Sensitivity of APSIM/ORYZA model due to estimation errors in solar radiation

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Abstract

Crop models are ideally suited to quantify existing climatic risks. However, they require historic climate data as input. While daily temperature and rainfall data are often available, the lack of observed solar radiation (R_s) data severely limits site-specific crop modelling. The objective of this study was to estimate R_s based on air temperature solar radiation models and to quantify the propagation of errors in simulated radiation on several APSIM/ORYZA crop model seasonal outputs, yield, biomass, leaf area (LAI) and total accumulated solar radiation (SRA) during the crop cycle. The accuracy of the 5 models for estimated daily solar radiation was similar, and it was not substantially different among sites. For water limited environments (no irrigation), crop model outputs yield, biomass and LAI was not sensitive for the uncertainties in radiation models studied here.

Key words: crop model, calibration, upland rice.

Análise de sensibilidade do modelo APSIM/ORYZA na estimava de erros na radiação solar

Resumo

Modelos de simulação de culturas são importantes para quantificar riscos climáticos. Esses modelos necessitam de dados climáticos como dados de entrada. Entretanto, dados diários de precipitação pluvial e temperatura são facilmente encontrados, enquanto dados de radiação solar (R_s) limitam-se à aplicação de modelos de simulação de culturas. O objetivo deste estudo foi estimar a R_s utilizando cinco modelos de estimativa de radiação solar com base na temperatura do ar e quantificar a propagação de erros na radiação simulada na produtividade, biomassa, área foliar e radiação solar acumulada durante o ciclo da cultura do arroz de terras altas simulados pelo modelo de simulação ORYZA/APSIM. A acurácia dos cinco modelos de estimativa da radiação solar foi similar e não foi diferente entre os diferentes locais. Para ambientes que ocorre estresse hídrico, as saídas do modelo ORYZA/APSIM produtividade, biomassa e índice de área foliar não foram sensíveis às incertezas provenientes da radiação solar estimadas neste estudo.

Palavras-chave: modelos de simulação, calibração, arroz de terras altas.

1. INTRODUCTION

During the last decade, demand for rice in Brazil as well as in the world has increased considerably. However, the area available for rice production in the South of Brazil is limited, largely due to environmental and social constraints, such as competing demands for freshwater, industry or domestic use. Hence there is increasing interest in the upland rice systems of the Brazilian savannahs. This region is characterized by high inter and intra annual yield variability as consequence of precipitation patterns: even during the rainy season, there is chance of water stress occurrence due to periods of no rain or rain amount below crop demand. Thus, better quantification of existing climatic risks is urgently needed (Maia et al., 2007) to provide the rice industry with information to better cope with existing climate variability and to adapt to likely future changes.

Crop models can be used to quantify effects of climate variability on yield variability and to explore options for coping with this variability (Akponikpèa et al., 2011). The greatest limitation for crop model application in this region is the lack of climate data (Heinemann et al., 2008). Global radiation (R_s) is the driving factor controlling photosynthesis and evapotranspiration and is consequently an important weather variable for various agro-ecological studies. The lack of observed R_s data severely limits site-specific modelling of crop growth (Donatelli et al., 2003). R_s at the earth surface depends on radiation at the top of the atmosphere (R_a) which can be calculated from latitude and day of year, based on astronomic equations. How much of R_a reaches the earth's surface depends on atmospheric transmissivity.

Several researchers have shown that atmospheric transmissivity can be estimated from maximum and minimum air temperatures (Bristow and Campbell, 1984; Donatelli and Campbell, 1998; Donatelli et al., 2003; Hargreaves and Samani, 1985), with daily R_s estimated with accuracies of 50 to 98%, while Farhadi Bansouleh et al. (2009) using the Hargreaves equations found strong interannual variation in accuracies, with R^2 values ranging from 0 to 55%. As air temperature is recorded by all meteorological stations, temperature-based estimation methods are directly applicable in any region, provided that some years of R_s data are available for calibration of empirical parameters amongst these models, the Bristow-Campbell is the most commonly used. Much of this work on estimation of R_s is driven by the need for R_s as an input to crop growth models. Few studies however have quantified the impact of errors in R_s on errors in yields. Quite consistently, these studies conclude that yields can be accurately simulated, even with considerable error in R_s (Farhadi Bansouleh et al., 2009; Xie et al., 2003). However, as the accuracy depends on the crop, environment and growth models used, results cannot be readily generalized for other scenarios.

The objective of this study are: i) to estimate solar radiation (R_s) in Goiás State, Brazil, by calibrating the models proposed by Bristow and Campbell (1984), Donatelli and Bellocchi (2001), Donatelli and Campbell (1998)[1], Donatelli et al. (2003) and Hargreaves and Samani (1985), and (ii) to quantify the propagation of errors in simulated R_s on several APSIM/ORYZA crop model seasonal outputs, namely: the upland rice yield, biomass, leaf area and total accumulated solar radiation during the crop cycle.

2. MATERIAL AND METHODS

APSIM/ORYZA Crop Model

ORYZA2000 is an explanatory, dynamic eco-physiological simulation model for rice (Bouman and Van Laar, 2006), integrated into APSIM (Agricultural Production Systems Simulator; Keating et al., 2003). APSIM/ORYZA simulates rice phenology, leaf area development, biomass production, yield and nitrogen accumulation in response to environmental variables such as temperature, solar radiation, soil water content and nitrogen fertilizer management. In this study, water availability was simulated via APSIM-SoilWat2 module while crop water requirement, which is based on potential evapotranspiration, was computed in the APSIM-Eo module. The APSIM framework also includes a nitrogen and carbon dynamics module 'soilN'.

