolf, 1986), the most complex model according to the Akaike Information Criterion (Confalonieri et al., 2009c), is the less robust. This could be explained considering that a model with a high number of parameters presents (i) a high number of degrees of freedom during the calibration process but also (ii) a high risk of including effects of specific sites and/or years in the values of parameters which should instead describe only the morphological and physiological features of the species (or varieties) simulated. If factors other than plant features are included in parameters values, the model could result unsuitable under conditions different from those used for its calibration. According to the simulations carried out in China, where LAI and AGB measured data were available, WARM showed a higher degree of robustness and better values for *RRMSE* and *EF* for the estimation of AGB. This reflects the lower accuracy of crop models in reproducing leaf area expansion, especially after the close canopy stage, already underlined by other authors (e.g., Bouman and van Laar, 2006). The lower robustness of CropSyst for the simulation of winter wheat AGB compared to rice AGB could be explained by the fact that, for the former, simulations were carried out under different levels of nitrogen fertilization, whereas only growth under potential conditions was simulated for rice. Therefore, wheat AGB values were probably affected by errors due to the need of simulating the nitrogen cycle in the plant-soil system.

In general, observing the average values for $I_R$ for each typology of model, it is possible to notice that robustness seems to decrease with increasing model complexity, with the best $I_R$ average value (1.0953) obtained by the meteorological models (against a value of 4.0983 for crop growth and development models). This is in agreement with the positive relationship between the length of the chain of simulated processes and the value of $I_R$ already discussed for N-limiting growing conditions.

Figure 1 shows the relationships between $I_R$ and the indices of agreement *RRMSE* and *EF*. The very low value for $R^2$ of the two regressions demonstrates that there are not redundancies between the information provided by $I_R$ and by the indices used for quantifying model accuracy. This should be considered decidedly important, since the concept of model robustness, in the proposed formalization, appears to be relatively independent from the model accuracy quantified during classical studies on model evaluation.

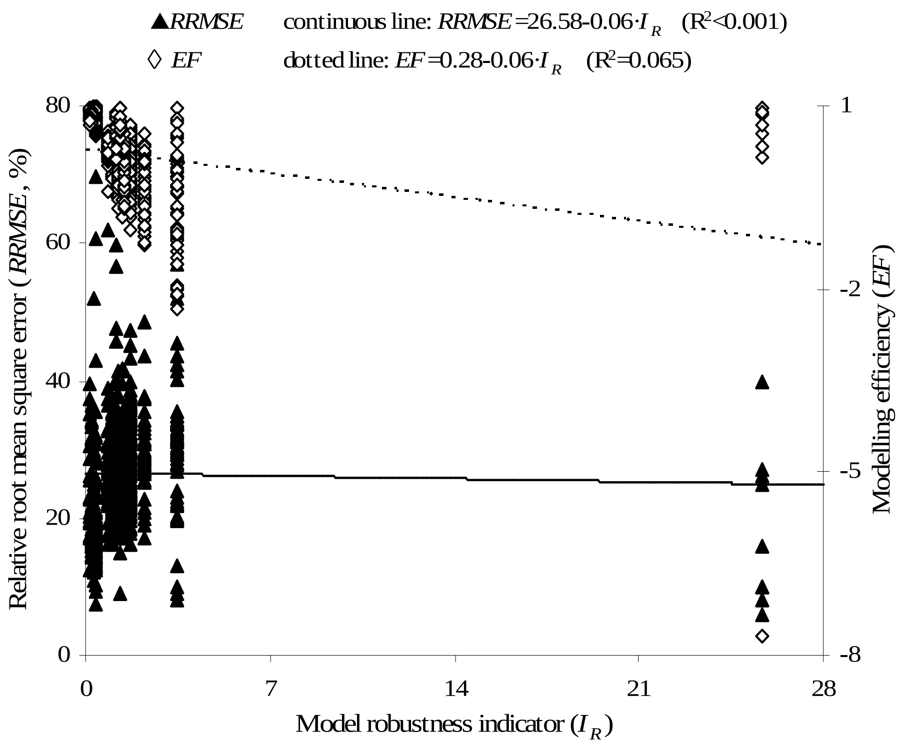


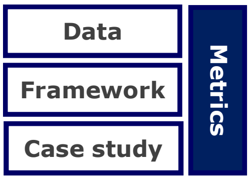

**Figure 1. Relationships and regression lines between model robustness indicator ($I_R$) and the indices of agreement relative root mean square error (*RRMSE*, %) and modelling efficiency (*EF*)**

### 8.5 Conclusions

The aim of this paper is far from proposing a final solution to the problem of quantifying model robustness. We simply would like to open a discussion on this important modelling issue. Quantifying the robustness of biophysical models under a wide range of conditions is crucial for whatever reasonable model evaluation. In fact, it allows to compare different modelling approaches according to their capability to avoid incoherent behaviours when used to extrapolate information about a system previously unexplored and, more generally, for a practical use of the biophysical models themselves.

The index we propose for characterizing a dataset from an agrometeorological point of view is just an attempt of deriving a simple normalized index based on rainfall and reference evapotranspiration, since the latter can be considered a synthetic representation of the culmination of numerous meteorological and agrometeorological processes. Of course, the concept of our robustness indicator is the ratio between the variability of model error and that of the conditions explored. In order to extend the use of the same robustness indicator to other typologies of model, a different index for characterizing the conditions of application must be used.

The independence of the information provided by the proposed indicator from the one related to the agreement between measured and simulated data under parameterization conditions strongly support the inclusion of $I_R$ in integrated systems for models evaluation.




# QUANTIFYING PLASTICITY IN SIMULATION MODELS

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Published in: Ecological Modelling (2012) 225, pp. 159-166

### 9.1. Abstract

Different methodologies for evaluating aspects of model performance going beyond the pure agreement between measured and simulated data have been recently proposed. These indicators and criteria for the evaluation of, e.g., complexity and robustness can be used in conjunction with well-known metrics for the evaluation of model accuracy – such as root mean square error and modelling efficiency – to get a deeper knowledge about models structure and behaviour. The aim of this paper is to propose an indicator of model plasticity, defined as the aptitude of a model to change the sensitivity to its parameters while changing the conditions of application. Sensitivity was here analysed using the Sobol' method for sensitivity analysis (SA). Concordance among parameters relevance (total order effect) estimated under different conditions allowed to quantify changes in the way models react to different environments. The concordance among the different SA results was related to the variability of a normalized agrometeorological indicator used to characterize the explored conditions. The plasticity indicator was tested using three different crop models (WARM, CropSyst, WOFOST; rice was simulated), 10 European locations, and 10 years for each location, for a total of 5,939,200 simulations and 300 SA experiments. Results indicated WOFOST as the most plastic, both within location, year, and by using all the combinations location $\times$ year, whereas WARM showed to be the less plastic across the conditions explored. Previous studies carried out on the same models in northern Italy seem to suggest a direct relationship between model complexity and plasticity, whereas model accuracy seems to be unrelated to these features. This consideration underlines that, in case of availability of different models with a similar degree of accuracy, different choices should be performed for different modelling studies, characterized by different aims and conditions of application.


**Keywords:** WARM, CropSyst, WOFOST, Model evaluation, Robustness.

## 9.2. Introduction

The evaluation of simulation models is recently moving from the simple assessment of the agreement between measured and simulated data towards the integrated evaluation of model features related to their theoretical formalization and behaviour. Especially when different approaches are compared, model evaluations are increasingly based on multi-metric techniques, where indicators specific for the assessment of different model features are applied and aggregated (Table 1).

