SUGARBEET MODEL DEVELOPMENT FOR SOIL AND WATER QUALITY ASSESSMENT

A Dissertation
Submitted to the Graduate Faculty
of the
North Dakota State University
of Agriculture and Applied Science

By

Mohammad Jahidul Anar

In Partial Fulfillment of the Requirements
for the Degree of
DOCTOR OF PHILOSOPHY

Major Department:
Agricultural and Biosystems Engineering

February 2018

Fargo, North Dakota

North Dakota State University
Graduate School

Title

SUGARBEET MODEL DEVELOPMENT FOR SOIL AND WATER QUALITY ASSESSMENT

By

Mohammad Jahidul Anar

The Supervisory Committee certifies that this ***disquisition*** complies with North Dakota State University's regulations and meets the accepted standards for the degree of

DOCTOR OF PHILOSOPHY

SUPERVISORY COMMITTEE:

Dr. Zhulu Lin
Chair

Dr. Mohamed Khan

Dr. Jasper M. Teboh

Dr. Amitava Chatterjee

Approved:

03/21/2018 — Dr. Sreekala Bajwa

Date — Department Chair

ABSTRACT

Sugarbeet (*Beta vulgaris*) is considered as one of the most viable alternatives to corn for biofuel production as it may be qualified as "advanced" biofuel feedstocks under the 'EISA 2007'. Production of deep rooted sugarbeet may play a significant role in enhancing utilization of deeper layer soil water and nutrients, and thus may significantly affect soil health and water quality through recycling of water and nutrients. A model can be useful in predicting the sugarbeet growth, and its effect on soil and water quality.

A sugarbeet model was developed by adopting and modifying the Crop Environment and Resource Synthesis-Beet (CERES-Beet) model. It was linked to the Cropping System Model (CSM) of the Decision Support System for Agrotechnology (DSSAT) and was termed as CSM-CERES-Beet. The CSM-CERES-Beet model was then linked to the plant growth module of the Root Zone Water Quality Model (RZWQM2) to simulate crop growth, soil water and NO_3-N transport in crop fields. For both DSSAT and RZWQM2, parameter estimation (PEST) software was used for model calibration, evaluation, predictive uncertainty analysis, sensitivity, and identifiability. The DSSAT model was evaluated with two sets of experimental data collected in two different regions and under different environmental conditions, one in Bucharest, Romania and the other in Carrington, ND, USA, while RZWQM2 was evaluated for only Carrington, ND experimental data.

Both DSSAT and RZWQM2 performed well in simulating leaf area index, leaf or top weight, and root weight for the datasets used (*d*-statistic = 0.783-0.993, *rRMSE* = 0.006-1.014). RZWQM2 was also used to evaluate soil water and NO_3-N contents and did well (*d*-statistic = 0.709-0.992, *rRMSE* = 0.066-1.211). The RZWQM2 was applied for simulating the effects of crop rotation and tillage operations on sugarbeet production. Hypothetical crop rotation and

tillage operation scenarios identified wheat as the most suitable previous year crop for sugarbeet and moldboard plow as the most suitable tillage operation method. Both DSSAT and RZWQM2 enhanced with CSM-CERES-Beet may be used to simulate sugarbeet production under different management scenarios for different soils and under different climatic conditions in the Red River Valley.

ACKNOWLEDGEMENTS

First of all, I would like to thank Almighty Allah, without His Blessed Benevolence nothing would have been possible. I would like also to extend my gratitude to my advisor, Dr. Zhulu Lin, for his continuous help, inspiration, thoughtfulness, and numerous suggestions. I would like to extend this gratitude to my other advisory committee members Drs. Mohamed Khan, Jasper Teboh, and Amitava Chatterjee for their valuable suggestions, support, and guidance.

I would also like to acknowledge USDA National Institute of Food and Agriculture for funding this research through the AFRI Foundational Program (Project No.: 2013-67020-21366). I would also like to acknowledge authorities for “Frank Bain Scholarship” and “Alan Dexter Sugarbeet Scholarship” for providing me their scholarships and encouraging my studies and research. I would also like to thank my father, Dr. A N M Wali Ullah, and my mother, Mrs. Jahanara Begum, for their continuous support and numerous prayers. Last but not least, I express my heartfelt gratitude to my beloved wife, Sharmin Sultana, for giving me strength and inspiration when I needed it most. I would also like to express heartfelt love for my little daughter, Adira Sehrish Anar, for inspiring me with her lovely smile.

DEDICATION

This dissertation work is dedicated to my Beloved Parents.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF APPENDIX TABLES

LIST OF APPENDIX FIGURES

CHAPTER 1. INTRODUCTION

Biofuel is defined as any fuel source that is derived from organic matter or biomass, which can then be used to produce heat and electricity, or used for transportation (Wang et al., 2011). Based on their potential to reduce net greenhouse gas (GHG) emission, Energy Independence and Security Act (EISA) in 2007 classified biofuels into three categories called conventional, advanced, and cellulosic biofuels, offering 20%, 50%, and 60% reduction in GHG emission respectively. Currently, 97% of the biofuels produced in the US are corn-based ethanol, which may offer up to 40% reduction in GHG emission (Canter et al., 2016; Flugge et al., 2017; Hettinga et al., 2009; Wang et al., 2011). But as the production of biofuel continued to increase, industrial demands for corn increased substantially, resulting in higher corn prices (Ziska et al., 2009). Rising corn prices encouraged current and potential ethanol producers to seek for alternative feedstock. Two crops, sugarbeet (*Beta vulgaris*) and sugarcane (*Saccharum officinarum*), are currently considered to be uniquely qualified as “advanced biofuels” under the EISA (Jessen, 2012). Compared to corn the use of sugarbeets for biofuel production also has less impact on food supply (Maung and Gustafson, 2011).

Sugarbeets are grown in a wide range of temperate climatic conditions and in a wide variety of soils ranging from sandy to silty clay or loam soils with high organic matter content and/or high clay content (Cattanach, 1991). In the U.S., sugarbeet is grown in 11 states spreading across four regions – Michigan in the Great Lakes region, Minnesota and North Dakota in the Upper Midwest region, Colorado, Montana, Nebraska, and Wyoming in the Great Plains region, and California, Idaho, Oregon, and Washington in the Far West region (USDA/ERS, 2016). (Fig. 1.1) (USDA/ERS, 2016). In 2016/17, about 57% of the nation’s total sugarbeet was produced in the Red River Valley (RRV) of western Minnesota and eastern North Dakota and its vicinity, while another 31% was harvested in Idaho and Michigan (USDA/ERS, 2018). (Table 1.1) (USDA/ERS, 2018).

Due to increasing demands of sugarbeet for sugar and biofuel production, its cultivation in these areas continues to increase. Some varieties of sugarbeets are salt-tolerant (Katerji et al., 2000), and the presence of salts in soils helps to mitigate the effect of soil-borne root rotting fungi to seedlings of sugarbeet (El-abyad et al., 1988). At the same time, deep-rooted sugarbeets are believed to hold potential for improving soil resource by complimenting other crops in the rotation and improving water and fertilizers use through nutrient recycling (Pates, 2011). In terms of water quality, deep-rooted sugarbeets are good at recovering nutrients from the soil profile and its long growing season favors the uptake of nutrients. Increased sugarbeet production thus may significantly affect soil and water quality. In those circumstances, models can play a vital role in understanding the plant growth processes and its impacts on soil and water quality in ways which will ultimately help to spread the production of sugarbeets in more economic ways.

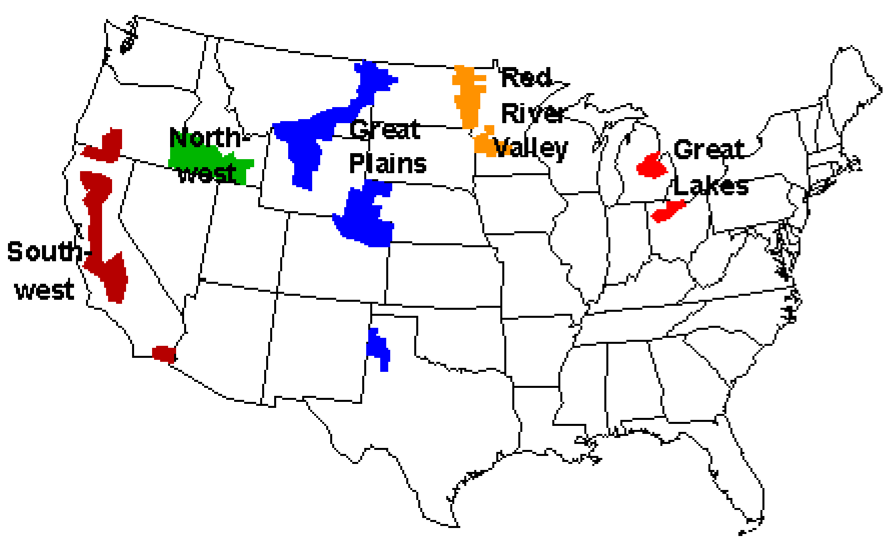


Figure 1.1. Sugarbeet production regions in the US (USDA/ERS, 2016a)

A number of sugarbeet growth models are currently available to describe its growth and yield. Some of these models are empirical and are developed based on the relationship between pre-harvested samples of sugarbeet and final yield. Examples of empirical models include PIEteR (Biemond et al, 1989; Smit et al., 1993), LUTIL (Spitters et al., 1989, 1990) and models developed by Modig (1992) etc. There are some other sugarbeet models, which are typically descriptive models that integrate the processes involved at different levels. These models assume that the system has a known structure, and the processes and components can be described mathematically. Some of these models are SUCROS (Spitters et al., 1989), GreenLab (Vos et al., 2007), Broom's Barn (Qi et al., 2005), Pilote (Taky, 2008), and CERES (Leviel, 2000) etc.

Table 1.1. Sugarbeet acreage, and yield in the US regions.

	Area Harvested			Yield		
	2014/15	2015/16 (1000 acres)	2016/17	2014/15	2015/16 (tons/acre)	2016/17
Great Lakes						
Michigan	150.0	151.0	148.0	29.3	31.7	31.0
Total	150.0	151.0	148.0	29.3	31.7	31.0
Upper Midwest						
Minnesota	434.0	435.0	431.0	22.5	28.0	28.5
North Dakota	214.0	206.0	211.0	23.8	27.9	28.9
Total	648.0	641.0	642.0	22.9	28.0	28.6
Great Plains:						
Colorado	29.3	27.3	27.5	31.3	35.1	34.6
Montana	44.4	43.7	45.2	32.3	33.0	31.7
Nebraska	45.9	46.8	47.0	29.1	28.4	32.4
Wyoming	30.0	31.2	30.0	27.8	30.1	29.9
Total	149.6	149.0	149.7	30.2	31.3	32.1
Far West:						
California	22.5	24.7	25.2	42.6	44.2	44.2
Idaho	169.0	172.0	170.0	37.3	38.3	38.9
Oregon	7.2	7.7	10.2	34.4	38.6	40.0
Total	198.7	204.4	207.3	37.8	39.0	39.7
Total U.S.	1,146.3	1,145.4	1,147.0	27.3	30.9	31.4

(Source: USDA/ARS, 2018)

All the current sugarbeet models simulate only the plant growth and yield and have no components to model the agricultural management effects on soil and water quality (Ma et al., 2012). All the current models are also restricted to the region and conditions for which they are developed (Vandendriessche and Ittersum, 1995). 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 (IBSNAT, 1993a; Jones et al., 1998; Hoogenboom et al., 2010). Its crop simulation models are used for many applications, ranging from on-farm and precision management to regional assessments of the impact of climate variability and climate change (Jones et al., 1998). It 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 (Saseendran et al., 2007; Ma et al., 2012). RZWQM2, a significant improvement from the early version of the RZWQM model, contains surface energy balance from the Simultaneous Heat and Water (SHAW) model (Flerchinger et al., 2012) and crop specific plant growth module from DSSAT. Currently, 23 crop growth modules from the DSSAT are linked to the (RZWQM2) to simulate crop yield, water flow, and transport of salts and nitrogen in crop field, though the current release of DSSAT (ver 4.7) have 42 specific crop models. However, no such physically based crop growth model has been developed for the deep-rooted sugarbeet.

1.1. Objectives

There are three objectives in our research, which are:

1) Develop a plant specific, DSSAT compatible sugarbeet growth model (CSM-CERES-Beet), calibrate and validate the model using the available field observed data, and conduct uncertainty analysis for CSM-CERES-Beet using Parameter Estimation (PEST) software.
2) Link the developed CSM-CERES-Beet model to RZWQM2, and analyze parameter sensitivity and identifiability of RZWQM2 for dryland sugarbeet modeling.
3) Evaluate the effects of crop rotations and tillage operations on sugarbeet yield and soil and water quality.

CHAPTER 2. LITERATURE REVIEW

2.1. Sugarbeet Growth Stages

Sugarbeet (*Beta vulgaris*) plant comprises four major compartments called leaves, shoot, fibrous root and storage root. Fibrous root system contributes to crop growth whereas storage roots store sugar. The partitioning of assimilates within these compartments are crucial for the growth dynamics and yield of sugarbeets. Rate of solar radiation interception is also vital, which is controlled by the area of leaves. The expansion of leaves is mostly important until full leaf cover is reached (Malnou et al., 2008). Therefore, any factors controlling the speed of leaf surface expansion are directly related to the final production. All these factors are strongly influenced by the production environment such as climate, irrigation, and fertilization (Milford et al., 1985).

Sugarbeet is a biennial crop, where epigeal germination leads to rosette development in the first years and flowering during the second year for seed production. But root crops like sugarbeets are usually harvested before the onset of winter frost in the first year for sugar or biofuel production (Panella et al., 2014; Cooke and Scott, 1993). For plant growth modeling, sugarbeet is usually treated as an annual crop assuming it is grown for sugar yield and not for seed production (Fick et al., 1971; Hunt, 1974, Spitters et al., 1989, Leviel, 2000, Leviel et al., 2001; Qi et al., 2005, Vos et al., 2007, Taky, 2008). For sugar production, sugarbeet's growth can be divided into four major stages: germination and emergence, canopy development, storage root growth, and pre-harvest stages (Sugarbeet Production Guide, 2013).

2.1.1. Germination and Emergence Stage

Germination and emergence of sugarbeet are temperature and moisture sensitive. Germination does not occur until the soil temperature reaches 3 ºC and requires generous presence of moisture at such low temperature (Guerif and Duke, 1998; Sugarbeet production guide, 2013). After germination and emergence, seedling growth is typically very slow due to slow appearance of leaves because of the cool temperatures. During this stage, the amount of solar radiation reaching the field is high, but most is wasted due to small sugarbeet canopy surface. This stage takes place for approximately 3 to 4 weeks.

2.1.2. Canopy Development Stage

The rate of appearance and the size of leaves also depend on temperature and increases as the weather gets warmer. During this stage, the photosynthate is used mainly to produce aboveground part of the plant, the leaves and stems, communally called the canopy. At canopy closure, when there is typically 3 times as much leaf surface as soil surface, light interception rate reaches its maximum. At this stage, 80-90% of the incident radiation can be captured if other factors are optimal (Sugarbeet production guide, 2013). The growth of crop foliage can be described by leaf area index (LAI) which can be expressed as an exponential function of the thermal time (T_{base} of 3 ºC) from the point of emergence to the point where the sugarbeet plant starts to compete for light (Guerif and Duke, 1998). This stage usually takes place for approximately 6 weeks.

2.1.3. Storage Root Growth Stage

Although some root growth takes place during the canopy development stage, most of the root grows after the canopy development slows down. At this stage the dry weight gain of a sugarbeet plant concentrates beneath the soil's surface to prepare the plant for winter (Sugarbeet production guide, 2013). Under favorable conditions, the early growth of the storage root is relatively rapid. This rapid growth of the sugarbeet root usually begins after about 6 weeks of germination and continues to accumulate dry matter linearly throughout the growing season. Size and depth of roots are affected by plant spacing at planting. Individual roots therefore become smaller or larger as the spacing between plants decreases or increases (Sugarbeet production guide, 2013).

2.1.4. Pre-harvest Stage

The pre-harvest stage usually occurs during early fall when decreasing light intensity and temperature result in lower rate of photosynthesis. At this stage, the plant directs nutrients and energy stores to the root as the last effort to prepare the plant for the cold season. But the amount of energy stores decreases gradually as the rate of photosynthesis decreases. It is around this time when farmers prepare to harvest the sugarbeets (Sugarbeet production guide, 2013).

2.1.5. Growth Patterns of Sugarbeet Plant Parts

For sugarbeet model development, the growth patterns of each part of the plant and the environmental factors affecting the growth needs to be well understood. From the discussions above, it is observed that the growth of leaves or canopy follows the laws of diminishing return pattern, where the development of canopy increases rapidly over time up to a certain period and then starts to decline slowly due to senescence of leaves and fibrous roots (Fig. 2.1). At this point most of the dry weight gain takes place on canopy. Growth of storage roots is slow during the early stages and accelerates after about 6 weeks of emergence. Soil temperature and solar radiation are the two most important factors affecting the growth and development during these stages. Solar radiation varies throughout the growing season with daily and seasonal changes in the sun's position, limiting the rate of photosynthesis. Photosynthesis is the basis for all plant growth. Distribution of the product of photosynthesis, photosynthate, affects the development of the different plant parts of sugarbeet. Therefore, to develop a plant growth model, leaf area index or canopy coverage should be considered with importance (Sugarbeet Production Guide, 2013).

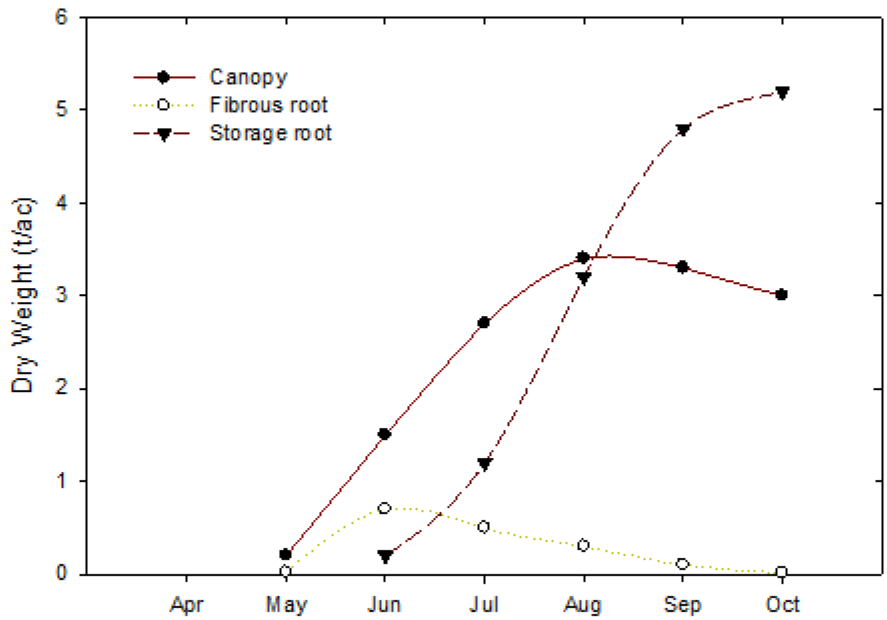


Figure 2.1. Seasonal growth curves for sugarbeet plant parts (adopted from Sugarbeet production guide, 2013).

2.2. Current Sugarbeet Growth Models

A number of sugarbeet growth models are currently available and the factors that contributed to the development of these models are: i) sugar yield forecasting with regard to production planning and economy, ii) incorporation of scientific knowledge and hypothesis testing in research, and iii) decision support systems at field level (Vandendriessche and Ittersum, 1995). The models that were developed based on these criteria were either empirical models or descriptive models. A review of the currently available sugarbeet growth models is given below:

2.2.1. Empirical Models

Empirical models are those that are developed based on the relationship between pre-harvested samples and final yields. In general, these types of models are easy to use and successful when applied within the range of sites and weather circumstances for which they were developed and tested (France and Thomley, 1984; Thornley and Johnson, 1990;

Vandendriessche and Ittersum, 1995). The procedures and the extent of beet sampling for these types of model development followed the guidelines developed by sugarbeet companies (Church and Gnanasakthy, 1983; van der Beek, 1993).

Some of these empirical models include PIEteR (Biemond et al., 1989; Smit et al., 1993), LUTIL (Spitter et al., 1989, 1990), and the models of Modig (1992) and Jaggard (1992). Among these models, models of Modig (1992) and Jaggard (1992) used linear regression of the dependent variables, while PIEteR (Biemond et al., 1989; Smit et al., 1993) used non-linear regression equations. The LUTIL model by Spitters et al. (1989, 1990) used simple regression methods. All these models consider weather data as a factor involved in model development, model developed by Modig, 1992 considered temperature (Modig, 1992) as a factor in model development, while models developed by Jaggard, 1992; LUTIL, PIEteR, and Day (1986) considered both solar radiation and temperature. LUTIL and the model developed by Modig (1992) also used sowing date as one of the factors, while PIEteR included soil as a factor (PIEteR).

Although these empirical models are easy to use, they lack detailed description of the processes involved in sugarbeet growth which are important for research purposes. Based on underlying mechanisms and their interactions, descriptive models have been developed.

2.2.2. Descriptive Models

Descriptive models were developed to build better understanding of the processes and mechanisms involved in sugarbeet growth and development. These types of models describe the plant's components and its growth processes at different stages in mathematical terms (Vandendriessche and Ittersum, 1995). Some of these descriptive models include SUBGRO (Fick, 1971), SUBGOL (Hunt, 1974), SIMBEET (Lee, 1983), SUBEMO (Vandendriessche, 1989), SUCROS (Spitters et al., 1989), dynamic sugarbeet model (Webb et al., 1997), CERES (Leviel, 2000) Broom's Barn (Qi et al., 2005), and Green Lab (Vos et al., 2007) etc. Recently, Lemaire et al. (2008) proposed a morphogenetic model for sugarbeet adopting the underlying concepts of the GreenLab model. Another simplistic mechanistic model was developed by Gholipouri et al. (2009) for simulating the sugarbeet growth and sugar accumulation under potential production condition.

2.2.2.1. SUBGRO

SUgar Beet GROwth (SUBGRO) (Fick, 1971) is a mechanistic sugarbeet growth model following the concepts of the ELCROS model (de Wit, 1965). This is a specific sugarbeet growth model that was developed on the basis that the photosynthates from a reserve pool are partitioned for respiration, growth, and energy storage. In this model, total dry weight of the sugarbeet ($TDWB$) is estimated from the sugar content ($SUGAR$) and the dry weight of the beet (DWB):

$$TDWB = DWB + SUGAR \tag{2.1}$$

where $SUGAR$ is simulated from sugar stored ($STSUG$) and the fraction of reserves (RES) in the beet.

$$SUGAR = STSUG + RES \times (DWB + STSUG)/TDW \tag{2.2}$$

where, TDW is the total dry weight of the sugarbeet plant.

SUBGRO simulates the growth rate of the beet and its storage root as the product of maximum relative growth rate ($DWBC$) and relative growth rate (RGR) at the current soil temperature (TS).

$$GRB = DWBC \times AFGEN(RGR, TS) \times AMIN1\begin{pmatrix} AFGEN(ERBG, PRES), \\ AFGEN(EWCBG, RWC) \end{pmatrix} \tag{2.3}$$

where, $ERBG$ is the limitation of the reserve level ($PRES$), $EWCBG$ is the relative water content (RWC) limitation and $AMIN1$ is the minimum value among the real arguments.

This model considered respiration as the percentage of carbohydrate produce only and did not include the effects of nitrogen on sugarbeet growth. This model also didn't consider the dry matter loss from senescence.

2.2.2.2. SUBGOL

To overcome the limitations of SUBGRO model, Hunt (1974) later modified the model and developed SUBGOL, which includes a respiratory submodel simulating respiration processes during growth and maintenance periods. The model also included a component of the elementary leaf senescence, in which sugarbeet leaf senescence increases with leaf's age and mutual shading of leaves.

2.2.2.3. SIMBEET

In 1983, Lee (1983) developed SIMulating sugarBEET (SIMBEET) to understand the connections among plant morphology, physiology, and the environmental factors. SIMBEET models the processes of photosynthesis, respiration, translocation, and senescence to simulate sugarbeet dry matter accumulation patterns in a one-hour time step. Each physiological development rate is estimated as the product of maximum possible growth rate and a series of factors that account for the effects of temperature, plant age, nitrogen, solar radiation, and nonstructural carbohydrate on the physiological rate.

The maximum relative growth rate (RGR) of the petioles, blades, crown, or top is simulated as a function of the dry weight of the particular plant part and the rate of change of dry weight per unit time.

$$RGR = \frac{1}{w} \times \frac{dw}{dt} \tag{2.4}$$

where, RGR is the maximum rate of relative growth in grams of dry matter produced per grams of plant tissue per unit time, w is the dry weight of tissue and $\frac{dw}{dt}$ is the rate of change of dry weight per unit time.

For the physiological rates other than growth (photosynthesis, respiration, translocation and senescence), the maximum relative growth rate (RxR) is estimated as a function of dry weight of the plant part and the rate of change of dry matter produced by physiological rate per unit time ($\frac{dw_x}{dt}$):

$$RxR = \frac{1}{w_{PT}} \times \frac{dw_x}{dt} \tag{2.5}$$

where, x represents photosynthesis, respiration, translocation, and senescence and PT represents the relevant plant tissue's weight.

This maximum relative growth rate is then multiplied by the grams of petiole, blade, crown and root per square meter of land area to get the final product as quantity of dry matter produced, converted, translocated or lost per unit time per unit area. When all the physiological factors are at optimum level the process operates at its maximum rate. Environmental factors are incorporated into actual growth rates of the respective plant parts. According to Lee (1983) the weakest component of the model is the translocation rate equations.

2.2.2.4. SUCROS

In 1989, Spitters et al. developed their SUCROS model based on the de Wit's sugarbeet model (van Laar et al., 1992). SUCROS stands for Simple and Universal CRop growth Simulator. This model simulates the potential crop growth based on light interception, photosynthesis, respiration, and partitioning of assimilates between the organs of the plants for practical applications, such as studies of climate effects on production and water management. Several versions of SUCROS have been published for different crops (sugarbeet, potato, maize, soybean etc.), each built on the original model (Spitters et al., 1989; Goudriaan and Van Laar, 1994). The model inputs include daily climatic data such as radiation, minimum and maximum temperature, during the growing periods.

The crop establishment simulator module of this model first describes the crop emergence. It then describes the early growth of the crop canopy by increasing the leaf area index (LAI) which is an exponential function of the thermal time from the point of emergence to the point where sugarbeet plants start to compete for light (Guerif and Duke, 1998). This exponential early growth of sugarbeet leaves can be described using a four-parameter model (Eq. 2.6).

$$LAI = LA_0 \times NPL \times exp[RGRL \times (ST - SEMREG)] \tag{2.6}$$

where, LAI is Leaf Area Index, LA_0 is the extrapolated leaf area per plant at emergence, NPL represents the number of plants emerged per unit area, $RGRL$ is the initial growth rate of leaves (ºC day^{-1}), ST is the sowing time, and $SEMERG$ is the thermal time needed for plant to emerge and is expressed as a temperature sum over a base temperature of 3 ºC since sowing date.

For sugarbeet, Spitters et al. (1989) provided default values for these parameters which are 120°C day for $SEMERG$, 11.1 plants m^{-2} for NPL, 0.84 cm^2 plant^{-1} for LA_0, and 0.156°C day^{-1} for RGRL. These values are not constant and can vary depending on various factors like seedbed characteristics, weather condition and other emergence characteristics.

Under ideal growth environment with ample supply of water and nutrients total growth rate of sugarbeet is calculated as a function of carbohydrate assimilation and requirement (Spitters et al., 1989):

$$GTW = (GPHOT - MAINT) / ASRQ \tag{2.7}$$

where, GTW is the total growth rate of the crop (kg $ha^{-1}d^{-1}$), $ASRQ$ is assimilate (CH_2O) requirement for dry matter production (kg kg^{-1}), $GPHOT$ is the daily total gross assimilation (CH_2O) (kg $ha^{-1}d^{-1}$), $MAINT$ is the maintenance respiration (CH_2O) of the crop (kg $ha^{-1}d^{-1}$). These parameters are determined by the following equations.

$$GPHOT = DTGA \times 30/44 \tag{2.8}$$

$$MAINT = AMIN1(GPHOT, MAINTS \times TEFF \times MNDVS) \tag{2.9}$$

$$ASRQ = FSH \times (1.46 \times FLV + 1.51 \times FST + ASRQSO \times FSO) + 1.44 \times FRT \tag{2.10}$$

where, $DTGA$ is the daily total gross CO_2 assimilation of the crop (kg $ha^{-1}d^{-1}$), $ASRQSO$ is the assimilate requirement for dry matter production of storage organs (kg kg^{-1}), FLV , FST and FRT are the fractions of dry matter increase allocated to leaves, shoots, and roots respectively, FSH and FSO are the fractions of total dry matter allocated to the shoots and storage organs respectively, $TEFF$ is the factor accounting for effect of temperature on maintenance respiration, $MAINTS$ is the maintenance respiration of the crop at base temperature, and $MNDVS$ is the factor accounting for the effect of the development stage on maintenance respiration.

