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A SIMPLE crop model

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A R T I C L E I N F O

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A B S T R A C T

Crop models are important tools for assessing the impact of climate change on crop production. While multiple models have been developed over the past decades for the major food and fiber crops such as wheat, maize, soybean, rice, and cotton, there are few or none for many other crops. The goal of this study was to develop a simple generic crop model (SIMPLE) that could be easily modified for any crop to simulate development, crop growth and yield. The crop model SIMPLE includes 13 parameters to specify a crop type, with four of these for cultivar characteristics. Commonly available inputs that are required for the crop model SIMPLE include daily weather data, crop management, and soil water holding parameters. The initial SIMPLE model was calibrated and evaluated for 14 different annual crops using observations for biomass growth, solar radiation interception, and yield from 25 detailed field experiments for a total of 70 treatments from 17 sites, resulting in a RRMSE of 25.4% for final yield. A sensitivity analysis comparing a C3, C4 and a legume crop showed an expected response to a gradual increase in temperature and atmospheric CO_2 concentrations. A regional gridded simulation for US potatoes reproduced the general observed patterns of spatial yield variability. Because the model is simple, it has several limitations, including the lack of response to vernalization and photoperiod effect on phenology. The model includes water, but no nutrient dynamics. However, an advantage of the model simplicity is that it can be easily adapted and evaluated for any new crop, based on literature data and field experiments, or general crop data such as sowing and harvest dates and yield statistics. The model is available in several simulation frameworks including a stand-alone version in R, Excel and as part of DSSAT.

1. Introduction

Crop models are important tools for simulating crop growth and development for agronomy questions, as well for climate impact assessments. Until now, multiple crop simulation models have been developed for major crops such as wheat (Asseng et al., 2013), maize (Bassu et al., 2014), rice (Li et al., 2015) and potato (Fleisher et al., 2017). However, there are only a few models for other important crops, such as oil and fiber crops, vegetables, and fruits. These other important crops are often part of cropping systems, contribute to agricultural food, feed, fiber, and energy, and are needed in the assessment of future cropping system under climate change. A full-scale process-based model often requires a large amount of data for model development, calibration and evaluation (Jones et al., 2003; Keating et al., 2003). For example, DSSAT, one of the most widely used crop models, has many genotype specific parameters that are required to define a new crop (Hoogenboom et al., 2010; Jones et al., 2003), and these parameters are not often readily available. Other relatively simple functions or models have also been developed, including Expolinear growth functions (Goudriaan and Monteith, 1990), the EPIC model (Izaurralde et al., 2006; Williams et al., 1989), the AquaCrop model (Steduto et al., 2009) and the LINTUL model (Haverkort et al., 2015). However, these models

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often still require a large number of parameters, like 22 for EPIC and 29 for AquaCrop.

An alternative option to dynamic crop models can be statistical models [non-dynamic regression; (Lobell and Asner, 2003)] to explore the impact of climate change on crops for which currently no crop models are available (Lobell and Asseng, 2017). During the past few years, several statistical models have been developed (Lobell and Asner, 2003; Nicholls, 1997; Schlenker and Roberts, 2009; Tack et al., 2015; Tao et al., 2008; Welch et al., 2010), and have become another method for climate impact assessments (Liu et al., 2016; Zhao et al., 2016, 2017). However, statistical models usually lack the intrinsic mechanism of the biophysical processes to separately consider climate factors and their interactions with genetics and crop management (Ciais et al., 2005; Lobell, 2007). Thus, statistical models are often restricted to assessing the climate impact of historical periods and are less applicable for future scenarios, especially when genetic and management adaptations are required.

The goal of this study was to develop a generic, but simple dynamic crop simulation model using generally known processes with few parameters and data requirements and without any crop-specific processes for easy application to a wide range of crops. The first objective was to implement the model, called "SIMPLE" [different to Simple Simulation Model - "SSM" (Soltani and Sinclair, 2012)] for the main cereal and grain legume crops for which experimental data were readily available. The second objective was to implement SIMPLE for vegetable and fruit crops for which less data was available. The final objective was to conduct a sensitive analysis to determine the response of SIMPLE to temperature, CO_2 and spatial variability.

2. Methods and materials

2.1. Model description

The SIMPLE model simulates crop growth, development, and yield using a daily time step, with a few functions or equations that account for the effect of daily temperature, heat stress, rainfall, and atmospheric CO_2 concentration. Many of the functions in SIMPLE have been employed in other models before.

Phenology

SIMPLE uses cumulative temperature to determine phenological development, consistent with CERES-Wheat (Ritchie et al., 1985). The cumulative temperature is calculated as follows:

$$\Delta TT = \begin{cases} \mathrm{T}-\mathrm{T}_{\mathrm{base}}, & \mathrm{T}>\mathrm{T}_{\mathrm{base}} \\ 0, & \mathrm{T}\leq\mathrm{T}_{\mathrm{base}} \end{cases} \tag{1}$$

$$\mathrm{TT}_{i+1} = \mathrm{TT}_i + \Delta\mathrm{TT} \tag{2}$$

TT_i is the cumulative mean temperature for the *i*th day, and ΔTT is the mean temperature to be added on a day. T is the daily mean temperature, and T_{base} is the base temperature for phenological development and also for crop growth. To keep the model simple, the temperature to calculate the time to maturity starts to accumulate when it is above the base temperature for a crop species, without considering an optimum temperature threshold. However, heat stress which accelerates canopy decline in the model will also hasten the time to maturity. A cumulative temperature requirement from sowing to maturity (Tsum) is used to reach physiological maturity in the model. The model does not consider any other growth stages.

Growth

Photosynthesis is based on the concept of radiation-use efficiency (Monteith, 1965) by which a fraction of daily photosynthetically active radiation is intercepted by the plant canopy and translated into crop biomass [Eqs. (3) & (4); refers to the total biomass generally without roots, unless the roots are part of the harvestable product of a crop], similar to other models like the EPIC model (Williams et al., 1989). Final yield is calculated as the product of biomass and harvest index (HI) (Eq. (5)) (Amir and Sinclair, 1991). The HI concept is similar to the CropSyst (Stockle et al., 2003) and AquaCrop (Steduto et al., 2009) models, but it is used as a constant without considering other environmental factors. The daily change in plant biomass is affected by daily temperature, heat (high temperature stress), drought stress, and atmospheric CO_2 concentration:

$$\mathrm{Biomass}_{\mathrm{rate}} = \mathrm{Radiation} \times f\mathrm{Solar} \times \mathrm{RUE} \times f(\mathrm{CO_2}) \times f(\mathrm{Temp}) \times \min(f(\mathrm{Heat}), f(\mathrm{Water})) \tag{3}$$

$$\mathrm{Biomass\_cum}_{i+1} = \mathrm{Biomass\_cum}_i + \mathrm{Biomass\_rate} \tag{4}$$

$$\mathrm{Yield} = \mathrm{Biomass\_cum}_{\mathrm{maturity}} \times \mathrm{HI} \tag{5}$$

