Indian Journal of Agricultural Sciences **88** (3): 379–86, March 2018/Article

Performance evaluation of Aqua Crop model for conservation agriculture based direct seeded rice (*Oryza sativa*)

ALI MOHAMMAD[1], SUSAMA SUDHISHRI[2], MAN SINGH[3], T K DAS[4], V K SHARMA[5] and NEETA DWIVEDI[6]

ICAR-Indian Agricultural Research Institute, New Delhi 110 012

Received: 30 August 2017 ; Accepted: 03 December 2017

ABSTRACT

Direct seeded rice (DSR) with conservation agriculture (CA) can be a good option to replace the highly water consuming puddle transplanted rice (*Oryza sativa* L.) for producing more per unit area with less water. The prediction of rice productivity through crop growth model is significant for further planning in water savings. There are various crop growth models used for predicting rice yield, but less information available on prediction of direct seeded rice under conservation agriculture. Therefore, the water driven FAO AquaCrop model (v.5.0) which requires minimum datasets was applied to the data generated from two years (2014 and 2015) field experimentation carried out in Research Farm, ICAR-Indian Agricultural Research Institute, New Delhi. The experiment was laid out in randomized block design in continuing experiment (5-6th year) with six CA practices in DSR and two puddle transplanted rice treatments and rice variety was PRH 10. The model was calibrated and validated using the data sets of *kharif* seasons of 2014 and 2015, respectively. The validated model prediction error statistics, i.e. root mean square error (RMSE), model efficiency (ME), index of agreement (d) and coefficient of determination (R^2) for grain yield, were 0.58, 0.72, 0.93, 0.96, and for biomass 1.11, 0.85, 0.95, 0.96, respectively, for all the treatments under CA based DSR treatments. It was observed under conservation agriculture with different levels of crop residues, the predicted yield have a good fit with the observed values with acceptable accuracy. Thus, water-driven FAO AquaCrop model can be applied to predict the yield of direct seeded rice grown under conservation agriculture in the semi-arid regions of India, particularly Indo-Gangetic plain (IGP).

Key words: AquaCrop model, Conservation agriculture, DSR, Rice yield, Water productivity

Rice (*Oryza sativa* L.) production governs India's food security, but the country will not be able to afford huge water supplies for transplanted rice in future (Dass *et al.* 2016, Mohammad *et al.* 2017). Direct seeding of rice (DSR) in irrigated rice (*Oryza sativa* L.) ecosystems (Kumar and Ladha 2011) can be a best option which could lead to potential water savings at the field level because of declined evaporation losses (Humphreys *et al*. 2010, Joshi *et al*. 2013, Farooq *et al*. 2011, Zhi 2002). It contains sowing pre-germinated seeds into a puddled soil surface (wet seeding), standing water (water seeding) or dry seeding into a prepared seedbed (dry seeding). Again, conservation agriculture which is being developed, adapted and promoted in Indo-Gangetic Plains (IGP) may be best practice to address these threats (Jat *et al*. 2014, Sapkota *et al*. 2014). The conservation agriculture principles such as minimum soil disturbance, permanent soil cover, and appropriate crop rotation with zero-till technology makes successful and contribute added advantage to the farmers (Jat *et al*. 2011, Das *et al*. 2014, Bhattacharyya *et al*. 2015, Freitas and Landers 2014, Mohammad *et al.* 2017).

The driving research in rice-based cropping systems is to increase water use efficiency and modify agricultural practices. Well-tested cropping systems models that capture interactions between soil water and nutrient dynamics, crop growth, climate and management can assist in the evaluation of new agricultural practices. Crop growth models are being developed utilizing water-driven, radiation-driven and energy-driven thoughts in growth engines to simulate yield, biomass and water productivity. The requirement of input data for all these models and their applicability to various agro-climatic regions and crops are of much consequence. The water-driven AquaCrop model version 5.0 (Food and Agricultural Organization 2015, Hsiao *et al*. 2009, Steduto *et al*. 2009 and 2012) developed by the Food and Agriculture Organization (FAO) needs minimal input data correlated to other crop models and is available with water and different residue percentage coverage. Therefore, Gaydon *et al*. (2012), Paredes *et al*. (2014) and Katerji *et al*. (2013) used the FAO AquaCrop model and

---

[1] Ex-M Sc student (e mail: alidawlatzai@yahoo,com), [2] Principal Scientist (e mail: susama.sudhishri@gmail.com), [3] Project Director, WTC (e mail: mansingh@iari.in), [4] Principal Scientist (e mail: tkdas64@gmail.com), [5] Principal Scientist (e mail: vksharma@gmail.com), [6] Senior Scientist, WTC (e mail: neeta.iari@gmail.com).

