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Original article

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Abstract – Rice is the staple food for about half of the world's population. Although global production has more than doubled in the last 40 years, food security problems still persist and need to be managed based on early and reliable forecasting activities. This is especially true since the frequency of extreme weather events is forecasted to increase by the intergovernmental panel on climate change (IPCC). The most advanced crop yield forecasting systems are based on simulation models. However, examples of operational systems implementing models which are suitable for reproducing the peculiarities of paddy rice, especially on small scales, are missing. The rice model WARM is used within the crop yield forecasting system of the European Commission. In this article we evaluated the WARM model for the simulation of rice growth under flooded and unflooded conditions in China and Italy. The WARM model simulates crop growth and development, floodwater effect on the vertical thermal profile, blast disease, cold-shock induced spikelet sterility during the pre-flowering period and hydrological peculiarities of paddy soils. We identified the most relevant model parameters through sensitivity analyses carried out using the Sobol' method and then calibrated using the simplex algorithm. Data from 11 published experiments, covering 13 locations and 10 years, were used. Two groups of rice varieties were identified for each country. Our results show that the model was able to reproduce rice growth in both countries. Specifically, the average relative root mean square error calculated on aboveground biomass curves was 21.9% for the calibration and 23.6% for validation. The parameters of the linear regression equation between measured and simulated values were always satisfactory. Indeed, intercept and slope were always close to their optima and R^2 was always higher than 0.79. For some of the combinations of country and simulated variable, the indices of agreement calculated for the validation datasets were better then the corresponding ones computed at the end of the calibration, indirectly proving the robustness of the modeling approach. WARM's robustness and accuracy, combined with the low requirements in terms of inputs and the implementation of modules for reproducing biophysical processes strongly influencing the year-to-year yield variation, make the model suitable for forecasting rice yields on regional, national and international scales.

WARM / *Oryza sativa* L. / simulation model / flooded conditions / micrometeorology / TRIS / yield forecast / climate change

1. INTRODUCTION

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

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

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yield forecasting on regional, national and international scales (Bannayan and Crout, 1999).

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

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

With 218 000 ha, Italy is the largest European producer of rice, followed by Spain with less than half of the area (96000). Portugal, Greece and France have around 20 000 ha each (EUROSTAT New Cronos database; http://ec.europa.eu/eurostat). Although these figures place European grown rice as a secondary crop for this continent, at the world level it is the most important food crop (Solh, 2003).

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

2. MATERIALS AND METHODS

2.1. Experimental data

Data used for this study include 11 datasets collected in field experiments carried out between 1999 and 2002 in China and between 1989 and 2004 in Italy under flooded and unflooded conditions (Tab. I and Fig. 1). In any case, soil moisture never limited crop growth: the only biophysical effect in the absence of flooding was the absence of the floodwater effect on temperature. These conditions are suitable for evaluating a rice model, looking at situations where water-saving management could play a major role.

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

For experiments Nos. 1, 2, 3 and 4, ECMWF (European Centre for Medium-Range Weather Forecast; http://www.ecmwf.int/) meteorological data were used. Data resolution is one degree latitude × one degree longitude. Weather data for experiments Nos. 5 and 6 were collected with a floating micrometeorological weather station placed inside the field (Confalonieri et al., 2005). For the simulations related

Table I. Datasets used for model calibration and validation. * Aboveground biomass; ** leaf area index; § flooded at the 3rd leaf stage.

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

to experiments Nos. 7, 8, 9, 10 and 11, weather data were collected with standard automatic weather stations installed near the fields.

2.2. Simulation model

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

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

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

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

where GDD_{cum} (°C-day) are the cumulated *GDDs*, GDD_{em} (°C-day) are the *GDDs* required to reach emergence, GDD_{flo} (°C-day) are the *GDDs* required to reach flowering, and GDD_{mat} (°C-day) are the *GDDs* required to reach physiological maturity.

