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Simulation of some of important traits in chickpea cultivars under different sowing date using CROPGRO-Pea model

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Abstract

A field experiment was conducted at research field of Islamic Azad University_Karaj Branch during 2009 to evaluation of Chickpea simulation using CROPGRO-Pea model at three sowing date, as a split plot experiment based on a completely randomized block design with three replications. In this experiment simulation of some traits such Biomass (B), Grain yield (GY) and Leaf Area Index (LAI), evaluated for some cultivars of Chickpea named Azad, Arman and Hashem using CROPGRO-Pea. According to results, model was successful in all of the traits simulation. Model explained well Biomass, as correlation coefficient in each sowing date was significant ($p<0.01$). Dimension variation d Wilmot coefficient for all of cultivars B, GY and LAI (S1-S3) was equal to (0.88-0.95), (0.77- 0.99) and (0.70-0.86), respectively. According to linearly regression correlation (1:1 line) simulation versus observed date for B, GY and LAI in all of the cultivars and sowing date obtained with equations of $y = 0.876x + 137.93$ ($R^2 = 0.81$), $Y= 1.103x + 13$, ($R^2= 0.99$) and $Y= 0.9x - 0.162$ ($R^2= 0.72$), respectively. These statistic parameters designated with high ability of model for simulation of B, GY and LAI trend in Chickpea under three different sowing date. This model is applicatory in prediction traits for sowing date management of Chickpea under Karaj climate.

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Introduction

Determination of sowing date for different cultivars of Chickpea in Karaj is difficult and expensive. Therefore for support of sowing date management and reduce of costs due to its, we need to consideration of soil, plant and weather integrate effects. Building models is a way to integrate knowledge and to make it available for various purposes (Goudriaan and Van Laar, 1994). An important implication of the dynamic models definition is awareness of a dynamic condition such as changes and evolution of the crop growth system over time (Wang *et al.,* 2005). Models for exploration and prediction are different in nature than those for disciplinary research and analysis. modeling has gained wide acceptance as a tool in research. It is also used education programs, and is a widely accepted instrument for policy making (Bruno *et al.,* 2011). Systems modeling is a highly useful tool for understanding the relationships among soil, plants, and other components in crop systems, especially for studying the relationships between system components over time. Agricultural models have been developed not only to understand the processes and interactions involving system components and their effects upon overall production but for their usefulness as decision support tools for evaluating management options (Zamora *et al.,* 2009).

With the new breakthroughs in computers and computer software for data processing, it is feasible and necessary to improve the existing thinking and research procedures. Thus, the objective of this work is to present a methodological foundation for research and analysis of biological systems, based on a system theoretical approach (Wang *et al.,* 2005). It is intended as an aid to the scientist in his quest for improving the accuracy of research. System analysis may be defined as the process of developing an abstract model of an existing system, such that the model would simulate the real system by means of a computer program (Goudriaan and Van Laar, 1994). Recently, process-based models with different levels of complexity have been developed to estimate crop yield in different regions (Betts, 2005; Costa *et al.,* 2009; Hansen, 2005). The Decision Support System for Agrotechnology Transfer (DSSAT) includes a set of models of crop growth and has been widely used in recent years as a useful computational tool in the evaluation of management options associated with environmental conditions. The modular structure of the DSSAT includes an outstanding model known as CROPGRO. This generic model for legumes allows the simulation of the growth and development of several crops, such as the dry bean, chickpea, peanut and soybean crops (Hoogenboom *et al.,* 2003).

