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Short Communication

SSM-iCrop2: A simple model for diverse crop species over large areas

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ABSTRACT

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 study, an existing model (SSM, Simple Simulation Models) was adapted to simulate a large number of plant species including orchard species and perennial forages. Simplification of some methods employed in the original model was necessary to deal with limited data availability for some of the plant species to be simulated. 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 the model for new crops/cultivars is easy and straight-forward. The resultant model (SSM-iCrop2) was parameterized and tested for more than 30 crop species of Iran using numerous field experiments. Tests showed the model was robust in the predictions of crop yield and water use. Root mean square of error as percentage of observed mean for yield was 18% for grain field crops, 14% for non-grain crops 14% for vegetables and 28% for fruit trees.

1. Introduction

Simulation models have become important tools in crop research. The models have been used in studies ranging from research focusing on crop physiology and plant organs, e.g. leaf photosynthesis, to food security studies at regional to global scales. For example, crop models have also been applied to evaluate various management and genetic options to improve crop yield (Sinclair, 2011; Sinclair et al., 2010; Vadez et al., 2017) and optimize the use of water and fertilizers (Wang et al., 2008; MacCarthy et al., 2009; Ferrise et al., 2010; Kropp et al., 2019). Crop models have also been used to assess the yield of crop plants (Lollato et al., 2017; van Loon et al., 2018) and their response to future climate change (ur Rahman et al., 2018; Hernandez-Ochoa et al., 2018).

In some model applications, such as those related to food security and climate change, estimates of crop yield under potential production and/or water-limited production conditions on a large scale (e.g. a country) are needed. For example, van Ittersum et al. (2013) stated that the use of crop models is imperative in the estimation of crop yield under potential and water-limited production conditions in yield gap analysis research. For such purposes, modeling nitrogen dynamics in soil and crop is not required and relatively simple models can be applied. On the other hand, in some other studies related to agricultural systems and food security, different plant species including horticultural species need to be simulated because the species compete for the limited resources of land and water and all contribute to human diets. In such studies, therefore, a wide range of plant species must be simulated, which is challenging for most simulation models.

Simple Simulation Models (SSM) are a group of crop models that date back to 1986 when a simple simulation model was developed for

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Table 1
List of crops and perennials covered in this study.

Crops	Vegetables	Fruit trees
Alfalfa	Cucumber	Almond
Barley	Melon	Apple
Bean	Onion	Apricot
Canola	Tomato	Date
Chickpea	Water melon	Fig
Clover		Grapes
Maize, silage		Olive
Maize, grain		Orange
Cotton		Peach
Lentil		Pistachio
Potato		Pomegranate
Rice		Saffron
Sesame		Walnut
Soybean		
Sugar beet		
Sugarcane		
Sunflower		
Wheat		

Table 2
Phenological stages that are simulated by SSM-iCrop2.

Stage name	description
EMR	Emergence in field crops; beginning leaf growth in trees and permanent forages
BRG	Beginning of root growth; equal to EMR in field crops
BSG	Beginning of effective seed growth or fruit growth (beginning linear harvest index)
BLS	Beginning of leaf senescence; equal to BSG in field crops
TRG	Termination of root growth; equal to BSG in field crops
TSG	Termination of seed growth or fruit growth (termination linear harvest index)
PM[a]	Physiological maturity (no increase in dry mass after the stage)
HAR	Harvest in field crops and harvest or leaf fall in tree crops

[a] TSG = PM in grain crops, but TSG is not the same as PM in trees plants because in some fruit trees like peach growth continues after TSG.

soybean (Sinclair, 1986). The framework has been improved and applied over the past 30 years to nearly all major grain crops including maize (Sinclair and Muchow, 1995), sorghum (Sinclair et al., 1997), wheat (Sinclair and Amir, 1992; Soltani et al., 2013), barley (Wahbi and Sinclair, 2005), peanut (Hammer et al., 1995), and chickpea (Soltani and Sinclair, 2011). A complete description of SSM can be found in Soltani and Sinclair (2012) and Soltani et al. (2013). For a comparison of the SSM model with other well-known crop models we refer to Soltani and Sinclair (2015).

SSM has also been applied in several geospatial studies related to food security (Sinclair et al., 2020), including wheat in the Middle East (Schoppach et al., 2017) and U.S. (Sciarresi et al., 2019), soybean in the US (Sinclair et al., 2010) and Africa (Sinclair et al., 2014), maize in the US (Messina et al., 2015), lentil in northeast Africa (Ghanem et al., 2015) and South Asia (Guiguitant et al., 2017), and peanut in sub-Saharan Africa (Vadez et al., 2017). However, the application of SSM has been limited to field crops so far.

