Predictions of Soybean Harvest Index Evolution and Evapotranspiration using STICS Crop Model

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ABSTRACT

In the last century, soybean (*Glycine max* L. Merr) genetic improvements have resulted in increased yield partly due to an increase in harvest index (HI). To account for these genetic improvements, an update of the soybean calibration of the STICS soil-crop model was carried out. The model was calibrated and evaluated for two sets of soybean plant parameters using datasets from the Ottawa region (ON, Canada); a low HI cultivar calibrated using datasets (1993-2008) of cultivars of maturity groups (MG) 00 and 0 and a high HI cultivar calibrated with more recent datasets (2016-2017) of cultivars of MG 0 and I. The model succeeded in reproducing the harvest index increase. LAI, shoot biomass, and yield were also well predicted for the high HI cultivars with a normalized root mean square error (NRMSE) of 34%, 10% and 14%, respectively, which was a great improvement compared to the default parametrization proposed in STICS for soybean. Under rainfed conditions, accurate simulation of evapotranspiration is a critical point to achieve good model performance. A comparison of the two crop evapotranspiration approaches available in STICS was also carried out. It showed that the resistive approach (NRMSE of 36%) was more efficient than

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the crop coefficient approach (NRMSE of 67%). This good performance of the model in predicting evapotranspiration allowed the model to perform equally well under water stress and non-water stressed conditions. The model could therefore be used in future studies to simulate the impact of water stress on soybean growth in Eastern Canada.

Abbreviations

CEF: Ottawa central experimental farm

CFIA: Ottawa Canadian food inspection agency

DM: Dry matter

EF: Nash-Sutcliffe model efficiency coefficient

ET_O: Reference crop evapotranspiration

ET_{10}: 10-days evapotranspiration

GDD: Growing degree days

HI: Harvest index

K_c: Empirical crop coefficient

LAI: Leaf area index

ME: Mean error

MG: Maturity group

NME: Normalized mean error

NRMSE: Normalized root mean square error

PAR: Photosynthetically active radiation

RMSE: Root mean square error

RUE: Radiation use efficiency

INTRODUCTION

In response to growing global demand, agricultural production is expected to increase by 60% by 2050 (Alexandratos and Bruinsma, 2012). One way to meet the demand is to increase yield, which can be achieved by genetic improvement. In some regions, yield gap between actual and potential yield is low. To increase the yield, genetic improvement would play a role on modifying the biomass repartition from shoot to grain. A way to measure this improvement is to use the harvest index (HI), which is the ratio of grain yield to aboveground biomass. Improved cultivars were developed around the globe for soybean (*Glycine max* L. Merr) and increases in yield and harvest index have been observed over the years in many Asian countries (Cui and Yu, 2005; Li et al., 2019) and in North (Burton and Miranda, 2013; Rowntree et al., 2013; Specht et al., 1999) and South America (Sentelhas et al., 2015; Satorre, 2011). Worldwide, an increase in soybean yield of about 28 kg ha^{-1} per year was observed between 1961 to 2019 (FAOSTAT, 2021).Even if better farming practices lead to increased soybean yield, Specht and Williams (1984) measured an increase in yield due to genetic improvement of 13 to 29 kg ha^{-1} per year for 240 cultivars released in North America in the years 1902 to 1977. A more recent study with 116 cultivars released between 1923 to 2008 showed an increase of 18.5 kg ha^{-1} per year (Rowntree et al., 2013). De Bruin and Pedersen (2008) also observed an increase of 25 kg ha^{-1} per year with 23 cultivars release between 1938 to 2004.

In Canada, harvested soybean area increased from 1.0 to 2.5 million ha in the last 20 years (FAOSTAT, 2021). Main production areas are in Ontario, Manitoba and Quebec with a total Canadian production of about 6 million tons in 2019 (Statistics Canada, 2020). Soybean cultivars are often classified into relative maturity group (MG), ranging from MG 000 to MG III in Canada, from shorter to longer growing season. This system makes it possible to compare new cultivars to those already established, where there is a difference of about 10 days between each groups to reach maturity (OMAFRA, 2017). In terms of growing degree days (GDD), calculated as the sum of daily average temperature above a base temperature (5^{o}C in this case), MG 00, MG 0 and MG I would correspond approximately to 1600-1800, 1800-2100 and 2100-2300 ^{o}C day. Photoperiod also has an influence on soybean growth. Early maturing cultivars have a longer critical photoperiod than late maturing cultivars, from 16 h d^{-1} for MG 0000 to 12 h d^{-1} for MG 10 (Yang et al., 2019). However, cultivars of lower MG like those grown in Canada would be less sensitive to photoperiod. Voldeng et al. (1997) and Morrison et al. (1999) studied agronomic traits and yield improvement of 41 cultivars from MG 0, 00, and 000 grown in Canada and found that genetic improvement of soybeans, from 1934 to 1992, increased yield by 29%. This improvement follows a quadratic function, meaning the main increase was made in the most recent years, and should tend to continue (Voldeng et al., 1997). Wilcox (2001) observed an increase between 22 to 30 kg ha^{-1} per year for cultivars of MG 00 to I released between 1943 to 1999 where the increase in lower MG was less than for the higher MG. This yield increase in time is consistent with results from Rowntree et al., (2013) where they still observed a yield increase with cultivars released up to 2008 in the Midwest region of the United States of America.

The use of crop models allows to deepen our understanding of crop processes by helping us to investigate the dynamics between soil, crop and weather conditions (Asseng et al., 2014). Several models have been used and evaluated for simulating different soybean processes (Archontoulis et al., 2014; Battisti et al., 2017; Ruiz-Nogueira et al., 2001; Teixeira et al., 2019; Wang et al., 2003; Zhao et al., 2019), but very few addressing the yield and HI evolution of cultivars suitable for regions of Eastern Canada (Jégo et al., 2010; Jing et al., 2017). Since cultivars evolve over time, it is important to revise the plant parameters of the models accordingly to obtain more accurate simulations.

In parallel to the cultivar evolution, crop models also evolve with the addition or refinement of processes. For example, the STICS crop model has undergone several improvements since its last calibration and performance evaluation for soybean in Eastern Canada (Jégo et al., 2010). To name a few, these changes include improved equations for simulating nitrification and denitrification, a new sub-model for simulating snow cover, and new equations for simulating humus mineralization (STICS team, 2020). All these changes have an impact on crop growth so the new calibration of the model is justified.

As soybean is mainly rainfed in Canada, accurate simulation of water stress is important. Crop coefficient is a commonly used method in predicting crop evapotranspiration. A reference crop evapotranspiration (ET_O) is multiplied by an empirical crop coefficient (K_c) integrating soil and crop descriptors: canopy resistance, soil-crop surface albedo, crop height and soil evaporation (Allen et al., 1998). While ET_O takes into account the weather variations, K_c takes into account the specific contribution of soil and crop on evapotranspiration (Pereira et al., 2015). However, this approach can be inconsistent in simulating the influence of plant microclimate and soil evaporation (Brisson et al., 2009), as their effect is combined in a single coefficient. Another approach, the resistive method, obtained good results in predicting evapotranspiration in a spring wheat study in Eastern Canada with the STICS model (Sansoulet et al., 2014). This method uses the Shuttleworth and Wallace daily time step model to estimate the soil evaporation and crop water requirement (Brisson et al., 1998). It weighs potential soil evaporation and crop transpiration using two parameters (resistances) associated with the plant canopy and the soil surface, as well as three aerodynamic resistances (Shuttleworth and Wallace, 1985). This allows simulation of crop transpiration and soil evaporation separately (Gong et al., 2019).

The objectives of this study were to (1) use recent experimental data to verify if Eastern Canadian soybean HI increased over the past decade, (2) update soybean parameters in the crop model STICS according to these possible cultivars improvements and (3) compare the model performance in predicting evapotranspiration using the resistive and crop coefficient approaches.

MATERIAL AND METHODS

Study sites and experimentation

A total of 21 datasets from different fields on two main sites located at the Ottawa Canadian Food Inspection Agency (CFIA) farm (45◦18'N, 75◦45'W; Ottawa, ON) and the Ottawa Central Experimental Farm (CEF) (45◦23'N, 75◦43'W, Ottawa, ON) were used for this study (Table 1). Data were collected during 10 years between 1993 to 2017. These datasets were selected for the quality and the quantity of data points, especially for the leaf area index (LAI), biomass, soil moisture and evapotranspiration observations. Sixteen datasets from years 1993 to 2008 had already been used to calibrate STICS soybean growth parameters in a previous version of STICS (STICS v6.9; Jégo et al., 2010). However, all variables had not been used in this previous study (i.e. soil moisture and evapotranspiration). The other five datasets are from the same sites but are more recent (2016 and 2017) and have never been used for model calibration or validation (Table 1).