Examples of the simulation efficiency of CROPGRO were presented by Ruíz-Nogueira *et al.*, (2001), who used the model to evaluate soybean growth and yield under water limitation conditions for three cultivars in different climatic conditions of northeast Spain. Hartkamp *et al.*, (2002) evaluated the performance of CROPGRO to predict phenology, growth, senescence and nitrogen accumulation in locations that represented different scenarios of environmental and agronomic management. The evaluation involved sensitivity analysis of various regimes of temperature and precipitation to identify regions suitable for the production of *Mucuna aterrima* as green manure. Faria *et al.*, (1997) used simulations with CROPGRO-Dry bean to evaluate different strategies for the irrigation management of beans in the State of Paraná. Meireles *et al.*, (2003) calibrated the CROPGRO-Dry bean model to quantify decreases in the yield of beans sown on 36 sowing dates in Santo Antônio de Goiás, Goiás State. In a study conducted in Maringá, State of Paraná, Dallacort *et al.*, (2005) used the model's simulation of the growth and development of the bean to determine the best sowing times for the cultivar IAPAR 57 from 1980 through 2000. Sensitivity experiments with CROPGRO to evaluate the effect of meteorological variables on the growth, development and yield of beans may contribute to improved management practices and to a better understanding of the interactions between climate and plants (Costa *et al.,* 2009; Jones *et al.,* 2003).

Andarzian *et al.,* (2008) with comparisons of the simulated and measured outputs under non-limiting conditions indicated satisfactory performance for predicting anthesis and maturity dates, and fair prediction of dry matter production and grain yield. The root-mean-square errors (RMSE) of yield were 3.5 d, 4 d, 0.65 t /ha, and 1.69 t/ ha, respectively. The model also proved to be a useful tool for the rough estimation of wheat yield potential at the regional level where there is access only to monthly weather data. This is in contrast to deterministic models where the predicted values are computed without consideration of their variability. Simulated and observed specific leaf area for palisade grass showed annual variation associated with seasonal variation in light and temperature (Bruno *et al.*, 2011).

In this sense, this study may serve as a tool to help in planning agricultural activities with less risk of adverse weather effects. Therefore calibration of CROPGRO model in different region such as Karaj for decision making in different management scenario is very important. In view of the importance of Chickpea for Iran and the need for a system of yield prediction, this study was conducted to evaluate the CROPGRO-Pea model as a crop-yield forecasting tool for the Chickpea cultivars 'Azad', 'Arman' and 'Hashem' under three different sowing date in Karaj (Alborz province, Iran). The aim of this study is evaluate of CROPGRO model for simulation of the reaction plant, soil and environment on grain yield and biomass (with different socio-economic and biophysical conditions) to different policy instruments in order to support agricultural planning at regional levels.

Materials and methods

Experiment details

In order to study of CROPGRO-Pea model on three cultivars of Chickpea (Arman, Azad and Hashem) under three different planting date under Karaj weather condition, an experiment conducted in form of split plot in based on randomize complete block design with three replicate in research field Islamic Azad university of Karaj branch in 2010 (35°43′N, 50°49′E, altitude 1174 Meter sea level (MSL). Experimental factors was three different sowing date 3 May (S1), 13 May (S2), 23 May (S3) as main plot and some cultivars of Chick pea include Arman, Azad and Hashem as sub plot. Each plot designed six rows of 6m length and inter and intra spacing of 0.5 m and 8 centimeters, respectively with plant density 25 plant/m^2. Application of plow and disc achieved to depth 30 cm and 15cm, respectively and then land surfacing carry out by leveler. Nitrogen manure with scale 150 kg/ha according to soil test to equal ratio at three stage before planting, flowering time and pod stage added to each plot. Seeds after disinfection and planted at three sowing date to soil depth 3 cm, by hand and then plant density regulated to rate of 25 plant/m2. Primary irrigation conducted after sowing and second irrigation 4 days next and others weekly. Weed control achieved in three times by hand. At first we required information for simulation including soil, weather and plant data supplied and identified to CROPGRO- Pea. Then data due to measured traits defined to model in specific sites. At the end data due to measured traits placed versus simulated data. At the end in based on statistic coefficients calculated by model showed value of model precise for LAI, B and GY.

Management data

Field management data including, plot dimensions, planting inter and intra, sowing depth, plant density, supplying land implementation, experimental treatments, cultivar identification and its genetic coefficient, irrigation management, sowing date, harvest time and soil important physical and chemical properties.

Soil data

Soil data including of physical and chemical properties at three different layers include surface, average and deep of soil such as: texture, density, organic percent, nitrogen, phosphorous and potassium available, soil pH, electrical conductance soil (EC).

