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Evaluating accuracy of DSSAT model for soybean yield estimation using satellite weather data

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ABSTRACT

Crop models allow simulating the development and yield of the crops, to represent and to evaluate the influence of multiple factors. The DSSAT cropping system model is one of the most widely used and contains CROPGRO module for soybean. This crop has a great importance for many southern countries of Latin America and for Argentina. Solar radiation and rainfall are necessary variables as inputs for crop models; however these data are not as readily available. The satellital products from Clouds and Earth's Radiant Energy System (CERES) and Tropic Rainfall Measurement Mission (TRMM) provide continuous spatial and temporal information of solar radiation and precipitation, respectively. This study evaluates and quantifies the uncertainty in estimating soybean yield using a DSSAT model, when recorded weather data are replaced with CERES and TRMM ones. Different percentages of data replacements, soybean maturity groups and planting dates are considered, for 2006–2016 period in Oliveros (Argentina). Results show that CERES and TRMM products can be used for soybean yield estimation with DSSAT considering that: percentage of data replacement, campaign, planting date and maturity group, determine the amounts and trends of yield errors. Replacements with CERES data up to 30% result in % RMSE lower than 10% in 87% of the cases; while the replacement with TRMM data presents the best statisticals in campaigns with high yields. Simulations based entirely on CERES solar radiation give better results than those with TRMM. In general, similar percentages of replacement show better performance in the estimation of soybean yield for solar radiation than the replacement of precipitation values.

1. Introduction

Simulation crop models allow to represent growth, development and yield of crops and to evaluate new technologies or conditions not yet explored. For these reasons, among others, the models are useful in dynamic and changing environments such as current agriculture, and can be used to estimate the impact of current and future climates on crop yields and food security. As Dokoohaki et al. (2016) state, crop models facilitate the clarification and evaluation of multidimensional relationships between factors affecting crops. These factors include planting date, cultivar selection, seeding rates, soil type, fertilizer and irrigation strategies, and seasonal weather patterns.

Long-term simulations require historical daily weather data that many times are not available. Alternatively, gridded weather databases are available, typically derived from: global circulation models, interpolated weather station data or remotely sensed surface data (van Wart et al., 2013).

Numerous models are available to predict crop growth, among these the Decision Support System for Agrotechnology Transfer (DSSAT) (Jones et al., 2003; Hoogenboom et al., 2012), the Agricultural Production Systems sIMulator (APSIM) (Keating et al., 2003) and the Soil, Water, Atmosphere, and Plant (SWAP) (van Dam et al., 1997).

The DSSAT cropping system model is one of the most widely used (Jones et al., 2017). This product was developed with a modular structure to facilitate its maintenance and to include additional components to simulate cropping systems, considering different soils, climates, and management conditions. DSSAT contains the CROPGRO plant growth module for grain legumes, particularly soybean (*Glycine* max L. *Merr.*), and others for maize (*Zea mays* L.), rice (*Oritza sativa* L.), wheat (*Triticum aestivum* L.) (Hoogenboom and Jones, 2015), etc. Modifications of DSSAT were introduced in order to simulate the effects of tillage and surface crop residues on soil water and organic matter dynamics (Porter et al., 2010). The DSSAT is used to simulate crop sequences over

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any number of years, such as would occur in crop rotations, and it is also used for studying the long-term effects of different management practices on growth, development and yield of a crop, as well as the soil water, carbon and nitrogen processes (Li et al., 2015).

Most crop simulation models require daily solar radiation, maximum and minimum air temperatures and precipitation (Abraha and Savage, 2008; Borges et al., 2010; Wang et al., 2015). Solar radiation is a necessary input for estimations; however these data are not as readily available as air temperature (Will et al., 2013; Almorox et al., 2017). Even at stations where solar radiation is observed there could be many days when solar radiation data are missing or lie outside the expected range due to equipment failure and other problems mainly in several Latin American countries. Particularly in Argentina, as indicated by Will et al. (2013), the problem of lack of sufficient radiation data in quantity and quality is widespread, and besides solar radiation is measured in few automatic weather stations.

On the other hand, there is no agency to centralize information, check the consistency of data and regularly calibrate the sensors (Hossain et al., 2014). In the literature a number of empirical models, statistical approaches coming from time-series analysis, neural networks and soft-computing techniques, have been applied to estimate the solar radiation (Besharat et al., 2013). However, the Angstrom–Prescott model (Prescott, 1940) which uses sunshine duration, is the most commonly used to estimate this variable.

In the last decade, the satellite-derived images are promising for estimating solar radiation data over large regions. These images provide information of global radiation with temporal continuity and spatial homogeneity (Zhang et al., 2014). Chen et al., (2014) developed a method to estimate the global-scale total, direct, and diffuse solar radiation using MODIS. Polo (2015) described the methodology for deriving solar radiation incident components from geostationary satellites, and he applied this methodology to Meteosat satellites images and generated solar radiation maps of Spain for the period of 2001–2011.

Due of the importance of the role of product data from Clouds and Earth's Radiant Energy System (CERES) to understand climate change, different studies were recently developed to evaluate the parameters of CERES on all types of surfaces matching ground-based observations (Sai Krishna et al., 2014; Pan et al., 2015; Zhang et al., 2015). In Almorox et al. (2017) the solar radiation generated by CERES and the surface radiation registers were compared and evaluated, for different meteorological stations located in Spain.

Another necessary variable for crop models is the precipitation; generally the models require the spatially distributed data as input to reflect the heterogeneity. Advances in remote sensing make possible a spatially and temporally continuous monitoring of rainfall, covering long periods of time and large areas. For this, satellital images are an alternative source of information (Cheema and Bastiaanssen, 2012). A number of quasi-global high-resolution satellite precipitation products have been developed over the past few years, including the Tropic Rainfall Measurement Mission (TRMM) launched by the National Aeronautics and Space Administration (NASA) and the Japan Aerospace Exploration Agency (JAXA) (Su et al., 2008; Meng et al., 2014). Yang and Nesbitt (2014) affirmed that the TRMM PR is unique, because it is the first space-aboard precipitation radar (PR) dedicated to rainfall measurement, and it has a long period of observation from space. Its advantages in measuring precipitation when compared to ground-based radar are obvious because of the global coverage, accurate calibration, downward viewing geometry, and lack of beam blockage.

The TRMM product was used with different accuracies results (Dinku et al., 2007; Villarini and Krajewski, 2007). Cheema and Bastiaanssen (2012) developed a calibration protocol for TRMM rainfall data at different spatial and temporal scales for Pakistan, India, China (Tibet) and Afghanistan.