**Table 1. Criteria for model evaluation, description and sample indices**

| Evaluation criteria | Description | Sample indices | References |
|---|---|---|---|
| Accuracy | The ability of the model to fit reference measured data | Root mean square error (RMSE) | Fox, 1981 |
| | | Modelling efficiency (EF) | Loague and Green, 1991 |
| | | Mean absolute error (MAE) | Schaeffer, 1980 |
| | | Coefficient of determination (R2) | Steel and Torrie, 1960 |
| Complexity | The parsimony of the model in representing the biophysical system | Akaike's information criterion (AIC) | Akaike, 1974 |
| | | Bayesian information criterion (BIC) | Schwarz, 1978 |
| Plasticity | The tendency of the model to change its behavior when applied to different conditions | Model plasticity (L) | This study |
| Robustness | The reliability of the model under different sets of conditions | Robustness indicator (IR) | Confalonieri et al., 2010 |

Aertsen et al. (2010) compared different approaches for predicting site quality in mountain forest by identifying three criteria: ecological interpretability, user-friendliness, and predictive performance, the latter in turns composed by three metrics: adjusted coefficient of determination, root mean square error (RMSE; Fox, 1981) and Akaike information criterion (AIC; Akaike, 1974). Confalonieri et al. (2009a) compared three models for rice simulation by assessing both their capability to reproduce observations and their complexity. The former was quantified with the correlation coefficient, modelling efficiency (EF; Nash and Sutcliffe, 1970), and probability of equal means by the paired Student t-test (P(t)), whereas the latter was evaluated using AIC and the ratio between relevant and total parameters identified via sensitivity analysis. Bregaglio et al. (2010) evaluated thirteen modelling solutions for the generation of hourly air relative humidity by comparing their robustness (IR; Robustness Indicator; Confalonieri et al., 2010), accuracy (EF; RMSE), the correlation between measured and simulated data (r) and the presence of patterns in residuals (Donatelli et al., 2004b). Basuki et al. (2009) compared different allometric equations for aboveground biomass estimation in tropical forests by evaluating their accuracy – using R2 and P(t) – and applicability, the latter using AIC. Confalonieri (2010) evaluated two crop simulators with regards to their balance, defined as the degree of homogeneity among parameters relevance.

The need for metrics going beyond the pure agreement between observations and simulated data led to the development and use of indicators and criteria for specific aspects of model structure. An evidence of their usefulness is provided by the frequent absence of correlation among them. Confalonieri et al. (2010a) analyzed the relationship between robustness and accuracy for different categories of agroecological models, founding no correlation between IR and two of the most used metrics for quantifying model accuracy: relative RMSE ($R2 < 0.001$) and EF ($R2 = 0.065$). In particular, they found that the Mahmood and Hubbard (2002) model for the estimation of global solar radiation was the most robust – although the less accurate – among the six alternative approaches compared by Abraha and Savage (2008).

Sensitivity analysis (SA) is aimed at identifying the parameters with the highest relevance on model outputs and it is often performed to select those on which to concentrate the efforts during the calibration. More in general, SA can be considered a powerful tool for the understanding of mathematical models (Tarantola and Saltelli, 2003; Jakeman et al., 2006), allowing users and developers to get information both on the behaviour of the models themselves and on the real systems models represent.

The aims of this paper are (i) to propose an indicator of model plasticity, intended as the model aptitude to change the sensitivity to its parameters under diverse conditions; (ii) to test the new indicator using different crop models, locations and years; (iii) to analyze results in terms of relationships with other evaluation metrics.

## 9.3. Materials and methods

### 9.3.1. Quantifying model plasticity

We defined model plasticity as the model tendency to change its behaviour – analyzed via SA techniques – when applied to different conditions. In practice, changes in model behaviour were quantified through the lack of concordance among the parameters relevance calculated under different locations and years. The indicator of model plasticity (L) is calculated according to Eq. (1):

$$L = TDCC \cdot e^{\sigma_{SAM}-1} \qquad [1]$$

where TDCC is the top-down concordance coefficient (Iman and Conover, 1987; 0 to +1) and σSAM is the standard deviation of the normalized agrometeorological indicator (SAM) proposed by Confalonieri et al. (2010a; -1 to +1; Eq. (2)).

$$SAM = \frac{Rain - ET0}{Rain + ET0} \qquad [2]$$

Rain (mm) and ET0 (mm) are, respectively, the cumulated rainfall and reference evapotranspiration calculated for the period of interest (March 1 – October 31 in this study).

An exponential dependence is used in Eq. (1) since it guarantees a higher discriminating capability (compared, e.g., to a linear one) for plasticity values close to zero (zero is the optimal value for the indicator). Moreover, simulation experiments carried out while defining Eq. (1) demonstrated that σSAM presents a distribution characterized by a marked asymmetry. An exponential relationship between σSAM and TDCC – the latter following a χ2 distribution (Helton et al., 2005) – proved to be able to satisfactorily reduce the asymmetries in the distribution of L.

TDCC was considered particularly suitable for comparing parameters rankings obtained from SA carried out under different conditions because of its capability of emphasizing agreement among rankings assigned to relevant parameters and of deemphasizing the disagreement among those assigned to less important parameters (Helton et al., 2005).

L ranges from 0 to about 1.51, with highest plasticity at 0.

### 9.3.2. Models and sensitivity analysis experiments

Three crop simulators have been chosen for testing the new indicator. They are WARM (Confalonieri et al., 2009b,c), CropSyst (Stöckle et al., 2003), and WOFOST (Van Keulen and Wolf, 1986). These models were selected because of the different approaches they use for simulating crop growth and because they have been successfully used in a variety of conditions: WARM and WOFOST are the models used by the European Commission within the MARS Crop Yield Forecasting System (http://mars.jrc.it/), whereas CropSyst has been used in many studies worldwide for evaluating the impact of management and climatic scenarios for a variety of crops (e.g., Donatelli et al., 1997; Tubiello et al., 2000; Monzon et al., 2006). WARM calculates daily biomass accumulation as a function of intercepted radiation, modulating radiation use efficiency (RUE) according to temperature, senescence, saturation of the enzymatic chains and atmospheric CO2 concentration. Aboveground biomass (AGB) is partitioned to the different plant organs according to development-dependent coefficients. Leaf area index (LAI) is derived by multiplying leaves biomass by a specific leaf area that decreases till mid-tillering using a quadratic function and is assumed as constant from mid-tillering to physiological maturity. A micro-meteorological module is used to account for floodwater effect on vertical thermal profile, in turns allowing to provide temperature at the meristematic apex for development and spikelet sterility, and mid-canopy temperature for thermal limitation to photosynthesis. CropSyst is based on the Tanner and Sinclair (1983) relationship between AGB, potential transpiration, vapour pressure deficit (VPD) and a VPD-corrected transpiration use efficiency (TUEVPD). The instability of the Tanner and Sinclair equation for low values of VPD leads to the adoption of a temperature-limited RUE approach when these conditions occur. CropSyst simulates leaf area development as a function of AGB, a constant specific leaf area and an empirical coefficient, without the simulation of dynamic AGB partitioning to the different plant organs. WOFOST is the most sophisticated in reproducing the biophysical processes involved with crop growth, calculating gross photosynthesis, growth (during photosynthates partitioning to plant organs) and maintenance respirations. Partitioning of assimilates is thus driven by growth respiration, development-specific partitioning factors, efficiencies of assimilates conversion into the different organs. Leaf area expansion is calculated as a function of temperature for leaf area index (LAI) lower than one, and derived from specific leaf area and development stage elsewhere. WOFOST implements a three-layer canopy representation, with a spherical leaf angle distribution and LAI split among the layers using a Gaussian integration. Leaves death is simulated by the three models as driven by senescence, with WOFOST reproducing this process also as a function of leaves self-shading. WOFOST is the model with the highest number of parameters to be specified/calibrated to define the morphological and physiological features of a variety (from about 40 to more than 100, according to the information available for parameters that change their values according to development stage or temperature). WARM and CropSyst are more parsimonious, with 10 and 12 parameters, respectively, directly involved with the simulation of biomass accumulation and leaf area expansion. The models are fully described in the seminal literature. In this study, the simulated crop was rice (Indica-type, medium-precocity variety). Models parameters and the related acronyms are shown in Appendix A.