Variability in emergence and early growth conditions in this model lead to a wide range of values for the parameters considered. Because of this, the simulation of the subsequent crop growth is also affected (Guerif and Duke, 1998).

2.2.2.5. SOWAN

SOWAN (Hendrickx, 1986) sugarbeet growth model was developed based on the components of SUCROS model. It connects dry matter of sugarbeet production with nitrogen and soil water balance. It included the procedures of SWATRE (Belmans et al., 1982), PAPRAN (Seligman and van Kuulen, 1981), and CERES (Ritchie, 1984) for soil water balance simulation and NITCROS (Hansen and Aslyng, 1984) and FIELD (Duffy et al., 1977) for nitrogen submodule description. It can simulate soil water balance and soil profile nitrogen processes for several soil layers up to 120 cm depths.

2.2.2.6. SUBEMO

SUgar BEet MOdeling (SUBEMO) is another specific sugarbeet growth model developed by Vandendriessche (1989) to simulate dry matter and sugar production. It simulates a pool of carbohydrates in beet resulting from photosynthesis and restoration of dry matter from senescence leaves. These pools of carbohydrates are used to sustain respiration, growth and sugar accumulation. For dry matter partitioning the model used the empirical teleonomic partitioning hypothesis of allocating dry matter to different plant part under given environment in such a way that the plants attain an optimal specific growth rate.

2.2.2.7. SIUCRA

SIUCRA (Burke, 1992) is a model developed to specifically simulate sugarbeet growth and development in Ireland. The central routine of this model describes photosynthesis as a function of photosynthetically active solar radiation, temperature, LAI, and crop specific parameters. This model included the effects of water stress on sugarbeet growth and adjusted the carbohydrates produced daily based on the degree of water stress. In the next step, the model computes the maintenance respiration rate and carbohydrates available for growth and development. Partitioning of dry matter to various plant parts depends on the stage of growth and age of the plant.

2.2.2.8. Webb et al. (1997)

The dynamical model of Webb et al. (1997) was developed considering soil nitrogen content and solar radiation as the driving variables. This is a parsimonious model with only 14 parameters, out of which 7 are associated with these driving variables. It models the crop as three parts; the shoot, the storage root, and the fibrous systems. The amount and partitioning of assimilates needed for the growth of the crop is affected by the amount of light intercepted and soil nitrogen content (Fig. 2.2).

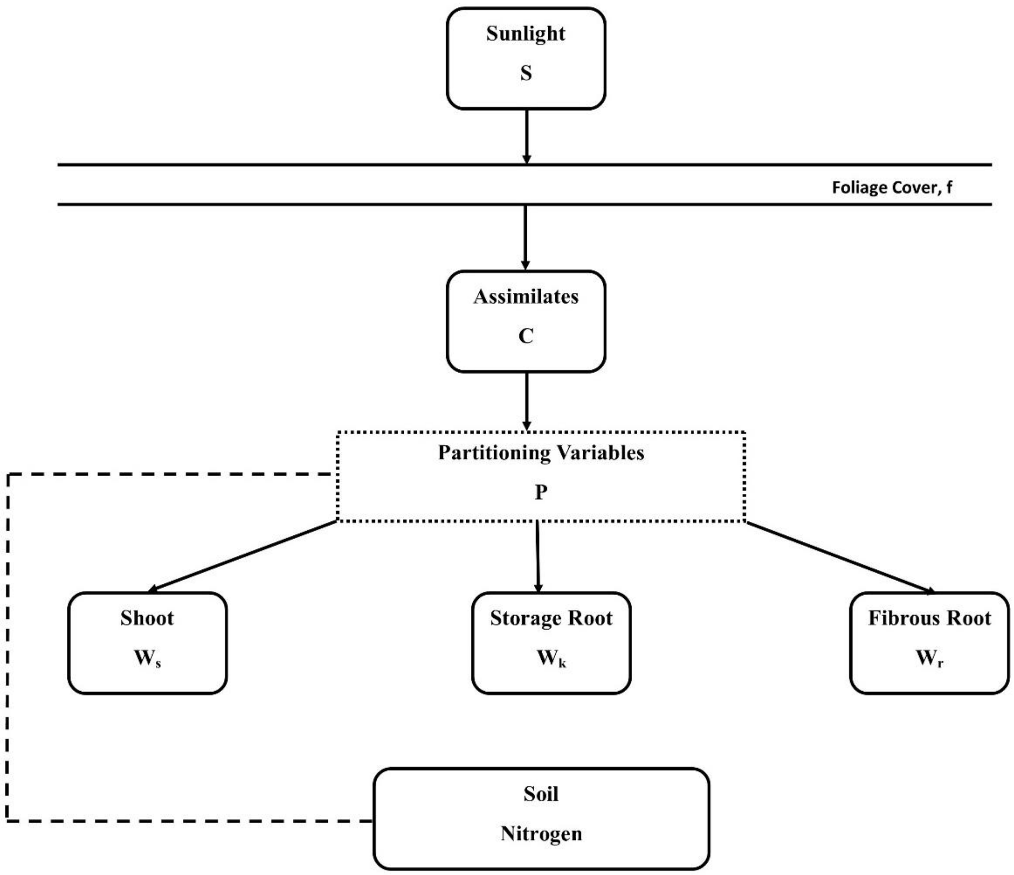


Figure 2.2. Schematic diagram of the dynamical model to describe the growth of sugarbeet in relation to driving variables soil radiation and soil nitrogen (redrawn from Webb et al., 1997).

In this model three differential equations were developed to estimate the rates of change in shoot, storage root, and fibrous root.

$$\frac{dW_s}{dt} = P^2 kfS - vW_s \tag{2.11}$$

$$\frac{dW_r}{dt} = P(1-P)kfS - \rho W_r \tag{2.12}$$

$$\frac{dW_k}{dt} = (1-P)kfS \tag{2.13}$$

where, W_s, W_r, and W_k are the mass of shoot, fibrous roots and storage root respectively, k is the conversion coefficient (kg M J^{-1}), P is the partitioning variables, S is total incident radiation (MJ m^{-2}), v and ρ are the death rates of shoot and fibrous root respectively and f is foliage coverage.

The foliage cover, f in this model is described by a modified Mitscherlich curve (Mead and Pike, 1975):

$$f = f_{max}\left(1 - e^{-W_s\gamma e^{-k_f(t-t_s)}}\right) \tag{2.14}$$

where γ the fraction of shoot mass W_s, t_s is the time of sowing, k_f is the rate of decreasing foliage cover and f_{max} is the maximum foliage cover.

Soil nitrogen partitioning variables (P) and total incident radiation are modeled using the following two different functions.

$$P = \alpha + \frac{\beta}{1+e^{\sigma(t-\mu)}} \tag{2.15}$$

$$S = \left(a + bsin\left(\frac{2\pi(t-g)}{365}\right)\right) \tag{2.16}$$

where, α is the minimum value of P, β is the maximum value of $P - \alpha$, σ is the rate parameter (T^{-1}), t is the time, a and b are vertical displacement factor and amplitude respectively and g is the horizontal displacement factor.

This model describes the plant growth in relation to soil nitrogen and solar radiation. Between these two, soil nitrogen is more amenable to control. The amount of solar radiation intercepted can be managed changing the sowing date of the crop although early sowing may result in frost damage.

2.2.2.9. STICS

STICS (Simulator mulTIdisciplinary for Cultures Standard (Brisson et al., 1998)) is a generic daily time-step model, which has already been applied to a wide variety of crops like maize, tomato, wheat, sugarbeet etc. This model has seven modules corresponding to the different mechanisms involved in plant growth. The original formulation of STICS describes the relationship between biomass production and intercepted radiation as a quadratic function. Among the seven modules available in STICS, some of them are dedicated to the management of environmental stresses, so that these processes can be easily implemented in the model. In the modified version of the STICS, thermal stress was added to improve the model simulation.

2.2.2.10. CERES-Beet

CERES (Crop Environment REsource Synthesis) was originally developed for maize by Jones and Kiniry (1986), but a sugarbeet version was developed by Leviel (2000). The CERES models provide a simple and coherent framework for the simulation of water, carbon, and nitrogen cycles in soil-plant systems. Over the past twenty years, these CERES-models have been widely used and tested in applications ranging from decision-aid in irrigation to global assessment of crop productivity (Rosenzweig and Parry, 1994). These models can simulate the succession of crops on a given field, and thus account for crop rotation effects.

The phenology module of CERES-Beet model considers four events, which are sowing, germination, emergence, and harvest. This model considers germination as a function of soil moisture content and assumes that emergence occurs after 40 Growing Degree Days, with a base temperature of 3°C (noted GDD_3). Net photosynthesis in the CERES-Beet is computed from intercepted photosynthetically active radiation (PARi) by means of a radiation use efficiency set to 2.8 g Dry Matter MJ $PARi^{-1}$. PARi is computed from LAI using the classical Beer-Lambert law of radiation transmission in turbid media. The extinction coefficient it set to 0.65. Throughout the growing season the produced biomass is partitioned among shoot, leaf, and roots.

2.2.2.11. Broom Barn's Model

Another process-based model, Broom's Barn sugarbeet growth model is a weather-driven daily time step simulation model (Qi et al., 2005). This model was developed from observations on beet crops grown at Broom's Barn considering the integrated effects of the important environmental variables like temperature, radiation, rainfall, potential evapotranspiration (PET), and soil available water capacity (SAWC) (Fig. 2.3). Under favorable growing conditions incoming solar radiation and temperature are the main factors determining the dry matter increase and sugar yield. The model uses a set of mathematical equations to calculate the everyday values of the percent foliage cover, amount of solar radiation intercepted by the canopy, net total dry matter production using a feasible radiation use efficiency, and its partitioning to sugar yield. To account for the effects of soil water stress, a simple soil water balance model for a free draining soil profile is coupled to the beet growth model, tracking the everyday amount of soil water available within the root zone and the radiation use efficiency is reduced in proportion to the ratio between actual and potential crop evapotranspiration.

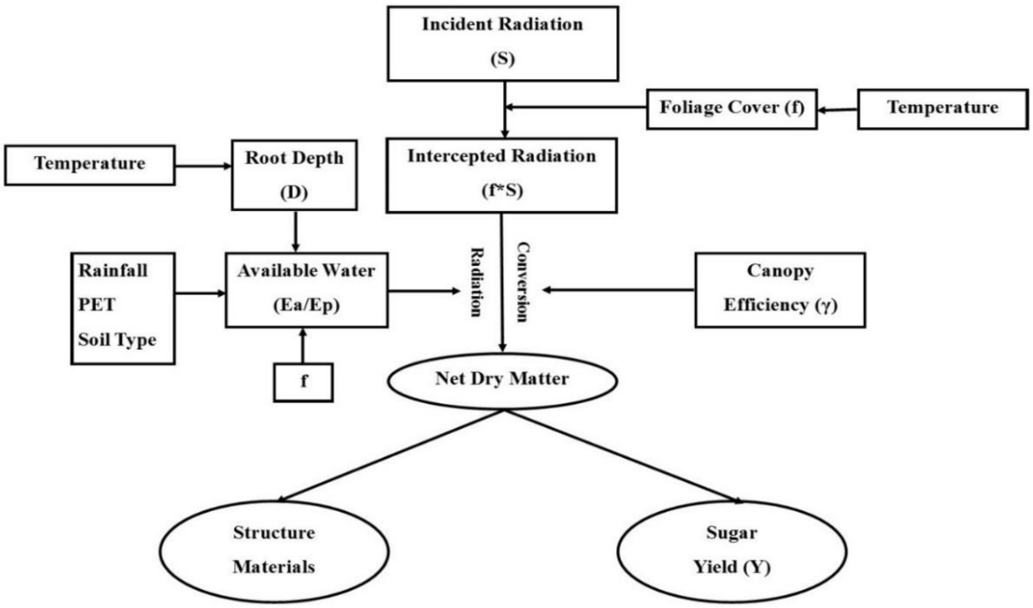


Figure 2.3. The components and controlling environmental variables in the Broom's Barn sugarbeet growth simulation model (Redrawn from Qi et al., 2005).

In this model the foliage/canopy cover is modeled following the formula of Werker and Jaggard (1997).

$$f = f_0 exp\left(\mu_{min}(T - T_0) + \frac{\mu_0 - \mu_{min}}{v}\left(1 - e^{-v(T-T_0)}\right)\right) \tag{2.17}$$

where, f_0 is the canopy coverage at 50% of the seedlings emergence at $T = T_0$, T is the accumulated temperature above 3º C, T_0 is the accumulated temperature from sowing to 50% crop emergence, μ_0 and μ_{min} are initial and final net relative canopy coverage (d^{-1}), and v is the rate from μ_0 to μ_{min}.

To account for the soil water stress' effect on crop canopy development, a stress factor was modeled as a logistic function based on the relative water content.

$$f_{stress} = \frac{2}{1+exp\{-f_{dt}(Q_{rel}-0.02)\}} - 1 \tag{2.18}$$

where, f_{dt} is the stress response factor, Q_{rel} is the fraction of transpirable water and is determined from the ratio of daily available water content and available water content at field capacity.

The total dry matter (W) (gm^{-2}) in this model is determined by summing the daily values of dry matter increase (ΔW) between crop emergence (t_0) and final harvest (t_f) whereas the final total sugar yield (Y) (gm^{-2}) is attained with respect to W, as shown below:

$$W = \frac{1}{\gamma} log\left\{1 + \gamma\varepsilon \sum_{t=t_0}^{t_f} \left(fS\frac{E_a}{E_p}\right)\right\} \tag{2.19}$$

$$Y = W - \frac{1}{k} log(kW + 1) \tag{2.20}$$

where, the daily values of dry matter increase are modeled using the formula $\Delta W = \varepsilon f S$, where ε is the intercepted radiation use efficiency (gMJ^{-1}), f is the fractional crop canopy cover and S is the global solar irradiation. In the equations, γ is the decaying coefficient of radiation conversion coefficient, k is the sugar partitioning coefficient and E_p and E_a are potential and actual crop evapotranspiration respectively.

The Broom's Barn sugarbeet growth model with its original parameter estimation can closely simulate the total dry matter production and sugar yields for crops grown on soils with available water contents up to 18% by volume at field capacity (Qi et al., 2005).

2.2.2.12. PILOTE

PILOTE is a crop-soil interaction generic model, which was first developed for sorghum and sunflower (Mailhol et al., 1996, 1997), but can be applied for a large variety of crops. The sugarbeet version of PILOTE model was developed by Taky (2008). It is designed to predict the actual evapotranspiration and the yield of crops, through the modeling of the LAI. There are two different versions of PILOTE sugarbeet model, one with hydric stress and the other without hydric stress. Daily biomass production ($I(t)$) at any day t in this model is computed using the following formula:

$$I(t) = 1 - exp(-k_B - LAI(t)) \tag{2.21}$$

where, k_B is the Beer-Lambert law extinction coefficient, and LAI is the leaf area index which is computed using the equation below:

$$LAI(t) = LAI_{max} \left(\frac{\tau(t)-\tau_e}{\tau_{max}}\right)^{\beta} exp\left[\frac{\beta}{\alpha}\left(1 - \left(\frac{\tau(t)-\tau_e}{\tau_{max}}\right)^{\alpha}\right)\right] \tag{2.22}$$

where, LAI_{max} the potential maximum value of LAI in non-limiting conditions, τ_{max} is the thermal time (in℃ day) necessary to reach maximum LAI, τ_e is the thermal time (in℃ day) of emergence, α and β are parameters. It is also possible to model growth and senescence separately, using two different values α_1 and α_2 depending on whether growth states are before or after τ_{max}. Biomass repartition to root and leaves in this model is done with an empirical harvest index computation method.

2.2.2.13. GreenLab

A morphogenetic model for sugarbeet model was developed by Lemaire et al. (2008). This model is based on GreenLab (de Reffye and Hu, 2003), a generic plant growth model. In this model, the morphogenetic process generating plant structure is considered in the model given that plant structure plays an important role during growth, especially under stress conditions.

The model's main hypothesis was that the biomass produced by each leaf is stored in a common reserve pools and reallocated among all plant arts according to their sink strengths. Initial seeds and leaves are considered as sources, from where stored biomass is supplied to the leaf and the root system that act as sinks.

The driving variables of this morphogenetic model are mostly phytomer appearance, expansion, and leaf senescence. These variables allow the simulation of the growth based on biomass production and biomass partitioning. Based on the time unit of the morphogenetic sequence of the phytomer appearance, the ecophysiological functioning time unit, called growth cycle, is computed. At growth cycle n, the empirical equation of net dry matter production Q_n is given by:

$$Q_{n=}PAR_n\,\mu\,S^p\left(1-exp\left(-k_B\,\frac{S_n}{S^p}\right)\right) \tag{2.23}$$

where, PAR is the incident photosynthetically active radiation at cycle n, μ is an empirical coefficient related to the radiation use efficiency, S^p is an empirical coefficient corresponding to a characteristic surface (related to the two dimensional projection of space potentially occupied by the plant onto x-y plane), S_n is the total leaf surface area of the plant at cycle n and k_B is the Beer-Lambert extinction coefficient. The estimated value of μ is 1.23 g MJ^{-1}, whereas the value of k_B is measured 0.7 and the value of $S^p$is estimated 0.021 (m^2) for the sugarbeet.

At every growth cycle, the photosynthate (or dry matter) produced is allocated to different plant parts according to their relative demands called sink strengths. The sink strength of a plant part depends on its type (blade, petiole and root in sugarbeet) and varies from its initiation to maturity which corresponds to the end of its expansion. Sink strengths of these organs are barycentric coefficients and one of these values must be kept fixed for computational purpose. For this reason, Lemaire et al. (2008) imposes that the blade sink strength is equal to 1. Table 2.1 gives the sink strength of different plant parts developed for sugarbeet (Lemaire et al., 2008).

Table 2.1. Sink strength of the different parts of sugarbeet plant.

Parameter	Description	Estimated (E), Measured (M) or Fixed (F)	Value
$\boldsymbol{p_r}$	Root Sink Strength	F	400
$\boldsymbol{p_b}$	Blade Sink Strength	F	1 (Reference Value)
$\boldsymbol{p_p}$	Petiole Sink Strength	E	0.4916
$\boldsymbol{q_p}$	Petiole Sink Correction	E	0.3894

Preliminary evaluation of this model indicated that it can be adapted to analyze the biomass production and its distribution among different plant parts. But this model still needs to be fully validated, particularly among seasons. Specially, the leaf development scheme of several seasons and several stress conditions needs to be studied.

2.2.2.14. Gholipouri et al. (2009)

Gholipouri et al. (2009) developed another simple and dynamic mechanistic model to simulate sugarbeet growth and accumulation of sugar under potential production scenarios. The driving variables of this model are temperature and solar radiation. This model divides the plant growth stages depending on the leaf growth rate. These stages are: emergence to end of the first stage, leaf development and initiation of root biomass growth, end of leaf growth and root development and saturation.

The crop growth rate in this model (CGR, g m^{-2} d^{-1}) is modeled as a function of radiation use efficiency (RUE), solar radiation ($ISRAD$, MJ m^{-2} d^{-1}), and a temperature correction factor (TCF):

$$CGR = ISRAD \times RUE \times TCF \tag{2.24}$$

The value of TCF is estimated as 1 within a range of 10 to 25 ˚C average daily air temperature and is linearly decreased to 0 when average daily air temperature decreases from 10 ˚C to 0 ˚C or increases from 25 ˚C to 35 ˚C.

Total dry mass increment (TDM) for each day is simulated using the formula:

$$TDM_i = TDM_{(i-1)} + CGR_i \tag{2.25}$$

where, $TDM_{(i-1)}$ is accumulated dry mass at previous time step (g dry mass m^{-2}).

This model can simulate the sugarbeet growth and yield with reasonable accuracy under different production scenarios. However, the model needs to be validated using more observations on a range of sugarbeet cultivars and on sites that have different growing seasons (Gholipouri et al., 2009).

All these models have been developed for simulating the growth and yield of crop under different agro-climatic conditions. All these models vary in the number of parameters needed and their complexity. A summary of the currently available descriptive models is listed in Table 2.2.

Table 2.2. Summary of the currently available descriptive sugarbeet growth models.

Model Name	Model Type Generic/ Specific	Model Scale Individual plant/Plot	Partitioning Scheme Empirical/Dynamic	Application	Limitations	References
Broom Barn's Model	Specific	Plot	Model computes overall dry matter. No partitioning is calculated	Simulate total crop growth and sugar yield	Distinctive cultivar effects were not calibrated. Needs parameter adjustments for soil available water content of greater than 18% by volume	Qi et al., 2005
CERES-Beet	Generic	Plot	Empirical harvest index. Dry matter produced is partitioned as a function of the phonological development stage	Can simulate sugarbeet growth under different soil and climatic conditions	Effect of cold temperatures cannot be parameterized	Leviel et al., 2000
Gholipouri et al., 2009	Specific	Plot	Dry matter available for each day crop growth is partitioned as a crop specific function of development stage	Sugarbeet growth and sugar accumulation simulation	Need more validation for other sugarbeet genotypes	Gholipouri et al., 2009
GreenLab	Generic	Individual plant	Partitioning is done based on source-sink relationship and sink strengths. Tops and roots are considered to be the two sinks whereas initial seeds and leaves are the sources	Describe the dynamics of source-sink interaction during sugarbeet growth	Limited efficiencies in environmental stress conditions	Lemaire et al., 2008
PILOTE	Generic	Plot	Empirical harvest index	Simulates sugarbeet growth and yield	Hydric stress is not included	Taky, 2008

Table 2.2. Summary of the currently available descriptive sugarbeet growth models (continued).

Model Name	Model Type Generic/ Specific	Model Scale Individual plant/Plot	Partitioning Scheme Empirical/Dynamic	Application	Limitations	References
SIMBEET	Specific	Plot	Empirical (Translocation rate equations are used.)	Simulates crop growth, root sucrose storage and senescence	Translocation rates is considered the poorest developed components	Lee, 1983
SIUCRA	Specific	Plot	Partitioning depends on the stage of growth, and update the state of the crops	Simulates crop growth and yield	Test Reference Year (TRY) is needed to run the model for yield prediction. TRY is a data file containing meteorological data for a typical year	Burke, 1992
SOWAN	Generic	Plot	Empirical	Simulates dry matter production under different soil and nitrogen conditions		Hendrickx, 1986
STICS	Generic	Plot	Empirical	It simulates the behavior of soil-crop system within 1 year	LAI is modelled with an empirical function	Brisson et al., 1998
SUBEMO	Specific	Plot	Empirical (Partitioning is based on teleonomic hypothesis.)	Simulates dry matter and sugar production	This model does not simulate emergence date	Vandendriessche, 1989
SUBEMOpo	Specific	Plot	Empirical (Partitioning is based on teleonomic hypothesis.)	Simulates the potential sugarbeet growth	More information is required for sucrose translocation and storage in sugarbeet	Vandendriessche, 2000

Table 2.2. Summary of the currently available descriptive sugarbeet growth models (continued).

Model Name	Model Type Generic/ Specific	Model Scale Individual plant/Plot	Partitioning Scheme Empirical/Dynamic	Application	Limitations	References
SUBGOL	Specific	Plot	Empirical (partitioning is based on source-sink strength)	Simulates sugarbeet growth and yield.	Needs more validation regarding crop growth predictions under different respiratory coefficients	Hunt, 1974
SUBGRO	Specific	Plot	Empirical	Simulates sugarbeet growth and sugar accumulation	Respiration is considered only as a percentage of carbohydrate produced	Fick, 1971
SUCROS	Generic	Plot	Dry matter produced daily is partitioned among various plant organs as a function of the phonological development stage	Simulates crop growth under different environmental conditions	Production is simulated under ample supply of nutrients, and in pest, disease and pest free conditions	Van Laar et al., 1982
Unnamed	Generic	Plot	Empirical	Estimates the behavior of soil-water-nitrogen in the root zone from crop emergence to harvest	Plant growth is not modeled in detail since the objective of the model is centered in the soil	Frere et al., 1970
Unnamed	Specific	Plot	Empirical (allometric equation is used to describe the relationship between leaf and total weight)	Simulates sugarbeet growth and yield	No theoretical basis for the allocation of photosynthates among organs	Patefield and Austin, 1971
Webb et al. 1997	Specific	Plot	Dynamic partitioning of dry matter based on soil-N content	Describes the partitioning of assimilates during sugarbeet growth based on soil-N	Effects of environmental stresses were not considered	Webb et al., 1997

Most of the current models concentrate on modeling the growth and yield of sugarbeet under ideal growth environments, none, but SIMBEET (Lee, 1983) assess the impacts of crop growth and management on soil and water quality. Such a model could be a point (one-dimensional) model with emphasis on management effects on soil water quantity and quality, and crop production. Physically based RZWQM2 model can estimate the effects of crop growth on soil and water quality. This model is linked to a crop growth module from DSSAT, and can be used for better simulation of crop production in addition to soil water quality (Ma et al., 2005; 2006). Deep rooted sugarbeet is not included in the DSSAT, and needs to be developed to work in linkage with RZWQM2 for soil and water quality assessment.

2.3. Model Development

To develop a sugarbeet model for estimating the impacts of sugarbeet growth on soil and water quality, adopting RZWQM is the best available approach because this specific model was developed for simulating agricultural management effects on crop production and soil and water quality (Ma et al., 2012). The generic plant growth module can be calibrated for any annual crop, although it has been used mostly for corn (*Zea mays L.*), wheat (*Triticum aestivum L.*) and soybean (*Glycine max L.*). RZWQM2, an upgraded version of RZWQM, included a crop specific plant growth module from the DSSAT for better simulation of crop growth along with soil and water quality assessment (Ma et al., 2012). Up to now, 42 crop models have been included in DSSAT (Hoogenboom et al., 2017). But RZWQMs is linked to an older version of DSSAT (version 4.0) that has only 23 crop models (Flerchinger et al., 2012; Ma et al., 2012). When DSSAT is used, the RZWQM2 feeds the daily soil moisture, soil N and evapotranspiration to the plant module and then retrieves daily N uptake and plant transpiration for its water and N balance (Ma et al., 2009).

The DSSAT model was originally developed by an international network of scientists, cooperating in the International Benchmark Sites Network for Agrotechnology Transfer project (Tsuji, 1998; Jones et al., 1998) to facilitate the application of crop models in a systematic approach to agronomic research. The DSSAT contains a number of independent programs that operate together to keep the crop simulation models at the center. In this original model, each individual crop had its own soil model components. The revised DSSAT is a new cropping system model (DSSAT-CSM), which includes all crops as modules using a single soil model (Fig. 2.4).

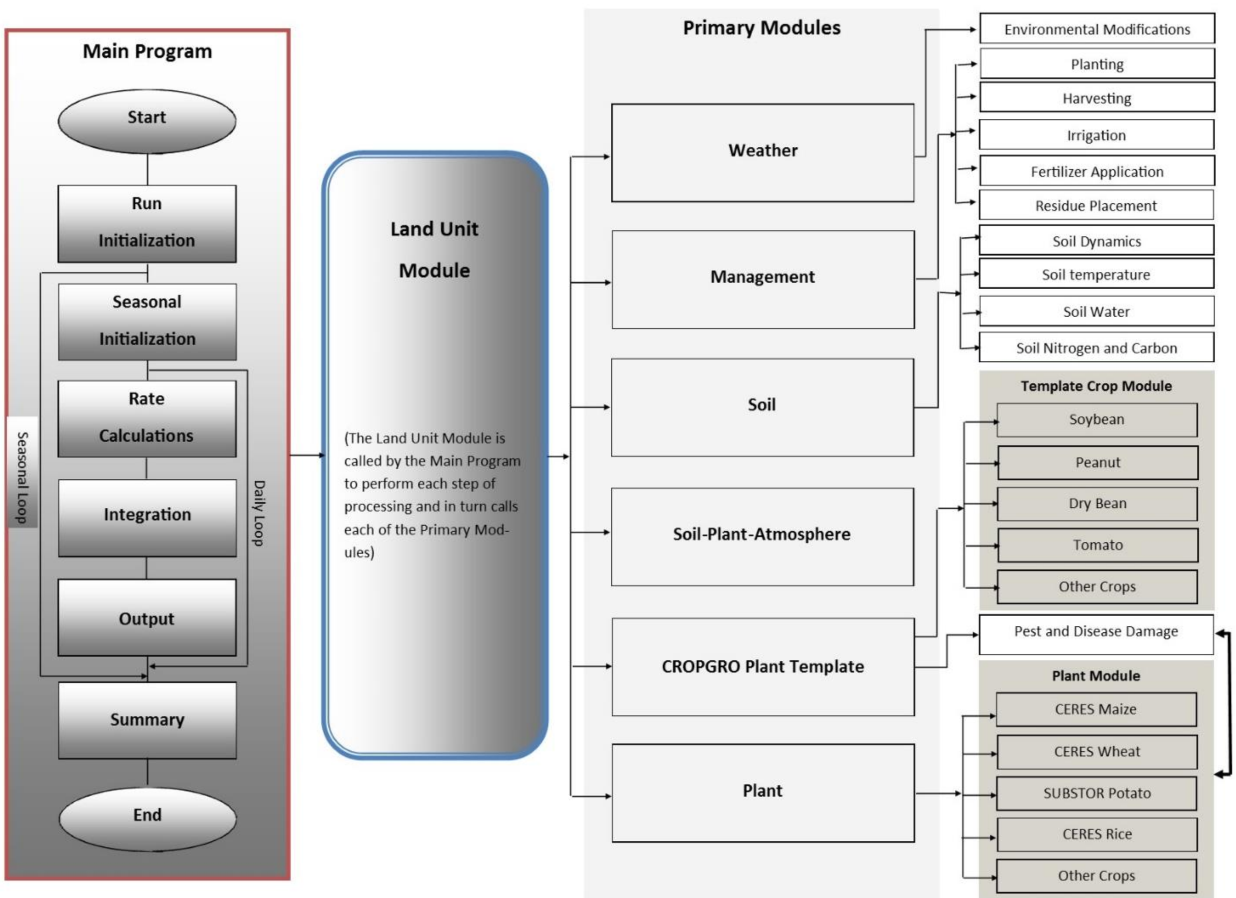


Figure 2.4. Overview of the components and modular structure of the DSSAT-CSM (Redrawn from Jones et al., 2003).