Thus, the objective of this study was to adapt, parameterize and evaluate the SSM model for simulating 32 crop species (listed in Table 1) including orchard species and perennial forages in Iran. As required data for parameterization of the original model (Soltani and Sinclair, 2012) were not available for all species included in the study, simplification of some approaches used in the original model was necessary.

2. Model description

SSM, as fully described by Soltani and Sinclair (2012), was used in this study. The model was originally constructed for field crop species and uses a daily time step. To simulate the growth and yield of a large number of plant species, some modifications of SSM were required. The resultant model is called SSM-iCrop2 and can be downloaded from: "https://sites.google.com/site/cropmodeling/-5-ssm-icrop2".

Algorithms were added to the SSM model to determine sowing dates of field crops. Seven sowing rules based on air temperature, rainfall or soil water conditions were included in the model along with a fixed sowing date which is used in some situations like double-cropping systems (refer to Table S1 in SI for definition of the rules). Only two sowing rules were used in the current simulations, but other rules are implemented in the model for future possible applications. The parameters related to these two sowing-date rules are presented in Table S2 in SI.

Crop phenology was simulated with temperature unit (thermal time or temperature sum) for defined growth stages. Dates for bud burst in orchards and the start of the spring re-growth in perennial forages such as alfalfa needed to be set for these species. It was assumed bud burst or beginning of spring re-growth occurs when cumulative temperature units from the first of January onwards reach or exceed a critical value (*ForReq*). *ForReq* was estimated and added in the model for all relevant species (see next section).

To predict phenology of orchards, it was necessary to re-define and add a few more phenological stages that could be simulated by the model. The list and definitions of the phenological stages is presented in Table 2. It should be noted that only *established* orchards and perennials are simulated by the model and, therefore, the early growth and development is not simulated. Phenological stages are defined and predicted based on cumulative temperature units adjusted by water deficit (if any); cardinal temperatures dictate the response of development rate to daily temperature experienced by the plant (Soltani and Sinclair, 2012; Chapters 6 and 15).

Simulation of changes in leaf area index (LAI) under non-water-limited and water-limited conditions as given in Soltani and Sinclair (2012; Chapter 9) is based on cumulative temperature unit and plant allometry, but is adjusted for water-deficit stress. As required data for the method described by Soltani and Sinclair (2012) were not available for all plant species included in the current study, a simple approach of using a common exponential regression function was used that describes LAI expansion as a function of normalized temperature unit (Williams et al., 1989; Soltani et al., 1999):

$$LAI = \frac{x}{x + e^{(AL - BL \times x)}} \times LAIMX \quad (1)$$

where x is fractional cumulative temperature unit (cumulated temperature unit until the current day divided by the full temperature unit required to harvest or maturity; 0–1), LAIMX is maximum expected LAI, and AL and BL are coefficients of the function. This function has been used in the EPIC (Williams et al., 1989; Ko et al., 2009) and SWAT models (Arnold et al., 2012; Kieu et al., 2018). In EPIC and SWAT, the value of LAIMX is an input, which may be influenced by growing conditions and plant density. In the current simulations, LAIMX was obtained as a product of maximum plant leaf area under optimal conditions (PLAMX) and plant density. PLAMX is assumed constant at usual plant densities but plant density may change depending on growing conditions, e.g. irrigated or rainfed conditions. PLAMX itself can be adjusted for plant density if necessary, but this needs more parameters (refer to Soltani et al., 1999). Coefficients AL and BL can be estimated internally by the model if coordinates of two points on the function are provided as input parameters. The impact of water-deficit stress on leaf area development and senescence is calculated as a function of the fraction transpirable (available) soil water (Soltani and Sinclair, 2012; Chapter 15).

Dry mass production is simulated on the basis of radiation interception and radiation use efficiency (RUE). RUE is defined as gram total above-ground dry mass produced per mega joule intercepted

Table 3
Definition of parameters in SSM-iCrop2 and their estimates for a wheat cultivar.