Weather and management data used for the simulation were extracted from the MARS database (Micale and Genovese, 2004) of the European Commission, with a spatial resolution of 25 km × 25 km. For each of the 10 countries shown in Table 2, the cell of the MARS grid with the widest rice-cropped surface was selected. For all the cells (locations hereafter), coordinates, rice acreages and adopted sowing dates are presented in Table 2. For each location, 10 years were considered, from 2000 to 2009.

**Table 2. Locations, rice acreages and sowing dates used for this study. Latitude and longitude refer to cell centroids**

| Country | Latitude (degrees) | Longitude (degrees) | Rice area (ha) | Sowing date |
|---|---|---|---|---|
| Bulgaria | 42.13 N | 24.46 E | 3268 | 20 May |
| France | 43.71 N | 4.63 E | 13637 | 29 April |
| Greece | 40.57 N | 22.59 E | 10558 | 8 May |
| Hungary | 47.14 N | 20.80 E | 4301 | 20 May |
| Italy | 45.42 N | 8.52 E | 45704 | 29 April |
| Macedonia | 41.93 N | 22.58 E | 2873 | 8 May |
| Portugal | 38.89 N | 8.63 W | 6333 | 8 May |
| Spain | 37.04 N | 6.11 W | 26332 | 20 May |
| Turkey | 40.93 N | 26.29 E | 7585 | 20 May |
| Ukraine | 45.47 N | 29.29 E | 197 | 20 May |

SA was performed by using the variance-based global SA method of Sobol’ (Sobol’, 1993), considered a reference in SA studies. This method allows the simultaneous exploration of the parameter hyperspace via

Monte Carlo or quasi Monte Carlo sampling. According to Sobol', the variance of the model output is decomposed into terms of increasing dimension, called partial variances, that represent the contribution of each single input (but even pairs, triplets, etc.) to the overall uncertainty of the model output. The relevance of parameters or parameter interactions is quantified as percentage contribution to the total variance, computed using a distribution of model responses (Tang et al., 2007). For independent parameters, the Sobol' variance decomposition can be written as:

$$V(y) = \sum_i V_i + \sum_{i<j} V_{ij} + \sum_{i<j<k} V_{ijk} + \ldots + V_{12\ldots k} \quad [3]$$

where Vi is the amount of variance of the model output y due to the ith parameter, Vij is the amount of y variance explained by the interaction of the ith and jth parameters, Vijk is the proportion of y variance due to the interaction of the ith, jth and kth parameters, k is the number of parameters, defining the k-dimensional hyperspace. This variance decomposition is used to derive sensitivity indices of different order as $S_i = \frac{V_i}{V}$, $S_{ij} = \frac{V_{ij}}{V}$, etc., with the total order effect for a parameter, Sti, equal to the sum of Si, Sij, … up to the kth order of analysis. The highest the value of Sti, the highest the overall influence of the parameter i (also in interaction with others) on the model output in the conditions explored. In this study, the value of St for each parameter was calculated according to Homma and Saltelli (1996) and Saltelli (2002), to reduce the computational cost of the analysis.

For WOFOST and CropSyst, the parameters on which the SAs were performed, their distributions and the sources of information used to derive the distributions are those used by Confalonieri (2010), whereas the same information for WARM was retrieved by Confalonieri et al. (2010b). Only the models parameters related to crop growth (i.e., biomass accumulation, assimilates partitioning, leaf area expansion) were considered in this study. The output variable evaluated was aboveground biomass at physiological maturity.

The number of simulations for each SA experiment was calculated as $(2n+2)\cdot 2^{\alpha}$, where n is the number of parameters and α is the lowest integer able to generate a number of simulations higher than $1000n$ (Saltelli, 2002). The total number of simulations performed in this study was 5,939,200 (three models, 10 years and 10 locations), with α equal to nine.

The significance of the differences in the mean values (calculated within location and within year) of TDCC and L achieved by the three models was tested using repeated-measures ANOVA, where the subject was either the location or the year, and the measure repeated on each subject the value of TDCC and L. Results of the Mauchly sphericity test (Mauchly, 1940) allowed to perform repeated-measure ANOVA on the values of TDCC and L.

## 9.4. Results

### 9.4.1. Sensitivity analysis results

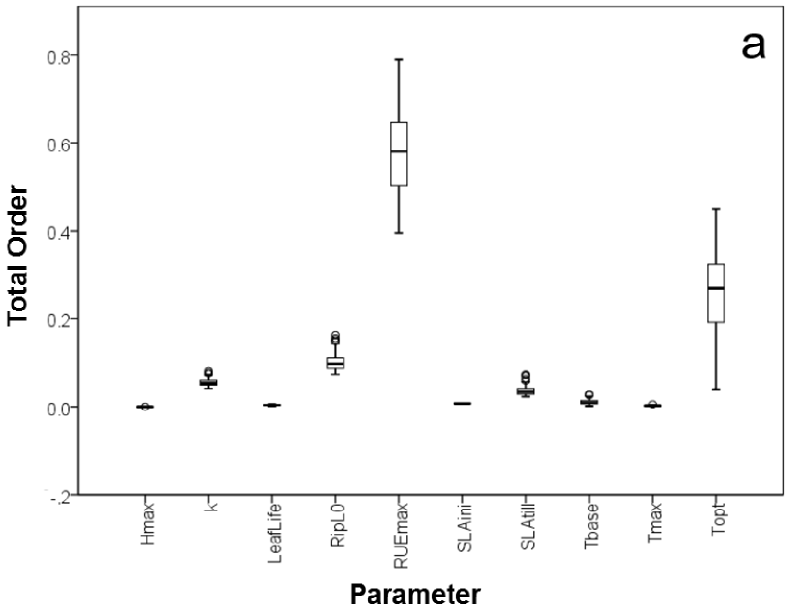
Results of the SA experiments are shown in Figs. 1 and 2. Box-plots in Fig. 1 are useful to get a graphical representation of the magnitude of the effect of the different conditions of application (locations $\times$ years) on parameters relevance. High values of total order effect (St) mean that the parameter has a high influence on the model output considered. Fig. 2 visualizes the distances among all simulations using the multi-dimensional scaling (MDS), where Euclidean distance is used to calculate the proximities among the St values (Richter et al., 2010). MDS in two dimensions (DIM_1 and DIM_2 in the charts) is useful to represent the distance among St values calculated for the parameters in different conditions of application.