Dass *et al.* (2012) DSSAT-CERES-Rice to evaluate water stress effects on yields and maturity durations. Amiri *et al.* (2011) assessed CERES-Rice, AquaCrop, and ORYZA 2000 models performance in simulation of rice biological and grain yield in response to various irrigation intervals and nitrogen levels. Moreover, the AquaCrop model simulates the fluctuation in obtainable crop biomass and harvestable yield in response to variation in soil moisture in the root zone (Geerts *et al*. 2010). Eventually, the recently promoted AquaCrop model is a user-friendly and practitioner-oriented sort of model, as it preserves an optimal balance among accuracy, robustness, and simplicity, and needs a relatively small number of parameters compared to other type of models, that is why this is one of the best among all types (Huang *et al*. 2009). In addition, the predictability of the AquaCrop model under irrigated conditions for various crops under varying agro-climatic environments has been confirmed by several researchers around the word (Heng *et al*. 2009, Hsiao *et al*. 2009, Araya *et al*. 2010, Iqbal *et al*. 2010, Hussein *et al*. 2011, Stricevic *et al*. 2011). Although there has been intensive work on crop modeling of staple crops, such as wheat, maize and rice, but not much has been done on direct-seeded rice under conservation agriculture. Crop growth and development are also imperative for effective calibration of crop growth models. There are many crop models that are either too general, or suitable only for specific crops and/or agro ecological zones. The AquaCrop model has not been applied to simulate the yield of direct seeded rice crop grown under conservation agriculture in the semi-arid climatic region of northern India. Therefore, the present study was undertaken to calibrate and validate AquaCrop model v.5.0 and evaluate its performance in predicting grain yield, biomass and water productivity for direct seeded rice grown in *kharif* season under conservation agricultural practice.

MATERIALS AND METHODS

For evaluating the performance of AquaCrop model, the required experimental and crop management data were generated by conducting the field experiment in clay loam soil at 14B block of Research Farm, ICAR-Indian Agricultural Research Institute (IARI), New Delhi, India (28°35´ N, 77°12´ E, altitude 228 m above mean sea level) during the monsoon season of 2014 and 2015 in an on-going experiment started from 2009-10. Climate data for use in the model were acquired from the automatic weather station (AWS) located near the experimental field. New Delhi has a sub-tropical and semi-arid climate with hot and dry summers and cold winters. The experiment was laid out in randomized complete block design consisting of eight treatments, ZT DSR - ZTM: zero till direct seeded rice (ZT DSR) - zero till mustard (ZTM) (T_1), ZT DSR + BM – ZTM: Zero till DSR + *Sesbania* brown manuring – ZTM (T_2); MR (mustard residue) + ZT DSR - RR (rice residue) + ZTM (T_3), MR + ZT DSR + BM - RR + ZTM (T_4), ZT DSR - ZTM - ZT SMB (summer mungbean) (without any crop residue) (T_5), MBR (Mungbean residue) + ZT DSR - RR + ZTM - MR + SMB (with three crops residue) (T_6), TPR (transplanted puddled rice) – ZTM (T_7), and TPR - CTM (conventional till mustard) (T_8), which was laid-out in a continuing experiment (5-6th year). AquaCrop model simulation needs use of different input parameters related to climate of the study area, crop growth, soil, field and irrigation management information. Although, the model includes a set of generic input parameters which can be selected and adjusted for different soil or crop types during the model calibration process. There is no specific module for DSR and conservation agriculture in AquaCrop model. But the residue percentage in each treatment plot (Mohammad *et al.* 2017) was incorporated as input parameter under tillage system. A list of input data used in the AquaCrop model is given in Table 1.

The weather data needed by the AquaCrop model are daily values of minimum and maximum air temperature, reference crop evapotranspiration (ET_0), rainfall and mean annual carbon dioxide concentration (CO_2). ET_0 was estimated through FAO model Cropwat (v.8.0) using the daily maximum and minimum temperature, wind speed at 2 m above the ground surface, solar radiation and mean relative humidity (RH). The weather parameters were collected from the automatic weather station located near the experimental farm. Rainfall amounts of 1094 and 719 mm were recorded during the crop growth season of 2014 and 2015, respectively.

Crop parameters

The maximum canopy cover (CC), date of emergence, duration of flowering, start of senescence, and maturity data recorded during conducting the experiment and used in the model calibration. Generic data comprising canopy decline coefficient, crop coefficient for transpiration at full canopy cover, soil water depletion thresholds for inhibition of leaf growth and stomatal conductance, and acceleration of canopy senescence were obtained from Hsiao *et al.* (2009) and used for model calibration. These parameters were postulated to be applicable to a wide range of conditions and not specific for a given crop cultivar (Heng *et al.* 2009). The upper and lower thresholds and the shape of the response curve were the parameters for each type of stress that defined the sensitivity and severity of a depleted soil profile. The upper threshold determined the onset of stress, while the lower threshold showed the point at which the physiological process completely ceases. The shape factor used in the AquaCrop model depicts the magnitude of the stresses which affect the crop yield. A shape factor of zero shows highest sensitivity of crop to water stress and more than zero indicates lower sensitiveness to water stress. The water stress is divided into expansion stress, stomatal closure stress and senescence stress coefficients. These coefficients were calibrated using the experimental data to acquire a better match between the AquaCrop simulated and observed data.

