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# Modeling growth, development and yield of Sugarbeet using DSSAT

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ABSTRACT

Sugarbeet (*Beta vulgaris*) is considered as one of the most viable feedstock alternatives to maize for biofuel production since herbicide resistant sugarbeet was deregulated by the United States Department of Agriculture in 2012. So far, only a few sugarbeet simulation models have been developed and these models are limited to application for local regions. The Decision Support System for Agrotechnology Transfer (DSSAT) provides a common framework for a cropping system study and currently has crop modules for > 40 crops. However, DSSAT currently does not include a model for sugarbeet. In this study, the Crop and Environment REsource Synthesis (CERES) Beet model was modified and incorporated into the current version of the Cropping System Model (CSM) to simulate growth, development, and yield of sugarbeet. The PEST optimizer was used for parameter estimation, transferability evaluation, and predictive uncertainty analysis. The sugarbeet model was evaluated with two sets of experimental data collected in two different regions and under different environmental conditions; one in Romania (Southeastern Europe) during 1997–1998 and the other in North Dakota, US (North America) during 2014–2016. After model calibration for specific cultivars, the CSM-CERES-Beet model performed well for the simulation of leaf area index, leaf number, leaf or top weight, and root weight for both datasets (*NSE* = 0.144–0.976, *rRMSE* = 0.127–1.014). Uncertainty analysis revealed that the calibrated CSM-CERES-Beet consistently over-predicted leaf number with false confidence, although measured leaf number also showed a significant variability. The model was successfully applied for predicting yield for six different sugarbeet cultivars grown in North Dakota during the 2014 to 2016 growing seasons. CSM-CERES-Beet could be applied for predicting sugarbeet yield for different soil and climatic conditions and various management scenarios for the Red River Valley in the US and other regions with environmental conditions favorable for sugarbeet production.

## 1. Introduction

Sugarbeet (*Beta vulgaris*) is grown commercially for refining sucrose from its roots. Sugarbeet was first discovered as a potential sucrose source in 1802 in central Europe (Panella et al., 2014). Since then, it has been grown around the world as a primary sucrose source alongside sugarcane. Sugarbeet's contribution to the world's sucrose production increased from approximately 37% in 1998–99 to 60% in 2010–11 (Sugarbeet Production Guide, 2013). Sugarbeet grown in the United States (US) is currently found in regions encompassing 11 states and it tends to be grown in rotation with other crops (USDA/ERS, 2018). The total sugarbeet planting area in the US was 0.47 million ha in 2016/17. The Red River Valley (RRV) of western Minnesota and eastern North Dakota and its vicinity are largest producers of sugarbeet. In 2016/17, 57% of the US total sugarbeet was produced in the RRV region, while 31% was produced in Idaho and Michigan (USDA/ERS, 2018).

Currently, 97% of the biofuels produced in the US is corn-based ethanol, which may offer up to a 40% reduction in greenhouse gas (GHG) emission (Canter et al., 2016; Flugge et al., 2017; Hettinga et al., 2009; Wang et al., 2011). Non-food grade sugarbeet (also known as energy beet) is envisioned as one of the most viable feedstock alternatives for two major reasons (Maung and Gustafson, 2011; Nahar and

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Pryor, 2013; Vargas-Ramirez et al., 2013). Firstly, when compared to corn-based ethanol, the use of sugarbeet for biofuel production has less impact on the food supply. Secondly, sugarbeet has the potential to be designated as feedstock for advanced biofuel, which should offer at least 50% net GHG emission reduction relative to gasoline (Foteinis et al., 2011; Jessen, 2012). It has been reported that sugarbeet is the most utilized sucrose containing feedstock for commercial biofuel production in European countries (Grahovac et al., 2011; Nahar and Pryor, 2013; Vargas-Ramirez et al., 2013). In contrast, biofuel production from sugarbeet in the US is nonexistent. Therefore, tremendous opportunities exist to expand sugarbeet production into the nontraditional or underutilized planting areas in the US (Miyake et al., 2015).

Dynamic crop simulation models for sugarbeet can play an important role in understanding plant growth processes (Webb et al., 1997), predicting crop yield, and helping producers and bio-refineries to make operation and business decisions (Tsuji et al., 1998; Vandendriessche and van Ittersum, 1995). When coupled with vadose zone hydrologic models, sugarbeet models can also be used to understand the plant-soil-water interactions in the field and to assess the impact of sugarbeet production on soil health and water quality in nontraditional ecoregions (Ma et al., 2012). There are currently only a few crop models available for simulating sugarbeet growth and production. These models were developed based on either the empirical relationship between pre-harvested samples of sugarbeet and final crop yield or the various plant growth processes involved at different growing stages (Vandendriessche and van Ittersum, 1995). Empirical models include PIEteR (Biemond et al., 1989; Smit et al., 1993), LUTIL (Spitters et al., 1989, 1990) and the model developed by Modig (1992). Process-based models include SUBGRO (Fick, 1971), SUBGOL (Hunt, 1974), SIMBEET (Lee, 1983), SUBEMO (Vandendriessche, 1989, 2000), SUCROS (Spitters et al., 1989), CERES-Beet (Leviel, 2000; Leviel et al., 2003), Broom's Barn (Qi et al., 2005), Green Lab (Vos et al., 2007), Pilote (Taky, 2008), and the model developed by Webb et al. (1997). Recently, a dynamic crop model was developed for predicting potential yield of fodder beet, a sugarbeet cultivar, using the APSIM modeling framework (Khaembah et al., 2017). Detailed reviews of sugarbeet models were provided by Vandendriessche and van Ittersum (1995) and Baey et al. (2014). However, most of these models are restricted to the regions and conditions for which they were originally developed (Vandendriessche and van Ittersum, 1995) and require different file and data structures and different modes of operation (Jones et al., 2003). Therefore, it is inappropriate to apply these models to regions and conditions for which they were not originally designed without proper evaluation (Baey et al., 2014).

The Decision Support System for Agrotechnology Transfer (DSSAT) provides a common platform for transferring production technology from one location to others by integrating the knowledge about soil, climate, crops, and management practices (Hoogenboom et al., 2010, 2017; IBSNAT, 1993a; Jones et al., 1998, 2003; Marin et al., 2015; McNider et al., 2015). DSSAT crop model applications range from on-farm precision management to regional assessments of the impact of climate change and variability (Jones et al., 1998, 2003; Li et al., 2015). DSSAT has also been coupled with the Root Zone Water Quality Model (RZWQM) to simulate the effect of agricultural management practices (e.g., irrigation, fertilization, planting date, and crop rotation) on pesticide transport, water use efficiency, water quality and crop production (Ma et al., 2005, 2006, 2012; Saseendran et al., 2007). The current release of DSSAT Version 4.7 incorporates process-based plant growth models for 42 specific crops but it does not include sugarbeet (Hoogenboom et al., 2017). Therefore, the objectives for this study were: 1) to develop a plant specific model in DSSAT for sugarbeet simulation, 2) to evaluate its performance and transferability using field data, and (3) to conduct uncertainty analysis for the developed model using Parameter Estimation (PEST) software.

## 2. Materials and methods

### 2.1. CSM-CERES-Beet model

The CERES-Beet model (Leviel, 2000; Leviel et al., 2003) was modified and adapted as a plant specific module for the Cropping System Model (CSM) in DSSAT, referred to as "CSM-CERES-Beet". We chose to adapt CERES-Beet into CSM-CERES-Beet mainly because a number of CERES models such as CERES-Maize and CERES-Wheat, have successfully been incorporated into DSSAT. In addition, Baey et al. (2014) indicated that CERES-Beet provided an overall good prediction for plant growth and crop yield after comparing it with four other sugarbeet models, including GreenLab (Vos et al., 2007), LNAS (Cournede et al., 2013), STICS (Brisson et al., 1998), and Pilote (Taky, 2008).