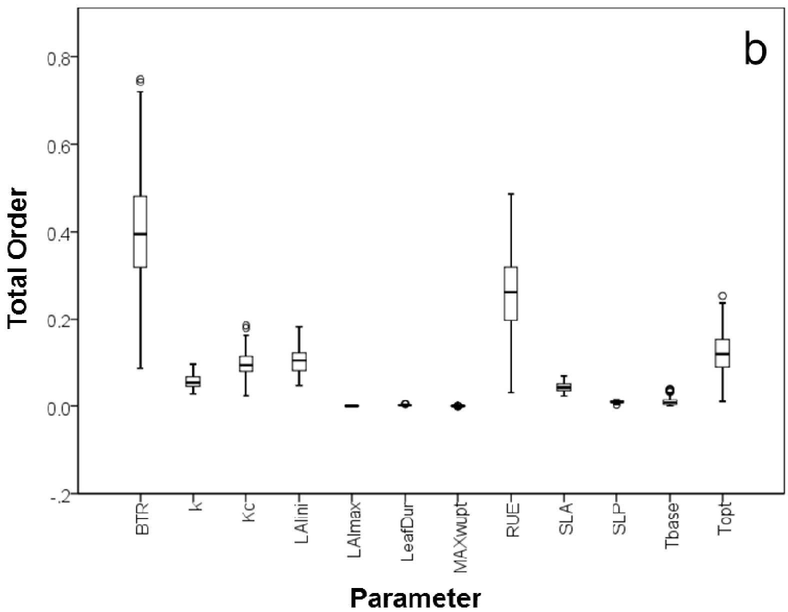
Figure 1.a shows the low variability in the relevance of the WARM parameters across locations and years. Among the parameters involved with daily biomass accumulation, maximum radiation use efficiency (RUEmax) and optimum temperature for growth (Topt) were those with the highest values of St, and also those with the greater St variability while changing conditions of application. Small changes, and small absolute values, were observed in the relevance of most of the parameters directly related to leaf area expansion, i.e., extinction coefficient for solar radiation (k), partitioning to leaves at emergence (RipL0), and specific leaf area at tillering (SLAtill). The variability in the parameters relevance was mainly due to the year effect in Spain, and to anomalies recorded for Spain in 2005 and Macedonia in 2002 (Fig. 2.a). These two locations differed from the others also for the general model behaviour: the points in Fig. 2.a referring to Macedonia and Spain are located respectively at the top-left and on the right with respect to those related to the other locations.

CropSyst presented a degree of variability in the parameters relevance similar to that discussed for WARM, although the influence of biomass-transpiration coefficient (BTR) on model output is strongly affected by the conditions of application (Fig. 1.b). As already discussed for WARM, the parameters involved with biomass accumulation, i.e., BTR, radiation use efficiency (RUE), and optimum temperature for growth (Topt) played a major role in influencing the model outputs, whereas those involved with leaf area expansion achieved lower and more stable St values. For both the models, thermal limitation to photosynthesis was mainly influenced by Topt, whereas base (Tbase) and, for WARM, maximum temperature (Tmax) had always a negligible impact on models behaviour. The variability among St values calculated for CropSyst was strongly influenced by the model behaviour in Spain (located on the right in Fig. 2.b) and Bulgaria (with most of the values on the left), and by the anomalies obtained in 2003 for Italy and France, and in 2000 for France.

WOFOST was the model which presented the greatest heterogeneity in parameters relevance while changing locations and years (Fig. 1.c). In some cases, e.g., maximum leaf CO2 assimilation rate at emergence (AMAXTB0), efficiencies of conversion into leaves (CVL) and storage organs (CVO), biomass partitioning to leaves at development stage code (DVS) equal to 0.5 (FLTB05), this was due to an overall variability among the conditions explored. In other cases, e.g., light use efficiency at 10°C (EFFTB10), partitioning to roots at flowering (FRTB1), specific leaf area at DVS equal to 0.35 (SLATB035), base temperature for leaves aging (TBASE), the variability is mainly due to anomalies (circles and stars in the figure, indicating values far more than 1.5 and 3 times the interquartile distance). Compared to WARM and CropSyst, WOFOST presented a noticeably higher number of anomalies, with almost all the parameters presenting different outlying values. The high heterogeneity in model behaviour was especially due to its different behaviour in Ukraine (Fig. 2.c), whose points are grouped at higher values on the X-axis, with a great variability along the other dimension. On the same chart, it is possible to notice that Spain values were generally located below most of the others, i.e., at lower values on the Y-axis. The most relevant anomalies were obtained for Greece (2004, 2007, 2008), Macedonia (2001, 2001, 2004), Hungary (2007, 2008), Turkey (2007), Italy (2003), and Spain (2006).

For all the models, the location effect weighted much more than the year one, with the latter practically not detectable in Fig. 2.



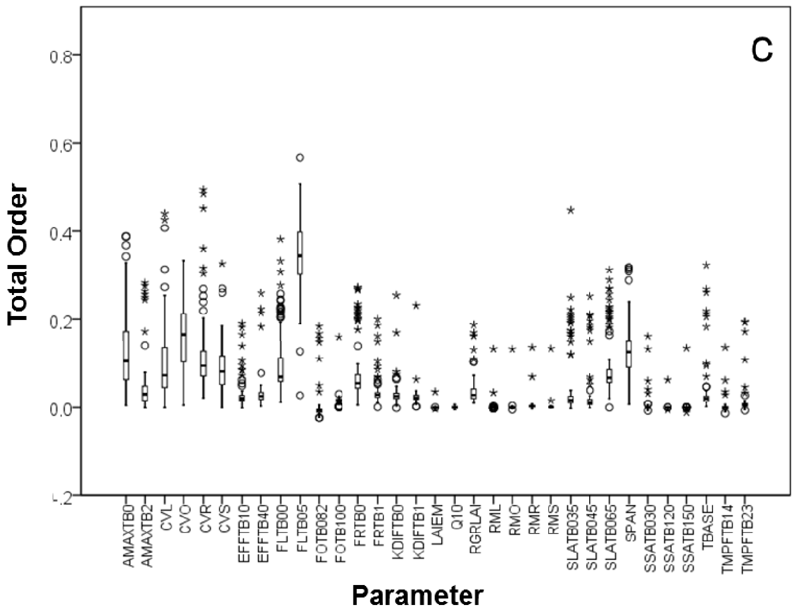
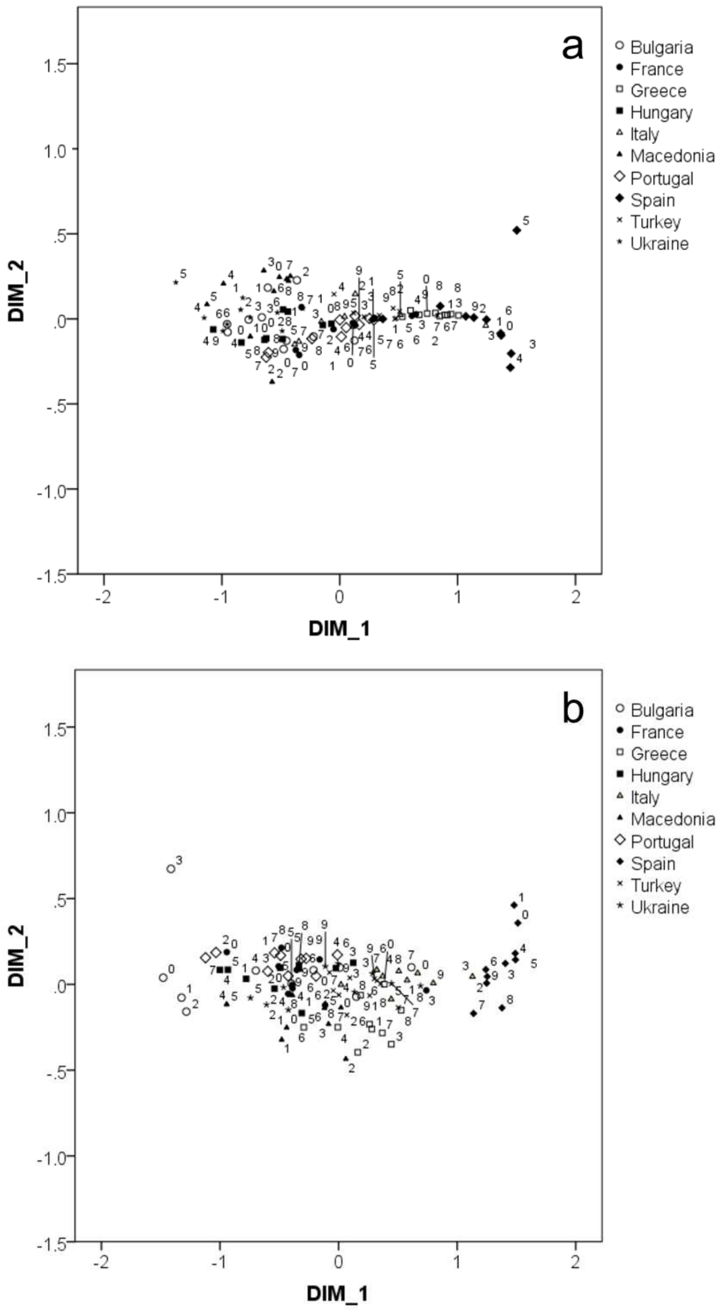