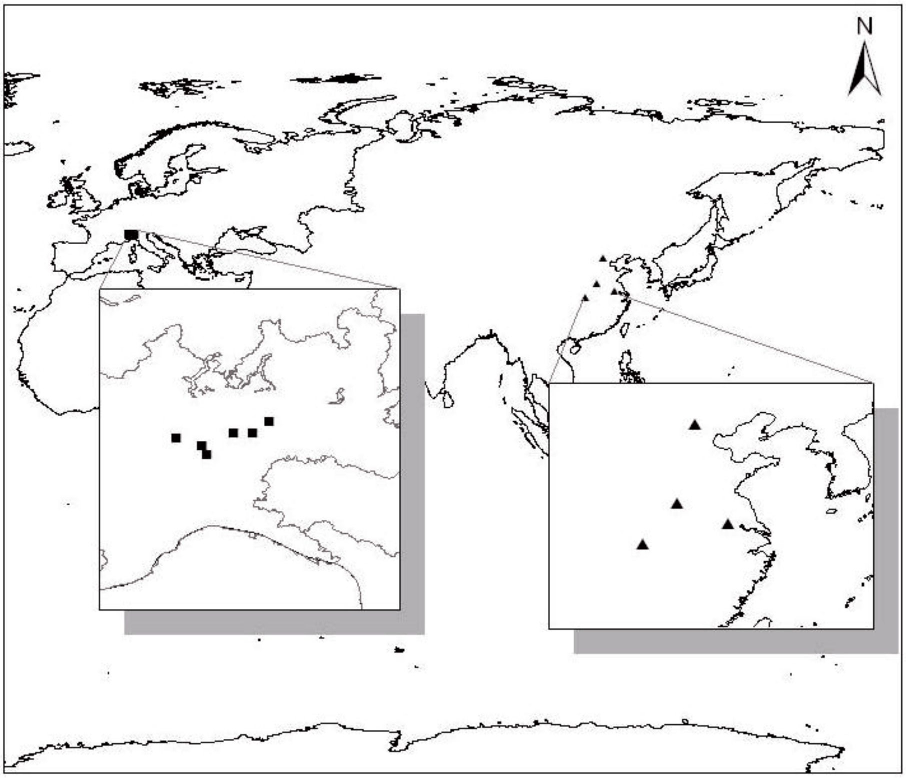

Figure 1. Locations where experiments used for calibration and validation were carried out.

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

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

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

$$RUE_{act} = RUE_{\max} \cdot T_{\lim} \cdot Rad\_F \cdot DVS\_F \cdot CO_2\_F \tag{4}$$

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

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

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

where T_{avg} (°C) is the mean daily air temperature; T_b (°C), T_{opt} (°C) and T_{max} (°C) are, respectively, the minimum, optimum and maximum daily mean temperature for growth; *C* is an empiric parameter set to 1.8 to make the beta distribution function assume the value of 0.5 when T_{avg} is the average of T_b and T_{opt}.

The factors accounting for saturation of the enzymatic chains involved in photosynthesis (*Rad_F*) and for the effect of senescence (*DVS_F*) are calculated using the following functions (Eqs. (6, 7)):

$$Rad\_F = \begin{cases} 1 & Rad < 25 \text{ MJ m}^{-2} \text{ d}^{-1} \\ 2 - 0.04 \cdot Rad & Rad \geqslant 25 \text{ MJ m}^{-2} \text{ d}^{-1} \end{cases} \tag{6}$$

$$DVS\_F = \begin{cases} 1 & DVS < 1 \\ 1.25 - 0.25 \cdot DVS & DVS \geqslant 1 \end{cases} \tag{7}$$

where *DVS* is the development stage numerical code.

AGB accumulated each day is assigned to leaves using a parabolic function (Eq. (8)) which assumes the maximum value (input parameter *RipL*0) at emergence and zero at flowering:

$$LeavesAGB_{day} = \begin{cases} AGB_{day} \cdot \left(-RipL0 \cdot DVS^2 + RipL0\right) & DVS < 1 \\ 0 & DVS \geqslant 1 \end{cases} \tag{8}$$

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

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

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

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

Stem biomass is computed by subtracting panicle and leaf biomasses from total *AGB*.

A daily factor accounting for spikelet sterility due to cold shocks during the period between *PI* and heading is calculated using equation (10):

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

where T_{thresh} (°C) is the threshold temperature below which cold-induced sterility damage is caused, T_h (°C) are the hourly temperatures (generated from the daily inputs according to Denison and Loomis, 1989), *DVS*11 is the *DVS* of the 11th day before heading ($DVS = 0.8$), and γ and δ are coefficients used to discriminate between varieties sensitive for few or many days around the 11th before heading, which corresponds to the middle of the period *PI*–heading. The integral of *SterilityF* is used to reduce $PanicleAGB_{day}$.

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

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

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

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

2.3. Sensitivity analysis

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

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

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

where *k* is the number of factors.

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

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

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

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

where $1 \leqslant i_1 < \ldots < i_s \leqslant k$ and $s = 1, \ldots, k$.