#### 2.1.1. CERES-Beet model

CERES-Beet is a daily step plant growth model, simulating a number of physiological processes such as phenological development, leaf, stem and root growth, biomass accumulation and partition, soil water and nitrogen transformations, nitrogen uptake and partitioning among plant components (IBSNAT, 1993a). The phenological development considers four major events: sowing, germination, emergence, and harvest. Of these four events, germination is a function of soil moisture content, and emergence occurs after 40 Growing Degree Days with a base temperature of 3 °C ($GDD_3$). Net photosynthesis is calculated from intercepted photosynthetically active radiation (*PAR*) by means of radiation use efficiency. The intercepted *PAR* is calculated from leaf area index (LAI) using the classical Beer-Lambert law of radiation transmission in turbid media (Leviel, 2000). The extinction coefficient for Beer-Lambert law is set to 0.65. In the early stage of a growing season, photosynthates are primarily partitioned into leaves made up of sheaths and blades. Blade dry matter demand is calculated from potential leaf area growth assuming a specific leaf area of 50 g dry matter $m^{-2}$, while sheath dry matter carbon demand is 80% of the leaf blade weight. After leaf partitioning, 85% of the remaining photosynthates are allocated to the roots, including the tap root, while the remaining 15% is allocated to the crown. In general, growth of leaves usually ceases after 1500 $GDD_3$, when the tap root becomes the main recipient of the partitioned photosynthates. Thereafter, virtually all of the dry matter (85%) is partitioned to root tuber formation after 1500 $GDD_3$ (Milford et al., 1988; Leviel, 2000). Final marketable sugarbeet yield is computed from total root dry matter assuming that 95% of root is harvested, and that roots have 82% moisture content (Leviel, 2000).

When developing CERES-Beet from CERES-Maize, Leviel (2000) assumed that there is only one plant development stage that is initiated at emergence and continued to harvest date as determined by cultivar parameters. Compared to maize, sugarbeet has no maturity date thus no criterion was chosen to determine the harvest date. Crop compartments were renamed for sugarbeet as leaves (corresponding to maize stems), crowns (instead of husks), seeds (instead of kernel) and roots (Leviel, 2000).

Since CSM-CERES-Beet was developed for simulating only beet root production, not seed production, we made the following changes in CSM-CERES-Beet.

#### 2.1.2. Genetic parameters G2 and G3

Like in other CERES models, genetic parameters G2 and G3 in CERES-Beet are related to seed growth and seed filling. We redefined G2 and G3 to correspond to sugarbeet leaf expansion rate and

**Table 1**
The genetic, ecotype, species, root and soil parameters of the CSM-CERES-Beet model.

| Parameter | Definition | Unit | DSSAT file |
|---|---|---|---|
| Genotype parameters | | | |
| P1 | Growing Degree Days (GDD) from the seedling emergence to the end of the juvenile phase | °C-d | .CUL |
| P2 | Photoperiod sensitivity | $hr^{-1}$ | .CUL |
| P5 | Thermal time from leaf growth to physiological maturity | °C-d | .CUL |
| G2 | Leaf expansion rate during leaf growth stage | $cm^2\,cm^{-2}\,d^{-1}$ | .CUL |
| G3 | Maximum root growth rate | $g\,m^{-2}\,d^{-1}$ | .CUL |
| PHINT | Phyllochron interval, the interval in thermal time between successive leaf tip appearances | °C-d | .CUL |
| Ecotype parameters | | | |
| RUE | Radiation use efficiency | g plant dry matter MJ $PAR^{-1}$ | ECO |
| DSGFT | GDD during effective root growth period | °C-d | ECO |
| Species parameters | | | |
| PARSR | Photosynthetically active solar radiation | MJ SRAD $m^{-2}\,day^{-1}$ | SPE |
| DSGT | Maximum days from sowing to germination before seed dies | days | SPE |
| DGET | GDD between germination and emergence after which the seed dies due to drought | °C-d | SPE |
| SWCG | Minimum available soil water required for seed germination | $cm^3\,cm^{-3}$ | SPE |
| Root parameters | | | |
| PORM | Minimum porosity required for supplying oxygen to roots for optimum growth | – | SPE |
| RLWR | Root length to weight ratio | – | SPE |
| Soil parameters | | | |
| SLPF | Soil fertility factor | – | .SOIL |

maximum root growth rate, respectively. In CERES-Beet, potential leaf area growth (*PLAG*, ($cm^2\,plant^{-1}$)) during the major leaf growth stage is simulated using the following two equations based on the total number of leaves (*TLNO*) produced at that stage (Leviel, 2000).

$$PLAG = 3.0 \times 170 \times TI \times min(AGEFAC, TURFAC, (1 - SATFAC)) \tag{1}$$

$$PLAG = 170 \times 3.5/((XN + 5.0 - TLNO)^2) \times TI \times min(AGEFAC, TURFAC, (1 - SATFAC)) \tag{2}$$

where, *TI* is a fraction of the phyllochron interval (*PHINT*) that occurred as a fraction of the current daily thermal time (*DTT*); *XN* is the number of leaves; *AGEFAC, TURFAC,* and *SATFAC* are the stress factors for nitrogen, drought, and waterlogging respectively. In the CSM-CERES-Beet model constant 170 in Eqs. (1) and (2) was replaced with *G*2, defined as "leaf expansion rate ($cm^2\,cm^{-2}\,d^{-1}$)" to provide more flexibility to simulate variable rates in potential leaf growth for different beet cultivars.

Sugarbeet root growth was modeled by adapting the tuber growth equation in SUBSTOR-Potato (IBSNAT, 1993b) for sugarbeet root formation during the effective root growth periods. The modified equation for root growth (*GRORT*, ($g\,plant^{-1}\,day^{-1}$)) in CSM-CERES-Beet is:

$$GRORT = G3 \times PCO2 \times \frac{ETGT}{PLTPOP} \times min(AGEFAC, TURFAC, (1 - SATFAC)) \tag{3}$$

where, *G*3 is the maximum root growth rate ($g\,m^{-2}\,d^{-1}$), *PCO*2 is the effect of $CO_2$ on growth rate, *ETGT* is the function of soil temperature on root growth, and *PLTPOP* is the population density ($plants\,m^{-2}$).

### 2.1.3. LAI

Besides redefining G2 and G3, we also made changes in calculating LAI. In CERES-Beet, *LAI* ($m^2\,m^{-2}$) is calculated using the following equation:

$$LAI = (PLA - SENLA) \times PLTPOP \times 0.0001 \tag{4}$$

where, *PLA* is the potential leaf area ($cm^2\,plant^{-1}$); *PLTPOP* is the number of plants ($plants\,m^{-2}$); and *SENLA* is the daily normal leaf senescence ($cm^2\,plant^{-1}$). In the original CERES-Beet equation, *SENLA* is set as zero, and only *PLA* and *PLTPOP* are involved in *LAI* calculation. To incorporate leaf senescence in CSM-CERES-Beet, *SENLA* was computed using the daily potential leaf senescence (*PLAS*,($cm^2\,plant^{-1}$)) following SUBSTOR-Potato (IBSNAT, 1993b).

$$SENLA_i = SENLA_{i-1} + PLAS \tag{5}$$

where, $SENLA_i$ is the normal leaf senescence at the current day ($cm^2\,plant^{-1}$) and $SENLA_{i-1}$ is the normal leaf senescence at the previous day. *PLAS* is calculated using the following equation:

$$PLAS = (PLA - SENLA_{i-1}) \times (1 - min(SLFW, SLFC, SLFT, SLFN)) \tag{6}$$

where, *SLFW*, *SLFC*, *SLFT* and *SLFN* are the stress factors (ranging from 0 to 1) for drought, solar radiation, temperature and nitrogen (IBSNAT, 1993b).

### 2.1.4. Leaf numbers

In CSM-CERES-Beet, the number of the leaves grown (*XN*), used to calculate potential leaf area (*PLA*) and *LAI*, is computed as a function of cumulative phyllochron intervals of fully expanded leaves (*CUMPH*) following the AROID-Taro model (Singh et al., 1998):

$$XN = CUMPH + 1.0 \tag{7}$$

where *CUMPH* on the current day, $CUMPH_i$, is calculated from the previous day's values, $CUMPH_{i-1}$, using Eq. (8).

$$CUMPH_i = CUMPH_{i-1} + DTT/(PHINT \times PC) \tag{8}$$

where *DTT* is the daily thermal time, *PHINT* is the phyllochron interval (i.e., the number of GDD required for new leaf emergence, °C-d), *PC* is a factor that is used to calculate the phyllochron interval for the current day.