**Figure 1. Box-plots of Sobol' total order effects (St) for WARM (a), CropSyst (b) and WOFOST (c) parameters resulting from all the locations and years for which sensitivity analyses were performed. Circles and stars indicate outlying values, respectively far more than 1.5 and 3 times the interquartile distance**


a
b
Bulgaria
France
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Hungary
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Macedonia
Portugal
Spain
Turkey
Ukraine
DIM_1
DIM_2

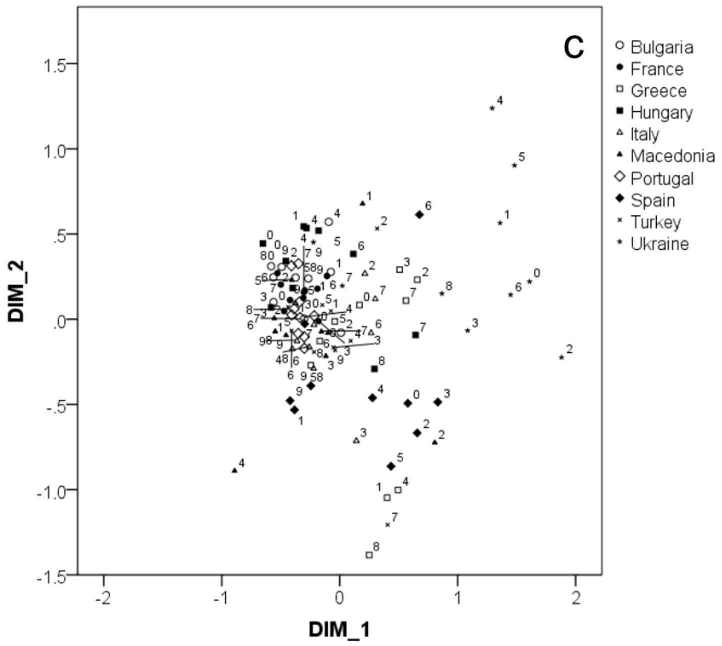


**Figure 2. Proximity of Sobol' total order effects for WARM (a), CropSyst (b) and WOFOST (c) represented in a common space using multi-dimensional scaling, displaying the effect of different locations and years on sensitivity analyses results. Figures close to the points indicate years from 2000 ('0') to 2009 ('9'). DIM_1 and DIM_2 represent the first and second dimension, respectively**

### 9.4.2. Models plasticity

Table 3 shows the values of σSAM, TDCC and L calculated within location (using all the years), within year (using all the locations), and those calculated using all data (10 locations $\times$ 10 years).

**Table 3. Standard deviation of the normalized agrometeorological indicator (SAM) calculated for the different years within each location, for the different locations within year, and for all the data. Corresponding values of top-down concordance coefficient (TDCC) and plasticity (L) calculated for the three models are presented. Means with different letters are significantly different for p<0.05 according to Bonferroni test**

| **Conditions explored** | | $\sigma_{SAM}$ | **TDCC** WARM | CropSyst | WOFOST | **L** WARM | CropSyst | WOFOST |
|---|---|---|---|---|---|---|---|---|
| Within location | Bulgaria | 0.153 | 0.999 | 0.860 | 0.898 | 0.428 | 0.369 | 0.385 |
| | France | 0.106 | 0.999 | 0.932 | 0.948 | 0.408 | 0.381 | 0.387 |
| | Greece | 0.073 | 0.999 | 0.985 | 0.814 | 0.395 | 0.390 | 0.322 |
| | Hungary | 0.154 | 0.999 | 0.938 | 0.932 | 0.429 | 0.403 | 0.400 |
| | Italy | 0.311 | 0.991 | 0.974 | 0.911 | 0.498 | 0.489 | 0.458 |
| | Macedonia | 0.175 | 0.998 | 0.941 | 0.845 | 0.437 | 0.412 | 0.370 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Portugal | 0.127 | 0.998 | 0.929 | 0.956 | 0.417 | 0.388 | 0.399 |
| | Spain | 0.091 | 0.966 | 0.970 | 0.845 | 0.389 | 0.391 | 0.340 |
| | Turkey | 0.118 | 0.998 | 0.983 | 0.917 | 0.413 | 0.407 | 0.380 |
| | Ukraine | 0.151 | 0.975 | 0.931 | 0.769 | 0.417 | 0.398 | 0.329 |
| | Mean | 0.146 | 0.992a | 0.944b | 0.883c | 0.423a | 0.403b | 0.377c |
| | St. dev. | 0.066 | ($p<0.001$) | | | ($p<0.001$) | | |
| Within year | 2000 | 0.191 | 0.991 | 0.869 | 0.868 | 0.441 | 0.387 | 0.387 |
| | 2001 | 0.241 | 0.990 | 0.861 | 0.794 | 0.463 | 0.403 | 0.372 |
| | 2002 | 0.261 | 0.996 | 0.863 | 0.801 | 0.476 | 0.412 | 0.383 |
| | 2003 | 0.183 | 0.977 | 0.859 | 0.855 | 0.432 | 0.380 | 0.378 |
| | 2004 | 0.176 | 0.981 | 0.879 | 0.760 | 0.430 | 0.386 | 0.334 |
| | 2005 | 0.269 | 0.947 | 0.897 | 0.848 | 0.456 | 0.432 | 0.408 |
| | 2006 | 0.226 | 0.989 | 0.961 | 0.814 | 0.456 | 0.443 | 0.376 |
| | 2007 | 0.186 | 0.998 | 0.915 | 0.846 | 0.442 | 0.405 | 0.375 |
| | 2008 | 0.157 | 0.996 | 0.942 | 0.833 | 0.428 | 0.405 | 0.359 |
| | 2009 | 0.192 | 0.996 | 0.963 | 0.891 | 0.444 | 0.429 | 0.397 |
| | Mean | 0.208 | 0.986a | 0.901b | 0.831c | 0.447a | 0.40 8b | 0.377c |
| | St. dev. | 0.038 | ($p<0.001$) | | | ($p<0.001$) | | |
| All locations and years | | 0.208 | 0.985 | 0.891 | 0.820 | 0.446 | 0.403 | 0.371 |

Within location, Italy experienced the highest variability among the weather conditions explored, whereas the main differences among locations within the same year were recorded for 2001, 2002, 2005 and 2006. Mean values for the three models are significantly different ($p<0.001$), for both TDCC and L, thus depicting clear behavioral differences among the models themselves in the way they react to weather conditions in terms of parameters relevance. WARM confirmed the lowest plasticity, with a very high concordance (TDCC) among the parameters rankings calculated under different conditions. Within location, WOFOST achieved the best value of L in seven out of 10 cases, whereas CropSyst obtained the best value of L in the other three sites (Bulgaria, France and Portugal). Within year, WOFOST was always the model with the highest plasticity, thus allowing to consider it as the one with the highest site-specific behaviour. The values of L calculated on all the datasets confirm the highest plasticity of WOFOST ($L = 0.371$), followed by CropSyst ($L = 0.403$).