Experimental data

Experimental data including of measured traits during growth processes (at 8 stages) and measured traits at the end of maturity.

Weather data: Weather data including of the most important parameters affected on growth include minimum and maximum daily temperature (Celsius), daily rain (mm) and sunny hours. The 30 days after planting to 10 days interval in 8 states was took samples at 1 m plant line to considering of edge effects for measuring some traits such LAI, B and GY.

Model evaluation: Analysis of data and means comparison achieved by means of SAS program and Duncan method, respectively. For comparison of simulated data versus measured data used by means of some evaluation indexes such as, Wilmot agreements index (d) (Willmott, 1985) and R^2 coefficient in line regression curve (1:1) (Wang *et al.*, 2005).

If d coefficient rate obtained by model was near to 1, this order shows that model was successful in traits simulation. In based on number of sample, d coefficient upper than 0.65 showed that model can be simulate trait acceptably. In fact, if R^2 rate in line 1:1 near to 1, model will description trait, suitably. For evaluation of model ability in trait predicting, r (correlation coefficient) rate in based on number of sample 8 was equal to 0.66-0.79 ($p<0.05$) and $r > 0.79$ ($p<0.01$) will significant (Soltani *et al.*, 2005).

Results and discussion

Biomass trend simulation

According to the results of trend variation simulation of biomass (Fig.1) in all of the cultivars at sowing date 3 May, model simulated Hashem cv. with lowest RMSE=798.7 kg/ha and highest d= 0.90, with highest precision. Dimension variation RMSE (798.7-856.89) kg/ha and d coefficient (0.89-0.90) obtained for all of the cultivars at sowing date 3 May, that showed model acted satisfactory in simulation of biomass trend at sowing date 3 May in all of the cultivars (Fig.1).

According to Fig.2 about variation trend of biomass, variation dimension rate of RMSE (585.88-611.02) kg/ha and Wilmot coefficient (0.94-0.95) obtained at sowing date 13 May. According to Fig. 3 trend variation of biomass in all of the cultivars at sowing date 23 May, variation dimension RMSE (713.84-1025.45) and d coefficient (0.88-0.94), showed that model acted acceptable in simulation of trend biomass at sowing date 23 May. In base of obtained of biomass simulation all of the cultivars at three sowing date (3, 13 and 23 May), model acted very good in Karaj, therefore this model must be applicatory in programming and decision making about sowing date management, specially about this cultivars (Hashem, Arman and Azad).

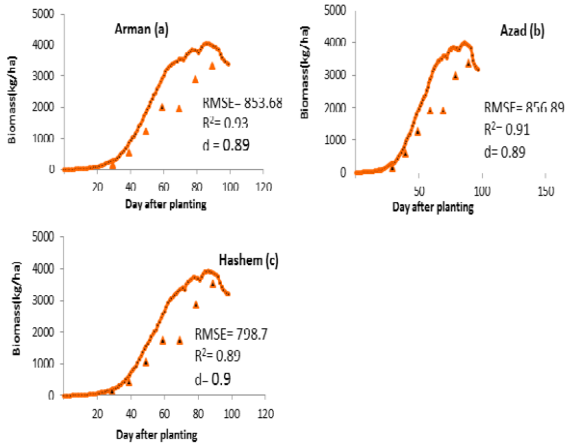

Fig. 1. The simulated trend of biomass (B) in sowing date 3 May.

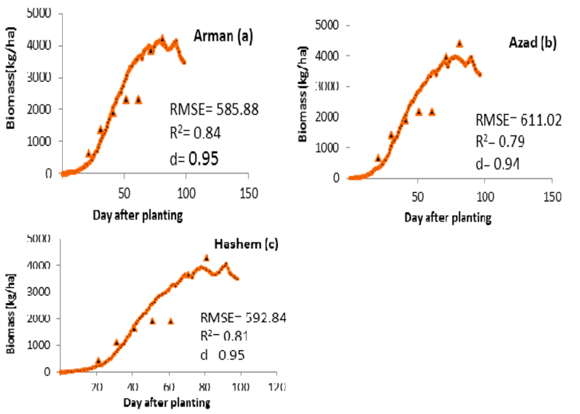

Fig. 2. The simulated trend of biomass (B) in sowing date 13 May.