Soil data of the experimental site needed as input parameters for AquaCrop are soil texture, field capacity

Table 1 Calibrated values of AquaCrop model input parameters for DSR as well as TPR treatments under conservation agriculture (*kharif* 2014)

Crop parameter	Description	ZT DSR - ZTM	ZT DSR + BM - ZTM	MR + ZT DSR – RR + ZTM	MR + ZT DSR + BM – RR + ZTM	MBR + ZT DSR – ZTM - SMB	MBR+ ZT DSR – RR + ZTM - MR +SMB	TPR - ZTM	TPR - CTM
Plant density	Plants/ha	833333	833333	833333	833333	833333	833333	333333	333333
CC o	CCo	4.17	4.17	4.17	4.17	4.17	3.57	5.0	5.0
Emergence	Days to 90% emergence (calendar) (days)	6	6	6	6	6	6	6	6
CGC	Canopy growth coefficient CGC (%)	9.2	9.1	9.0	9.2	9.2	9.7	13.4	13.2
CDC	Canopy decline coefficient CDC (%)	10.9	8.8	8.8	9.4	8.3	8.0	8.0	8.0
	Canopy decline (days)	22	25	24	26	29	33	33	31
CC x	Maximum canopy cover (%)	75	70	68	77	78	85	85	80
Zr (min)	Min effective rooting depth (m)	0.1	0.1	0.1	0.1	0.1	0.10	0.1	0.1
Zr (max)	Max effective rooting depth (m)	0.3	0.3	0.3	0.3	0.3	0.30	0.3	0.30
Kc_u	Coefficient for transpiration	1.1	1.09	1.09	1.1	1.1	1.10	1.1	1.10
	Green canopy cover (%)	60	60	60	60	60	60	50	50
	Reduction with age (%/day)	0.15	0.15	0.15	0.15	0.15	0.15	0.15	0.15
Water productivity	Water productivity (g/m^2)	15	16	16	15	15	15.2	17	18.7
Canopy stress	Ks p(upper)	0.25	0.25	0.25	0.23	0.23	0.25	0.25	0.25
	Ks p(lower)	0.6	0.6	0.6	0.60	0.6	0.55	0.55	0.55
	Shape factor	3	3	3	3	3	3	3	3
Stomatal stress	Ks p(upper)	0.25	0.25	0.25	0.29	0.29	0.50	0.5	0.5
Canopy senesc.	Ks p(upper)	0.85	0.85	0.85	0.70	0.70	0.85	0.85	0.85
T base	Base temperature (°C)	10	10	10	10	10	10	10	10
T upper	Upper temperature (°C)	30	30	30	30	30	30.0	30.0	30.0

(θ_{FC}), permanent wilting point (θ_{PWP}), saturated hydraulic conductivity (K_{sat}) and volumetric water content at saturation (θ_{sat}). The experiment site did not include any restrictive soil layer to prevent the expansion of root growth. Soil samples were collected from three depths at 0-15, 15-30 and 30-45 cm and analysed.

Irrigation and field management are two significant components considered in the AquaCrop model. For irrigation scheduling, soil moisture content was measured periodically by gravimetric method from 0-15, 15-30, and 30-45 cm soil depth before each irrigation to know the status of the present soil moisture content at the crop root zone and deciding when and how much to irrigate. The quantity of irrigation water to be applied was measured by digital instrument naming star flow meter which was first calibrated and programed in the computer then installed in the channel. The field management components were the fertility and crop residue levels and bunds to eliminate surface runoff.

Calibration of the AquaCrop model was completed by using the observed values from the field experiment during *kharif* 2014 as model input and then simulating the output, viz. the grain and biomass yield. Later on, the predicted output values were correlated with the observed grain and biomass yield. The distinction among the predicted and observed data were minimized by using a trial and error approach in which a specific input variable was chosen as the reference variable at a time and adjusting only those parameters that were familiar to influence the reference variable the most. The procedure was repeated to arrive at the closest match between the simulated and observed values for each treatment combination.

The crop file in AquaCrop contained crop-specific parameters belonging to seven phenological crop growth stages, fertility, and temperature stress parameters (Steduto *et al.* 2009). There are five parameters that conclude the development of canopy cover, viz. canopy growth coefficient (CGC), canopy decline coefficient (CDC), days to emergence, days to senescence, and days to full maturity. The CGC controls the rate at which the canopy expands and the CDC controls how fast the canopy dies off at the end of the growing season. The simulated grain biomass yields were correlated with the observed data during *kharif* 2014. This process was repeated several times while model calibration to list a set of parameters that produced results in line with the measured data.

The calibrated values of CGC and CDC at all residual, non-residual and conventional levels of direct seeded rice were observed 9.2, 9.1, 9.0, 9.2, 9.2, 9.7, 13.4 and 13.2%; 10.9, 8.8, 8.8, 9.4, 8.3, 8.0, 8.0, and 8.0% day^{-1}, for treatments T_1, T_2, T_3, T_4, T_5, T_6, T_7 and T_8, respectively. Crop growing periods in days from sowing to emergence, flowering, senescence and maturity were 6, 65, 95 and 110 days, respectively.