The DSSAT-CSM model has a main driver program, a land unit module, and module for the primary components that make up a land unit in a cropping system. The primary module contains the weather, soil, plant, soil-plant-atmosphere interface, and management components which collectively describe the time changes in soil and plants that occur on a single land unit in response to weather and management.

Each of the modules has six operational steps which are initialization, season initialization, rate calculations, integration, daily output, and summary output. The main program controls when each of these steps is active, and when each module performs the intended tasks. This feature allows each module to read its own inputs, initialize itself, compute rates, integrate its own state variables, and write outputs completely independent from the operation of other modules (Kraalingen, 1995).

In the DSSAT-CSM, there are two different ways of introducing new crops. In the first approach, a new module can be introduced for a crop by interfacing it with the plant module. This approach was used to interface the CERES and other crop models, which were operated as standalone crop models in DSSAT v3.5, such as cassava, potato, sunflower and sugarcane. In this approach, the model developer needs to code only for the crop growth module and adhere it to the interface of the Plant module and simply add it to the rest of the code. This approach is advantageous because it allows one to test a model from outside the DSSAT group.

Second approach for introducing a new crop is the use of Crop Template approach. This method is usually implemented with CROPGRO template approach that allows the model developer to modify values in a Crop Template file without changing the code for crop growth module. This approach has been used to develop models for a number of different crops like tomato (Scholberg et al., 1997), faba bean (Boote et al., 2002) and velvet bean (Hartkamp et al.,

2002) etc. This approach of using a Crop Template is usually less prone to errors. To develop a sugarbeet growth model to interface it with DSSAT plant growth module, we adopted the first approach and used CERES-Beet model.

2.4. Summary

Many sugarbeet models have already been developed to describe the growth and development of sugarbeet. These models are either empirical or process based descriptive models. However, none of these models, but SIMBEET simulate the effects of sugarbeet growth on soil and water quality. RZWQM, developed by USDA-ARS, is a process-based model that simulates crop growth along with its impact on soil and water quality assessment. RZWQM2, a significant upgrade from earlier version of RZWQM, included the crop specific growth modules from DSSAT for better simulations of crop growth and its impacts on soil and water quality. Unfortunately, no sugarbeet model is currently available for DSSAT or RZWQM2. To develop a sugarbeet model for the assessment of its effect on soil and water quality, a crop growth model will first be developed from the existing models and coded for DSSAT. Once the sugarbeet model is successfully developed, calibrated, and incorporated to the DSSAT, it will be linked to RZWQM2 for the assessment of crop management on soil and water quality.

CHAPTER 3. MODELING GROWTH, DEVELOPMENT AND YIELD FOR SUGARBEET USING DSSAT[1]

3.1. Abstract

Sugarbeet (*Beta vulgaris*) is considered as one of the most viable feedstock alternatives to corn for biofuel production after 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 are restricted to local regions. The Decision Support System for Agrotechnology Transfer (DSSAT) provides a common framework for a cropping system study and currently has plant growth modules for more than 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 for 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, USA (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 (*d*-statistic = 0.783-0.993, *rRMSE* = 0.127-1.014). Although uncertainty analysis revealed that the calibrated CSM-CERES-Beet consistently over-predicted leaf numbers

---

[1] This article is co-authored by Mohammad J. Anar, Zhulu Lin, Gerrit Hoogenboom, Vakhtang Shelia, William D. Batchelor, Jasper M. Teboh, Michael Ostlie, Blaine G. Schatz, and Mohamed Khan. Mohammad J. Anar had the primary responsibility for model development, data collection, model evaluation, and article write up. Dr. Zhulu Lin helped in model development, write up, and article proof reading. Drs. Gerrit Hoogenboom, Vakhtang Shelia, and William D. Batchelor helped in model evaluation, incorporation, and article proof reading. Drs. Jasper M. Teboh, Michael Ostlie, and Mohamed Khan helped in field experiment and proof reading. Blaine G. Schatz helped in field data analysis.

with false confidence, the model was successfully applied to simulate the yields for six different sugarbeet cultivars grown in North Dakota, USA in 2014-2016. CSM-CERES-Beet may be applied to simulate sugarbeet production for different soils under different management scenarios and climatic conditions in the Red River Valley and other regions.

Keywords: Biofuel, Bioenergy; Crop and Environment REsource Synthesis (CERES); Cropping System Model; Decision Support System for Agrotechnology Transfer (DSSAT); Parameter Estimation (PEST)

3.2. 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 is 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). Sugarbeets grown in the United States are currently found in regions encompassing 11 states and they tend to be grown in rotation with other crops (USDA/ERS, 2018). The total sugarbeet planting area in the U.S. was 1.16 million acres (0.469 million ha) in 2016/17. The Red River Valley (RRV) of western Minnesota and eastern North Dakota and its vicinity is the largest region in terms of sugarbeet production. In 2016/17, 57% of the nation's total sugarbeets were produced in the RRV region, while 31% were produced in Idaho and Michigan (USDA/ERS, 2018).

Currently, 97% of the biofuels produced in the United States is corn-based ethanol, which may offer up to a 40% reduction in 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 Pryor, 2013; Vargas-Ramirez et al., 2013). One is that, compared to corn-based ethanol, the use of sugarbeet for biofuel production has less impact on the food supply; and the other is that sugarbeet has the potential to be designated as feedstock for advanced biofuel, which should offer at least 50% net greenhouse gas (GHG) emission reduction relative to gasoline (Foteinis et al., 2011; Jessen, 2012). It is 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 U.S is nonexistent. Therefore, tremendous opportunities exist to expand sugarbeet production into the nontraditional or underutilized planting areas in the US (Miyake et al., 2015), which, in turn, may cause environmental concerns such as soil health and water quality degradation.

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 on soil health and water quality of growing sugarbeets in nontraditional sugarbeet growing areas (Ma et al., 2012). A number of crop models are currently available for simulating sugarbeet growth and production. These models were developed based on either the empirical relationship observed between pre-harvested samples of sugarbeet and final crop yields 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 a., 1989, 1990) and the model developed by Modig (1992). Process-based models include SUBGRO (Fick et al., 1971), SUBGOL (Hunt, 1974), SIMBEET (Lee, 1983), SUBEMO (Vandendriessche, 1989), 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 fodder beet (a sugarbeet cultivar) potential yield model was developed for the APSIM (Khaembah et al., 2017). Excellent reviews of sugarbeet models were provided by Vandendriessche and van Ittersum (1995) and Baey et al. (2014). Most of these models are restricted to the regions and conditions for which they were developed (Vandendriessche and van Ittersum, 1995) and require different file and data structures and different modes of operation (Jones et al., 2003). For this reason, it is not appropriate 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; 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). The 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; Ma et al., 2006; Ma et al., 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 (i.e., CSM-CERES-Beet), 2) to evaluate the performance of CSM-CERES-Beet with field data and the model's transferability, and (3) to conduct uncertainty analysis for CSM-CERES-Beet using Parameter Estimation (PEST) software.

3.3. Materials and Methods

3.3.1. CSM-CERES-Beet

The CERES-Beet model (Leviel, 2000; Leviel et al., 2003) was modified and adapted as a plant specific module for the Cropping System Model in DSSAT, referred as "CSM-CERES-Beet". We chose to adapt CERES-Beet into CSM-CERES-Beet mainly because a number of CERES models (including CERES-Maize) were previously 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, GreenLab (Vos et al., 2007), LNAS (Cournede et al., 2013), STICS (Brisson et al., 1998), and Pilote (Taky, 2008).

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 (GDD), with a base temperature of 3°C. 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 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 (GDD with a base temperature of 3 °C), when the tap root becomes the main recipient of the partitioned photosynthates. Thereafter, virtually all of the dry matter (85%) is portioned to root tuber formation after 1500 GDD (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).

Like in other CERES models, genetic parameters G2 and G3 in CERES-Beet are related to seed growth and seed filling. Since CSM-CERES-Beet was developed for simulating only beet root production, not seed production, we redefined G2 and G3 to correspond to sugarbeet leaf expansion rate and maximum root growth rate, respectively. In CERES-Beet, potential leaf area growth ($PLAG$) 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).

$$PLAG = 3.0 \times 170 \times TI \times min(AGEFAC, TURFAC, (1. - SATFAC)) \tag{3.1}$$

$$PLAG = 170 \times 3.5/((XN + 5.0 - TLNO)^2) \times TI \times min(AGEFAC, TURFAC,\ (1. - SATFAC)) \tag{3.2}$$

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, soil water, and waterlogging respectively. In the CSM-CERES-Beet model constant 170 in Eqs (3.1) and (3.2) was replaced with $G2$, 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 ($GRORT$) in CSM-CERES-Beet is:

$$GRORT = G3 \times PCO2 \times \frac{ETGT}{PLTPOP} \times\ min(AGEFAC, TURFAC, (1. - SATFAC)) \tag{3.3}$$

where, $G3$ is the maximum root growth rate (g m^{-2} d^{-1}), $PCO2$ is the effect of CO_2 on growth rate, $ETGT$ is the function of soil temperature on root growth, $PLTPOP$ is the population density (plants m^{-2}).

Besides redefining G2 and G3, we also made the following changes when developing CSM-CERES-Beet. First, in CERES-Beet, LAI is calculated using the following equation:

$$LAI =\ (PLA - SENLA) \times PLTPOP \times 0.0001 \tag{3.4}$$

where, PLA is the potential leaf area (cm^2 plant^{-1}); $PLTPOP$ is the number of plants; 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 ($PLAS$) following SUBSTOR-Potato (IBSNAT, 1993b).

$$SENLA_i = SENLA_{i-1} + PLAS \tag{3.5}$$

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:

$$PLAS = (PLA - SENLA_{i-1}) \times \left(1 - min(SLFW, SLFC, SLFT, SLFN)\right) \tag{3.6}$$

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

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

$$XN = CUMPH + 1.0 \tag{3.7}$$

where $CUMPH$ on the current day, $CUMPH_i$, is calculated from the previous day's values, $CUMPH_{i-1}$, using Eq. (3.8).

$$CUMPH_i = CUMPH_{i-1} + DTT/(PHINT \times PC) \tag{3.8}$$

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

Third, Harvest Index (HI) in the model is computed as the ratio between total dry matter of the root ($Yield$) and total dry matter of the entire sugarbeet ($Biomass \times 10 + Yield$)

following the SUBSTOR-Potato (IBASNAT, 1993b) and AROID-Taro models (Singh et al., 1998).

$$HI = \frac{Yield}{\left((Biomass \times 10) + Yield\right)} \tag{3.9}$$

The input data required to run the CSM-CERES-Beet model are standard inputs required by DSSAT. They include site information, daily weather (daily solar radiation (SRAD (MJ m^{-2})), daily maximum and minimum temperature (℃), 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, and plant density, fertilizer application date and rate, tillage, irrigation, and residue incorporation.

The cultivar coefficients for the CSM-CERES-Beet model include $P1, P2, P5, G2, G3$ and $PHINT$. Their definitions and units are listed in Table 3.1, along with other relevant DSSAT model parameters.

Table 3.1. CSM-CERES-Beet parameters.

Parameter	Definition	Unit	DSSAT file
	Genetic parameters		
P1	Growing Degree Days (GDD) from the seedling emergence to the end of the juvenile phase	℃-d	.CUL
P2	Photoperiod sensitivity	hr^{-1}	.CUL
P5	Thermal time from pennicle initiation to physiological maturity	℃-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	℃-d	.CUL
	Ecotype parameter		
RUE	Radiation use efficiency	g plant dry matter MJ PAR^{-1}	.ECO
DSGFT	GDD during effective root growth period	℃-d	.ECO
	Species parameter		
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	Growing degree days between germination and emergence after which the seed dies due to drought	℃-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 parameter		
SLPF	Soil fertility factor	—	.SOIL

3.3.2. Field Experiment and Data

3.3.2.1. Carrington Research and Extension Center, North Dakota, USA

CSM-CERES-Beet was first evaluated with experimental data collected at the Carrington Research Extension Center (CREC) (47.510N, -99.123W), Carrington, North Dakota (ND), USA. A specific cultivar of sugarbeet (proprietary materials from Betaseed, Shakoppe, MN, denoted as CREC in this Chapter) was cultivated in rotation with other crops (not shown) in a randomized complete block design with four replicates, testing 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 in 2014, 2015 and 2016 (Fig. 3.1) using recommended practices (Khan, 2014). The plots illustrated with an upward slanted cell fill pattern were planted with sugarbeet in 2014; the plots with a downward slanted fill pattern were planted in 2015; the vertical slanted filled plots were planted in 2016; and the plots with horizontal lines were planted in all 3 years. The soil properties of the Carrington, ND experimental plots (Table 3.2) and field management data for 2014 and 2016 (Table 3.3) are provided. Soil texture was determined using the hydrometer method, while soil organic matter (OM) content was determined by loss of weight on ignition at 360 °C, and the salts by a conductivity meter in a 1:1 soil:water suspension. All lab analyses were conducted at the Agvise Laboratories, Northwood, ND. 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. 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 (47.509N, -99.132W).

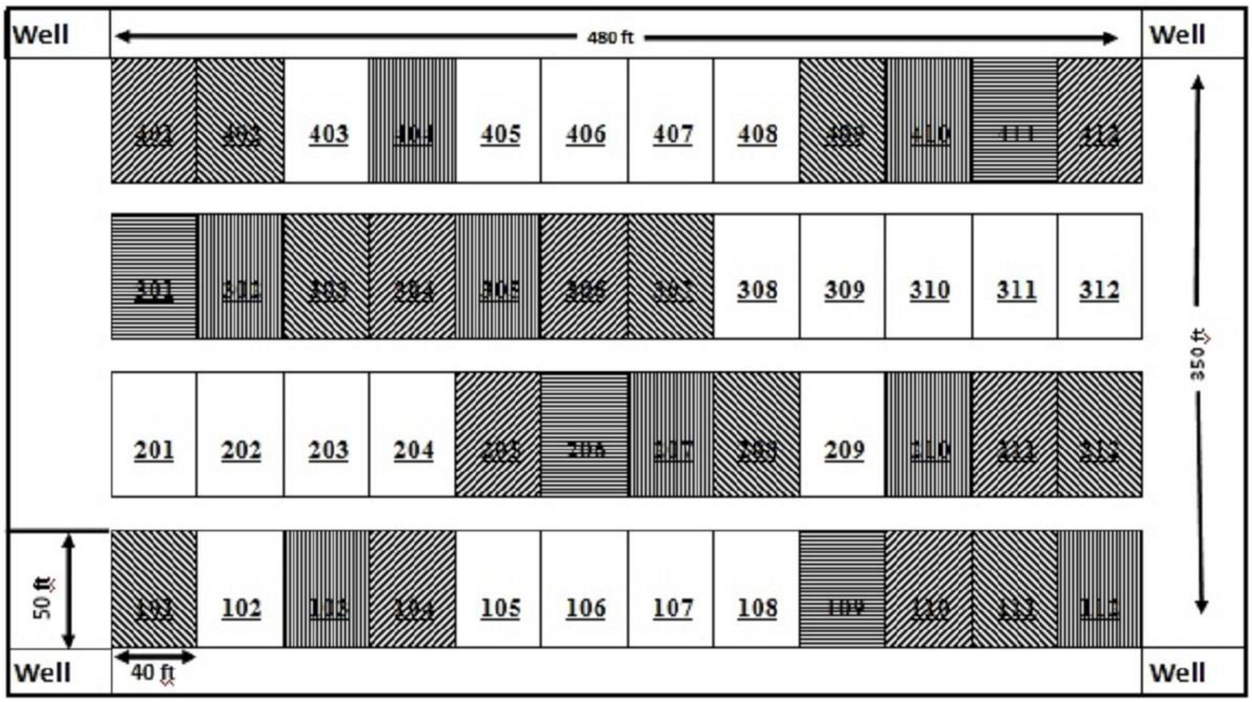


Figure 3.1. Schematic of field experimental plots planted for sugarbeet in: 2014 (upward slanted fill), 2015 (downward slanted fill), 2016 (vertical fill) and all 3 years (horizontal fill).

Table 3.2. Average soil characteristics of the experimental plots at Carrington Research Extension Center, North Dakota, USA.

Depth (cm)	% Sand	% Silt	% Clay	Soil Type	% OM	EC 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		

Table 3.3. Field management for sugarbeet experimental plots at Carrington Research Extension Center, 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 as Urea: 112.08 kg ha^{-1} (100 lbs ac^{-1}) P as MAP: 22.42 kg ha^{-1} (20 lbs ac^{-1}) S as AS: 11.21 kg ha^{-1} (10 lbs ac^{-1})	N as Urea: 112.08 kg ha^{-1} (100 lbs ac^{-1}) P as MAP: 22.42 kg ha^{-1} (20 lbs ac^{-1}) S as AS: 11.21 kg ha^{-1} (10 lbs ac^{-1})
Fertilizer application date	May 26	May 11
Harvesting	October 17	October 11

Each year, 6 out of 12 plots were randomly selected to collect plant growth data from. In each plot, eight sugarbeet plant were harvested to collect samples of leaf, stems, and roots periodically for top and root mass measurements. Sample fresh and dry weights were measured, and leaf numbers were counted. The Leaf Area Index (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 at 4 or 5 different dates during the 2014 growing season, at 8 different dates in 2015, and at 9 different dates in 2016. The 2016 dataset was used for model calibration and the 2014 and 2015 (discussed in Appendix) datasets for model evaluation.

3.3.2.2. Bucharest, Romania

CSM-CERES-Beet 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 evaluate the model's transferability. The Romanian dataset was used for the original CERES-Beet model development (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 (Leviel et al., 2003). Sugarbeet was planted on 29th April, 1997 and 4th April, 1998 in five experimental plots of 42 m² 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 yields under non-limiting water conditions. Further details on the field experiment and the experimental data that were collected can be found in Leviel (2000).

3.3.2.3. 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. This study was conducted to evaluate 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 plantation and no irrigation was applied.

The same five cultivars 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 cultivar parameters were calibrated, while other parameters were kept as the same as those calibrated for the 2016 Carrington dataset.

3.3.3. Model Calibration and Evaluation

CSM-CERES-Beet model calibration 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:

$$\phi(b) = [y - y'(b)]^T \, Q[y - y'(b)] \tag{3.10}$$

where Q is a weight matrix, 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. Parameters that minimize this equation were attained by solving the normal equations using the Gauss-Marquardt-Levenberg (GML) gradient search algorithm (Doherty, 2010).

The Carrington calibration dataset comprised 35 field observations divided into four different observation groups (leaf number count, LAI, and top and root weights). On a given sampling date, the field observation for each group was 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). Each observation group formed a component of the objective function (Eq. 3.10). 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.

Fifteen parameters were selected for adjustment by PEST based on prior knowledge of the model, which included that the CSM-CERES-Beet model was sensitive to these parameters. For these 15 parameters, default values as well as lower and upper bounds were specified based on literature reviews. 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).

3.3.4. 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 both relative root mean square error ($rRMSE$) and index of agreement (d) as indicators of model fit. $rRMSE$ is the root mean square error normalized to the mean of the observed values (Eq. 3.11):

$$rRMSE = \frac{\sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - y_i')^2}}{|\overline{y}|} \tag{3.11}$$

where, $\overline{y}$ 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. The index of agreement is estimated using Eq. (3.12):

$$d = 1 - \frac{\sum_{i=1}^{m}\left(y_i - y_i'\right)^2}{\sum_{i=1}^{m}(|y_i' - \overline{y}| + |y_i - \overline{y}|)^2} \tag{3.12}$$

where the symbols are defined as the same in Eq. (3.11). The value of d varies between 0 and 1, with higher values indicating better fit (Legates and McCabe, 1999).

3.3.5. 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 normally or log-normally distributed and that their bounds span their 95% confidence intervals (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% confidence intervals (CI's) of various model predictions.

Second, the posterior uncertainty of CSM-CERES-Beet was explored using the null space Monte Carlo calibration-constrained method, facilitated through using the 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" and "calibration null space" (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 these model runs were used to calculate the 95% CI's. The readers are referred to Doherty (2007; 2016a, b) and Doherty et al. (2010) for details about the null space Monte Carlo analysis method and the uses of the RANDPAR and PNULPAR utilities.

3.4. Results and Discussion

3.4.1. CSM-CERES-Beet Calibration/evaluation and Uncertainty Analysis

For calibration of the CSM-CERES-Beet model with the 2016 field experimental data collected at Carrington, ND, USA, the final PEST run required 8 optimization iterations and 242 model runs. Based on stability criterion, the number of singular values used in SVD was 7 on an iteration-by-iteration basis. It reduced the total objective function by 45% and total sum of weighted squared residuals by 16%. The parameter values obtained from model calibration were then used for model evaluation with the 2014 field data. Table 3.4 lists the goodness of fit statistics for model calibration (2016) and evaluation (2014).

In terms of d-statistics, the model did very well for all four plant growth variables (i.e., LAI, leaf number, dry top weight and dry root weight). All of the d values were greater than 0.924 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 less than 0.3 except for LAI in 2014.

Table 3.4. CSM-CERES-Beet model calibration and validation using the CREC (USA) dataset.

Observation Group	Index of agreement (d)		Relative root mean square error ($rRMSE$)	
	Calibration (2016)	Evaluation (2014)	Calibration (2016)	Evaluation (2014)
Leaf area index	0.981	0.971	0.188	0.318
Leaf number	0.974	0.924	0.127	0.168
Top weight	0.971	0.975	0.203	0.276
Root weight	0.987	0.993	0.228	0.194

Note: CREC – Carrington Research and Extension Center.

The graphical comparisons of the model-simulated and observed plant growth variables are also shown in Fig. 3.2 for 2016 and Fig. 3.3 for 2014, along with the prior and posterior 95% CI's for model simulations of these plant growth variables. The model-simulated values in 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. 3.2(b))

It is not surprising that the prior 95% CI's are wider than the posterior ones for all model predictions (Fig. 3.2 and Fig. 3.3). 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.

It is also interesting to notice 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 the leaf numbers almost throughout the entire growing season (see Fig. 3.2b). This implies that the model has false confidence in simulating sugarbeet leaf numbers and requires further testing with different data sets of data and might require further model improvement. CSM-CERES-Beet follows the AROID-Taro model (Singh et al., 1998) to simulate leaf numbers (Eq. (3.7) and (3.8)) because sugarbeet and taro have similar number of total leaves (approximately 22-30) per mature plant (Fick, 1971; Goenaga, 1995).

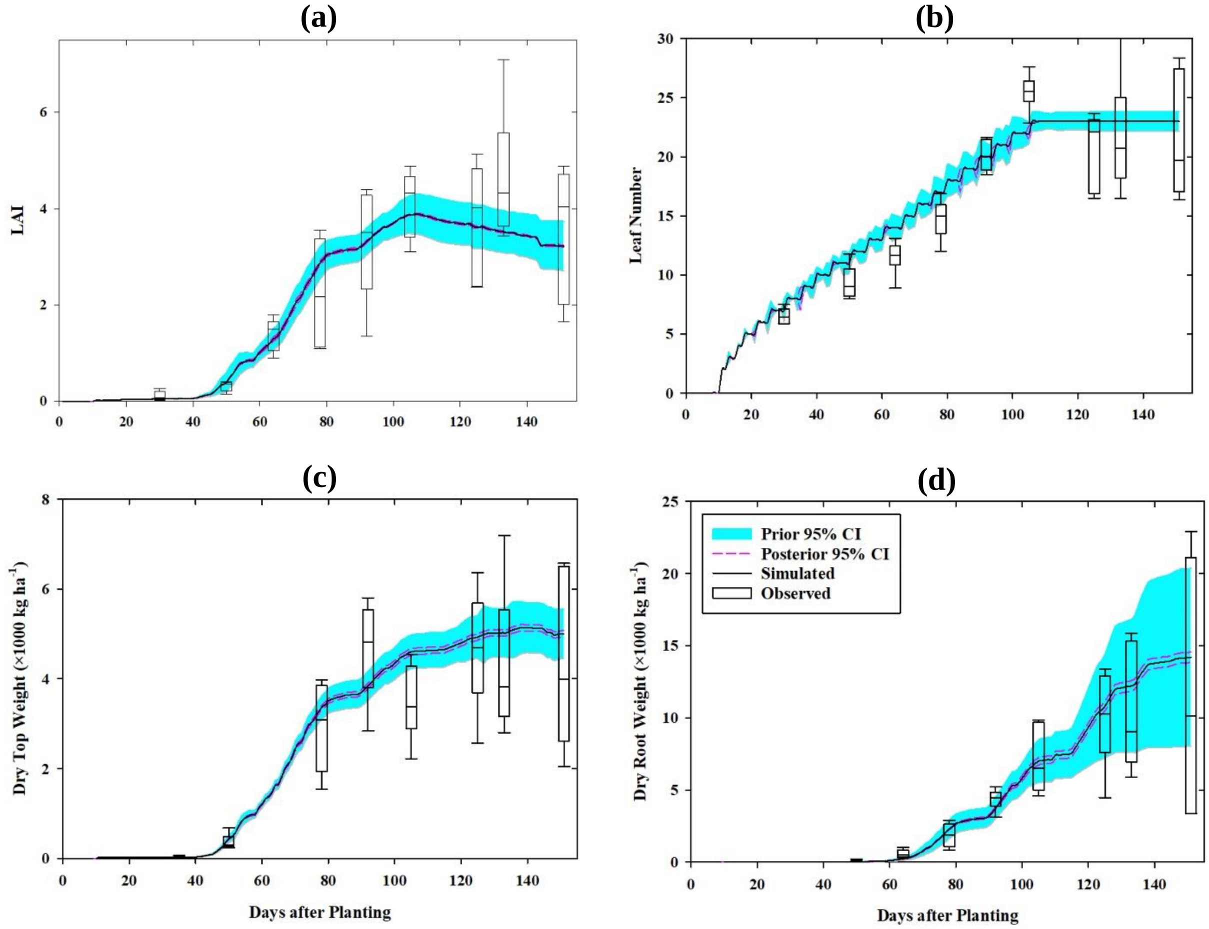


Figure 3.2. Model-simulated and observed values of (a) leaf area index (LAI), (b) leaf number, (c) top weight, and (d) root weight for model calibration (2016) and their 95% confidence intervals (CI's). Notes: Observed values are plotted in the boxplots with the medians shown as the lines within the 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.