Solar Radiation Models

It was compared five models for estimating daily solar radiation (R_S), namely: BC - Bristow and Campbell (1984); HG - Hargreaves (1981) modified by Hunt et al. (1998); CD[1]; DB - Donatelli and Bellocchi (2001) and modular model DCBB – Donatelli et al. (2003). Four amongst these models (BC, CD, DB and DCBB) estimate the actual atmospheric transmissivity for the ith day of the year as a function of clear sky transmissivity (τ) and daily maximum (T_{max}) and minimum (T_{min}) temperatures. τ was assumed to be equal to 0.75 as suggested by Fletcher and Moot (2007).

$$R_{sBC}=0.75\left[1-\exp\left(\frac{-b\Delta T_i^{\,c}}{\Delta T_{avg}}\right)\right]R_a \qquad (1)$$

$$R_{sCD}=0.75\,[1-\exp(-b\,(0.017\exp(\exp(-0.053\Delta T_{avg})))\,\Delta T_i^{\,2} f_1(T_{min}))]R_a \qquad (2)$$

$$R_{sDB}=0.75\,[1-f_2(i)]\left[1-\exp\left(\frac{-b\Delta T_i^{\,c}}{\Delta T_{avg}}\right)\right]R_a \qquad (3)$$

$$R_{sDCBB}=0.75\,[1+f_2(i)]\left[\frac{-b\Delta T_i^{\,2} f_1(T_{min})}{\Delta T_{avg}}\right]R_a \qquad (4)$$

$$R_{sHG}=b\,R_a\sqrt{T_{max}-T_{min}}+c \qquad (5)$$

where R_a is the daily potential radiation (MJ m^{-2} day^{-1}), calculated with standard astronomic equations based on day of year and latitude (Goudriaan and Van Laar, 1994) $\Delta T = T_{max} - (T_{min} + T_{min+1})/2$, ΔT_{avg} is the mobile week temperature based on centred mobile

(1) As described in DONATELLI, M.; CAMPBELL, G.S. A simple model to estimate global solar radiation. In: CONGRESS OF THE EUROPEAN SOCIETY FOR AGRONOMY, 5., 1998, Nitra, Slovak Republic. Proceedings… [S.l.]: European Society for Agronomy, 1998. p.133-134.

mean (as the average over 7 days around) of maximum and minimum temperature (ºC); and b and c are parameters separately calibrated for each site and model. In equations 2–4 two functions f_1 and f_2 are used:

$$f_1(\mathrm{T_{min}})=e^{\left(\frac{T_{min}}{T_{nc}}\right)} \tag{6}$$

$$f_{2\,(i)}=c_1[\sin(i\times c_2\times\pi/180)+\cos(i\times f_3(c_2)\times\pi/180)] \tag{7}$$

where T_{nc} is the summer night temperature factor to avoid underestimation of solar radiation in summer (Bechini et al., 2000); i= day of year, c_1 and c_2 are empirical model parameters for general seasonal factors (Mavromatis and Jagtap, 2005). In the equation defining f_2(i), f_3 is calculated as:

$$f_3(c_2)=1\text{-}1.9\times c_3+3.83\times c_3^2 \tag{8}$$

where c_3 = c_2 – integer(c_2). Empirical parameters were calibrated using daily radiation data of the even years, for each of the stations listed in table 1. Next, the models were validated using the odd year data. The parameters b and c for BC, CD, DB and DCBB models were estimated by ordinary least squares. For HG model, they were fitted by nonlinear least squares via the iterative method based on Gauss-Newton algorithm by using MASS package from R software (R Development Core Team, 2012: http://www.r-project.org). T_{nc}, c_1 and c_2 parameters were fitted by ordinary least squares based on T_{min} (T_{nc}) and day of year (c_1 and c_2) as described by Bellocchi et al. (2003) and Donatelli et al. (2004). All parameters were calibrated for each weather station separately.

A number of researchers have shown that R_s values are also dependent on rainfall, altitude and latitude (Hunt et al., 1998, Weiss and Hays, 2004). It was plotted radiation model residuals against rainfall to investigate whether the models were biased or more inaccurate at the high and low rainfall levels.

Data Collection and Crop Simulation

Daily maximum and minimum temperatures and global solar radiation data from weather stations in Goiás state (Table 1) were provided by the Meteorological and Hydrological System of Goiás State (SIMEHGO – "www.simego.sectec.go.gov.br/"). Data set available at each location ranged from 4 to 6 years. Data from even years was used for calibration of equations 1 to 8 and from odd ones for validation. The crop model APSIM/ORYZA for upland rice was calibrated to simulate crop responses environmental factors considering either observed or estimated solar radiation. Inputs to this model include daily weather data (minimum and maximum temperature, precipitation and solar irradiance), soil properties, initial soil water content, cultivar genetic characteristics, planting date, and N fertilizer management. The soil properties used as input for the crop model represent the most common soil type (Oxisols, covering 46% of the upland rice region, Embrapa, 1999). We used characteristics of the most commonly grown cultivar in the region, BRS Primavera (Lorençoni et al., 2010). Model prognostic variables were simulated for nine locations and three planting dates, 1-Nov, 1-Dec and 31-Dec, corresponding to beginning, middle and end of planting season, respectively. The row spacing, plant density and nitrogen fertilization represent the local recommendation for upland rice in the region, 35 cm, 200 plant m^{-2} and 20 kg ha^{-1} of N at the planting date, 40 kg ha^{-1} at begin of tillering, and 40 kg ha^{-1} at begin of panicle initiation. Simulations started at least six months before each planting date in order to allow the establishment of a realistic soil water profile on the basis of rainfall patterns occurring before sowing because no irrigation was applied in the simulations. APSIM/ORYZA seasonal outputs analyzed in this study were yield; maximum accumulated biomass; maximum leaf area index (LAI) and accumulated solar radiation during the crop cycle (SRA).

Table 1. Weather station localization, altitude, period and number of years used in this study

ID	Weather Station name	Lat	Lon	Alt (m)	Period	# of years
01	Ceres	-15.31	-49.60	739	2002-2007	6
02	Anápolis	-16.33	-48.95	1136	2005-2008	4
03	Anicuns	-16.46	-49.96	692	2006-2009	4
04	Vianópolis	-16.74	-48.52	1110	2004-2007	4
05	Cristalina	-16.77	-47.61	1189	2005-2008	4
06	Palmeiras de Goiás	-16.80	-49.93	596	2000-2001 2004-2005	4
07	Jandaia	-17.05	-50.15	637	2005-2008	4
08	Vicentinópolis	-17.74	-49.81	648	2000-2005	6
09	Jataí	-17.88	-51.71	696	2004-2009	6

ID: identification. Lat: latitude. Lon: longitude. Alt: altitude.