### 2.1.5. Harvest index

The Harvest Index (*HI*) in the model is computed as the ratio between total dry matter of the root (*Yield*, $kg\,ha^{-1}$) and total dry matter

**Table 2**
Average soil characteristics of the experimental plots for Carrington, North Dakota, USA.

| Depth (cm) | % Sand | % Silt | % Clay | Soil Type | % Organic Matter | Electrical Conductivity mmhos/cm |
|---|---|---|---|---|---|---|
| 0–15 | 45 | 34 | 21 | Loam | 4.0 | 0.16 |
| 15–30 | 47 | 36 | 17 | Loam | 3.6 | 0.25 |
| 30–45 | 49 | 28 | 23 | Loam | | |
| 45–60 | 53 | 28 | 19 | Sandy loam | | |
| 60–120 | 65 | 25 | 10 | Sandy loam | | |

of the entire sugarbeet (*Biomass* (kg ha$^{-1}$) × 10 + *Yield*) following the SUBSTOR-Potato (IBASNAT, 1993b) and AROID-Taro models (Singh et al., 1998).

$$HI = \frac{Yield}{((Biomass \times 10) + Yield)} \tag{9}$$

### 2.1.6. Input data

The input data for the CSM-CERES-Beet model are the standard inputs required by DSSAT. They include site information, daily weather (daily solar radiation, MJ m$^{-2}$, daily maximum and minimum temperature, °C, and daily precipitation, mm), soil profile characteristics, initial soil condition, cultivar characteristics, and field management practices (Hunt et al., 2001; Hoogenboom et al., 2012). The primary field management practices include sugarbeet planting date, planting depth, plant density, the fertilizer application dates, rates, and types, tillage, irrigation application dates and rates, and residue incorporation.

The cultivar coefficients for the CSM-CERES-Beet model include *P*1, *P*2, *P*5, *G*2, *G*3 and *PHINT*. Their definitions and units are listed in Table 1, along with other relevant DSSAT model parameters.

## 2.2. Field experiments and data

### 2.2.1. Carrington, North Dakota, USA

CSM-CERES-Beet was first evaluated with experimental data collected at the Carrington Research Extension Center (47.510 N, −99.123 W), Carrington, North Dakota (ND), USA. In this, a specific cultivar of sugarbeet (proprietary materials from Betaseed, Shakoppe, MN, denoted as CREC hereafter) was cultivated in rotation with other crops (not shown) in a randomized complete block design with four replicates, to test the effects of crop rotation and tillage practices on soil health and water quality. Twelve plots (12.3 m × 15.2 m) were cultivated for sugarbeet production using recommended practices (Khan, 2014). Plots were sown in 2014, 2015, and 2016 as illustrated in Fig. A1. The soil properties of the Carrington, ND experimental plots are provided in Table 2. Field management data for 2014 and 2016 are provided in Table 3, while that for 2015 is provided in Table A1. Soil texture was determined using the hydrometer method (Gee and Or, 2002), while soil organic matter (OM) content was determined by loss of weight on ignition at 360 °C (Combs and Nathan, 2015), and electrical conductivity by a conductivity meter in a 1:1 soil:water suspension (Whitney, 2015). All lab analyses were conducted at the Agvise Laboratories, Northwood, ND. The minimum weather inputs required to run the CSM-CERES-Beet were collected by the North Dakota Agricultural Weather Network (NDAWN) station located at Carrington, ND, USA (47.509 N, −99.132 W).

A strong damaging wind gust (~ 22.5 m s$^{-1}$) occurred around 65 days after planting during the 2015 growing season (July 28–29, 2015). Since CSM-CERES-Beet was not designed to simulate the damages caused by unexpected events such as strong wind gusts or freezing temperature, the field management data and model simulation results for 2015 are not discussed in the main text, but provided in the Appendix.

Each year, 6 out of 12 plots were randomly selected to collect plant growth data from. In each plot, eight sugarbeet plants were harvested to collect samples of leaf, stems, and roots periodically for top and root mass measurements. Sample fresh and dry masses were measured and leaf numbers were counted. The LAI was measured for each selected plot using the ground-based measurement method based on radiative transfer theory (Hemayati and Shirzadi, 2011). Field data were collected on 4 or 5 different dates during the 2014 growing season, on 8 different dates in 2015, and on 9 different dates in 2016. The 2016 data were used for model calibration and the 2014 and 2015 data were used for model evaluation.

### 2.2.2. Bucharest, Romania

The CSM-CERES-Beet model was also evaluated using field data collected in Bucharest, Romania, in 1997 and 1998 for a different cultivar, i.e., Emma, and different environmental conditions to determine the model's transferability. The Romanian data were used for the development of the original CERES-Beet model (Leviel, 2000). The soils in the experimental sites were reddish brown forest soil with silt-clay texture (38% clay), and pH value of 6.8. The study region climate is continental, with average temperatures of −1.2 °C during the winter, 10.4 °C during the spring and autumn, and 21.3 °C during the summer. Annual average rainfall is 550 mm. Sugarbeet was planted on 29th April 1997 and 4th April 1998 in five experimental plots of 42 m$^2$ area that comprised 14 rows of crop, with a 50 cm row spacing. The nitrogen fertilization rate was 300 kg N ha$^{-1}$. Irrigation was also applied to obtain plant growth and yield under non-limiting water conditions. Further details on the field experiment and the experimental data that were

**Table 3**
Field management for sugarbeet experimental plots for Carrington, North Dakota, USA.

| Field management | 2014 | 2016 |
|---|---|---|
| Planting date | May 27 | May 12 |
| Planting stand | 74,000 seeds ha$^{-1}$ (29,959 seeds ac$^{-1}$) | 74,000 seeds ha$^{-1}$ (29,959 seeds ac$^{-1}$) |
| Fertilizer | N (added as Urea): 112.1 kg N ha$^{-1}$ (100 lb. N ac$^{-1}$)<br>P (added as MAP): 22.4 kg P ha$^{-1}$ (20 lb. P ac$^{-1}$)<br>S (added as AS): 11.2 kg S ha$^{-1}$ (10 lb. S ac$^{-1}$) | N (added as Urea): 112.1 kg N ha$^{-1}$ (100 lb. N ac$^{-1}$)<br>P (added as MAP): 22.4 kg P ha$^{-1}$ (20 lb. P ac$^{-1}$)<br>S (added as AS): 11.2 kg S ha$^{-1}$ (10 lb. S ac$^{-1}$) |
| Fertilizer application date | May 26 | May 11 |
| Harvesting | October 17 | October 11 |

collected can be found in Leviel (2000).

#### 2.2.3. Sugarbeet field data for yield simulation

The CSM-CERES-Beet model was further applied to simulate the yields of five different sugarbeet cultivars (proprietary seed materials from Betaseed, Shakopee, MN and Crystal Beet Seed, Moorhead, MN) grown in Prosper and Hickson, ND, in 2016. Both cities are within 240 km (~150 miles) from Carrington, ND. The soil type is clay loam in Prosper, ND, and silt clay in Hickson, ND. Weather data used for model simulation for the study sites in Prosper, ND, and Hickson, ND, were collected from NDAWN stations located in Prosper, ND (47.002 N, −97.115 W) and Leonard, ND (46.732 N, −97.241 W), respectively. This study was conducted to evaluate the model's performance in simulating yields of different sugarbeet cultivars from different seed companies. The planting rate was 150,237 seeds $ha^{-1}$ (60,825 seeds $ac^{-1}$) at both sites. Urea was applied at the rate of 24.66 kg $ha^{-1}$ two days before planting and no irrigation was applied.

The same five cultivars (denoted as Cultivars A to E) were planted at both sites and CSM-CERES-Beet was first calibrated for different cultivars using the Prosper, ND field data and then evaluated using the Hickson, ND data. Only genetic parameters were calibrated, while other parameters were kept as the same as those calibrated for the 2016 Carrington dataset.

### 2.3. Model calibration and evaluation

The calibration of the CSM-CERES-Beet model was conducted using PEST (Parameter ESTimation), which is a model independent parameter estimation software package (Doherty, 2010). The objective function to be minimized by PEST was expressed as:

$$\phi(b) = [y - y'(b)]^T Q [y - y'(b)] \tag{10}$$

where $Q$ is a diagonal weight matrix with the squared observation weights on the diagonal, $y$ is a vector of field observations, $y'(b)$ is a vector of model outputs from the CSM-CERES-Beet model, based on parameter vector $b$, and collocated with the observations in $y$, and $T$ indicates matrix transpose. The parameters that minimize this equation were obtained by using the Gauss-Marquardt-Levenberg (GML) gradient search algorithm (Doherty, 2010).

A weighted multicomponent objective function was constructed, similar to that used in Lin and Radcliffe (2006) and Necpálová et al. (2015). Each observation was assigned to an observation group that formed a component of the objective function (Eq. (10)). An inter-group weighting strategy was defined using the PEST utility PWTADJ1 (Doherty and Welter, 2010) such that all the groups contributed equally to the objective function at the beginning of the estimation process. This ensured that each observation group contributed equally to the process, irrespective of the number of observations per group, units of measure, and other confounding factors.