Soybean crop has a great importance for many southern countries of Latin America and for Argentina, particularly, considering the economic yield obtained by farmers and the sown surface (Sayago et al., 2017; Zhong et al., 2016). The US Department of Agriculture (USDA) estimated that the soybean world production in 2015/16 growing season was 317.6 million tons. The soybean sown surface for Latin American countries which appear among the top 10 soybean producers in the world (FAO, 2017), for the 2015/16 campaign was: 33,200,000 ha in Brazil (Ministério da Agricultura, Pecuária e Abastecimento, 2017); 20,479,000 ha in Argentina (Ministerio de Agroindustria, 2017); 3,370,000 ha in Paraguay (Ministerio de Agricultura y Ganadería, 2017) and 1,140,000 ha in Uruguay (Ministerio de Ganadería, Agricultura y Pesca, 2017).

This study evaluates and quantifies the uncertainty that arises in estimating soybean yield using a DSSAT model, when recorded weather data (solar radiation and precipitation), are replaced with satellite products (CERES and TRMM). Different percentages of data replacements, soybean maturity groups and planting dates are considered for 2006–2016 period.

2. Materials and methods

2.1. Satellite images

Solar radiation data from satellite were obtained from CERES (http://neo.sci.gsfc.nasa.gov/), which were produced, archived, and made available to the scientific community by the Langley Research Center (LaRC), the Atmospheric Sciences Data Center (ASDC), and the National Aeronautics and Space Administration (NASA) by the FLASHFlux project (http://flashflux.larc.nasa.gov/).

FLASHFlux data are produced using CERES, which measures reflected and emitted solar radiation from the top of the atmosphere, convolved with MODIS measurements from both the Terra and Aqua satellite. CERES has three channels, one short wave measuring reflected sunshine in the region from 0.3 to 5.0 μm, another measurement of thermal radiation emitted by the Earth, between 8.0 and 12.0 μm, and a third, which accounts for the full spectrum of outgoing radiation from Earth.

The spatial and temporal resolutions of the product used in this study were 0.25° latitude/longitude and daily, respectively, for the time period July 2006 to July 2016. Further details about the algorithms and data processing are described in the work of Pan et al. (2015).

The precipitation data were obtained from the TRMM satellite (https://neo.sci.gsfc.nasa.gov/view.php?datasetId=TRMM_3B43D), which has both passive and active sensors on board, and measured rainfall since 1997 (Cheema and Bastiaanssen, 2012). It is a low-latitude satellite that includes one precipitation radar (PR), along with a multi-channel passive TRMM microwave imager (TMI) and a visible and infrared (IR) scanner, a cloud and earth radiant energy sensor and a lightning imaging sensor. The TMI compliments the PR by providing the total hydrometeor (liquid and ice) content within precipitation systems. The spatial resolution of the product used in this study was 0.25° latitude/longitude and the temporal one was daily, for the period July 2006 to July 2016.

2.2. CROPGRO soybean - DSSAT model

The CROPGRO Soybean model included in DSSAT v4.6 was used to simulate the daily soybean growth until the stage of physiological maturity and harvest, and then quantify the yield. Four modules that interact compose this software: development, and carbon, water and nitrogen balance.

CROPGRO Soybean requires as input data those related to climate (maximum and minimum temperature, global solar radiation and precipitation, among others), soil (physical and chemical properties of each profile horizon), crop management (residues, planting dates, fertilization, irrigation, etc.) and the genetic coefficients of the cultivars. Although the computation time is daily, some processes like photosynthesis or phenological evolution use a time step.

This crop simulation model needs cultivar coefficients. Salmerón and Purcell (2016) showed that the accuracy of the model was similar when phenological coefficients of CROPGRO were used instead of cultivar specific ones. These authors proved that the set of generic coefficients tested across a wide range of latitudes and planting dates were able to predict main developmental stages with sufficient accuracy for many agronomic purposes. For this, in this work the CROPGRO Soybean cultivar coefficients were used.

In order to analyse and evaluate the different factors related to the soybean yield three varieties with different maturity groups (MG III, MG IV and MG V) were considered. Three planting dates were evaluated (PD1:10/15, PD2:10/30 and PD3:11/15) for ten agricultural campaigns between the years 2006 and 2016, allowing to consider different photothermal and water regimes to which the crop could be exposed. The simulation period for each campaign was from 10/1 to 4/30.

To evaluate the effect of the substitution of registered solar radiation data with CERES images, in each crop season, the observed data were randomly replaced for 10–100% (in 10% steps), with 10 repetitions for each percent of replacement. The same methodology was used for the precipitation data substitution obtained from TRMM images. Finally, the comparison between the yield (in kg ha^{-1}) obtained by CROPGRO Soybean using registered data and the results considering separately CERES or TRMM data with different replacement percentages was made.

2.3. Model application site

For the present work data from EEA Oliveros (INTA - Santa Fe province, Argentina 32°33′S; 60°51′W), which is one important agricultural region, (Fig. 1), acquired between July 2006 and July 2016 were used.

In this area, the predominant soils are Acuic Argiudoll (Barbieri et al., 2017), many of which show a marked physical deterioration, evidenced by compaction in the upper horizon. These processes affect root growth of crops and produce a decrease in the rate of water infiltration (Cosentino and Pecorari, 2002). For DSSAT soil inputs, data up to 240 cm depth were used (Table 1). For Root Growth Factor (SRGF) a value equal to 0.50 was considered for Lower boundary of a soil layer from 25 to 147 cm and for the last (240 cm) such value was 0.35.

The climate of the region is humid mesothermal with no (or little) water deficit. Regarding temperature, summers are hot and humid, with monthly mean temperatures of 23 °C, and winters are temperate and dry, with mean temperatures of 12 °C. The mean annual precipitation for Santa Fe Province, is approximately 1300 mm in the northeastern region, gradually decreasing to less than