Parameter	Name	Value
Phenology		
Base temperature for development (°C)	TBD	0
Lower optimum temperature for development (°C)	TP1D	25
Upper optimum temperature for development (°C)	TP2D	28
Ceiling temperature for development (°C)	TCD	40
Temperature unit from 1st January to bud burst or spring regrowth (°C)	ForReq	–
Temperature unit for emergence or beginning leaf growth (°C)	tuEMR	132
Temperature unit for beginning of seed or fruit growth (°C)	tuBSG	1620
Temperature unit for termination of seed or fruit growth (°C)	tuTSG	2172
Temperature unit for physiological maturity (end of dry mass accumulation) (°C)	tuPM	2170
Temperature unit for harvest or leaf fall (°C)	tuHAR	2400
Leaf area development and senescence		
Point #1 for normalized leaf area vs normalized temperature unit (x1, y1) [a]	x1, y1	(0.2, 0.06)
Point #2 for normalized leaf area vs normalized temperature unit (x1, y1) [a]	x2, y2	(0.5, 0.88)
Maximum expected leaf area index[b]	LAIMX	6.5
Temperature unit for beginning leaf senescence (°C)	tuBLS	1620
Leaf senescence rate coefficient	SRATE	1
Low temperature/freezing threshold for leaf death (°C)	FrzTh	-5
Relative leaf death per each degree below low temperature/freezing threshold	FrzLDR	0.01
Heat threshold temperature for leaf senescence (°C)	HeatTH	30
Relative increase in leaf senescence rate per each degree above heat threshold (°C)	HtLDR	0.1
Dry mass accumulation		
Base temperature for dry matter production (°C)	TBRUE	0
Lower optimum temperature for dry matter production (°C)	TP1RUE	15
Upper optimum temperature for dry matter production (°C)	TP2RUE	22
Ceiling temperature for dry matter production (°C)	TCRUE	35
Extinction coefficient for photosynthetically active radiation	KPAR	0.65
Radiation use efficiency under optimal growth conditions (g MJ-1)	RUE	2.2
Coefficient for response of RUE to CO2 concentration	C3C4	0.8
Yield formation		
Maximum harvest index/Liner increase in harvest index (g g-1 d-1)	HImax	0.5
Fraction of dry mass remobilizable from the vegetative tissue to the developing seeds/fruits (g g-1)	FRTRL	0.2
Grain conversion coefficient (g g^{-1})	GCC	1
Water relations		
Temperature unit for beginning root growth (°C)	tuBRG	132
Temperature unit for termination root growth(°C)	tuTRG	1620
Initial depth of roots at emergence or beginning leaf growth (mm)	iDEPORT	200
Maximum effective depth of water extraction from soil (mm)	MEED	1000
Transpiration efficiency coefficient (Pa)	TEC	5.8
FTSW[c] threshold when dry matter production starts to decline	WSSG	0.3
FTSW threshold when leaf area development starts to decline	WSSL	0.4
A coefficient that specifies acceleration or retardation in development in response to water deficit	WSSD	0.4

[a] Used as maximum plant leaf area under optimal condition (PLAMX: 186 cm^2 per plant) product by plant density (350 plant per m^2 for irrigated conditions).
[b] can be replaced with AL and BL coefficients (Eq. (1)) if they are available.
[c] FTSW is fraction transpirable soil water.

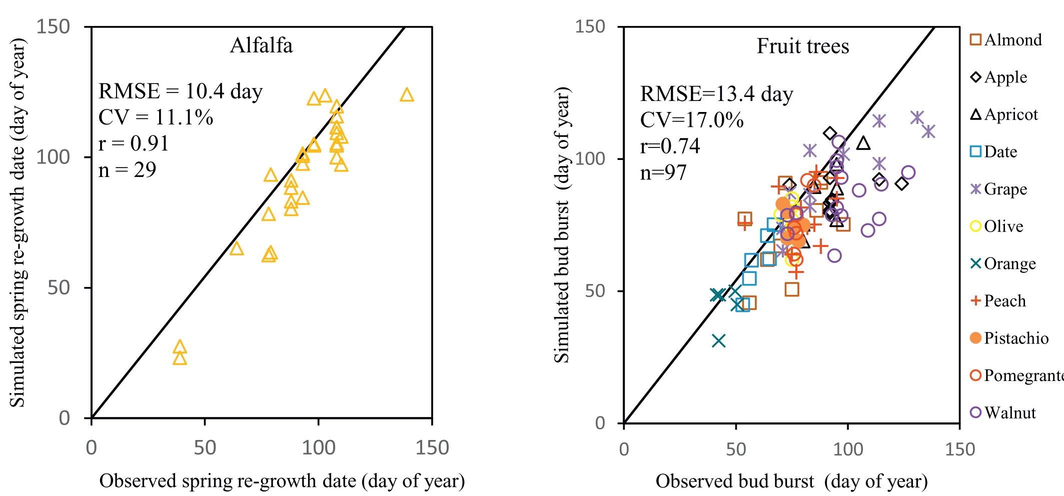

Fig. 1. Simulated versus observed date (as day of year) of beginning spring re-growth in alfalfa and bud-burst in fruit trees.

