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Estimating crop model parameters for simulating soybean production in Iran conditions☆

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Abstract – Crop modelling has the potential to contribute to food security. In this study, to provide a simple model for estimating the soybean potential yield and phenological stages in Iran, a simulation model (SSM_iCrop2) was parameterized and tested. This model estimates the soybean phenological stages and potential yield based on the weather data (minimum and maximum temperature, solar radiation and rainfall) using the phenological models such as leaf area development, mass production and partitioning and soil water balance. Regarding the model parametrization, the two maturities groups of 3 and 5 with the temperature unit of 2000 and 2400 growth degrees day (GDD) were chosen. The model evaluation results indicated that the soybean yield ranged between 1.9 and 4.8 with the average of 3.5 $t.ha^{-1}$, while the range of simulated yield changes between 1.8 and 4.7 with the average of 3.7 $t.ha^{-1}$. Comparing the observed yield to the simulated yield, values of r, CV and RMSE were obtained 0.84, 13%, 0.5 $t.ha^{-1}$ which indicates the high accuracy of the model. All of these results indicated that the estimated model parameters are high accuracy for use in the simulation of soybean yield at the country level.

Keywords: parameterization / evaluation / food security / crop model / climate change

Résumé – **Estimation des paramètres d'un modèle de culture simulant la production de soja en Iran.** La modélisation des cultures peut contribuer à la sécurité alimentaire. Dans cette étude, un modèle de simulation (SSM_iCrop2) a été paramétré et testé afin d'estimer les stades phénologiques et le rendement potentiel du soja en Iran. Ce modèle simple s'appuie sur une base de données météorologiques (température minimale et maximale, rayonnement solaire et précipitations) pour estimer la phénologie, la surface foliaire, la production et l'allocation de la biomasse, et le bilan hydrique du sol. Pour le paramétrage du modèle, seuls les groupes de maturité III et V correspondant à des sommes de température de 2000 et 2400 degrés-jours ont été retenus. Les résultats de l'évaluation du modèle ont indiqué que le rendement observé du soja se situait entre 1,9 et 4,8 $t.ha^{-1}$, avec une moyenne de 3,5 $t.ha^{-1}$, tandis que la gamme des rendements simulés variait de 1,8 à 4,7 $t.ha^{-1}$ avec une moyenne de 3,7 $t.ha^{-1}$. En comparant le rendement observé au rendement simulé, on a obtenu des valeurs de r, CV et RMSE de 0,84, 13%, 0,5 $t.ha^{-1}$,respectivement, ce qui souligne la grande précision du modèle. Tous ces résultats indiquent que les paramètres estimés pour ce modèle sont suffisamment précis pour être utilisés dans la simulation du rendement du soja au niveau national.

Mots clés : paramétrage / évaluation / sécurité alimentaire / modèle de culture / changement climatique

1 Introduction

Soybean (*Glycine max*) is one of the most important oilseed crops cultivated in the world. Soybean crop area and production in Iran are about 66 000 hectares and 151 000 tons, respectively which does not meet the domestic needs, so imported soybean meal to Iran amounted to 2.37 million tonnes with the worth of $1.5 billion in 2012 (Ministry of Agriculture Jihad, 2016). Also, imported soybean oil was about 800 000 tonnes worth $960 million in 2013 (FAOSTAT, 2013). So far, several attempts have been made using field experiments to better understand factors affecting crop yield

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per unit area. Field experiments on the crop response to various environmental conditions are laborious and costly. Due to these constraints, crop models can be useful tools to study and estimate the yield (Geerts and Raes, 2009) A mathematical model is an equation or set of equations that describes the behaviour of each system quantitatively (Soltani, 2009). To predict the crop growth, studies on phenology, mass production and partitioning, leaf area development and soil water balance are required (Dadrasi and Torabi, 2016). Precise prediction of the crop phenology is one of the essential features of the simulation models. The mass production and partitioning are largely regulated by the timing of developmental stages in crop simulation models (Soltani, 2012). Simple models can be more efficient in yield analysis and investigate the limiting factors due to easy manufacturing, testing, applying, understanding and interpretation of results; In addition it needs minimum inputs (Sinclair and Muchow, 1999). One of the other benefits of modelling is the prediction of the food production status in one area and making decisions based on environmental changes. Models apply a variety of plant and environmental parameters to simulate crop growth and they should be calibrated and evaluated before being used (Hsiao *et al.*, 2009). In some models, the parameters related to plant characteristics may have been calculated according to the climate of a certain region, which is not usable in other regions or may not have acceptable performance. Therefore, to predict the crop growth and yield by the model, the compatibility of the equations with the relationships between the different processes of growth and yield and the climatic conditions of the study area, access to the input parameters and the model efficiency in predicting growth and yield should be considered (Torabi *et al.*, 2011).