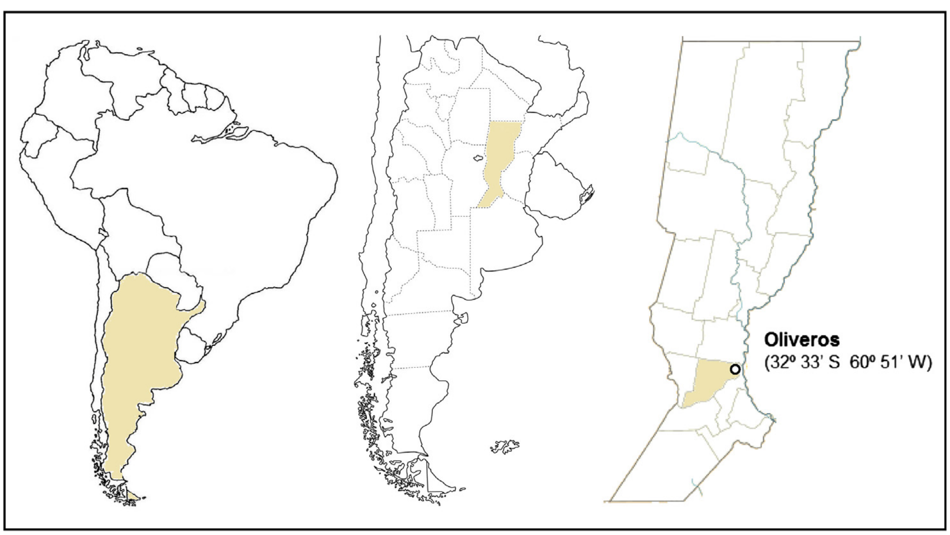

Fig. 1. Localization of the model application site.

Table 1
Soil parameters for EEA Oliveros (INTA), Argentina.

SLB	SLMH	SLLL	SDUL	SSAT	SBDM	SLOC	SLCL	SLSI	SLNI	SLHW	SCEC
25	A1	0.055	0.200	0.390	1.20	1.53	21.5	74.5	0.15	5.5	19.4
37	B1	0.165	0.308	0.386	1.25	0.75	29.0	69.5	0.10	5.8	21.0
51	B2	0.251	0.384	0.399	1.30	0.93	48.5	49.0	0.09	5.7	24.6
85	B2	0.254	0.386	0.401	1.30	0.47	49.0	49.0	0.07	6.1	36.4
112	B2	0.216	0.353	0.386	1.30	0.28	40.5	58.0	0.06	6.1	32.2
147	B3	0.183	0.322	0.389	1.25	0.12	33.0	63.5	0.04	6.2	30.2
240	C1	0.176	0.317	0.388	1.20	0.08	31.5	65.5	0.04	6.4	26.6

Parameters: SLB: Lower boundary of a soil layer (cm), SLMH: Master horizon, SLLL: Lower limit of plant extractable soil water (cm^3 cm^{-3}), SDUL: Drained upper limit (cm^3 cm^{-3}), SSAT: Saturate upper limit (cm^3 cm^{-3}), SBDM: Soil bulk density (g cm^{-3}), SLOC: Soil organic carbon concentration (%), SLCL: Clay (%), SLSI: Silt (%), SLNI: Total Nitrogen concentration (%), SLHW: pH in water, SCEC: Cation exchange capacity ($cmol^{+}kg^{-1}$).

Table 2
Meteorological data and omission data days, for campaigns between 2006 and 2016 registered in EEA Oliveros (INTA).

Campaign	Mean maximum temperature (°C)	Mean minimum temperature (°C)	Maximum solar radiation (MJ m^{-2} d^{-1})	Minimum solar radiation (MJ m^{-2} d^{-1})	Rainfall (mm)	Omission (days)
2006/07	27.7	17.0	40.0	0.3	1235	3
2007/08	28.5	15.7	32.6	1.8	583	3
2008/09	29.9	16.4	41.4	2.5	590	1
2009/10	28.3	16.7	29.1	1.8	941	2
2010/11	28.9	14.9	33.5	1.9	849	50
2011/12	28.4	15.9	28.9	0.5	796	17
2012/13	28.9	15.3	31.6	2.1	881	0
2013/14	29.4	16.4	29.8	1.5	981	0
2014/15	29.4	16.8	29.7	2.7	889	0
2015/16	28.5	16.6	29.7	1.5	1095	0

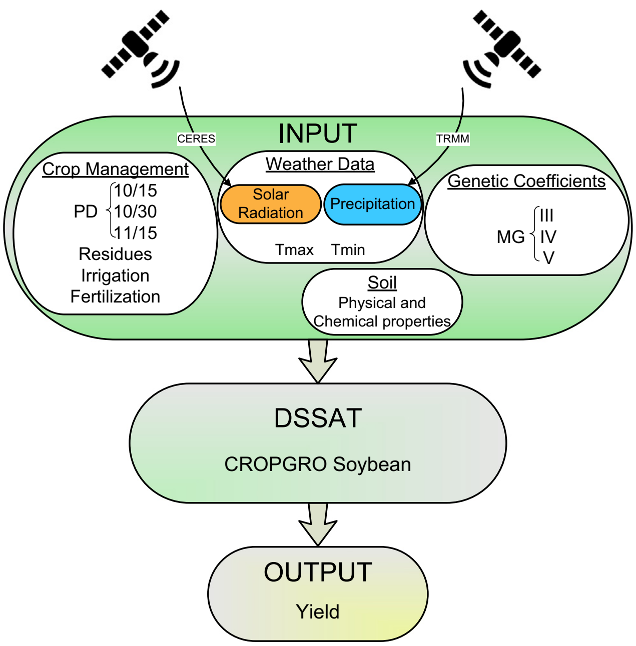

Fig. 2. Schematic diagram of the methodology.

950 mm towards the western and southwestern regions. The annual precipitation regime has minimum values in winter (June–July–August), with less than 30% of the annual precipitation, and maximum values in summer (January–February–March) (Venencio and García, 2011). The recorded data were daily values of maximum (*TMAX*) and minimum air temperature (*TMIN*), solar radiation (*SRAD*) and rainfall (*RAIN*), obtained from INTA Oliveros station (Table 2) (http://inta.gob.ar/documentos/informes-agrometeorologicos-de-eea-oliveros). Daily extraterrestrial solar radiation (*Ra*) was calculated according to the latitude and the day of the year (Allen et al., 1998).

Data were checked for outliers using the criteria proposed by Liu et al. (2009), which were missing measurements for any *TMAX*, *TMIN* or *SRAD*, $TMAX \leq TMIN$ and $SRAD/Ra \geq 1$.The omission of solar radiation data was solved by replacing its value in the missing days with the radiation obtained from Armstrong Prescott equation.

In the study region soybean cultivars correspond to maturity groups III, IV and V. Soybean is grown under no-till systems, with a distance between furrows of 0.52 m, and the planting date is concentrated between October and November. Harvesting takes place during the months of March and April, and weed controls and fertilization are carried out during the campaign.

As a summary, Fig. 2 shows the streamlines of the processes applied to crop, soil and weather data (registered and satellital), in order to estimate soybean yield with CROPGRO.