The Carrington calibration dataset comprised 35 field observations divided into four different observation groups (leaf number count, LAI, and top and root weights). The top and root weights are dry masses of all above- and below-ground plant parts, respectively. On a given sampling date, the field observations for each group were taken as the *average* of the data collected. The Bucharest calibration dataset comprised 32 observations grouped into three different observation groups (LAI, leaf weight, and root weights).

Fifteen parameters were selected for adjustment by PEST based on prior knowledge that CSM-CERES-Beet model was sensitive to these parameters (Anar et al., 2017). For these 15 parameters, default values as well as lower and upper bounds were specified based on information from literature. All the adjustable parameters were log-transformed to strengthen the linear relationships between parameters and model simulated values (Doherty and Hunt, 2010). The truncated singular value decomposition (SVD) regularization method was used to ensure numerical stability and the level of truncation was calculated automatically based on a stability criterion (Aster et al., 2005; Moore and Doherty, 2005; Tonkin and Doherty, 2005).

### 2.4. Evaluation of model performance

Best parameter values obtained from inverse modeling were used to run CSM-CERES-Beet, and prediction errors were calculated for the calibration and evaluation datasets. Model performances were evaluated by comparing the simulated and *average* observed values of the sugarbeet root mass, top mass, leaf number and LAI. Various statistics have been used to assess DSSAT performance (Timsina and Humphreys, 2006; Rinaldi et al., 2007; Yang et al., 2014), and reviewed by others (Kobayashi and Salam, 2000). However, each statistic addresses only a specific aspect of a model's performance and no single statistic provides an overall model evaluation. We calculated root mean square error (*RMSE*), relative root mean square error (*rRMSE*), and Nash-Sutcliffe Efficiency (*NSE*) as indicators of model fit (e.g., Gaydon et al., 2017). *rRMSE* is the root mean square error normalized to the mean of the observed values (Eq. (11)):

$$rRMSE = \frac{\sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - y_i')^2}}{|\bar{y}|} \tag{11}$$

where, $\bar{y}$ is the mean of the observed values, $y_i$ is the observed value, $y_i'$ is the simulated value and $m$ is the number of observations. Moriasi et al. (2007) suggest a value of ≤0.70 for *rRMSE* considered acceptable for model performance.

*NSE* is calculated using Eq. (12):

$$NSE = 1 - \frac{\sum_{i=1}^{m}(y_i - y_i')^2}{\sum_{i=1}^{m}(y_i - \bar{y})^2} \tag{12}$$

where the symbols are defined as the same in Eq. (11). The value of *NSE* varies between -∞ to 1 with higher values indicating a better fit (Legates and McCabe, 1999). A value of 1 indicates a perfect fit, while a value of 0 suggests the model is only as good as the mean of the observations and negative values suggest the mean of the observations is a better predictor than the model.

### 2.5. Predictive uncertainty analysis

Predictive uncertainty analysis of CSM-CERES-Beet was also conducted using the utilities associated with PEST. First, the prior uncertainty was established using the RANDPAR utility, which was employed to generate 1000 random parameter sets based on the prior covariance matrix of the 15 adjustable CSM-CERES-Beet parameters. The prior covariance matrix was constructed by assuming that model parameters are independent (Anar et al., 2017) and normally or log-normally distributed and that their bounds span their 95% confidence intervals (CI's) (Doherty, 2013). Next, these 1000 random parameters sets were used to run CSM-CERES-Beet and the outputs of these model runs were used to compute the 95% CI's of various model predictions.

Second, CSM-CERES-Beet was then evaluated for posterior uncertainty using the null space Monte Carlo calibration-constrained method, facilitated by RANDPAR and PNULPAR utilities. The premise of the null space Monte Carlo method is that the parameter space can be properly decomposed into orthogonal "calibration solution space (comprised of $p$ linear combinations of parameters informed by the calibration dataset)" and "calibration null space (comprised of $d$-$p$ calibration-insensitive parameter combinations, where $d$ is the total

**Table 4**
CSM-CERES-Beet calibration and evaluation using the Carrington (North Dakota, USA) dataset.

| Observation Group | Root mean square error (*RMSE*) | | Relative root mean square error (*rRMSE*) | | Nash-Sutcliffe Efficiency (*NSE*) | |
|---|---|---|---|---|---|---|
| | Calibration (2016) | Evaluation (2014) | Calibration (2016) | Evaluation (2014) | Calibration (2016) | Evaluation (2014) |
| Leaf area index | 0.489 | 0.604 | 0.188 | 0.318 | 0.914 | 0.881 |
| Leaf number | 2.15 | 2.15 | 0.127 | 0.168 | 0.892 | 0.769 |
| Top weight | 627.9 | 717.8 | 0.203 | 0.276 | 0.872 | 0.896 |
| Root weight | 1167.0 | 1177.2 | 0.228 | 0.194 | 0.940 | 0.976 |

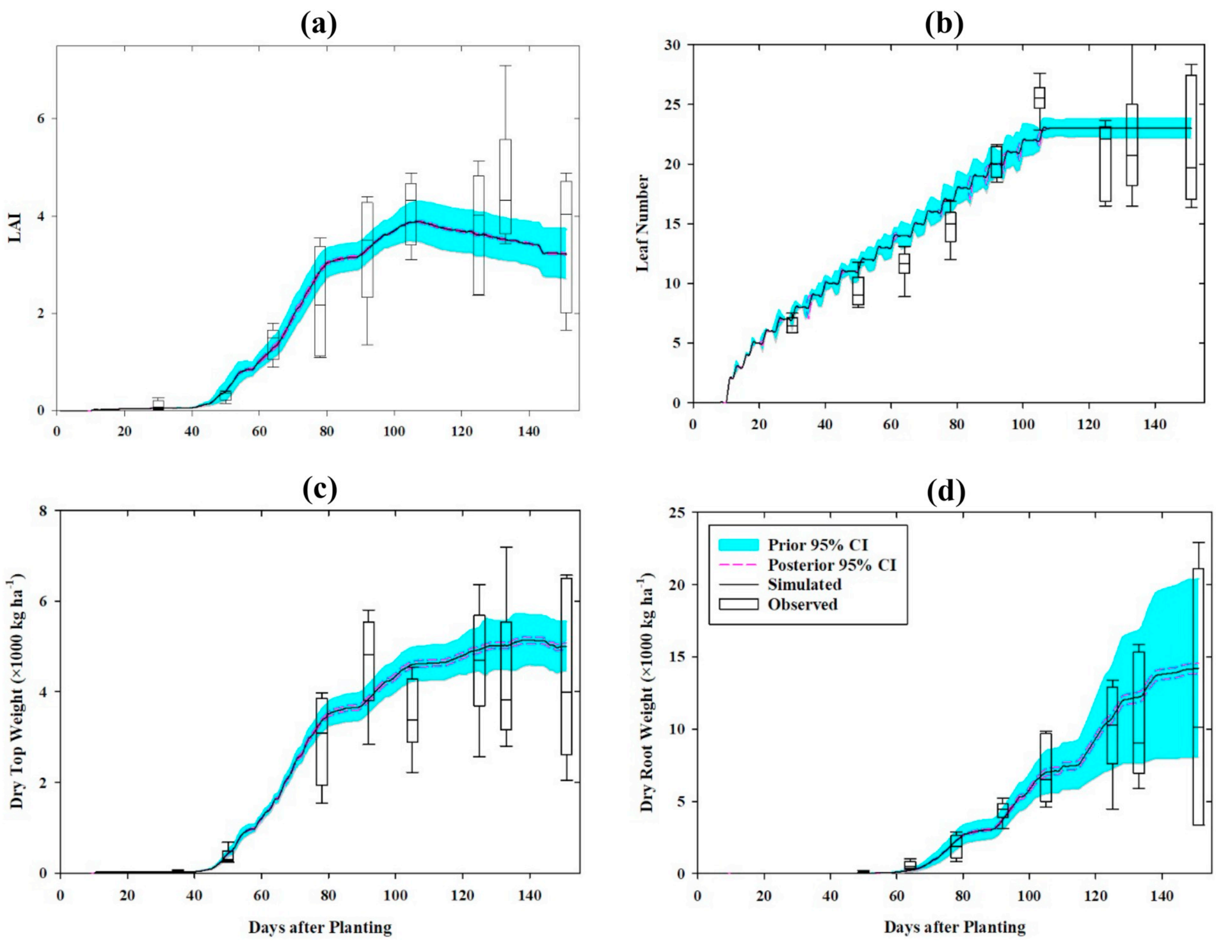


**Fig. 1.** Model-simulated and observed values of (a) leaf area index (LAI), (b) leaf number, (c) dry top weight, and (d) dry root weight for model calibration (2016) and their 95% confidence intervals (CI's). Notes: Observed values are plotted in the boxplots with the medians shown as the lines within the boxes, the 25th and 75th percentiles as the tops and bottoms of the boxes, and the 5% and 95% percentiles as the whiskers below and above the boxes.

number of parameters)" (Moore and Doherty, 2005). In this method, many random realizations of parameter sets are first generated using the RANDPAR utility in conjunction with the prior parameter covariance matrix (Doherty, 2016b). For each realization, the calibrated parameter field is then subtracted from the randomly generated parameter field. The resulting parameter difference is projected into the calibration null space, and the projected difference is then re-added to the calibrated parameter field. These steps are implemented using the PNULPAR utility. For the posterior uncertainty analysis of the calibrated CSM-CERES-Beet, we used the RANDPAR and PNULPAR utilities to create 1000 random calibration-constrained parameter sets. These parameter sets were then used to run CSM-CERES-Beet and the outputs of the model were used to calculate the 95% CI's. The readers are referred to Doherty (2007, 2016a, 2016b) and Doherty and Hunt (2010) for details about the null space Monte Carlo analysis method and the uses of the RANDPAR and PNULPAR utilities.

