Europ. J. Agronomy 34 (2011) 20–25

Contents lists available at ScienceDirect

European Journal of Agronomy

journal homepage: www.elsevier.com/locate/eja

A model for simulating the height of rice plants

Roberto Confalonieri[a,*], Simone Bregaglio[a,b], Alexandra Stella Rosenmund[c], Marco Acutis[a], Igor Savin[d]

[a] University of Milan, Department of Plant Production, via Celoria 2, I-20133 Milan, Italy
[b] Agriculture Research Council, Research Centre for Industrial Crops, Bologna, Italy
[c] European Commission Joint Research Centre, IPSC, MARS Unit, AGRI4CAST, Ispra, Italy
[d] Space Research Institute, Russian Academy of Sciences, Moscow, Russia

ARTICLE INFO

Article history:
Received 8 February 2010
Received in revised form
21 September 2010
Accepted 24 September 2010

Keywords:
Oryza sativa L.
Biomass partitioning
Allocation pattern
Model robustness
Akaike's information criterion
WARM

ABSTRACT

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

1. Introduction

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

Despite the small effort invested by crop modellers for developing reliable approaches for plant height simulation, this variable is decidedly important in determining plant behaviour and yield potential (Yang et al., 2006). As an example, plant height is one of the main driving variables for modelling yield losses due to lodging (Berry et al., 2003; Sterling et al., 2003). According to the mechanistic lodging model proposed by Baker et al. (1998), the height of the plant centre of gravity (function of plant height) is one of the key variables for determining lodging risk, because of its influence on the stem base bending moment. The same Authors calculated that lodging risk moves from 0.039 to 0.704 in the range of variation (20–80 cm) of wheat centre of gravity height. A reliable simulation of plant height is also important for implementing three-dimensional approaches for canopy architecture (Pronk et al., 2003), in case of intercropping simulations, and for modelling crop–weeds interaction, since it is one of the main factors influencing the plant capability to compete for light interception (Kropff and Van Laar, 1993). Plant height is also crucial for modelling the profile of meteorological variables inside the canopy (e.g., Uchijima, 1976), and this is particularly important in complex micrometeorological environments like those characterizing paddy rice. Confalonieri et

* Corresponding author. Tel.: +39 02 50316515; fax: +39 02 50316575.
E-mail address: roberto.confalonieri@unimi.it (R. Confalonieri).

1161-0301/$ – see front matter © 2010 Elsevier B.V. All rights reserved.
doi:10.1016/j.eja.2010.09.003

Table 1
Data sets used for model parameterization and validation.

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

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

al. (2005) proposed the TRIS model for the simulation of the floodwater effect on vertical thermal profile, needing plant height as input. Coupling TRIS with a rice crop model simulating plant height would provide the routines involved with aboveground biomass (AGB) accumulation with temperatures correctly affected by floodwater, increasing the suitability of the model in reproducing the real system. The relevance of the relationship between floodwater and temperature along the rice canopy profile (function of plant height) has been underlined in many studies (e.g., Nishiyama, 1995; Dingkuhn et al., 1995). Moreover, analysis of field experimental data demonstrated good correlations between plant height and productivity: Khomiakov (1989) used plant height as an indicator within a crop yield prediction system based on simple regression models. The relevance of plant height in cropping systems analysis emerges also from the Russian agro-meteorological crop monitoring system: according to their recommendations (Methodical recommendations, 1988), plant height should be measured 5–10 times during crop growing season.

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

2. Materials and methods

2.1. Experimental data

Data were collected in eight experiments carried out between 1991 and 2000 in Russia, Japan, and Texas (US) (Table 1). During the Russian experiments, plant height and phenological stages – among other variables – were determined. Plant height was measured from the soil surface to the upper leaf edge before heading and to the top of the panicle later on. Data were collected within the activities of the Russian agro-meteorological crop monitoring system, carried out to estimate yields under growing conditions representative of the main Russian rice districts, located in the regions Krasnodar, Primorsky, and Astrakhan. These districts are sited in areas vocated for rice, although temperatures are usually lower than in West European districts. Water availability allowed adopting flood irrigation. Local, well-adapted varieties were grown, able to assure satisfying production levels (around 6 t ha^{-1}), with a cycle length decreasing with longitude. Experimental data from Japan and Texas were derived from Oguro et al. (2001) and Sass et al. (1992), respectively. The former refers to the investigation of the relationships between satellite vegetation indices and biophysical rice plant features (e.g., plant height, *LAI*), whereas the latter is about the assessment of the influence of management practices on methane emission from paddy rice fields. For all the experiments, management practices allowed to prevent water and nutrients stresses and to keep the fields weed and pest free. ECMWF ERA 40 (European Centre for Medium-Range Weather Forecast; http://www.ecmwf.int/) meteorological data were used for all the simulations.