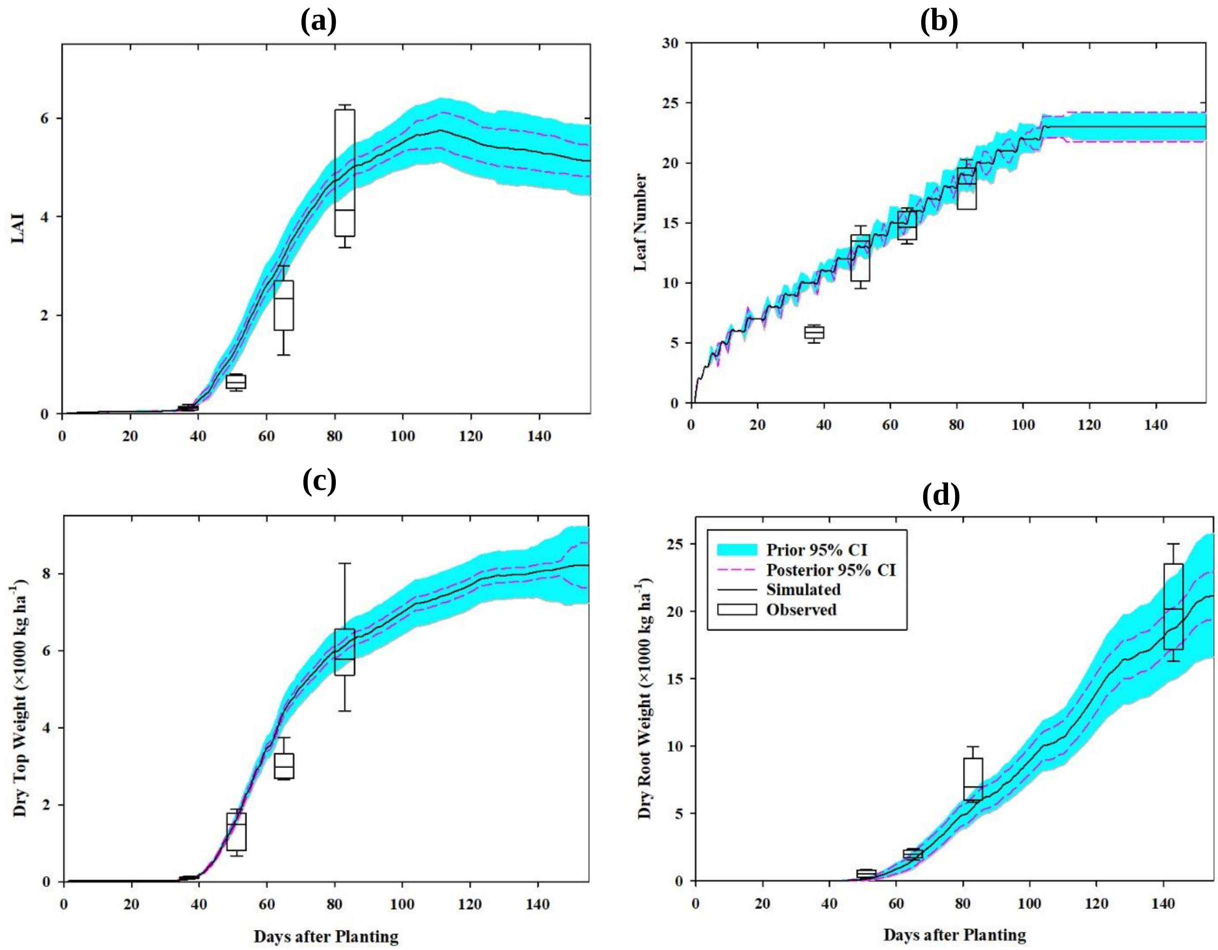


Figure 3.3. Model-simulated and observed values of (a) leaf area index (LAI), (b) leaf number, (c) top weight, and (d) root weight for model validation (2014) and their 95% confidence intervals (CI's). Notes: Observed values are plotted in boxplots with the medians shown as the lines within the boxes, 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.

3.4.2. 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 3.5). Two tests were performed. First, the model calibrated for the 2016 Carrington data was evaluated for the Bucharest 1997 and 1998 datasets. Secondly, the model was calibrated for the 1997 Becharest data and evaluated for the Bucharest 1998 data. The goodness-of-fit statistics (*d* and *rRMSE*) for each case are shown in Table 5. The first set of *d* and *rRMSE* values (Columns 2

& 4) were calculated when the model was calibrated with the 2016 Carrington dataset, while the second set of *d* and *rRMSE* values (Columns 3 & 5) were calculated when the model was re-calibrated with the 1997 Bucharest dataset.

Table 3.5. CSM-CERES-Beet model evaluation using the Bucharest (Romania) dataset.

Observation Group	Index of agreement (*d*)		Relative root mean square error (*rRMSE*)	
		1997 data		
	Calibrated with 2016 Carrington data	Calibrated with 1997 Bucharest data	Calibrated with 2016 Carrington data	Calibrated with 1997 Bucharest data
Leaf area index	0.974	0.980	0.227	0.202
Leaf weight	0.860	0.917	0.541	0.428
Root weight	0.902	0.983	1.014	0.356
		1998 data		
	Calibrated with 2016 Carrington data	Calibrated with 1997 Bucharest data	Calibrated with 2016 Carrington data	Calibrated with 1997 Bucharest data
Leaf area index	0.967	0.912	0.533	0.394
Leaf weight	0.836	0.783	0.351	0.566
Root weight	0.979	0.955	0.257	0.424

Two observations may be made after inspecting the goodness of fit statistics in Table 3.5. First, the CSM-CERES-Beet model was able to match the Bucharest dataset reasonably well regardless of which dataset was used to calibrate the model. The *d* statistics were all greater than 0.85, except for the 1998 Bucharest leaf weight. Most *rRMSE* but four were less than 0.5. Second, CSM-CERES-Beet only performed slightly better when it was calibrated using the 1997 Bucharest dataset compared to calibration using the 2016 Carrington dataset.

The graphical comparison of model-simulated with the observed plant growth variables for the Bucharest dataset is shown for 1997 in Fig. 3.4 and for 1998 in Fig. 3.5. In 1997, the model performed exceptionally well in simulating LAI, for which the model calibrated with the

Carrington dataset performed even better than the one calibrated with the Bucharest dataset (Fig. 3.4a). However, both models consistently under-predicted leaf weight late in the season (Fig. 3.4b). The model calibrated with the Carrington dataset over-predicted the root weight almost throughout the growing season, while the model calibrated with the Bucharest dataset did very well (Fig. 3.4c). This is not surprising because the cultivars were different in these two experiments and genetic coefficients derived for the CREC cultivar were different than those calibrated for the Emma cultivar planted in Bucharest (Table 3.6). In 1998, the model did better in terms of simulating leaf weight (Fig. 3.5b, but under-predicted LAI after leaf senescence later in the season (Fig. 3.5a). Both calibrations did reasonably well in terms of simulating root weight (Fig. 3.5c).

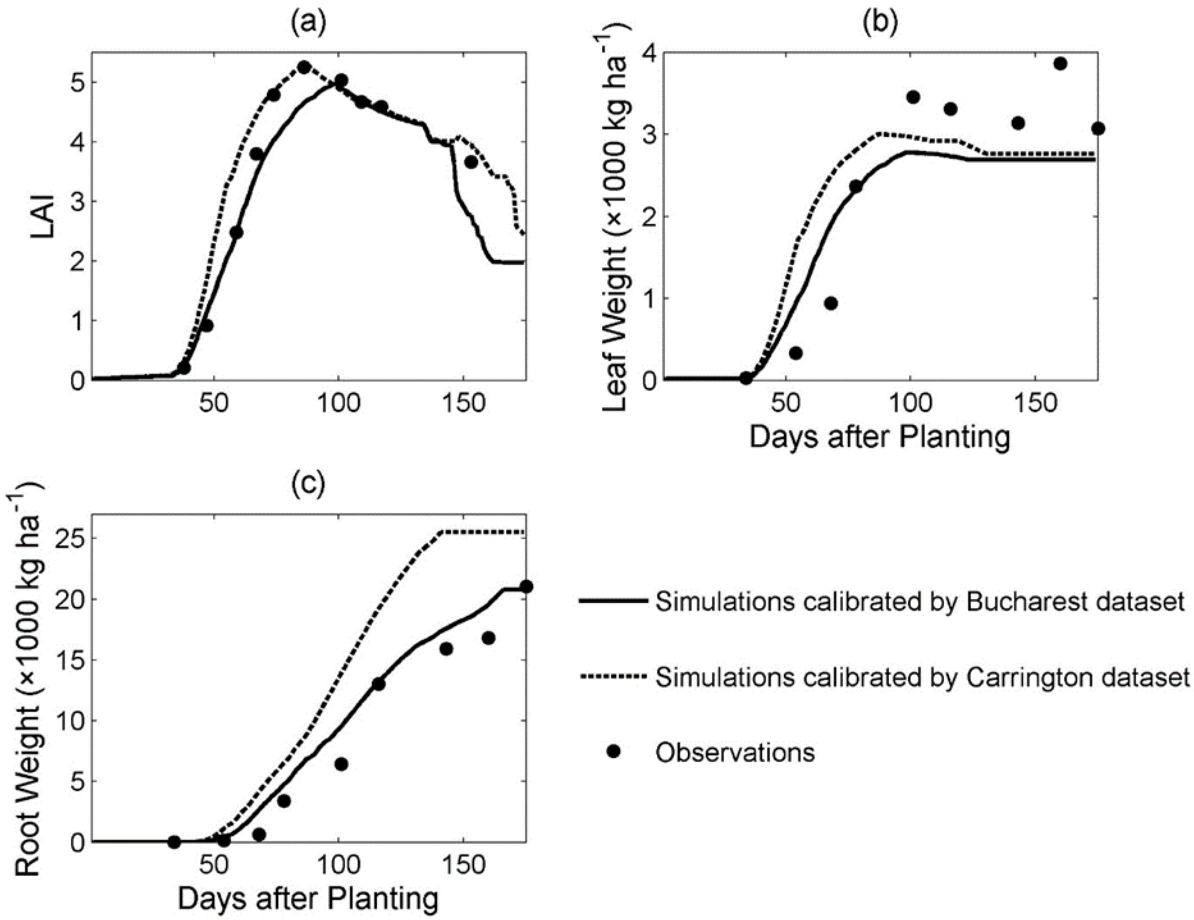


Figure 3.4. Graphical comparisons of model-simulated and observed values of (a) leaf area index, (b) leaf weight, and (c) root weight in 1997 (Bucharest, Romania).

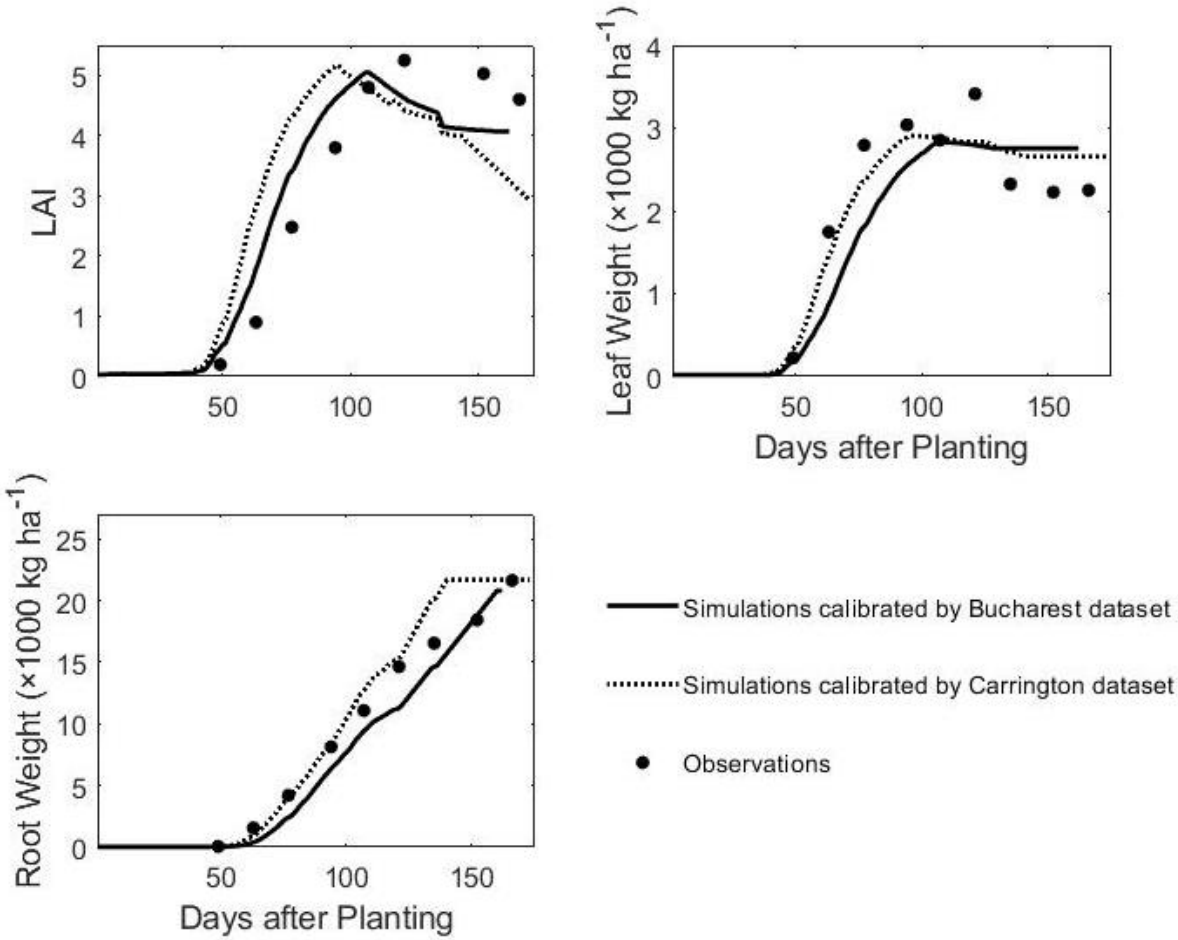


Figure 3.5. Graphical comparisons of model-simulated and observed values of (a) leaf area index, (b) leaf weight, and (c) root weight in 1998 (Bucharest, Romania).

A comparison of the parameter values calibrated with the 2016 Carrington and the 1997 Bucharest datasets is shown in Table 3.6. 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 3.6. Four parameters (i.e., $P1$, $G2$, $G3$, and $PHINT$) are genetic parameters that are expected to vary by cultivar and RUE (radiation use efficiency) is a parameter that is expected to be different for different ecotypes within a species. Table 3.6 shows that the CREC sugarbeet cultivar required smaller values for $P1$ (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 gMJ^{-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 environments and climates, however, genetic coefficients must be developed for each cultivar (see also Confalonieri et al., 2016).

Table 3.6. CSM-CERES-Beet calibrated parameters for the two study sites.

Parameter (unit)	Initial value	Lower bound	Upper bound	Calibrated values by the CREC dataset	Calibrated values by the Bucharest dataset
P1 (°C-d)	920	920	1100	*940*	*969*
P2 (hr^{-1})	0.001	0.00	0.01	0.001	0.001
P5 (°C-d)	700	660	900	700	730
G2 ($cm^2\ cm^{-2} d^{-1}$)	170	160	220	*220*	*160*
G3 ($g\ m^{-2} day^{-1}$)	20	20	50	*37.5*	*25.2*
PHINT (°C)	38.9	38	49	*42.0*	*43.4*
RUE (g plant dry matter MJ PAR^{-1})	2.8	2.8	4.2	*3.7*	*3.3*
DSGFT (°C-d)	170	160	200	170	170
PARSR (MJ SRAD $m^{-2}\ day^{-1}$)	0.48	0.46	0.52	0.52	0.52
DSGT (days)	40	35	45	40.0	40.0
DGET (°C)	150	140	160	150	150
SWCG ($cm^3\ cm^{-3}$)	0.02	0.01	0.04	0.02	0.02
PORM (unitless)	0.05	0.01	0.10	0.05	0.05
RLWR (unitless)	0.82	0.82	1.82	0.84	0.84
SLPF (unitless)	1	0.7	1	1	1

3.4.3. Sugarbeet Yield Simulation

The calibrated CSM-CERES-Beet model can be used to simulate sugarbeet yield. Figure 3.6 compares the model-simulated and observed yields 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 yields were the average fresh yields harvested from the twelve experimental plots. The CSM-CERES-Beet model output sugarbeet yields in terms of dry weight, which was converted into fresh yields assuming 82% moisture content in the beets. The model-simulated yield standard deviations were estimated based on prior uncertainty analysis described above. Figure 3.6 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 in the growing season of 2015 and resulted in lower observed yield for 2015.

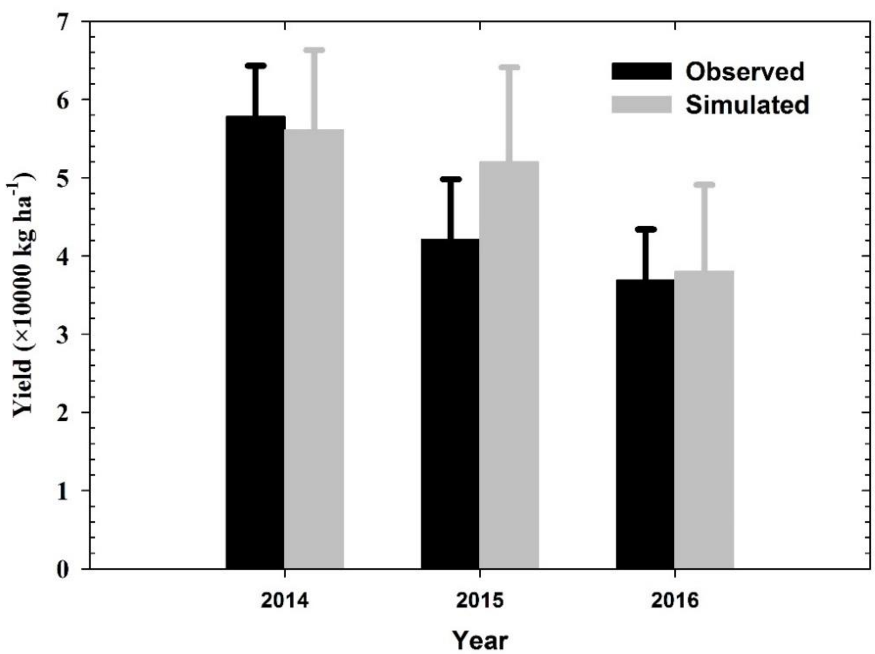


Figure 3.6. Observed and simulated yields of sugarbeet planted in Carrington Research and Extension Center, North Dakota, USA. Note: the vertical bars are average observed or model-simulated yields and the short horizontal lines are standard deviations.

The CSM-CERES-Beet model was also applied to simulate the yields of five different sugarbeet cultivars grown in Prosper and Hickson, ND, in 2016. The average observed and model-simulated yields for these five sugarbeet cultivars and the CREC cultivar planted in 2014-

2016 are shown in Fig. 3.7. Figure 3.7a compared the observed vs. simulated yields for the six cultivars for model calibration, while Fig. 3.7b shows the yield comparison for model evaluation. The fact that the simulated vs. observed yields 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 yields for different sugarbeet cultivars. Calibrated genetic parameters for the five cultivars used in Prosper and Hickson, ND are given in Table 3.7.

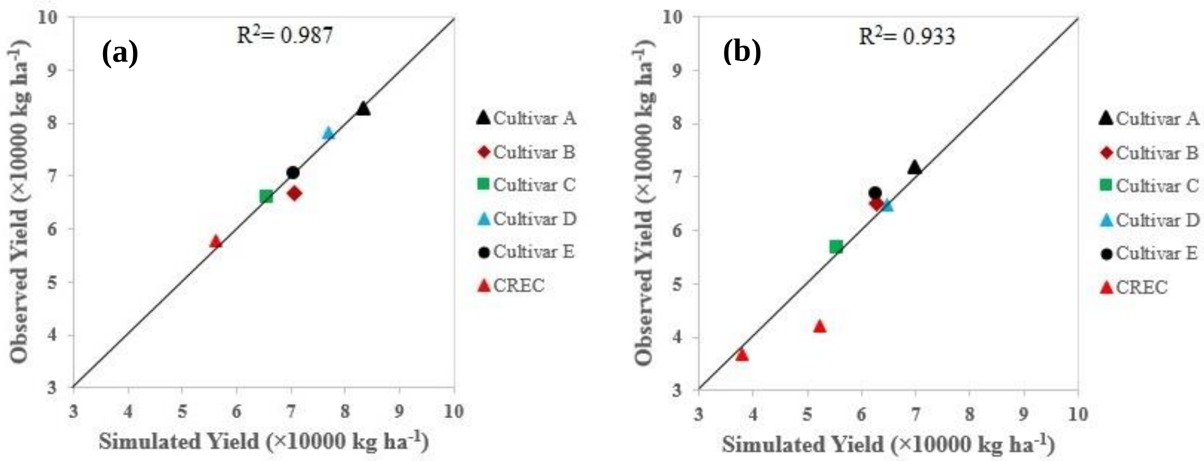


Figure 3.7. Observed and simulated sugarbeet yields with CSM-CERES-Beet model for (a) model calibration, and (b) model evaluation for six sugarbeet cultivars planted in North Dakota, USA in 2014-2016.

Table 3.7. 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})	0.000	0.000	0.000	0.000	0.000
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

3.5. Conclusions

CSM-CERES-Beet, the DSSAT compatible sugarbeet model, was developed based on modifications of the CERES-Beet. 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. After calibrating model parameters for specific cultivars, CSM-CERES-Beet performed well in simulating LAI, leaf number, leaf or top weight, and root weight for both datasets. The CSM-CERES-Beet 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. 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.

One limitation about the model is that uncertainty analysis revealed that the calibrated CSM-CERES-Beet consistently over-predicted leaf numbers with false confidence (i.e., small confidence intervals), although it did not affect the model's capabilities in simulating sugarbeet's yield. In the future, the developed model will be applied to simulate sugarbeet production under different management scenarios for different soils and under different climatic conditions in the Red River Valley. 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 to assess the associated environmental impacts.

CHAPTER 4. ANALYSIS OF PARAMETER SENSITIVITY AND IDENTIFIABILITY OF ROOT ZONE WATER QUALITY MODEL (RZWQM) FOR DRYLAND SUGARBEET MODELING[2]

4.1. Abstract

Sugarbeet is being considered as one of the most viable feedstock alternatives to corn for biofuel production since herbicide-resistant energy beets were deregulated by the USDA in 2012. Growing sugarbeets for biofuel production may have significant impacts on soil health and water quality in the north-central regions of the U.S., where 50% of the nation's total sugarbeets were produced in 2015. Almost all the current sugarbeet models simulate only plant growth and yield but have no capability to simulate the effects of sugarbeet production on soil and water quality. The Root Zone Water Quality Model (RZWQM) is a widely used model that simulates crop yield, water flow, and transport of salts and nitrogen in crop fields. RZWQM is currently linked to 23 specific crop models in the Decision Support System for Agrotechnology Transfer (DSSAT) version 4.0, not including a sugarbeet model. In this study, the Crop and Environment REsource Synthesis (CERES) in RZWQM was adapted for sugarbeet simulation to model the soil and water quality impact of sugarbeet for biofuel production. The Beet model was then evaluated against dryland sugarbeet production at the Carrington Research and Extension Station (North Dakota) in 2014 and 2015. The PEST (Parameter ESTimation) tool in RZWQM was used for parameter estimation and sensitivity and identifiability analysis. The model did reasonably well in both 2014 (d-statistic = 0.709 to 0.992; $rRMSE$ = 0.066 to 1.211) and 2015 (d-statistic =

[2] This article is co-authored by Mohammad J. Anar, Zhulu Lin, Liwang Ma, Patricia N. Bartling, Jasper M. Teboh, and Michael Ostlie. Mohammad J. Anar had the primary responsibility for model development, incorporation, evaluation and write up. Dr. Zhulu Lin helped in model evaluation, result analysis, and article write up. Drs. Liwang Ma and Patricia N. Bartling helped in model incorporation and result analysis and proof reading. Drs. Jasper M. Teboh and Michael Ostlie helped in field experiment and proof reading.

0.733 to 0.990; $rRMSE$ = 0.043 to 0.930) in terms of simulating leaf area index, top weight, root weight, soil water content, and soil nitrates. Under dry conditions, the most sensitive soil parameters were soil bulk densities and saturated hydraulic conductivities in different layers. Identifiability analysis also showed that three to five model parameters may be identifiable by calibration datasets. RZWQM enhanced with a sugarbeet module and its parameter analysis can be used for water use optimization under dryland conditions.

Keywords: Biofuels, CERES, DSSAT, RZWQM, Sugarbeet.

4.2. Introduction

Biofuel is defined as any fuel source that is derived from biomass and can be used to produce heat, electricity, or transportation fuel (Wang et al., 2011). Based on their potential to reduce net greenhouse gas (GHG) emission, the Energy Independence and Security Act (EISA) of 2007 classified biofuels into three categories called conventional, advanced, and cellulosic biofuels, offering 20%, 50%, and 60% reduction in GHG emission respectively. Currently, 97% of the biofuels produced in the U. S. are corn-based ethanol, which may offer up to 40% reduction in GHG emission when compared with gasoline on an equivalent energy basis (Hettinga et al., 2009; Wang et al., 2011; Canter et al., 2016; Flugge et al., 2017). Two crops, sugarbeet (*Beta vulgaris*) and sugarcane (*Saccharum officinarum*), are currently considered to be uniquely qualified as “advanced biofuels” under the EISA of 2007 (Jessen, 2011). In addition, compared to corn, the use of non-food grade sugarbeets (or “energy beets”) for biofuel production has less impact on food supply (Maung and Gustafson, 2011; Nahar and Pryor, 2013; Vargas-Ramirez et al., 2013).

Sugarbeet is grown in a wide range of temperate climatic conditions and in a wide variety of soils ranging from sandy to clay, silty clay or silty clay loam soils with high organic matter and/or high clay content (Cattanach, 1991). In the U.S., sugarbeet is grown in 11 states spreading across four regions – Michigan in the Great Lakes region, Minnesota and North Dakota in the Upper Midwest region, Colorado, Montana, Nebraska, and Wyoming in the Great Plains region, and California, Idaho, Oregon, and Washington in the Far West region (USDA/ERS, 2016). In 2015, about 50% of the nation's total sugarbeets were produced in the Red River Valley (RRV) of western Minnesota and eastern North Dakota and its vicinity, while another 34% was harvested in Idaho and Michigan (USDA/ERS, 2016).

It is 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, there is no history of biofuel production from sugarbeets in the U.S. Hence, tremendous opportunities exist to expand sugarbeet production into the nontraditional sugarbeet planting areas in the U.S. and models can be very useful in understanding sugarbeet growth processes in the nontraditional planting areas and their effect on soil health and water quality.

A number of crop models have been developed to describe sugarbeet's growth and yield production. Models based on empirical relationships include PIEteR (Biemond et al, 1989; Smit et al., 1993), LUTIL (Spitters et al., 1989, 1990) and the model developed by Modig (1992). Examples of process-based models include SUBGRO (Fick et al., 1971), SUBGOL (Hunt, 1974), SUCROS (Spitters et al., 1989), CERES-Beet (Leviel, 2000), 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), etc. Excellent reviews of sugarbeet models were provided by Vandendriessche and Ittersum (1995) and Baey et al. (2014). However, all these models, except SIMBEET (Lee, 1983), simulate only plant growth and yield of sugarbeet and do not simulate agricultural management effects on soil and water quality (see also Ma et al., 2012). One approach is to incorporate a sugarbeet growth model into the Root Zone Water Quality Model (RZWQM) to study the plant-soil-water interactions in sugarbeet fields.

RZWQM, developed by USDA Agricultural Research Service, is a process-based, one-dimensional, subsurface model based on the knowledge acquired of the physical, chemical, and biological processes in the root zone. It has been widely used for simulating agricultural management effects on crop production and soil health and water quality (Jaynes and Miller, 1999; Ahuja et al., 2000; Saseendran et al., 2007; Malone et al., 2010; Ma et al., 2012). RZWQM2 is a significant upgrade from the earlier version of RZWQM (Ma et al., 2012). It incorporates surface energy balance from the SHAW (Simultaneous Heat and Water) model (Flerchinger et al., 2012) and the crop-specific growth modules from DSSAT (Decision Support System for Agrotechnology Transfer) (Jones et al., 2003). But, it currently does not include a sugarbeet module. A new CSM (Crop System Module)-CERES-Beet model has been recently incorporated into DSSAT by adopting CERES-Beet (Leviel, 2000; Anar et al., 2015), which can be readily linked to RZWQM2 (Anar and Lin, 2016). Therefore, the objectives of this study are 1) to calibrate and validate RZWQM2 for modeling crop growth and soil water and nitrate contents in dryland sugarbeet fields, and (2) to evaluate the sensitivity and identifiability of RZWQM2 model parameters related to sugarbeet modeling using the Parameter Estimation (PEST) software (Doherty, 2005; 2010; 2016 a,b; Necpálová et al., 2015).

4.3. Materials and Methods

4.3.1. RZWQM and CSM-CERES-Beet

Two approaches may be taken to develop a new crop growth module in RZWQM2 for sugarbeet. One is to parameterize the generic plant growth module in RZWQM2 for sugarbeet.

The other is to develop a crop specific plant growth module for sugarbeet in DSSAT, which, in turn, may be linked to the plant growth module of RZWQM2. Since no model was available in DSSAT for sugarbeet, Anar et al. (2015) modified and incorporated CERES-Beet (Leviel, 2000) into DSSAT 4.6.1 and the resultant sugarbeet model is termed CSM-CERES-Beet. Baey et al. (2014) showed that CERES-Beet provided an overall good prediction for plant growth and yield for sugarbeets after comparing CERES-Beet with four other sugarbeet models, namely, GreenLab (Vos et al., 2007), LNAS (Cournede et al., 2013), STICS (Brisson et al., 1998), and Pilote (Taky, 2008).

CSM-CERES-Beet is a daily step process-based model, simulating a number of processes such as phenological development, growth of leaves, stems and roots, biomass accumulation and partition, soil water and nitrogen transformations, nitrogen uptake and partitioning among plant components (Leviel, 2000). CSM-CERES-Beet considers sugarbeet as an annual crop for beet production purposes and classified the phenology into four events: sowing, germination, emergence and harvest. In CSM-CERES-Beet, crop growth stages are distinguished based on degree-day threshold parameters (i.e. P1, P5, PHINT) with a base temperature of 3° C. During the early growth stages, 15 to 40 % of the daily dry matter produced is partitioned into root. After the full canopy development, 85% of the daily dry matter produced is partitioned into root tuber formation (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). CSM-CERES-Beet was calibrated and validated using PEST (Doherty, 2016 a,b) against two sets of plant growth data collected for different sugarbeet varieties grown in two different regions – one in Romania and the other in North Dakota, USA (see also Anar et al., 2015). CSM-CERES-Beet was then readily linked to RZWQM2 (version 4.0 beta) to model sugarbeet production and its impact on soil and water quality.