2.4. Model performance statistics

Model performance was evaluated comparing yield values with coefficient of determination (R^2), root mean square error (*RMSE*) and percent root mean square error (*%RMSE*); this last statistic was calculated as follows:

$$\%RMSE = 100\frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(Yield_s i_{ps} - Yield_r d)^2}}{\frac{1}{n}\sum_{i=1}^{n} Yield_r d} \tag{1}$$

where $Yield_r d$ and $Yield_s i_{ps}$ are estimated yield with registered data and satellite image data (p = replaced percentage and s = CERES or TRMM satellite data), respectively, for n observations.

3. Results and discussion

When the temporal evolution of solar radiation recorded in Oliveros and provided by CERES was analysed, for all campaigns considered in this work (Fig. 3), it became evident that the deviation between the measured and derived from CERES values is very small. It is important to note that the shapes of both curves (radiation in different months of each campaign) were respected in the whole period. Peak solar radiation occurs in January, which is coincident with the early soybean reproductive stages (R1-R4), and then decreases slightly in March when most of the seed filling phase (R5-R6) takes place. This same pattern was observed for this crop by Grassini et al. (2014), in inverted shape because they worked in northern hemisphere.

Fig. 4 indicates that the daily CERES data show a strong consistency with the in situ observations with average R^2 = 0.849 and $RMSE$ = 3.44 MJ m^{-2} d^{-1} for the whole period. van Wart et al. (2015) also evaluated the relationship between observed and estimated by NASA POWER daily solar radiation for Oliveros in the period 1998–2009, obtaining values of R^2 = 0.8 and $RMSE$ = 4.6 MJ m^{-2} d^{-1}. These values are similar to those observed by Jia et al. (2016) who presented average R^2 = 0.79 and $RMSE$ = 2.90 MJ m^{-2} d^{-1} for 340 worldwide locations. Also, Bai et al. (2010) showed *RMSE* and R^2 values of 3.4 MJ m^{-2} d^{-1} and 0.8, respectively, when comparing 10 years of daily solar radiation data from 39 ground stations across the five maize planting regions of China, with NASA-POWER database. Gilabert et al. (2018) used SEVIRI/MSG satellite images to calculate solar global irradiation, in Spain for the year 2011. Daily PAR (Photosynthetically Active Radiation in MJ m^{-2} d^{-1}) was obtained as 46% of the daily irradiation. The resulting PAR presented a mean absolute error ranging from 0.5 MJ m^{-2} d^{-1} to 0.9 MJ m^{-2} d^{-1}.

These results pointed out that error in estimating daily solar radiation from satellite data are similar to those obtained with other methods. Hunt et al. (1998) estimated solar radiation for

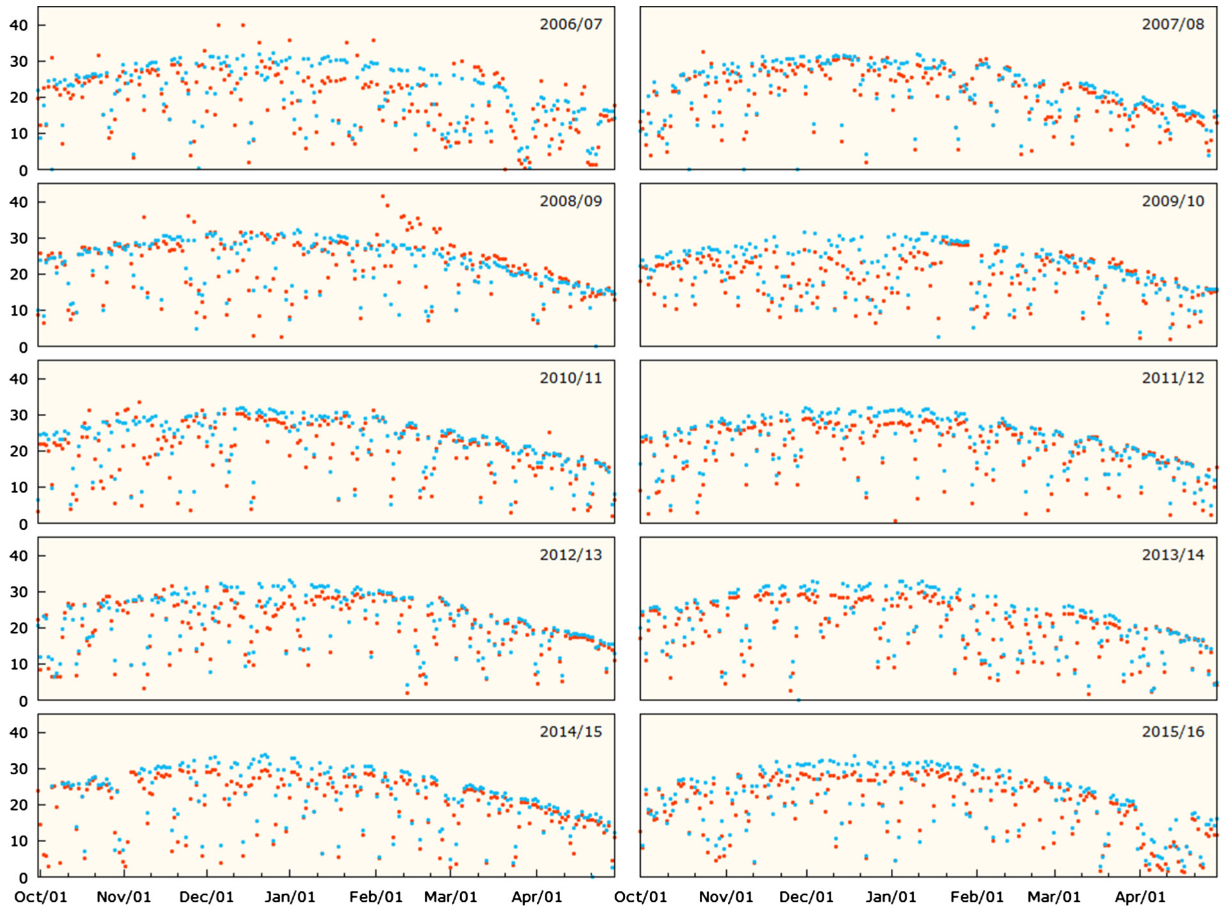

Fig. 3. Values of registered (•) and estimated by CERES (•) solar radiation (MJ m^{-2} d^{-1}) for all soybean campaigns between 2006 and 2016.