The surface method of irrigation with measured quantity of water was applied to different treatments based on soil moisture deficit criteria in this study. The management-allowed depletion (MAD) of 50% was considered as the initial condition in the model and the similar condition was practised in the experiment using soil moisture deficit-based irrigation scheduling. Therefore, the irrigation schedule information was used as input to the model by specifying the date and depth of irrigation water through starflow meter during the crop growth period. During the two years of the experiment, irrigation water was applied through 12 and 18 irrigations in DSR and TPR treatments with a total depth of 1103 and 1679 mm, respectively, and effective rainfall depth was 790 and 769 mm in DSR and TPR treatments, respectively during *kharif* 2014. Moreover, during *kharif* 2015, the total depth of 16 and 20 irrigations was 924 and 1442 mm in DSR and TPR treatments, respectively, and effective rainfall depth was 495 and 491 mm in DSR and TPR treatments, respectively. The input data of irrigation depth for *kharif* 2014 was used in the model during the calibration, whereas, the data of *kharif* 2015 was used for validation of the AquaCrop model.

The field management database of AquaCrop included the data of soil fertility, crop residue, and surface practices. Runoff from the surface of the field was considered in the model. But no storage of water on top of the field was considered, which confirmed the real field condition observed during the years of the experiment. The recommended dose of N, P and K fertilizers was applied to all the experimental plots. All plant growth parameters shown in Table 1 were measured during both the years of the experiment.

The calibrated AquaCrop model was further validated using the data of irrigation depths and the weather parameters which were observed during the rice crop growing season of *kharif* 2015 to predict the grain and biomass yield. Further, these predicted values were correlated with the observed values generated from the experiment and the model validation performance statistics were analysed.

The integrity among the simulated and observed values after calibration and validation of AquaCrop model was evaluated by using the prediction error statistics (Sudhishri *et al,* 2016). The prediction error (*Pe*), coefficient of determination (R^2), index of agreement (*d*), model efficiency (*ME*) and root mean square error (*RMSE*) were used as the error statistics to evaluate both the calibration and validation results of the model. The R^2, *d* and *E* were used to determine the predictive power of the model.

The root mean square error (RMSE) was calculated to determine prediction accuracy of the developed models. The RMSE is zero for perfect fit and increased values of RMSE indicate higher discrepancies between predicted and observed values. The root mean square error between observed and predicted values was determined by the following relationship.

$$RMSE = \sqrt{\frac{\sum_{j=1}^{n}\left(y_j - \hat{y}_j\right)^2}{n}} \tag{1}$$

The coefficient of determination (R^2) or correlation coefficient (R) is an indicator of degree of closeness between observed and predicted values. If observed and predicted values are completely independent, the R^2 will be zero. The coefficient of determination was estimated by the following equation (Nash and Sutchiffe 1970).

$$R^2 = \left[\frac{\sum_{j=1}^{n}\left\{\left(y_j - \bar{y}\right)\left(\hat{y}_j - \bar{\hat{y}}\right)\right\}}{\left\{\sum_{j=1}^{n}\left(y_j - \bar{y}\right)^2 \sum_{j=1}^{n}\left(\hat{y}_j - \bar{\hat{y}}\right)^2\right\}^{1/2}}\right]^2 \tag{2}$$

where, yj and $\hat{y}_j$ are observed and predicted values, $\bar{y}$ and $\bar{\hat{y}}$ are mean of observed and predicted values, respectively, n is the number of observations and j is an integer varying from 1 to n.

Following equation has been used to determine prediction error:

$$P_e = \left[\left\{\frac{yi - \hat{y}}{\hat{y}}\right\} * 100\right] \tag{3}$$

where, $\hat{y}$ and y_j are predicted and observed data.

The following equation has been used to determine model efficiency (Nash and Sutcliffe 1970):

$$ME = 1 - \frac{\sum_{i=1}^{n}\left(yj - \hat{y}\right)^2}{\sum_{i=1}^{n}\left(yj - \bar{y}\right)^2} \tag{4}$$

where, yj and $\hat{y}$ are observed and predicted data, $\bar{y}$ is mean value of yj and n is the number of observations.

Index of agreement (d)

The index of agreement was calculated using the Willmott (1982) equation:

$$d = 1 - \frac{\sum_{i=1}^{n} \left(\hat{y} - yj\right)^2}{\sum_{i=1}^{n} \left(\left|\hat{y} - \overline{y}\right| + \left|yj - \overline{y}\right|\right)^2} \quad (5)$$

where, yj and $\hat{y}$ are observed and predicted data, $\overline{y}$ is mean value of yj and n is the number of observations.