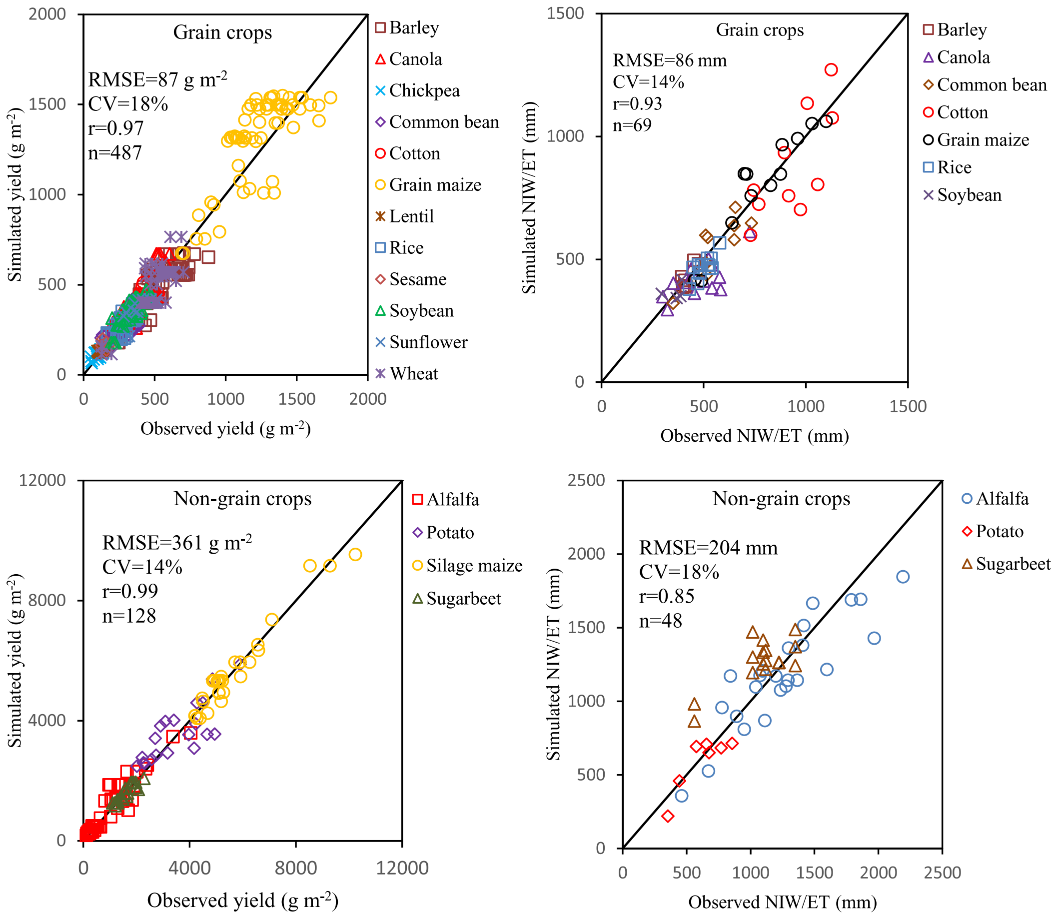

Fig. 2. Simulated versus observed yields (fresh weight basis) and net irrigation water (NIW) or evapotranspiration (ET) in grain and non-grain crops.

photosynthetically active radiation. In potato and sugar beet, the above-ground dry mass includes tuber and storage roots. Based on leaf photosynthesis response to temperature, water-deficit stress, and atmospheric CO_2 concentration, there are explicit functions to adjust RUE (Soltani and Sinclair, 2012; Chapter 10). Dry mass distribution between vegetative tissues and grains, and dry mass re-translocation later in the growing season, allow estimation of harvestable (or economic) yield (Soltani and Sinclair, 2012; Chapter 11). In the current simulations, harvestable yield formation is based on the linear increase in harvest index concept, which requires the slope of the harvest index increase versus time during the yield formation period (PDHI) (Spaeth and Sinclair, 1985; Soltani et al., 2013). Bindi et al. (1997) used the concept in simulating yields of grapes. To make the model simple for a wide range of plant species, PDHI is calculated within the model from the input of maximum harvest index under optimal conditions (HI_{max}). In forage crops, a HI_{max} of 0.9 to 0.95 was applied depending on species. The fraction of dry mass that can be remobilized (FRTRL) from the vegetative tissue to the developing seeds/fruits is another input parameter required by the model (Soltani and Sinclair, 2012).

The soil water balance and crop responses to soil-water deficit and excess in SSM are described by Soltani and Sinclair (2012; Chapters 13, 14 and 15). Briefly, the soil profile is divided into two layers: a top layer (usually 15- to 20-cm deep) and a second layer that includes the first layer plus the soil depth occupied by roots. The soil water balance of the two layers is calculated separately. Water additions to the extractable soil water result from precipitation, irrigation, and increasing rooting depth. Water removal from the soil occurs via deep drainage, run-off, soil evaporation, and plant transpiration. As the model simulates established orchards and perennials, initial root depth of these perennial species may be chosen equal to maximum effective depth of water extraction, which itself is an input parameter to the model. The effect of soil water deficit and excess on leaf area development and senescence, dry mass accumulation, and phenological development are each calculated from functions based on the fraction of transpirable (available) soil water.