For each dataset, daily climatic data (minimum and maximum temperatures, precipitation, wind speed, relative air humidity and solar radiation) were measured at a weather station on or nearby the experimental site (< 1 km) (Table 2). For the years considered in this study, cumulative precipitation from April to October ranged from 391 to 758 mm, with dry years in 1997 at CFIA and 2016 at CEF. Normal rainfall for this region is 602mm (Table 2). GDD above 5°C were also greatly variable with values ranging from 1983 to 2340 ^{o}C day.

Cumulative solar radiation exhibited variations with values ranging from 3428 to 3904 MJ m^{-2}. These values show that the datasets chosen are suitable for calibrating and evaluating the model over a large range of climatic conditions of Eastern Canada.

In Eastern Canada, soybean is generally in rotation with maize (*Zea Mays*). Mesbah et al. (2018), showed that main soils where maize is produced in this region are loam, silty loam and silty clay loam, with some clay and silty clay soils in the south of the province of Quebec. This is consistent with soil textures used in the present study which included sandy loam, loam, silty clay loam and clay loam soils with clay content varying from 10.6 to 37.3% (Table 3). Soil properties of the surface layer (0-30cm) were measured or obtained from detailed soil surveys conducted at each site (Table 3). Field capacity and wilting point were estimated using equations from Saxton et al. (2006). The available water content ranged from 38 to 46 mm for the surface layer (30 cm) and from 86 to 111 mm for an average soil depth of 90 cm.

Crop management data were collected to create the crop management files of the simulation units. All treatments were rainfed except at the CEF farm in 2016 and 2017 where treatments with and without irrigation were carried out (Table 1). Water input was 200 mm in 2016 and 92 mm in 2017. No nitrogen fertilization was applied. Conventional tillage was used in spring and fall. Sowing dates occurred between 12 May and 9 June and harvest dates between 20 September and 17 October. When harvest date was not available, it was calculated by the model when seed maturity had reached 15% moisture content.

Shoot biomass (which includes all the aboveground parts of the plant, including seeds and pods), seed yield and LAI were measured in most of these datasets (Table 1). For datasets ranging from 1994 to 2008, details about field measurements can be found in Jégo et al. (2010). For newer datasets (2016 and 2017 at CFIA and CEF), LAI was measured with the same methodology with LAI-2000 and 2200 (LAI-2000 & 2200, LI-COR, Lincoln, NE). Shoot biomass was measured several times during the growing season using either quadrats (0.20 to 0.40 m^2) or 15-20 plants. Final harvest at maturity was done using combine harvesters equipped with yield monitors at CFIA site, or a plot combine where the biomass and seed were weighed manually with a scale after harvest at CEF site. Compared to the study of Jégo et al. (2010), additional field data were used in order to evaluate the ability of the model to simulate the water balance of soybean fields. These new data included volumetric soil moisture and actual evapotranspiration. Soil moisture was measured with Time Domain Reflectometry probes, inserted horizontally at several depths up to 100 cm and measured continuously in 2016 and 12 to 22 times per growing season in CFIA 1996, 1997 and 1999 experiments. Actual evapotranspiration was measured with flux towers installed in some CFIA fields using the eddy covariance method (Pattey et al., 2006). Half-hourly latent heat fluxes were screened and aggregated to daily and 10-day evapotranspiration data as described in Pattey et al. (2001).

STICS crop model

STICS (version 9.0) is a dynamic soil-crop model that calculates crop biomass accumulation, as well as water, nitrogen and carbon budgets on a daily time step (Brisson et al., 1998; 2002; 2003; 2009). Input data required to use the model are crop management (crop types and agricultural practices like fertilization, crop residues inputs, irrigation, soil tillage, sowing and harvesting dates), climate (solar radiation, minimum and maximum temperature, rainfall, wind speed and air moisture) and soil properties (constant soil attributes like pH, organic N, clay content, albedo, evaporation, and initial water and nitrogen profiles). The output variables are related to production quantity (e.g. seed yield, aboveground biomass, LAI) and quality (e.g. seed nitrogen and oil content), environment (water, carbon, and nitrogen), and the evolution of soil water and nitrate content. Production is limited under water and nitrogen stresses, but biotic stresses are not taken into account. This model can be used with different soil and climate conditions, different types of crops, and for various agricultural practices. The STICS model was initially parameterized and evaluated for bare soil, wheat, and maize (Brisson et al., 1998; 2002) and later adapted for other crops (Brisson et al., 2003).

The soil is divided into a maximum of five horizons, but calculation of microporosity (or textural porosity) are done by 1 cm layer increments, which is the resolution required to derive relevant nitrate concentration (Mary et al., 1999). Water transport in soil micropores is calculated for each 1-cm layer using a tipping-bucket approach. The daily water budget allows calculation of the water status of the soil, including actual evaporation and crop transpiration, as well as indices of water stress that reduce leaf growth and net photosynthesis in plants. The daily water budget is based on estimating the water requirements of the soil–leaf system on the one hand and the water supply to the soil–root system on the other. In STICS, two approaches are available to calculate evapotranspiration: the crop coefficient approach and the more mechanistic resistive approach based on the model of Shuttleworth and Wallace adapted to STICS (Brisson et al., 1998; Shuttleworth and Wallace, 1985). The crop coefficient approach uses the potential evapotranspiration calculated by the Penman formula (Penman, 1948) as a driving variable. This can be considered as an approach using a global resistance parameter controlling fluxes between the atmosphere and the soil-plant system. With the resistive approach, the interactions between soil and canopy fluxes are taken into account with controlling resistances associated with plants and soil. The resistive model is an efficient tool for explaining the energy budget of canopies (Sene, 1994) and was adapted to STICS by Brisson et al. (1998). The daily nitrogen budget takes into account mineralization from soil humus and crop residues, denitrification, nitrogen uptake , and symbiotic nitrogen fixation by leguminous crops.

Model calibration and performance evaluation

First, the HI was calculated for each dataset to 1) verify the temporal evolution reported by Morrison et al. (1999) and 2) to divide the datasets between old datasets using cultivars with low HI and more recent datasets using cultivars with greater HI. The apparent and actual HI were calculated. The STICS model uses the apparent HI (ratio of seed dry weight to shoot biomass) and does not take into account the fallen leaves prior harvest for some of the parameters calibrated (e.g., parameters *irmax* and *vitircarb*). However, the actual HI (ratio seed dry weight/(shoot and fallen leaves (prior harvest) dry weight)) was also calculated for comparison purposes with the literature. Based on these results, we decided to perform two calibration/evaluation processes: one using the 1994-2008 data for calibrating/evaluating a cultivar with low HI, and another one using the 2016-2017 data for calibrating/evaluating a more recent cultivar with greater HI. The model will therefore have two sets of plant parameters representing Eastern Canadian soybean cultivars with low and high HI that we named CanSoyEst low HI and CanSoyEst high HI cultivars.

Datasets used for the calibration and performance evaluation are identified in Table 1.Five datasets were used for calibration of the cultivar with low HI and one dataset was used for calibration of the cultivar with high HI. Other datasets were used for the crop model performance evaluation. Three methods have been used to calibrate the model, depending on the parameters: calculation of the value of the parameter using field measurements, values found in the literature, or values optimized by minimization of the difference between model outputs and field measurements (Table 4). Regarding calibration by optimization, all parameters were not estimated at the same time. First, the parameters related to LAI dynamic were optimized by minimizing the difference between simulated and measured LAI. Then, the parameters related to shoot biomass were optimized by minimizing the difference between simulated and measured shoot biomass. Finally, parameters related to seed yield were optimized by minimizing the difference between simulated and measured seed yield and nitrogen content of the seed.