RESULTS AND DISCUSSION

AquaCrop model calibration performance

The input data values pertaining to crop residue under conservation agriculture direct seeded rice used in the calibration of the model are indicated in Table 1. It was observed from the Table 1 that the input parameter ranges did not vary much for DSR treatments, whereas the parameters were different for the TPR treatments. The calibrated and observed data of grain and biomass yield for all treatments combination were indicated in Fig 1 and prediction error percentage in Table 2. It was observed that the maximum and minimum error in grain yield prediction was in MBR+ ZT DSR – RR + ZTM - MR + SMB and MR + ZT DSR – RR + ZTM treatments, amounting to 3.6 and 0.24%, respectively (Table 2). The best calibration results for grain yield were with the lowest prediction error (0.24%) for percentage of coverage of all residues, amounting 78%, whereas the maximum prediction error of 3.6% was observed for percentage of coverage of all residues, amounting 73.6%. Similarly, the maximum and minimum prediction errors for biomass yield were for the TPR – CTM and ZT DSR + BM – ZTM treatments with -1.09 and -4.32%, respectively (Table 2). The highest (-1.09%) biomass yield prediction error was for percentage of coverage of residues, amounting 0.0%, and the lowest error (-4.32%) was for percentage of coverage of brown manuring residue, amounting 43%. The highest prediction error was observed for the TPR – CTM treatment, which may be because of the zero residue application under the conventional tillage system. The prediction error of biomass yield was highest for TPR – CTM treatment (Table 2). The statistical parameters of the calibrated model for all the treatments under different crop residue coverage were shown in Table 3. It was observed that the model was calibrated for grain yield with root mean square error (RMSE), model efficiency (ME), index of agreement (d) and coefficient of determination (R^2) values of 0.22, 0.81, 0.94, 0.86, and for biomass yield 0.25, 0.79, 0.95, 0.96, respectively. However, the d and R^2 parameters were close to 1 for grain and biomass yields predictions, showing better calibration of the model, however, there was some slightly over prediction of grain and biomass yield throughout the calibration process (Fig 1).

Table 2 Prediction error percentage during calibration and validation periods of AquaCrop

Treatment	Calibration period		Validation period	
	Yield	Biomass	Yield	Biomass
ZT DSR - ZTM	15.95	-2.13	-17.12	-14.83
ZT DSR + BM - ZTM	1.20	-4.32	-14.42	-22.20
MR + ZT DSR – RR + ZTM	0.24	-1.76	-10.50	-22.46
MR + ZT DSR + BM – RR + ZTM	0.70	-1.80	-42.09	-24.45
MBR + ZT DSR – ZTM - SMB	0.43	-2.28	-12.41	2.18
MBR+ ZT DSR – RR + ZTM - MR + SMB	3.60	-1.27	-14.88	5.67
TPR - ZTM	0.78	-1.35	-5.01	0.54
TPR - CTM	0.19	-1.09	-9.83	0.53

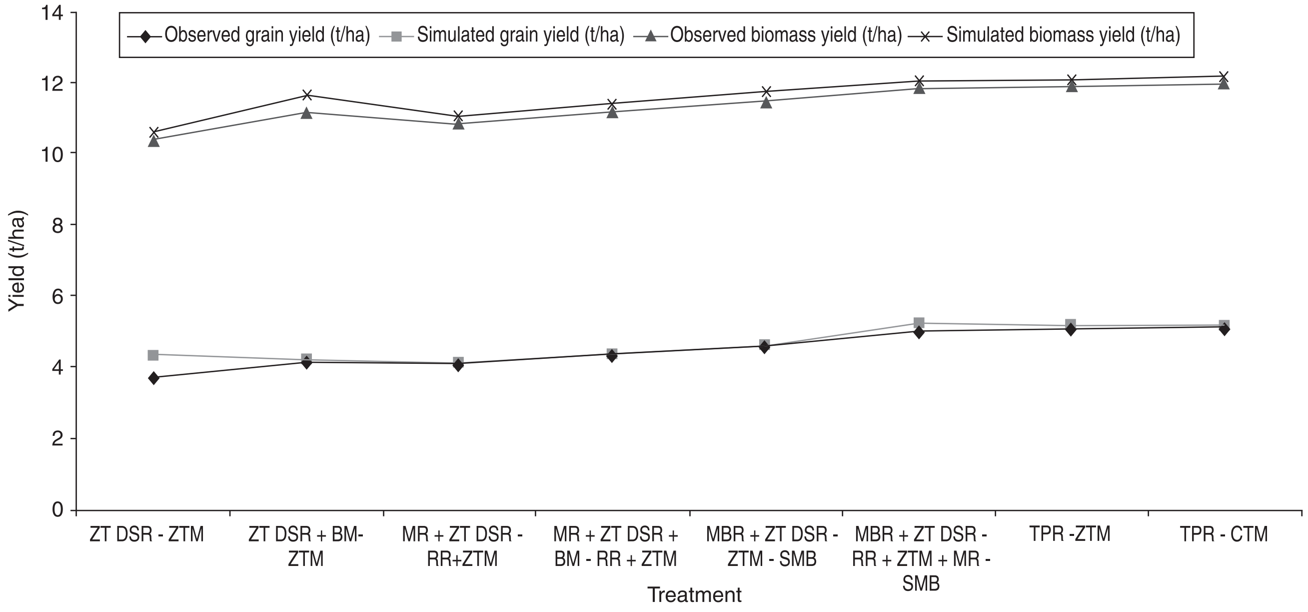

Fig 1 Observed and simulated yield under calibration of AquaCrop model.