Model validation

The accuracy of the solar radiation models was compared via descriptive statistics that indicate the degree of agreement between results based on either, monthly and daily observed or estimated solar irradiance as input data. The goodness of fit was assessed by the following measures: (i) parameter estimates (slope and intercept) of the regression line between estimated and measured values; (ii) correlation coefficient (r) (iii) the relative root mean squared error (RRMSE, equation 9), an indicator of the overall relative accuracy of the model; (iv) the systematic root mean square error (RMSEs), a measure of the model's linear (or systematic) bias (equation 10) and (v) the mean absolute error (MAE, equation 11), the arithmetic mean of absolute residuals. Small MAE values indicate a method with low overall mean error.

$$\text{RRMSE}=100\text{x}\left(\frac{((\frac{1}{n})\sum[(R_{est}-R_{obs})^2)^{0.5}]}{\sum\frac{R_{obs}}{n}}\right) \tag{9}$$

$$\text{RRMSEs}=\left[\frac{1}{n}\sum_{i=1}^{n}|\hat{R}_{est}-R_{obs}|^2\right]^{0.5} \tag{10}$$

$$\text{MAE}=\frac{1}{n}\sum_{i=1}^{n}|R_{est}-R_{obs}| \tag{11}$$

where R_{obs} and R_{est} are, respectively, the observed and estimated daily solar radiation, n the number of days used for model fitting and $\hat{R}_{est}$ is the best estimate of the predicted quantity calculated with the intercept (a) and slope (b) of the least-squares regression between R_{obs} and R_{est}, $\hat{R}_{est}$ = a + bx_i.

To quantify the influence of inaccuracies in solar radiation estimates on APSIM/ORYZA seasonal outputs (Y) the model was run once a time using observed radiation or radiation estimated by each radiation model, resulting in a pair $Y_{R\text{-}obs}$ and $Y_{R\text{-}est}$ values for each radiation model and output variable. Differences between $Y_{R\text{-}obs}$ and $Y_{R\text{-}est}$, here referred to as ΔY were then calculated for yield, biomass, maximum leaf area index (LAI) and accumulated solar radiation (SRA). We assessed the discrepancies between $Y_{R\text{-}obs}$ and $Y_{R\text{-}est}$ for each radiation model by several graphical and descriptive analysis: (i) box-and-whiskers plots of ΔY for displaying range of deviances, outliers and bias resulting from radiation estimation; (ii) deviance measures (r, MAE and RRMSE) previously described for evaluation of radiation models themselves and RMSE (root mean square error); (iii) similarity measures: the index of agreement d (Wilmott, 1981; equation 12) and the coefficient of efficiency (Nash and Sutcliffe, 1970; equation 13) as joint measures of bias and accuracy and (iv) empirical cumulative distribution function (ecdf).

Thus what we present is a sensitivity analysis. The analysis shows how sensitive APSIM/ORYZA model output is to estimation errors in solar radiation. The accuracies reported therefore do not provide information on how good APSIM/ORYZA is at simulating actual yields. In this study model accuracy is considered excellent when RRMSE<10%; good if 10%≤RRMSE<20%; fair if 20%≤RRMSE<30%; and poor if RRMSE≥30% (Jamieson et al., 1991); d and E are summary measures which accounts for accuracy. They range from 0 to 1 and minus infinity to 1, respectively. Basically, d represents the ratio between the mean square error and the "potential error" (Willmot, 1984) and E determines the relative magnitude of the residual variance ("noise") compared to the measured data variance ("information") (Moriasi et al., 2007). For both similarity measures, higher values indicate better agreement.

$$d=1-\left(\frac{\sum_{i=1}^{n}(Y_{R\_obs}-Y_{R\_est})^2}{\sum_{n}^{i}(|Y_{R\_est}-\bar{Y}_{R\_obs}|+|Y_{R\_obs}-\bar{Y}_{R\_obs}|)^2}\right) \tag{12}$$

$$E=1-\left(\frac{\sum_{i=1}^{n}(Y_{R_{obs}}-Y_{R_{est}})^2}{\sum_{i=1}^{n}(Y_{R_{obs}}-\bar{Y}_{R_{est}})^2}\right) \tag{13}$$

The ecdf functions for the observed ($Y_{R\text{-}obs}$) and estimated ($Y_{R\text{-}est}$) seasonal crop model outputs (yield, biomass, LAI and SRA) was calculated and the maximum vertical distance between $Y_{R\text{-}obs}$ and $Y_{R\text{-}est}$ ecdf's was determined by the Kolmogorov-Smirnov test (K-S).

3. RESULTS AND DISCUSSION

In the study region, the daily air temperature range increases from April, the beginning of the dry period, to August, which is the top of dry period and decrease from September, begin of the wet period, to December. For upland rice, the planting window is from November to December and rice is harvested in April. This period shows the lowest daily temperature range.

The local empirical parameter estimates obtained for the five models are described in table 2. Few papers actually report estimated values for these parameters. The parameter estimates listed here for the CD and DB models are similar to the ones described by Bellocchi et al. (2003). However, for the BC model, *b* parameter

Table 2. Parameter estimates of solar radiation models at each location (wheather station)

Model	Empirical Parameters	Weather Station ID								
		1	2	3	4	5	6	7	8	9
BC	b	0.96	0.70	0.75	0.69	0.39	0.87	1.93	0.42	0.94
	c	1.38	1.60	1.59	1.47	1.89	1.36	1.12	1.71	1.42
CD	b	0.13	0.46	0.42	0.18	0.51	0.13	0.13	0.30	0.23
DB	b	0.20	0.28	0.28	0.19	0.30	0.17	0.24	0.21	0.24
	c_1	0.04	-0.02	0.00	0.05	-0.06	0.04	0.06	0.02	0.01
	c_2	1.41	1.46	1.22	0.46	1.46	0.76	1.03	0.74	0.74
DCBB	b	0.17	0.24	0.23	0.16	0.26	0.14	0.20	0.17	0.20
	c_1	0.04	-0.02	0.00	0.04	-0.06	0.04	0.05	0.01	0.01
	c_2	1.41	1.46	1.22	0.46	1.46	0.76	1.03	0.74	0.74
HG	b	0.18	0.17	0.18	0.18	0.16	0.17	0.17	0.14	0.18
	c	-4.80	-0.07	-1.98	-3.69	1.42	-4.03	-2.15	0.82	-2.71