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

$$S_{i1...is} = \frac{D_{i1...is}}{D} \tag{15}$$

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

Table II. Parameter values and sources of information (C: calibrated parameters; L: literature; E: local experience; M: measured; D: default). ChE and ChL represent the sets of parameters for, respectively, early and late Chinese varieties; and ItI and ItJ the parameters for indica- and japonica-type varieties grown in Italy. GDD: growing degree days. AGB: aboveground biomass.

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

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

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

2.4. Model parameterization and validation

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

Both for China and Italy, two sets of crop parameters were calibrated and validated: Chinese early and late varieties, respectively, ChE and ChL, and Italian indica- and japonica-type varieties, respectively, ItI and ItJ. Table I shows the datasets used for calibrating and validating the four groups of varieties.

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

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

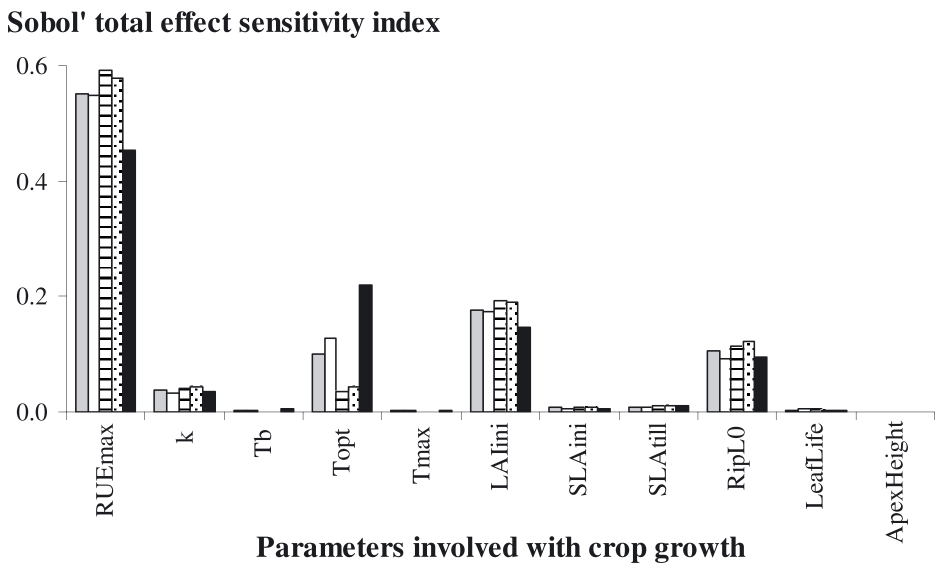

Figure 2. Results of the sensitivity analyses carried out using the Sobol' method: total order effects for the WARM parameters involved in crop growth. Grey, white, striped, dotted and black series refer, respectively, to Tuanlin, Changping, Gaozhai, Jiangpu and Italy. The most relevant parameters are those involved in radiation-use efficiency and its thermal limitation (RUE_{max} and T_{opt}), leaf area expansion at early stages (LAI_{ini} and $RipL0$) and light penetration into the canopy (k). T_{opt} decreases its relevance with decreasing latitude, because lower latitudes correspond to more suitable thermal conditions for the crop.

the parameters of the linear regression equation between observed and predicted values.

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

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

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

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

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

3. RESULTS AND DISCUSSION

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

3.1. Sensitivity analysis

Figure 2 compares the sensitivity analysis results for North-Italian conditions to those obtained for the four Chinese locations under study. RUE_{max} is always ranked first. Averaging results for the four Chinese sites, the main difference between sensitivity indices computed for the two countries is that T_{opt} is ranked second in Italy, whereas it appears less important than LAI_{ini} and $RipL0$ in China. T_{opt} is considered more relevant with increasing latitude: within Chinese datasets, it is ranked fourth at latitudes between 30° 52' N and 34° 02' N, and third