### 9.5. Discussion

In general, the low plasticity calculated for WARM explains the similarity between the SA results obtained in this study and those obtained for the same model by Confalonieri et al. (2010b), with RUEmax and Topt gaining the highest relevance measures. The only difference is the absence – in the present study – of the parameter initial leaf area index, not present anymore as editable parameter in the WARM version used in this study (2.0.0; January 26, 2009). The high WOFOST tendency of changing the parameters relevance observed in this study is probably able to explain part of the differences between the parameters rankings obtained in this study and those discussed by Ceglar at al. (2011). The two studies present only three parameters in common among the 10 top-ranked: CVO, SPAN, and SLATB, the first involved with the conversion of assimilates into storage organs biomass, the others in green leaf area dynamics. However, the study from Ceglar et al. (2011) was about maize grown in Slovenia, therefore the main part of the difference is probably to be attributable to the different crop simulated.

Considering the two models based on the concept of net photosynthesis, i.e., CropSyst and WARM, it is possible to notice that most of the variability in their outputs is explained by their sensitivity to the parameters directly related to biomass accumulation (given a certain amount of radiation intercepted), i.e., BTR, RUE and Topt for CropSyst; RUEmax and Topt for WARM. These parameters are directly related to the transformation of radiation (and of water potentially transpired for CropSyst) and with thermal limitation to the transformation itself. Both the models are decidedly less sensitive to the parameters related to green leaf area evolution and radiation interception, like specific leaf area, leaf area duration and extinction coefficient for solar radiation. A possible explanation is that parameters directly involved in net photosynthesis play a key role during the whole crop cycle, whereas interception is limiting only before the closed-canopy stage and when senescence processes decrease the amount of green leaf area. The lower importance of RUE in CropSyst compared to that of RUEmax in WARM (the parameters have the same biophysical meaning in the two models) is due to the fact that CropSyst uses the RUE-based approach for biomass accumulation only in days with low values of VPD, otherwise using a TUEVPD-based one. This explains also the lower importance of Topt in CropSyst, since the temperature limitation is directly applied in CropSyst only within the RUE-based approach.

Confalonieri et al. (2010a) discussed the relationships among the same three models in terms of accuracy, robustness and complexity, using rice experiments carried out in different Italian sites from 1989 to 2004. They found that WARM was the model with the best values of relative RMSE, whereas the best values for EF was achieved by WOFOST. Moreover, WARM was the simplest according to AIC and the most robust, whereas WOFOST resulted as the most complex model, but with the poorest robustness. These results – although derived from a limited dataset – seems to support considerations from other Authors, e.g., Jakeman and Hornberger (1993), Monteith (1996), Passioura (1996), suggesting that an increase in model complexity – in turns leading to an increase in data requirements – could be, to a certain extent, even counterproductive, especially for operational purposes. This because of the increase in the amount of information needed to parameterize the models and to the increase in the degrees of freedom during the calibration: the higher the number of parameters, the higher the number of uncertain factors that could be introduced in the model to fit site/season-specific observations.

Although three models are not enough to draw conclusions about the relationships among metrics referring to different aspects of models behaviour, it is interesting to notice that the simplest model, WARM, resulted as the most robust and the less plastic, whereas the most complex achieved the best value for plasticity and the worst for robustness. This leads to hypothesize relationships between model complexity and metrics related to the predictability of its behaviour, i.e., robustness and plasticity. The higher adherence of SUCROS-type crop models (van Keulen et al., 1982) – such as WOFOST – to the real system reflects both its complexity and its capability to change behaviour in response to diverse environmental conditions, i.e., it seems to reflect the phenotypic plasticity typical of crops. In any case, the limitation of the conditions explored by Confalonieri et al. (2010a) leads to consider the existence of this kind of relationship as just a possibility to be verified through extensive, dedicated, multi-model evaluation studies.

## 9.6. Conclusions

Simulation models are increasingly used to support decision making under a variety of management, socio-economic and pedo-climatic scenarios. The different aims and conditions of application underline the need of selecting the most suitable model among those available for the specific typology of simulation study. A reasonable choice can be carried out only by deriving an evaluation criterion from the specific aims and context, i.e., spatial scale, availability of measured data for model calibration, quality of driving variables, etc. The criterion should be quantitative and able to account for the aspects of model behaviour considered as the most relevant for the specific case, thus allowing to rank the available models and to select the most suitable ones.

In this paper, we proposed and tested an indicator of model plasticity, intended as the capability of simulation models to change the way they react to a changing environment, by consequently changing the relevance of their parameters. This can be considered a simple way to get an idea of how the processes referring to the parameters change their relative importance in influencing the output under different conditions. The usefulness of such an indicator is clear when a model is used to analyze the system it represents, e.g., to understand which are the crop features (represented by model parameters) most affecting productivity, under a specific pedological, climatic, management scenario. In this case, in fact, model plasticity can be used to evaluate the plasticity of the underlying system. In the case of agroenvironmental models, this assumes a great importance, because of the pronounced phenotypic plasticity intrinsic in the modelled entities.

The three models used in this study, i.e., WARM, CropSyst and WOFOST, were already evaluated in previous works and their accuracy, complexity and robustness quantified under the conditions experienced by rice in northern Italy. The fact that different metrics awarded a different model as the best among those compared supports the need for developing and using criteria for evaluating the model features considered most relevant in different application contexts. This would allow to screen the available approaches and to identify the most suitable ones for specific purposes, also in case of multi-model studies targeting uncertainty estimation.

**Acknowledgements**

This study has been partially funded under the EU FP7 collaborative project, Grant Agreement N° 270351, Crop monitoring as an E-agriculture tool in developing countries (E-Agri).