## 3. Results and discussion

### 3.1. CSM-CERES-Beet calibration, evaluation and uncertainty analysis

The CSM-CERES-Beet model was calibrated against the 2016 field experimental data collected at Carrington, ND, USA, using PEST. Model calibration was able to reduce the total objective function by 45% and total sum of weighted squared residuals by 16%. The parameter values obtained from the model calibration were then used for model evaluation with the 2014 field data. Table 4 lists the goodness of fit statistics for model calibration (2016) and evaluation (2014).

In terms of *NSE*, the model did very well for all four plant growth variables (i.e. LAI, leaf number, top weight and root weight). All of the

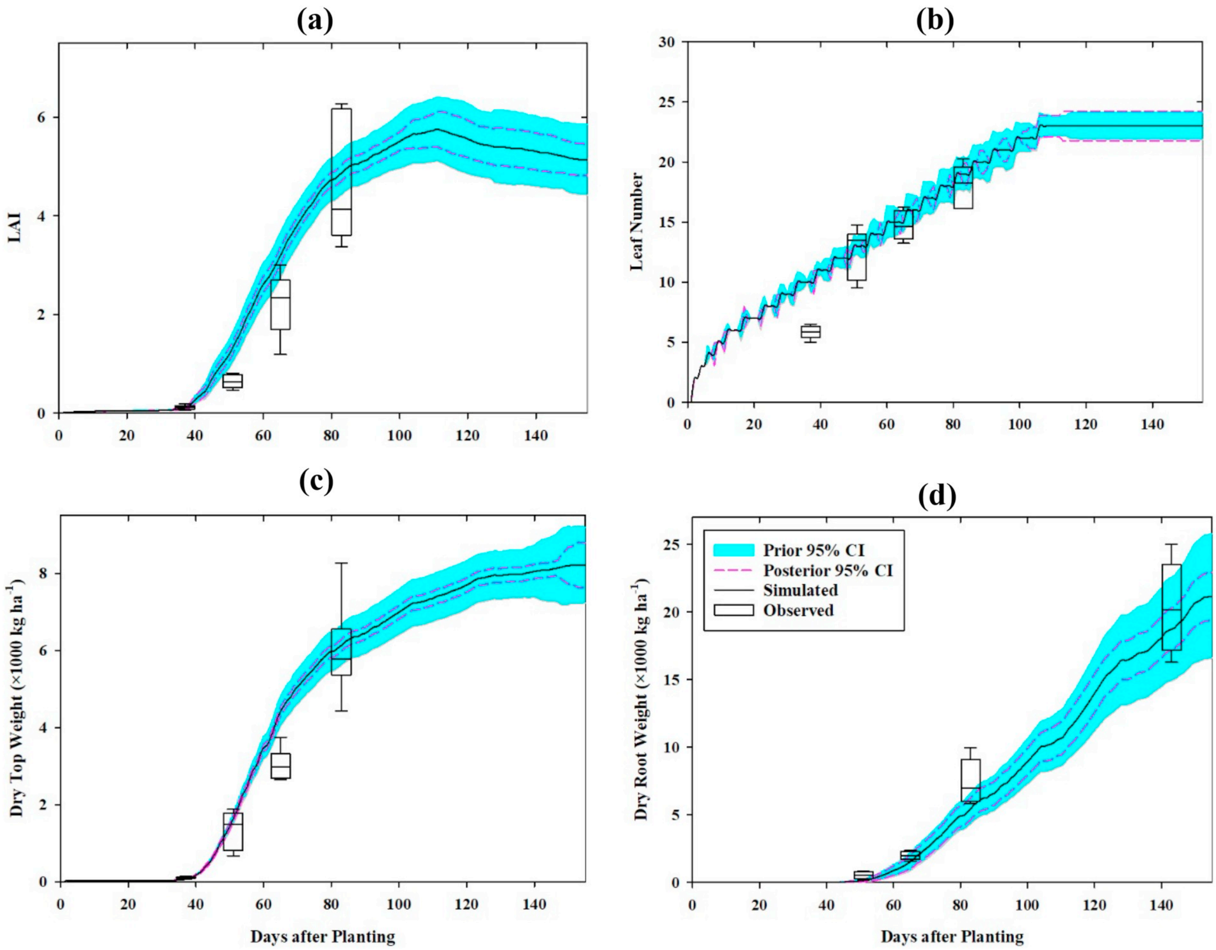


**Fig. 2.** Model-simulated and observed values of (a) leaf area index (LAI), (b) leaf number, (c) dry top weight, and (d) dry root weight for model evaluation (2014) and their 95% confidence intervals (CI's). Notes: Observed values are plotted in boxplots with the medians shown as the lines within the boxes, the 25th and 75th percentiles as the tops and bottoms of the boxes, and the 5% and 95% percentiles as the whiskers below and above the boxes.

*NSE* values were > 0.76 for both model calibration and evaluation. In terms of *rRMSE*, the model did very well for model calibration and reasonably well for model evaluation. Most *rRMSE*'s were < 0.3 except for LAI in 2014.

The graphical comparisons of the model-simulated and observed plant growth variables are also shown in Fig. 1 for 2016 and Fig. 2 for 2014, along with the prior and posterior 95% CI's for model simulations of these plant growth variables. The model-simulated values for both 2014 and 2016 tracked the median values of the observed variables except for leaf numbers in 2016, for which the CSM-CERES-Beet slightly over-predicted the median observed values for most of the growing season (Fig. 1b).

It is not surprising that the prior 95% CI's are wider than the posterior ones for all model predictions (Fig. 1 and Fig. 2). The model calibration process was able to reduce model predictive uncertainties by constraining those model parameters that have significant bearing on model predictions into a narrower space (Moore and Doherty, 2005). It should be noted that only parametric uncertainty is considered in our predictive uncertainty analysis. For example, other sources of uncertainties, such as uncertainties from model inputs like soil or weather data, and uncertainties from model structure (Beck, 1987; Palosuo et al., 2011) were not considered in our study.

It is also interesting to note that the posterior CI's of leaf number are narrower than those of other plant growth variables and yet CSM-CERES-Beet consistently over-predicted final leaf numbers almost throughout the entire growing season (Fig. 1b). However, the observed leaf number also showed a significant variability, especially towards full canopy cover. The model requires further testing with more precise data sets and might require further model improvement. CSM-CERES-Beet follows the AROID-Taro model (Singh et al., 1998) to simulate leaf number (Eq. (7) & (8)) because sugarbeet and taro have a similar final leaf number (approximately 22–30) per mature plant (Fick, 1971; Goenaga, 1995). However, *PC*, a factor used to compute the fraction of phyllochron interval at the present day in Eq. (8), is currently a

**Table 5**
CSM-CERES-Beet evaluation using the Bucharest (Romania) dataset.

| Observation Group | Root mean square error (*RMSE*) | | Relative root mean square error (*rRMSE*) | | Nash-Sutcliffe Efficiency (*NSE*) | |
|---|---|---|---|---|---|---|
| | Calibration (1997) | Evaluation (1998) | Calibration (1997) | Evaluation (1998) | Calibration (1997) | Evaluation (1998) |
| Leaf area index | 0.455 | 0.958 | 0.122 | 0.263 | 0.930 | 0.740 |
| Leaf weight | 650.6 | 801.9 | 0.285 | 0.358 | 0.775 | 0.144 |
| Root weight | 2046.3 | 3207.8 | 0.238 | 0.268 | 0.930 | 0.834 |