4.3.2. Field Experiment

Field experiments for dryland sugarbeet cultivation were conducted at the Carrington Research Extension Center (CREC), Carrington, North Dakota, USA (Lat. 47.510, Long. -99.123). CREC is located outside of RRV and is considered a nontraditional sugarbeet planting area. A specific cultivar of sugarbeet (proprietary materials from Betaseed, Shakoppe, MN) bred for biofuel purposes was cultivated in rotation with wheat, corn and soybeans (not shown) in a randomized complete block design with four replicates for testing the effects of crop rotation and tillage on soil health and water quality. A total of twelve plots with dimensions of 12.19 m × 15.24 m (40 ft × 50 ft) were cultivated for dryland sugarbeet production. Soils of the experimental plots were loamy with an average pH of 7.0. Plots that were used for sugarbeet cultivation are shown in Fig. 4.1. Plots planted with sugarbeet in 2014 are shown with upward slanted fill, whereas those in 2015 are shown in downward slanted fill. Plots with horizontal fill were planted with sugarbeet in both 2014 and 2015. Field management data and soil profiles are provided in Tables 4.1 and 4.2. Soil texture was determined using the hydrometer method, while soil organic matter (OM) content was determined by loss of weight on ignition at 360 °C, and the salts by a conductivity meter in a 1:1 soil:water suspension. All lab analyses were conducted at the Agvise Laboratories, Northwood, ND. The weather data required to run RZWQM2 were collected from North Dakota Agricultural Weather Network (NDAWN) station located at Carrington, North Dakota, USA (Lat. 47.509, Long. -99.132). The required weather files (i.e., .met, .brk, and .sno) were then generated using RZWQM2’s weather generation wizard.

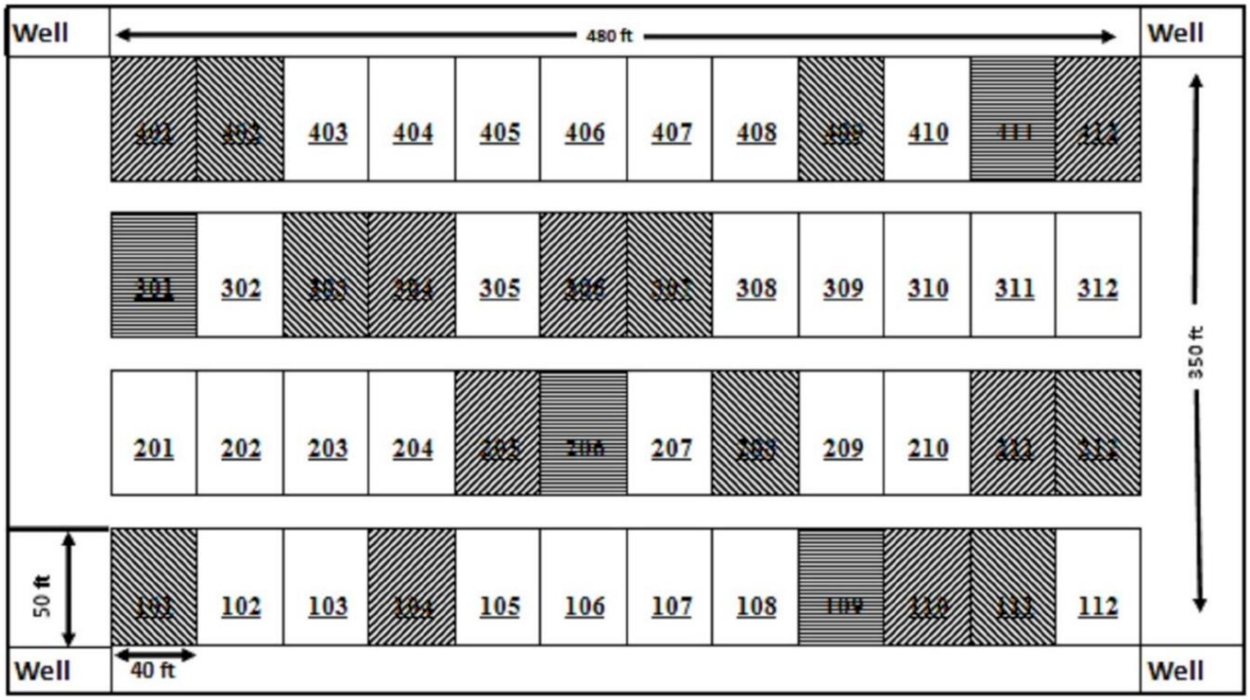


Figure 4.1. Schematic of field experimental plots planted with sugarbeet in: 2014 (upward slanted fill), 2015 (downward slanted fill), and both 2014 and 2015 (horizontal fill).

Table 4.1. Field management for sugarbeet experimental plots at Carrington Research Extension Center, North Dakota, USA.

Field management	2014	2015
Planting date	27 May	1 June
Planting density	98,842 seeds ha^{-1} (40,000seeds ac^{-1})	122, 932 seeds ha^{-1} (49,749 seeds ha^{-1})
Fertilizer	N as Urea: 112.08 kg ha^{-1} (100 lb ac^{-1}) P as MAP: 22.42 kg ha^{-1} (20 lb ac^{-1}) S as AS: 11.21 kg ha^{-1} (10 lb ac^{-1})	N as Urea: 112.08 kg ha^{-1} (100 lb ac^{-1}) P as MAP: 22.42 kg ha^{-1} (20 lb ac^{-1}) S as AS: 11.21 kg ha^{-1} (10 lb ac^{-1})
Fertilizer application date	26 May	31 May
Harvesting	17 Oct.	17 Oct.

Table 4.2. Average soil characteristics of the experimental plots at Carrington Research Extension Center, North Dakota, USA.

Depth (cm)	% Sand	% Silt	% Clay	Soil Type	% OM	EC (mmhos cm^{-1})
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		

Each year, 6 out of 12 plots were randomly selected to collect plant growth data. In each plot, eight sugarbeet plants were harvested for sampling of leaves, stems, and roots periodically. Both fresh weight and dry weights of the samples were measured. Leaf Area Index (LAI) was measured using the indirect ground-based measurement method based on radiative transfer theory (Breda, 2003). Soil water content (SWC) and soil nitrate concentration data were also collected from a number of different plots. Five plots in 2014 and 8 plots in 2015 were selected for SWC and soil nitrate data collection. Soil water contents in four different soil layers (0-15, 15-30, 30-45, and 45-60 cm) were measured using in-situ neutron probes (Troxler, NC). Soil samples were also analyzed in laboratory periodically for soil profile nitrate concentrations in the four different layers.

4.3.3. Parameter Estimation

Nonlinear regression methods as implemented in PEST were used to estimate model parameters of RZWQM2 for sugarbeet modeling. Nonlinear regression method involves estimation of model parameters by minimizing an objective function using iterative optimization. The process ends when the objective function reaches a minimum value (Doherty, 2010). The objective function is expressed in general form as (Doherty, 2010):

$$\Phi(b) = [y - y'(b)]^T Q[y - y'(b)] \tag{4.1}$$

where, Q is a weight matrix, y is a vector of observations, $y'(b)$ is a vector of simulated values produced by the model based on parameter vector b, and T indicates matrix transpose. Both y and $y'(b)$ should have the same dimension. Parameters that minimize this equation are attained by solving the normal equations using the Gauss-Marquardt-Levenberg (GML) gradient search algorithm (Doherty, 2010).

The calibration dataset comprises 65 observations divided into 5 different observation groups: LAI (4), top weight (4), root weight (5), soil water content (32), and soil profile NO3--N content (20) (Table 4.3). On a given sampling date, the field observation for each group was taken as the average of the data collected. Each observation group formed a component of the objective function (Eq. 4.1). 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, irrespective of the number of observations per group, units of measurement, and other confounding factors.

Table 4.3. Field observations included in RZWQM2 calibration and validation.

Observation group (unit)	Data source	No. of observations (2014)	No. of observations (2015)
Leaf area index (unitless)	Ground-based measurement	4	8
Top weight (kg ha^{-1})	Harvested top plant parts	4	8
Root weight (kg ha^{-1})	Harvested root	5	8
Soil water content ($cm^3\ cm^{-3}$)	Neutron probe readings	32	24
Soil profile nitrate (μg g^{-1})	Laboratory analysis	20	20

The twenty-seven parameters to be adjusted by PEST were selected based on prior sensitivity analyses of the model (Table 4.4). These adjustable parameters are anticipated to affect sugarbeet growth, soil water content, and nitrate concentrations in soils. For these 27 adjustable parameters, initial values as well as lower and upper bounds were specified based on a literature review. 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 (Aster et al., 2005; Moore and Doherty, 2005; Tonkin and Doherty, 2005; Nolan et al., 2011).

Table 4.4. RZWQM2 parameters adjusted by PEST for sugarbeet modeling.

Parameter	Definition	Unit	Depth (cm)	Initial value	Lower bound	Upper bound	Estimated value
BD1	Bulk density	g cm^{-3}	0-15	1.531	1	2	1.438
BD2	Bulk density	g cm^{-3}	15-30	1.084	1	2	1.091
BD3	Bulk density	g cm^{-3}	30-45	1.102	1	2	1.106
BD4	Bulk density	g cm^{-3}	45-60	1.000	1	2	1.00
BD5	Bulk density	g cm^{-3}	60-90	1.793	1	2	1.873
Ks1	Saturated hydraulic conductivity	cm h^{-1}	0-15	1	1	20	1.18
Ks2	Saturated hydraulic conductivity	cm h^{-1}	15-30	1	1	20	1.04
Ks3	Saturated hydraulic conductivity	cm h^{-1}	30-45	2	1	20	3
Ks4	Saturated hydraulic conductivity	cm h^{-1}	45-60	2	1	20	3
Ks5	Saturated hydraulic conductivity	cm h^{-1}	60-90	2	1	20	3
P1	Growing Degree Days (GDD) from the seedling emergence to the end of the juvenile phase	℃ d	—	950	950	1100	970
P2	Photoperiod sensitivity		—	0.001	0.00	0.01	0.001
P5	Thermal time from pennicle initiation to physiological maturity	℃ d	—	700	660	900	700
G2	Maximum possible seed growth number	—	—	900	700	1000	900
G3	Seed filling rate during the linear vegetative filling stage	mg $seed^{-1}d^{-1}$	—	5.5	1	100	5.5
PHINT	Phyllochron interval, the interval in thermal time between successive leaf tip appearances	℃ d	—	38.9	38	49	38.9
RUE	Radiation use efficiency	g MJ^{-1}	—	2.8	2.8	4.2	3.3
PARSR	Photosynthetically active solar radiation	MJ m^{-2} d^{-1}	—	0.48	0.46	0.52	0.52
SDSZ	Maximum potential seed size	mg $seed^{-1}$	—	0.275	0.25	0.30	0.275

Table 4.4. RZWQM2 parameters adjusted by PEST for sugarbeet modeling (continued).

Parameter	Definition	Unit	Depth (cm)	Initial value	Lower bound	Upper bound	Estimated value
RSGR	Relative seed growth rate below which plant may mature early	mg d^{-1}	—	0.10	0.10	0.20	0.10
RSGRT	Number of consecutive days relative seed growth rate is below RSGR that triggers early maturity	d	—	1	0.01	2	1
CARBOT	Number of consecutive days CARBO is less than .001 before plant matures due to temperature, water or nitrogen stress	d	—	7	5	8	7
DSGT	Maximum days from sowing to germination before seed dies	d	—	40	35	45	40
DGET	Growing degree days between germination and emergence after which the seed dies due to drought	℃ d	—	150	140	160	150
SWCG	Minimum available soil water required for seed germination	cm^3 cm^{-3}	—	0.02	0.01	0.04	0.02
PORM	Minimum porosity required for supplying oxygen to roots for optimum growth	—	—	0.05	0.01	0.10	0.04
RLWR	Root length to weight ratio	—	—	0.82	0.82	1.82	0.84

4.3.4. Parameter Correlation, Sensitivity and Identifiability

Pre-calibration parameter correlations were obtained from the correlation coefficient matrix by employing a standard GML parameter estimation method implemented in PEST. The relative composite sensitivity of each parameter with respect to each observation group and the entire calibration dataset at the beginning of the parameter estimation process was calculated based on the magnitude of the column of the Jacobian matrix corresponding to the ith parameter with each entry in that column multiplied by the squared weight associated with that observation group and the absolute value of that parameter using Eq. (4.2):

$$s_i = \sqrt{(J^T QJ)_{ii}} \times |v_i| \tag{4.2}$$

where J is the Jacobian matrix, Q is the diagonal matrix whose elements are comprised of the squared weights of the observation, and $|v_i|$ is the absolute value of the parameter. The sensitivities of a parameter represent the amount of change in the model-simulated values per unit change in a parameter's value (Poeter and Hill, 1997).

Parameter identifiability represents the calibration dataset's ability to constrain model parameters (Doherty and Hunt, 2009) and it is usually obtained through SVD of the weighted Jacobian matrix calculated based on initial parameter values (Necpálová et al., 2015). The premise is that the parameter space of a model can be properly decomposed into orthogonal "calibration solution space" and "calibration null space" (Moore and Doherty, 2005). The calibration solution space is a subset of parameter space comprising combinations of parameters that can be estimated uniquely by the calibration dataset, whereas the calibration null space can be thought of as combinations of parameters that cannot be estimated by the calibration dataset (Doherty and Hunt, 2009).

Therefore, the identifiability of a parameter describes the degree to which that parameter can be determined uniquely by relating the contributions of each adjustable parameter to any of the eigenvectors spanning the calibration solution space. Since eigenvectors are normalized, the largest value of a parameter's contribution to an eigenvector is 1.0. Parameters with low identifiability cannot be estimated because they have a large projection onto the calibration null space, due to correlation with other parameters or low sensitivity to all observations. In contrast, parameters with an identifiability value of 1.0 can be uniquely estimated because they are entirely projected onto the calibration solution space. The identifiability of the ith parameter is calculated as the sum of the squared ith components of all eigenvectors spanning the calibration solution space (Doherty, 2010).

In this study, the boundary between the calibration solution and null spaces was set at a specific singular value calculated using the SUPCALC utility (Doherty and Hunt, 2009; Doherty, 2016b). PEST utility IDENTPAR was then used to compute the parameter identifiability for each of the observations (Doherty, 2016b). The number of singular vectors used to compute identifiability differed between the observation groups from 4 to 11 by means of the different number of field observations. Parameters with identifiability greater than 0.7 were considered to be identifiable with the available calibration dataset (Nolan et al., 2011; Necpálová et al., 2015).

4.3.5. Model Evaluation

Best parameters obtained from inverse modeling using 2014 dataset were validated with data from 2015. We calculated both relative root mean square error ($rRMSE$) and index of agreement (d) as indicators of goodness of fit. The $rRMSE$ is the root mean square error normalized to the mean of the observed values:

$$rRMSE = \frac{\sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - y_i{}')^2}}{|\overline{y}|} \tag{4.3}$$

where, m is the number of observations, $\overline{y}$ is the mean of the observed values, $y_i{}'$ is the model simulated value and y_i is observed value. The index of agreement is estimated using the following equation:

$$d = 1 - \frac{\sum_{i=1}^{m}\left(y_i - y_i'\right)^2}{\sum_{i=1}^{m}(|y_i' - \bar{y}| + |y_i - \bar{y}|)^2} \tag{4.4}$$

The index of agreement is more sensitive than traditional correlation measures to differences between observed and simulated means and variances. The value of d varies between 0 and 1, with higher values indicating better fit (Legates and McCabe, 1999).

4.4. Results and Discussion

4.4.1. RZWQM2 Calibration

The sugarbeet module in RZWQM2 was calibrated using 2014 field data collected at CREC. The PEST optimization required 9 optimization iterations and 433 model calls to minimize the objective functions. The number of singular values used in SVD ranged from 9 to 20 on an iteration-by-iteration basis, based on a stability criterion. The total objective function was decreased by 34.2%. Table 4.5 summarizes the measures of the goodness of model prediction to the observations of crop growth, SWC, and soil nitrate content in 2014 and 2015. In general, the model did very well in terms of both d-statistic and rRMSE. The d-statistic ranged from 0.709 to 0.992 for model calibration and 0.733 to 0.990 for model validation, while the rRMSE took values of 0.066-1.211 for model calibration and 0.043-0.930 for model validation.

Table 4.5. RZWQM2 calibration and validation results for individual observation groups.

Observation group	Index of agreement (d)		Relative root mean square error (rRMSE)	
	Model calibration, 2014	Model validation, 2015	Model calibration, 2014	Model validation, 2015
Leaf area index	0.960	0.891	0.345	0.464
Top weight	0.977	0.877	0.239	0.507
Root weight	0.933	0.885	0.204	0.735
Root yield	—	—	0.006	0.016
SWC (0-15 cm)	0.894	0.863	0.139	0.193
SWC (15-30 cm)	0.974	0.945	0.066	0.043
SWC (30-45 cm)	0.826	0.989	0.132	0.044
SWC (45-60 cm)	0.709	0.925	0.179	0.088
Soil profile nitrate	0.992	0.990	0.203	0.214
Soil nitrate (0-15 cm)	0.881	0.895	0.457	0.573
Soil nitrate (15-30 cm)	0.926	0.903	0.856	0.930
Soil nitrate (30-45 cm)	0.925	0.802	0.650	0.715
Soil nitrate (45-60 cm)	0.825	0.733	1.211	0.710

4.4.1.1. Plant Growth

Simulation of plant growth in a water quality model is important because it affects the hydrology and chemical uptake in a plant-soil-water system. For this reason, plant growth variables (LAI, top weight, and root weight) were first calibrated against 2014 field observations and then validated against 2015 field observations. In 2014, the model showed a good fit for LAI, top weight, and root weight by closely tracking the medians of the observed values (Fig. 4.2). In 2015, model's performance was less than ideal when compared with the observed values (Fig. 4.3). The model was consistently over-predicting the observed values between 67th and 100th days after planting for LAI, top weight and root weight (Fig. 4.3). This might be due to a strong wind gust (~ 22.5 m s^{-1}) occurring around the 65th day after planting (28-29 July 2015). This less than satisfactory model performance in 2015 are also reflected in model evaluation statistics (Table 4.5). CSM-CERES-Beet is not designed to simulate the damage caused by unexpected events such as strong wind gusts in the early plant development stage or freezing temperature close to harvesting. These limitations were also discussed in Leviel (2000).

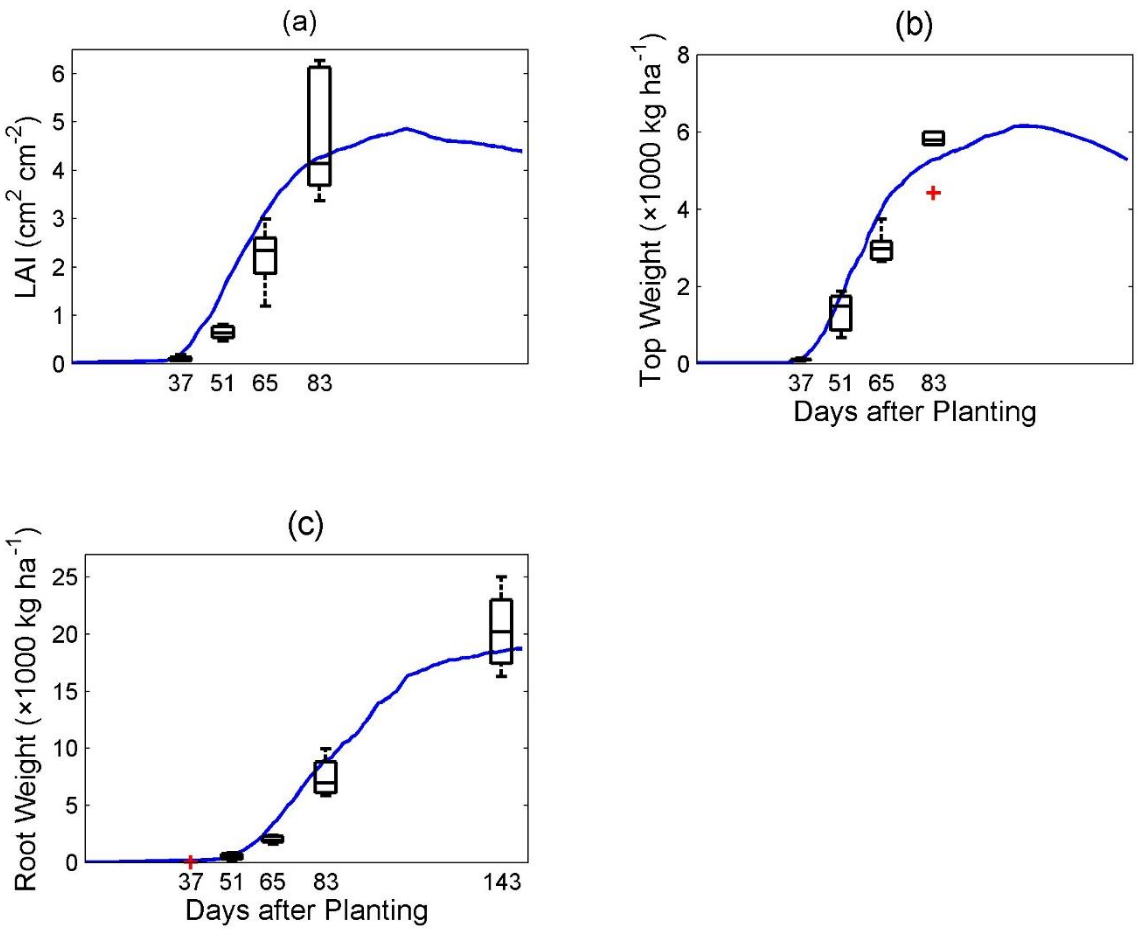


Figure 4.2. Model-simulated and observed values of (a) leaf area index, (b) top weight and (c) root weight for model calibration in 2014. Notes: Observed values are plotted in boxplots with the medians shown as the lines within the boxes, the 25th and 75th percentiles as the tops and bottoms of the boxes, the 5% and 95% percentiles as the whiskers below and above the boxes, and the plus signs (+) as outliers.

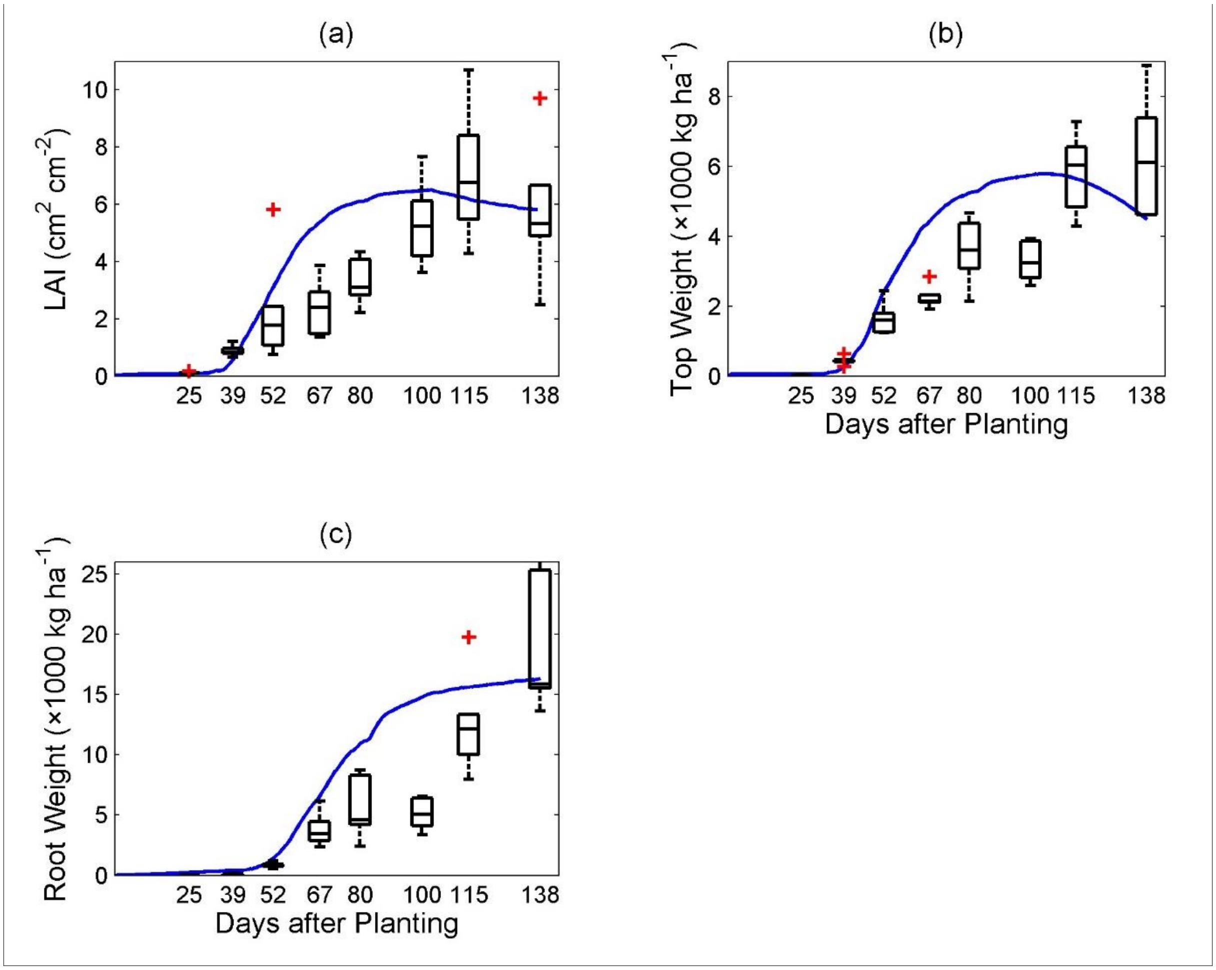


Figure 4.3. Model-simulated and observed values of (a) leaf area index, (b) top weight and (c) root weight for model validation in 2015. Notes: Observed values are plotted in boxplots with the medians shown as the lines within the boxes, the 25th and 75th percentiles as the tops and bottoms of the boxes, the 5% and 95% percentiles as the whiskers below and above the boxes, and the plus signs (+) as outliers.

The calibrated model was also used to simulate the average sugarbeet root yields in 2014 and 2015 (Fig. 4.4). In both years, the average observed yields along with their standard deviations were computed from the yields from all the twelve sugarbeet plots (Fig. 4.1). For the model-simulated root yields, the dry weights output by the model were converted to fresh yields assuming 82% moisture content in the beets. Fig. 4.4 shows that RZWQM2 did very well in simulating the average observed yields of sugarbeet in both years. The *rRMSE* was 0.006 in 2014 and 0.016 in 2015 (Table 4.5).

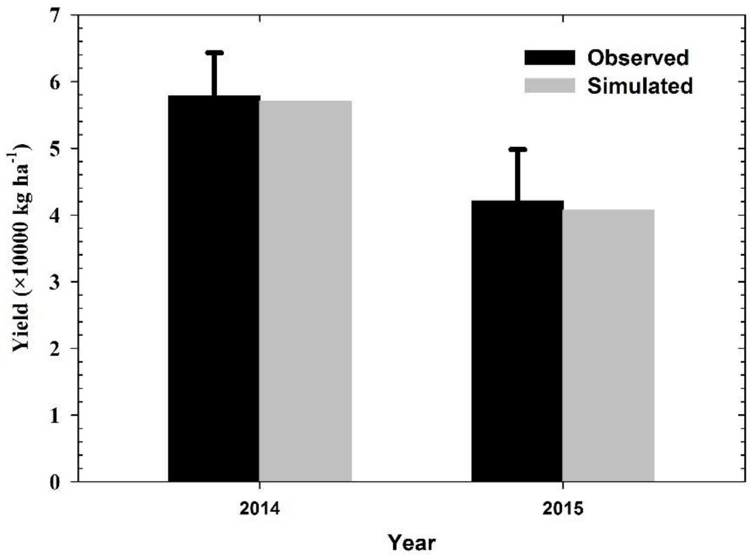


Figure 4.4. Model-simulated and the average observed root yields of sugarbeet planted in Carrington Research and Extension Center, North Dakota, USA. Note: The short vertical lines above the average observed yields are standard deviations.

4.4.1.2. Soil Water Content and Soil Nitrate

Observed and simulated soil water content at four different soil depths up to 60 cm were plotted for 2014 (Fig. 4.5) and 2015 (Fig. 4.6). In 2014, soil water content was measured from five plots at the first sampling date and they were measured from two plots in other times. In 2015, soil water content readings were taken from eight plots throughout the year.