## 9.7. Appendix A. Parameters names and acronyms for the models WARM, CropSyst and WOFOST

| Parameter | Acronym | Parameter | Acronym |
|---|---|---|---|
| WARM | | WOFOST | |
| Max. radiation use efficiency | RUEmax | Leaf area index at emergence | LAIEM |
| Ext. coeff. for solar radiation | k | Relative leaf area growth rate | RGRLAI |
| Base temperature for growth | Tbase | Specific leaf area at DVS[a] = 0.35 | SLATB035 |
| Opt. temperature for growth | Topt | Specific leaf area at DVS = 0.45 | SLATB045 |
| Ceil. temperature for growth | Tmax | Specific leaf area at DVS = 0.45 | SLATB065 |
| Initial specific leaf area | SLAini | Life span of leaves growing at 35ºC | SPAN |
| Specific leaf area at tillering | SLAtill | Base temperature for leaf ageing | TBASE |
| Partition coeff. leaves (early) | RipL0 | Ext. coeff. for diffuse light (DVS = 0.0) | KDIFTB0 |
| Leaf duration | LeafLife | Ext. coeff. for diffuse light (DVS = 1.0) | KDIFTB1 |
| Maximum panicle height | Hmax | Light use efficiency at Tavg[b] = 10°C | EFFTB10 |
| | | Light use efficiency at Tavg[b] = 40°C | EFFTB40 |
| | | Max. leaf $CO_2$ assimilation (DVS =0.0) | AMAXTB0 |
| | | Max. leaf $CO_2$ assimilation (DVS =2.0) | AMAXTB2 |
| | | AMAX reduction factor at Tavg = 14°C | TMPFTB14 |
| | | AMAX reduction factor at Tavg = 23°C | TMPFTB23 |
| | | Efficiency of conversion into leaves | CVL |
| CropSyst | | Efficiency of conversion into panicles | CVO |
| Biomass-transpiration coeff. | BTR | Efficiency of conversion into roots | CVR |
| Radiation use efficiency | RUE | Efficiency of conversion into stems | CVS |
| Opt.temperature for growth | Topt | Relative increase in respiration rate per 10 ºC of Tavg increase | Q10 |
| Maximum water uptake | MAXwupt | Relative maintenance respiration rate for leaves | RML |
| Initial leaf area index | LAIini | Relative maintenance respiration rate for storage organs | RMO |
| Maximum leaf area index | LAImax | Relative maintenance respiration rate for roots | RMR |
| Specific leaf area | SLA | Relative maintenance respiration rate for stems | RMS |
| Stem-leaf partition | SLP | Fraction biomass to roots (DVS = 0.0) | FRTB0 |
| Leaf duration | LeafDur | Fraction biomass to roots (DVS = 1.0) | FRTB1 |
| Ext. coeff. for global radiation | k | Fraction of aboveground dry matter to leaves (DVS = 0.0) | FLTB00 |
| Crop coefficient | Kc | Fraction of aboveground dry matter to leaves (DVS = 0.5) | FLTB50 |
| Base temperature for growth | Tbase | Fraction of aboveground dry matter to panicles (DVS = 0.82) | FOTB082 |
| | | Fraction of aboveground dry matter to panicles (DVS = 1.0) | FOTB100 |
| | | Specific stem area (DVS = 0.3) | SSATB030 |
| | | Specific stem area (DVS = 1.2) | SSATB120 |
| | | Specific stem area (DVS = 1.5) | SSATB150 |

[a] Development stage code (0.0): emergence; 1.0: flowering; 2.0: physiological maturity).
[b] Average air daily temperature (°C).

# GENERAL DISCUSSION AND PERSPECTIVES

## 10.1. The development achieved

The original plan of this doctorate was to target specifically the development of a library of model tools to simulate the impact of airborne diseases on crops. A reference model and software architecture was identified as suitable to develop a modelling framework for airborne diseases; it provided from the very beginning of this doctorate the infrastructure to organize modelling knowledge and make it operational. However, it became soon evident that formalizing and implementing disease models to be coupled to crop models had to be integrated by several other actions, in order to develop model tools that could be used operationally.

Firstly, the problem of the input data represents a crucial issue, because the quality of the data used to feed the plant disease models strongly influences the goodness of their response, and consequently their reliability. Furthermore, in order to use the appropriate time resolution for the biophysical processes involved, there is the need to handle hourly data. Such data are almost always unavailable when working on large areas and/or in climate change studies, thus needing their estimation starting from daily values. Also, it is somehow surprising the uncertainty resulting from literature review on pathogen response to temperature and to humidity, making the definition of parameters sets very difficult. One other problem which is still pending is that the vast majority of data available for diseases epidemics and impacts are not integrated by the needed information to model the whole system disease-crop-soil. Being the impact of diseases also subject to the state of the host, using incomplete datasets for simulating the system with the target of model either evaluation or calibration confounds the origin of disagreement between simulated data and the reference data used. This aspect has led to a plethora of highly specific, with respect to site, host, and management conditions, diseases models. Such models can be used effectively for in season estimates of epidemics progression, but are completely useless for scenario analysis such the ones required by a changing climate. The problem of input data can consequently be summarized as a detrimental lack of integration in research between plant pathologists/modellers and agronomists/crop modellers.

Secondly, the aspects of model evaluation, which are not only related to disease models, but more in general to the bio-physical modelling. Comparing whole modelling solutions as finalized products for system simulation has a clear role given a specific context, unchangeable modelling resources at a specific time, and assuming that the reference data to test the modelling solutions are adequate to limit the possible effect of misuse of calibration, degrading process based models to fully empirical models. However, it provides a very weak link to the evaluation of specific modelling approaches which are produced by research. This suggests evaluating modelling solution at fine granularity, as discussed in one of the papers presented in this thesis (i.e., Chapter 3). Once that is achieved, several metrics can assist in model evaluation. The usefulness of considering a broad range of metrics in model evaluation, although not providing statistical significance, allows getting an articulated insight on model performance. The multivariate nature of the issue is explicitly stated, the rules are easy to read, and the numerical scores easy to tune to match expert opinions. Consequently, part of the work of this thesis has targeted the aspect of multiple metrics and metric composition for model evaluation.

The current state of development of the framework to model airborne diseases certainly has not reached its final stage. However, it provides the analysis of the problem with the explicit target of modelling disease-crop interaction in scenario analysis, and makes available a substantial set of model tools and utilities which make possible targeting analysis at the level of abstraction presented in the case studies of this thesis.

I also trust that this work has provided one output which is considered of major interest from modelling, which is highlighting what is needed in the domain specific knowledge, thus providing food for research.

### 10.2. Specific objectives

The specific objectives of this doctorate were:

1. The implementation and evaluation of models for the estimation of meteorological data to be used as input for plant disease models, with particular attention to leaf wetness;
2. The development of a framework for the simulation of a generic fungal plant airborne disease, implementing an epidemic simulation

model for fungal plant pathogens to be coupled with a crop growth simulation model;
3. The application of the modelling solutions developed in case studies for climate change impact studies;
4. The development of advanced evaluation criteria for the evaluation of complex biophysical modelling solutions.

The main concept at the base of the realization of the whole work is that, in order to manage the extreme complexity of the biophysical processes simulated, ranging from the relationships between meteorological variables and epidemic development to the physiological interactions between plants and pathogens, the adoption of the state-of-the-art of software engineering technology is not an option, but the unavoidable prerequisite. Furthermore, although the need for a finer granularity of model units, at least to avoid duplication, is a declared goal of the modelling community since many years, technological bottlenecks have precluded model reuse. This is the reason why the agro-meteorological models developed during this doctorate were implemented following the component-oriented design, which encapsulate the solutions of specific modelling problems into reusable, discrete, replaceable and interchangeable software units (i.e., the components).

According to this concept, after the identification of hourly air temperature, hourly air relative humidity and leaf wetness duration as the main meteorological driving variables of the development of a fungal plant airborne epidemic, I co-developed and programmed two software components (i.e., *AirTemperature*, presented in Chapter 2 and *LeafWetness*, presented in Chapter 4) for the estimation of such variables. The multi-model approach implemented in these components favored the comparison among the diverse models implemented, either as single algorithms or as linked in modelling solutions (e.g., Chapter 3 and Chapter 4), aiming at identifying the best modelling solutions in the specific conditions of analysis. The fulfillment of the first objective resulted crucial for the progress of the work because the availability of libraries of approaches for the simulation of meteorological variables allowed checking the goodness of the diverse estimation methods before using them to feed the plant disease models, thus limiting the uncertainty and the errors related to the quality of input data.