According to linearly regression correlation (1:1 line) simulation versus observed date for biomass in all of the cultivars and sowing date (Fig.4) obtained equation of $y=0.876x+137.93$ ($R^2=0.81$), showing that model acted significantly trend variation of biomass. This result agrees with others researchers in chickpea and other crops. Almost competition of crop with weed in field condition caused reduce of precision of simulation (Soltani *et al.,* 2005; Banayan *et al.,* 2003), but suitable control weed avoiding about this problem, therefore model acted well for simulation of biomass.

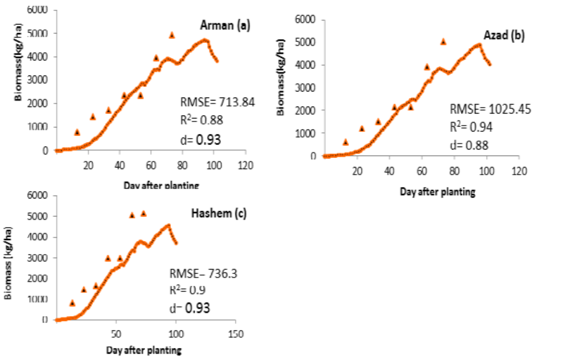

Fig. 3. The simulated trend of biomass (B) in sowing date 23 May.

Banayan *et al.,* (2003) declared that rate of MBE (2.5) and RMSE (3.2) in yield had 20% mean of observed data (1.76 ton/ha). Simulation of dry matter production probably is center section of a model that it is under effects of phonological development and leaf area variation. Simulation of biomass is important because this traits using of harvest index determined grain yield (Soltani *et al.,* 2005).

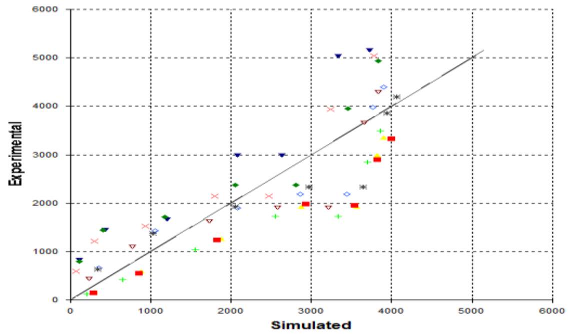

Fig. 4. The regression relation of simulated and observed biomass (B) for all of cultivars and sowing date.

R^2= 0.81, Y= 0.876x + 137.93.

Grain yield trend simulation

According to the results of trend variation simulation of GY (Fig. 4) in all of the cultivars at sowing date 3 May, model for simulation this trait acted very good. Dimension variation RMSE (59.79-123.12) kg/ha and d coefficient (0.99-0.99) obtained for all of the cultivars at sowing date 3 May, that showed model acted satisfactory in simulation of GY trend at sowing date 3 May in all of the cultivars (Fig.4).

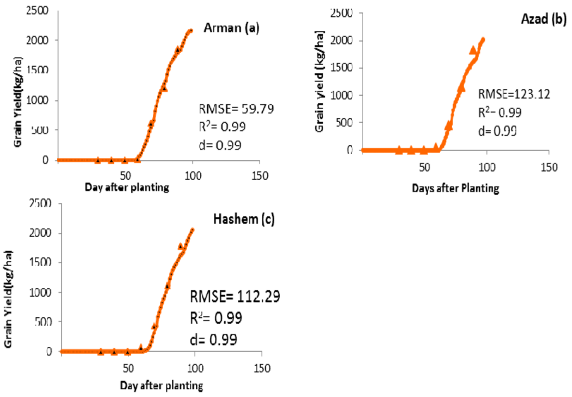

Fig. 5. The simulated trend of grain yield (GY) in sowing date 23 May.