Some used models for simulation of soybean yield and phenological stages include EPIC (Williams and Watson, 1985), SoySim (Setiyono *et al.*, 2010), CROPGRO-Soybean (Boote *et al.*, 1998) and APSIM (Keating *et al.*, 2003). There is another a group of plant models, called SSM_iCrop2 (Soltani *et al.*, 2020a). SSM_iCrop2 model simulated a large number of plant species including orchard species and perennial forages (Soltani *et al.*, 2020a).

Therefore, the aim of this study was to determine the SSM_iCrop2 parameters in simulating main cultivars soybean growth and yield in Iran to provide a tool for analysing yield-limiting factors, optimizing field management and identifying the factors that influence the yield increase in certain environmental conditions.

2 Material and methods

2.1 Data used

To parameterize and evaluate the model, in major areas in terms of soybean cultivation, data of various studies on soybean (treatments without any growth and development limiting factors or environmental stresses) was applied (Tab. 1). About 35% of published paper was applied to parameterize the model (include 34 situations for days to maturity and 26 situations for yield) and about 65% other was utilized to evaluate it (include 49 situations for yield). Parameterization of SSM_iCrop2 is straightforward as presented in Appendix I of Soltani and Sinclair (2012). Briefly, the model is tested using different values for a specific parameter, then values are chosen that provide the closest match to the observations of the major outputs, frequently final yield. Also, several model parameters that are fixed within different soybean cultivars (such as cardinal temperature) were obtained from credible references.

2.2 Crop model

The model used in this study was SSM_iCrop2[1] (Soltani and Sinclair, 2012; Soltani *et al.*, 2020a). The model includes daily phenology progress, leaf area development and senescence, dry matter production, yield formation, and soil water balance. Responses of crop processes to solar radiation, temperature, water availability, and cultivar differences are included in the model. Soil water sub-model accounts for soil water additions from precipitation or irrigation, and increasing rooting depth and water removal *via* deep drainage, run-off, soil evaporation, and plant transpiration. The soil profile is divided into two layers: one top layer of 15–20 cm thickness and a second layer that includes the first layer and its depth increases by root growth. Soil water balance of both layers is calculated separately. The effect of water deficit and excess on leaf area development and senescence, dry mass accumulation, and phenological development are simulated. The model also accounts for the effect of freezing temperatures on plant leaf area that might take place in early spring sowings or winter sowings. The model has been tested extensively for a wide range of plant species and proved to be robust (Soltani *et al.*, 2020a).

Some of the parameters required in the SSM_iCrop2 model for soybean are presented in Table 2.

2.2.1 Weather data

Meteorological information of each experimental site including minimum and maximum daily temperature, daily precipitation, and solar radiation were obtained from the nearest meteorological station. Outliers and missing data were then estimated and restored using the WeatherMan program (Hoogenboom *et al.*, 2004).

2.2.2 Soil data

The required soil information included soil albedo index, Drainage coefficient, soil water volume in the field capacity, wilting point and saturation conditions. There is no local digitized soil database for crop modeling in Iran, so the HC27 database (Koo and Dimes, 2013) was utilized. The resolution of the soil database is also important. HC27 soil database used in the current study has a resolution of 10-km which may seem coarse. Tests using SSM_iCrop2 for crop and horticultural species indicated that using HC27 soil profiles compared to actual, measured soil profiles resulted in similar output for yield and the net amount of irrigation water requirements or evapotranspiration with no significant difference with respect to mean, variance and distribution (Nehbandani *et al.*, 2020b).

[1] This model can be downloaded from: "https://sites.google.com/site/cropmodeling/-5-SSM_iCrop2".

Table 1. Experiments used for parameterization and evaluation of SSM_iCrop2.