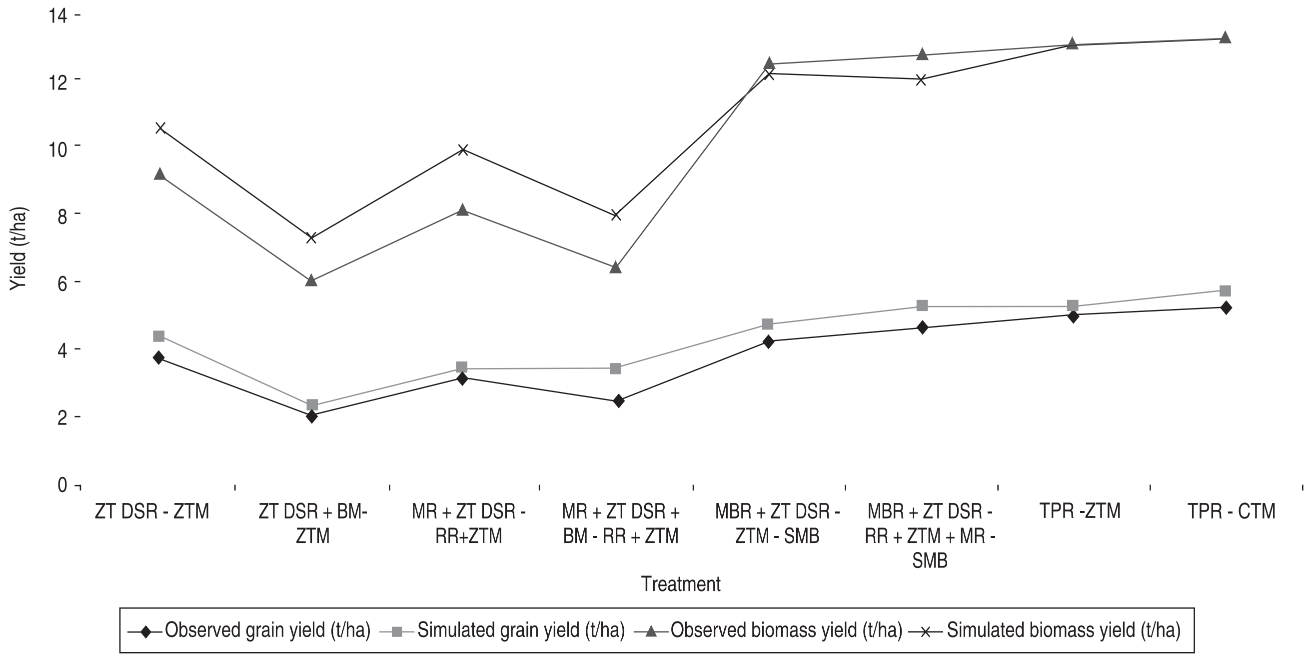

Fig 2 Observed and simulated yield under validation of AquaCrop model.

Table 3 Statistical evaluation parameters of the calibrated and validated AquaCrop model for rice crop

Model output parameter	Calibration period				Validation period			
	RMSE	d	ME	R^2	RMSE	d	ME	R^2
Yield (t/ha)	0.22	0.94	0.81	0.86	0.58	0.93	0.72	0.950
Biomass (t/ha)	0.25	0.95	0.79	0.96	1.11	0.95	0.85	0.960

RMSE=Root mean square error; d=index of agreement; ME= model efficiency; R^2= coefficient of determination

AquaCrop model validation performance

It was observed that the maximum and minimum prediction error of grain yield at the time of model validation with the data of 2015 was -5.01 and -42.09% for the TPR – ZTM and MR + ZT DSR + BM – RR + ZTM treatments, respectively (Table 2). Moreover, the maximum and minimum prediction error for biomass observed as 5.67 and -24.45% for the MBR+ ZT DSR – RR + ZTM - MR + SMB and MR + ZT DSR + BM – RR + ZTM treatments, respectively (Table 2). The prediction error statistics of model validation results using the data of all treatments and for all DSR and TPR systems were shown in Table 3. It was observed prediction error statistics of root mean square error (RMSE), model efficiency (ME), index of agreement (d) and coefficient of determination (R^2) values for grain and biomass yield during model validation for all treatment combinations were 0.58, 0.72, 0.93, 0.96, and 1.11, 0.85, 0.95, 0.96, and 1.00, -1427.43, 0.05, 0.003, respectively. It was observed from prediction error statistics that the grain and biomass yield predictions were in line with the observed data. The prediction error statistics of d and R^2 for validation of the grain yield for all the treatments indicated a value close to 1 (i.e. 0.95 and 0.93, respectively). However, there was slight overestimation of yield for all the treatments of the experiment (Fig 2) but were not significant as also observed by Zeleke *et al.* (2011) and Simba *et al.* (2013). Overall, it was observed from the d and R2 values that the grain and biomass yield, prediction by the AquaCrop model under different levels of crop residues and treatments in the experiment have a good fit with the observed values and with acceptable accuracy. Overall, the grain and biomass yield predictions by the AquaCrop model for direct seeded rice treatments were observed to be better than the conventional puddle transplanted rice treatments. Thus, water-driven FAO AquaCrop model could be used for rice yield prediction in DSR under similar condition in Indo-Gangetic Plain (IGP). However, AquaCrop model needs to be validated across crops and locations for its better acceptance.