Fig. 4.5 shows that the model-simulated soil water content at the top two soil layers (0-15 and 15-30 cm) followed the trends of the observed soil water content very well over the entire growing season of 2014 (Fig. 4.5(a) & 4.5(b)). The d-statistics for these two layers were 0.894 and 0.974 and *rRMSE* were 0.139 and 0.066, respectively (Table 4.5). However, in the deeper two layers (30-45 and 45-60 cm), RZWQM2 over-predicted the SWC in the early part of the growing season and under-predicted the SWC in the latter part of the growing season. The deeper it goes, the greater is the degree of over- or under-prediction of the model-simulated SWC

(Fig. 4.5(c) and 4.5(d)). According to soil water balance provided by RZWQM2 (Table 4.6), the total transpiration in the sugarbeet plots at CREC accounted for ~60% of the total water losses in 2014 and 2015 and the water loss through plant transpiration was about 5 times larger than that through soil evaporation. Land et al. (1999) and Martin and Watts (1999) argued that inaccurate simulation of ET and/or LAI might have contributed to over- or under-predictions of SWC (see also Malone et al., 2010). In the past, Jaynes and Miller (1999) observed that RZWQM under-predicted ET mostly during dry conditions in September in a 4-year corn-soybean rotation field with clarion loam soil. Farahani et al. (1996), however, observed that RZWQM provided reasonable ET predictions although it tended to under-predict ET at smaller LAI values (<0.5) and over-predict ET at greater LAI values.

Fig. 4.6 shows that, during the 2015 growing season, RZWQM2 was able to simulate the SWC's in all four layers well up to around the 70th day after planting. After that, the model started to under-predict the SWC's in the top layer (0-15 cm, Fig. 4.6(a)) and the bottom layer (45-60 cm, Fig. 4.6(d)), while maintaining good simulations for the middle two layers (15-30 and 30-45 cm, Fig. 4.6(b) & (c)). Processes that affect soil water content include soil evaporation, crop transpiration, surface runoff, snowmelt, deep drainage, rooting depth and tile flow. Root development to deeper soils along with changes in LAI may alter ET in an ecosystem (Tanaka et al., 2004). Deep-rooted crops can maintain ET by absorbing water from deeper soils and maintain ET throughout the year (Jackson et al., 2000). ET from vegetation depends on LAI and leaf physiological characteristics (i.e. carboxylation ate) in conjunction with hydrological and meteorological variables (e.g., precipitation, radiation, temperature, wind speed, etc.).

When a crop is small, actual evapotranspiration is also low. As the growing season progresses, LAI and rooting depth of the crop also increases allowing more evaporative surfaces and deeper areas for extracting water for ET (Jackson et al., 2000; Tanaka et al., 2004). The ability of soil transmitting water to plant roots and the evaporative demand from the environment together determine actual crop evapotranspiration. Inaccurate simulation of LAI during the period of 70-100 days after planting may have contributed to the under-predictions of SWC's in the top and bottom layers.

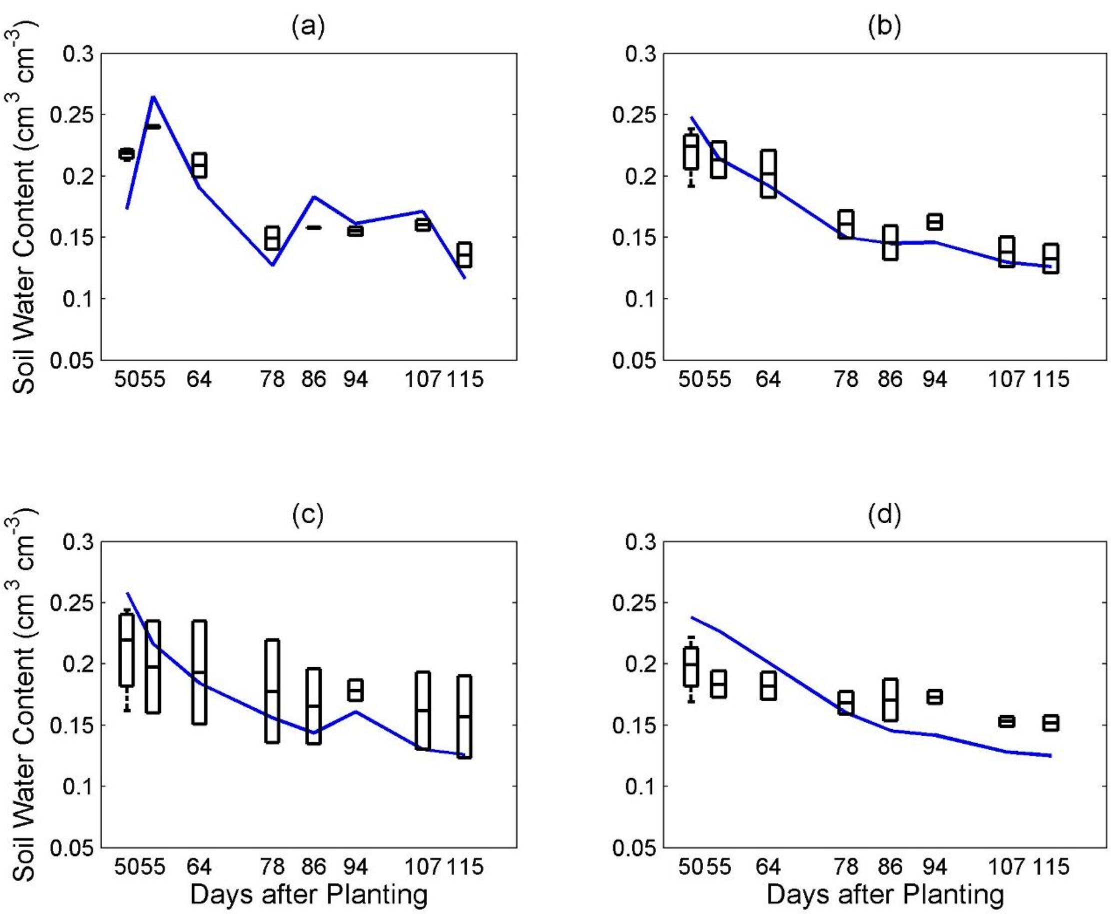


Figure 4.5. Soil water content at different soil depths (a) 0-15 cm, (b) 15-30 cm, (c) 30-45 cm and (d) 45-60 cm in 2014. Notes: Observed values are plotted in boxplots with the medians shown as the lines within the boxes, the 25th and 75th percentiles as the tops and bottoms of the boxes, and the 5% and 95% percentiles as the whiskers below and above the boxes.

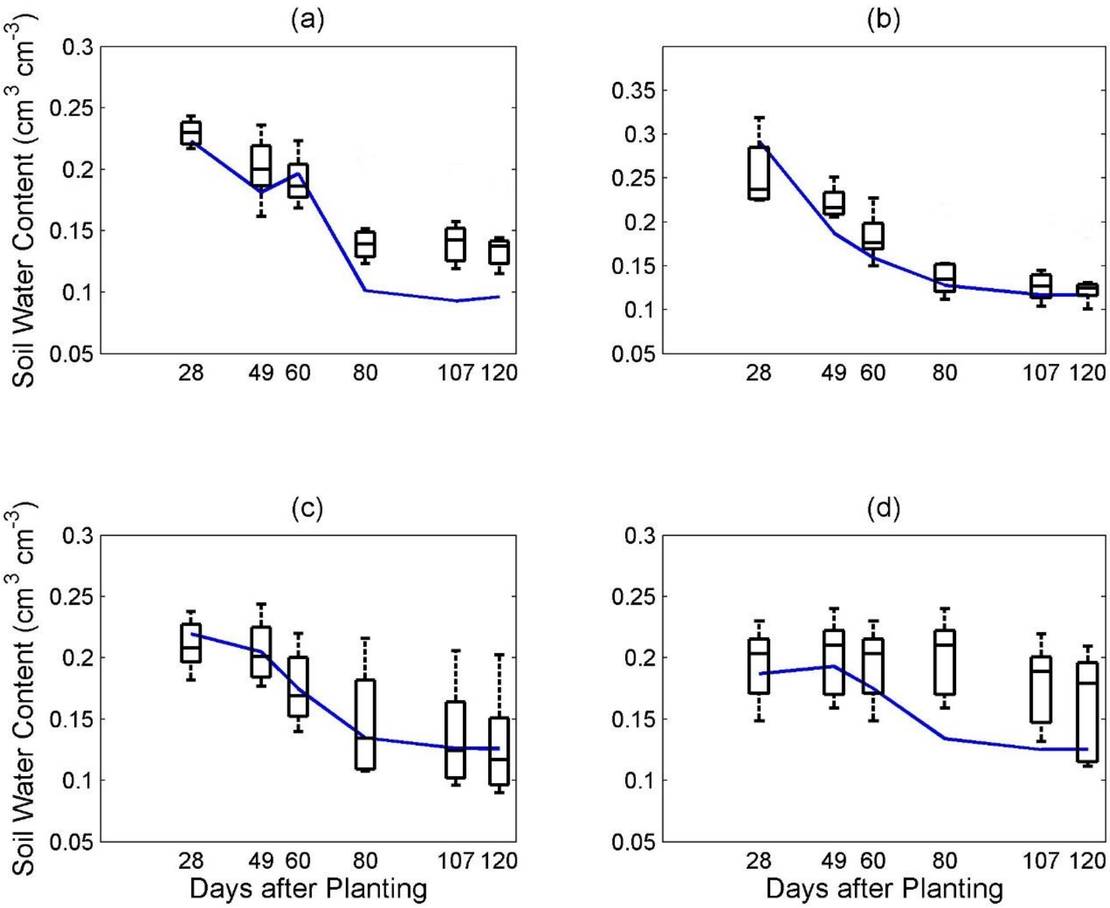
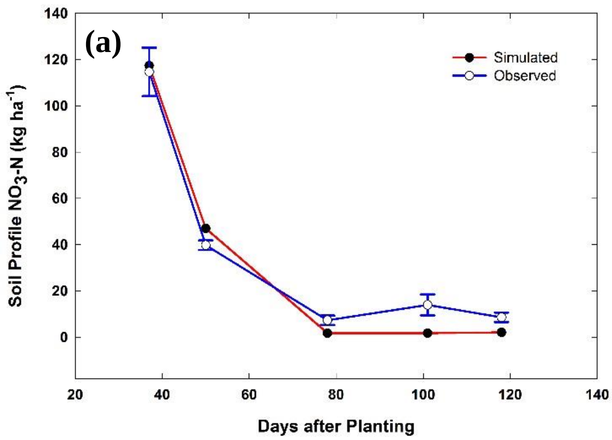


Figure 4.6. Soil water content at different soil depths (a) 0-15 cm, (b) 15-30 cm, (c) 30-45 cm and (d) 45-60 cm in 2015. Notes: Observed values are plotted in boxplots with the medians shown as the lines within the boxes, the 25th and 75th percentiles as the tops and bottoms of the boxes, and the 5% and 95% percentiles as the whiskers below and above the boxes.

Table 4.6. Soil water mass balance for sugarbeet plots at Carrington Research and Extension Center, North Dakota, US.

	2014 Initial day: 25 May 2014 End day: 17 Oct. 2014			2015 Initial day: 31 May 2015 End day: 17 Oct. 2015		
Variables	Water gains (cm)	Water losses (cm)	Balance (cm)	Water gains (cm)	Water losses (cm)	Balance (cm)
Initial soil water	18.88			18.87		
Final soil water		11.60			11.49	
Total rainfall	32.97			21.46		
Total runoff		6.41			1.47	
Evaporation		5.65			4.27	
Transpiration		27.92			22.84	
Total drainage		0.27			0.25	
Total	51.85	51.85	0.00	40.32	40.32	0.00

As for soil nitrate, the RZWQM2 simulated nitrate concentration in the entire soil profile (namely “soil profile nitrate”) was plotted against the observed soil nitrate in Fig 4.7 (a, b) and nitrate concentrations at different soil depths are plotted in Fig. 4.8 and 4.9. Overall, the model did very well in simulating the soil profile nitrate throughout the entire growing seasons of 2014 (Fig. 4.7 (a)) and of 2015 (Fig. 4.7 (b)), especially during the early plant growth stages. The d-statistic for model calibration (2014) and model validation (2015) were 0.987 and 0.990, respectively (Table 4.5). For soil nitrate contents at different depths, model did reasonably well considering that the model was calibrated against the observed soil profile nitrates only. The *d*-statistics were 0.733-0.926 and *rRMSE* were 0.457-1.211 including both model calibration and validation periods (Table 4.5). In 2014, the model under-predicted the nitrate content in the top layer (0-15cm) and over-predicted the nitrate contents in the other layers (15-30cm, 30-45cm, and 45-60cm) during the early growing season (Fig. 4.8). In 2015, the model generally under-predicted the soil nitrate contents in all but one layers (Fig. 4.9). In addition, nitrogen mass balance in the soil profile (Table 4.7) shows that 63-66% of soil nitrogen input was from fertilization and 31-35% was from net mineralization of soil organic matters in 2014 and 2015.



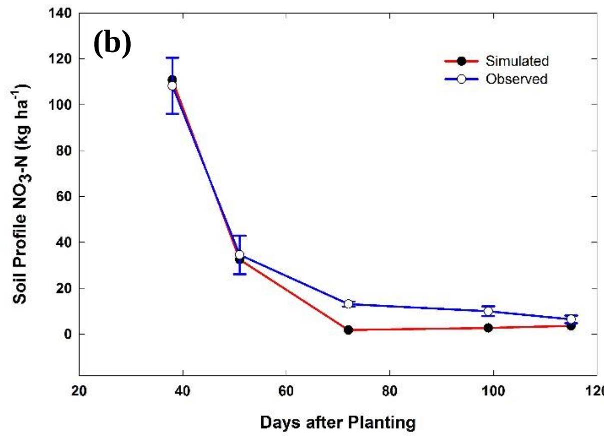


Figure 4.7. Total soil profile NO_3-N for (a) model calibration (2014) and (b) model validation (2015). Notes: The vertical bars and whiskers represent the standard errors for observed soil NO_3-N contents in sugarbeet plots.

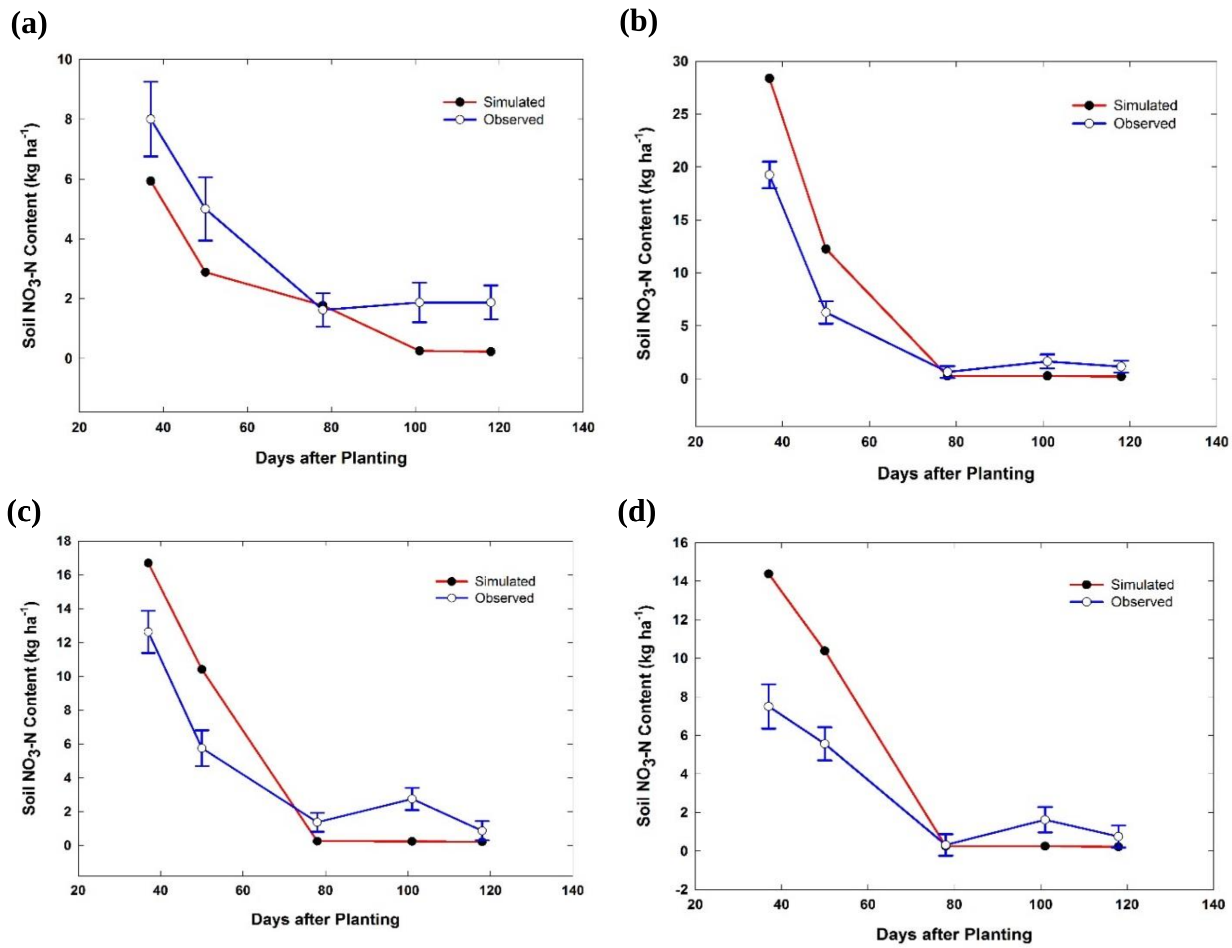


Figure 4.8. Soil NO_3-N content at different soil depths (a) 0-15 m, (b) 15-30 cm, (c) 30-45 cm and (d) 45-60 cm in 2014. Notes: The vertical bars and whiskers represent the standard errors for observed soil NO_3-N contents in sugarbeet plots.

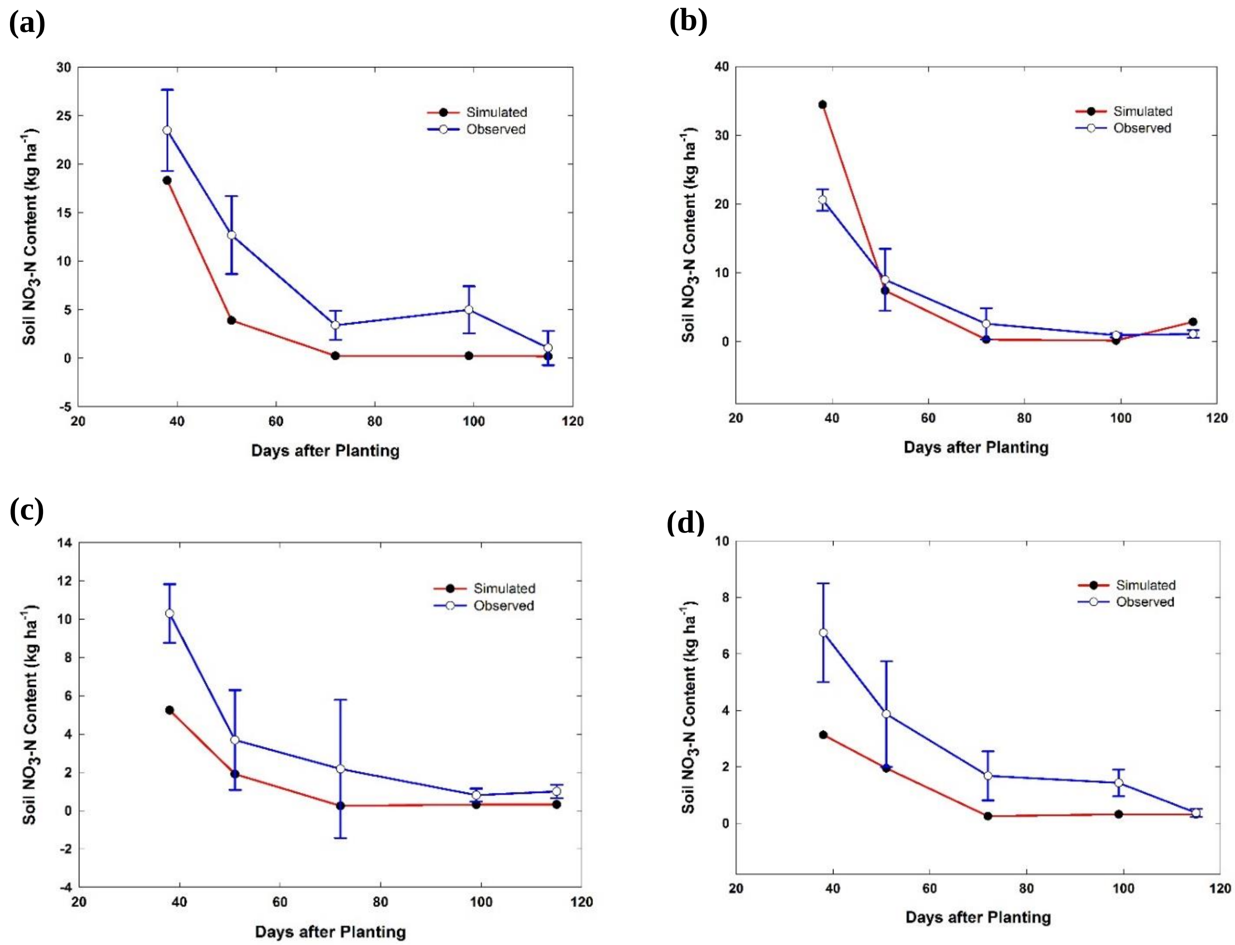


Figure 4.9. Soil NO_3-N content at different soil depths (a) 0-15 cm, (b) 15-30 cm, (c) 30-45 cm and (d) 45-60 cm in 2015. Notes: The vertical bars and whiskers represent the standard errors for observed soil NO_3-N contents in sugarbeet plots.

Table 4.7. Soil nitrogen mass balance for sugarbeet plots at Carrington Research and Extension Center, North Dakota, US.

	2014 Initial day: 25 May 2014 End day: 17 Oct. 2014			2015 Initial day: 31 May 2015 End day: 17 Oct. 2015		
Variables	N gains (kg ha^{-1})	N losses (kg ha^{-1})	Balance (kg ha^{-1})	N gains (kg ha^{-1})	N losses (kg ha^{-1})	Balance (kg ha^{-1})
Initial soil N	2.37			2.18		
Final soil N		12.46			19.79	
Inorganic fertilizer	112			112		
Total plant N uptake		159.02			143.28	
Total denitrification		2.26			2.27	
Total N losses to drainage		0.53			0.42	
Nitrogen losses to runoff		2.25			1.00	
Greenhouse gas emission		0.48			0.43	
Net mineralization	62.67			53.01		
Total	177.00	176.96	0.04	169.19	169.19	0.00

4.4.2. Estimated Parameter Values and Correlations

Estimated parameter values obtained from model calibration are shown in Table 4.3. Through the SVD-based regularization procedure, PEST changed the values of 14 out of 27 parameters. The parameter values changed most were: BD1, BD5, Ks1, Ks3, Ks4, Ks5, P1 and RUE. Except P1 and RUE, these parameters are bulk densities and saturated hydraulic conductivities of different soil layers that affect water and nutrient contents in the soil profile. P1 is related to the length of the sugarbeet growth cycle from the seedling emergence to the end of juvenile phase, while RUE determines the radiation use efficiency of the crop that may vary from 2.8 to 4.2 g plant dry matter MJ^{-1} for sugarbeet (Leviel, 2000).

Table 4.8 displays the correlation coefficient matrix of RZWQM2 parameters for sugarbeet. A careful examination of Table 4.8 identified six parameter correlations with absolute value of correlation coefficient $|r| \geq 0.8$ (highlighted in the table). Among these six large parameter correlation coefficients only the correlation coefficient between BD2 and Ks2 exceeded the magnitude of 0.95, which is an indication of highly correlated parameters that may not be uniquely estimated in the inverse modeling process (Poeter and Hill, 1997).

Incidentally, all the large parameter correlation coefficients ($|r| \geq 0.8$) identified in this study were negative, indicating that the strongly correlated parameters have opposite effect on each other. Among these six strongly or highly correlated parameter pairs, three pairs were between soil parameters related to soil water movement in the soils (i.e. BD2 vs. Ks2, BD5 vs. Ks5, and BD5 vs. Ks1). It is not surprising that the bulk densities and hydraulic conductivities of the same soil layers (e.g., BD2 vs. Ks2 and BD5 vs. Ks5) were strongly but negatively correlated to each other. This suggests that, when calibrating RZWQM2, it makes more sense to fix soil bulk density values while allowing the inverse modeling software such as PEST to automatically adjust soil hydraulic conductivities. Another two strongly correlated parameter pairs were between plant parameters (i.e., P1 vs. PHINT and RUE vs. PARSA). Only one strongly correlated parameter pair was between a soil parameter and a plant parameter (i.e., BD5 vs. PHINT).

Table 4.8. Correlation coefficient matrix of RZWQM2 parameters for sugarbeet modeling. Strong correlations (r > 0.8) are highlighted.

	BD1	BD2	BD3	BD4	BD5	Ks1	Ks2	Ks3	Ks4	Ks5	P1	P2	P5	G2	G3
BD1	1.00	0.00	0.01	0.04	0.49	-0.48	0.01	-0.04	0.25	-0.29	-0.05	-0.02	-0.09	-0.01	-0.02
BD2		1.00	-0.63	0.62	-0.38	0.21	-0.98	0.28	0.75	0.48	-0.51	-0.17	-0.29	-0.17	-0.11
BD3			1.00	-0.72	0.41	-0.33	0.60	-0.74	-0.16	-0.49	0.28	0.05	0.07	0.05	0.03
BD4				1.00	-0.24	0.06	-0.57	0.61	0.27	0.51	-0.66	-0.11	-0.19	-0.11	-0.11
BD5					1.00	-0.88	0.45	-0.16	0.11	-0.82	0.21	0.19	0.31	0.19	0.13
Ks1						1.00	-0.30	0.14	-0.27	0.74	-0.06	-0.03	-0.18	-0.03	-0.02
Ks2							1.00	-0.24	-0.70	-0.55	0.48	0.21	0.30	0.21	0.11
Ks3								1.00	-0.16	0.29	-0.15	-0.01	0.03	-0.01	-0.01
Ks4									1.00	-0.11	-0.33	-0.01	-0.20	-0.01	-0.01
Ks5										1.00	-0.50	-0.18	-0.30	-0.18	-0.15
P1											1.00	0.12	0.73	0.12	0.08
P2												1.00	0.11	0.11	0.13
P5													1.00	0.02	0.16
G2														1.00	0.04
G3															1.00

	PHINT	RUE	PARSR	SDSZ	RSGR	RSGRT	CARBOT	DSGT	DGET	SWCG	PORM	RLWR
BD1	-0.47	-0.36	-0.22	-0.01	-0.02	-0.03	-0.01	-0.07	-0.06	-0.02	-0.07	-0.05
BD2	0.53	0.31	0.19	-0.07	-0.10	-0.13	-0.09	-0.11	-0.10	-0.11	-0.11	-0.15
BD3	-0.39	-0.23	-0.21	0.02	0.01	0.04	0.03	0.06	0.05	0.03	0.03	0.09
BD4	0.34	0.18	0.15	-0.08	-0.11	-0.17	-0.06	-0.11	-0.09	-0.11	-0.08	-0.13
BD5	-0.82	-0.51	-0.33	0.09	0.09	0.19	0.13	0.16	0.13	0.13	0.16	0.21
Ks1	0.59	0.37	0.18	-0.02	-0.02	-0.04	-0.02	-0.06	-0.02	-0.02	-0.05	-0.07
Ks2	-0.57	-0.27	-0.17	0.11	0.08	0.13	0.11	0.13	0.11	0.11	0.16	0.23
Ks3	0.27	0.13	0.09	-0.01	-0.01	-0.03	-0.01	-0.02	-0.01	-0.01	-0.02	-0.03
Ks4	0.10	0.05	0.05	-0.01	-0.01	-0.03	-0.01	-0.03	-0.01	-0.01	-0.01	-0.04
Ks5	0.71	0.43	0.32	-0.11	-0.13	-0.15	-0.15	-0.17	-0.15	-0.15	0.11	0.13
P1	-0.80	0.15	0.16	0.06	0.08	0.11	0.08	0.09	0.08	0.08	-0.31	0.52
P2	-0.21	0.05	0.11	0.11	0.10	0.13	0.14	0.09	0.13	0.13	-0.08	0.06
P5	-0.43	-0.23	-0.09	0.12	0.11	0.16	0.16	0.16	0.14	0.16	0.36	-0.70
G2	0.07	0.04	0.04	0.02	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.03
G3	0.08	0.07	0.05	0.01	0.01	-0.02	-0.02	-0.11	-0.06	0.03	0.09	0.17

Table 4.8. Correlation coefficient matrix of RZWQM2 parameters for sugarbeet modeling. Strong correlations (r > 0.8) are highlighted (continued).