Location and year	Treatments	References
Parameterization		
Gorgan, 2002	Sowing date, Cultivars	Zeinali *et al.*, 2003
Gorgan, 2011	Cultivars, Sowing date	Gorzin *et al.*, 2015
Ghaemshahr, 2010	Irrigation	Akbari Nodehi, 2012
Gharakhil, 2009	Cultivars, Plant density, Sowing date	Rameeh and Aghabozorgi, 2016
Ardabil, 2013	Seed inoculation	Sidi Sharifi and Khoramdel, 2013
Gorgan, 2002	Cultivars, Plant density	Zahleht Salmasi *et al.*, 2004
Mahmod abad, 2015	Cultivars, Nitrogen fertilizer	Mahmodi and Zakipour, 2016
Gorgan, 2002	Cultivars, Plant density	Zahleht Salmasi *et al.*, 2004
Mahmod abad, 2015	Cultivars, Nitrogen fertilizer	Mahmodi and Zakipour, 2016
Sari, 2011	Cultivars, Sowing date	Ghanbari Malayder *et al.*, 2015
Evaluation		
Gorgan, 2012	Crop density, Cultivars	Nehbandani, 2013
Babulsar, 2001	Zinc and Potassium fertilizer	Habibzadeh *et al.*, 2003
Gorgan, 2006 and 2007	Cultivars, Plant density	Raeisi and Hezarjeribi, 2013
Gorgan, 2005	Plant density	Najafi, 2006
Gorgan, 2011 and 2012	Irrigation	Hosaini *et al.*, 2016
Ardabil, 2011	Seed inoculation, Nitrogen fertilizer	Sidi Sharifi and Khoramdel, 2013
Ghaemshahr, 2010	Cultivars, Planting patern	Namdari and Mahmoodi, 2013
Moghan, 2007 and 2008	Cultivars, Plant density, Sowing date	Razmi, 2010
Sari, 2010	Cultivars	Fazeli *et al.*, 2016
Gorgan, 2011	Cultivars, Plant density	Mosnei *et al.*, 2015
Daland, 2014	Seed inoculation	Ghana, 2016
Ardabil, 2009	Cultivars, Sowing date	Mousavi and Chavoshi, 2013
Nekah, 2010	Irrigation	Akbari Nodehi, 2011
Bilesowar, 2011	Seed inoculation, Nitrogen fertilizer	Zendeh *et al.*, 2016
Sari, 2002	Irrigation	Qajar Sepanlou and Behminar, 2004
Gorgan, 2011 and 2012	Irrigation	Faraji, 2016
Ardabil, 2013	Seed inoculation	Seyed Sharifi, 2015

Table 2. Required weather, soil and crop management input to run SSM_iCrop2.

Input data	Abv	Unit
Weather data		
Maximum daily temperature	TMAX	°C
Minimum daily temperature	TMIN	°C
Solar radiation	SRAD	MJ $m^{-2}d^{-1}$
Daily rainfall	RAIN	mm
Soil data		
Soil albedo	SALB	–
Drainage factor	DRAINF	–
Volumetric soil water content at drained upper limit	IDUL	mm mm^{-1}
Volumetric soil water content at crop lower limit	ILL	mm mm^{-1}
Volumetric soil water content at saturation	ISAT	mm mm^{-1}
Curve number	CN	–
Soil depth	SOLDEP	mm
Crop management		
Planting date	PDOY	day
Initial soil water at start of simulation	ISW	mm
Irrigation threshold level (for automatic irrigation)	IRGLVL	–

2.2.3 Crop management data

The required crop management information included sowing date, soil moisture content during simulation, irrigation level. This data was obtained from the articles in Table 1.

In this model, GDD was applied to determine the difference between soybean maturity groups. For this purpose, the phenological data of maturity groups 3 and 5 (major maturity groups that are grown in Iran) were used (Tab. 1). The GDD was calculated (based on soybean cardinal temperatures) for each phenological step.