ACKNOWLEDGEMENT

The authors are grateful to different scientists who are involved in conservation agriculture experiments going on in ICAR-Indian Agricultural Research Institute, New Delhi for their support. Authors also express their gratitude to ICAR-IARI for providing the financial and technical assistance for undertaking the experiment.

REFERENCES

Amiri E, Razavipour T, Rezaei Mojtaba and Khaledian M R. 2011. Water productivity of rice under varying crop density and irrigation management (Field and modeling approach). *ICID 21st Congress, Tehran, International Congress on Irrigation and Drainage,* pp 15-23.

Araya A, Habtu S, Hadgu K M, Kebede A and Dejene T. 2010. Test of AquaCrop model in simulating biomass and yield of water deficit and irrigated barley. *Agricultural Water Management* **97**: 1838–46.

Bhattacharyya Ranjan, Das T K, Sudhishri S, Dudwal B, Sharma A R, Bhatia A and Singh Geeta. 2015. Conservation agriculture effects on soil organic carbon accumulation and crop productivity under a rice–wheat cropping system in the western Indo-Gangetic Plains. *European Journal of Agronomy* **70**: 11–21.

Das T K, Bhattacharyya Ranjan, Sudhishri S., Sharma A R, Saharawat Y S, Bandyopadhyay K K, Sepat Seema, Bana R S, Aggarwal Pramila, Sharma R K, Bhatia A, Singh Geeta, Datta S P, Kar A, Singh Billu, Singh Parmendra Pathak H, Vyas A K and Jat M L. 2014. Conservation agriculture in an irrigated cotton–wheat system of the western Indo-Gangetic Plains: Crop and water productivity and economic profitability. *Field Crops Research* **158**: 24–33.

Das T K, Bandyopadhyay K K, Bhattacharyya Ranjan, Sudhishri S, Sharma A R, Behera U K, Saharawat Y S, Sahoo P K, Pathak H, Vyas A K, Bhar L M, Gupta H S, Gupta R K and Jat M.L. 2016. Effects of conservation agriculture on crop productivity and water-use efficiency under an irrigated pigeonpea–wheat cropping System in the western indo-gangetic plains. *Journal of Agricultural Science:* 1–16.

Dass Anchal, Nain Ajit Singh, Sudhishri S and Chandra Subhash. 2012. Simulation of maturity duration and productivity of two rice varieties under system of rice intensification using DSSAT v 4.5/CERES-Rice model. *Journal of Agrometeorology* **14**(1): 26–30.

Dass A, Chandra S*,* Choudhary A K, Singh G and Sudhishri S. 2016. Influence of field re-ponding pattern and plant spacing on rice root-shoot characteristics, yield, and water productivity of two modern cultivars under SRI management in Indian Mollisols. *Paddy and Water Environment* **14**: 45–59.

Farooq M, Siddique Kadambot H M, Rehman H, Aziz T, Lee Dong-Jin and Wahid A. 2011. Rice direct seeding: Experiences, challenges and opportunities. *Soil & Tillage Research* **111**: 87–98.

Freitas P L de and Landers J N. 2014. The transformation of agriculture in Brazil through development and adoption of zero tillage conservation agriculture. *International Soil and Water Conservation Research* **2**(1): 35–46.

Food and Agricultural Organization (FAO). 2015. AquaCrop: The FAO crop-model to simulate yield response to water. http://www.fao.org/nr/water/aquacrop.html (October, 2015).

Gaydon D S, Probert M E, Buresh R J, Meinke H, Suriadi A, Dobermann A,Bouman B and Timsina J. 2012. Rice in cropping systems-Modelling transitions between flooded and non-flooded soil environments. *Europian Journal of Agronomy* **39**: 9– 24.

Geerts S, Raes D and Garcia M. 2010. Using AquaCrop to derive deficit irrigation schedules. *Agricultural Water Management* **98**: 213–6.

Heng L K, Hsiao T C, Evett S, Howell T and Steduto P. 2009. Validating the FAO AquaCrop model for irrigated and water deficient field maize. *Agronomy Journal* **101**: 488–98.

Hira G S. 2009. Water management in northern states and the food security of India. *Journal of Crop Improvement* **23**: 136–57.

Hsiao T C, Heng L K, Steduto P, Rojas-Lara B, Raes D and Fereres E. 2009. AquaCrop the FAO crop model to simulate yield response to water: III. Parameterization and testing for maize. *Agronomy Journal* **101**: 448–59.

Huang Y, Yu Y, Zhang W, Sun W, Liu S, Jiang J, Wu J, Yu W, and Yang Z. 2009. Agro-C: A bio-geophysical model for simulating the carbon budget of agro-ecosystems. *Agricultural and Forest Meteorology* **149**: 106–29.

Humphreys E, Kukal S S, Christen E W, Hira G S, Singh B, Yadav S and Sharma R K. 2010. Halting the groundwater decline in north-west India – Which crop technologies will be winners? *Advances in Agronomy* **109**: 155–217.