BC: Bristow-Campbell; HG: Hargreaves; CD: Donatelli-Campbell; DB: Donatalli-Bellocchi and DCBB: modular model

Table 3. Accuracy of solar radiation models by site as measured by overall model mean of the following measures

Model			Wheater Station ID										
			1	2	3	4	5	6	7	8	9	Mean	S.D.
BC	Calibration	RRMSE	11.58	12.31	12.62	16.1	13.06	9.92	11.4	13.3	13.09	12.5	1.63
		MAE	2.3	2.73	2.69	3.08	2.93	2.05	2.38	2.43	2.57	2.55	0.31
		r	0.78	0.69	0.74	0.71	0.72	0.83	0.73	0.74	0.77	0.75	0.04
		RMSEs	3.09	3.62	3.51	4.25	3.72	2.55	3.22	3.11	3.43	3.39	0.45
	Validation	RRMSE	11.76	14.93	12.95	15.7	15.16	11.48	13.3	14.9	13.45	13.72	1.44
		MAE	2.35	2.79	2.8	3.06	2.83	2.24	2.31	2.85	2.66	2.67	0.28
		r	0.77	0.70	0.69	0.71	0.73	0.81	0.75	0.71	0.73	0.73	0.04
		RMSEs	3.12	3.57	3.62	3.93	3.44	2.90	3.00	3.48	3.53	3.40	0.31
CD	Calibration	RRMSE	12.06	12.72	13.05	16.2	13.3	10.27	12.5	13.6	13.59	12.93	1.51
		MAE	2.37	2.76	2.71	3.1	2.99	2.06	2.59	2.5	2.64	2.62	0.3
		r	0.79	0.69	0.74	0.72	0.72	0.84	0.73	0.75	0.77	0.75	0.04
		RMSEs	3.04	3.57	3.48	4.13	3.70	2.50	3.18	3.07	3.43	3.34	0.44
	Validation	RRMSE	12.14	15.61	13.40	16.00	15.53	11.19	14.4	15.1	14.11	14.14	1.56
		MAE	2.42	2.84	2.8	3.03	2.91	2.16	2.43	2.88	2.76	2.71	0.28
		r	0.77	0.71	0.69	0.70	0.73	0.81	0.75	0.73	0.73	0.74	0.04
		RMSEs	3.14	3.55	3.60	3.98	3.44	2.84	3.03	3.39	3.54	3.39	0.32
DB	Calibration	RRMSE	12.82	12.72	13	16.5	13.04	12.07	11.9	13.6	13.96	13.16	1.35
		MAE	2.54	2.73	2.68	3.09	2.85	2.53	2.45	2.49	2.71	2.65	0.2
		r	0.77	0.69	0.74	0.71	0.73	0.80	0.75	0.75	0.77	0.75	0.03
		RMSEs	3.14	3.61	3.47	4.25	3.84	2.68	2.95	3.10	3.50	3.39	0.45
	Validation	RRMSE	12.58	15.49	13.24	17	15.53	11.92	14.2	15.4	14.47	14.37	1.54
		MAE	2.58	2.8	2.77	3.25	2.88	2.31	2.4	2.96	2.81	2.76	0.27
		r	0.75	0.71	0.69	0.66	0.73	0.79	0.75	0.71	0.72	0.72	0.04
		RMSEs	3.20	3.56	3.58	4.01	3.49	3.00	3.00	3.39	3.54	3.42	0.30
DCBB	Calibration	RRMSE	14.56	12.75	12.99	17.6	13.15	15.69	13.7	14.1	15.18	14.19	1.63
		MAE	2.98	2.73	2.7	3.2	2.84	3.33	2.93	2.58	2.96	2.88	0.26
		r	0.77	0.69	0.75	0.70	0.72	0.83	0.77	0.75	0.76	0.75	0.04
		RMSEs	3.14	3.61	3.47	4.25	3.84	2.68	2.95	3.10	3.63	3.41	0.46
	Validation	RRMSE	14.72	15.51	13.22	17	15.38	16.21	16.8	16.2	15.77	15.49	1.19
		MAE	3.00	2.79	2.78	3.28	2.86	3.23	2.92	3.10	3.05	2.99	0.17
		r	0.73	0.71	0.69	0.64	0.73	0.79	0.76	0.71	0.72	0.72	0.04
		RMSEs	3.28	3.56	3.58	4.15	3.49	3.08	3.00	3.50	3.63	3.47	0.32
HG	Calibration	RRMSE	11.82	13.14	13.24	16.7	14.88	10.3	11.5	15.3	13.58	13.43	1.91
		MAE	2.43	3.07	2.91	3.37	3.54	2.10	2.46	2.84	2.73	2.84	0.44
		r	0.77	0.62	0.70	0.68	0.58	0.81	0.72	0.62	0.75	0.70	0.08
		RMSEs	3.16	3.89	3.72	4.40	4.34	2.66	3.27	3.63	3.56	3.63	0.52
	Validation	RRMSE	12.52	16.12	13.47	16.7	16.91	12.53	13.5	15.8	13.78	14.65	1.68
		MAE	2.56	3.15	2.99	3.48	3.34	2.57	2.39	3.04	2.84	2.97	0.37
		r	0.73	0.62	0.66	0.66	0.61	0.75	0.74	0.66	0.71	0.68	0.05
		RMSEs	3.34	3.90	3.78	4.19	4.02	3.20	3.09	3.73	3.62	3.65	0.35

S.D.: standard deviation. BC: Bristow-Campbell. CD: Donatelli-Campbell. DB: Donatalli-Bellocchi. DCBB: modular model. HG: Hargreaves. RRMSE: relative root mean square error, %; MAE: mean absolute error, MJ m2 day-1; r: correlation coefficient and RMSEs: systematic root mean square error, MJ m2 day-1.

was higher (0.42 to 1.93) than the one reported in Bellocchi et al. (2003), ranging from 0.08 to 0.6. According to Liu et al. (2008), for the BC model, *b* parameter is more affected than *c* by different ways of calculating the monthly mean temperature (ΔTm) correction. In this study, ΔTm was calculated as centred week mobile average (ΔT_{avg}). Also we did not have set the *c* parameter as fixed for the BC model, but calibrated it separately for each location. Parameter *c* ranged from 1.12 to 1.89. For the HG model, parameters *b* and *c* are similar to those ones found by Liu et al. (2008). They ranged from 0.14 to 0.18 and -4.80 to 1.42, respectively.