Biomass_rate is the daily biomass growth rate, and $\mathrm{Biomass\_cum}_i$ is the cumulative biomass until the *i*th day. *f*Solar is the fraction of solar radiation intercepted by a crop canopy, and RUE is the radiation use efficiency. *f*(heat), *f*(CO_2), *f*(Temp) and *f*(Water) are the heat stress, CO_2 impact, temperature impact, and drought stress on biomass growth, respectively. *f*Solar is based on Beer-Lambert's law of light attenuation (Ross, 2012) and solar radiation interception, but not leaf area index, similar to the AquaCrop model (Steduto et al., 2009). *f*Solar for leaf growth and senescence period is calculated as follows:

$$Solar = \begin{cases} \dfrac{f\mathrm{Solar\_max}}{1+e^{-0.01\times(\mathrm{TT}-\mathrm{I}_{50A})}}, & \textit{leaf growth period} \\ \dfrac{f\mathrm{Solar\_max}}{1+e^{0.01\times(\mathrm{TT}-(\mathrm{T}_{\mathrm{sum}}-\mathrm{I}_{50B}))}}, & \textit{leaf senescence period} \end{cases} \tag{6}$$

I_{50A} is the cumulative temperature required for leaf area development to intercept 50% of solar radiation during canopy closure, and I_{50B} is the cumulative temperature required from maturity to 50% of radiation interception during canopy senescence. *f*Solar_max is the maximum fraction of radiation interception that a crop can reach. *f*Solar_max is considered as a management parameter, not a crop parameter, to account for different plant spacings. For most high-density crops, this value is set at 0.95.

Temperature, heat, drought and CO_2 impact

The impact of temperature on biomass growth rate (Ritchie et al., 1985) (Fig. 1a) is calculated as follows:

$$f(\mathrm{Temp}) = \begin{cases} 0 & T < \mathrm{T}_{\mathrm{base}} \\ \dfrac{\mathrm{T}-\mathrm{T}_{\mathrm{base}}}{\mathrm{T}_{\mathrm{opt}}-\mathrm{T}_{\mathrm{base}}} & \mathrm{T}_{\mathrm{base}} \leq T < \mathrm{T}_{\mathrm{opt}} \\ 1 & T \geq \mathrm{T}_{\mathrm{opt}} \end{cases} \tag{7}$$

Here, T is the daily mean temperature, and T_{base} and T_{opt} are the base and optimal temperature for biomass growth, respectively, for a given crop species.

The impact of heat stress on biomass growth rate (Fig. 1b) is based on APSIM-Nwheat (Asseng et al., 2011). The heat stress factor is calculated as follows:

$$f(\mathrm{heat}) = \begin{cases} 1 & \mathrm{T}_{\mathrm{max}} \leq \mathrm{T}_{\mathrm{heat}} \\ 1 - \dfrac{\mathrm{T}_{\mathrm{max}}-\mathrm{T}_{\mathrm{heat}}}{\mathrm{T}_{\mathrm{extreme}}-\mathrm{T}_{\mathrm{heat}}} & \mathrm{T}_{\mathrm{heat}} < \mathrm{T}_{\mathrm{max}} \leq \mathrm{T}_{\mathrm{extreme}} \\ 0 & \mathrm{T}_{\mathrm{max}} > \mathrm{T}_{\mathrm{extreme}} \end{cases} \tag{8}$$

Here, T_{max} is the daily maximum temperature, T_{heat} is the threshold temperature when biomass growth rate starts to be reduced by heat stress, and $T_{extreme}$ is the extreme temperature threshold when the biomass growth rate reaches 0 due to heat stress.

The cumulative temperature required to reach 50% of radiation interception during canopy senescence (I_{50B}) is increased by heat stress (i.e., faster canopy senescence).

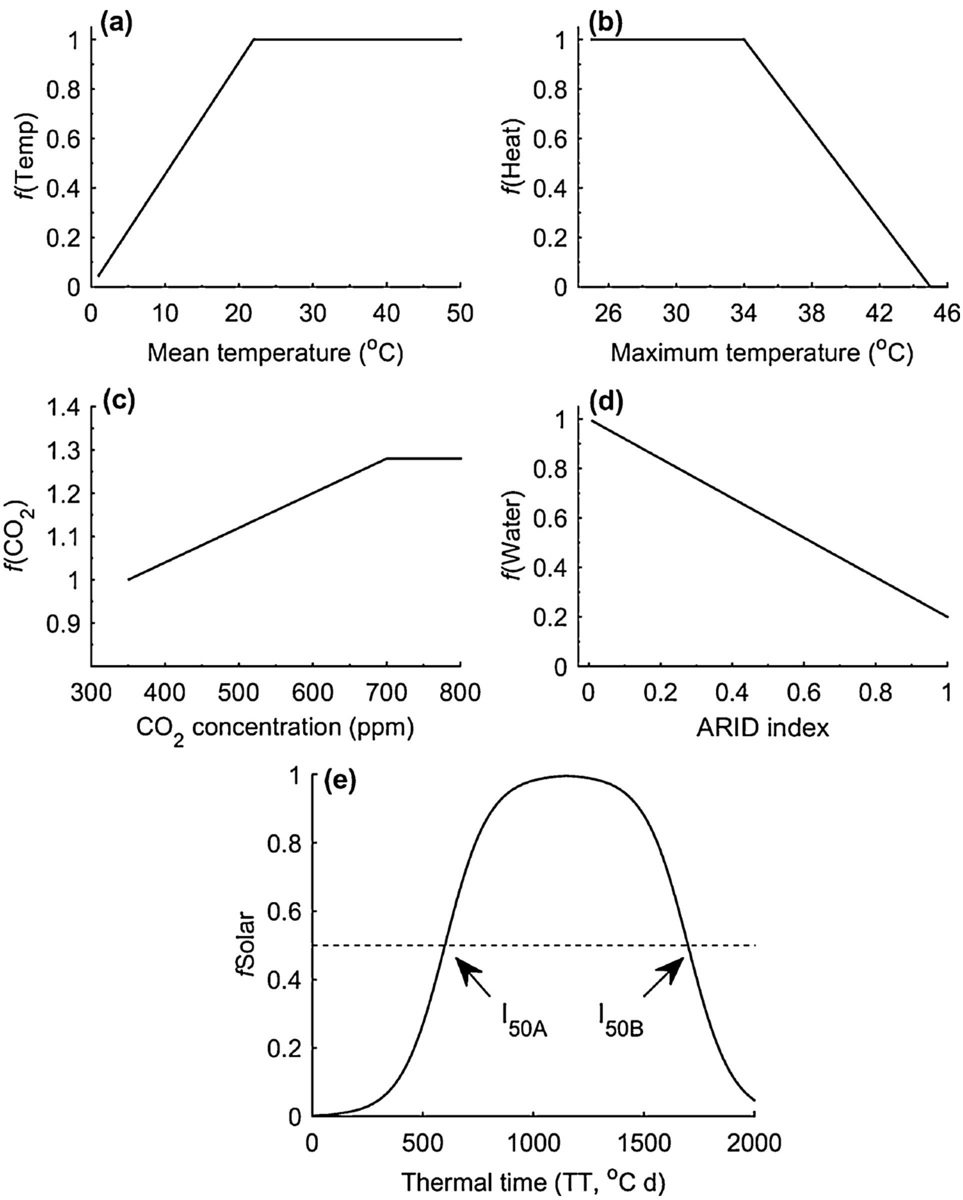

Fig. 1. (a–d) Effects of daily temperature, heat, atmospheric CO_2 concentration, and drought stress on radiation use efficiency (RUE). (e) Example of dynamics of fraction of radiation interception (fSolar) in the SIMPLE model with I_{50A} being a cultivar parameter characterizing the vigor of canopy closure and I_{50B} being a cultivar parameter characterizing the decline of a canopy for radiation interception.