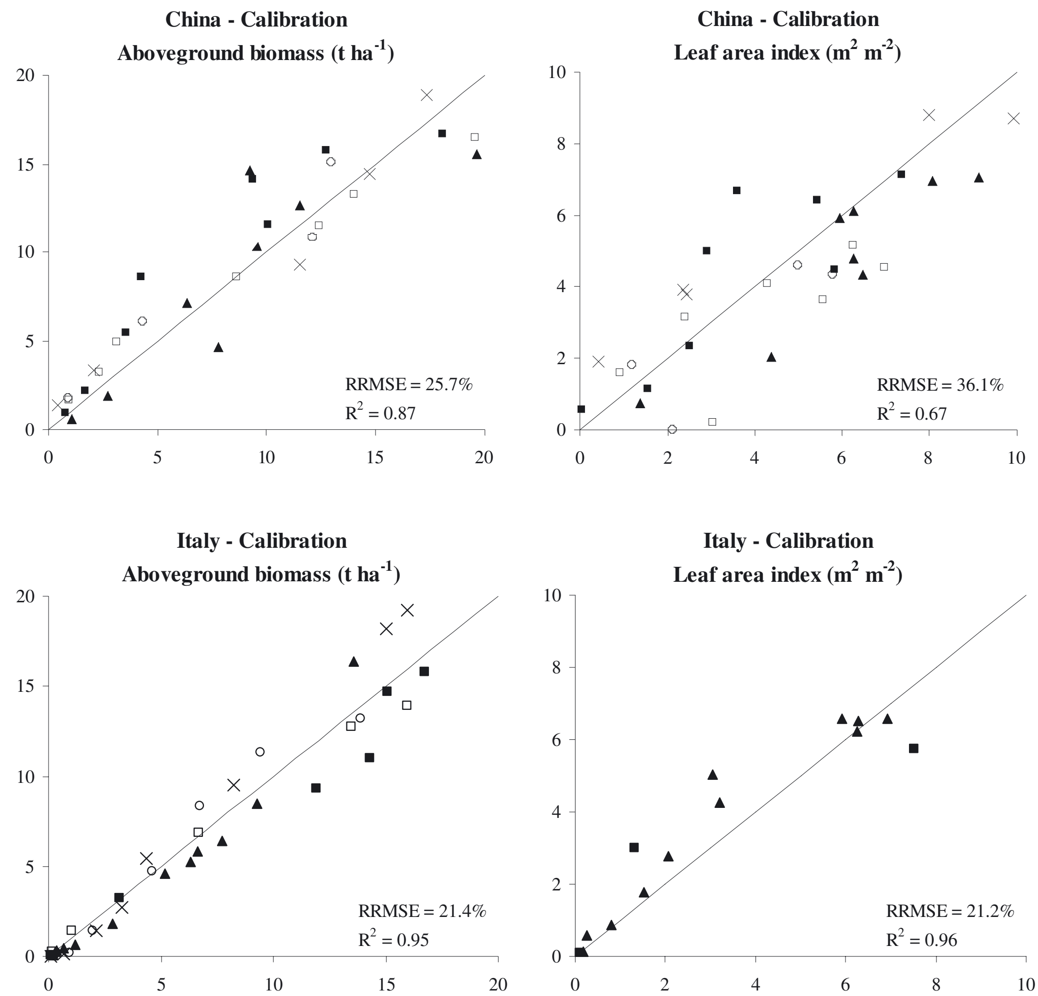

Figure 3. Measured (X-axis) and simulated (Y-axis) aboveground biomass and leaf area index values after calibration. For the Chinese datasets: black triangle, black square, white circle, white square and black cross refer, respectively, to Changping 2001, Changping 2002, Gaozhai 2001 (flooded), Jiangpu 2002 and Tuanlin 2000. For Italian datasets: the same symbols refer to Opera 2004, 2002, Castello d'Agogna 1995, Mortara 1996 and Vercelli 1990.

at a latitude of 40° 02' N; it is ranked second in Italy, where latitudes are slightly higher than 45° N. The reason is related to the S-shaped function used for modeling the photosynthesis response to temperature (see Eq. (5)): temperatures increase with decreasing latitude, thus getting closer to T_{opt} and leading T_{lim} to assume values which are in the region of the S-shaped function characterized by a plateau. This is translated into small variations in the output and therefore into decreasing relevance for decreasing latitude. Sensitivity analyses carried out for all the sites under study using the Sobol' method allowed one to identify the parameters RUE_{max}, LAI_{ini}, T_{opt}, *RipL*0 and k as the most relevant. Therefore, these parameters were those on which we concentrated during the calibration.

3.2. Calibration of crop model parameters

Parameter values with the source of information or after calibration are shown in Table II. Base and optimum temperatures are in the range of those reported, respectively, by Sié et al. (1998) and Casanova et al. (1998). Maximum temperatures are coherent with those used by Mall and Aggarwal (2002) for the CERES-Rice and ORYZA1 models. Similar values were also used by Confalonieri and Bocchi (2005) for the CropSyst model. Measured values of RUE_{max} were derived from Bouman et al. (2006) for the group of varieties ChE and by Boschetti et al. (2006) for ItI and ItJ. Although the values measured by these authors could appear quite spread, they fall within the range of those published (e.g. Kiniry et al., 2001; Campbell et al., 2001). The value of 0.5 for k is consistent with that reported by other authors (e.g. Dingkuhn et al., 1999). The values of SLA_{ini} and SLA_{till} are within the range of those measured by Dingkuhn et al. (1998) and by Boschetti et al. (2006). Although not identified as relevant by the sensitivity analysis, SLA_{till} and *LeafLife* were calibrated to allow the model to reproduce measured leaf area index curves.