An important feature of the SSM model is that transpiration is calculated by the intimate relationship between transpiration rate and plant growth (Tanner and Sinclair, 1983). Hence, the estimates are based on plant growth characteristics and not on the commonly used empirical meteorological approaches. The model accounts for the impact of CO_2 concentration on transpiration via modification of a mechanistically defined transpiration efficiency coefficient (Soltani et al., 2013).

3. Materials and methods

Model parameterization and evaluation was performed for each of the 32 plant species (Table 1). The model requires a maximum of 37 parameters per crop to simulate crop growth and yield. The parameters are divided into five groups: (i) phenology with 10 parameters, (ii) leaf area with nine parameters, (iii) dry mass accumulation with seven parameters, (iv) yield formation with three parameters, and (v) water relations with eight parameters (Table 3). Parameterization of SSM-iCrop2 is straightforward as presented in Appendix I of Soltani and Sinclair (2012). Most parameters are obtained from well-watered crops. Parameters in the functions accounting for soil water deficits are obtained from controlled soil-drying experiments.

Data on plant development, growth, and yield from published and unpublished studies/reports were collected from different locations across Iran for model parameterization. More than 300 published

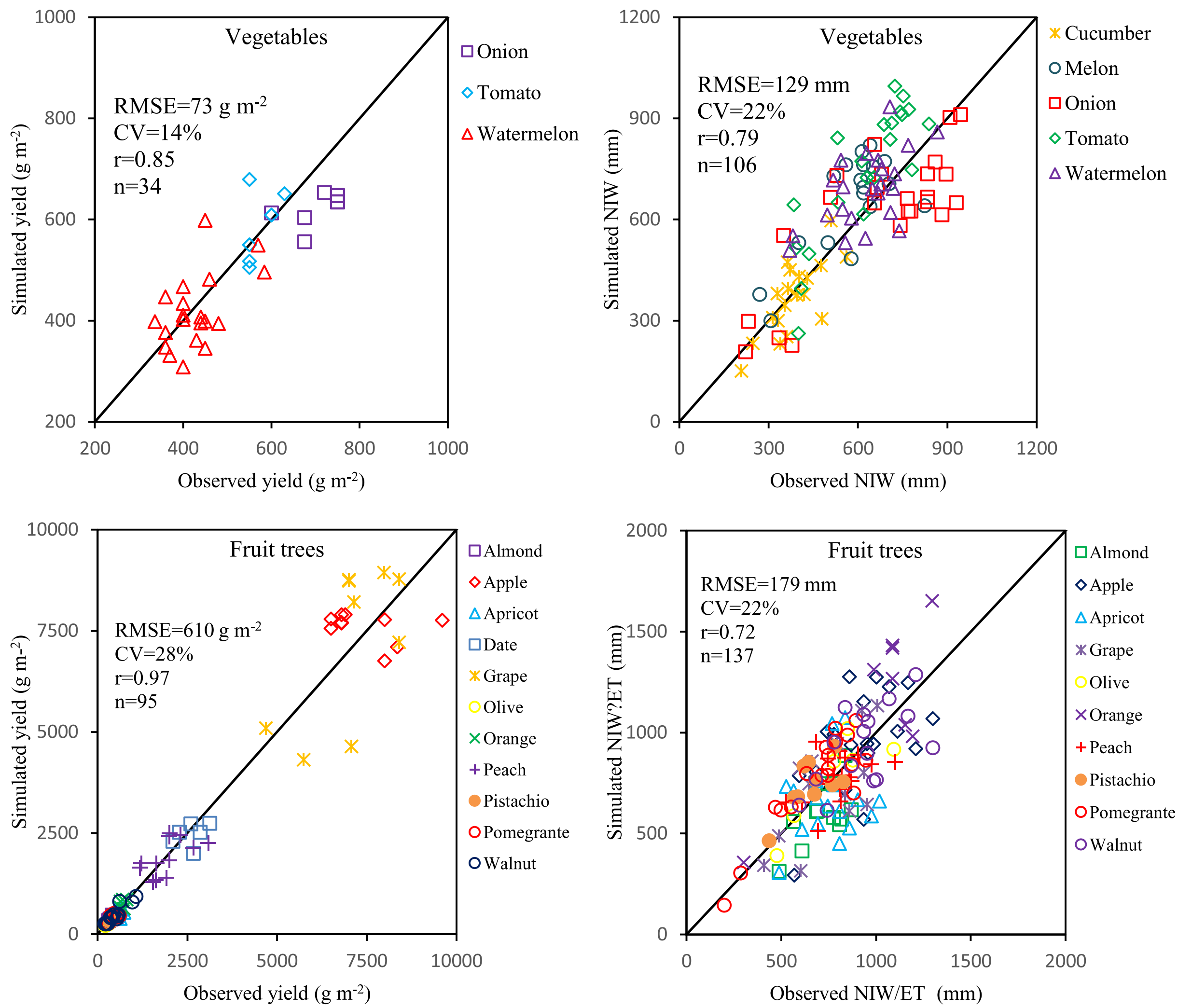

Fig. 3. Simulated versus observed yields (fresh weight basis) and net irrigation water (NIW) or evapotranspiration (ET) in vegetables and fruit trees.

papers and many local research reports and theses were used in model parameterization and evaluation (Listed in SI). Testing of model performance was done using data independent from those used in model parameterization.