2.2. Models for plant height

Table 2 presents the compared approaches for simulating plant height. Two out of five (Confalonieri et al., 2005; Bechini and Stöckle, 2007) need *LAI* as driving variable, whereas the Lizaso et al. (2005) model needs a decimal phenological code. Four out of five models require maximum plant height as input parameter. The model proposed by Kotera and Nawata (2007) is the only one which calculates the daily increase in crop height, therefore needing the state of the day before to derive the value of the current day.

The model proposed in this study simulates plant height as the result of the competition for assimilates between stems and the other plant organs. It needs as input the percentage of AGB partitioned to stems, which is available for all the crop models implementing a daily partitioning of assimilates, e.g., all the models belonging to the SUCROS and CERES families. In case no daily partitioning of assimilates is explicitly simulated, like in CropSyst (Stöckle et al., 2003), the simple approach of the WARM rice model (Confalonieri et al., 2009a,b) can be used. According to this approach, the percentage of AGB partitioned to leaves (P_{LEAVES}; 0.0–1.0) is calculated using Eq. (1):

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

where *DVS* is a development stage code assuming the values of 0.0, 1.0, and 2.0, respectively, at emergence, flowering, and physiological maturity; *RipL0* (0.0–1.0) is the AGB partitioned to leaves at

Table 2
Models for the simulation of plant height compared in this study.

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

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

emergence. Like in SUCROS-derived models, *DVS* is obtained by normalizing the thermal time accumulated before and after flowering. The percentage of AGB partitioned to panicles ($P_{PANICLES}$; 0.00–1.00) results from Eq. (2):

$$P_{PANICLES} = \begin{cases} 0 & 0 \le DVS < 0.7 \\ -1.9 \cdot DVS^2 + 5.4 \cdot DVS - 2.9 & 0.7 \le DVS \le 1.5 \\ 1 & 1.5 < DVS \le 2.0 \end{cases} \quad (2)$$

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

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

2.3. Models parameterization and evaluation

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

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

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

$$I_R = \frac{\sigma_{EF}}{\sigma_{SAM}} \quad (4)$$

where *n* is the number of observed/simulated pairs, *MSE* is the mean square error, *T* is the number of inputs in the model, σ_{EF} and σ_{SAM} are the population standard deviations of EF and of the synthetic agrometeorological indicator (see Table 1).

3. Results and discussion

Fig. 1 shows that the proposed model (grey circles) was able to reliably reproduce the time course of plant height for most of the datasets, without systematic patterns related to specific locations, years, phenological phases or cultivar size. A slight overestimation affected model predictions in the last part of the cycle for the Slaviansk – 1999 dataset, whereas an opposite behaviour can be observed for the data collected in Hiroshima. On the contrary, the model proposed by Kotera and Nawata (2007) strongly underestimated observations in all the datasets, especially in the central part of the cycle (black dashes). In some cases, the accumulated gap was partially recovered during the ripening phase. The model from Lizaso et al. (2005) demonstrated to be sufficiently accurate in most of the situations (white triangles), whereas the other approaches always showed a marked underestimating tendency. It is interesting to notice the satisfying behaviour demonstrated by the two models requiring less input (variables and parameters), i.e., the Confalonieri et al. (2005) and Lizaso et al. (2005) approaches.

The accuracy indices (RRMSE, EF, CRM) shown in Table 3 confirm these considerations. The model proposed in this study obtained the best values of RRMSE (mean RRMSE = 13.87%, ranging from 8.02% to 20.87%) and EF (mean EF = 0.86, ranging between 0.70 and 0.96) in seven out of eight datasets and the best CRM values in half of them. CRM was negative in half of the cases, demonstrating the absence of any over- or underestimating behaviour. The model from Lizaso et al. (2005) achieved the best CRM for the remaining datasets, and was ranked second in four out of eight cases according to RRMSE and EF. The approach from Confalonieri et al. (2005) was ranked second in four cases (three Russian datasets and the one from Texas) according to both RRMSE and EF. The approach proposed by Kotera and Nawata (2007) performed always worse, with negative EF values in all the datasets.