The agreement between observed and simulated aboveground biomass values after calibration is shown in Figure 3 and Table III. In general, WARM presents a reasonable

Table III. Indices of agreement between measured and simulated aboveground biomass (AGB; t ha^{-1}) and leaf area index (LAI; m^2 m^{-2}) values. * Flooded at the 3rd leaf stage.

Dataset Country	Activity	Location	Year	Variable	Flooded	RRMSE (%)	EF	CRM	Slope	Intercept (t ha^{-1})	R^2
China	Calibration	Changping	2001	AGB		28.6	0.79	0.04	0.96	0.76	0.79
		Changping	2002			35.6	0.77	–0.24	0.93	–1.17	0.88
		Gaozhai	2001		X	20.8	0.91	–0.11	0.99	–0.77	0.93
		Jiangpu	2002		X	17.1	0.95	0.03	1.26	–1.95	0.99
		Tuanlin	2000			15.4	0.96	–0.02	1.01	–0.31	0.96
		Changping	2001	LAI		34.0	0.57	0.14	1.08	0.38	0.64
		Changping	2002			39.7	0.59	–0.15	0.78	0.36	0.70
		Gaozhai	2001		X	37.6	0.52	0.24	0.87	1.19	0.73
		Jiangpu	2002		X	40.1	0.31	0.24	0.95	1.18	0.56
		Tuanlin	2000			28.2	0.87	–0.17	1.28	–2.30	0.97
	Validation	Changping	2001	AGB		28.9	0.69	0.18	0.85	2.77	0.84
		Changping	2002			25.7	0.87	–0.03	0.88	0.62	0.88
		Gaozhai	2001			15.0	0.95	–0.10	1.02	–0.99	0.97
		Jiangpu	2001		X	25.1	0.89	–0.18	0.86	–0.12	0.97
		Tuanlin	1999			10.4	0.99	–0.01	1.05	–0.48	0.99
		Changping	2001	LAI		59.9	0.12	0.26	0.71	2.37	0.34
		Changping	2002			45.7	0.46	0.00	0.76	0.83	0.51
		Gaozhai	2001			33.8	0.66	0.21	0.93	0.88	0.79
		Jiangpu	2001		X	24.4	0.79	–0.03	0.78	0.62	0.86
Italy	Calibration	Opera	2004	AGB	X	23.7	0.93	0.07	0.88	0.83	0.96
		Vignate	2002		X	17.3	0.92	0.12	1.08	0.46	0.96
		Castello d'Agogna	1995		X	19.6	0.95	–0.04	0.90	0.34	0.96
		Mortara	1996		X	13.3	0.98	0.06	1.13	–0.53	0.99
		Vercelli	1990		X	27.9	0.91	–0.14	0.80	0.57	1.00
		Opera	2004	LAI	X	22.8	0.91	–0.13	0.96	–0.31	0.94
		Vignate	2002		X	47.5	0.81	0.01	1.31	–0.88	0.86
	Validation	Castello d'Agogna	1996	AGB	X	23.1	0.93	0.08	1.22	–0.96	0.98
		Gudo Visconti	1990		X	43.1	0.73	–0.33	0.77	–0.09	0.98
		Vercelli	1989		X	14.3	0.97	–0.05	0.88	0.59	0.99
		Opera	2002		X	14.0	0.96	–0.08	0.88	0.43	0.99
		Castello d'Agogna	1994		X	31.7	0.89	–0.24	0.86	–0.30	0.98
		Velezzo Lomellina	1999		X*	32.0	0.94	–0.17	0.83	0.12	1.00
		Opera	2002	LAI	X	56.8	0.68	–0.04	1.17	–0.63	0.70

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

3.3. Validation of crop model parameters

Figure 4 and Table III show the results of the crop parameter test. Despite a general slight overestimation, both for China and Italy, WARM accurately simulates aboveground biomass values, also during the validation. For China, as