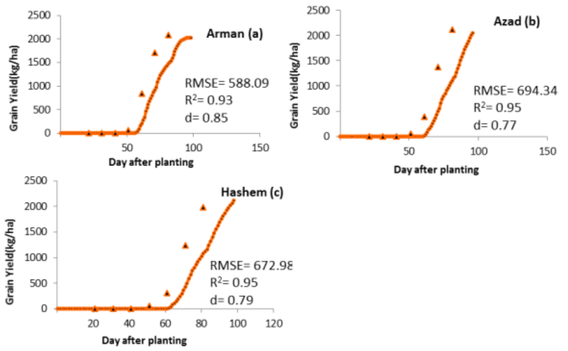

Fig. 6. The simulated trend of grain yield (GY) in sowing date 13 May.

According to Fig.5 about variation trend of GY, variation dimension rate of RMSE (588.09-694.34) kg/ha and Wilmot coefficient (0.77-0.85) obtained at sowing date 13 May. According to Fig. 6 trend variation of GY in all of the cultivars at sowing date 23 May, variation dimension RMSE (1112.88-1119.32) and d coefficient (0.59-0.84), showed that model acted acceptable in simulation of trend biomass at sowing date 23 May. Indeed, model precision was reduced in base on delay of sowing date relate to optimum sowing date.

In base of obtained of GY simulation all of the cultivars at three sowing date (3, 13 and 23 May), model acted acceptable under Karaj climate, but this model must be calibrate after numerous experiments under different locations and times, then will capability for programming and decision making in sowing date management, specially about this cultivars. According to linearly regression correlation (1:1 line) simulation versus observed date for GY in all of the cultivars and sowing date (Fig.11) obtained equation of y=1.103 x +13 (R^2=0.99), showing that model acted acceptable in simulation variation of GY in growth duration.

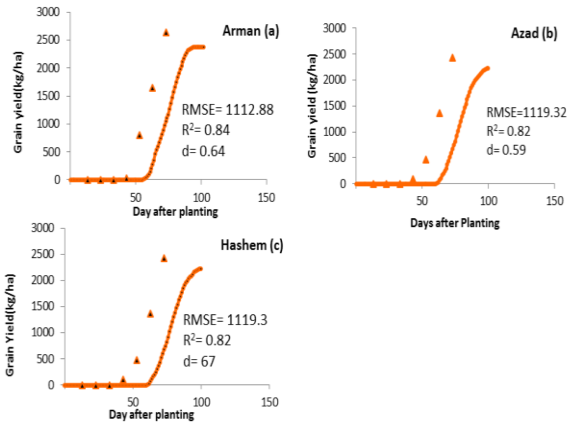

Fig. 7. The simulated trend of grain yield (GY) in sowing date 23 May.

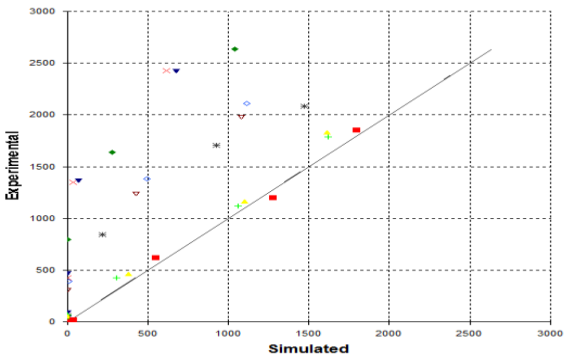

Fig. 8. The regression relation of simulated and observed grain yield (GY) for all of cultivars and sowing date. R^2= 0.99, Y= 1.103x + 13.

Banayan *et al.,* (2003) and Jamieson *et al.,* (1998) reported good accuracy for simulated grain yield and large error for simulated biomass production by CERES-Wheat. In explaining the higher error of biomass prediction compared whit grain yield simulation, they concluded that there was no close link in the model between its ability to predict grain yield and biomass. Timsina and Humphreys, (2006) reported that simulation of crop growth with the CERES-Wheat model under non-limiting water and N conditions in the sub-tropical environments of India, Nepal, Bangladesh and Australia had normalized RMSE of 15–17% for biomass, and 7–17% for grain yield. Also in study of Banayan *et al.,* (2003) in evaluation of grain yield in some wheat cultivars using CERES model, rate of RMSE in GY created to 668 kg/ha or 18.2%.