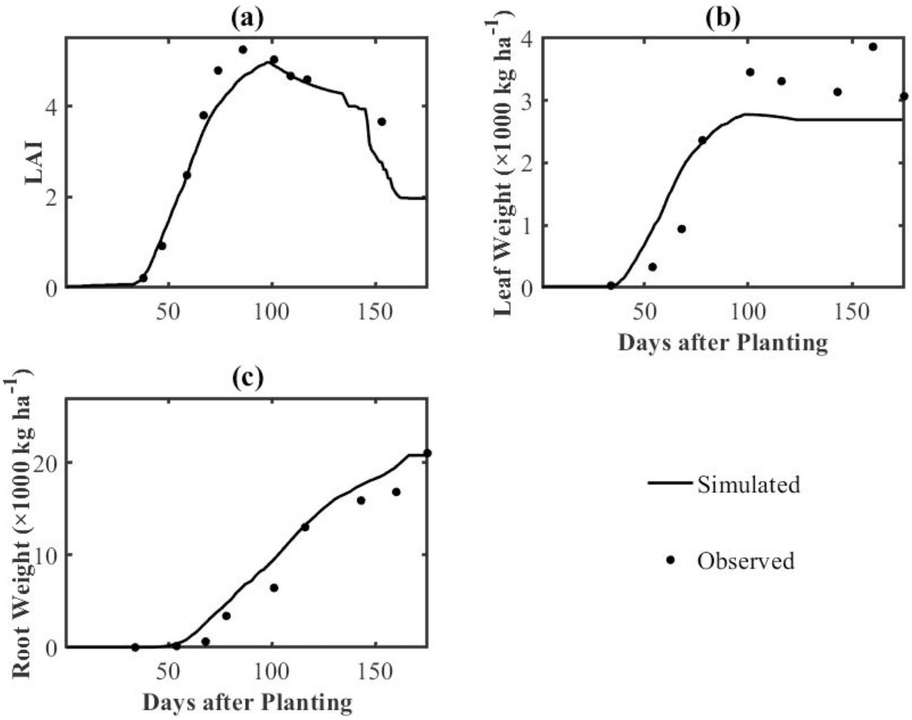


**Fig. 3.** Graphical comparison of model-simulated with observed values for (a) leaf area index (LAI), (b) leaf weight, and (c) root weight for 1997 in Bucharest, Romania.

common parameter for all crop models included in DSSAT. This parameter may be varied for different crops to improve leaf number simulation.

### 3.2. CSM-CERES-Beet transferability

To examine CSM-CERES-Beet's transferability, the model's performance was also evaluated with the experimental data collected in Bucharest, Romania, in 1997 and 1998 (Table 5). The model was *re*-calibrated for the 1997 Bucharest data and evaluated using the Bucharest 1998 data. The goodness-of-fit statistics are shown in Table 5. The CSM-CERES-Beet model was able to match the Bucharest dataset reasonably well. The *NSE* values were all > 0.74, except for the 1998 Bucharest leaf weight; while all *rRMSE* were < 0.36.

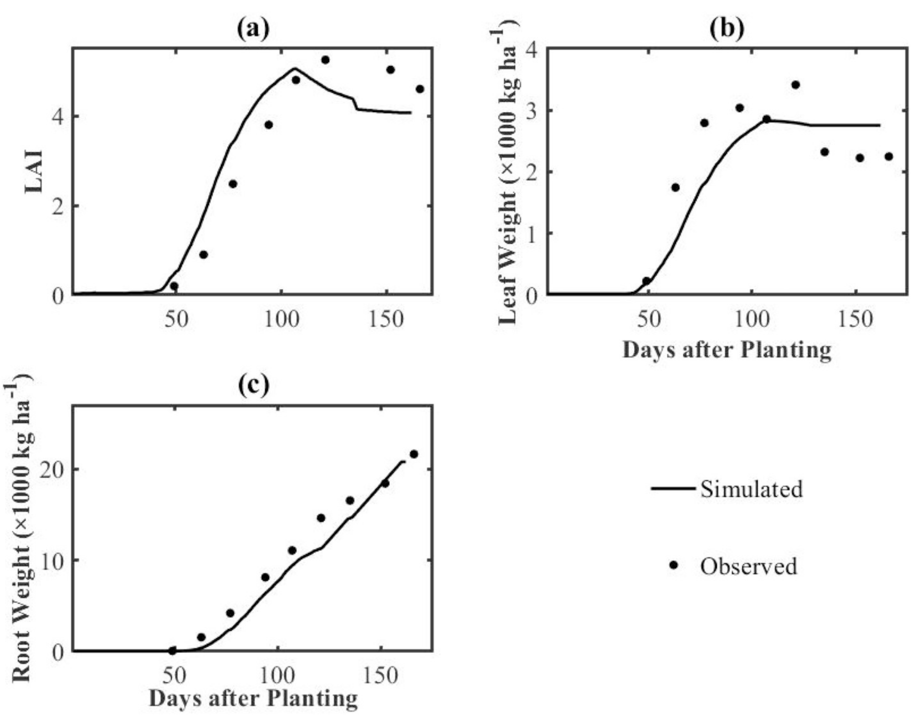


**Fig. 4.** Graphical comparison of model-simulated with observed values for (a) leaf area index (LAI), (b) leaf weight, and (c) root weight for 1998 in Bucharest, Romania.

**Table 6**
Final genetic parameters for the CSM-CERES-Beet bases on calibration for the two study sites.

| Parameter (unit) | Definition | Initial value | Lower bound | Upper bound | Calibrated for CREC cultivar | Calibrated for Emma cultivar |
|---|---|---|---|---|---|---|
| *P1* (°C-d) | *Growing Degree Days (GDD) from the seedling emergence to the end of the juvenile phase* | *920* | *920* | *1100* | *940* | *969* |
| P2 ($hr^{-1}$) | Photoperiod sensitivity | 0.001 | 0.00 | 0.01 | 0.001 | 0.001 |
| P5 (°C-d) | Thermal time from leaf growth to physiological maturity | 700 | 660 | 900 | 700 | 730 |
| *G2* ($cm^2 cm^{-2} d^{-1}$) | *Leaf expansion rate during leaf growth stage* | *160* | *160* | *220* | *220* | *160* |
| *G3* ($g\,m^{-2}\,day^{-1}$) | *Maximum root growth rate* | *20* | *20* | *50* | *37.5* | *25.2* |
| *PHINT* (°C) | *Phyllochron interval, the interval in thermal time between successive leaf tip appearances* | *38.9* | *38* | *49* | *42.0* | *43.4* |
| *RUE* (*g plant dry matter MJ PAR*$^{-1}$) | *Radiation use efficiency* | *2.8* | *2.8* | *4.2* | *3.7* | *3.3* |
| DSGFT (°C-d) | GDD during effective root growth period | 170 | 160 | 200 | 170 | 170 |
| PARSR (MJ SRAD $m^{-2}\,day^{-1}$) | Photosynthetically active solar radiation | 0.48 | 0.46 | 0.52 | 0.52 | 0.52 |
| DSGT (days) | Maximum days from sowing to germination before seed dies | 40 | 35 | 45 | 40.0 | 40.0 |
| DGET (°C) | Growing degree days between germination and emergence after which the seed dies due to drought | 150 | 140 | 160 | 150 | 150 |
| SWCG ($cm^3\,cm^{-3}$) | Minimum available soil water required for seed germination | 0.02 | 0.01 | 0.04 | 0.02 | 0.02 |
| PORM (unitless) | Minimum porosity required for supplying oxygen to roots for optimum growth | 0.05 | 0.01 | 0.10 | 0.05 | 0.05 |
| RLWR (unitless) | Root length to weight ratio | 0.82 | 0.82 | 1.82 | 0.84 | 0.84 |
| SLPF (unitless) | Soil fertility factor | 1.0 | 0.7 | 1.0 | 1.0 | 1.0 |

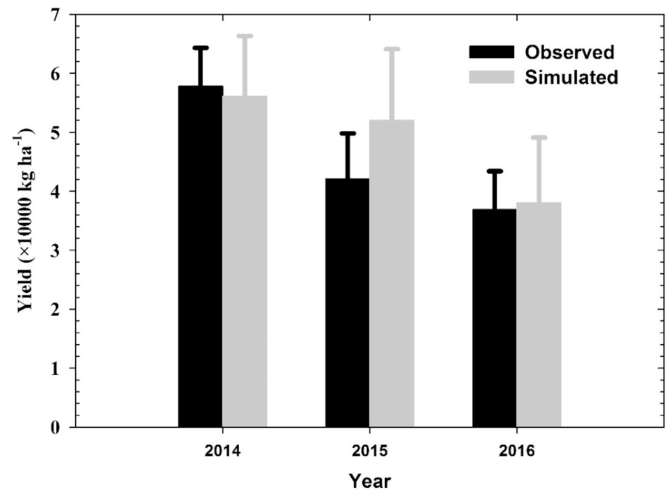


**Fig. 5.** Observed and simulated yield of sugarbeet planted at the Carrington, North Dakota, USA. Note: The vertical bars are average measured or model-simulated yields and the short horizontal lines are standard deviations.