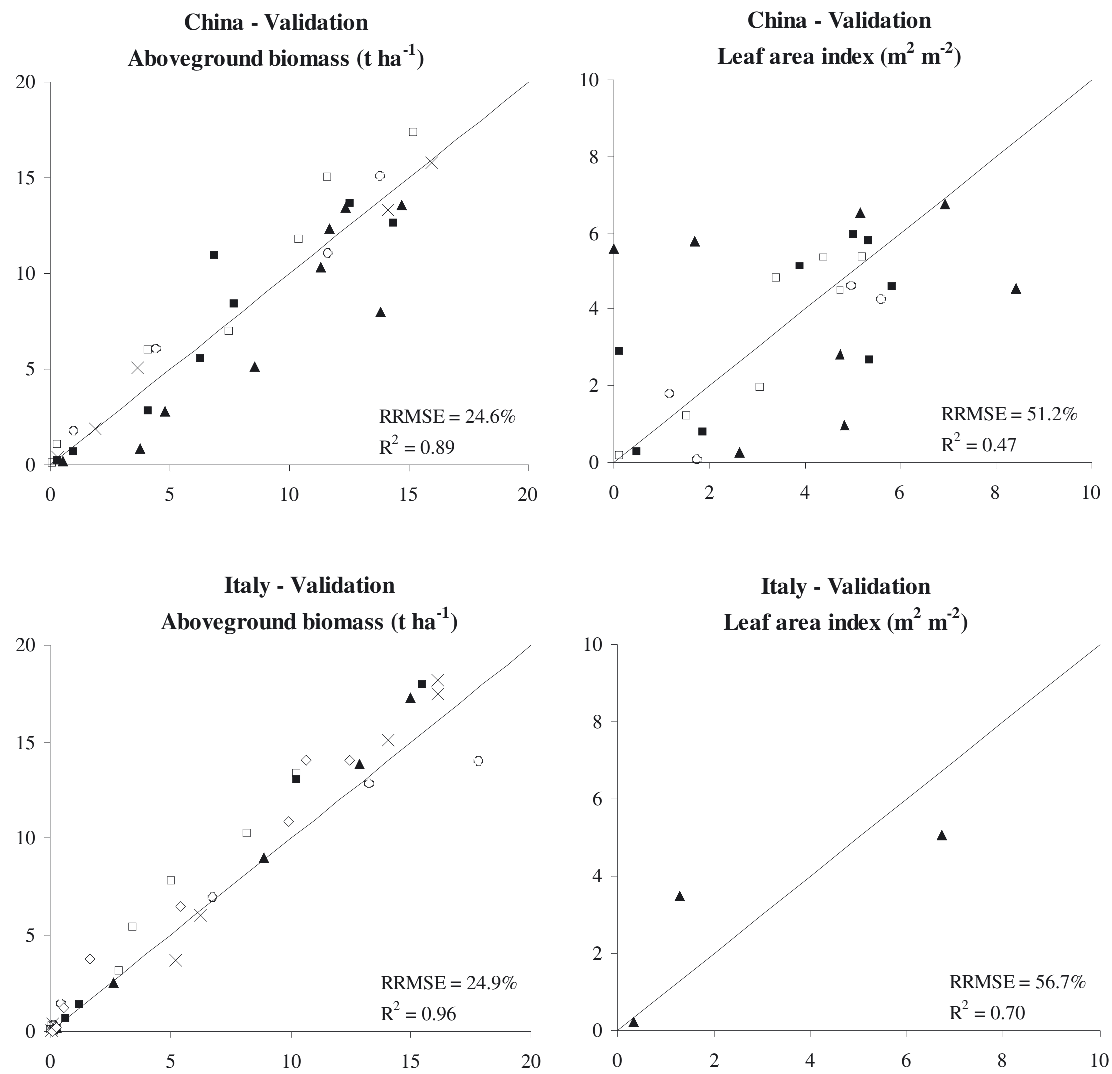

Figure 4. Measured (X-axis) and simulated (Y-axis) aboveground biomass and leaf area index values after validation. For the Chinese datasets: black triangle, black square, white circle, white square and black cross refer, respectively, to Changping 2001, Changping 2002, Gaozhai 2001 (unflooded), Jiangpu 2001 and Tuanlin 1999. For Italian datasets: the same symbols refer to Opera 2002, Velezzo 1999, Castello d'Agogna 1996, Gudo Visconti 1990 and Vercelli 1989; the white rhombus refers to Castello d'Agogna 1994.

already discussed for the calibration phase, the best values of fitting indices were calculated for the late varieties.

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

4. CONCLUSIONS

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

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

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