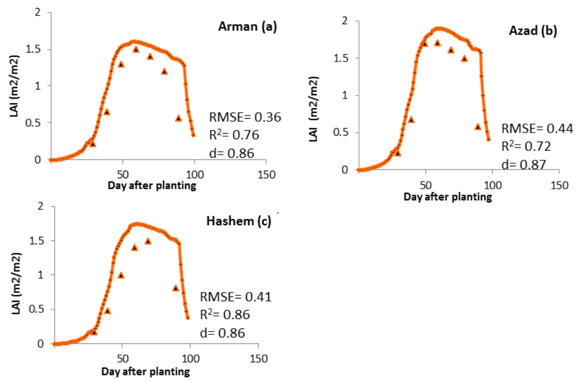

Fig. 9. The simulated trend of leaf area index (LAI) in sowing date 3 May.

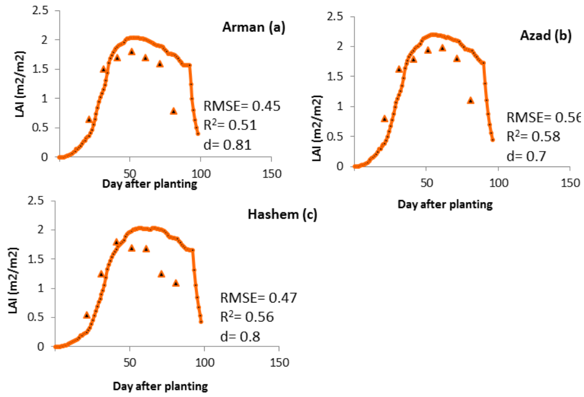

Fig. 10. The simulated trend of leaf area index (LAI) in sowing date 13 May.

Leaf area index (LAI) simulation

According to the results of trend variation simulation of LAI (Fig.9) in all of the cultivars at sowing date 3 May, model for simulation this trait acted well. Dimension variation RMSE (0.36-0.44) and d coefficient (0.86-0.87) obtained for all of the cultivars at sowing date 3 May, that showed model acted satisfactory in simulation of LAI index at sowing date 3 May in all of the cultivars (Fig.9).

According to Fig.10 about variation trend of LAI, variation dimension rate of RMSE (0.45-0.56) and Wilmot coefficient (0.70-0.81) obtained at sowing date 13 May. According to Fig. 11 trend variation of LAI in all of the cultivars at sowing date 23 May, variation dimension RMSE (0.40-0.48) and d coefficient (0.77-0.86), showed that model acted acceptable in simulation of trend LAI at sowing date 23 May. Indeed, model precision for prediction LAI in comparison to B and GY was lower. Rate of LAI in crops intensively correlated to plant density, competition to weeds, water available and almost have low precision (Soltani *et al.*, 2005).

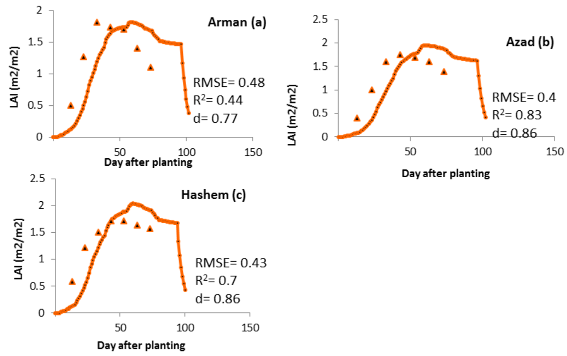

Fig. 11. The simulated trend of leaf area index (LAI) in sowing date 23 May.