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

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

The model proposed accounts for the impact of agrometeorological conditions on plant height by means of the cultivar specific parameters involved with partitioning of assimilates (*RipL0*), development (growing degree days to reach flowering and maturity; see Eqs. (1) and (2)), and stature (H_{max}). In this study, we calibrated the parameters related to crop development using observed phenological data, and we set H_{max} to values retrieved via interviews to local experts. The available information was not enough

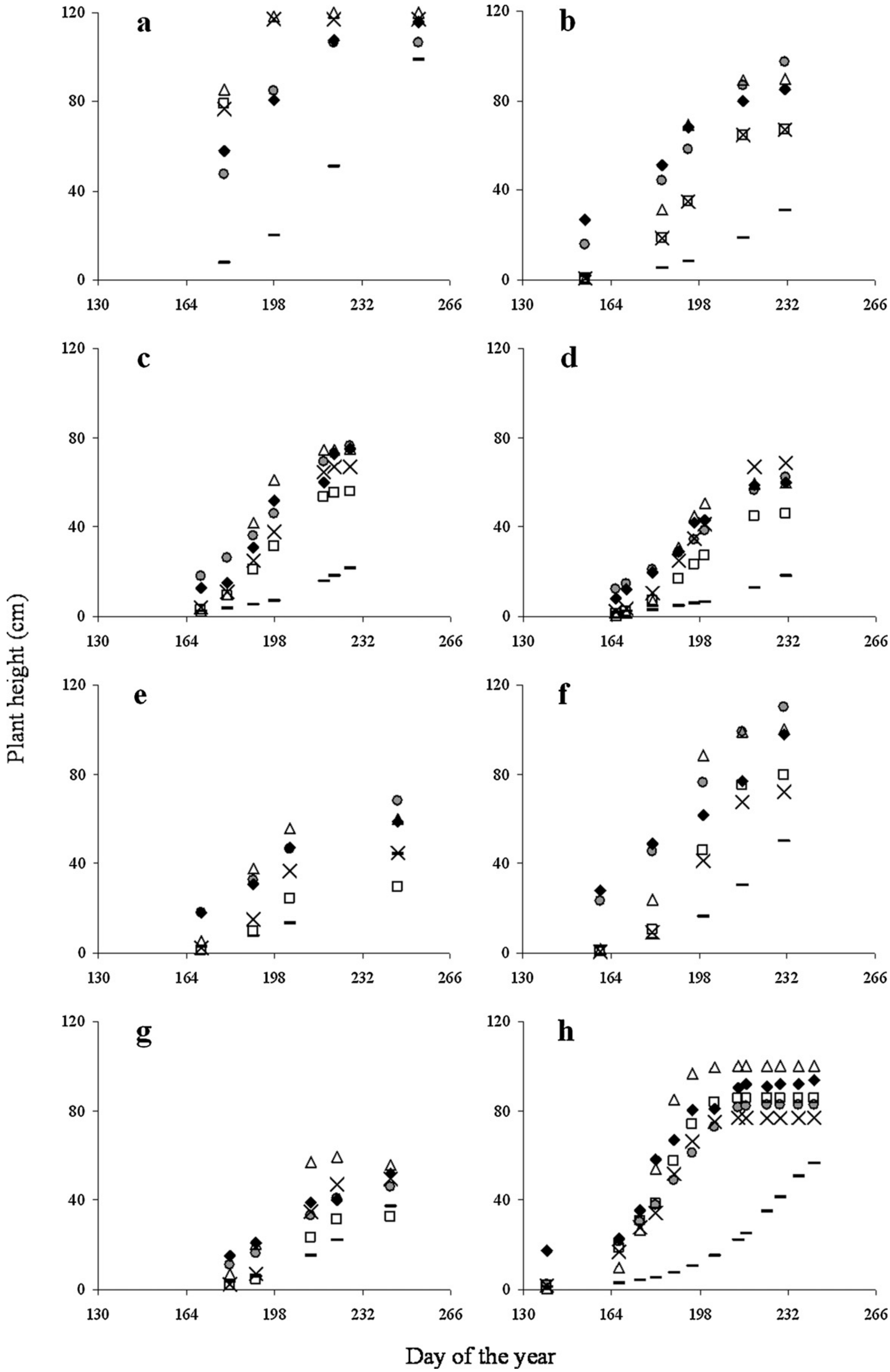

Fig. 1. Comparison between measured values (♦) and those simulated by the five models under test: ●, model proposed in this study; □, Bechini and Stöckle (2007); △, Lizaso et al. (2005); ×, Confalonieri et al. (2005); –, Kotera and Nawata (2007); a. Beaumont – 1991; b. Slaviansk – 1997; c. Novoselskoe – 1997; d. Novoselskoe – 1998; e. Volnoe – 1999; f. Slaviansk – 1999; g. Volnoe – 2000; h. Hiroshima – 2000.