A previous study on spring wheat showed that the resistive approach implemented in STICS performed well for predicting crop evapotranspiration in Eastern Canada (Sansoulet et al., 2014). Therefore, this approach was used to predict evapotranspiration for the calibration step. However, considering that the crop coefficient approach, which is also available in STICS, is more widely used, an evaluation of the model performance in predicting evapotranspiration with both methods was carried out before the performance evaluation step on all datasets containing evapotranspiration data (Table 1). Default settings were used for both approaches. For the crop coefficient approach, ET_O was calculated using the Penman equation (Penman, 1948), and the default value *kmax* (maximum crop coefficient) was 1.3. For the resistive approach, the default value proposed in STICS for the *rsmin* parameter (minimal stomatal resistance of leaves) was used (250 s m^{-1}). All datasets including evapotranspiration data were used to compare the performance of both approaches (Ottawa CFIA 1997, 1999, 2008 and 2016) using the crop growth parameters calibrated in the previous step. After calibration and the selection of evapotranspiration method, the model was run on the performance evaluation datasets to evaluate its performance in predicting LAI, shoot biomass, seed yield, nitrogen content in seed, soil moisture and evapotranspiration. An evaluation of the model performance predicting LAI, shoot biomass and seed yield, with and without water stress was also carried out. The presence of water stress was considered when the index of stomatal water stress (*swfac)* mean, over the growing season, was less than 0.9. In STICS, *swfac* is the ratio of the soil available water content above wilting point (*teta*) and the soil water content limiting transpiration and photosynthesis (*testomate*) (Brisson et al., 2009). If *teta* is higher than *tetstomate, swfac* is set equal to 1, meaning no water stress occurred. Without any other stress, a swfac value of 0.9 results in a reduction of shoot biomass by 10% due to water stress.

Finally, after performance evaluation of the two new cultivars, their performance was compared with the performance obtained with the cultivar previously calibrated in STICS version 6.9 by Jégo et al. (2010), called CanSoyEst 6.9, and implemented in the version 9.0 for this study, and also compared with the performance of the default plant file distributed with the version 9.0 of the STICS model (Table 4). CanSoyEst low and high HI simulation results used to carry out the performance evaluation were pooled and the statistics recalculated. For the CanSoyEst 6.9 and the default settings, the model was also run on all the performance evaluation datasets (Table 1). As the default plant file offers two cultivars options, variety 00 (MG 00) was used with the low HI evaluation datasets and the variety I (MG I) for the high HI evaluation datasets, as the low HI datasets includes MG 0 and 00 cultivars and the high HI datasets mainly has MG I cultivars. A flow chart illustrating the timeline of steps taken and datasets used at each step of the model calibration and evaluation is shown in the supplemental material.

To evaluate the model performance in both calibration and evaluation steps, statistical analysis were carried out using the Nash-Sutcliffe model efficiency coefficient (EF), the mean error (ME) and its relative value (normalized mean error, NME) and the root mean square error (RMSE) with its relative value (normalized root mean square error, NRMSE) (Eqs. 1-5). The NRMSE, NME and EF are presented.

$$EF = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \bar{O})^2} \quad (1)$$

$$ME = \frac{1}{n}\sum_{i=1}^{n}(O_i - P_i) \quad (2)$$

$$NME = 100\left(\frac{ME}{\bar{O}}\right) \quad (3)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(O_i - P_i)^2} \quad (4)$$

$$NRMSE = 100\left(\frac{RMSE}{\bar{O}}\right) \quad (5)$$

where O_i is the observed value, $\bar{O}$ the mean of the observed value, P_i the predicted value and n the number of observations. EF can range from -∞ to 1 where the model is more accurate when the value is closer to 1. A value below 0 would indicate that the observed mean would be a better predictor than the model itself. ME value can range from -∞ to ∞ and RMSE value can range from 0 to ∞. Values of ME and RMSE closer to 0 show better model performance. Therefore, an NRMSE closer to 0 than to 100%, and an NME closer to 0 than ±100% also show better model performance. As proposed in Jamieson et al. (1991), the simulation is considered to be excellent when NRMSE ≤10%, good when 10% < NRMSE ≤20%, fair when 20% < NRMSE≤30%, and poor when NRMSE >30%.

RESULTS

Harvest index evolution

Our datasets suggested that the apparent HI had increased over time with the release of new cultivars (Figure 1). The datasets from 1993 to 2008 contain observations from cultivars released in 1987 (Maple Glen), 1990 (AC Bravor), 1992 (AC Harmony), 1999 (2702R) and 2004 (90M20). For these datasets, the average apparent HI was 0.34 and the actual HI was of 0.26 (Figure 1) which is a bit lower than actual HI value of 0.32 reported by Morrison et al. (1999) for cultivars released around 1990. The more recent datasets (2016 and

2017) include observations from cultivars released in 2011 (91Y61) and 2014 (P06T28R) and had a greater apparent and actual HI than the oldest datasets, with an average value of 0.55 for the apparent HI and of 0.4 for the actual HI (Figure 1). Therefore, the oldest datasets, from 1993 to 2008, were used for the calibrations and evaluations of the CansoyEst low HI cultivar, while the most recent datasets (2016-2017) were used for the CanSoyEst high HI cultivar. In our dataset, this apparent HI increase can be explained by both a slight increase in seed yield and a decrease in shoot biomass.

Cultivars calibration

CanSoyEst low HI

The CanSoyEst 6.9 cultivar was already calibrated in a previous version of STICS (Version 6.9) by Jégo et al. (2010), but the calibration needed to be revisited for the CanSoyEst low HI as a number of processes has evolved from version 6.9 to version 9.0 and because new studies and literature references have became available. The values of the calibrated parameters of CanSoyEst 6.9 and CanSoyEst low HI are presented in Table 4.

Multiple parameters were adjusted based on the literature. The minimal temperature, below which emergence is stopped, *Tgmin*, was decreases from 5 to 4^{o}C, as proposed by Lamichhane et al. (2020). The optimal temperature for plant growth, *Teopt*, was decreased to 23^{o}C, based on the literature (Baker et al., 1989; Boote, 2011; Thomas, 2001), since the previous temperature of 28^{o}C led to an underestimation of biomass accumulation compared to the observations. The temperature beyond which the leaf expansion starts to slow down, *Tcmax*, was reduced from 45 to 40^{o}C (Setiyono et al., 2008). The temperature at which the crop development, the leaf growth and senescence stop, *Tcxstop*, was previously set too high

(100°C). This temperature threshold is never reached under field condition, but it determines how the leaf growth declines after the optimum temperature (*Tdmax*) since, in the model, the crop development response follow a linear decrease between *Tdmax* and *Tcxstop* (Brisson et al., 2009). By setting *Tcxstop* to 60°C, leaf growth has a steeper linear decrease and the LAI temporal variation was better predicted. Finally, the temperature beyond which the seed filling stops, *Tmaxremp*, was increased to 37°C as a temperature between 35 to 39°C has been observed to be severely affecting seed weight during the reproductive phase (Nahar et al., 2016). Parameters used to define the nitrogen dilution curves were modified as the critical N concentration is found to be lower for high total biomass value than previously supposed (Divito et al., 2016). Parameters of the critical nitrogen dilution curve, *adil* and *bdil,* were decreased to 3.7%N and 0.08, respectively, while parameters of the maximal nitrogen dilution curve a*dilmax* was adjusted to 1.4 × *adil* and *bdilmax* was set at the same value as *bdil*. The minimal temperature at which the N_2 fixation is optimal, *Tempnod2*, was reduced to 24°C, which is in the range of values found in the literature (Lindemann and Ham, 1979; Malik et al., 2018; Montanez et al., 1995; Zhang et al., 1996). The increase rate of the nitrogen harvest index, *vitirazo*, was slightly increased from 0.025 to 0.027 g seed gDM^{-1} d^{-1} as the simulated seed nitrogen content was lower than observed in the literature with the initial value.

The rate of change of the carbon harvest index, *vitircarb,* was adjusted by calculating the daily increase of the observed harvest index from the beginning of seed filling to seed maturity. The adjusted value is 0.016 g seed g DM^{-1} d^{-1}. By default, *vitprophuile* and *vitpropsucre* were set to 0 g gDM^{-1} °C d^{-1}. These parameters represent the increased rate for oil and sugar harvest index, respectively. Based on the literature, the oil content in soybean was estimated to be about 20% of the DM content (Hymowitz et al., 1972) and the sugar content around 10% of the DM content (Hymowitz and Collins, 1974). With an estimation of

450 ^{o}C day between the start of seed filling and maturity, *vitprophuile* was calculated and set to 0.0004 g gDM^{-1} ^{o}C d^{-1} and *vitpropsucre* to 0.0002 g gDM^{-1} ^{o}C d^{-1}.