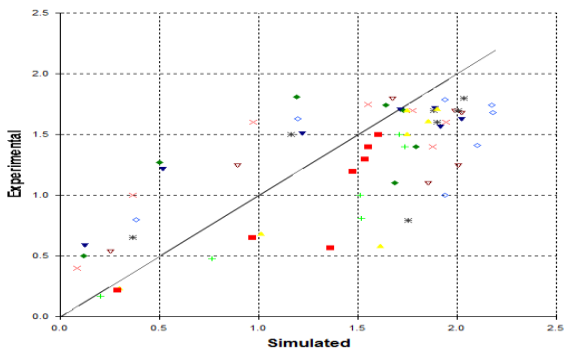

Fig. 12. The regression relation of simulated and observed leaf area index (LAI) for all of cultivars and sowing date. R2= 0.72, Y= 0.9x - 0.162.

In base of obtained of LAI simulation all of the cultivars at three sowing date (3, 13 and 23 May), model acted acceptable under Karaj climate, but this model must be calibrate after numerous experiments under different locations and times, then will capability for prediction of LAI, specially about first sowing date in this experiment. According to linearly regression correlation (1:1 line) simulation versus observed date for LAI in all of the cultivars and sowing date (Fig.12) obtained equation of y=0.9x+0.162 (R^2=0.72), showing that model acted acceptable in simulation variation of LAI in growth duration.

Based on the correlation diagram between observed and simulated mounts in biomass sowing date in 3 May, R^2 was 0.91 (Fig 10a), which indicates the acceptable capability of the model for biomass simulation. Based on the correlation diagram between observed and simulated mounts in biomass sowing date in 23 May, R^2 was 0.94 (Fig 10c), which it has best result. According to Fig (10b) regression curve of biomass simulated rate among measured rates, lowest R^2 (0.79) 3 cultivars at 13 May Y= 86x + 237.61.

References

Andarzian B, Bakhshandeh AM, Bannayan M, Emam G, Fathi G, Alami Saeed G. 2008. WheatPot: a simple model for spring wheat yield potential using monthly weather data. Biosystem Engineering. **99,** 487-495. http://dx.doi.org/10.1016/j.biosystemseng.2007.12.008

Banayan M, Crout NMJ, Hoogenboom G. 2003. Application of the CERES- wheat model for within season prediction of winter wheat yields in the United Kingdom. Agronomy Journal **95,** 114-125. http://dx.doi.org/10.2134/agronj2003.0114

Betts RA. 2005. Integrated approaches to climate-crop modeling: needs and challenges. Philosophical Transactions of the Royal Society B: Biological Sciences **360(1463),** 2049-2065. http://dx.doi.org/10.1098/rstb.2005.1739

Bruno C, Carlos GS, Kenneth J, Marcio AS, Alderman D. 2011. Adapting the CROPGRO perennial forage model to predict growth of *Brachiaria brizantha*. Field Crops Research **120,** 370-379. http://dx.doi.org/10.1016/j.fcr.2010.11.010

Costa LC, Justino F, Oliveira LJC, Sediyama G, Ferreira WPM, Lemos CF. 2009. Potential forcing of CO2, technology and climate changes in maize (*Zea mays*) and beans (*Phaseolus vulgaris*) yields in the

southern part of Brazil. Environmental Research Letters. **4(1),** 14013-14023.
http://dx.doi.org/10.1088/1748-9326/4/1/014013

Dallacort R, Rezende R, Freitas PSL, Faria R T, Azevedo TLF, Junior JBT. 2005. Utilização do modelo Cropgro-drybean na determinação das melhores épocas de semeadura da cultura do feijão para a região de Maringá, Estado do Paraná, Brasil. Acta Scientiarum. Agronomy **27(2),** 349-355.
http://dx.doi.org/10.4025/actasciagron.v27i2.1855

Faria RT, Folegatti MV, Frizzone JA, Saad A M. 1997. Determination of a long-term irrigation strategy for drybeans in Parana State-Brazil. Scientia Agricola. **54,** 155-164.
http://dx.doi.org/10.1590/S01039016199700030001 8

Goudriaan J, Van Laar HH. 1994. Simulation of crop growth processes. Dordrecht (Netherlands): Kluwer Academic Publishers. 238 pages.