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

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

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

for a reliable calibration of *RipL0*, which was therefore set to the model default value. Further studies aiming at refining the calibration of *RipL0* would probably improve the model performances. The model capability of capturing the variability among sites and years – together with the fact that the model is only driven by temperatures (via the accumulation of growing degree days) – underlines the importance of this weather variable in influencing the biological processes involved with plant height.

4. Conclusions

The proposed model for rice plant height proved to be accurate in the explored conditions, reproducing correctly the behaviour of plants grown in eight experiments carried out in Russia, Japan and Texas between 1991 and 2000. The satisfactory values obtained for all the evaluation metrics allow considering the proposed model as more accurate and robust than the other four models compared, and the relationship between its performances and the number of inputs required allows considering it as the most efficient.

Some studies investigated the influence of genetic and management factors like dwarfing genes (e.g., Yang et al., 2006), plant density, because of the competition for light (Ballaré et al., 1991), fluctuating water depth (e.g., Vergara et al., 1976), rate and timing of nitrogen supply (Shimono et al., 2007). Although these factors are not accounted for by the proposed model, its level of empiricism is lower with respect to the existing approaches. In fact, the idea of simulating plant height as the result of the competition for assimilates between stems and the other plant organs represents a robust base for further modelling studies accounting for other genetic and management key factors modulating plant height increase.

The importance of plant height in influencing yield potential (e.g., because of its effect in modulating susceptibility to lodging) and its relationship with environmental and management factors should encourage the modellers community to develop and improve reliable, process-based approaches for the simulation of this variable and to test them within system models.

References

Akaike, H., 1974. A new look at the statistical model identification. IEEE Trans. Automat. Contr. 19, 716–723.
Baker, C.J., Berry, P.M., Spink, J.H., Sylvester-Bradley, R., Griffin, J.M., Scott, R.K., Clare, R.W., 1998. A method for the assessment of the risk of wheat lodging. J. Theor. Biol. 194, 587–603.