The minimal specific leaf area parameters, *slamin*, was decreased from 200 to 160 cm^{2} g^{-1} based on the observed data, which is closest to the range of the minimum values found in the literature (e.g., Lugg and Sinclair, 1979; Yusuf et al., 1999). Two parameters defining cumulative thermal time between different stages of LAI growth were optimized to better fit the predicted LAI values with the measured LAI. The duration between the emergence and the end of juvenile phase, *stlevamf*, was decreased from 100 to 92 ^{o}C d, and the duration between the end of juvenile phase and the end of leaf growth, *stamlax*, was increased from 280 to 300 ^{o}C d. The *adens* parameters, representing the plants ability to withstand an increase in density due to branching or tillering, was also optimized to best fit on LAI, as well as the *durvieF* parameters which represent the lifespan of leaf. *Adens* was reduced from -0.50 to -0.78, and *durvieF* from 200 to 196. Finally the parameter *abscission* was also optimized by minimizing the difference between simulated and measured LAI because this process was not well predicted by the model as noted by Jégo et al. (2010). This parameter value, between 0 and 1, determines the proportion of leaves falling on the ground, 1 being all the leaves. This parameter was increased from 0.2 to 0.8. All these changes have led to a very good estimate of the LAI dynamic with the CanSoyEst low HI cultivars (Figure 2 and 3) with a NRMSE of 19.3% and almost no bias (Table 5).

The parameter *efcroirepro*, which is the maximum radiation use efficiency (RUE) during the seed filling phase, has been optimized with the shoot dry biomass observations. It was decreased from the previous calibration from 3.5 to 2.35 g MJ^{-1}PAR (Photosynthetically Active Radiation). This is in the range of RUE observed in the literature for soybean, between 2.1 to 2.63 g MJ^{-1}PAR over the season (Rochette et al., 1995; Sinclair and Muchow, 1999). With these changes, shoot dry biomass was well simulated (Figures 2 and 3) with a NRMSE of 21.8% and a NME of -5.7% (Table 5).

Two cumulative thermal time parameters controlling the onset of seed filling and the seed maturity stage were calibrated using seed yield observations. The duration between emergence and seed filling onset, *stlevdrp*, was reduced from 525 to 380 ^{o}C d, and the duration between the onset of seed filling and maturity of the seed, *stdrpmat*, was increased by 150 ^{o}C d passing from 250 to 400 ^{o}C d. Another parameter, *stdrpdes*, determining the cumulative thermal time between onset of seed filling and the beginning of seed drying was adjusted to be equal to *stdrpmat* (400 ^{o}C d) in order to start the seed drying process right after maturity. The prediction of the seed yield with these cultivars was good with a slight overestimation of 3.1% (NME) and a NRMSE prediction error of 8.3% (Table 5).

As for the water flux variables, the 10-days evapotranspiration was well predicted with an NRMSE of 17.6% and an overestimation of 7.8% (NME) (Table 5). The prediction of the soil water reserve over the entire soil profile (90cm) was also good with an NRMSE of 15.0% and a bias below 10% (Table 5).

CanSoyEst high HI

Several parameters of CanSoyEst low HI needed to be recalibrated using the high HI datasets from 2016-2017. The values of calibrated parameters are presented in Table 4. Based on the seed yield and the shoot biomass observed from the five recent datasets, the average apparent HI was calculated, leading to an increase of the parameter *irmax* from 0.5 to 0.6 (Figure 1). The stem/leaf ratio, *tigefeuil*, was decreased from 1 to 0.5 based on the field observations. The observations showed equal to slightly higher mass of green leaves produced, compared to the CanSoyEst low HI datasets, but lower mass of stems, which explained the *tigefeuil* ratio decrease. The maximum specific leaf area of green leaves, *slamax*, was also calculated with the observed values and decreased to 250 cm^2 g^{-1}, which leads to smaller or thicker leaves, as observed by Morrison et al. (1999). The parameter *vitircarb* was increased from 0.016 to 0.025 g seed g $biomass^{-1}$ d^{-1} by computing the daily increase of the observed apparent HI of the recent high HI cultivars, from the beginning of seed filling to seed maturity.

Four parameters were optimized to fit the predicted LAI value to the observed one. *Stlevamf* was decreased to 35 ^{o}C d while *stamflax* was increased to 345 ^{o}C d. *Adens* was increased to -0.42 while *durvieF* was decreased to 145. These changes have led to some excellent predictions of the LAI (Figure 2) with a slight underestimation of 7% (NME) and a NRMSE of 8.8% (Table 5). Following this optimization, two parameters, *efcroiveg* and *efcroirepro*, have been optimized to best fit the shoot dry biomass observations. The maximum radiation use efficiency during the vegetative phase, *efcroiveg*, were slightly reduced to 2.4 g MJ^{-1}, and *efcroirepro* decreased from 2.35 to 2.15 g MJ^{-1} which is more consistent with the literature. This lead to an accurate prediction of the shoot dry biomass (Figure 2) with a NRMSE of 6.6% and a NME of -0.5% (Table 5). *Vitirazo* was increase from 0.027 to 0.037 by optimization to fit the seed nitrogen concentration (*CNgrain*) predictions to the nitrogen measurements.

Methods of calculation of evapotranspiration

As briefly described above, the 10-d evapotranspiration (ET_{10}) was fairly well predicted for the calibration dataset. The comparison of the two evapotranspiration models on all datasets that included evapotranspiration data confirmed that the resistive approach performed better than the crop coefficient approach with less bias (NME of 15.0% instead of 34%), less error prediction (NRMSE of 36% instead of 67%) and greater R^2 (Figure 4). These results confirmed the choice of using the resistive approach for calibration and performance evaluation steps.

Performance evaluation of the cultivars

CanSoyEst low HI

To evaluate the performance of CanSoyEst Low HI, eleven datasets were used (Table 1). The LAI predictions were poor (Figure 5) with an error of 36.2% (Table 6), but is in the range of the ones obtained by Jégo et al. (2010). However, the predictions are underestimated by only 11.6% on average and the efficiency was good with an EF higher than 0.6 (Table 6). The shoot biomass was well predicted (Figure 5) with almost no bias (NME < 5%), a high model efficiency (0.84) and a fair NRMSE of 29.8% (Table 6). Prediction error was better for the seed yield (NRMSE = 22.3%) than the shoot biomass, but the overestimation was slightly greater with a NME equal to 14.8% (Table 6). Soil available water was well predicted with a NRMSE of 14.9% and an overestimation of about 10% (Table 6). The ET_{10} was less accurately predicted than the other variables with a NRMSE of 49.6% and was overestimated by 36.4% (Table 6). Two years (1997 and 1999) with evapotranspiration data were used to validate the low HI cultivars. While the model prediction was good in 1997 (NRMSE of 19.1% and NME of 10.4%), evapotranspiration was largely overestimated by the model in 1999 (NRMSE of 71.3% and NME of 62.0%). This overestimation can be explained mostly by an overestimation of the shoot biomass at the end of the 1999 growing season and is probably not related to the calculation of evapotranspiration itself.

CanSoyEst high HI

Four datasets were used to evaluate the performance of the cultivar CanSoyEst High HI, one from the CFIA site in 2016 and three from the CEF site in 2016 and 2017. The statistical results are presented in Table 6. The prediction error was high for the LAI and ET_{10} with an

NRMSE of 33.8 and 32.2%, respectively, fairly good for the soil available water (22.8%), but good to excellent for the shoot dry biomass (9.9%), seed yield (14.0%), seed nitrogen concentration (6.0%) and oil content (9.6%). LAI error prediction is generally higher than the shoot biomass prediction as there is more incertitude on the LAI measurement. This can explain a part of the low model performance on the LAI prediction. Results obtained on LAI prediction are in the same range or slightly better than those obtained by Jégo et al. (2010) with STICS v6.9 on the Ottawa sites (NRMSE ranging from 27.9% to 38.2%). It should also be noted that, despite the fairly high prediction error, the other statistical criteria for LAI were good, with almost no bias (NME of 4.3%) and a very good EF and R^2 (Table 6 and Figure 5). The model prediction was excellent for the shoot biomass (Figure 5) with a small underestimation of 4.4%. With only 3 observations, the N and oil content of the seed was well predicted with an overestimation of 5 to 9% (Table 6). However, the values of these two variables are fairly stable and the model is not a better predictive tool than the average of the measurements, as indicated by the negative EF.

Simulation of harvest index

For the low HI cultivars, the seed yield predicted by the model was generally good, except for the 1993-CEF-00, 1996-CEF-0 and 1996-CEF-00 datasets, where the model overestimated it by 0.7 to 1.1 t DM ha^{-1} (Figure 6). As explained in Jégo et al. (2010), this overestimation could be explained by disease, frost before harvest, or an underestimation of the water stress by the model during the reproductive stage leading to lower seed size. For the high HI cultivars, the model also predicted well the seed yield, even though a slight constant underestimation between 0.1 to 0.5 t DM ha^{-1} is observed (Figure 6).