The graphical comparison of model-simulated with the observed plant growth variables for the Bucharest dataset is shown for 1997 in Fig. 3 and for 1998 in Fig. 4. In 1997, the model performed exceptionally well in simulating LAI (Fig. 3a) and root weight (Fig. 3c), but consistently under-predicted leaf weight late in the season (Fig. 3b). In 1998, the model did well in terms of simulating leaf weight (Fig. 4b), but under-predicted LAI after leaf senescence later in the season (Fig. 4a). The model also did reasonably well in terms of simulating root weight (Fig. 4c).

A comparison of the parameter values calibrated with the 2016 Carrington and the 1997 Bucharest datasets is shown in Table 6. Out of the 15 adjustable parameters, five parameters had taken different values when CSM-CERES-Beet was calibrated for the two different cultivars. The parameters with different values are italicized in Table 6. Four parameters (i.e., *P*1, *G*2, *G*3, and *PHINT*) are genetic parameters that are expected to vary by cultivar while *RUE* (radiation use efficiency) is a parameter that is expected to be different for different ecotypes within a species. Table 6 shows that the CREC sugarbeet cultivar required smaller values for *P*1 (thermal time from emergence to end of juvenile phase) and *PHINT* (phyllochron interval) than the Emma sugarbeet cultivar, indicating that the CREC cultivar requires less time to complete its first stage of growth (emergence to end of juvenile phase) and less thermal time between successive leaf tip emergence. Compared to the Emma cultivar, the CREC cultivar required greater values for *G2* (leaf expansion rate) and *G3* (maximum root growth rate), indicating greater leaf expansion and root growth for the CREC cultivar. The CREC cultivar also has greater values for *RUE*. Leviel (2000) found *RUE* values ranged from 2.47 to 4.2 g $MJ^{-1}$ among sugarbeet cultivars, but the reasons are not well understood (Li et al., 2002). These results indicate that the CSM-CERES-Beet model can be used for different soil and weather conditions. However, the genetic coefficients are unique for local cultivars and must be determined for each cultivar similar to the other DSSAT crop models (Confalonieri et al., 2016; Hoogenboom et al., 2017).

### 3.3. Sugarbeet yield simulation

The calibrated CSM-CERES-Beet model can be used to simulate sugarbeet growth and development and predict final yield. Fig. 5 compares the model-simulated and observed yield for the sugarbeet planted in Carrington, ND research plots, including the year 2015 which had a significant windstorm event that damaged the crop. The observed yield was the average fresh yield harvested from the twelve experimental plots. The CSM-CERES-Beet model output sugarbeet yield in terms of dry weight, which was converted into fresh yields assuming 82%

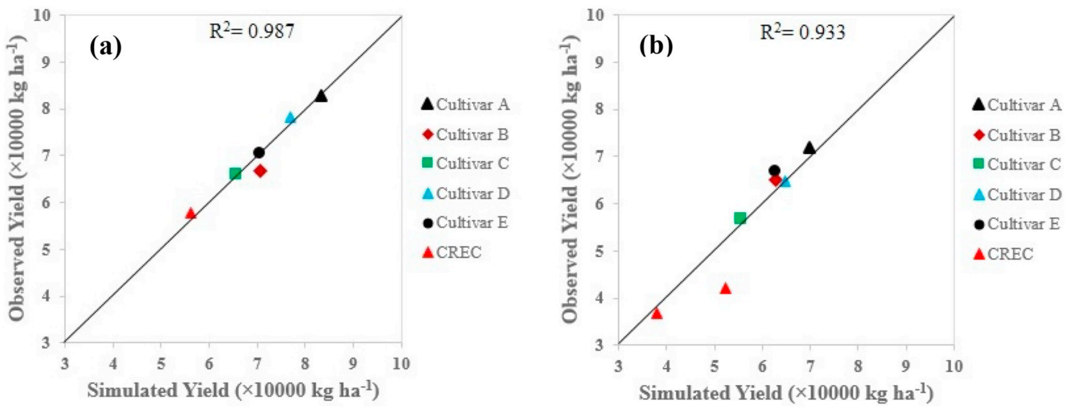


**Fig. 6.** Observed and simulated sugarbeet yield with CSM-CERES-Beet model for (a) model calibration, and (b) model evaluation for six sugarbeet cultivars planted in North Dakota, USA in 2014–2016. Note: Diagonal solid line indicates 1:1 reference line.

**Table 7**
Genetic parameters for the five cultivars used in Prosper and Hickson, ND.

| Parameter (unit) | Cultivar A | Cultivar B | Cultivar C | Cultivar D | Cultivar E |
|---|---|---|---|---|---|
| P1 (°C-d) | 940 | 990 | 990 | 960 | 970 |
| P2 ($hr^{-1}$) | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |
| P5 (°C-d) | 700 | 730 | 700 | 700 | 700 |
| G2 ($cm^2\ cm^{-2} d^{-1}$) | 220 | 220 | 170 | 170 | 220 |
| G3 ($g\ m^{-2}\ day^{-1}$) | 37.5 | 33.5 | 27.5 | 37.5 | 32.5 |
| PHINT (°C) | 38.90 | 43 | 43 | 39 | 43.40 |

moisture content in the beets. The model-simulated yield standard deviations were estimated based on the prior uncertainty analysis described previously. Fig. 5 shows that the CSM-CERES-Beet model was able to closely simulate sugarbeet yield for 2014 and 2016. However, the model over-estimated sugarbeet yield for 2015, primarily because of the wind gust damage that occurred early during the growing season and resulted in lower observed yield.

The CSM-CERES-Beet model was also applied to simulate the yield of five different sugarbeet cultivars grown in Prosper and Hickson, ND, in 2016. The average observed and model-simulated yield for these five sugarbeet cultivars and the CREC cultivar planted in 2014–2016 are shown in Fig. 6. The fact that the simulated vs. observed yield fall on or close to the 1:1 line ($R^2$ = 0.987 for calibration and $R^2$ = 0.933 for evaluation) is a good indication of CSM-CERES-Beet's capability of simulating yield for different sugarbeet cultivars. The final calibrated genetic parameters for the five cultivars used in Prosper and Hickson, ND are presented in Table 7.

## 4. Conclusions

The CSM-CERES-Beet crop model for the simulation of sugarbeet growth, development and yield is based on modifications of the CERES-Beet model. The model was evaluated against two sets of plant growth data collected for different sugarbeet cultivars grown in two different regions and under different conditions – one in Romania (Southeastern Europe) during 1997–1998 and the other in North Dakota, USA (North America) during 2014–2016. The CSM-CERES-Beet model performed well in simulating LAI, leaf number, leaf or top weight, and root weight for both datasets. The model was also successfully applied to simulate the yields for five different sugarbeet cultivars grown in North Dakota, USA in 2016, with a range of observed yields between 56,670 to 82,719 kg $ha^{-1}$. The evaluation for the model's transferability suggested that the model's genetic parameters should be *re*-calibrated when CSM-CERES-Beet is used to simulate different sugarbeet cultivars.

The CSM-CERES-Beet has some limitations because the original model was based on the CERES-Maize model. Some assumptions and simplifications should be further improved when additional data and new research findings become available. The current model also does not handle nitrogen uptake and thus response, which is another area that should be improved in the future. Nevertheless, as the sugarbeet production may be expanded into the nontraditional planting areas in the region due to potential demand for biofuel production, the DSSAT model enhanced with the new sugarbeet module can be used for in-season yield forecasting and economic analysis.

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## Appendix A

For 2015, the CSM-CERES-Beet consistently over-predicted the observed values between the 67th to 100th days after planting for all four plant variables (Fig. A2). This might be caused by a strong wind gust (~ 22.5 m $s^{-1}$) occurring around the 65th days after planting (July 28–29, 2015). The CSM-CERES-Beet was not designed to simulate the damages caused by unexpected events such as strong wind gusts or freezing temperature, which was also noted by Leviel (2000) when discussing the limitations of CERES-Beet.