The accuracy of the five models evaluated (Equations 1–5) was similar (Table 3): based on the average RRMSE values (Table 3) all were classified as good. The BC model showed the lowest mean RMSE and MAE values for calibration as well as validation. BC and CD model showed the lowest mean systematic error values (RMSEs) for calibration and validation. Considering all data set (Figure 1a–e), the r

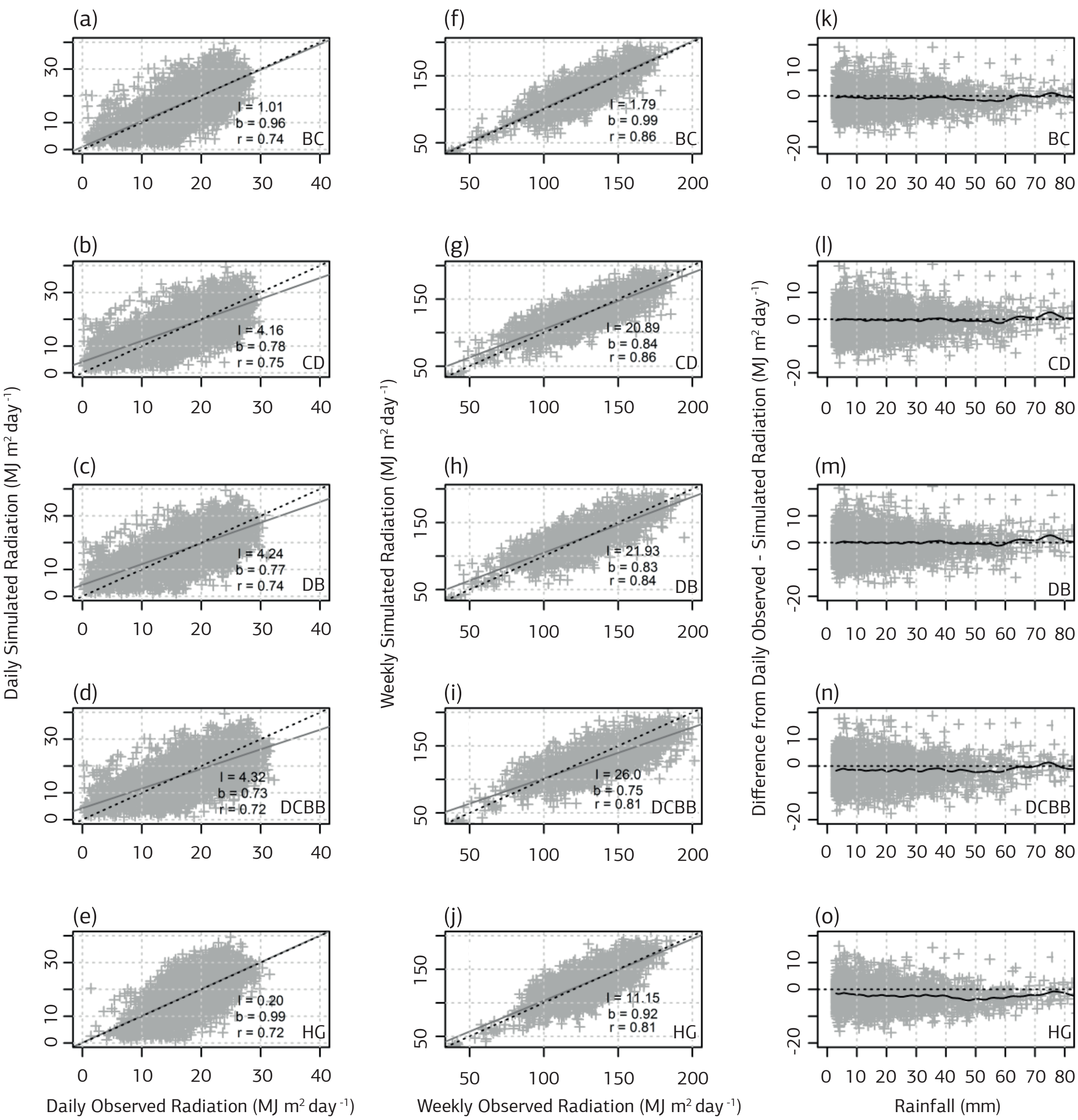

Figure 1. Scatterplots for daily observed radiation versus daily simulated radiation (a–e), weekly observed radiation versus weekly simulated radiation (f–j), being the black dashed line the 1:1 and gray full line the fitted regression line and I is the intercepted, b the slope and r the coefficient of determination for the regression line Scatterplots at the right columns of the panel (k–o) show difference between daily observed and simulated radiation for each model, as function of daily rainfall amount. BC: Bristow and Campbell; HG: Hargreave; CD: Donatelli and Campbell; DB: Donatelli & Bellocchi and DCBB: modular model.

ranged from 0.72 to 0.75. These values are lower than the ones found in European studies (Trnka et al., 2005), but similar to values presented in a Northern Australian study (Liu and Scott, 2000) and some values obtained from locations in North America (Ball et al., 2004). The CD model showed the highest degree of linear relationship between measured and simulated R_s (highest r value) followed by the BC and DB models (Figure 1b). Comparing the slopes and intercepts of the linear regressions between daily measured and predicted R_s, the HG model showed the slope (b) and intercepted (I) closest to 1 and 0, respectively, followed by the BC model (Figure 1a,e). The weekly aggregation of measured and predicted radiation values (Figure 1f–j) lead to increased r (0.81 to 0.86), minimizing the discrepancy. In this case, the BC and CD models showed the highest degree of agreement between measured and simulated R_s (highest r value) followed by the DB model. The BC model showed the slope and intercept closest to 1 and 0, respectively (Figure 1f). The highest residuals for all radiation models (Figure 1k–o)) corresponded to days with low rainfall values (≤10 mm). The BC, CD, DB and DCDB models had the cubic smoothing spline regression parallel the zero residual line, showing no relationship between bias and rainfall. The HG and DCBB overestimated radiation under rainfall. Probably, adding rainfall variable in these two models will improve their performance under rainfall days.