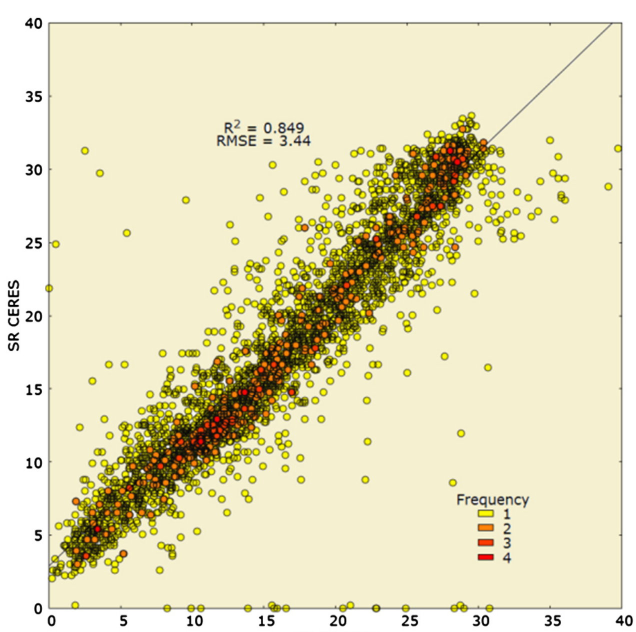

Fig. 4. Frequencies of scatter plot of the CERES and in situ daily samples (solar radiation expressed in MJ m^{-2} d^{-1}).

use in crop modeling from maximum temperature, the difference between maximum and minimum temperature, precipitation and precipitation squared data, establishing *RMSE* values of 4.1 MJ m^{-2} d^{-1} for Ontario. Quej et al. (2017), using a Gaussian model, estimated solar radiation at 6 sites in Mexico and obtained *RMSE* and R^2 values between 0.97 and 1.50 MJ $m^{-2}d^{-1}$ and 0.83–0.90, respectively.

Several authors state that crop simulation models could be affected by the quality of solar radiation data (Abraha and Savage, 2008; Biswal et al., 2014; Wang et al., 2015). For this reason, we present statistics (Table 3) that show the adjustment between registered data in the meteorological station and those acquired from satellite CERES, for each one of the replacement percentages used.

The average errors for the three planting dates, as can be seen in Table 3, varied between 1.88 and 4.13 MJ $m^{-2}d^{-1}$, considering all the percentages of replacement data with those from CERES. These values are comparable to those reported by Zhang et al. (2017) for several authors in different locations. In each campaign, it is important to note that the increase in the replacement percentage did not produce significant variations in *RMSE* values. The 2006/07 campaign presented the highest errors, for all replacement percentages, and the minimums were registered in 2013/14.

Precipitation data, registered and informed by TRMM are presented in Table 4. Only for 2010/11 and 2014/15 campaigns, satellite values were lower than the registered ones. In the remaining campaigns, TRMM overestimated precipitation with differences between 26 and 223 mm.

In Table 5, similarly to the solar radiation variable, the adjustment between registered precipitation and those acquired from TRMM, for three planting dates and for each of the replaced percentages are presented. *RMSE*, for the whole period of time considered in the model, varied between 6.16 mm and 19.68 mm; these

Table 3
Average *RMSE* (MJ m^{-2} d^{-1}), considering three planting dates, for the adjustment between daily solar radiation registered in EEA Oliveros (INTA) and obtained by CERES, according to percentages of replaced data.

Campaign	Percentage of replaced data									
	10	20	30	40	50	60	70	80	90	100
2006/07	3.94	4.06	4.10	3.96	4.04	4.10	4.08	4.05	4.13	4.11
2007/08	2.05	2.08	2.10	2.12	2.16	2.13	2.18	2.16	2.14	2.15
2008/09	3.67	3.44	3.80	3.81	3.67	3.60	3.71	3.75	3.76	3.74
2009/10	3.21	3.11	3.14	3.22	3.14	3.24	3.22	3.22	3.18	3.20
2010/11	3.38	3.66	3.25	3.81	3.52	3.66	3.76	3.77	3.72	3.72
2011/12	2.60	2.56	2.26	2.49	2.48	2.57	2.65	2.59	2.63	2.62
2012/13	2.42	2.45	2.47	2.47	2.46	2.50	2.46	2.45	2.47	2.47
2013/14	1.88	1.96	2.05	1.99	1.98	1.98	2.00	2.00	2.01	2.00
2014/15	2.30	2.26	2.26	2.28	2.24	2.29	2.30	2.31	2.31	2.31
2015/16	2.11	2.22	2.30	2.24	2.28	2.31	2.35	2.37	2.41	2.45

Table 4
Cumulative rainfall (mm) registered in EEA Oliveros (INTA) and obtained by TRMM, for campaigns between 2006 and 2016.

Campaign	Registered	TRMM
2006/07	1235	1287
2007/08	583	611
2008/09	590	613
2009/10	941	1057
2010/11	849	746
2011/12	796	822
2012/13	881	1058
2013/14	981	1089
2014/15	889	824
2015/16	1095	1130

values represent minimum differences with respect to the total precipitation registered in each campaign. The highest values were observed in 2010/11 while the minimums in 2011/12.

Results shown in Table 5 are similar to those presented by van Wart et al. (2015) who found *RMSE* values of 11 mm in the 1998–2009 period for Oliveros, when they compared daily observed rainfall data with those estimated by TRMM.

Soybean yields obtained using DSSAT model, at different planting dates, campaigns and maturity groups, with solar radiation and rainfall data recorded, are presented in Table 6.

CROPGRO estimated soybean yields between 599 and 5583 kg ha^{-1} when registered values of solar radiation and precipitation were used, for the area of application of this study (Table 6). The yield values obtained from CROPGRO correspond to the average yields recorded for the same region, which were between 2010 and 5630 kg ha^{-1} approximately (Enrico et al., 2013; Enrico and Gentili, 2016). A special case is observed in campaign 2008/09 where the yield values were much lower than the average for the whole period. As Papa and Tuesca (2014) stated, in this campaign there were atypical drought conditions and Pognante et al. (2011) confirmed that in the year 2008 the biggest drought of the last 50 years occurred in Argentina. On the other hand, the yield reached the highest values in 2014/15. For this campaign in Oliveros, Enrico and Gentili (2016) indicated that the distribution of precipitation and the abundance of incident solar radiation favored the optimum production.

The different combinations of planting date, maturity group and agricultural campaigns, generated different genotype-environment combinations for the simulation, which comprise an important number of scenarios.

The yields obtained with CROPGRO when replacing different percentages of the values of recorded solar radiation with that estimated by CERES, are shown in Fig. 5.