2.3 Model evaluation

The statistical indices used for model evaluation were the coefficient of variation (CV), root mean square error (RMSE) and correlation coefficient (r). Also, the 1:1 line with 20% discrepancy was used to show the amount of deviation of the simulated *versus* the observed values. These statistical indices were calculated as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2}, \tag{1}$$

$$CV = \frac{\sqrt{n\sum(x_i - \bar{x})^2}}{\sum x_i}, \tag{2}$$

$$r = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2}\sqrt{\sum_{i=1}^{n}(y_i - \bar{y})^2}}, \tag{3}$$

where x_i is the observed values, y_i is the simulated values, n is the number of observations, $\bar{x}$ is the mean observed values including days to maturity or grain yield in the independent experiments, and $\bar{y}$ is the mean simulated values including days to maturity or grain yield.

2.4 Sensitivity analysis

Sensitivity analysis is the study of how the different input variations of a mathematical model influence the variability of its output (Monod *et al.*, 2006). In this research, we used local sensitivity analysis, which evaluates the local impact of the variation in the input factors on a model response, focusing on sensitivity in vicinity of a set of factor values. The evaluation is conducted through gradients or partial derivatives of the output functions at these factor values, while the values of other input factors are kept constant.

To get full coverage of parameter value space and considering that the runtime for one execution of the SSM_iCrop2 model is very short, we set the parameters for the different variation ranges, separately. In the model, about 10% of the crop parameters are approved to be varied with cultivar and environment (Bouman and van Laar, 2006; Tan *et al.*, 2017). In previous studies, Tan *et al.* (2017) selected 16 parameters for uncertainty and sensitivity analysis, while Sexton *et al.* (2017) selected 14 parameters for this purpose. In this study, 7 parameters were used for sensitivity analysis (including tuHAR, LAIMX, KPAR, IRUE, TEC, Himax and HImin). Variation range set at ±30% perturbation of the default parameter values. The selection of perturbation range (±30%) was based on Tan *et al.* (2017) and Noorhosseini *et al.* (2018). For sensitivity analysis, grain yield ($t.ha^{-1}$) and WTOP (accumulated above-ground dry matter, $t.ha^{-1}$) were extracted as model outputs. Box plot (created with SAS software) was used to show changes in grain yield and WTOP under different parameter variation ranges. For create box plots, SAS 9.4 was used.

3 Results and discussion

3.1 SSM_iCrop2 model parameterization

To parameterize the SSM_iCrop2 model, common soybean cultivars in Iran (groups 3 and 5) were considered. All the parameters indicated in Table 3 were necessary for estimating soybean growth and production. Based on these parameters, SSM_iCrop2 model could simulate the yield and days to maturity. The results showed that the soybean observed yields varied between 1.9 and 4.7 with an average of 3.5 $t.ha^{-1}$ and the range of simulated yield changes between 1.8 and 4.4 with an average of 3.9 $t.ha^{-1}$. The root mean square error (RMSE) was 0.48 $t.ha^{-1}$ which is equivalent to 14% of both the mean of simulated and observed yields, and the correlation coefficient (r) was 0.63 (Fig. 1). The coefficient of variation in field experiments is usually between 20 to 30% (Dadrasi and Torabi, 2016). All data were within the range of ±20% of grain yield which indicates the accurate estimation of the model parameters. Regarding the phenological feature of days to maturity, the model had a good estimation so that the observed time intervals ranged from 104 to 154 days with an average of 127 days and the simulated time intervals ranged between 108 and 147 days with an average of 127 days (Fig. 2). For this feature, RMSE, the coefficient of variation (CV) and r were 12 days, 9% and 0.60, respectively. Therefore, the results of parametrization based on days to maturity are considered optimal at the country level.

3.2 Model evaluation

To evaluate the model, the values of simulated yield was compared to the observed values. For this purpose, a set of experimental data was used (Tab. 1). For simulation, required inputs for the model and the weather data of the areas in the studied years were provided as a file to the model. The values that were estimated in the parameterization section (Tab. 3) were applied as parameters. The results showed that the model had a very good prediction of the average yield. The evaluation results of yield showed that the observed yield ranged between 1.9 to 4.8 $t.ha^{-1}$ with an average of 3.5 $t.ha^{-1}$ and simulated yield changes between 1.8 to 4.5 $t.ha^{-1}$ and with an average of 3.7 $t.ha^{-1}$. Also, RMSE, r and CV were 0.46 $t.ha^{-1}$, 0.84 and 13% (Fig. 3), which indicated a high accuracy in the soybean yield estimation in considered provinces. Therefore, this model can be applied for different purposes.

Table 3. SSM_iCrop2 parameter estimates for soybean in Iran.