Impact of estimated solar radiation on simulated crop model output

Considering pooled data from all weather stations, all evaluated radiation models (Equations 1–5) were classified in same class of accuracy (RRMSE<10%) for predicting yield, biomass and SRA (Table 4) which is not surprising considering that they simulated R_s with similar accuracies (Table 3). Only the HG model, for maximum LAI showed an RRMSE higher than 10%. In this study, all crop models outputs showed RMSE higher than MAE (Table 4). The ratio RMSE/MAE is an indicator of regression outliers (Legates and Mccabe, 1999). The highest difference between RMSE and MAE for yield was observed for BC model (80 kg ha^{-1}) and the lowest for the HG model (68 kg ha^{-1}). The HG model also showed the highest r for yield (0.99). All radiation models resulted in similar values for the index of agreement (d) for yield (Table 4). However, the coefficient of efficiency (E) for yield was different among models. Based on this index, the best models for estimated radiation to predict yield are BC, CD and DCBB. The use of daily solar radiation estimated by BC and HG as input to APSIM/ORYZA leads to overestimation of yield as characterized by boxes bellow the zero line (high frequency of $Y_{R\text{-obs}} < Y_{R\text{-est}}$) in Figure 2.

Conversely, when radiation was estimated via the CD, DB and DCBB models, the referred output variables showed an underestimation tendency. For maximum biomass, the highest difference between RMSE and MAE was observed for the DCBB model (151 kg ha^{-1}) and the lowest for the BC model (92 kg ha^{-1}). In this case the BC and HG models showed the highest r (0.97) (Table 4). Based on d, the best models were BC, CD and DCBB. Nevertheless, BC model showed the highest E. BC and HG models also leads to overestimate the maximum biomass as showed in Figure 2b, being the degree of overestimation higher for HG. For maximum LAI, the HG model accounted for the highest

Table 4. Measures of agreement among APSIM/ORYZA outputs (yield, biomass, maximum LAI and solar radiation accumulated (SRA) during the crop cycle) simulated using either observed radiation or radiation estimated by empirical models

		Yield	Biomass	LAI	SRA	Average
BC	RRMSE	6.9	4.1	5.9	5.3	5.6
	RMSE	261	493	0.22	104	215
	MAE	181	401	0.16	82	166
	r	0.97	0.97	0.95	0.62	0.88
	d	0.99	0.99	0.99	0.98	0.99
	E	0.97	0.96	0.95	0.59	0.87
CD	RRMSE	7.4	5.3	7.4	5.4	6.4
	RMSE	279	636	0.27	106	255
	MAE	212	497	0.21	86	199
	r	0.93	0.96	0.94	0.65	0.87
	d	0.99	0.99	0.99	0.97	0.99
	E	0.97	0.95	0.92	0.56	0.85
DB	RRMSE	8.3	6	8.4	6.7	7.4
	RMSE	316	723	0.31	129	292
	MAE	245	581	0.24	105	233
	r	0.96	0.96	0.93	0.58	0.86
	d	0.99	0.98	0.98	0.92	0.97
	E	0.96	0.93	0.89	0.34	0.78
DCBB	RRMSE	7.2	5.2	7.1	9.9	7.4
	RMSE	272	621	0.26	192	271
	MAE	197	470	0.19	155	206
	r	0.97	0.96	0.93	0.34	0.80
	d	0.99	0.99	0.99	0.92	0.97
	E	0.97	0.95	0.92	-0.41	0.61
HG	RRMSE	8.9	8.6	10.3	6.7	8.6
	RMSE	331	1028	0.41	130	372
	MAE	273	880	0.32	104	314
	r	0.98	0.97	0.95	0.6	0.88
	d	0.99	0.96	0.96	0.93	0.96
	E	0.95	0.86	0.82	0.34	0.74

RRMSE: relative root mean square error (%). RMSE: root mean square error (for yield and biomass kg ha^{-1}, for SRA MJ m^{2} day^{-1}).
MAE: mean absolute error (for yield and biomass kg ha^{-1}, for SRA MJ m^{2} day^{-1}).
r: correlation coefficient. d: -index of agreement. E: coefficient of efficiency.
BC: Bristow-Campbell; HG: Hargreaves; CD: Donatelli-Campbell; DB: Donatalli-Bellocchi and DCBB: modular model