Ballaré, C.L., Scopel, A.L., Sánchez, R.A., 1991. On the opportunity cost of the photosynthate invested in stem elongation reactions mediated by phytochrome. Oecologia 86, 561–567.
Bechini, L., Stöckle, C.O., 2007. Integration of a cropping systems simulation model and a relational database for simple farm-scale analyses. Agron. J. 99, 1226–1237.
Berry, P.M., Sterling, M., Baker, C.J., Spink, J., Sparkes, D.L., 2003. A calibrated model of wheat lodging compared with field measurements. Agric. For. Meteorol. 119, 167–180.
Bouman, B.A.M., Van Laar, H.H., 2006. Description and evaluation of the rice growth model ORYZA2000 under nitrogen-limited conditions. Agric. Syst. 87, 249–273.
Confalonieri, R., Mariani, L., Bocchi, S., 2005. Analysis and modelling of water and near water temperatures in flooded rice (*Oryza sativa* L.). Ecol. Model. 183, 269–280.
Confalonieri, R., Gusberti, D., Bocchi, S., Acutis, M., 2006. The CropSyst model to simulate the N balance of rice for alternative management. Agron. Sustain. Dev. 26, 241–249.
Confalonieri, R., Rosenmund, A.S., Baruth, B., 2009a. An improved model to simulate rice yield. Agron. Sustain. Dev. 29, 463–474.
Confalonieri, R., Acutis, M., Bellocchi, G., Donatelli, M., 2009b. Multi-metric evaluation of the models WARM, CropSyst, and WOFOST for rice. Ecol. Model. 220, 1395–1410.
Confalonieri, R., Bregaglio, S., Acutis, M., 2010. A proposal of an indicator for quantifying model robustness based on the relationship between variability of errors and of explored conditions. Ecol. Model. 221, 960–964.
Delmotte, S., Vay, S., Tittonel, P., Kichou, A., Lopez-Ridaura, S., 2010. Evaluating the variation of rice yields in Camargue using the WARM crop growth model. In: Proceedings of Agro2010 XI ESA Congress, 29 August–3 September, Montpellier, France, pp. 373–375.
Dingkuhn, M., Sow, A., Samb, A., Diack, S., Asch, F., 1995. Climatic determinants of irrigated rice performance in the Sahel—I. Photothermal and microclimatic responses of flowering. Agric. Syst. 48, 385–410.
Jones, C.A., Kiniry, J.R., 1986. CERES-Maize. A simulation model of maize growth and development. Texas A&M Univ. Press, College Station.
Khomiakov, V.N., 1989. Evaluation of the Agro-eco System Status. Gidrometizdat, Leningrad, 218 pp.
Kotera, A., Nawata, E., 2007. Role of plant height in the submergence tolerance of rice: a simulation analysis using an empirical model. Agric. Water Manage. 89, 49–58.
Kropff, M.J., Van Laar, H.H., 1993. Modelling Crop–Weed Interactions. CAB International in association with the International Rice Research Institute, Wallingford, U.K, 274 pp.
Lizaso, J.I., Batchelor, W.D., Boote, K.J., Westgate, M.E., 2005. Development of a leaf-level canopy assimilation model for CERES-Maize. Agron. J. 97, 722–733.
Loague, K.M., Green, R.E., 1991. Statistical and graphical methods for evaluating solute transport models: overview and application. J. Contam. Hydrol. 7, 51–73.
Methodical Recommendations for Compilation of the Agrometeorological Yearly Book, 1988. Leningrad, Gidrometizdat, 142 pp.
Nishiyama, I., 1995. Damage due to extreme temperatures. In: Matsuo, T., Kumazawa, K., Ishii, R., Ishihara, K., Hirata, H. (Eds.), Science of the Rice Plant—Vol. 2. Physiology. Food and Agriculture Policy Research Centre, Tokyo, Japan, 769–800 pp.
Oguro, Y., Imamoto, C., Suga, Y., Takeuchi, S., 2001. Monitoring of rice field by Landsat-7 ETM+ and Landsat-5 TM data. In: Proceedings of the 22nd Asian Conference on Remote Sensing, Vol. 1, 5–9 November 2001, Singapore, pp. 7–12.
Pronk, A., Goudriaan, J., Stilma, E., Challa, H., 2003. A simple method to estimate light interception by nursery stock conifers: a case study of eastern white cedar. Neth. J. Agric. Sci. 51, 279–295.
Sass, R.L., Fisher, F.M., Wang, Y.B., Turner, F.T., Jund, M.F., 1992. Methane emission from rice fields: the effect of floodwater management. Global Biogeochem. Cycles 6, 249–262.
Shimono, H., Hasegawa, T., Moriyama, M., Fujimura, S., Nagata, T., 2005. Modelling spikelet sterility induced by low temperature in rice. Agron. J. 97, 1524–1536.
Shimono, H., Okada, M., Yamakawa, Y., Nakamura, H., Kobayashi, K., Hasegawa, T., 2007. Lodging in rice can be alleviated by atmospheric CO_2 enrichment. Agric. Ecosyst. Environ. 118, 223–230.
Sterling, M., Baker, C.J., Berry, P.M., Wade, A., 2003. An experimental investigation of the lodging of wheat. Agric. For. Meteorol. 119, 149–165.
Stöckle, C.O., Donatelli, M., Nelson, R., 2003. CropSyst, a cropping systems simulation model. Eur. J. Agron. 18, 289–307.
Uchijima, Z., 1976. Microclimate of the rice crop. In: Proceedings of the Symposium on Climate and Rice, IRRI, pp. 115–140.
Van Diepen, C.A., Rappoldt, C., Wolf, J., van Keulen, H., 1988. Crop Growth Simulation Model WOFOST. Documentation Version 4.1. Centre for World Food Studies, Wageningen.
Van Keulen, H., Penning de Vries, F.W.T., Drees, E.M., 1982. A summary model for crop growth. In: Penning de Vries, F.W.T., van Laar, H.H. (Eds.), Simulation of Plant Growth and Crop Production. Simulation Monographs, Pudoc, Wageningen, pp. 87–98.
Vergara, B.S., Jackson, B., De Datta, S.K., 1976. Deep water rice and its response to deep water stress. In: Climate and Rice. International Rice Research Institute, Los Baños, Philippines, pp. 301–319.
Yang, G., Xing, Y., Li, S., Ding, J., Yue, B., Deng, K., Li, Y., Zhu, Y., 2006. Molecular dissection of developmental behaviour of tiller number and plant height and their relationship in rice (*Oryza sativa* L.). Hereditas 143, 236–245.