Parameter	Name	Value	Reference
Phenolog			
Base temperature for development (°C)	TBD	7	(Soltani and Sinclair, 2012)
Lower optimum temperature for development (°C)	TP1D	27	(Soltani and Sinclair, 2012)
Upper optimum temperature for development (°C)	TP2D	34	(Soltani and Sinclair, 2012)
Ceiling temperature for development (°C)	TCD	45	(Soltani and Sinclair, 2012)
Temperature unit for emergence or beginning leaf growth (°C)	tuEMR	68–82	Parameterization
Temperature unit for beginning of seed or fruit growth (°C)	tuBSG	1200–1440	Parameterization
Temperature unit for termination of seed or fruit growth (°C)	tuTSG	1700–2088	Parameterization
Temperature unit for physiological maturity (end of dry mass accumulation) (°C)	tuPM	1700–2088	Parameterization
Temperature unit for harvest or leaf fall (°C)	tuHAR	2000–2400	Parameterization
Leaf area development and senescence			
Point #1 for normalized leaf area *vs.* normalized temperature unit (x1, y1)	x1, y1	(0.15, 0.05)	Parameterization
Point #2 for normalized leaf area *vs.* normalized temperature unit (x1, y1)*	x2, y2	(0.5, 0.95)	Parameterization
Maximum expected leaf area index*	LAIMX	2.5–4	Parameterization
Temperature unit for beginning leaf senescence (°C)	tuBLS	1200–1440	Parameterization
Leaf senescence rate coefficient	SRATE	1	Fixed for soybean
Low temperature / freezing threshold for leaf death (°C)	FrzTh	8	(Soltani and Sinclair, 2012)
Relative leaf death per each degree below low temperature/ freezing threshold	FrzLDR	0.01	(Soltani and Sinclair, 2012)
Heat threshold temperature for leaf senescence (°C)	HeatTH	37	(Soltani and Sinclair, 2012)
Relative increase in leaf senescence rate per each degree above heat threshold (°C)	HtLDR	0.1	(Soltani and Sinclair, 2012)
Dry mass accumulation			
Base temperature for dry matter production (°C)	TBRUE	10	(Soltani and Sinclair, 2012)
Lower optimum temperature for dry matter production (°C)	TP1RUE	20	(Soltani and Sinclair, 2012)
Upper optimum temperature for dry matter production (°C)	TP2RUE	30	(Soltani and Sinclair, 2012)
Ceiling temperature for dry matter production (°C)	TCRUE	40	(Soltani and Sinclair, 2012)
Extinction coefficient for photosyntheticaly active radiation	KPAR	0.65	(Soltani and Sinclair, 2012)
Radiation use efficiency under optimal growth conditions (g MJ^{-1})	RUE	1.8	(Soltani and Sinclair, 2012)
Coefficient for response of RUE to CO2 concentration	C3C4	0.8	Fixed for soybean
Yield formation			
Maximum harvest index/Liner increase in harvest index (g g^{-1} d^{-1})	HImax	0.34–0.40	Parameterization
Fraction of dry mass remobilizable from the vegetative tissue to the developing seeds/fruits (g g^{-1})	FRTRL	0.25	Parameterization
Grain/fruit moisture content (%, dwb)	MC	13	Fixed for soybean
Water relations			
Temperature unit for beginning root growth (°C)	tuBRG	68–82	Parameterization
Temperature unit for termination root growth (°C)	tuTRG	1200–1440	Parameterization
Initial depth of roots at emergence or beginning leaf growth (mm)	iDEPORT	200	Fixed for soybean
Maximum effective depth of water extraction from soil (mm)	MEED	1000	Fixed for soybean
Transpiration efficiency coefficient (Pa)	TEC	4.5	(Soltani and Sinclair, 2012)
FTSW threshold when dry matter production starts to decline	WSSG	0.25	(Soltani and Sinclair, 2012)
FTSW threshold when leaf area development starts to decline	WSSL	0.31	(Soltani and Sinclair, 2012)
A coefficient that specifies acceleration or delaying in development in response to water deficit	WSSD	0.4	(Soltani and Sinclair, 2012)

* Used as maximum plant leaf area under optimal condition (PLAMX) product by plant density.