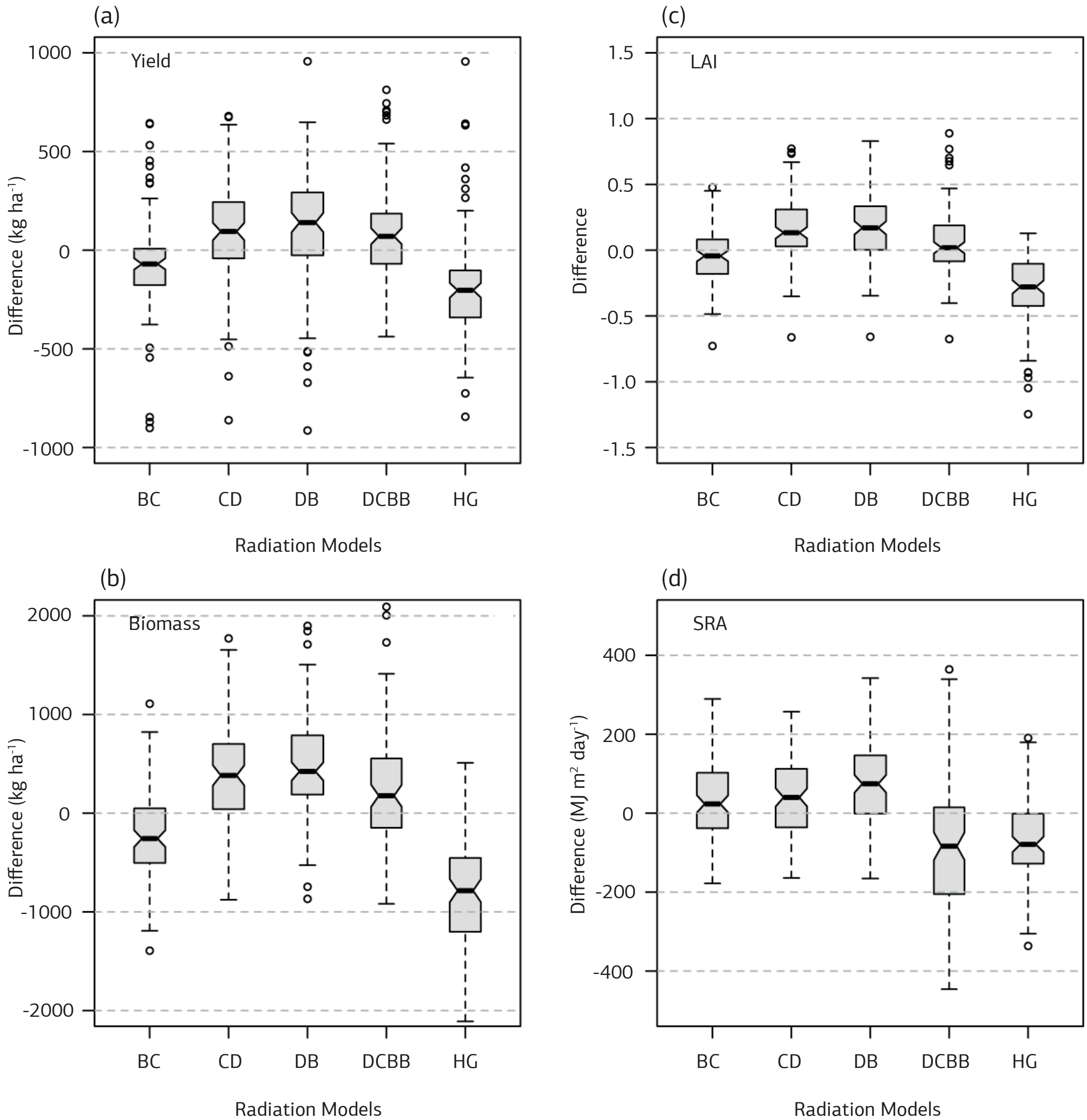

Figure 2. Box plot for crop model output difference ΔY (model output using observed daily radiation minus respective model output using simulated daily radiation), considering pooled data from locations and planting dates for (a) simulated yield, (b) simulated Biomass, (c) simulated max LAI and (d) simulated SRA (solar radiation accumulated during crop cycle). BC: Bristow and Campbell; CD: Donatelli and Campbell; DB: Donatelli and Bellocchi; DCBB: modular model and HG: Hargreave. The bottom and top edges of the box are located at the 25^{th} and 75^{th} sample percentiles of ΔY. The center horizontal line is drawn at the median and the black dot, at the mean. The vertical lines, or whiskers, extends from the box as far as the data extend, to a distance at most 1.5 interquartile range.

difference between RMSE and MAE (0.10) and the lowest difference by the BC and CD models (0.06). The BC and HG had the highest r values. According to d, the best models for maximum LAI were BC, CD and DCBB. Based on E, the best model was BC (Table 4). For this crop model output, BC and HG models showed the same trend as yield and biomass. Both models leads to overestimate the maximum LAI as showed in Figure 2c. However, the degree of overestimation is higher for the HG model. For SRA, the DCBB model accounted for the highest difference between RMSE and MAE (37 MJ m^2 day^{-1}). The CD model showed the lowest difference (20 MJ m^2 day^{-1}). The CD model also showed the highest r (0.65). According to d and E, the best model was BC (Table 4). For SRA, a quite different pattern was observed: radiation estimated via the BC, CD and DB models lead to simulated SRA values below the corresponding ones obtained by using observed radiation as model input. The HG and DCBB models showed an opposite tendency (Figure 2d). Taking into account the average of the deviance measures (RRMSE, RMSE, MAE and r) and similarity measures (d and E) for all crop models output studied here, the BC model had the lowest