The apparent HI was well predicted by the model compared to the apparent HI calculated from fields observations (Figure 7). For the low HI cultivars, all the predicted HI were well into the range of the measured ones. However, for the high HI cultivars, the predicted HI were slightly underestimated. This can be explained by the underestimation of the seed yield discussed previously.

Comparison between the new parameters and previous versions of plant parameters

The use of the CanSoyEst low and high HI cultivars improved the accuracy of simulations for most of the variables compared to the use of the default 00 and I cultivars distributed with STICS version 9.0 and compared to the CanSoyEst 6.9 cultivar proposed by Jégo et al. (2010). These improvements were particularly marked for LAI, shoot dry biomass, seed yield, ET_{10} and seed N concentration (Table 7). Only the soil available water did not show an improvement with an NRMSE of 21.3% for the CanSoyEst low and high HI parameters, compared to an NRMSE of 19% for the default and 14.2% for the CanSoyEst 6.9 parameters (Table 7). Statistics were also calculated for the harvest index predictions to evaluate the gain performance associated with the use of the low and high Hi cultivars proposed in this study. With the two new cultivars, the model performed fairly well, with an NRMSE of 23.8%, an NME of -7.9% and an EF of 0.5, compared to the model performance with the default or CanSoyEst 6.9 cultivars (Table 7). Results for the seed oil content are not presented as the model with the default and CanSoyEst 6.9 settings was not simulating the oil content with the parameter *vitprophuile* equal to 0 (Table 4).

Influence of water stress on the model performance

Four of the validation datasets were considered as water-stressed (swfac<0.9): 1993-CEF-0, 1993-CEF-00 and 2008-CFIA-F4-0 for the low HI cultivar and 2016-CEF-1 for the high HI cultivars. The other datasets used for validation were not water-stressed. The model performance was, in general, similar for both stressed and non-stressed predictions (Table 8), which suggests that the model can be used with confidence in both water stressed and non-stressed situations.

DISCUSSION

In the present study, the main increase in HI is due to a decrease in the shoot biomass, while the seed yield increase was marginal. This doesn't follow the observations of Morrison et al. (1999) where they observed that harvest index increased with the year of cultivars release, but could not detect the influence of the year of release on the dry biomass. Therefore, they attribute the increase in yield to an increase in the number or size of the seeds (Morrison et al., 1999). However, the small yield increase and the shoot biomass decrease observed in the present study may not be representative of the long term trend since data from only two climatic years (2016 and 2017), and only two cultivars, were used to represent the high HI cultivars. The parameters *vitircarb* has been increased by 9 g seed g^{-1} d^{-1} for the CanSoyEst high HI cultivars, which should lead, other things being equal, to an increase in seed mass between the low and high HI cultivars parametrized.

Given the evolution of cultivars over time, the crop models must be flexible enough to allow parameterization of new cultivars. STICS made it possible to adjust effectively the parameters for improving the simulation of newer cultivars. In this study, newer cultivars, not only have a higher apparent HI than CanSoyEst low HI, but were also part of a higher maturity group. The CanSoyEst low HI is based on cultivars of the maturity group 00 and 0, while the CanSoyEst high HI was configured according to observations of cultivars of the maturity groups 0 and I. The better model performance to predict HI with the CanSoyEst low and high HI parameters, compared to the default settings, shows that CanSoyEst low and high HI account for the difference in the harvest index and maturity groups in Eastern Canada, even if the default STICS version 9.0 plant file already contained cultivars for two maturity group.

Considering the climatic trends, this shift in maturity group is consistent with longer growing season. Thus, parameters, such as the stages length, were probably more affected by the change in maturity groups than by the higher apparent HI. Effectively, besides the length of the *stlevamf* that was shorter for the high HI cultivars compared to the low HI, all other phenological stages needed more degree days for the high HI cultivars because low maturity groups mature earlier than the higher groups (Liu et al., 2017). Calibration of crop models for a range of maturity groups has already proven to be an efficient way of using crop models. For example, Teixeira et al. (2019) calibrated the model DSSAT- CSM- CROPGRO-Soybean for different maturity group (5 to 8.5) instead of different cultivars and achieved good model performance. This avoids having to calibrate each new cultivar individually, as shown in Salmerón and Purcell (2016) for cultivars of maturity groups 3 to 6.

Compared to previous studies on soybean modelling, the performance level of our simulation results was generally in the same range or slightly better. Battisti et al. (2017) calibrated and evaluated the performance of five crop models for simulations of soybean growth in southern Brazil. Models compared were APSIM Soybean, AQUACROP, DSSAT CSM-CROPGRO-Soybean, FAO-Agroecological Zone and MONICA. They achieved an NRMSE between 37 to 44% with the prediction of the shoot biomass after calibration, which is not as good as the results achieved in the present study with the STICS model, even though they obtained relatively good index of agreement (d-index) and coefficient of determination (R^2). They achieved model performances similar to what we achieved for the seed yield prediction, with a NRMSE around 19% for every model they evaluated. An NRMSE of 18% for the seed yield prediction was also achieved by Jing et al. (2017) while evaluating the

CSM-CROPGRO-Soybean model in the Ottawa region with some of the same datasets used in this study.

The performance level of the predictions made with the new CanSoyEst low and high HI settings was also generally better than with the default and the previously set CanSoyEst 6.9 settings, especially for the LAI, shoot biomass yield, seed yield, ET_{10}, harvest index and seed N content. However, for some variables like seed yield, oil and N content, the efficiency resulted in negative values, which implied that the model does not offer a better prediction than the mean of observations. This is often the case for variables measured only at harvest and with a low inter-annual variability. Though, compared to the default settings, or the parameters set by Jégo et al. (2010), an improvement in the efficiency to predict seed yield and N content can be observed, going from -3.2 to -0.2 for the default and newly parametrized settings, respectively.

In addition to cultivar improvement, climatic variation is also a major factor affecting crop growth. In rainfed regions, accurate simulation of water stress is very important. It requires to adequately simulate soil water content and evapotranspiration. Our results showed that soil water content was well predicted with low NRMSE and NME comparable to those found by Coucheney et al. (2015) in an extensive evaluation of the STICS model performance. Concerning the evapotranspiration, despite precipitation during the growing season slightly below the climate normal in 1997 and 1999, no long and significant period of water stress (*swfac*<0.8) occurred during the four years where evapotranspiration data were available. Our results confirm those reported in Sansoulet et al. (2014) that the resistive approach implemented in STICS provides better results than the crop coefficient approach. STICS performance for predicting evapotranspiration (RMSE < 1.5 mm for daily evapotranspiration; data not shown) was close to, or better, than the performance reported for other models. For instance, Mbangiwa et al. (2019) reported RMSE values comprised between 0.66 to 3.15 mm for daily evapotranspiration with the AquaCrop model.

Conclusion

The upward trend of soybean harvest index observed in previous studies has continued in recent years. Our results show that the STICS crop model was able to reproduce well the increase of the apparent harvest index through the updated calibration of a low harvest index cultivar representative of maturity group 00 and 0, and the calibration of a new cultivar with a higher harvest index representative of maturity groups 0 and 1. The improvement of plant and cultivar parameters allowed a good performance of the model, especially on the predictions of the shoot biomass and seed yield.

Our study also presents the first evaluation of a crop model on the prediction of soybean evapotranspiration in Canada. Using the resistive approach to predict the evapotranspiration was effective. Simulation results showed that the model performance was good and in the same range as the values reported in studies from other climatic regions. The ability of the model to predict accurately soil available water and evapotranspiration, as well as LAI, shoot biomass, and seed yield during water-stressed growth seasons should allow using the model to better quantify and analyze the impact of water shortage on soybean growth and yield in Eastern Canada.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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FIGURE 1. Calculated harvest index (HI) for the two cultivar groups (low and high HI) resulting from the observed dataset. Data for the CanSoyEst low HI calculation come from five cultivars (Maple Glen, AC Bravor, AC Harmony, 2702R and 90M20), and from two cultivars (91Y61 and P06T28R) for the CanSoyEst high HI calculation. Vertical bar represent ± one standard deviation around the mean.