3.3 Sensitivity analysis of model parameters

The comparison of the averages presented in Figures 4 and 5 showed that the change in the values of the tuHAR, LAIMX and KPAR parameters in the SSM_iCrop2 model caused a difference in the total dry matter predicted by the model (Figs. 4 and 5). Among these parameters, the change in the amount of KPAR caused a difference in the amount of simulated dry matter, increasing and decreasing the amount of KPAR by 30% changed the total dry matter from 11.1 $t.ha^{-1}$ (constant and unchanged parameter) to 14.4 (increase in KPAR value) and 7.8 $t.ha^{-1}$ (decrease in KPAR value). Also, in terms of grain yield (considering 13% moisture content at the harvest time), changes in the values of tuHAR, LAIMX, KPAR and

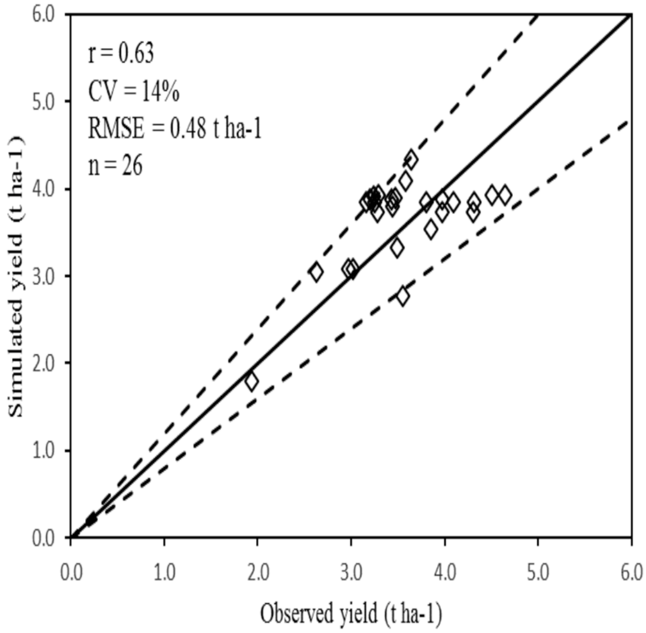

Fig. 1. Simulated *versus* measured dry soybean yield by SSM_iCrop2 model based on data used in model parameterization. The ±20% discrepancy lines are indicated by dashed lines. Solid line is 1:1 line.

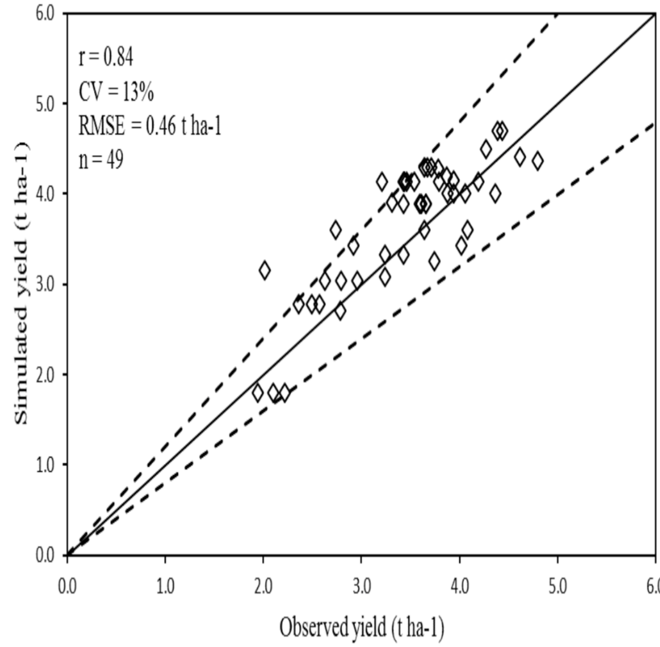

Fig. 3. Simulated *versus* measured dry soybean yield by SSM_iCrop2 model based on data used in model evaluation. The ±20% discrepancy lines are indicated by dashed lines. Solid line is 1:1 line.