	PHINT	RUE	PARSR	SDSZ	RSGR	RSGRT	CARBOT	DSGT	DGET	SWCG	PORM	RLWR
PHINT	1.00	-0.29	0.09	0.05	0.08	0.17	-0.11	0.12	0.10	0.13	0.11	-0.79
RUE		1.00	-0.89	0.02	0.05	0.21	0.03	0.05	0.08	0.17	-0.15	0.71
PARSR			1.00	0.03	0.04	0.05	-0.11	0.11	0.06	0.03	-0.16	0.53
SDSZ				1.00	0.01	0.11	0.13	0.09	0.01	0.03	0.03	0.03
RSGR					1.00	0.23	-0.02	0.06	0.09	0.11	0.01	0.01
RSGRT						1.00	0.12	0.08	0.03	0.08	0.08	0.08
CARBOT							1.00	0.07	0.05	0.03	0.05	0.05
DSGT								1.00	0.11	0.09	0.04	0.04
DGET									1.00	0.05	0.01	0.01
SWCG										1.00	0.17	-0.15
PORM											1.00	0.27
RLWR												1.00

4.4.3. Parameter Sensitivity and Identifiability

The relative sensitivities of parameters with respect to the five observation groups and all observations are plotted in Fig. 4.10. A close inspection of all six subfigures of Fig. 4.10 reveals that almost all the sensitive parameters, except for PHINT, with respect to any observation groups including plant growth variables (i.e., LAI, top and root weights) were soil bulk densities and saturated hydraulic conductivities of soils in different layers. This implies that the soil water content was a strong limiting factor to the sugarbeet growth at CREC. This shouldn't be surprising because it was a dryland sugarbeet system without any use of irrigated water. The most sensitive parameters may be different when modeling irrigated conditions, under which soil water content may not be as a strong limiting factor for plant growth as under dry conditions. We should also note that the local sensitivity analysis conducted in this study was based on initial parameter values. The diagnosis results may be different if calibrated parameter values are used or if global sensitivity analysis methods are used (Ferreira et al., 1995; Ma et al., 2000).

Fig. 4.10 shows that besides soil property parameters, LAI and top weight were very sensitive to PHINT, a plant phenological parameter (Fig. 4.10(a) & (b)). PHINT, defined as phyllochron interval (Table 4.4), is the thermal time interval (or the sum of the degree days) required to grow the phytomer unit of successive leaves. Therefore, PHINT is directly related to the growth of phytomer units, a basic unit for the phenological development and vegetative growth of a crop. The development and growth of sugarbeet are actually characterized by the repeated formation, expansion, and subsequent senescence of the phytomer units (Wilhelm and McMaster, 1995). Fig. 4.10 also shows that root weight and soil nitrate are less sensitive to PHINT (Fig. 4.10(c) and (e)), while soil water content are not sensitive to PHINT at all (Fig. 4.10(d)). Overall, the most sensitive parameters for sugarbeet under dry conditions include the bulk densities (BD1-5), saturated hydraulic conductivities (Ks1-5), and PHINT (Fig. 4.10(f)).

The parameter identifiability with respect to the five observation groups and all observations is plotted in Fig. 4.11. Parameter identifiability represents the observation group's ability to constrain the model parameters. The height of the vertical bars measures the parameter's identifiability and the shades of different colors correspond to the individual contributions from each of all eigenvectors spanning the calibration solution space. Fig. 4.11 (a)-(c) shows that the information contained in the observations of LAI, top weight and root weight was sufficient to estimate three RZWQM2 parameters – BD1 or BD2, Ks1, and PHINT – two were soil parameters and the other was a plant parameter. Four soil parameters (BD1-3 and Ks1) may be estimated by the observed soil water contents in the four soil layers (Fig. 4.11(d)), while only three soil parameters (BD3-4 and Ks1) may be estimated by the observed soil nitrate concentrations. Overall, five RZWQM2 parameters may be identifiable by the entire calibration dataset (Fig. 4.11(f)). It is worth mentioning that Ks1 was identifiable by any of the observation groups (Fig. 4.11(a)-(f)), while PHINT was identifiable by any of the observations of plant variables such as LAI, top weight and root weight (Fig. 4.11(a)-(c)).

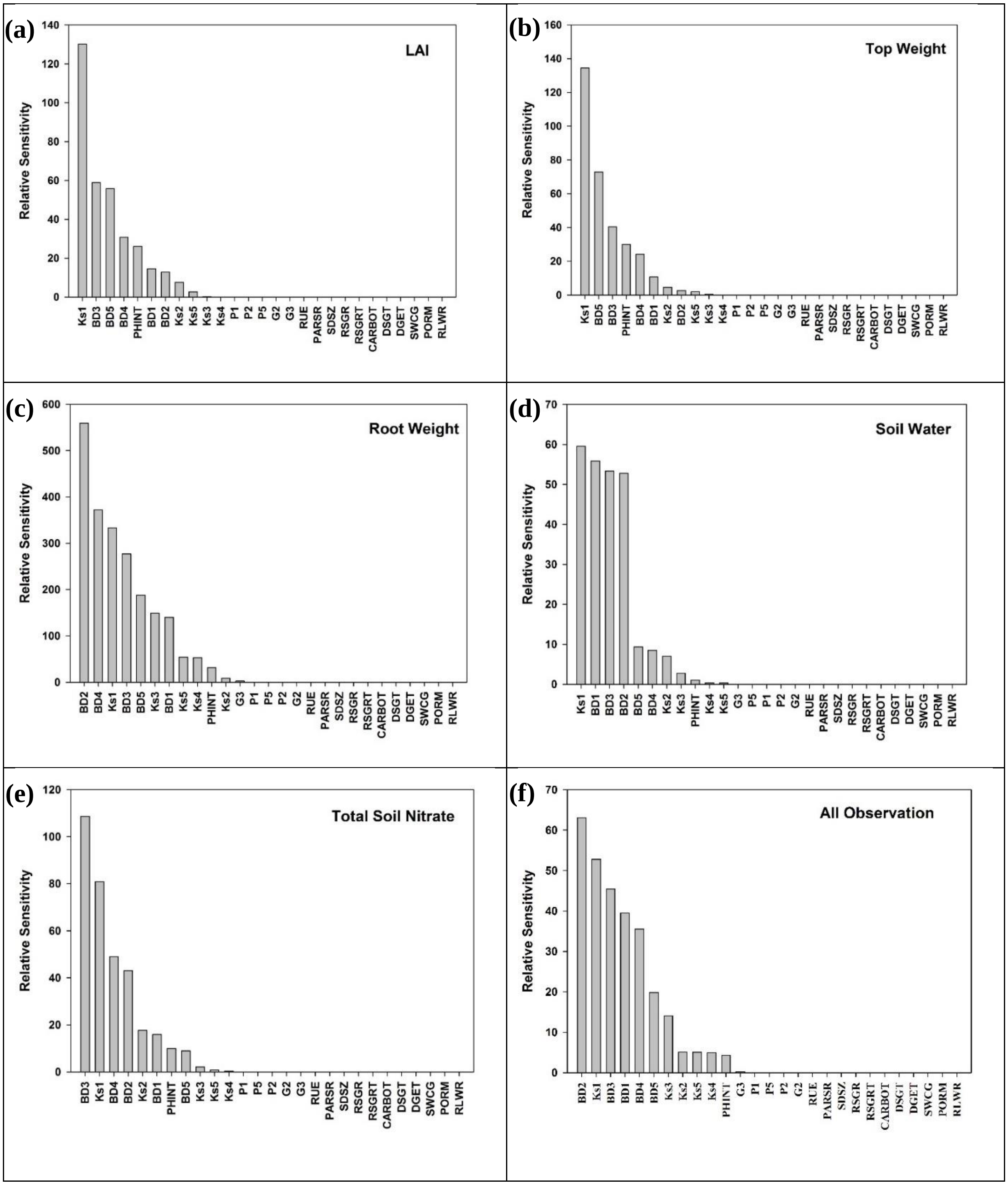


Figure 4.10. Bar plot of RZWQM2 relative composite sensitivities with respect to individual observations and to the entire calibration dataset based on their initial values. Parameter definitions are shown in Table 4.4.

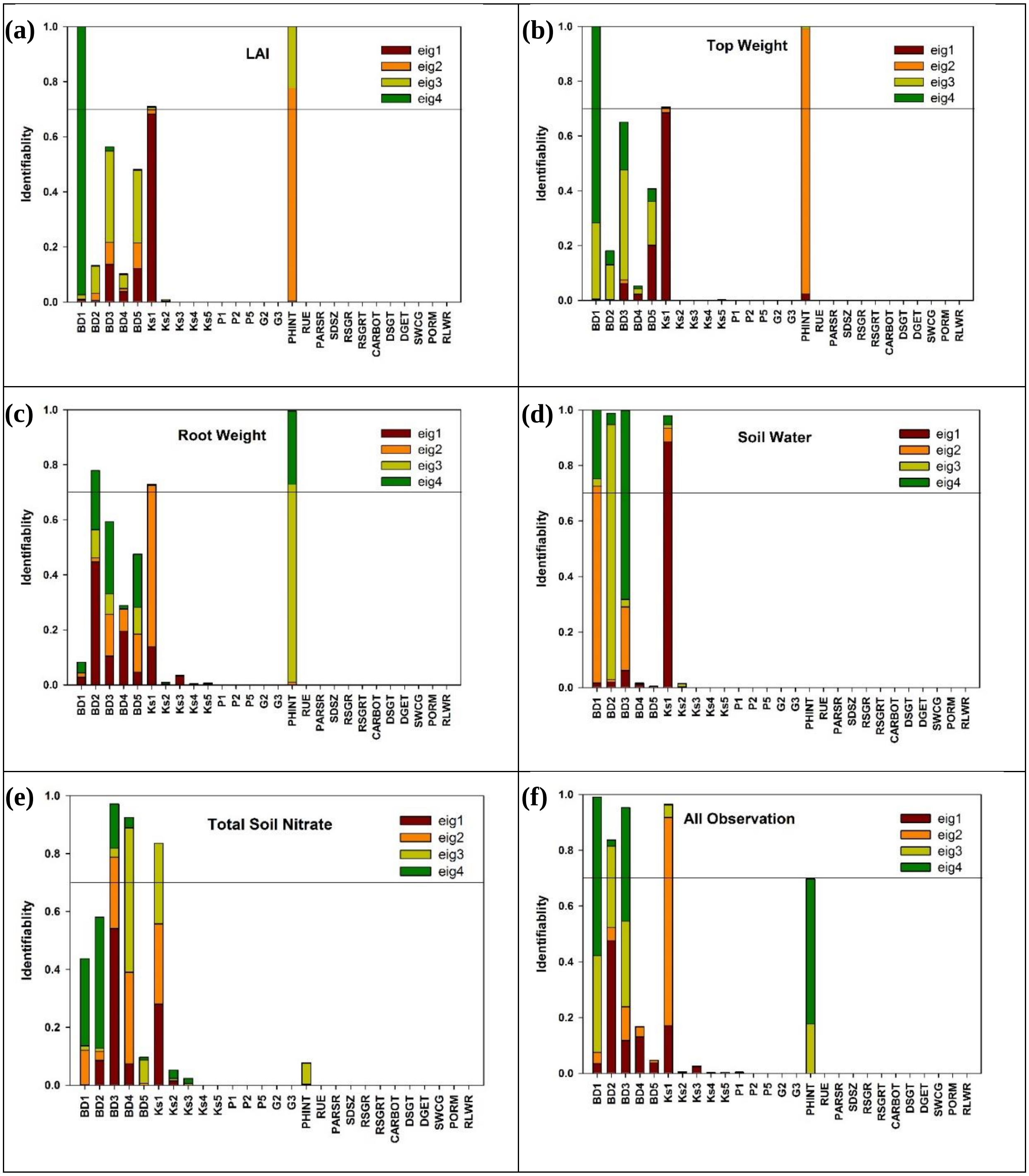


Figure 4.11. Bar plot of RZWQM2 parameter identifiability at the beginning of the inverse modeling by selected observation groups.

4.5. Conclusions

The CSM-CERES-Beet model was incorporated into RZWQM2 through a linkage to DSSAT. The RZWQM2 model was then applied to model dryland sugarbeets planted in the Carrington Research and Extension Center, North Dakota, USA, in 2014 and 2015. The model did reasonably well in both 2014 and 2015 in terms of simulating LAI, top weight, root weight, SWC, and soil nitrates. The d-statistic ranged from 0.709 to 0.992 in 2014 for model calibration and 0.733 to 0.990 in 2015 for model validation. The corresponding ranges for *rRMSE* were 0.066-1.211 and 0.043-0.930, respectively.

Soil water balance analysis shows that the water loss through plant transpiration was about 5 times larger than that through soil evaporation in the sugarbeet plots in 2014 and 2015 and the total transpiration accounted for ~60% of the total water losses in both years. Soil nitrogen mass balance analysis shows that more than 60% of soil nitrogen input was from fertilization and 31-35% was from net mineralization of soil organic matters.

Sensitivity analysis using PEST shows that, under dry conditions when soil available water becomes a strong limiting factor to sugarbeet growth, the most sensitive parameters were soil bulk densities and saturated hydraulic conductivities in different layers. The only sensitive plant parameter was PHINT that determines the thermal time needed for leaf appearance. Identifiability analysis shows that 3-5 model parameters may be identifiable by the calibration datasets that include observations of LAI, top weight, and root weight, as well as SWC's and soil nitrate concentrations in four different soil layers. More interestingly, the saturated hydraulic conductivity in the top layer (Ks1) was identifiable by any of the observation groups, while PHINT was identifiable by any of the observations of plant variables such as LAI, top weight and root weight. Our study demonstrated that the sensitivity analysis methods of PEST, which are based on linear theory, can be computed with modest computational burden and can readily accommodate parameter correlations.

In the future, the developed model will be applied to simulate sugarbeet production under different management scenarios for different soils and under different climatic conditions in the Red River Valley. As the sugarbeet production may be expanded into the nontraditional planting areas in the region due to potential demand for biofuel production, RZWQM2 enhanced with a sugarbeet module can be used to assess the associated environmental impacts.

CHAPTER 5. MODELING THE EFFECTS OF CROP ROTATION AND TILLAGE OPERATION ON SUGARBEET YIELD USING THE ROOT ZONE WATER QUALITY MODEL (RZWQM2)[3]

5.1. Abstract

Sugarbeet is considered to be one of the most viable alternatives to corn for biofuel production as it may be qualified as "advanced" biofuel feedstocks under the "EISA 2007". Prudent crop rotation and tillage operations may significantly affect the production of deep-rooted sugarbeet. Simulation of the effects of crop rotation and tillage operations on sugarbeet production will be helpful in proper management decision making. For simulating the effects of crop rotation and tillage operations on sugarbeet production, CSM-CERES-Beet, CSM-CERES-Maize, CROPSIM-Wheat, and CROPGRO-Soybean models included in the RZWQM2 were calibrated and evaluated using the field experimental data of crop yield, soil water, and NO_3-N content from the North Dakota State University Carrington Research Extension Center from 2014-2016. Model performed reasonably well in simulating crop yield, soil water, NO_3-N contents ($rRMSE$ = 0.055-2.773, d = 0.541-0.997). Five hypothetical crop rotations and 4 tillage operation scenarios were then generated to simulate their effects on sugarbeet yield and soil nitrate content. Twenty eight years (1990-2017) of model runs under these scenarios identified wheat as the most suitable previous year crop for sugarbeet. Among the tillage operations, moldboard plow performed better compared to other tillage methods.

Keywords: Crop rotation, Root Zone Water Quality Model (RZWQM2), Sugarbeet, Tillage

[3] This article is co-authored by Mohammad J. Anar, Zhulu Lin, Amitava Chatterjee, Mohamed Khan, Jasper M. Teboh, and Michael Ostlie. Mohammad J. Anar had the primary responsibility for model run, model evaluation and article write up. Dr. Zhulu Lin helped in result analysis, article write up, and proof reading. Drs. Amitava Chatterjee, Mohamed Khan, Jasper M. Teboh, and Michael Ostlie helped in field experiment, result analysis, and proof reading.

5.2. Introduction

Bioenergy crops are popular renewable energy sources due to their capabilities of improving national energy security and mitigating greenhouse gas (GHG) emissions from fossil fuels. The Renewable Fuel Standard of the US Energy Independence and Security Act (EISA) of 2007 has set a national target of 136 billion liters of renewable fuels by 2022, of which 61 billion liters are expected from advanced biofuels (USEPA, 2010). Under the EISA of 2007, advanced biofuels are classified as non-grain based biofuels derived from lignocellulosic biomass such as timber chips and perennial grasses, sugar crops such as sugarcane and sugarbeets, and waste materials including crop residues and urban waste (Congress, 2007). Currently the US is still reliant on corn, which is a grain-based source of bioethanol, but it is not sufficient to meet the renewable fuel targets. Furthermore, use of corn for biofuel production has a significant impact on food supply demand.

Energy beets, a variety of sugarbeet (*Beta vulgaris*), are being considered for biofuel production because of their high sugar content that could potentially produce twice as much ethanol per acre compared to other feedstocks (corn or cellulose) (Shapouri et al., 2006; Panella, 2010). Unlike conventional sugarbeets, energybeets are specialized non-food grade varieties (Maung and Gustafson, 2011; Kakani et al., 2012; Nahar and Pryor, 2013; Vargas-Ramirez et al., 2013) grown mainly for industrial use including bioenergy production. The largest region for sugarbeet production in the US is in or close to the Red River Valley (RRV) of western Minnesota and eastern North Dakota, where 57% of the nation's total sugarbeets were produced in 2016/17, while Idaho and Michigan contributed 31% of the total US production (USDA/ERS, 2018). In the RRV, 650,000 acres of lands were cultivated for sugarbeets in 2016/17 (USDA/ERS, 2018). Maung and Gustafson (2011) estimated this acreage would increase to about half a million if ten to twenty 20-Million Gallon per year sugarbeet processing plants for biofuel production are built in the region. In 2011, sugarbeet production in the RRV region generated a direct economic impact of $1.7 billion (Bangsund et al., 2012). Considering the increasing demands and economic impacts of sugarbeet, identifying prudent agronomic management practices (i.e. crop rotation and tillage operations) and new production areas are important.

Agronomic management practices like crop rotation and tillage practices can play a significant role in sugarbeet growth and yield by maximizing profits through proper utilization of fertilizers and soil nutrients. Crop rotation is effective in suppressing certain diseases, pests, and weeds of sugarbeet (Sugarbeet Production Guide, 2013). Tillage operations affect nutrient cycling by altering soil structure and the decomposition of crop residues and soil organic matter (Katupitiya et al., 1997). However, crop rotation or tillage operations may also result in a negative impact on sugarbeet yield if not prudently and timely decided. A positive or negative crop rotational and tillage operation response depends on many factors including soil moisture, fertility and compaction, plant residues, diseases, weeds, insects, or allelopathy (Havlin et al., 1990; Hao et al., 2001).

In the RRV region, sugarbeet production typically follows small grains, such as hard red spring wheat (HRSW) (*Triticum aestivum L.*). However, in the southern part of the RRV and in the Southern Minnesota Beet Sugar Cooperative growing area (Renville, MN), sugarbeet production generally follows a previous crop of corn (*Zea mays*). Sims (2004) reported a negative effect of corn residue on sugarbeet yield, although the effect appeared not to be related to nitrogen (N) availability. When corn directly follows sugarbeets, it is frequently not as productive as corn after soybeans or other rotational crops. This is referred to as corn-following-sugar beets (CFS) syndrome (Sims, 2004; Overstreet et al., 2007). Although deep-rooted sugarbeets are generally thought to hold potential for improving soil resources by complimenting other crops in the rotation and improving use of water and fertilizers, it is one of the few crops that do not host beneficial fungi called arbuscular mycorrhizae (Sims, 2004). Crops following sugarbeet are therefore more likely to suffer from nutrient deficiencies or be less resistant to drought stress due to lower colonization of beneficial mycorrhizal fungi.

Following a typical HRSW crop, wheat residue had minimal or no effect on the following year's sugarbeet root yield and quality (Sims, 2004). Wheat generally produces tremendous amounts of residue which can help to reduce soil erosion providing a protective barrier for the seedling. It can also help to conserve soil moisture and buildup of soil organic matter. If the N from wheat residue decomposition become available during the later state of sugarbeet growth, it will impact the quality of sugarbeet by increasing the impurities.

Another crop that has increased in acreage in the sugarbeet growing areas in the RRV is soybean (*Glycine max*). Currently, it is not recommended that sugarbeet be grown after a previous crop of soybean because leguminous crops like soybean leave less residues and more nitrogen in the soil compared to other crops in the rotation (Hao et al., 2001). Crop rotation research in the RRV reported reductions in both sugarbeet root yield and quality (recoverable sucrose per ton of beet) when grown after soybean compared to when grown after a small grain crop (Smith and Dexter, 1988). However, Soine and Severson (1975), Nordgaard et al., (1982), and Sims (2009) found little or no positive effect of a previous crop of soybean on sugarbeet root yield and quality.

Tillage operations may affect crop yields by affecting soil physical, chemical, and biological processes. Tillage affects soil bulk density, hydraulic conductivity and penetration resistance, therefore affecting water infiltration, internal drainage, and aeration of the soil (Jabro et al., 2010). It may also affect plant population, weed, pest, and disease infestation. Reduced or conservation tillage with increased surface residues prevents loss of organic matter from soil and may impact crop production (Havlin et al., 1990).

Interactive uses of field experiment and ecosystem-level modeling can be useful in identifying proper and timely agronomic practices for sustainable agriculture and enhanced environmental quality. The models that are currently available to assess the impacts of agricultural management on water quality include CREAMS (Knisel, 1980), GLEAMS (Leonard et al., 1986), EPIC (Sharpley and Williams, 1990), NLEAP (Shaffer et al., 1991), and OPUS (Smith, 1992). However, none of these models simulate the impacts of root zone processes on water quality and are limited to a narrow range of agricultural practices (Hanson et al., 1998). The Root Zone Water Quality Model (RZWQM) was developed to address these concerns (Saseendran et al., 2007; Ma et al., 2012).

The process-based RZWQM has been widely used for simulating agricultural management effects on crop production and soil and water quality (Ma et al., 2012). The model was applied to simulate the effect of agricultural management practices (irrigation, fertilization, planting date, and crop rotation) on pesticide transport, water use efficiency, water quality, and crop production (Jaynes and Miller, 1999; Saseendran et al., 2007; Malone et al., 2010). RZWQM2 is a significant upgrade from the early version of the RZWQM model. It contains surface energy balance from the SHAW (Simultaneous Heat and Water) model (Flerchinger et al., 2012) and the crop-specific growth modules from DSSAT (Decision Support System for Agrotechnology Transfer) (Jones et al., 2003). A new DSSAT based sugarbeet model (CSM-CERES-Beet) has recently been incorporated to RZWQM2 (version 4.0) for simulating the effects of sugarbeet growth on soil health and water quality (Anar et al., 2017). The objective of our current research is to simulate the effects of crop rotation and tillage operations on sugarbeet yield and soil nitrate content in the RRV and its vicinity. Although the RRV has its distinctive features, the lessons learned from this context can be extended to other regions in the US and around the world.

5.3. Materials and Methods

5.3.1. Experimental Site Description

Field experiments were conducted at the Carrington Research Extension Center, Carrington, North Dakota (47.510N, -99.123W). Soils of the experimental plots were loam with an average pH of 6.8. Average soil profile characteristics of the study plots are listed in Table 5.1. The climate of the study area is typically a continental climate with cold winters and hot summers, with average annual temperatures of 4.3℃ and precipitation of 477 mm. Average monthly higher precipitation (84 mm) is observed in June and average higher monthly temperature (26.6℃) is observed in July.

Table 5.1. Average characteristics of the soil profiles at Carrington Research Extension Center study area.

Depth (cm)	% Sand	% Silt	% Clay	Soil Type	% OM	EC 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		

The weather inputs required to run RZWQM2 were collected from North Dakota Agricultural Weather Network (NDAWN) station at Carrington, ND (47.509N, -99.132W and Elevation 476 meter). Weather data for 1990 to 2017 were collected and the required .met, .brk, and .sno files were generated using the weather generating function of RZWQM2.

The experimental site consisted a total of 48 plots of 15.24m × 12.2m (50ft × 40ft) size. Sugarbeets were cultivated along with corn, soybean, and wheat. Cultivars of sugarbeet, corn, and wheat used for the crop rotation experiments are X401, DKC33-78RIB, and Prosper, respectively. For soybean, Dairy-Land 0404 variety was used for the first two years and Proseed 3020 for the third year. A list of the planting date, harvest date, planting density, and fertilization rate for each crop is given in Table 5.2. Fertilizers were broadcasted on the surface one day before planting. All the crops were rain-fed with no irrigation.

Table 5.2. Crop management details for the field experiment.

Crop	Crop management	2014	2015	2016
Corn	Planting:	May 23	May 23	May 09
	Harvesting:	Nov 03	Nov 03	Oct 24
	Planting density:	98,800 seeds ha^{-1}	98,800 seeds ha^{-1}	98,800 seeds ha^{-1}
	Fertilization:	N: 201 kg ha^{-1}	N: 201 kg ha^{-1}	N: 201 kg ha^{-1}
		P: 22.42 kg ha^{-1}	P: 22.42 kg ha^{-1}	P: 22.42 kg ha^{-1}
		S: 11.21 kg ha^{-1}	S: 11.21 kg ha^{-1}	S: 11.21 kg ha^{-1}
Soybean	Planting:	Jun 02	Jun 04	May 19
	Harvesting:	Oct 10	Oct 10	Oct 10
	Planting density:	494,000 seeds ha^{-1}	494,000 seeds ha^{-1}	494,000 seeds ha^{-1}
	Fertilization:	None	None	None
Sugarbeet	Planting:	May 27	Jun 01	May 12
	Harvesting:	Oct 17	Oct 17	Oct 11
	Planting density:	121,030 seeds ha^{-1}	121,030 seeds ha^{-1}	121,030 seeds ha^{-1}
	Final Stand:	74000 seeds ha^{-1}	118,560 seeds ha^{-1}	Varied seeds/ha
	Fertilization:	N: 112 kg ha^{-1}	N: 112 kg ha^{-1}	N: 112 kg ha^{-1}
		P: 22.42 kg ha^{-1}	P: 22.42 kg ha^{-1}	P: 22.42 kg ha^{-1}
		S: 11.21 kg ha^{-1}	S: 11.21 kg ha^{-1}	S: 11.21 kg ha^{-1}
Wheat	Planting:	May 23	May 23	May 13
	Harvesting:	Sep 03	Sep 03	Aug 26
	Planting density:	2.9 million seeds ha^{-1}	2.9 million seeds ha^{-1}	2.9 million seeds ha^{-1}
	Fertilization:	N: 168 kg ha^{-1}	N: 168 kg ha^{-1}	N: 168 kg ha^{-1}
		P: 22.42 kg ha^{-1}	P: 22.42 kg ha^{-1}	P: 22.42 kg ha^{-1}
		S: 11.21 kg ha^{-1}	S: 11.21 kg ha^{-1}	S: 11.21 kg ha^{-1}

For sugarbeet, samples of leaf, stem, and root were collected periodically for top and root mass measurements. Both fresh and dry weights of the samples were measured. Leaf area index (LAI) was measured using the ground-based measurement method based on radiative transfer theory (Hemayati and Shirzadi, 2011). For other crops, final yield data were recorded at harvest. Soil water content (SWC) and soil nitrate concentration data were also collected from a number of different sugarbeet plots. Soil water contents in four different soil layers (0-15, 15-30, 30-45, and 45-60 cm) were measured using in-situ neutron probes (Troxler, NC). Soil samples were also analyzed in the laboratory periodically for soil profile nitrate concentrations in four different layers.

5.3.2. Crop Rotation for Model Calibration and Evaluation

For the calibration and evaluation of the models, 4 different crop rotation sequences from the field experiment were used. Table 5.3 lists the crop rotation sequences with their plot numbers used in model calibration and evaluation. In these field experiment scenarios, sugarbeet followed only wheat or sugarbeet, corn followed only sugarbeet, wheat followed soybean or corn, and soybean followed only corn as the previous crop (Table 5.3). In each sequence, the first-year crop was used for model calibration and the crops in the following two years were used for model evaluation.

Table 5.3. Plots for the five crop rotation sequences.

Sequences	First Year Crop (2014)	Second Year Crop (2015)	Third Year Crop (2016)	Plots
A	Soybean	Wheat	Sugarbeet	103, 210, 305, 404
B	Sugarbeet	Corn	Soybean	101, 212, 307, 402
C	Wheat	Sugarbeet	Corn	104, 110, 205, 211, 304, 306, 401, 409
D	Sugarbeet	Sugarbeet	Sugarbeet	109, 206, 301, 411

5.3.3. Tillage Operations

The effects of conventional tillage (CT) and no tillage (NT) were compared in the sugarbeet plots. Each sugarbeet plot was equally divided into two halves with CT performed in one half of the plot by disking to a depth of 7.5 cm and NT in the other half. Tillage was performed in the fall of the previous year. Before planting, a field cultivator was used for land preparation by cultivating the soil to a depth of 5 cm.