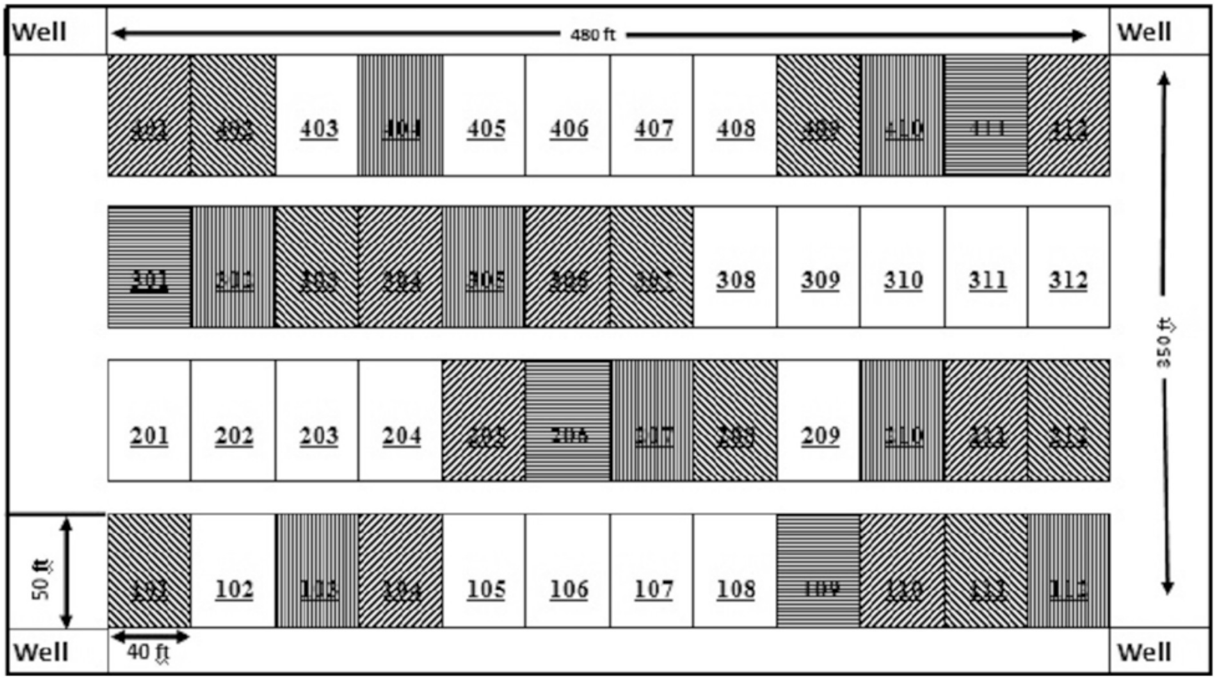


**Fig. A1.** Schematic of field experimental plots planted for sugarbeet in: 2014 (upward slanted fill), 2015 (downward slanted fill), 2016 (vertical fill) and all 3 years (horizontal fill).

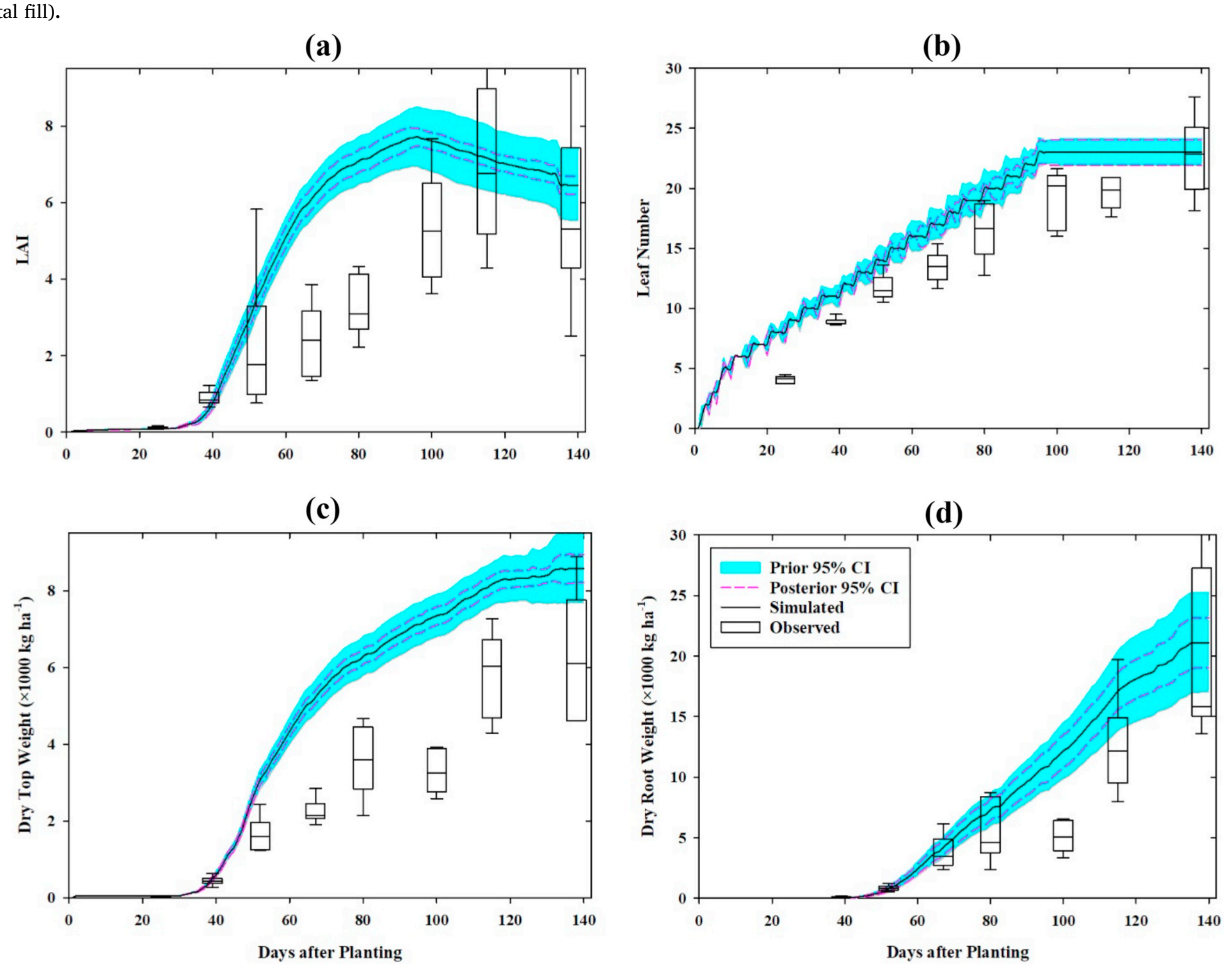


**Fig. A2.** Model-simulated and observed values of (a) leaf area index (LAI), (b) leaf number, (c) dry top weight, and (d) dry root weight for model evaluation (2015) and their 95% confidence intervals (CI's). Notes: Observed values are plotted in the boxplots with the medians shown as the lines within the boxes, the 25th and 75th percentiles as the tops and bottoms of the boxes, and the 5% and 95% percentiles as the whiskers below and above the boxes.

Table A1
Field management for 2015 sugarbeet experimental plots for Carrington, North Dakota, USA.

| Field management | 2015 |
|---|---|
| Planting date | June 01 |
| Planting stand | 122, 932 seeds ha$^{-1}$ (49,749 seeds ac$^{-1}$) |
| Fertilizer | N (added as Urea): 112.1 kg N ha$^{-1}$ (100 lb. N ac$^{-1}$) |
| | P (added as MAP): 22.4 kg P ha$^{-1}$ (20 lb. P ac$^{-1}$) |
| | S (added as AS): 11.2 kg ha$^{-1}$ (10 lb. S ac$^{-1}$) |
| Fertilizer application date | May 31 |
| Harvesting | October 17 |

Table A2
CSM-CERES-Beet evaluation using the Carrington (North Dakota, USA) dataset (2015).

| Observation Group | Root mean square error (*RMSE*) | Relative root mean square error (*rRMSE*) | Nash-Sutcliffe Efficiency (*NSE*) |
|---|---|---|---|
| Leaf area index | 1.50 | 0.444 | 0.569 |
| Leaf number | 3.52 | 0.243 | 0.630 |
| Top weight | 1295.4 | 0.444 | 0.637 |
| Root weight | 2367.0 | 0.396 | 0.867 |

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