$$I_{50B,\ i+1} = I_{50B,\ i} + I_{max,\ heat} \times (1 - f\,(heat)) \tag{9}$$

Here, $I_{max,heat}$ is the maximum daily reduction in I_{50B} due to heat stress.

CO_2 impact on the biomass growth rate.

Similar to other studies (Bindi et al., 1996; Ewert et al., 2002; Van Ittersum et al., 2003), RUE increases linearly (linear is used for simplicity, but it is likely to be curvilinear) until the concentration of CO_2 is 700 ppm. When CO_2 concentration is higher than 700 ppm, RUE is kept constant due to likely saturation of RUE to elevated CO_2. The impact of CO_2 on RUE in the SIMPLE model is calculated as follows:

$$f\,(CO_2) = \begin{cases} 1 + S_{co_2} \times (CO_2 - 350) & 350ppm \le CO_2 < 700ppm \\ 1 + S_{co_2} \times 350 & CO_2 > 700ppm \end{cases} \tag{10}$$

S_{CO2} is the crop-specific sensitivity of RUE to elevated CO_2 (e.g., S_{CO2} is usually less for C-4 crops than for C-3 crops), and CO_2 is the atmospheric CO_2 concentration.

Drought stress impact on RUE and radiation interception.

A simple water budget routine is used for the water balance simulation and to determine drought stress without requiring detailed soil profile water holding characteristics.

$$f\,(Water) = 1 - S_{water} \times ARID \tag{11}$$

Here, ARID is the ARID index after Woli et al. (2012), which is a standardized index ranging from 0 (no water shortage) to 1 (extreme water shortage and associated drought stress). ARID is calculated based on water availability and reference evapotranspiration – ET_o. S_{water} is the sensitivity of RUE to the ARID index.

$$ARID = 1 - \frac{\min(ET_o,\ 0.096{*}PAW)}{ET_0} \tag{12}$$

PAW is plant-available water content in the soil profile for the rooting depth, while 0.096 is a generic daily root water uptake constant (Woli et al., 2012), representing the maximum fraction of available water extracted in a day. PAW is calculated from a simple water balance function, including precipitation, irrigation, surface runoff, deep drainage [more details from Woli et al. (2012)]. ET_o is the reference evapotranspiration, calculated by using the Priestley and Taylor (1972) approach. ET_o is not divided into soil evaporation and crop transpiration in the model to keep it simple. The drought stress function is similar to that used by Sinclair et al. (1984) where crop stress starts at < 75% plant available water. However, the one depth logic from Woli et al. (2012) used in SIMPLE could be inadequate in some situations of prolonged drought, but it was chosen here for simplicity and consistency across model details. Drought stress reduces the RUE (Eq. (3)) and accelerates the decrease in the radiation interception:

$$I_{50B,\ i+1} = I_{50B,\ i} + I_{max,\ water} \times (1 - f(\text{water})) \tag{13}$$

Here, $I_{max,water}$ is the maximum daily increase in I_{50B} due to drought stress.

In addition, the radiation interception is affected when the drought stress becomes severe enough, similar to the AquaCrop model (Steduto et al., 2009).

$$f Solar\_\ \text{water} = \begin{cases} 0.9 + f(\text{water}) & f(\text{water}) < 0.1 \\ 1 & f(\text{water}) \geq 0.1 \end{cases} \tag{14}$$

After the model had been developed based on the above equations, the parameters were set with data from the literature, specific field experiments or by logic.

2.2. Model parameters and inputs

The SIMPLE model includes nine species parameters to specify crop types and four cultivar parameters characterizing cultivar differences (Table 1a). Species parameters were derived from accepted values in the literature, including RUE, T_{base}, T_{opt}, HI, and S_{CO2} from other crop models if they existed, or estimated in relation to crops with known parameters. Species parameters were not calibrated. We calibrated only cultivar parameters within a reasonable range (but kept cultivar parameter constant for the same cultivar when grown in different years or locations). This calibration refers to the specific data sets of above-ground dry matter accumulation (calibrated Tsum), fraction of radiation interception (calibrated I50 A and I50B), and final yield (dry grain, dry tuber, dry root, dry fruit, etc.) (calibrated HI).

Input variables required to run the SIMPLE model include weather (daily maximum/minimum temperature, rainfall, and solar radiation), atmospheric CO_2 concentration, sowing/harvesting date, irrigation, initial variables (biomass/ cumulative temperature/fraction of solar radiation interception if different from zero), and four variables characterizing the soil (Table 1b, Table 2), including fraction of plant available water-holding capacity (AWC; one number for entire soil profile, limited by potential root depth), runoff curve number (RCN), deep drainage coefficient (DDC), and root zone depth (RZD, a fixed maximum depth) (Table 1b, Table 2). The four variables are used to calculate the ARID drought stress index [see Woli et al. (2012) for more details]. If initial biomass, fraction of solar radiation interception -is different from zero, they can also be set.

2.3. Sensitivity analysis

To test the sensitivity to potential future climate conditions of crop yield, a single-year sensitivity analysis was carried out with incremental changes in temperature and atmospheric CO_2 concentration (mean

Table 1a
Crop and cultivar parameter values used in the SIMPLE model.