4. Results

SSM-iCrop2 was parameterized for 32 major agricultural plants of Iran. As an illustration, model parameters and their estimates for a wheat cultivar are given in Table 3. Parameter estimates for other plant species and cultivars (93 cases) can be found at https://sites.google.com/site/cropmodeling/-5-ssm-icrop2. 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 (Table 3). For example, temperature unit for termination seed growth and for physiological maturity are the same for grain crops. Temperature unit for beginning root growth and for emergence are the same for many species. Temperature unit for beginning leaf senescence and for termination root growth can be set equal to temperature unit for beginning of seed growth in grain crops. Many plant species share similar estimates of extinction coefficient and fraction of re-translocation. The fraction of re-translocation itself is not important for some plant species including sugar beet, potato and many fruit trees as the formation of yield in these species starts very early during the plant life cycle when dry mass is low and hence the translocation to harvested organ is not important.

Only three parameters of the 37 were enough to differentiate between cultivars within a species, i.e., (1) temperature unit from sowing to harvest, (2) maximum plant leaf area, and (3) the slope of linear increase in harvest index (or maximum harvest index under optimal conditions). Only in rice, RUE was also varied between cultivars. These are cultivar-dependent parameters. The other parameters are species-dependent that may remain constant for all cultivars within a species. Many of the parameters, especially species-related parameters, can easily be obtained from literature (e.g. Soltani and Sinclair, 2012). The small number of cultivar-dependent parameters does not mean that there is no genetic variation for other parameters. It rather indicates that at the level at which the present model describes the crop processes, conventional cultivars of each species share common estimates for many parameters. All the parameters can be changed for new cultivars if required.

SSM has not previously been used to simulate the development, growth, and yield of forages and perennial fruit species. Simulation results for spring re-growth of alfalfa and bud-burst in fruit species are shown in Fig. 1 and Table S3 in SI as examples of comparison between model output and observations. Relative RMSE (CV: coefficient of variation) was 11% for the date of spring re-growth in alfalfa and 17% for bud burst in fruit trees. The correlation coefficient (*r*) between simulated and observed date of spring re-growth in alfalfa was 0.91 ($P \leq .01$) and 0.74 ($P \leq .01$) for bud burst.

Figs. 2 and 3 present model evaluation results for species grouped as grain field crops, non-grain field crops, vegetables and fruit trees. Table S4 in SI summarizes r and CV for yield and net irrigation water or evapotranspiration for individual plant species covered by this study. CV for yield was 18% for grain field crops, 14% for non-grain crops and r was greater than 0.95 ($P \leq .01$) for both grain and non-grain field crops (Fig. 2). For vegetables, yield was predicted by the model with a CV of 14% and r of 0.85 ($P \leq .01$), and for fruit trees yield prediction had a CV = 28% and $r = 0.98$ ($P \leq .01$) (Fig. 3). For net irrigation water or evapotranspiration, r was 0.93 ($P \leq .01$) and CV was 14% in grain crops, r was 0.85 ($P \leq .01$) and CV was 18% in non-grain crops (Fig. 2). For vegetables, net irrigation water or evapotranspiration was predicted with CV = 22% and $r = 0.79$ ($P \leq .01$) and for fruit trees CV = 22% and $r = 0.72$ ($P \leq .01$) (Fig. 3).

5. Discussion

Overall, the statistics of the results from the simulations was within the common range of CV and r of many other model testing results, e.g. Soltani and Sinclair (2015) and Zhao et al. (2019). The statistics indicate that the SSM-iCrop2 model provides reasonable prediction of crop yield and net irrigation water or evapotranspiration for the diverse plant species in Iran.

The SSM-iCrop2 parameterized for 32 crop species proved to be relatively easy to develop and test. Its transparency also provides the basis for the simulation results and variations to be explored and understood (Soltani and Sinclair, 2012). Although the model is simple, it is still mechanistic based on functional responses of plant processes to managerial, genetic and environmental factors and can be used to explore the role of various breeding and husbandry options to increase plant production and to optimize water use. The model is applicable in studies in which yield and/or water use for diverse crop species need to be simulated. For instance, the model has successfully been applied in a global food security project, i.e., GYGA (Global Yield Gap Atlas; van Ittersum et al., 2013). In this project, the model was used to provide potential yield, water-limited potential yield and evapotranspiration of wheat, barley, rice, maize, chickpea, common bean, soybean, cotton, rapeseed, potato and sugar beet under irrigated and rainfed conditions of Iran (http://www.yieldgap.org/iran). The model parameterized for 32 crop species was used to assess food self-sufficiency scenarios for Iran in 2030 (Soltani et al., 2020).