Hansen JW. 2005. Integrating seasonal climate prediction and agricultural models for insights into agricultural practice. Philosophical Transactions of the Royal Society B: Biological Sciences **360(1463),** 2037-2047.
http://dx.doi.org/10.1098/rstb.2005.1747

Harnos N. 2006. Applicability of the AFRCWHEAT2 wheat growth simulation model in Hungray. Applied Ecology and Environmental Research. **4(2),** 55-61.

Hartkamp AD, Hoogenboom G, Gilbert RA, Tarawali AJ, Gijsman AJ, Bowen W, White JW. 2002. Adaptation of the CROPGRO growth model to velvet bean (*Mucuna prurients*) II. Cultivar evaluation and model testing. Field Crops Research. **78(1),** 27-40.
http://dx.doi.org/10.1016/S0378-4290(02)00090-4

Hoogenboom G, Huck MG, Peterson CM. 1987. Root growth rate of soybean as affected by drought stress. Agronomy Journal. **79,** 607-614.
http://dx.doi.org/10.2134/agronj1987.00021962007 900040004x

Hoogenboom G, Jones JW, Wilkens PW, Hunt LA, Portes CH, Batchelor WD, Hunt LA, Boote KJ, Singh U, Uehara G, Bowen WT, Gusman AJ, Du Toit AS, White JW, Tsuji GY. 2003. Decision support system for agrotechnology transfer: version 4.0. Honolulu: University of Hawaii. [CD-ROM].

Jones JW, Hoogenboom G, Porter C H, Boote KJ, Batchelor WD, Hunt LA, Wilkens PW, Singh U, Gijsman AJ, Ritchie JT. 2003. The DSSAT cropping system model. European Journal of Agronomy **18,** 235-265.
http://dx.doi.org/10.1016/S1161-0301(02)00107-7

Meireles EJL, Pereira AR, Sentelhas PC, Stone LF, Zimmermann FJP 2003. Risco Climático de quebra de produtividade da cultura do feijoeiro em Santo Antônio de Goiás, GO. Bragantia. **62(1),** 163-171.
http://dx.doi.org/10.1590/S000687052003000100020

Ruiz-Nogueira B, Boote KJ, Sau F. 2001. Calibration and use of CROPGRO-soybean model for improving soybean management under rainfed conditions. Agricultural Systems. **68(2),** 151-173.
http://dx.doi.org/10.1016/S0308-521X(01)00008-7

Soltani A, Torabi B, Zarei H. 2005. Modeling crop yield using a modified harvest index– based approach: application in chickpea. Field Crops Research **91,** 273-285.
http://dx.doi.org/10.1016/j.fcr.2004.07.016

Timsina J, Humphreys E. 2006. Performance of CERES-Rice and CERES-Wheat models in rice–wheat systems: A review. Agricultural Systems **90,** 5-31.
http://dx.doi.org/10.1016/j.agsy.2005.11.007

Wang X, He X, Williams JR, Izaurralde RC, Atwood JD. 2005. Sensitivity and uncertainty analyses of crop yields and soil organic carbon simulated with EPIC. Transactions of the ASAE **48 (3),** 1041-1054.
http://dx.doi.org/10.13031/2013.18515

Whisler FD, Acock B, Baker DN, Fye RE, Hodges HF, Lambert JR, Lemon HE, Mckinion JM, Reddy VR. 1986. Crop simulation models in agronomic systems. Advances in Agronomy. **40,** 141-208.
http://dx.doi.org/10.1016/S0065-2113(08)60282-5

Willmott CJ, Akleson GS, Davis RE, Feddema JJ, Klink K M, Legates DR, Odonnell J, Rowe CM. 1985. Statistic for the evaluation and comparison of models. Journal of Geophysical Research **90,** 8995-9005.
http://dx.doi.org/10.1029/JC090iC05p08995

Zamora DS, Jose S, Jones JW, Cropper WP. 2009. Modeling cotton production response to shading in a pecan alleycropping system using CROPGRO. Agroforestry Systems **76,** 423–435.
http://dx.doi.org/10.1007/s10457-008-9166-x