No.	Crop	Cultivar	Cultivar parameters				Species parameters								
			T_{sum}	HI	I_{50A}	I_{50B}	T_{base}	T_{opt}	RUE	I_{50maxH}	I_{50maxW}	T_{max}	T_{ext}	S_{CO2}	S_{water}
1	Wheat	Yecora Rojo	2200	0.36	480	200	0	15	1.24	100	25	34	45	0.08	0.4
		Batten	2150	0.34	280	50	0	15	1.24	100	25	34	45	0.08	0.4
2	Rice	IR72	2300	0.47	850	200	9	26	1.24	100	10	34	50	0.08	1.0
3	Maize	McCurdy 84aa	2050	0.50	500	50	8	28	2.10	100	12	34	50	0.01	1.2
4	Soybean	Bragg	2500	0.35	680	300	6	27	0.86	120	20	36	50	0.07	0.9
		Williams82	2350	0.40	600	200	6	27	0.86	120	20	36	50	0.07	0.9
5	Dry bean	Porrillo Sintetico	2700	0.40	450	600	5	27	0.80	90	20	32	45	0.07	0.9
6	Peanut	FLORUNNER	3100	0.35	520	550	10	28	1.20	100	5	36	50	0.07	2.0
7	Potato	Sebago	2400	0.85	500	350	4	22	1.30	50	30	34	45	0.10	0.4
		Desiree	2700	0.80	690	400	4	22	1.30	50	30	34	45	0.10	0.4
		Zibaihua	2500	0.45	690	500	4	22	1.30	50	30	34	45	0.10	0.4
		Jinguan	2400	0.45	690	450	4	22	1.30	50	30	34	45	0.10	0.4
		Russet Burbank	2300	0.90	500	400	4	22	1.30	50	30	34	45	0.10	0.4
		Hilite Russet	2500	0.90	480	400	4	22	1.30	50	30	34	45	0.10	0.4
8	Cassava	MCol-1684	5400	0.65	650	300	12	28	1.10	100	15	38	50	0.07	1.0
9	Tomato	SunnySD	2800	0.68	520	400	6	26	1.00	100	5	32	45	0.07	2.5
		Agriset761	2300	0.50	550	300	6	26	1.00	100	5	32	45	0.07	2.5
10	Sweetcorn	GSS0966 sh2	1900	0.40	500	250	8	27	1.70	100	5	34	50	0.01	2.0
11	Greenbean	Bronco Habit 1	1600	0.45	370	300	5	27	0.86	100	10	32	45	0.07	0.4
12	Carrot	Kazan F1	2450	0.70	550	250	4	22	1.00	100	5	32	45	0.07	2.0
13	Cotton	Deltapine77	4600	0.40	680	200	11	28	0.85	40	10	35	50	0.09	1.2
14	Banana	Prata Anã	6600	0.19	600	400	10	25	0.80	100	5	34	45	0.07	2.5

Note: The crops are ordered by cereals, legumes, root crops, oil crops, vegetables, fiber, and fruits.
T_{sum}: Cumulative temperature requirement from sowing to maturity (°C d).
HI: Potential harvest index.
I_{50A}: Cumulative temperature requirement for leaf area development to intercept 50% of radiation (°C d).
I_{50B}: Cumulative temperature till maturity to reach 50% radiation interception due to leaf senescence (°C d).
T_{base}: Base temperature for phenology development and growth (°C).
T_{opt}: Optimal temperature for biomass growth (°C).
RUE: Radiation use efficiency (above ground only and without respiration) (g MJ^{-1} m^{-2}).
I_{50maxH}: The maximum daily reduction in I_{50B} due to heat stress (°C d).
I_{50maxW}: The maximum daily reduction in I_{50B} due to drought stress (°C d).
T_{max}: Threshold temperature to start accelerating senescence from heat stress (°C).
T_{ext}: The extreme temperature threshold when RUE becomes 0 due to heat stress (°C).
S_{CO2}: Relative increase in RUE per ppm elevated CO_2 above 350 ppm.
S_{water}: Sensitivity of RUE (or harvest index) to drought stress (ARID index).

Table 1b
Site information and related soil parameters used in single bucket soil model for calculation of ARID drought stress index (Woli et al., 2012). The soil parameters were from literature or estimated from general soil information for the location.

Crop No.	Crop	Site	Treatment	Year	Soil parameters AWC	RCN	DDC	RZD	Ref.
1	Wheat	Maricopa, USA	FACE	1995	0.12	70	0.3	800	(Kimball et al., 1999)
		Maricopa, USA	FACE	1992	0.12	70	0.3	800	(Tubiello et al., 1999)
		Lincoln, New Zealand	Water	1991-1992	0.18	60	0.7	1200	(Jamieson et al., 1995)
		Maricopa, USA	Heat	2007-2008	0.12	70	0.3	800	(Ottman et al., 2012)
2	Rice	Los Banos, Philippines		1992	0.12	70	0.3	400	DSSAT v4.7
3	Maize	Gainesville, USA	Water	1982	0.12	70	0.3	1500	(Bennett et al., 1986)
4	Soybean	Gainesville, USA	Water	1978	0.07	60	0.7	800	(Wilkerson et al., 1983)
		Ames, USA	Year	1988,1990	0.14	75	0.6	1900	US Soybean Association
		Wooster, USA	Water	1988,1990	0.18	75	0.4	2200	US Soybean Association
5	Drybean	Gainesville, USA	Water	1986	0.08	65	0.5	700	(Hoogenboom et al., 1994)
6	Peanut	Gainesville, USA		1984	0.05	65	0.5	1800	(Bourgeois et al., 1991)
7	Potato	Canberra, Australia	Radiation	1970	0.12	60	0.65	1500	(Sale, 1973)
		Huhhot, China	Year	1996	0.12	75	0.6	300	(Gao et al., 2003)
				1998					(Liu et al., 2003)
		WuMeng, China	Cultivar	1999	0.1	70	0.6	300	Personal contact
		Benton, USA	Cultivar	1992-1995	0.1	64	0.8	1200	(Alva et al., 2002)
8	Cassava	Palmira, Colombia		1978	0.13	85	0.4	1500	(Veltkamp, 1985)
9	Tomato	Gainesville, USA		1996	0.19	85	0.1	800	(Boote et al., 2012)
		Bradenton, USA		1994	0.14	66	0.5	1000	(Boote et al., 2012)
10	Sweetcorn	Citra, USA		2002	0.25	60	0.7	1500	(Lizaso et al., 2007)
11	Green bean	Gainesville, USA		2007	0.08	65	0.5	1000	(Djidonou, 2008)
12	Carrot	Trzciana, Poland		2003	0.09	75	0.4	500	(Smoleń and Sady, 2008)
13	Cotton	Maricopa, USA	FACE	1989	0.12	70	0.3	600	(Mauney et al., 1994)
14	Banana	Campo Grande, Brazil		2005-2006	0.11	70	0.5	1500	(Camili et al., 2015)

AWC: Fraction of plant available water-holding capacity.
RCN: Runoff curve number.
DDC: Deep drainage coefficient.
RZD: Root zone depth (mm).

Table 2
Input variables needed to run SIMPLE model.