In general, as is observed in Fig. 5, the resulting CROPGRO estimates present different behaviours, depending not only on the planting date and maturity group, but mainly on the yield value. According to Rivington et al. (2006), crop yield is influenced by the four meteorological data variables acting in conjunction with each other; in this case yield represents the cumulative impact of all variances in the climate data used by DSSAT.

Considering all campaigns, planting dates and maturity groups, in 68% of the cases, the estimations present %*RMSE* less than 10%. These cases increase to 87% when the percentage of data substitution is up to 30%. In the 2013/14 campaign, where there was a good adjustment between recorded and obtained from CERES radiation (Table 3), similar behaviour was observed for the yield estimation, in which 92% of the cases had %*RMSE* less than 10% for all the planting dates, maturity groups and replacement percentages. On the other hand, for the 2006/07 campaign which had the worst radiation adjustment, only 60% of the cases had %*RMSE* less than 10%. However, crop yield is directly influenced by changes in the intensity and seasonal accumulation of meteorological factors

Table 5
Average *RMSE* (mm), considering three planting dates, for the adjustment between whole campaign precipitation registered in EEA Oliveros (INTA) and obtained by TRMM, according to percentages of replaced data.

Campaign	Percentage of replaced data									
	10	20	30	40	50	60	70	80	90	100
2006/07	13.36	13.79	14.75	14.29	14.98	14.87	14.51	14.65	14.82	14.72
2007/08	7.19	6.16	7.19	6.85	7.45	7.24	7.37	7.31	7.26	7.30
2008/09	12.91	14.20	13.59	14.51	14.75	15.00	14.05	14.56	14.15	14.41
2009/10	15.43	16.54	16.09	16.17	17.02	17.88	17.78	17.49	17.62	17.66
2010/11	17.92	17.58	18.66	20.58	18.15	18.97	19.54	19.10	19.68	19.45
2011/12	6.71	6.42	6.74	6.65	6.57	6.77	6.66	6.66	6.71	6.69
2012/13	7.98	10.84	12.07	12.57	11.74	12.13	11.36	12.04	11.90	12.01
2013/14	7.88	10.11	10.92	10.84	10.63	10.27	10.35	10.51	10.65	10.61
2014/15	11.73	12.73	12.47	12.76	13.41	13.68	13.20	13.70	13.64	13.59
2015/16	12.38	12.46	12.92	14.22	13.36	13.72	14.59	14.29	14.78	14.98

Table 6
CROPGRO soybean yield estimation (kg ha^{-1}) using registered solar radiation and rainfall, considering planting dates (PD) and maturity groups (MG) for all campaigns.

Campaign	PD: 10/15			PD: 10/30			PD: 11/15		
	MG III	MG IV	MG V	MG III	MG IV	MG V	MG III	MG IV	MG V
2006/07	3981	4033	4667	2959	3451	4592	1997	2872	4009
2007/08	2854	2747	2947	3047	3172	3251	2396	3049	3133
2008/09	599	873	1447	730	879	2158	1163	2176	2953
2009/10	4084	4803	5391	3951	4678	5384	3722	4570	5180
2010/11	1234	2179	3154	1152	3102	3726	2537	3071	3338
2011/12	1740	2300	2053	1824	2679	3248	2600	3678	4027
2012/13	2681	2737	4153	1847	2288	3737	1088	1823	2874
2013/14	3382	4411	5053	3453	4517	5137	3733	4527	4957
2014/15	4385	5341	5583	4498	5093	5375	4339	4848	5097
2015/16	2299	1540	1882	1607	2127	1538	1868	1892	3358

Note: higher and lower yields for each MG and PD are coloured in dark and light gray, respectively.

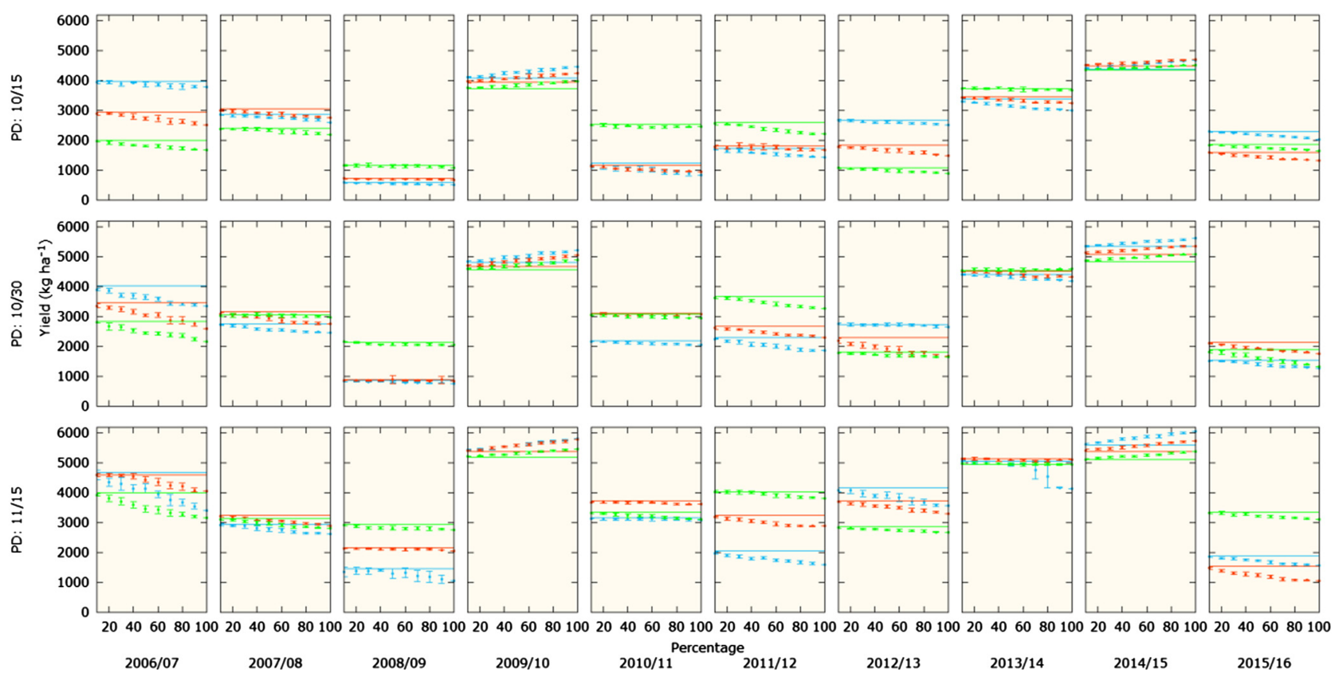

Fig. 5. Mean and deviations of soybean yields obtained by CROPGRO using different replacement percentages of solar radiation data (ten repetitions) for three planting dates and MG III (–), MG IV (–) and MG V (–) for all campaigns. Solid lines represent yield obtained with recorded solar radiation.