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.agsy.2020.102855.

References

Arnold, J.G., Moriasi, D.N., Gassman, P.W., Abbaspour, K.C., White, M.J., Srinivasan, R., Santhi, C., Harmel, R.D., van Griensven, A., van Liew, M.W., Kannan, N., 2012. SWAT: model use, calibration, and validation. Trans. ASABE 55 (4), 1491–1508.
Bindi, M., Miglietta, F., Gozzoni, B., Orlandini, S., Seghi, L., 1997. A simple model for simulation of growth and development in grapevine. I. Model description. Vitis. 36 (2), 67–71.
Ferrise, R., Triossi, A., Stratonovitch, P., Bindi, M., Martre, P., 2010. Sowing date and nitrogen fertilisation effects on dry matter and nitrogen dynamics for durum wheat: an experimental and simulation study. Field Crop Res. 117 (2–3), 245–257.
Ghanem, M.E., Marrou, H., Biradar, C., Sinclair, T.R., 2015. Production potential of lentil (Lens culinaris Medik.) in East Africa. Agric. Syst. 137, 24–38.
Guiguitant, J., Marrou, H., Vadez, V., Gupta, P., Kumar, S., Soltani, A., Sinclair, T.R., Ghanem, M.E., 2017. Relevance of limited-transpiration trait for lentil (Lens culinaris Medik.) in South Asia. Field Crop Res. 209, 96–107.
Hammer, G.L., Sinclair, T.R., Boote, K.J., Wright, G.C., Meinke, H., Bell, M.J., 1995. A peanut simulation model: I. model development and testing. Agron. J. 87 (6), 1085–1093.
Hernandez-Ochoa, I.M., Asseng, S., Kassie, B.T., Xiong, W., Robertson, R., Pequeno, D.N.L., Sonder, K., Reynolds, M., Babar, M.A., Milan, A.M., Hoogenboom, G., 2018. Climate change impact on Mexico wheat production. Agric. Forest. Meteorol. 263, 373–387.
Kieu, N.L., Jeong, J., Reyes, M.R., Jha, M.K., Gassman, P.W., Doro, L., Hok, L., Boulakia, S., 2018. Evaluation of the performance of the EPIC model for yield and biomass simulation under conservation systems in Cambodia. Agric. Syst. 166, 90–100.
Ko, J., Piccinni, G., Guo, W., Steglich, E., 2009. Parameterization of EPIC crop model for simulation of cotton growth in South Texas. J. Agric. Sci. 147 (2), 169–178.
Kropp, I., Nejadhashemi, A.P., Deb, K., Abouali, M., Roy, P.C., Adhikari, U., Hoogenboom, G., 2019. A multi-objective approach to water and nutrient efficiency for sustainable agricultural intensification. Agric. Syst. 173, 289–302.
Lollato, R.P., Edwards, J.T., Ochsner, T.E., 2017. Meteorological limits to winter wheat productivity in the US southern Great Plains. Field Crop Res. 203, 212–226.
MacCarthy, D.S., Sommer, R., Vlek, P.L., 2009. Modeling the impacts of contrasting nutrient and residue management practices on grain yield of sorghum (Sorghum bicolor (L.) Moench) in a semi-arid region of Ghana using APSIM. Field Crop Res. 113 (2), 105–115.
Messina, C.D., Sinclair, T.R., Hammer, G.L., Curan, D., Thompson, J., Oler, Z., Gho, C., Cooper, M., 2015. Limited-transpiration trait may increase maize drought tolerance in the US Corn Belt. Agron. J. 107 (6), 1978–1986.
Schoppach, R., Soltani, A., Sinclair, T.R., Sadok, W., 2017. Yield comparison of simulated rainfed wheat and barley across Middle-East. Agric. Syst. 153, 101–108.
Sciarresi, C., Patrignani, A., Soltani, A., Sinclair, T., Lollato, R.P., 2019. Plant traits to increase winter wheat yield in semiarid and subhumid environments. Agron. J. 111, 1–13.
Sinclair, T.R., 1986. Water and nitrogen limitations in soybean grain production I. model development. Field Crop Res. 15 (2), 125–141.
Sinclair, T.R., 2011. Challenges in breeding for yield increase for drought. Trends Plant Sci. 16 (6), 289–293.
Sinclair, T.R., Amir, J., 1992. A model to assess nitrogen limitations on the growth and yield of spring wheat. Field Crop Res. 30 (1–2), 63–78.
Sinclair, T.R., Muchow, R.C., 1995. Effect of nitrogen supply on maize yield: I. modeling physiological responses. Agron. J. 87 (4), 632–641.