Input variables		Unit
Weather variables	Daily maximum temperature (TMAX)	°C
	Daily minimum temperature (TMIN)	°C
	Daily rainfall amount (RAIN)	Mm
	Daily solar radiation (SRAD)	MJ m^{-2} day^{-1}
	Atmospheric CO2 concentration	Ppm
Soil characteristics	Fraction of plant available water-holding capacity in considered soil bucket (AWC)	—
	Runoff curve number (RCN)	—
	Deep drainage coefficient (DDC)	—
	Active main root zone depth (RZD)	Mm
Crop management variables	Sowing date (SowingDate)	—
	Harvesting date (HarvestDate)	—
	Irrigation (Irri)	Mm
Initial variables	Initial biomass (InitialBio)	Kg
	Initial cumulative temperature (InitialTT)	°C d
	Initial fraction of solar radiation interception (InitialFsolar)	—

temperature change: + 1 °C, + 2 °C, + 3 °C, + 4 °C, + 5 °C and CO_2 change: (+50 ppm, +100 ppm, +150 ppm, +200 ppm, +250 ppm) using contrasting crop types including a C3 (wheat, base experiment after Kimball et al., 1999), a C4 [maize, base experiment after Bennett et al. (1986)] and legume (soybean, base experiment after DSSAT v4.7 data set).

2.4. Regional simulation

To test the model's capacity to simulate spatial heterogeneity, the SIMPLE model was used to simulate potato tuber dry matter in irrigated potato growing areas (0.5*0.5 grids) in the Pacific Northwest of the US for counties with > 2000 ha planted with potatoes (USDA National Agricultural Statistics Service). Potatoes in the US are harvested well before the natural maturity of the crop by killing the vines. In SIMPLE, the accumulated temperature requirement of a model was set for each grid cell, assuming that green canopy cover for potatoes will be approximately 80% at harvest. The accumulated temperature requirement for leaf area development to 50% of canopy cover was set as a constant of 680 °C d (cumulative daily mean temperature above base temperature of 4 °C). The accumulated temperature requirement backwards from maturity to 50% of canopy cover due to canopy senescence was set as constant at 400 °C d (cumulative daily mean temperature above 4 °C). The cumulative temperature requirement from sowing to maturity (T_{sum}, cumulative daily mean temperature above 4 °C) is a cultivar constant but not a species parameter, which was set so that canopy cover at harvest date was about 80%. The HI was calibrated with reported gridded yields from Monfreda et al. (2008).

3. Results

Simulated and observed patterns of total biomass for eight crops, including cereals, root crops, vegetables, and a fruit crop (i.e., rice, soybean, potato, green bean, sweet corn, tomato, peanut, and cassava) are shown in Fig. 2. The observed biomass dynamics were in general well simulated with the SIMPLE model. The SIMPLE model also captured the large differences from a wide range of growing season duration (70 to 350 days) resulting in a wide range of total biomass growth (1 to 26 t ha^{-1}) across crops.

The model also simulated important responses to environmental growing conditions, such as drought stress (Fig. 3). For a field experiment conducted in Gainesville, USA in 1982 (Bennett et al., 1986), three different drought stress treatments were applied to a maize crop, including rainfed, full-irrigated, and drought stress at the vegetative growth phase (intermediate drought stress). For the full-irrigated treatment, the drought stress simulated by SIMPLE model was very low during the whole season. Drought stress was higher for the rainfed and

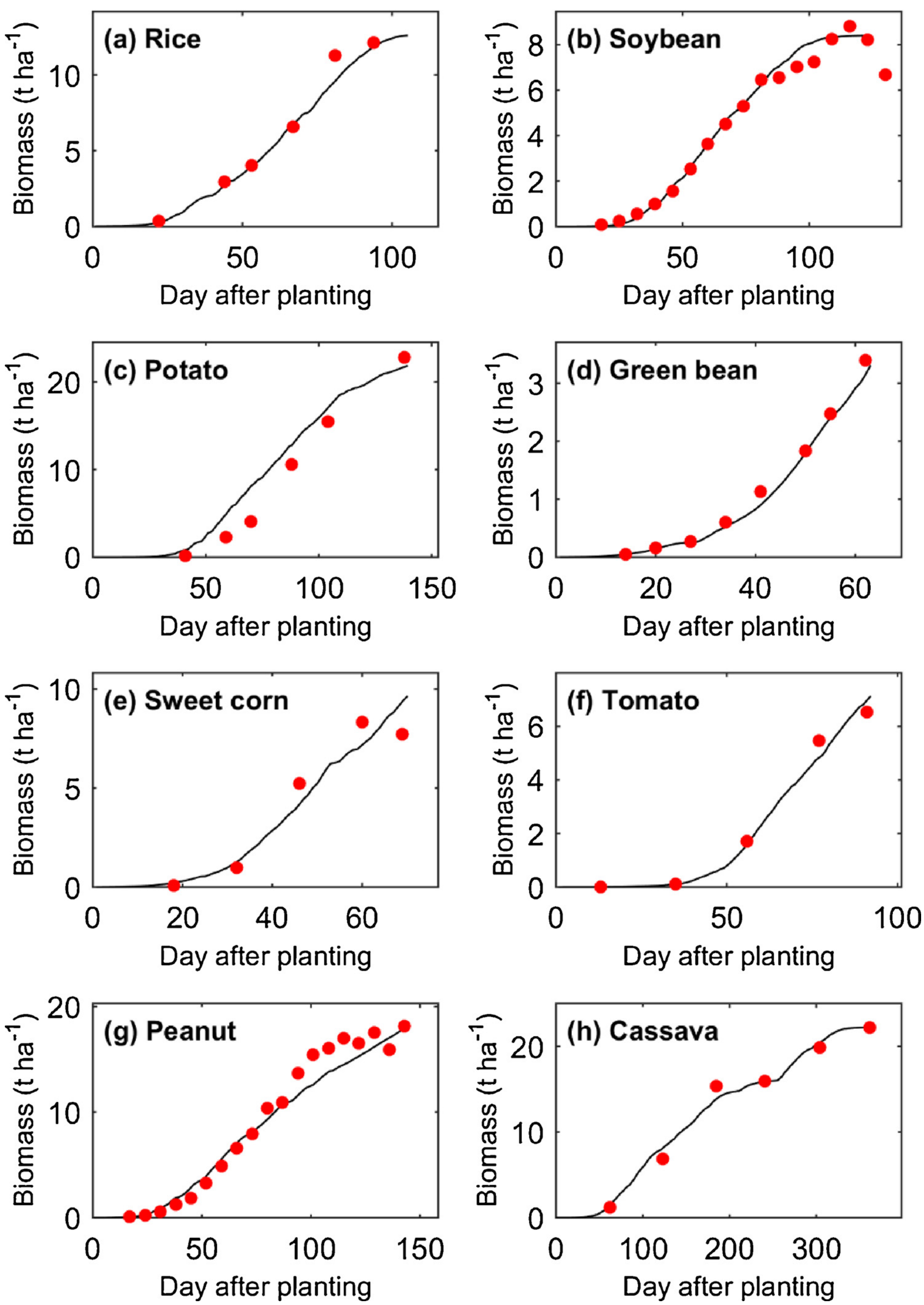

Fig. 2. Simulated (lines) and observed (symbols) total biomass (generally without roots; note that some of the observations have not accounted for abscised biomass material toward the end of the growing season, e.g., soybean) for different crops (a–h). See for source of observed data Table 1b.

intermediate drought stress treatments (Fig. 3b), especially during 70–90 days after planting [*f*(water) reached 0]. As a result, the drought stress caused a decline in the interception of solar radiation (*f*Solar) for the rainfed and intermediate drought stress treatments, consistent with the measurements. As showed in Fig. 3c, the drought stress during the late stage caused an acceleration of canopy senescence of maize by increasing I_{50B} (Eq. (14)). Because the drought stress accelerated canopy senescence, the maturity date for the rainfed treatment was advanced by 3 days compared to the other two treatments. For the biomass dynamics shown in Fig. 3d, the difference in the time of biomass production was well reproduced by the model.