The second general objective was achieved by developing four software components (presented in Chapter 5) that can be linked in a unique modelling solution for the simulation of a plant airborne fungal disease. This realization is in agreement with the demand of agronomists or researchers in plant pathology, that ask for the development of generic disease forecasting models, within a reusable and compatible modelling framework suitable for simulating different plant diseases. In fact these components can be used to simulate the progress of the epidemics caused by several pathogenic fungi on several crops by changing specific model parameters, with a clear biological meaning. The same approach can be used to simulate the effects of agriculture management options on disease progress. These components mainly implement collection of models already published in literature and, rather than having the claim to represent the final solution to plant disease modelling issue, represent a solid base to compare, extend or replace the approaches implemented according to the specific aims or decisions of the user.

The operative application of the modelling tools developed during this doctorate in the case study presented in Chapter 6 allowed highlighting that the consideration of biotic yield losses due to plant diseases in climate change studies could deeply modify the forecasts made by considering only the potential production level. The simulations carried out on the whole Latin America subcontinent proved the effectiveness of the software components developed to be linked with crop growth models in a unique modelling solution able to simulate both the development of the epidemic and the impact of such epidemic on crop production in large area studies.

The development of new metrics for model evaluation, specifically aimed at assessing model performance in small scale applications, was justified by the need of considering other aspects than the pure agreement between reference and simulated data in such studies. In fact, when users have to trust the model in conditions far from those in which the model itself was calibrated and tested, features as the model robustness (Chapter 8), intended as the capability of a model to maintain the same degree of error in diverse conditions of application, becomes fundamental. Furthermore, the use of sensitivity analysis techniques to develop an index for quantifying model plasticity (Chapter 9) allows gaining an in-depth knowledge of the model capability to adapt its response across diverse environmental conditions, like the ones experienced in large area application studies.

## 10.3. Future perspectives

The work carried out during this doctorate opens and facilitates new developments.

Firstly, the software architecture adopted in the development of the components promotes the implementation both of alternate approaches for the simulation of the same process and of models for biophysical processes not yet considered. The software components can be thus considered means to share knowledge with multiple uses as discussed in the chapters of this thesis.

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

### 10.3.1. Consolidating the framework

The robustness of the modelling solutions developed could be enhanced via a better definition of model parameters values (e.g., via specific experimental trials or via calibration procedures), and by a more precise characterization of the degree of genetic resistance in diverse host cultivars.

As for many other modelling needs, a possibly shared database of reference data and parameter set could be developed for an increasingly effective testing and calibration of models, with respect to the impact on plants.

### 10.3.2. Extending framework use

A possible application of the modelling solution for the simulation of a generic plant disease epidemic can be done to estimate the impact of agro-management practices for pathogen control on state variables which are of interest for environmental analysis. This could also be done in climate scenario analysis adding another dimension in impact assessment and adaptation studies. Even if the original development of the components is targeted to be applied on herbaceous crops, they should be extended and adapted for the simulation of fungal pathogens of tree crops. In principle, the framework accommodates already for implementing this capability via sets of parameters, but the application coupling diseases to fruit trees needs to be evaluated to validate the abstraction at the base of the diseases framework architecture.

Although knowledge to be abstracted to models could be a limiting factor, the simulation of pathogen complexes could be a further extension. Pathogen complexes are of course a closer representation to the real system and their representation is of great interest in estimating crop pathogen pressure in future scenarios of climate and agro-management.

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

## 10.4. Concluding remarks

Although the importance of modelling diseases in crop production was set decades ago, the focus has always been on the development of tools to assist tactical decision making by farmers. As for other aspects of the estimate of behavior of crop performance and agricultural management, robust, but highly empirical models have been developed. Such models, crop specific, cannot be used in conditions different from the ones in which they were developed, hence precluding exploring new environments and new climatic conditions. The increasing demand for estimates of crop production, which neither can exclude the role of plant diseases, nor can assume it as a constant for an environment, requires process based models in which the level of empiricism does not preclude extrapolating to new conditions.

The work of this thesis is in that direction and can be considered as a shift of paradigm in addressing the problem of developing model tools for crop-diseases interaction. Targeting modeling of the abstraction of core processes to develop a framework for airborne diseases simulation, although very ambitious, aims at developing model tools more tightly link to physiological research of plant pathogen. The work has allowed highlighting knowledge gaps, and may suggest research actions to allow developing quantitative methods more strongly linked to the biological system, possibly providing researchers new stimuli in defining their projects.

The framework developed, even if with clear further goals for development, has allowed running analysis under scenarios of climate change which could not be run otherwise. It has been a demanding work and it requires strong commitment for its further development. However, it could be one of the many step to move beyond both statistical models and a misuse of process based model via calibration which leads only to data fitting, instead of forecasting models.

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# RIASSUNTO

Gli effetti dei cambiamenti climatici sullo sviluppo sociale ed economico dell'umanità vengono ormai studiati da diverse decadi. Secondo l'organismo internazionale "Intergovernmental Panel on Climate Change" (IPCC), la mancata implementazione di misure efficaci ed adeguate per limitare l'emissione di gas serra porterà ad impatti consistenti e parzialmente irreversibili sull'ambiente, e di conseguenza sulla società. In questo contesto, la valutazione ex-ante delle dinamiche future delle malattie delle piante gioca un ruolo fondamentale, poiché esse contribuiscono a determinare i livelli effettivi di produzione di molte colture agrarie in molti areali, influenzando in tal modo la disponibilità di cibo e la sicurezza alimentare. La stima dei possibili impatti sulla produzione alimentare, a partire dall'agricoltura, risulta essere essenziale al fine di sviluppare strategie per alleviare le conseguenze del cambiamento climatico. Per effettuare tali analisi, la modellistica di simulazione basata su processi offre la capacità di catturare l'elevata non linearità delle risposte dei processi biofisici alle condizioni di contorno. Nonostante ciò, essa è stata utilizzata solo marginalmente per stimare scenari d'impatto di malattie delle piante sulle produzioni colturali, a causa della limitata disponibilità di approcci e di strumenti modellistici. Questo lavoro rappresenta un tentativo di rispondere all'esigenza di disporre di una piattaforma software per la simulazione di una generica fitopatia fungina che possa essere accoppiata a un modello di simulazione colturale al fine di migliorare la stima dei livelli delle produzioni agrarie in scenari di cambiamento climatico.

La prima sezione del lavoro tratta della valutazione di modelli per la stima di dati meteorologici e per la simulazione della bagnatura fogliare, variabile guida del processo di infezione dei patogeni fogliari. Questa analisi è giustificata dall'esigenza di fornire dati di qualità in ingresso ai modelli delle malattie delle piante e dalla scarsa disponibilità di dati orari in database a larga scala.

La seconda sezione presenta l'implementazione e la calibrazione della piattaforma generica di simulazione e la sua analisi effettuata mediante uso estensivo di tecniche di analisi di sensibilità.

La terza sezione tratta dell’applicazione della soluzione di modellazione sviluppata, accoppiata a un simulatore colturale, al fine di stimare l’impatto del cambiamento climatico in America Latina.

Nell’ultima sezione, vengono presentati nuovi criteri e metriche per la valutazione dei modelli biofisici, specifici per testarne il comportamento in condizioni climatiche eterogenee quali quelle esplorate negli studi di cambiamento climatico.

**Parole chiave:**

Malattie delle piante, cambiamento climatico, modelli di previsione di fitoepidemie, valutazione dei modelli di simulazione.