Sinclair, T.R., Muchow, R.C., Monteith, J.L., 1997. Model analysis of sorghum response to nitrogen in subtropical and tropical environments. Agron. J. 89 (2), 201–207.
Sinclair, T.R., Messina, C.D., Beatty, A., Samples, M., 2010. Assessment across the United States of the benefits of altered soybean drought traits. Agron. J. 102 (2), 475–482.
Sinclair, T.R., Marrou, H., Soltani, A., Vadez, V., Chandolu, K.C., 2014. Soybean production potential in Africa. Glob. Food. Secur. 3 (1), 31–40.
Sinclair, T.R., Soltani, A., Marrou, H., Ghanem, M., Vadez, V., 2020. Geospatial assessment for crop genetic and management improvements. Crop Sci. https://doi.org/10.1002/csc2.20106. accepted:.
Soltani, A., Sinclair, T.R., 2011. A simple model for chickpea development, growth and yield. Field Crop Res. 124 (2), 252–260.
Soltani, A., Sinclair, T.R., 2012. Modeling Physiology of Crop Development. Growth and Yield, CABI, Wallingford, UK.
Soltani, A., Sinclair, T.R., 2015. A comparison of four wheat models with respect to robustness and transparency: simulation in a temperate, sub-humid environment. Field Crop Res. 175, 37–46.
Soltani, A., Ghassemi-Golezani, K., Khooie, F.R., Moghaddam, M., 1999. A simple model for chickpea growth and yield. Field Crop Res. 62, 213–224.
Soltani, A., Maddah, V., Sinclair, T.R., 2013. SSM-wheat: a simulation model for wheat development, growth and yield. Int. J. Plant. Prod. 7 (4), 711–740.
Soltani, A., Alimagham, M., Nehbandani, A., et al., 2020. Future food self-sufficiency in Iran: a model-based analysis. Glob. Food Secur. 24, 100351.
Spaeth, S.C., Sinclair, T.R., 1985. Linear increase in soybean harvest index during seed-filling 1. Agron. J. 77 (2), 207–211.
Tanner, C.B., Sinclair, T.R., 1983. Efficient water use in crop production: research or re-search? In: Taylor, H.M., Jordan, W.R., Sinclair, T.R. (Eds.), Limitations to Efficient Water Use in Crop Production. ASA, CSSA, and SSSA, Madison, WI, pp. 1–27.
ur Rahman, M.H., Ahmad, A., Wang, X., Wajid, A., Nasim, W., Hussain, M., Ahmad, B., Ahmad, I., Ali, Z., Ishaque, W., Awais, M., 2018. Multi-model projections of future climate and climate change impacts uncertainty assessment for cotton production in Pakistan. Agric. Forest. Meteorol. 253, 94–113.
Vadez, V., Halilou, O., Hissene, H.M., Sibiry-Traore, P., Sinclair, T.R., Soltani, A., 2017. Mapping water stress incidence and intensity, optimal plant populations, and cultivar duration for African groundnut productivity enhancement. Front. Plant Sci. 8, 432.
van Ittersum, M., Cassman, K.G., Grassini, P., Wolf, J., Tittonell, P., Hochman, Z., 2013. Yield gap analysis with local to global relevance - a review. Field Crop Res. 143, 4–17.
van Loon, M.P., Deng, N., Grassini, P., Edreira, J.I.R., Wolde-Meskel, E., Baijukya, F.,

Marrou, H., van Ittersum, M.K., 2018. Prospect for increasing grain legume crop production in East Africa. Eur. J. Agron. 101, 140–148.
Wahbi, A., Sinclair, T.R., 2005. Simulation analysis of relative yield advantage of barley and wheat in an eastern Mediterranean climate. Field Crop Res. 91 (2–3), 287–296.
Wang, X., Gassman, P.W., Williams, J.R., Potter, S., Kemanian, A.R., 2008. Modeling the impacts of soil management practices on runoff, sediment yield, maize productivity, and soil organic carbon using APEX. Soil Tillage Res. 101 (1–2), 78–88.
Williams, J.R., Jones, C.A., Kiniry, J.R., Spanel, D.A., 1989. The EPIC crop growth model. Trans. ASAE 32 (2), 497–0511.
Zhao, C., Liu, B., Xiao, L., Hoogenboom, G., Boote, K., Kassie, B.T., Pavan, W., Shelia, V., Kim, K.S., Hernandez-Ochoa, I.M., Wallach, D., Porter, C.H., Stockle, C.O., Zhu, Y., Asseng, S., 2019. A SIMPLE crop model. Eur. J. Agron. 104, 97–106.