In a well-irrigated and fertilized field wheat experiment conducted at Maricopa, USA, different planting dates and supplemental heating were applied as treatments, creating a range of growing season temperatures from 15 °C to 32 °C. After calibrating the SIMPLE model with one of the low temperature treatments of the experiments, the model was applied to all other treatments with the same parameter set. The simulated wheat yield response to growing season mean temperature is similar to that of the observed yields (Fig. 4a). The yield declined from approximately 8 t ha^{-1} to zero when growing season temperature increased from 15 °C to 32 °C. In the SIMPLE model, heat stress accelerates canopy senescence by increasing I_{50B} (Eq. (9)), which results in an advanced maturity date and reduced yield; the impact of heat stress here is similar to the impact of drought stress. Fig. 4b shows another comparison of simulated and observed total biomass of cotton crops from a free-air CO_2 enrichment experiment (FACE) at Maricopa, USA. For the control (350 ppm) and high CO_2 (550 ppm) treatments, the simulations reproduced the difference in total biomass dynamics, and the

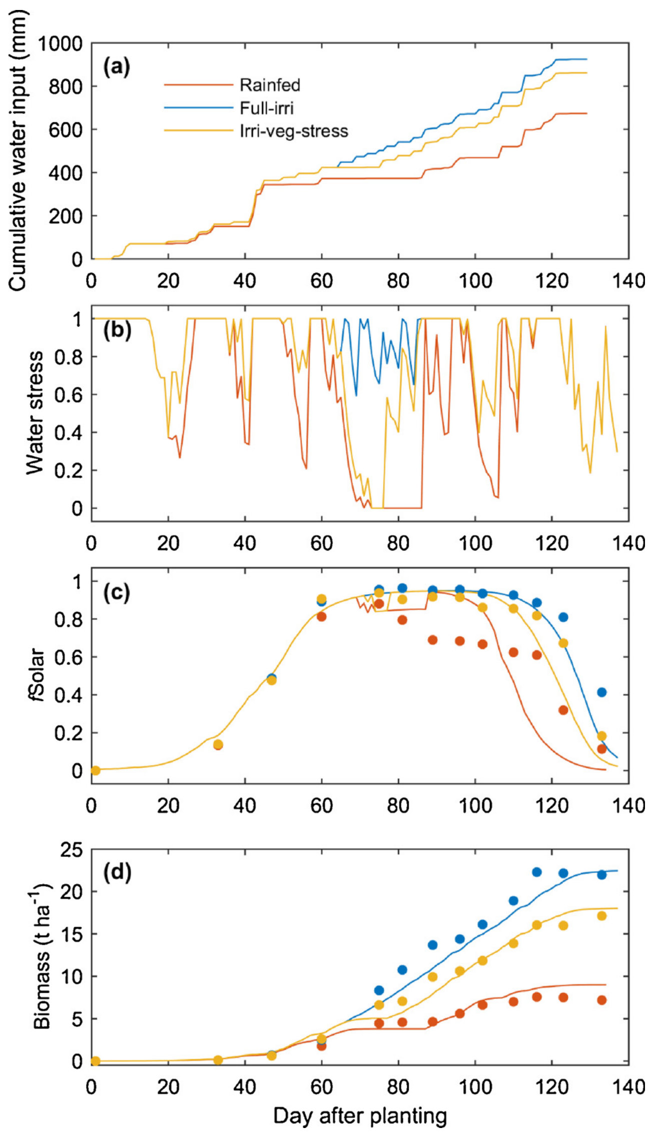

Fig. 3. Model performance demonstrating the impacts of different drought stresses on maize. (a) Cumulative water input (rainfall + irrigation). (b) ARID drought stress index after Woli et al. (2012). (c) fraction of intercepted photosynthesis active radiation – *f*Solar. (d) total aboveground biomass. Simulations are shown as lines. Observed data (symbols) after Bennett et al. (1986).

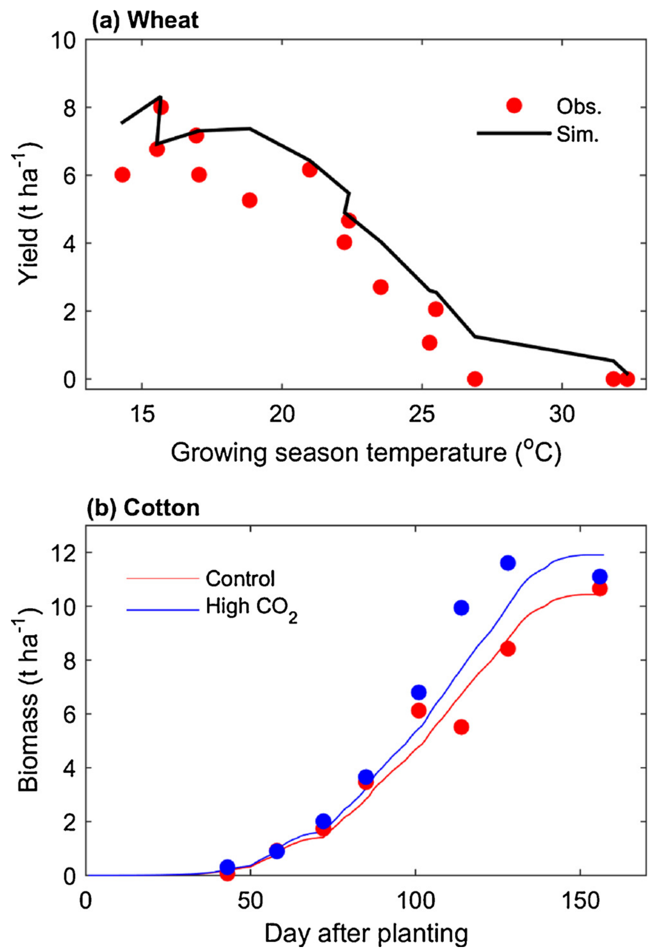

Fig. 4. Simulated (lines) versus observed (symbols) (a) grain yields of wheat under a wide range of growing season temperatures and (b) total aboveground biomass of cotton under different atmospheric CO_2 concentrations. Observed data for wheat after Ottman et al. (2012) and Martre et al. (2017) and for cotton after Mauney et al. (1994).

200-ppm enrichment of CO_2 concentration increased the simulated final biomass by 14%, similar to the observation.