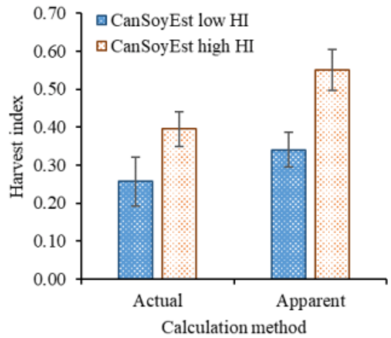


FIGURE 2. Calibration performance of the CanSoyEst low and high HI cultivars for predicted a) leaf area index (LAI) and b) shoot dry biomass.

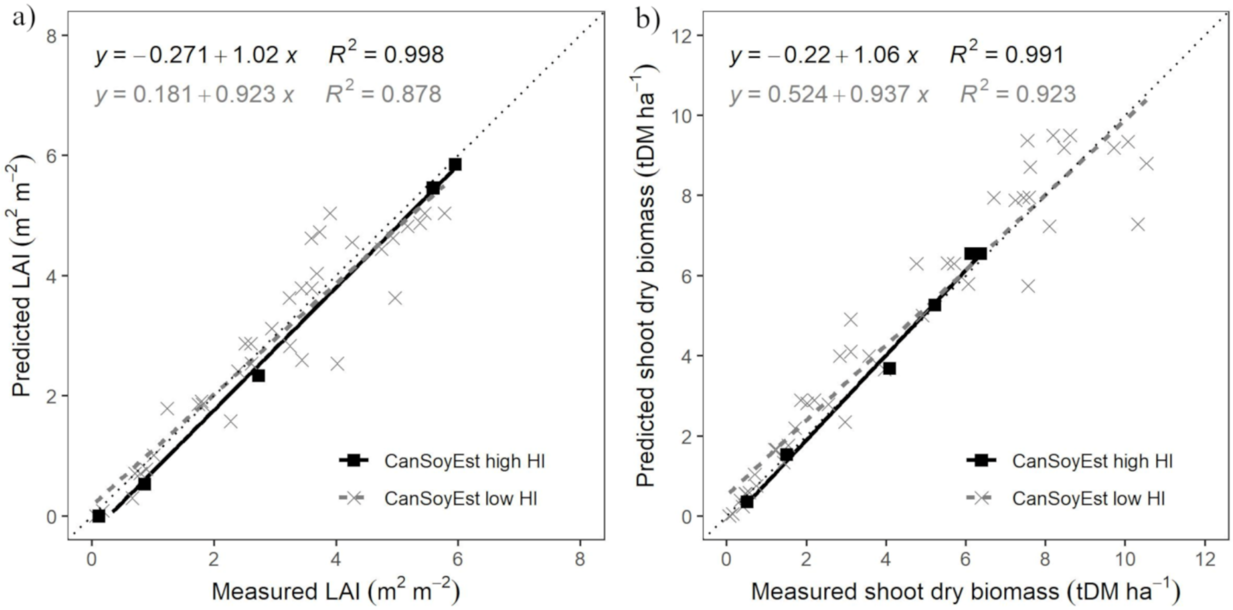


FIGURE 3. Predicted (curves) versus measured (circles) a)leaf area index and b)shoot biomass for the datasets used for calibration of CanSoyEst low HI (1994, 1995 and 2008) and high HI (2016).

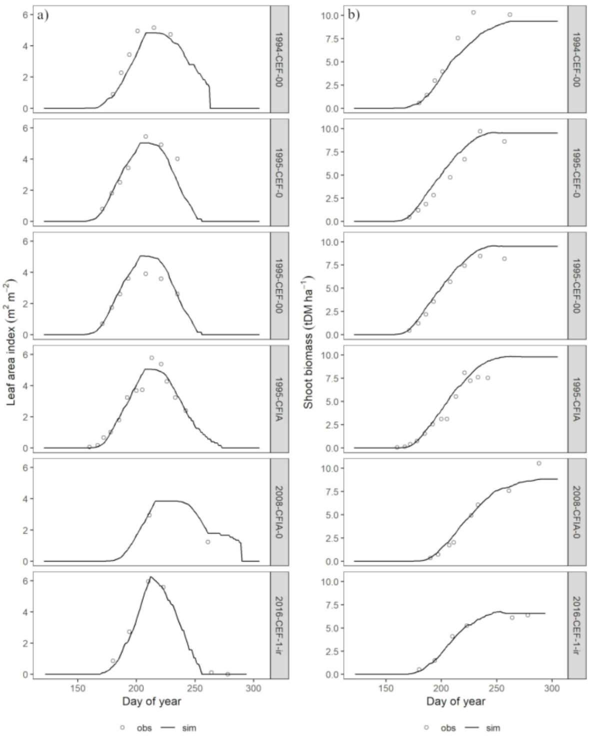


FIGURE 4. Predicted and measured 10-day evapotranspiration (ET_{10}) with the resistive and the crop coefficient approaches.

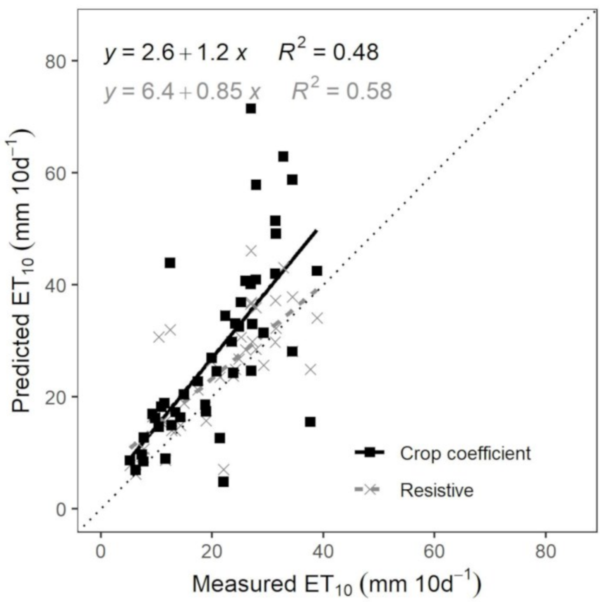
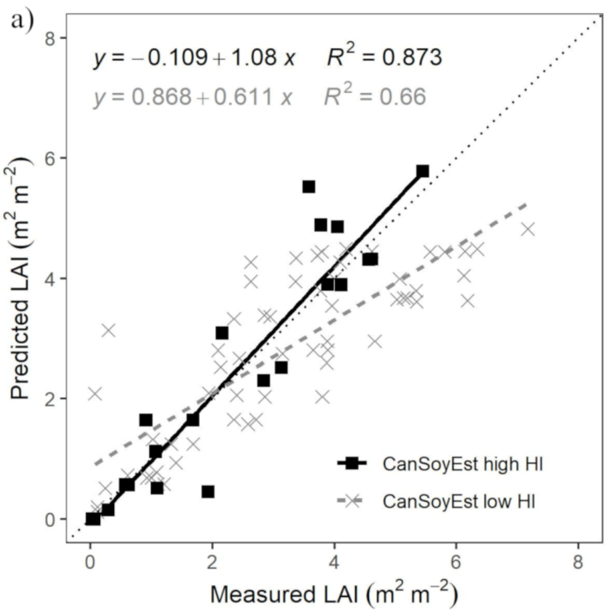


FIGURE 5. Evaluation of the CanSoyEst low and high HI cultivars prediction performance for the a) leaf area index (LAI) and b) shoot dry biomass.



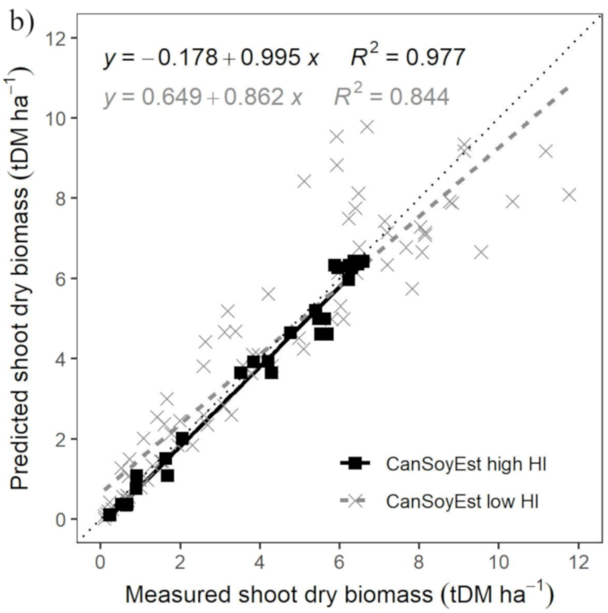


FIGURE 6. Evaluation of the soybean seed yield prediction performance for the CanSoyEst low and high HI cultivars at CFIA and CEF sites.