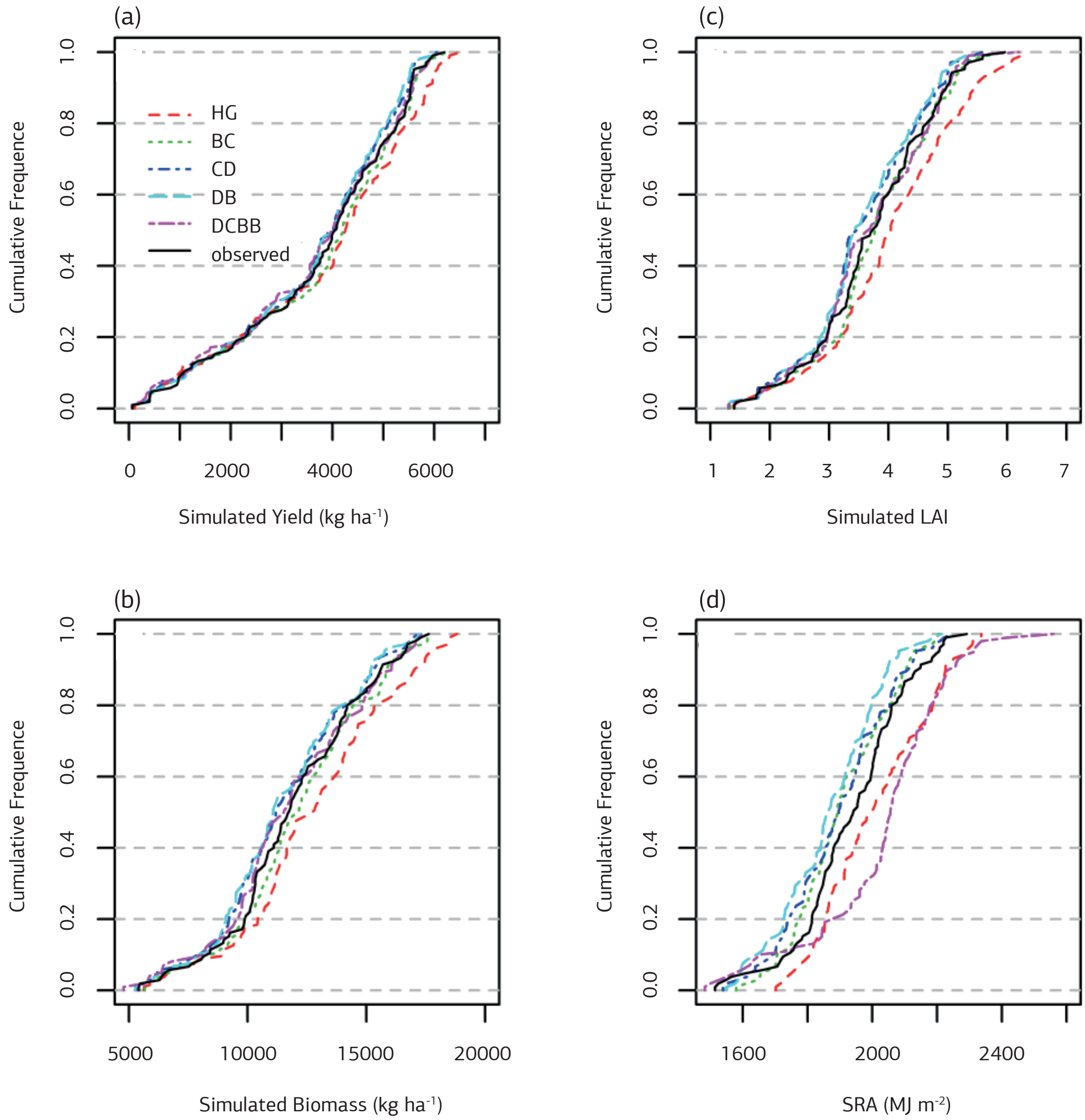

Figure 3. The estimated and observed empirical cumulative distribution function (ecdf) for the seasonal crop models output (a) yield, (b) biomass, (c) maximum leaf area index (LAI) and (d) accumulated solar radiation during crop cycle (SRA). BC: Bristow-Campbell; HG: Hargreaves; CD: Donatelli-Campbell; DB: Donatelli-Bellocchi and DCBB: modular model.

values for RRMSE, RMSE and MAE and the highest for r, d and E (Table 4).

The ecdf curve for $Y_{R\text{-}obs}$ and $Y_{R\text{-}est}$ seasonal crop model outputs were plotted in Figure 3. The quantile values derivate from ecdf for $Y_{R\text{-}obs}$ and $Y_{R\text{-}est}$ are showed in Table 5. For the seasonal crop model outputs yield, biomass and LAI, the ecdf curves for $Y_{R\text{-}obs}$ and $Y_{R\text{-}est}$ was quite similar (Figure 4a–c). It was also observed for the quantile values showed in table 5. Based on the K-S test, the ecdf curves for $Y_{R\text{-}obs}$ and $Y_{R\text{-}est}$ did not differ statistically at 10% of significance (Table 5, p value). It means that for a limited water environment (no irrigation) solar radiation is not the main driven for yield, biomass and LAI and soil water available has an important role for these crop model outputs. Then, crop model outputs yield, biomass and LAI are not sensitive for the solar radiation models studied here (BC, HG, DCBB and CD). Based also in the p value from K-S test (Table 5), the radiation model that showed the minimum vertical distance from $Y_{R\text{-}obs}$ and $Y_{R\text{-}est}$ ecdf curve for yield was BC and DCBB ($p>0.05$), for biomass and LAI was also BC model ($p>0.05$). For SRA, it was observed difference at level of 5% of significance between $Y_{R\text{-}obs}$ and $Y_{R\text{-}est}$ ecdf curve for DB, DCBB and HG solar radiation model (Table 5, p value). However, this difference in the accumulated solar radiation during the crop cycle was not enough to affected yield, biomass and LAI.

Table 5. Quantile values (0, 25, 50, 75 and 100%) and p values of Kolmogorov-Smirnov (K-S) test between observed and estimated empirical cumulative distribution function (ecdf) for crop models output (yield, biomass, maximum leaf area index (LAI) and solar radiation accumulated during crop cycle (SRA))

Quantile (%)	Yield (kg ha^{-1})						Biomass (kg ha^{-1})					
	$Y_{R\text{-}obs}$	BC	CD	DB	DCBB	HG	$Y_{R\text{-}obs}$	BC	CD	DB	DCBB	HG
0	65	74	70	62	62	115	5413	5674	5303	5275	4780	5640
25	2627	2649	2631	2631	2557	2610	10197	10353	9651	9493	9785	10918
50	4050	4201	3969	4031	3983	4265	11717	12160	11191	11079	11517	12702
75	5019	5076	4864	4868	5075	5255	13887	13996	13355	13394	14086	14753
100	6203	6247	6052	6058	6123	6496	17626	17646	17176	17308	17363	18818
K-S test (*p* value)		0.99	0.97	0.62	0.99	0.29		0.92	0.40	0.24	0.69	0.12
Quantile (%)	**LAI**						**SRA (MJ m^{-2})**					
	$Y_{R\text{-}obs}$	BC	CD	DB	DCBB	HG	$Y_{R\text{-}obs}$	BC	CD	DB	DCBB	HG
0	1.40	1.33	1.30	1.30	1.30	1.39	1514	1579	1539	1550	1482	1702
25	3.05	3.29	3.03	2.97	3.03	3.33	1830	1803	1785	1743	1940	1866
50	3.70	3.77	3.49	3.42	3.61	4.03	1942	1892	1896	1861	2056	1994
75	4.40	4.62	4.36	4.28	4.56	4.83	2048	2017	2013	1982	2162	2157
100	5.96	5.96	5.57	5.41	6.20	6.32	2292	2204	2250	2213	2559	2337
K-S test (*p* value)		0.87	0.18	0.34	0.65	0.15		0.20	0.11	0.02	<0.01	0.04

$Y_{R\text{-}obs}$ – crop model output obtained using observed radiation. BC: Bristow-Campbell. HG: Hargreaves. CD: Donatelli-Campbell. DB: Donatalli-Bellocchi and DCBB: modular model.

4. CONCLUSION

Five models for estimated daily solar radiation were tested in their agreement and showed similar accuracy (r=0.68 to 0.75, RMSE=12 to 14%). For water limited environments (no irrigation) the crop model outputs yield, biomass and LAI is not sensitive for the uncertainties in radiation models studied here (BC, CD, DB, HG and DCBB). Among the radiation models studied here, the BC model show the minimum vertical distance between $Y_{R\text{-}obs}$ and $Y_{R\text{-}est}$ ecdf's (highest *p* value) for all crop models outputs (yield, biomass, LAI and SRA).

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