Hussein F, Janat M, and Yakoub A. 2011. Simulating cotton yield response to deficit irrigation with the FAO AquaCrop model. *Spanish Journal of Agricultural Research* **9**: 1319–30.

Iqbal M A, Bodner G, Heng L K, Eitzinger J and Hassan A. 2010. Assessing yield optimization and water reduction potential for summer-sown and spring sown maize in Pakistan. *Agricultural Water Management* **97**: 731–7.

Jat M L, Saharawat Y S and Gupta Raj. 2011. Conservation agriculture in cereal systems of south Asia: Nutrient management perspectives. *Karnataka Journal of Agrocultural Science* **24**(1): 100–5.

Jat R A, Wani S P and Sahrawat K L. 2012. Conservation Agriculture in the Semi-Arid Tropics: Prospects and Problems. *Advances in Agronomy* **117**: 191–273.

Jat R K, Sapkota T B, Singh R G, Jat M.L, Kumar Mukesh and Gupta R K. 2014. Seven years of conservation agriculture in a rice–wheat rotation of Eastern Gangetic Plains of South Asia: Yield trends and economic profitability. *Field Crops Research* **16**4: 199–210.

Joshi Ekta, Kumar Dinesh, Lal B, Nepalia V, Gautam Priyanka and Vyas A K. 2013. Management of direct seeded rice for enhanced resource - use efficiency. *Plant Knowledge Journal* **2**(3): 119–34.

Katerji Nader, Campi Pasquale and Mastrorilli Marcello. 2013. Productivity, evapotranspiration, and water use efficiency of corn and tomato crops simulated by AquaCrop under contrasting water stress conditions in the Mediterranean region. *Agricultural Water Management* **130**: 14– 26.

Kumar Virender and Ladha, Jagdish K. 2011. Direct seeding of rice: Recent developments and future research needs. *Advances in Agronomy* **111:** 297–413.

Mahajan G, Chauhan B S, Timsina J, Singh P P and Singh K. 2012. Crop performance and water and nitrogen-use efficiencies in dry-seeded rice in response to irrigation and fertilizer amounts in northwest India. *Field Crop Research* **134**: 59–70.

Mohammad Ali, Sudhishri Susama, Das T K, Singh Man, Sharma V K and Dwivedi Neeta. 2017. Conservation agriculture responses to yield and water productivity in direct seeded rice (*Oryza sativa*). *Annals of Plant and Soil Research* **19**(1): 46–53.

Nash J E, and Sutcliffe J V. 1970. River flow forecasting through conceptual models. I. A discussion of principles. *Journal of Hydrology* **10**: 282–90.

Paredes P, Melo-Abreu de J P, Alves I, and Pereira L S. 2014. Assessing the performance of the FAO AquaCrop model to estimate maize yields and water use under full and deficit irrigation with focuson model parameterization. *Agricultural Water Management* **144**: 81–97.

Rodell M, Velicigna I, and Famiglientti J S. 2009. Satellite-based estimates of groundwater depletion in India. *Nature* **460**: 999–1002.

Sapkota T B, Majumdar Kaushik, Jat M. L, Kumar A, Bishnoi D K, McDonald A J and Pampolino Mirasol. 2014. Precision nutrient management in conservation agriculture based wheat production of Northwest India: Profitability, nutrient use efficiency and environmental footprint. *Field Crops Research* **155**: 233–44.

Simba Malvern, Farai Mubvuma, Michael Murwendo and Talen Chikodzi David. 2013. Prediction of yield and biomass productions: A remedy to climate change in semi-arid regions of Zimbabwe. *IJAAR* **1**: 14–21.

Steduto P, Hsiao T C, Fereres E and Raes D. 2012. Crop yield response to water. FAO Irrigation and Drainage Paper No. 66, FAO, Rome. http://www.fao.org/nr/water

Steduto P, Hsiao T C R D, and Fereres E. 2009. AquaCrop—the FAO crop model to simulate yield response to water: I. Concepts and underlying principles. *Agronomy Journal* **101**: 426–37.

Stricevic R, Cosic M, Djurovic N, Pejic B and Maksimovic L. 2011. Assessment of the FAO AquaCrop model in the simulation of rainfed and supplementally irrigated maize, sugar beet and sunflower. *Agricultural Water Management* **98**: 1615–21.

Sudhishri S, Kumar A and Singh J K. 2016. Comparative evaluation of neural network and regression based models to simulate runoff and sediment yield in an outer Himalayan watershed. *Journal of Agricultural Science and Technology* **18**: 681–94.

Willmott C J, 1984. On the evaluation of model performance in physical geography. (*In*) *Spatial Statistics and Models*, pp 443-60. Gaile, G L, Willmott C J (Eds). D. Reidel, Boston.

Zeleke Tilahun, Ketema, Luckett David and Cowley Raymond. 2011. Calibration and testing of the FAO AquaCrop Model for canola. *Agronomy Journal* **103**(6): 1610–9.

Zhi M. 2002. Water efficient irrigation and environmentally sustainable irrigated rice production in China. http://www.icid.org/wat_mao.pdf