In total, to calibrate and test the SIMPLE model, 1139 measured data were used, including growth of biomass, radiation interception, and yield for 14 crops from 25 field experiments (70 treatments) at 17 sites (Fig. 5 and Table 3). The observed yields varied from 0 to 19.1 t ha^{-1}. The comparison with observations indicates that the simulations were reasonable for total biomass (RRMSE 25.7%) and yield (RRMSE 25.4%). However, Fig. 5a also indicates some over/underestimates of yield, mostly for potatoes.

An increase in temperature consistently reduced yield for selected single-year experiments for wheat, maize, and soybean, but the impact varied among the three crops (Fig. 6a). The yield reduction in soybean with increasing temperature (10% reduction per °C) appears much larger than wheat and maize (5–6% reduction per °C), especially when the temperature increase is > 3 °C. With an increase in CO_2 concentration yield increased for wheat (8% per 100 ppm) and soybean (7% per 100 ppm) (C-3 crops), but only had a small impact on maize (1% per 100 ppm) (C-4 crops) (Fig. 6b).

Fig. 7 shows a 0.5*0.5° grid of cell-based simulations for potato yield in the main irrigated potato growing area (the Pacific Northwest of the US) during the 2000s with the SIMPLE model. The simulated and reported patterns for potato tuber dry weight are generally similar. On average, the comparison of simulated and reported tuber dry yield resulted in a RRMSE of 13.9%.

4. Discussion

SIMPLE is a simple process-based crop model. In contrast to other common crop models, such as DSSAT (Jones et al., 2003) and APSIM (Keating et al., 2003), the SIMPLE model has less parameter input requirements, including nine species and four cultivar parameters. This simplicity makes it suitable for a wide range of crops for which there are limited information and data available, especially for the non-common cereals and legumes, as well as fruits and vegetables. The SIMPLE model was initially parameterized for 14 different crops, including several common cereals and legumes for which detailed data sets were available. The relatively limited number of equations and parameter of the SIMPLE model made it easy to understand and to add new crops including lesser studied crops such as fruits (e.g., banana) or vegetables (e.g., carrots). The model is currently available in several simulation frameworks including a stand-alone version in R, Excel and DSSAT. The R and Excel versions are available from the corresponding author upon request; the DSSAT version will be available with the next

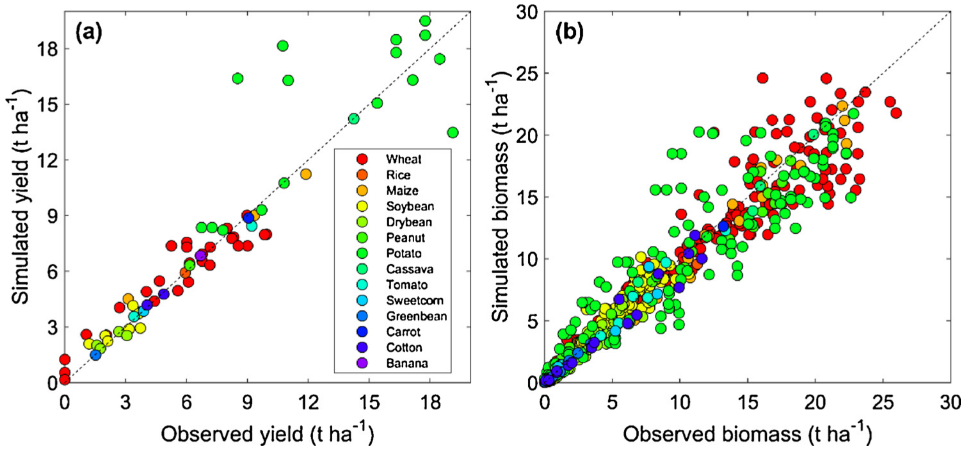

Fig. 5. Simulated versus observed for (a) yield and (b) total biomass (over time) after calibration (The SIMPLE model was calibrated with a subset of the dataset, but the model performance is shown for the entire dataset). Note that some of the observation have not accounted for abscised biomass toward the end of the growing season (e.g., soybean). See for source of observed data Table 1b.

Table 3
.Summary of SIMPLE model performance after calibration at 17 sites for 14 crops. The SIMPLE model was calibrated with a subset of the dataset, but the model performance is shown for the entire dataset.

Model attribute	Data points	Observation	R^2 (1:1)	Slope	RRMSE
Yield (t ha^{-1})	70	0-19.1	0.87	0.97	25.4%
Total biomass[a] (t ha^{-1})	596	0-26.0	0.92	0.89	25.7%
*f*Solar	473	0-1	0.65	0.81	29.5%

[a] Total biomass was generally without roots. Note that some of the observation have not accounted for dropped biomass material towards the end of the growing season, e.g. soybean.

DSSAT version release. One advantage of SIMPLE is that it can be easily applied to regional scale simulations (in stand-alone R version only). For example, in the SIMPLE model, only four parameters were used to characterize the soils, and the parameters could be easily derived from a world soil database, such as FAO/IIASA Harmonized World Soil Database (IIASA/FAO, 1996). Despite its simplicity, it still includes basic physiological responses to temperature, heat stress, drought stress, and atmospheric CO_2 concentrations to simulate biomass and yield that are similar to observations. For instance, the RRMSE for potato yield was 26.4% compared to 37.2% RRMSE for the DSSAT-SUBSTOR-potato model (Raymundo et al., 2017). The RRMSE for wheat yield was 17.8% with SIMPLE compared to 11–24% RRMSE across several wheat models (Asseng et al., 2015). Note, that datasets used for the model testing differed across studies in these comparisons. At the regional scale, the SIMPLE model could simulate the spatial variability of potato tuber dry yield in the US with a RRMSE of 13.9%, a lower error than the detailed DSSAT-SUBSTOR-potato model, which was reported to have a RRMSE of 56% across countries (Raymundo et al., 2018).

The SIMPLE model also includes a number of limitations due to its simplicity (e.g., the lack of soil-crop nutrient dynamics, which is important for many low input systems). However, this is likely to be less important for many fruit and vegetable crops in industrial countries, which often receive sufficient nutrient inputs due to their high cash value, but less so in some developing countries. A main limitation of SIMPLE is the lack of phenology sensitivity to vernalization and photoperiod, which can be important in some crops and cultivars, such as carrots. In addition, while radiation-use efficiency varies with temperature, water availability, and CO_2 levels, the SIMPLE model does not consider the impacts of diffused light on RUE. For example, if the diffused light component is significantly different in some regions [e.g., regions with high air pollution (Yang et al., 2013)], the RUE parameter would need to be adjusted accordingly. Some main effects of crop management practice are also not included, such as sowing density (partly only via maximum light interception) or sowing depth, which could have some impact on growth and yield. Also, the assumption of a fixed harvest index could be a limitation in some terminal drought environments (Moser et al., 2006). While the SIMPLE model can easily be extended with other features, it does not consider frost, pest, and disease impacts, similar to most other crop models. The SIMPLE model also lacks an ability to simulate excessive moisture impacts on crop growth. While this model has clear limitations due to its simplicity and other, more detailed crop models might be better suited for specific tasks, the SIMPLE model can be used for a wide range of applications on climate variability and climate change, crop management, including irrigation, planting date, crop and cultivar choice.