throughout the crop cycle, so not necessarily an adequate estimate of daily solar radiation implies a good estimation of soybean yield.

da Silva et al. (2016) used estimated daily solar radiation for the Triangulo Mineiro region (Brazil), with different temperature-based models as input for SoySim software. Although the radiation models have presented similar suitability, when these data were used for simulating the potential soybean yield, the performances diverged considerably. Also, Abraha and Savage (2008) estimated total dry biomass of corn with CropSyst model in seven worldwide locations. They found that the comparison of the ranking (obtained from aggregation of several statistical indices) between the models for daily solar radiation estimation and total biomass simulation was difficult because of the difference in the time scale used in calculations.

The results of the CROPGRO model simulations for different percentages of precipitation replacement with TRMM data are shown in Fig. 6. In general, not only the yield values obtained, but the repetitions for each one of them, show different deviations of the average value. Yield biases differed strongly among the PD and MG considered. It can be observed that, only when high yields are recorded, the estimates with TRMM, for each replacement percentage, show the smallest deviations considering the ten repetitions. In all other cases, important deviations are observed. For the 2008/09 campaign, which recorded the lowest yields, MG III showed the smallest deviations for the first two planting dates and the averages were close to the yield obtained with recorded precipitation data.

The use of TRMM data as input in CROPGRO, as opposed to CERES substitution, brought out a worse performance of yield estimations. Considering all campaigns, planting dates and maturity groups, only in 30% of the cases, the estimations presented *%RMSE* less than 10%. These cases increase slightly to 38% when the data substitution percentage is up to 30%. In the 2011/12 campaign, where there was a good adjustment between recorded and obtained from TRMM precipitation (Table 5), 10% of the cases had *%RMSE* less than 10% for all the planting dates, maturity groups

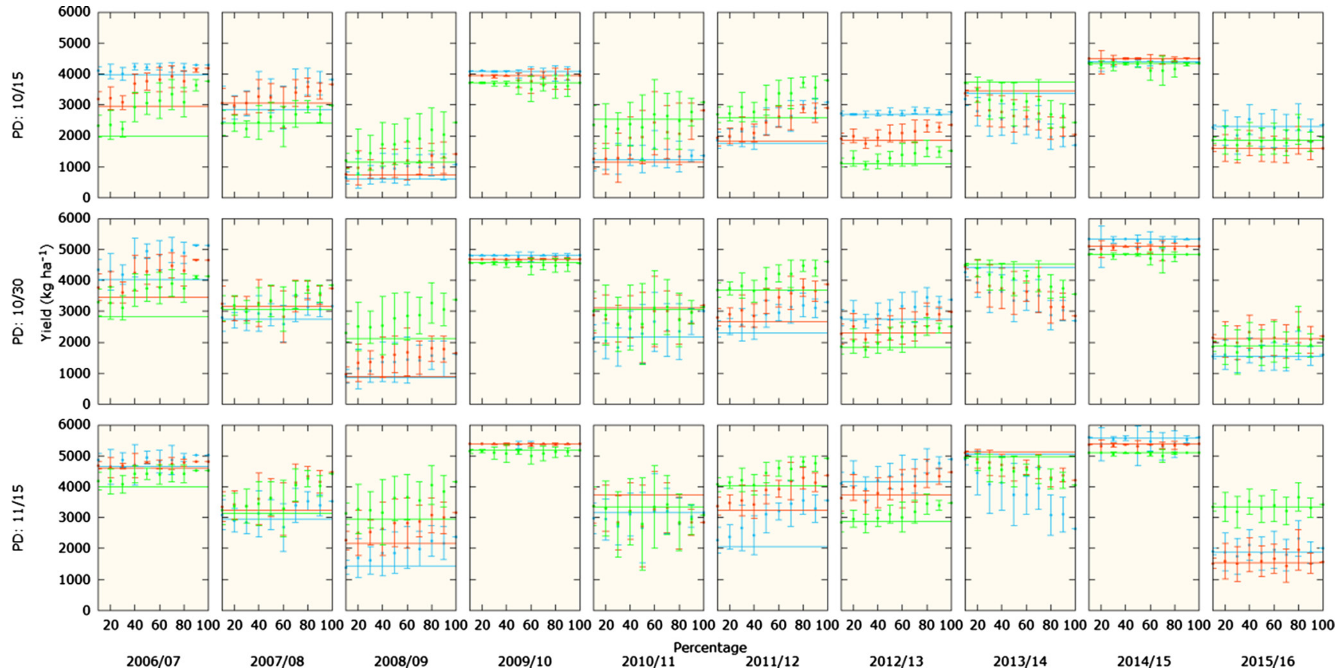

Fig. 6. Mean and deviations of soybean yields obtained by CROPGRO using different replacement percentages of precipitation data (10 repetitions) for three planting dates and MG III (–), MG IV (–) and MG V (–) for all campaigns. Solid lines represent yield obtained with recorded precipitation.

Table 7
Percent *RMSE* and *RMSE*, for campaigns with best adjustment between yields obtained using registered and CERES solar radiation data.

Maturity Group	Campaign	%RMSE and (*RMSE* in kg ha^{-1})									
		10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
		PD: 10/15									
MG III	2006/07	1.6 (64)	1.6 (62)	2.8 (1 1 1)	1.4 (54)	3.5 (1 3 9)	3.5 (1 3 7)	4.7 (1 8 8)	5 (1 9 7)	5 (2 0 0)	5.1 (2 0 3)
MG IV	2012/13	1.1 (29)	1.8 (50)	1.5 (42)	1.4 (39)	1.9 (51)	1.7 (47)	1.5 (42)	1.8 (49)	3 (82)	3.2 (88)
MG V	2010/11	0.4 (14)	1.5 (47)	1.4 (44)	1.5 (47)	1.9 (60)	2.1 (67)	1.9 (59)	1.9 (58)	2 (63)	2.5 (80)
		PD: 10/30									
MG III	2014/15	0.7 (30)	1.2 (54)	1.5 (66)	1.9 (86)	2.1 (95)	2.6 (1 1 6)	3.3 (1 4 8)	3.9 (1 7 7)	4.2 (1 8 7)	4.4 (1 9 9)
MG IV	2010/11	1.6 (48)	1.1 (35)	1.5 (47)	2.1 (64)	1.5 (47)	1.4 (44)	1.6 (50)	1.4 (42)	0.6 (20)	0.5 (15)
MG V	2013/14	0.4 (19)	0.9 (47)	0.4 (22)	1 (53)	0.9 (44)	1 (54)	1.6 (83)	1.4 (72)	0.9 (48)	0.4 (22)
		PD: 11/15									
MG III	2013/14	0.4 (15)	0.8 (30)	0.9 (34)	0.8 (32)	1.8 (67)	2.1 (77)	1.8 (68)	1.3 (47)	1.6 (61)	1.5 (56)
MG IV	2013/14	0.5 (21)	1.6 (73)	1.3 (59)	1.6 (72)	1.2 (53)	1.5 (69)	1.2 (53)	1.2 (56)	1.3 (57)	1.3 (58)
MG V	2013/14	0.5 (24)	0.9 (43)	0.7 (34)	0.7 (34)	0.7 (34)	1.1 (53)	0.8 (39)	0.7 (33)	0.5 (25)	0 (1)