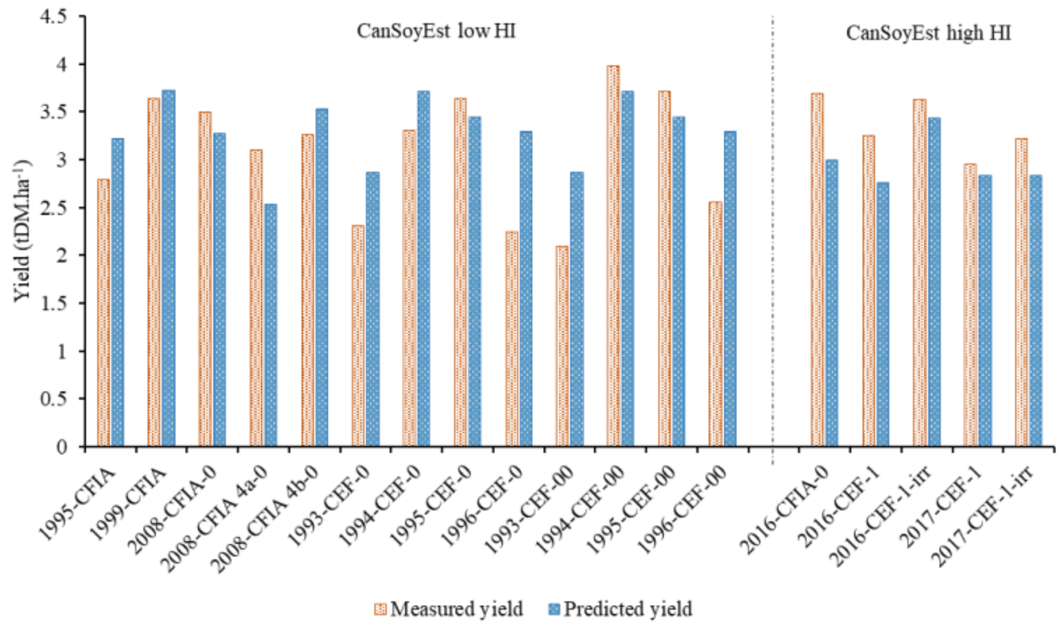


FIGURE 7. Apparent harvest index (HI) observed and predicted for the low (1993-2008) and high HI cultivars (2016-2017).

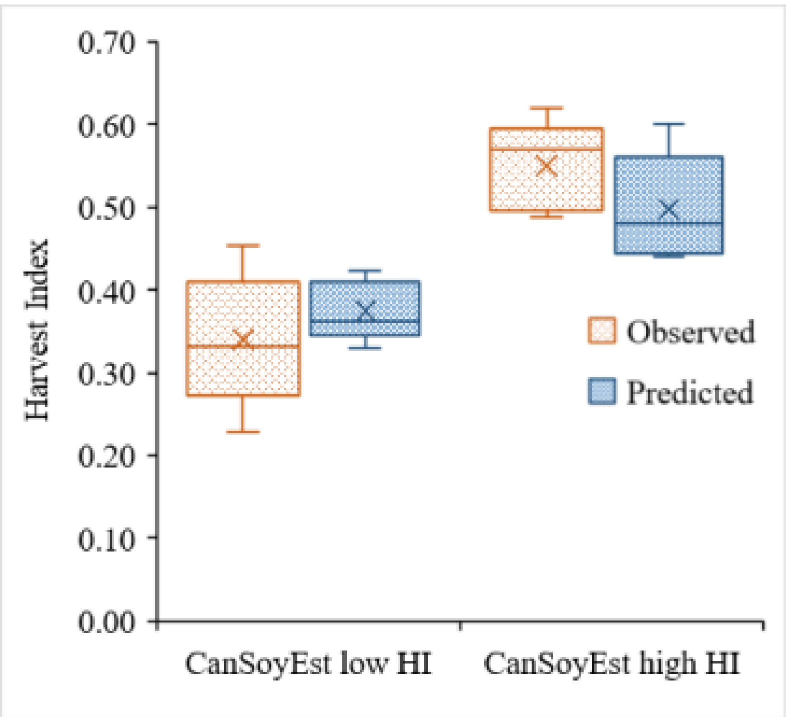


TABLE 1. Description of the datasets used for the calibration and performance evaluation of the two cultivar groups with a low and a high harvest index (HI); CanSoyEst low HI and CanSoyEst high HI

Location[a]	Year	Field #	Cultivar	MG[b]	Irrigation	Name	Sowing date	Harvest date	Number of measurements: Green LAI[c]	Biomass	Yield	N content	Oil content	Soil moisture	Evapo-transpiration
CanSoyEst low HI															
Calibration															
CFIA	1995	23	-	-	No	1995-CFIA	May 25	> Oct. 4	13	13	1	-	-	-	-
	2008	14	90M20	0	No	2008-CFIA-0	June 9	Oct. 15	2	8	1	-	-	28	158
CEF	1994	51	AC Harmony	00	No	1994-CEF-00	May 24	-	7	8	1	-	-	-	-
	1995	51	AC Bravor	0	No	1995-CEF-0	May 19	-	7	8	1	-	-	-	-
	1995	51	AC Harmony	00	No	1995-CEF-00	May 19	-	7	8	1	-	-	-	-
Performance evaluation															
CFIA	1996	25	-	-	No	1996-CFIA	May 28	> Oct. 4	7	10	-	-	-	22	-
	1997	19	Maple Glen	00	No	1997-CFIA-00	June 2	Sept. 24	9	10	-	-	-	12	89
	1999	25	2702R	-	No	1999-CFIA	May 26	Oct. 7	3	5	1	-	-	13	122
	2001	16	-	-	No	2001-CFIA	May 12	Sept. 20	3	3	-	-	-	-	-
	2008	4	AC Bravor	0	No	2008-CFIA-F4-0	May 26	Oct. 15	2	6	1	-	-	-	-
	2008	14	AC Bravor	0	No	2008-CFIA-F14-0	May 26	Oct. 15	-	6	1	-	-	-	-
CEF	1993	51	AC Bravor	0	No	1993-CEF-0	May 18	-	7	8	1	-	-	-	-
	1993	51	AC Harmony	00	No	1993-CEF-00	May 18	-	7	8	1	-	-	-	-
	1994	51	AC Bravor	0	No	1994-	May 24	-	7	8	1	-	-	-	-

						CEF-0									
	1996	51	AC Bravor	0	No	1996-CEF-0	May 23	-	7	8	1	-	-	-	-
	1996	51	AC Harmony	00	No	1996-CEF-00	May 23	-	7	8	1	-	-	-	-
CanSoyEst high HI															
Calibration															
CEF	2016	51	91Y61	1	Yes	2016-CEF-1-irr	May 20	Oct. 4	6	6	1	1	1	-	-
Performance evaluation															
CFIA	2016	14	P06T28R	0	No	2016-CFIA-0	May 12	Oct. 17	7	9	1	-	-	161	191
CEF	2016	51	91Y61	1	No	2016-CEF-1	May 20	Oct. 4	6	6	1	1	1	-	-
	2017	51	91Y61	1	Yes	2017-CEF-1-irr	June 3	Oct. 6	6	6	1	1	1	-	-
	2017	51	91Y61	1	No	2017-CEF-1	June 3	Oct. 6	6	6	1	1	1	-	-

[a] CFIA: Ottawa Canadian Food Inspection Agency, CEF: Ottawa Central Experimental Farm

[b] Maturity group. Range from 0000 to X, from shorter to longer growing season, respectively (Yang et al., 2019).

[c] Leaf area index

TABLE 2. Climate data between April and October from on-site weather station and climate normals (1981-2010; Environment and Climate Change Canada, 2020)

Location[a]	Year	Cumulative rainfall	GDD[b] (5°C)	Cumulative radiation
		mm	°C d	MJ m^{-2}
CEF	1993	629	2030	3521
	1994	598	2081	3610
	1995	690	2198	3795
	1996	689	2075	3519
	2016	391	2327	3840
	2017	758	2265	3428
CFIA	1995	648	2158	3795
	1996	538	1983	3519
	1997	405	1984	3778
	1999	527	2340	3904
	2001	489	2247	3814
	2008	632	2076	3866

	2016	554	2234	3461
Normals	1981-2010	602	2151	3682

[a] CFIA: Ottawa Canadian Food Inspection Agency, CEF: Ottawa Central Experimental Farm

[b] Growing degree days 5°C base temperature

TABLE 3. Soil properties of the surface layer (0-30 cm) of the two sites.