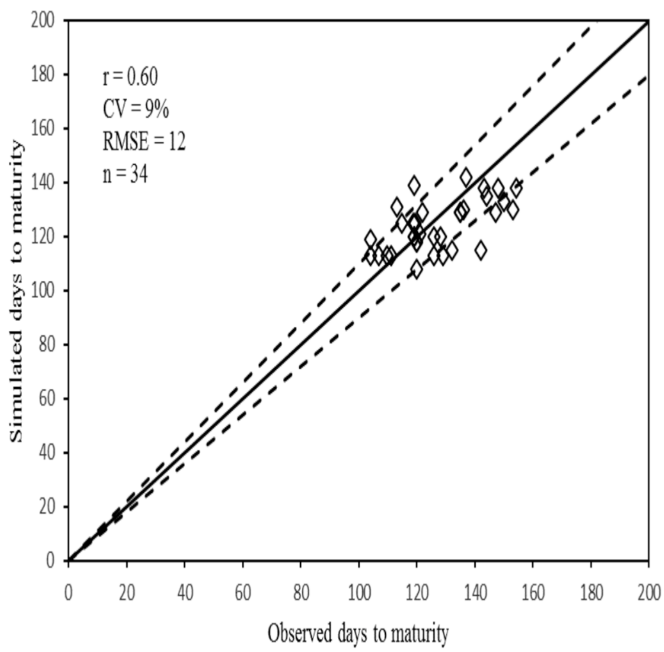

Fig. 2. Simulated *versus* measured days to maturity by SSM_iCrop2 model based on data used in model parameterization. The ±20% discrepancy lines are indicated by dashed lines. Solid line is 1:1 line.

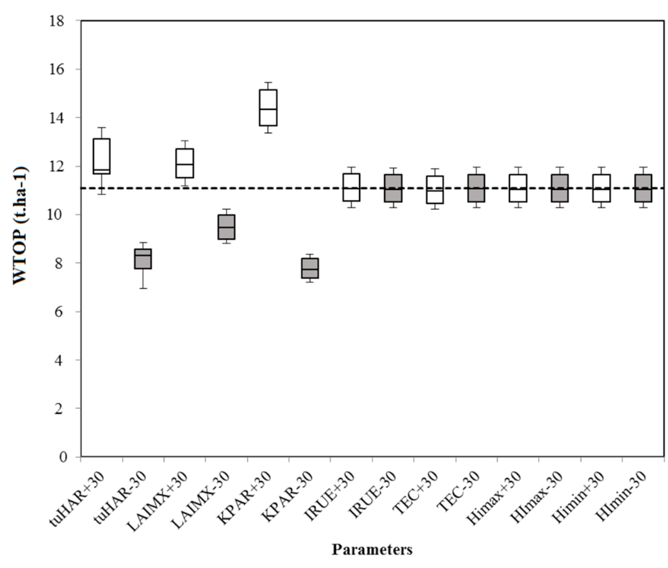

Fig. 4. The ranking of influential cultivar-specific parameters for WTOP (Accumulated above-ground dry matter, t ha^{-1}) under different parameter variation ranges included +30% (White), −30% (Grey) and Standard (Dotted line).

HImax parameters caused differences in predicted yield by model. Among these parameters, KPAR and HImax caused the highest difference in the predicted total dry matter. Analysis of the KPAR parameter showed that by increasing and decreasing KPAR about 30%, the grain yield varied from 4.6 $t.ha^{-1}$ (constant and unchanged parameter) to 6.0 (increase in KPAR value) and 3.2 $t.ha^{-1}$ (decrease in the amount of KPAR). Also, Increasing and decreasing the HImax parameter value by 30% changed the grain yield from 4.6 $t.ha^{-1}$ to 6.0 and 3.2 $t.ha^{-1}$, respectively. The most sensitive parameters for the total dry matter were tuHAR, LAImax, and KPAR. The increase and decrease of 30% in the values of these three parameters changed the total dry matter. In terms of grain yield sensitivity to the change of parameters, different results were achieved,