and replacement percentages. In the 2010/11 campaign, which had the worst precipitation adjustment, only 4.4% of the cases had %*RMSE* less than 10%.

Ramarohetra et al. (2013) showed that satellite rainfall estimations error affected the simulations of pearl millet in Niger differently. When annual water is limiting, crop yield simulations were highly sensitive to biases in the estimated cumulative rainfall amount. On the other hand, when cumulative rainfall amounts were not limiting for crop yield or when it is well estimated by satellite, crop yield simulations were sensitive to error in rainfall distribution. Similarly, Heinemann et al. (2002) simulated soybean yield using CROPGRO model with different levels of rainfall biases and found that in dry years the greatest change occurred, whereas wet years showed the smallest change.

Tables 7 and 8 show, for CERES and TRMM data respectively, the %*RMSE* and *RMSE* of the campaign with the best performance in yield estimation, for all levels of replacement, considering each planting date and maturity group.

As can be seen in Table 7, the 2013/14 campaign exhibited the best performance in estimating soybean yield, when replacing 100% of registered solar radiation with CERES data (in 4 of the 9 best estimates). This campaign presented the best *RMSE* solar radiation estimations (Table 3). Although for the other cases errors may be higher (Fig. 5), as Nonhebel stated in Rivington et al.

Table 8
Percent *RMSE* and *RMSE*, for campaigns with best adjustment between yields obtained using registered and TRMM precipitation data.

Maturity Group	Campaign	%*RMSE* and (*RMSE* in kg ha^{-1})									
		10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
		PD: 10/15									
MG III	2014/15	0.1	5.1	2.4	0.2	2.5	2.1	0.7	0.4	0.4	0.3
		(5)	(224)	(105)	(9)	(111)	(91)	(30)	(19)	(19)	(14)
MG IV	2009/10	0.2	0.2	0.1	0.1	3.4	3.2	0.2	1.8	1.8	0.1
		(10)	(11)	(7)	(7)	(163)	(152)	(10)	(89)	(86)	(3)
MG V	2009/10	0.1	0.1	0.1	0.1	2.2	1.8	0.1	0.1	0.1	0.1
		(5)	(5)	(3)	(6)	(118)	(99)	(4)	(4)	(3)	(3)
		PD: 10/30									
MG III	2014/15	0.2	8.3	3.6	0.4	0.7	5	3	1.9	0.2	0.2
		(9)	(372)	(160)	(17)	(30)	(227)	(135)	(84)	(9)	(10)
MG IV	2009/10	0.1	0.2	0.2	0.2	0.3	1.9	0.3	1.8	1.7	0.1
		(6)	(10)	(9)	(8)	(12)	(89)	(13)	(84)	(79)	(6)
MG V	2009/10	0.1	0.1	0.2	0.7	0.2	0.9	0.2	0.8	0.3	0.1
		(4)	(5)	(9)	(40)	(8)	(47)	(13)	(40)	(14)	(4)
		PD: 11/15									
MG III	2014/15	0.8	2.7	3.7	0.9	2	8.5	11.4	6.9	1.3	0.1
		(34)	(119)	(160)	(40)	(88)	(370)	(495)	(299)	(58)	(6)
MG IV	2014/15	0.1	0.2	2.3	0.3	0.9	5	9.3	3.5	0.2	0
		(5)	(12)	(114)	(15)	(46)	(243)	(449)	(168)	(10)	(1)
MG V	2014/15	0.1	0.1	1.4	0.2	0.2	1.5	4.5	0.8	0.1	0.1
		(3)	(7)	(71)	(10)	(10)	(75)	(230)	(41)	(7)	(4)

(2006), inaccuracies in solar radiation of 10% and in temperatures of 1 °C resulted in yield estimation errors of up to 1 tha^{-1}, using SUCROS model.

The 2014/15 and 2009/10 campaigns were the only ones that presented the best performances in estimating soybean yield, when replacing observed precipitation with TRMM data (Table 8). These campaigns coincide with the highest obtained yields, using registered data. According to Rolla et al. (2018) who evaluated the impact of future climate on wheat, maize and soybean yield in the Pampas region (Argentina), the climate parameter showing the highest spatial variability is the rainfall frequency and distribution. They pointed out that when the rainfall frequency and distribution is coincident with specific crop critical periods, could impact crop growth with different degrees of severity, according to the level of water stress.

4. Conclusions

The simulations of soybean yield using a DSSAT model (CROPGRO soybean) when replacing solar radiation and precipitation data obtained from satellite images (CERES and TRMM, respectively) in different percentages, demonstrate that the uncertainty in the radiation and precipitation data have different influence on the results. The percentage of data replacement with satellite data, and the campaign, the planting date and the maturity group of the crop, determine the amounts and trends of yield errors.

Simulations based entirely on CERES solar radiation gave better results of yield estimation than those with TRMM precipitation estimations. Similar percentages of replacement showed better performance in the estimation of soybean yield for solar radiation than with the replacement of precipitation values.

Solar radiation satellite data is particularly suitable with replacements of less than 30%, without regard to yield obtained in the campaign or crop physiological parameters; while the replacement of precipitation, with TRMM data, was adequate in simulations with high yields.

Although precipitation and solar radiation from satellite data are widely employed, in a crop-modeling framework their use can introduce large biases in crop yield simulations. A possible explanation involves not only the magnitude of the error but also the moment of occurrence of the error, since the yield is a value that summarizes the different meteorological conditions to which the crop was subjected throughout its growth season.

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