The main objective of the SIMPLE model was to provide a simulation model based on known principles of crop physiology but with relatively few equations and parameters. The use of basic crop physiology and its simplicity makes this model also attractive as a teaching tool.

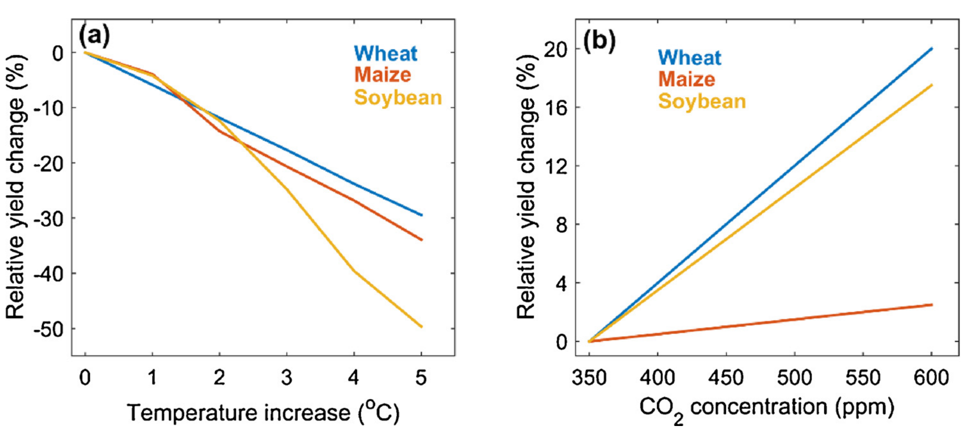

Fig. 6. Simulated yields for wheat, maize and soybean with (a) increasing temperature and (b) elevated atmospheric CO_2 concentration. Simulated experiments for wheat with basic inputs from full-irrigated treatment after Kimball et al. (1999), for maize with basic inputs from full-irrigated treatment after Bennett et al. (1986), and soybean with basic inputs from irrigated treatment after DSSAT v4.7.

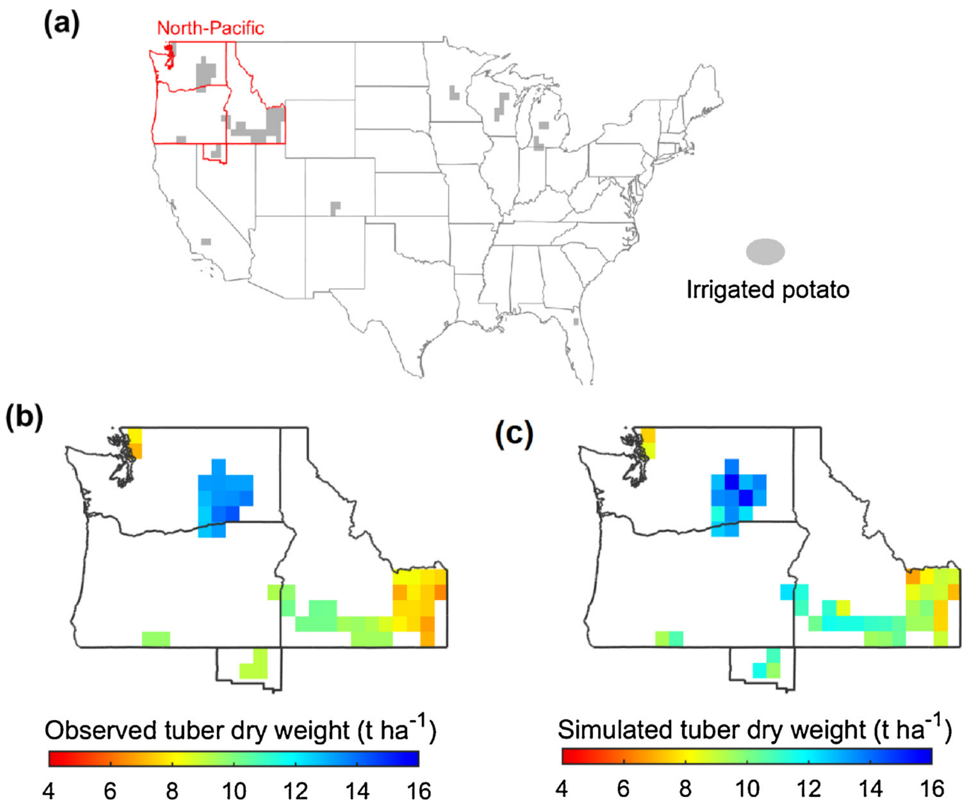

Fig. 7. (a) Irrigated potato growing area in the Pacific Northwest of the US for counties with > 2000 ha, from USDA National Agricultural Statistics Service. (b) Reported potato yields and (c) simulated potato yields for the year 2000 for 51 grid cells with 0.5°. Reported yields are from Monfreda et al. (2008). All presented potato yields are at 0% moisture. RRMSE at grid level is 13.9%. Note, T_{sum} (cumulative temperature requirement from sowing to maturity) was calibrated for each cell with reported harvest dates and HI (harvest index) against reported yields.

When teaching about crop models, it is useful if students can start with an existing model and then modify the equations or add new processes and examine the behavior of the modified model. When teaching about methods, a teacher wants students to be able to apply sensitivity analysis, calibration, and other techniques to a crop model. This requires that the students understand the base model fully and then have the ability to modify the computer code. Furthermore, it is important that the starting model be a realistic description of a crop. Until now, one choice has been to use a very simplified partial crop model, which only includes a subset of major processes [e.g., the simplistic maize model in Wallach et al. (2013)]. Another possibility for teaching is to start from an existing crop model. However, existing models are generally complicated, so teaching students the content and the practicalities of working with them is time-consuming and often not realistic to achieve in class. Also, there is usually a limited scope for modifying such models and applying new techniques of analysis or calibration may be very difficult. On the other hand, the SIMPLE model is both simple and realistic. It has been tested as a teaching tool in 2018 in a modeling course in the Agricultural and Biological Engineering Department at the University of Florida. The student project was to propose some modification of the model. For example, the model had to take into account a disease, and then to do one or more of sensitivity analysis, calibration, or evaluation.

5. Conclusion

SIMPLE is a simple generic crop model developed based on known principles of crop physiology with relatively few equations and parameters. It is sufficiently simple that others can easily understand, use, modify, and extend it. The model has been successfully compared with more than 1000 actual measurement values and has shown to reproduce most of these in simulations. The SIMPLE model can be used for future climate impact assessments, especially for crops not available in other model platforms. However, like most other crop models, it has some clear limitations and users need to be aware of these in applications.

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