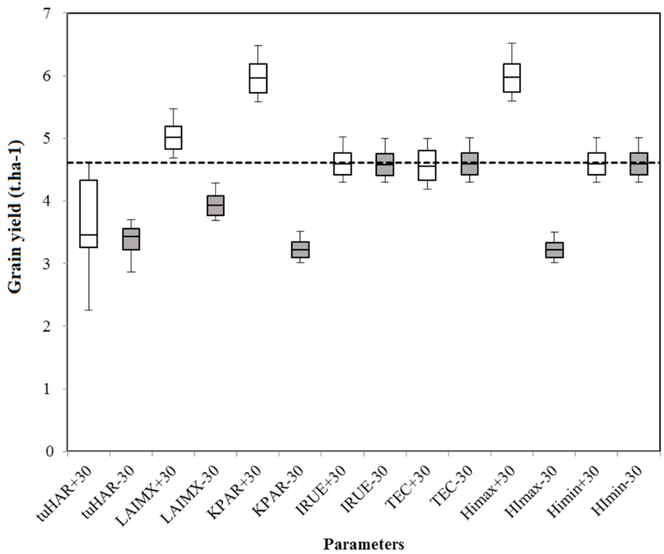

Fig. 5. The ranking of influential cultivar-specific parameters for grain yield ($t.ha^{-1}$) under different parameter variation ranges included +30% (White), −30% (Grey) and Standard (Dotted line).

so that, in addition to the parameters affecting the dry matter, increasing and decreasing the total amount of HImax by 30% caused the most significant difference on grain yield simulated by the model. An interesting point about the grain yield was the effect of the 30% change in the tuHAR parameter, which appears to be due to the increase and decrease in the growth period of the soybean. By 30% increase in the amount of tuHAR, the vegetative growth period was increased and reproductive stage (seed filling) starts in the undesirable temperatures so yield decreased. A 30% decrease in the tuHAR amount resulted in yield reduction due to the decrease in the vegetation and reproductive growth periods which causes less dry matter transfer to the seed.

Our results indicated the SSM_iCrop2 model simulates growth and yield with reasonable accuracy across a wide range of environments in the Iran. For example, in the validation data set, observed grain yields ranged from 1.9 to 4.8 $t.ha^{-1}$, sowing dates were as April 8 to July 31, and cultivars differed in maturity from MG 3 and MG 5. SSM_iCrop2 achieves this robust simulation capability with only 9 parameters variable.

SSM_iCrop2 model has considerable advantages compared with other models. Although SSM_iCrop2 requires a maximum of 37 parameters, the actual relevant number of parameters is about half of the total number (*i.e.*, between 15 and 20 depending on plant species) because many parameters are interconnected and some parameters are not important for some species (Soltani *et al.*, 2020a). Whereas, the APSIM and DSSAT models needed 292 and 211 parameters to estimate the potential yield and phenological stages, respectively. (Noorhosseini *et al.*, 2018). Due to the number of required parameters, the SSM_iCrop2 model can simulate the phenological stages of growth in a large area such as a country.

It is worth noting that, in the model can easily use an Excel spreadsheet to provide input and produce output, and also it is open source.

The studies that have been done using SSM_iCrop2 model include the following:

Soltani *et al.* (2020b) estimated total plant production at province and country levels by SSM_iCrop2 and a bottom-up scaling protocol (GYGA). They provided a framework within which assessing the possibility of increasing national plant production *via* intensification, optimizing water allocation across plant species at province and country levels by changing the cropping pattern, and assessing and prioritizing possible ways of adapting a country's agriculture to limited land and water resources and climate change. Alizadeh Dehkordi *et al.* (2020) evaluated potential yield of wheat by using the SSM_iCrop2 model in the Northwest of Iran. Nehbandani *et al.* (2020a) estimated soybean potential yield, amount of net irrigation water, evapotranspiration, vapour-pressure deficit, and soybean water productivity using the SSM_iCrop2 model in Iran. Also, they investigated relationships between potential yield and environmental factors (accumulated solar radiation, rainfall, maximum temperature, and minimum temperature during the soybean growing season).

4 Conclusion

Crop models are essential in undertaking large scale estimation of crop production of diverse crop species, especially in assessing food availability and climate change impacts. In this research, crop simulation model (SSM_iCrop2) parameters were estimated and evaluated. The model requires limited, readily available input information. The simulations account for plant phenology, leaf area development and senescence, dry matter accumulation, yield formation, and soil water balance in a daily time step. Parameterization of this model is easy and straightforward. The results of this study showed that the SSM_iCrop2 model provides reasonable prediction of development stages and yield for the soybean in Iran. The sensitivity analysis of the parameter values showed that the most effective parameter on the total dry matter and grain yield are KPAR and HImax, respectively. This model can help find the best management plans to achieve the potential yield for different regions of the country.

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