Location[a]	Field no.	Canadian soil texture	Clay content	Field capacity	Wilting point	Bulk density	pH
			%w	%v	%v	g cm^{-3}	
CEF	51	Loam	18	27.9	14.4	1.29	6.0
CFIA	4	Sandy loam	10.6	14.3	7.8	1.30	6.0
		Silty Clay		33.6	20.0		
	14	Loam	31.3			1.33	6.8
	16	Clay loam	37.3	37.7	24.7	1.30	6.3
	19	Clay loam	32.5	34.7	18.2	1.40	7.0
	23	Clay loam	30.0	33.7	19.5	1.38	6.0
	25	Loam	27.5	28.8	18.5	1.32	6.6

[a] CFIA: Ottawa Canadian Food Inspection Agency, CEF: Ottawa Central Experimental Farm

TABLE 4. Crop growth parameters of the default plant file distributed with version 9.0 of STICS, the previous cultivar CanSoyEst 6.9 calibrated by Jégo et al. (2010) in STICS version 6.9 and the newly calibrated cultivars for low and high HI calibrated in the version 9.0 of STICS. (See Supplemental Materials for the definitions of the parameters)

Parameters	Formalisms	Default MG 00	Default MG I	CanSoyEst 6.9	CanSoyEst low HI	CanSoyEst high HI	Unit	Calibration type
Cultivar parameters								
stlevamf	LAI [a]	100	90	100	92	35	°C d	Optimization
stamflax	LAI	450	530	280	300	345	°C d	Optimization
adens	LAI	-0.5	-0.5	-0.5	-0.78	-0.42	-	Optimization
durvieF	LAI	200	200	200	196	145	-	Optimization
stlevdrp	Phenology	500	800	525	380	380	°C d	Optimization
stdrpmat	Phenology	510	520	250	400	600	°C d	Optimization
stdrpdes	Phenology	500	500	300	400	600	°C d	Calculation
Plant parameters								
Tgmin	Germination	5		5	4	4	°C	Literature
vitircarb	Yield quantity	0.015		0.015	0.016	0.025	g seed g^{-1}d^{-1}	Calculation
abscission	LAI	0.2		0.2	0.8	0.8	-	Optimization
Teopt	Biomass	28		28	23	23	°C	Literature
efcroiveg	Biomass growth	3		3	3	2.4	g MJ^{-1}	Optimization
efcroirepro	Biomass growth	3.5		3.5	2.35	2.15	g MJ^{-1}	Optimization
tigefeuil	Biomass partitioning	1		1	1	0.5	-	Calculation
Tcmax	Biomass growth	45		45	40	40	°C	Literature
Tcxstop	Biomass growth	100		100	60	60	°C	Literature
Tmaxremp	Yield quantity	30		30	37	37	°C	Literature
vitpropsucre	Yield quality	0		0	0.0002	0.0002	g sugar g^{-1}d^{-1}	Calculation
vitprophuile	Yield quality	0		0	0.0004	0.0004	g oil g^{-1} d^{-1}	Calculation
vitirazo	Yield quality	0.025		0.025	0.027	0.037	g seed g^{-1}d^{-1}	Optimization
irmax	Harvest index	0.5		0.5	0.5	0.6	-	Calculation

adil	Nitrogen uptake	5.35	5.35	3.7	3.7	N %	Literature
bdil	Nitrogen uptake	0.44	0.44	0.08	0.08	-	Literature
adilmax	Nitrogen uptake	8.5	8.5	5.2	5.2	N %	Calculation
bdilmax	Nitrogen uptake	0.44	0.44	0.08	0.08	-	Calculation
slamax	LAI	300	300	300	250	$cm^2\ g^{-1}$	Calculation
slamin	LAI	200	200	160	160	$cm^2\ g^{-1}$	Calculation
Tempnod2	N fixation	30	30	24	24	°C	Literature

[a] Leaf area index

TABLE 5. Normalized root mean square error (NRMSE), normalized mean error (NME) and model efficiency (EF) of the predicted leaf area index (LAI), shoot dry biomass, seed yield, seed nitrogen concentration, 10-days evapotranspiration (ET_{10}) and soil available water (0-90 cm) for calibration of the CanSoyEst low and high HI cultivars

Cultivar groups		**LAI**	**Shoot dry biomass**	**Seed yield**	**Seed nitrogen concentratio n**	**ET_{10}**	**Soil available water**
Low HI	NRMSE (%)	19.3	21.8	8.3	NA[a]	17.6	15.0
	NME (%)	1.5	-5.7	3.1	NA	-7.8	10.0
	EF	0.88	0.92	0.47	NA	0.80	-0.58
High HI	NRMSE (%)	8.8	6.6	NA	14.2	NA	NA
	NME (%)	7.0	-0.5	NA	-14.2	NA	NA
	EF	0.99	0.99	NA	NA	NA	NA

[a] Statistic not available due to lack of data to make statistical calculations.

TABLE 6. Normalized root mean square error (NRMSE), normalized mean error (NME) and model efficiency (EF) of the predicted leaf area index (LAI), shoot dry biomass, seed yield, 10-days evapotranspiration (ET_{10}), soil available water (0-90cm), seed C/N ratio and oil content for performance evaluation of the CanSoyEst low and high HI cultivars

Cultivar groups	**Statistics**	**LAI**	**Shoot dry biomass**	**Seed yield**	**ET_{10}**	**Soil available water**	**Seed N concentratio n**	**Oil content**
Low HI	NRMSE (%)	36.2	29.8	22.3	49.6	14.9	NA[a]	NA
	NME (%)	11.6	-1.8	-14.8	-36.4	-9.9	NA	NA
	EF	0.65	0.84	-0.32	-0.61	0.14	NA	NA
High HI	NRMSE (%)	33.8	9.9	14.0	32.2	22.8	6.0	9.6
	NME (%)	-4.3	4.4	12.6	-1.5	-21.4	-4.6	-8.7
	EF	0.85	0.97	-2.03	0.61	-2.76	-370.25	-7.16

[a] Statistic not available due to lack of data to make statistical calculations.

TABLE 7. Comparison of the model performance between the default parameters from the Stics model version 9.0, the parameters set by Jégo et al. (2010) (CanSoyEst 6.9) and the new parameters (CanSoyEst low and high HI)

Cultivars	**Statistics**	**LAI**[a]	**Shoot dry biomass**	**Seed yield**	**Harvest index**	**ET_{10}**[b]	**Soil available water (0-90cm)**	**Seed N concentration**
Default	NRMSE[c] (%)	118.5	61.5	35.7	51.2	44.1	19.0	40.0
	NME[d] (%)	-47.4	-13.3	-25.3	24.3	-25.1	-16.4	39.8
	EF[e]	-1.94	0.25	-3.16	-1.32	0.06	-1.18	-16496
CanSoyEst 6.9	NRMSE (%)	42.9	39.5	42.7	60.6	71.5	14.2	15.6
	NME (%)	18.7	9.1	35.4	47.2	-38.7	-10.9	11.1
	EF	0.62	0.69	-4.95	-2.25	-1.45	-0.22	-2517.8
CanSoyEst low and high HI	NRMSE (%)	36.1	26.4	19.5	23.8	42.1	21.3	6.0
	NME (%)	8.4	-0.1	-4.6	-7.9	-18.6	-18.8	-4.6
	EF	0.73	0.86	-0.24	0.50	0.15	-1.72	-370.25

[a] Leaf area index
[b] 10 days evapotranspiration
[c] Normalized root mean square error
[d] Normalized mean error
[e] Nash-Sutcliffe model efficiency coefficient

TABLE 8. Model performance with water stressed and non-stressed datasets

Water stress	**LAI**[a]			**Shoot biomass**			**Seed yield**		
	NRMSE[b]	**NME**[c]	**EF**[d]	**NRMSE**	**NME**	**EF**	**NRMSE**	**NME**	**EF**
	---------- % ----------			--------- % ---------			----------- % ---------		
Stressed	26.5	11.2	0.64	21.9	6.8	0.89	22.6	-2.6	-0.50
Not stressed	37.2	7.1	0.68	27.5	-2.7	0.85	18.1	-5.6	-0.41

[a] Leaf area index
[b] Normalized root mean square error
[c] Normalized mean error
[d] Nash-Sutcliffe model efficiency coefficient