5.3.4. Model Calibration

Crop genetic parameters were calibrated for specific crop models available in RZWQM2 v. 4.0, CSM-CERES-Maize for corn, CROPSIM-Wheat for wheat, CROPGRO-Soybean for soybeans, and CSM-CERES-Beet for sugarbeet. Only grain yields at harvest were measured for corn, wheat, and soybean in 214-2016. The crop genetic parameters for these crops were manually calibrated using the observed grain yields in 2014 and these calibrated parameters are listed in Tables 5.4-5.6. Although two varieties of soybean were used during the study period, only one set of parameters were calibrated. For sugarbeet, PEST was used to calibrate the cultivar parameters of CSM-CERES-Beet against field observations of LAI, top weight, and root weight throughout the growing season. Please refer to Anar et al. (2017) for detail discussion. For completeness, the calibrated cultivar parameters for sugarbeet are also listed in Table 5.7. Once the models were calibrated, they were evaluated for the following two years (2015 and 2016) in all four crop rotation sequences.

Table 5.4. Cultivar parameter values for corn (DKC33-78RIB).

Parameter name	Calibrated value
P1: Thermal time from seedling emergence to the end of juvenile phase (℃-days)	120
P2: Delay in development for each hour that daylength is above 12.5 hours (days hr^{-1})	0.40
P5: Thermal time from silking to physiologic maturity (℃-days)	860
G2: Maximum possible number of kernels	850
G3: Kernel filling rate (mg day^{-1})	18
PHINT: Phyllochorn interval in thermal time between successive leaf tip appearance (℃-days)	34

Table 5.5. Cultivar parameter values for wheat (prosper).

Parameter name	Calibrated value
P1V: Days at optimum vernalizing temperature required to complete vernalization	28
P1D: % reduction in development when photoperiod in 10 hr less than the threshold (P1DT=20hr)	75
P5: Grain filling duration phase (℃-days)	500
G1: Kernel number per unit canopy weight at anthesis (#/g)	35
G2: Standard kernel size under optimum condition (mg)	60
G3: Standard non-stressed dry weight of a single tiller at maturity (g)	4
PHINT: Phyllochorn interval in thermal time between successive leaf tip appearance (℃-days)	60

Table 5.6. Cultivar parameter values for soybean (dairy-land 0404).

Parameter name	Calibrated value
CSDL: Critical short-day length below which reproductive development progresses with no day length effect (hr)	14.84
PPSEN: Slope of the relative response of development to photoperiod with time (hr^{-1})	0.10
EM-FL: time between plant emergence to flower appearance (℃-days)	18
FL-SH: Time between first flower and first pod (℃-days)	10
FL-SD: Time between first flower and first seed (℃-days)	15
SD-PM: Time between first seed and physiologic maturity (℃-days)	37.59
FL-LF: Time between first flower and end of leaf expansion (℃-days)	17
LFMAX: Maximum leaf photosynthesis rate at 30℃ ($CO_2 m^{-2} s^{-}$)	2.60
SLAVR: Specific leaf area of cultivar under standard growth condition ($cm^2 g^{-1}$)	280
SIZLF: Maximum size of full leaf (cm^2)	180
XFRT: Maximum fraction of daily growth that is partitioned to seed and shell	1
WTPSD: Maximum weight per seed (g)	0.19
SFDUR: Seed filling duration for pod cohort at standard growth conditions (℃-days)	23
SDPDV: Average seed per pod under standard condition (#/pod)	2.20
PODUR: Time required for cultivar to reach final pod load under optimal conditions (℃-days)	8

Table 5.7. Cultivar parameter values for sugarbeet (X401).

Parameter name	Calibrated value
P1: Thermal time from seedling emergence to the end of juvenile phase (℃-days)	940
P2: Photoperiod sensitivity (hr^{-1})	0.001
P5: Thermal time from pennicle initiation to physiological maturity (℃-days)	700
G2: Leaf expansion rate during leaf growth stage ($cm^2 cm^{-2} d^{-1}$)	220
G3: Maximum root growth rate ($g\text{-}m^{-2} d^{-1}$)	37.5
PHINT: Phyllochorn interval in thermal time between successive leaf tip appearance (℃-days)	43

Soil bulk density and saturated hydraulic conductivity values for different soil layers, up to 120 cm, were calibrated using PEST based on average soil profile water content and nitrate content in the sugarbeet plots (Anar et al., 2017). Since we did not have measurements of soil water content at 1/3 bar suction head ($\theta_{1/3}$) or 15 bar suction head (θ_{15}), the Brooks-Corey (BC) parameters were estimated based on soil texture classes according to Rawls et al. (1982) by the RZWQM2 model (Fang et al, 2010; Ma et al., 2012) (Table 5.8). Except for residual water content (θ_r), other BC parameters (θs, ψ_b, and λ) were adjusted based on bulk density (ρ_b) by the model according to the relationships defined among the BC parameters (Ahuja et al., 2000; Ma et al., 2012). The water content at any suction head (e.g., $\theta_{1/3}$, θ_{15}) could also be computed from these BC parameters. Table 5.8 lists the parameter values for soil hydraulic properties at different soil depths when the model was calibrated.

Table 5.8. Brooks-Corey parameters used in simulations.

Horizon Depth (cm)	Bulk density ρ_b (g cm^{-3})	Saturated hydraulic conductivity K_{sat} (cm h^{-1})	Saturated water content θ_s ($cm^3 cm^{-3}$)	Residual water content θ_r ($cm^3 cm^{-3}$)	Bubbling pressure ψ_b (cm)	Particle size distribution index λ	1/3 bar water content $\theta_{1/3}$ ($cm^3 cm^{-3}$)	15 bar water content θ_{15} ($cm^3 cm^{-3}$)
15	1.438	1.18	0.413	0.027	2.17	0.217	0.156	0.083
30	1.091	1.04	0.554	0.027	0.485	0.151	0.223	0.111
60	1.106	3.00	0.548	0.027	0.517	0.137	0.242	0.120
90	1.000	3.00	0.622	0.041	0.275	0.166	0.219	0.093
120	1.873	3.00	0.293	0.041	2.736	0.463	0.068	0.048

5.3.5. Model Evaluation

For the evaluation of the model performances we calculated both relative root mean square error ($rRMSE$) and index of agreement (d) as indicators of goodness of fit. The rRMSE is the root mean square error normalized to the mean of the observed values:

$$rRMSE = \frac{\sqrt{\frac{1}{m}\sum_{i=1}^{m}(y_i - y_i')^2}}{|\overline{y}|} \tag{5.1}$$

where, m is the number of observations, $\overline{y}$ is the mean of the observed values, $y_i{}'$ is the model simulated value and y_i is observed value. The index of agreement is estimated using the following equation:

$$d = 1 - \frac{\sum_{i=1}^{m}(y_i - y_i')^2}{\sum_{i=1}^{m}(|y_i' - \overline{y}| + |y_i - \overline{y}|)^2} \tag{5.2}$$

The index of agreement is more sensitive than traditional correlation measures to differences between observed and simulated means and variances. The value of d varies between 0 and 1, with higher values indicating better fit (Legates and McCabe, 1999).

5.3.6. Hypothetical Scenarios for Crop Rotation and Tillage Effects

Since data for crop rotation and tillage effect on sugarbeet yield were not available for substantial periods of time, we generated hypothetical crop rotational and tillage operation scenarios to simulate their effects on sugarbeet yield and soil nitrate content. In the following crop rotation scenarios sugarbeet would follow corn, wheat, soybean, and sugarbeet as previous crop: 1) corn-sugarbeet-wheat-sugarbeet, 2) wheat-sugarbeet-corn-sugarbeet, 3) soybean-sugarbeet-wheat-sugarbeet, 4) wheat-sugarbeet-soybean-sugarbeet, and 5) continuous sugarbeet. We ran the scenarios for 28 years from 1990-2017 to simulate the effects of each of the crops on sugarbeet yield and soil nitrate content. The 28 years weather input data were obtained from NDAWN weather station at Carrington, ND. We used the same planting date, planting density, planting depth, row width, and fertilization rate for all the years. Table 9 shows the planting management data for different crops used in the hypothetical crop rotation scenarios.

Table 5.9. Crop management data used to run hypothetical crop scenarios.

Crop management	Corn	Soybean	Sugarbeet	Wheat
Planting:	May 23	Jun 02	May 27	May 23
Harvesting:	Nov 03	Oct 10	Oct 17	Sep 03
Planting density:	98,800 seeds ha^{-1}	494,000 seeds ha^{-1}	74000 seeds ha^{-1}	2.9 million seeds ha^{-1}
Fertilization:	N: 201 kg ha^{-1} P: 22.42 kg ha^{-1} S: 11.21 kg ha^{-1}	N: 50 kg ha^{-1}	N: 112 kg ha^{-1} P: 22.42 kg ha^{-1} S: 11.21 kg ha^{-1}	N: 168 kg ha^{-1} P: 22.42 kg ha^{-1} S: 11.21 kg ha^{-1}

To simulate the effects of tillage operations on sugarbeet yield, we selected four different tillage operation methods; moldboard plow (MP, to a depth of 15 cm), chisel plow (CP, to a depth of 13 cm), field cultivator (FC, to a depth of 10 cm), and no tillage (NT). Tillage operations were applied on the continuous sugarbeet rotation plots for the same 28 years from 1990-2017. Crop management data for sugarbeet were same as described in table 5.9.

5.4. Results and Discussion

5.4.1. Model Calibration and Evaluation

5.4.1.1 Crop Rotation Yield Evaluation

Figure 5.1 shows the graphical comparisons of the observed and the model-simulated crop yields for the four crop rotation sequences in 2014-2016. For all the four rotation sequences, crop genetic parameters were calibrated in 2014 and the models were run continually for the following two years using the same calibrated parameters. Overall, the model performed well in simulating crop yields for all four crops in the four crop rotation sequences. Table 5.10 shows that all $rRMSE$ were smaller than 0.25 and d-statistic were greater than 0.95. However, the yields of all the crops (i.e., sugarbeet, corn, and wheat) planted in 2016, the last year of the rotation sequences, were overestimated by the crop models by 14.61-112.7%. A close inspection of Fig. 5.1 reveals that the observed crop yields in 2016 were generally lower than those in the previous years. For example, the average grain yields of wheat were 4006.0 and 3458.66 kg ha^{-1} in 2014 and 2015 respectively but was only 1724.47 kg ha^{-1} in 2016. The yields of corn and sugarbeet were also lower in 2016. No soybeans were planted in 2016 in any of these four sequences. One of the reasons why the observed yield of sugarbeet was lower in 2016 was that the average final crop stands of sugarbeet were lower in 2016 (i.e., 46,574 plants ha^{-1}) than those in 2014 (i.e., 74,000 plants ha^{-1}) and 2015 (i.e., 98,800 plants ha^{-1}). This may be also true for other crops. The other reason may be that the planting dates for all crops 10-20 days earlier in 2016 compared to those in 2014 and 2015 (see Table 5.2).

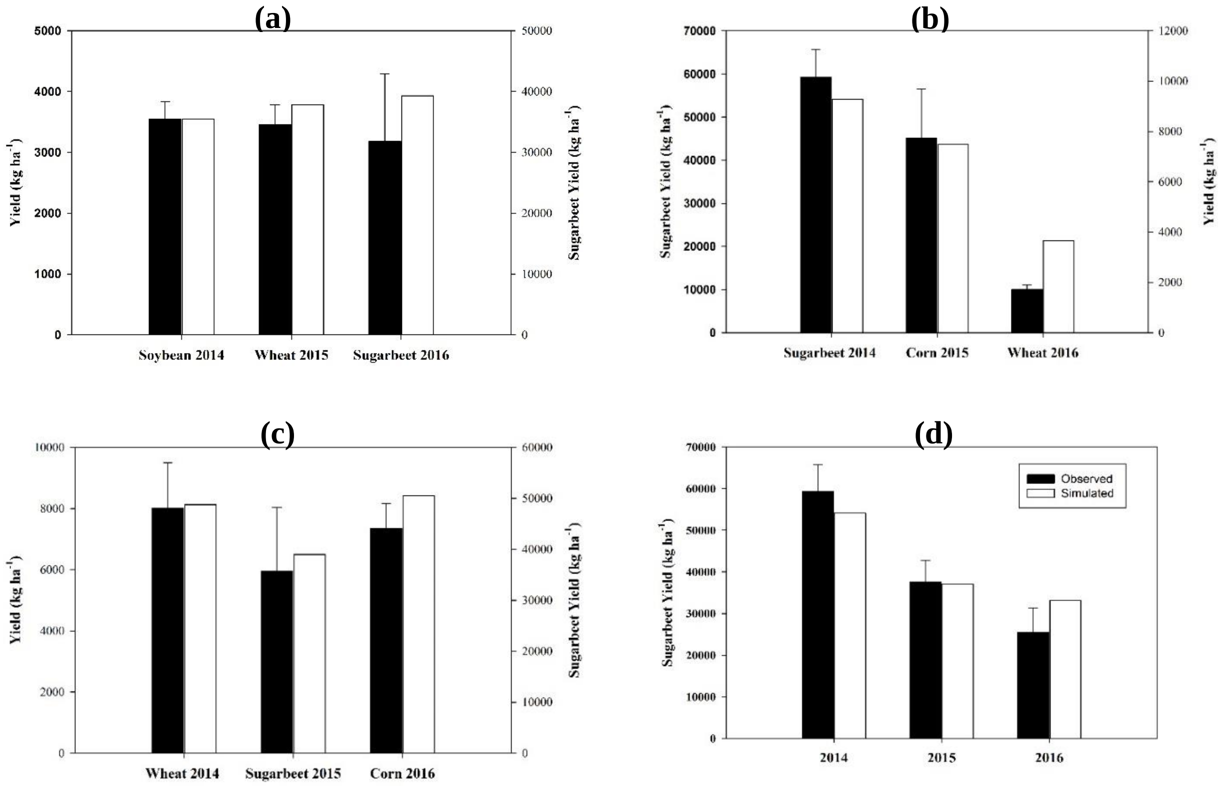


Figure 5.1. Calibration and evaluation of the models for the crop rotation sequences, a) soybean-wheat-sugarbeet (seq. A), b) sugarbeet-corn-soybean (seq. B), c) wheat-sugarbeet-corn (seq. C), d) continuous beet (seq. D). Notes: Crops models were calibrated in 2014 and evaluated in 2015 and 2016.

Table 5.10. Model evaluation results for crop rotation sequence yields, soil water content, and soil nitrate contents.

Observations (year)	Rotation	Layer	$rRMSE$	d-statistics
Yield (2014-2016)	Seq A		0.242	0.982
	Seq B		0.147	0.997
	Seq C		0.118	0.997
	Seq D		0.100	0.949
Soil Water Content (2016)	Seq A	0-15 cm	0.224	0.709
		15-30 cm	0.229	0.722
		30-45 cm	0.135	0.877
		45-60 cm	0.195	0.541
	Seq D	0-15 cm	0.070	0.676
		15-30 cm	0.099	0.564
		30-45 cm	0.055	0.704
		45-60 cm	0.083	0.668
Soil NO_3-N (2016)	Seq A	0-15 cm	2.773	0.654
		15-30 cm	0.990	0.765
		30-45 cm	1.110	0.652
		45-60 cm	1.392	0.500
	Seq D	0-15 cm	0.662	0.873
		15-30 cm	0.242	0.982
		30-45 cm	1.35	0.616
		45-60 cm	1.605	0.610

5.4.1.2. Soil Water and NO_3-N Contents

The model was also evaluated for the soil profile water and NO_3-N contents. The observed and the model simulated soil profile water contents in the sugarbeet plots for Sequences A and D are presented in Fig. 5.2, while the observed and the model simulated soil nitrate contents in the sugarbeet plots for Sequences A and D are presented in Fig. 5.3. The model evaluation statistics, $rRMSE$ and d-statistics, are listed in Table 5.10. As shown in Fig. 5.2 & 5.3, the model simulated soil water contents and soil nitrate contents in the sugarbeet plots for both sequences reasonably well. As expected, the model did better in simulating soil water contents than soil nitrate contents. The rRMSE ranged between 0.055 to 0.229 for water soil water contents and 0.662 to 2.773 for soil nitrate contents, while the d-statistics ranged between

0.541 to 0.877 for soil water contents and 0.500 to 0.982 for soil nitrate contents (see Table 5.10).

It is worth noting that errors in computations of the model simulated soil water and NO_3-N may be introduced by lack of site specific specification of a single set (for different soil layers) of average bulk density and K_{sat} values to represent all experimental plots in the model, when there could be considerable spatial heterogeneity in observed soil properties across the field (Ma et al., 2007; Saseendran et al., 2007). Simulation errors in daily profile NO_3-N concentration could also be due to uncertainties in the calibration for different soil organic and microbial pools and the extent to which these errors propagated into the daily mineralization of organic matter in the model (mainly through microbial processes) (Saseendran et al., 2007).

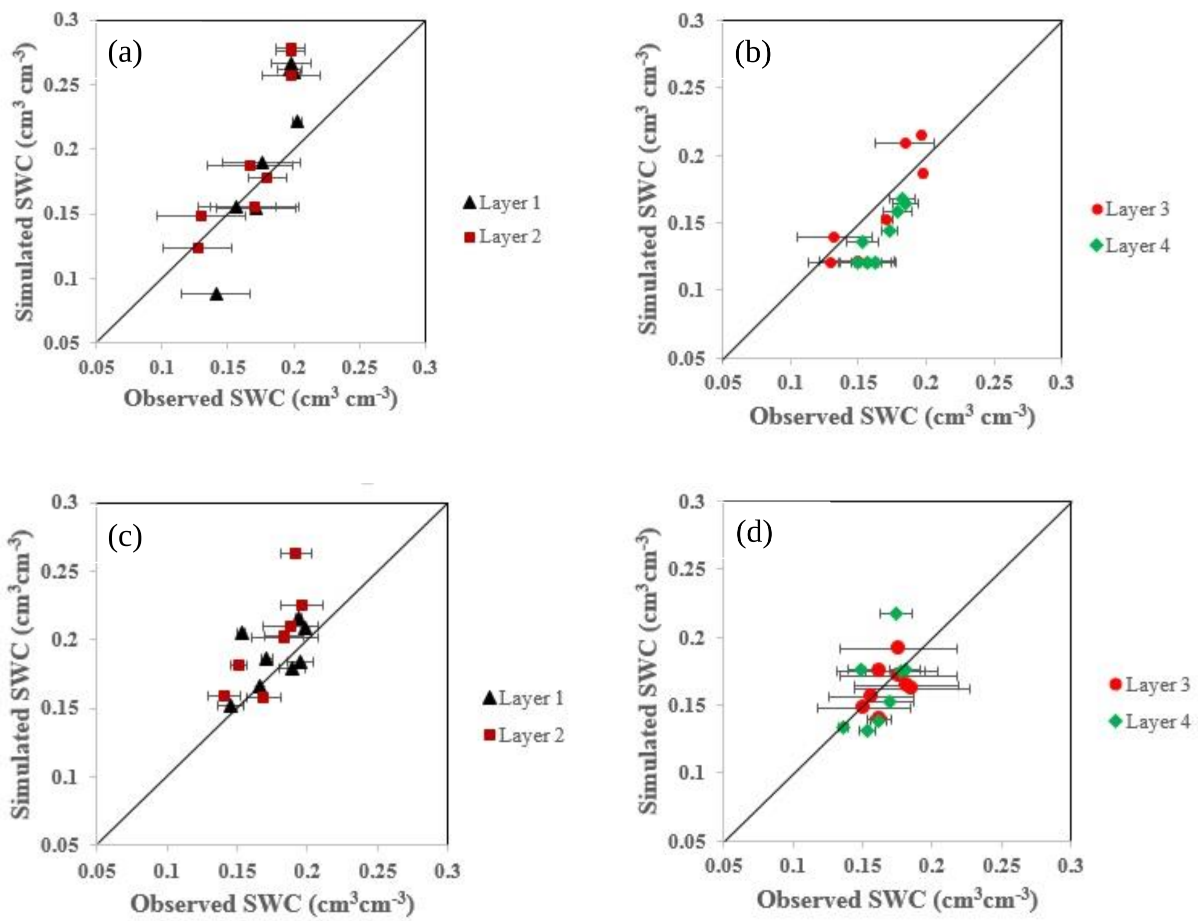


Figure 5.2. Soil profile water content (SWC) in sugarbeet plots in 2016: (a) layers 1 &2 & (b) layers 3 & 4 in Sequence A, and (c) layers 1 & 2 and (d) layers 3 &4 in Sequence D. Notes: The horizontal bars and whiskers represent the standard errors for observed soil water contents in sugarbeet plots.

It is interesting to note that the soil water contents in the top two layers (Fig. 5.2a and 5.2c) in the sugarbeet plots were more variable than those in the bottom two layers (Fig. 5.2b and 5.2d) for both Sequences A and D. Although both were observed in the same year (2016), the soil water contents in the sugarbeet plots for Sequence A (grown after wheat, Fig. 5.2a and 5.2b) were more variable than those for Sequence D (continuous beet, Fig. 5.2c and 5.2d). Like soil water, the soil NO_3-N contents in the top two layers (Fig. 5.3a and 5.3c) in the sugarbeet plots were more variable than those in the bottom two layers (Fig. 5.3b and 5.3d) for both Sequences A and D. Fig. 5.3 also shows that the soil NO_3-N contents in the top two layers were greater than those in the bottom two layers. It is also interesting to note that the soil nitrate contents in the bottom two layers in the sugarbeet plots for Sequence D (continuous beet) were much smaller than those for Sequence A (grown after wheat). This is may be due lower utilization of NO_3-N by wheat in the previous year. In his research, Sims (2009) also observed greater NO_3-N following wheat and soybean compared to that of sugarbeet.

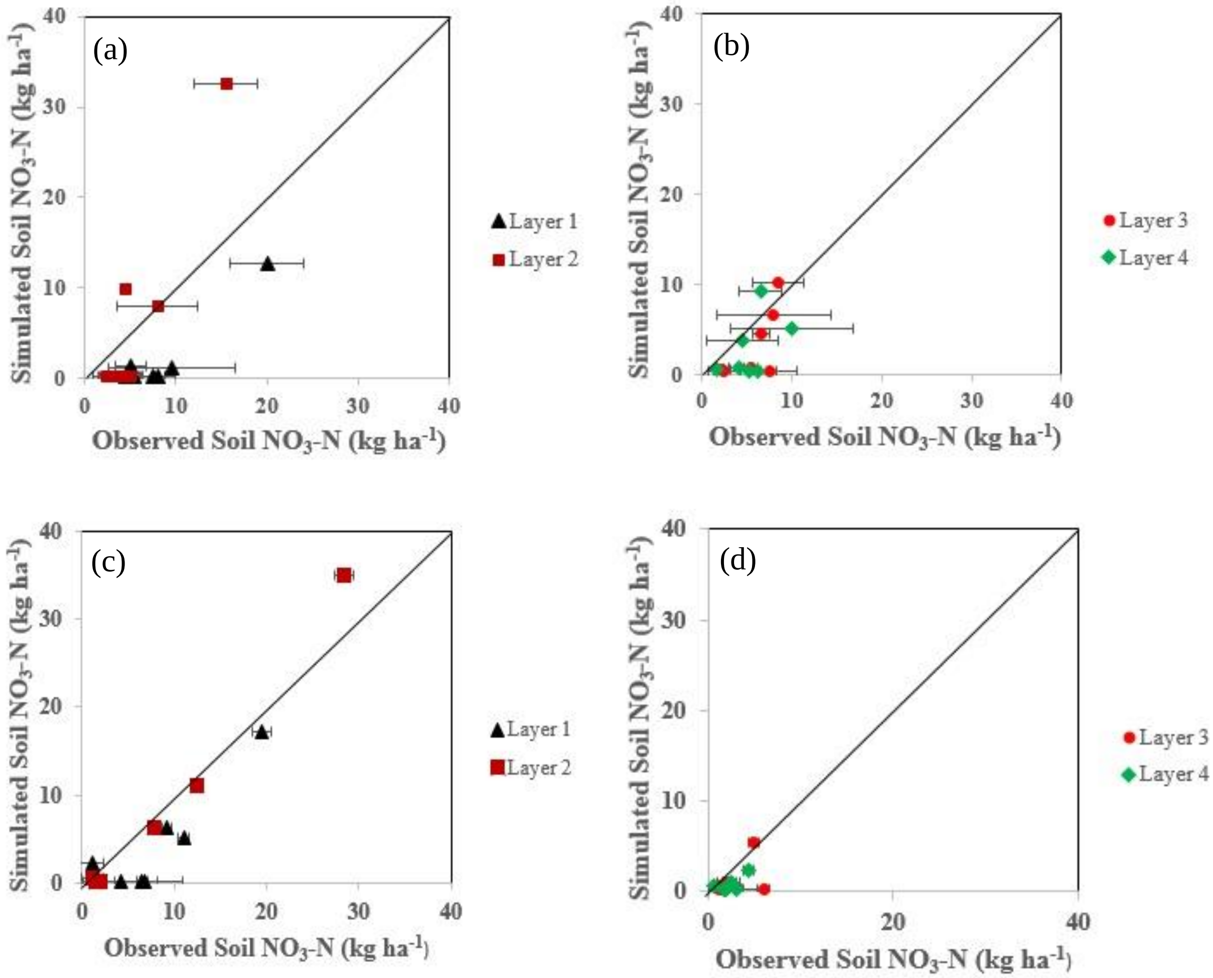


Figure 5.3. Soil profile NO_3-N content in sugarbeet plots in 2016: (a) layers 1 &2 & (b) layers 3 & 4 in Sequence A, and (c) layers 1 & 2 and (d) layers 3 &4 in Sequence D. Notes: The horizontal bars and whiskers represent the standard errors for observed soil water contents in sugarbeet plots.

5.4.1.3. Tillage Effects Evaluation

The newly developed sugarbeet model, CSM-CERES-Beet, was also evaluated to simulate the effect of tillage operations (NT and CT) on sugarbeet yields in 2015 and 2016. As shown in Fig. 5.4, the model did reasonably well in simulating sugarbeet yields under both tillage scenarios, except that the model over-predicted the sugarbeet yield in 2015 for NT. Fig. 5.4 also shows that CT operations produced higher sugarbeet yields compared to NT operations in both 2015 and 2016. Tillage operations may have affected the final sugarbeet plant stand. Final average sugarbeet plant stands were approximately 46,574 and 15,675 (plants ha^{-1}) for the CT and NT operation fields respectively. Unfortunately, final sugarbeet stands for tillage and no tillage operations were not recorded for 2015. A higher weeds infestation were also observed in the fields in 2016 production year.

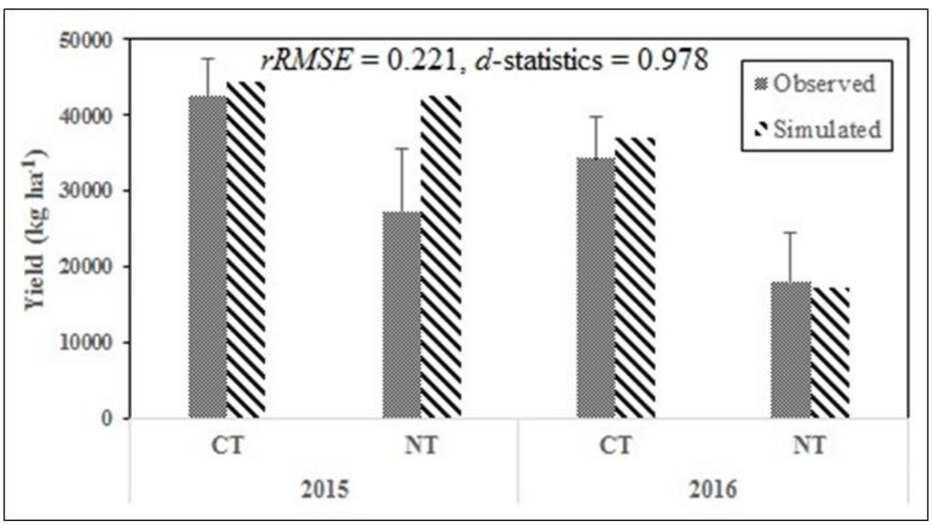


Figure 5.4. Effects of tillage operations on sugarbeet yields. Note: CT–conventional tillage, NT – no tillage.

5.4.2. Effects of Crop Rotation on Sugarbeet Yield and Soil Nitrate

Figure 5.5 shows the model-simulated sugarbeet yields after following different previous crops in the five hypothetical crop rotation scenarios. The average of the sugarbeet yields over the 28 years simulation period were also plotted as boxplot in Fig. 5.6 to compare the overall effects of the four previous crops on sugarbeet yield. Fig. 5.6 shows that sugarbeet had the highest yield when the previous crop was wheat, while it had lowest yield when it followed soybean. The effect of corn and sugarbeet as previous crop is in-between. Overstreet et al. (2007) and Sims (2009) also observed greater sugarbeet yields when it followed wheat compared to following corn or soybean. In their research they also observed lowest sugarbeet yield when it followed corn, and slightly higher yield when it followed soybean. However, in our model simulations, sugarbeet had higher yields when following corn compared to following soybean.

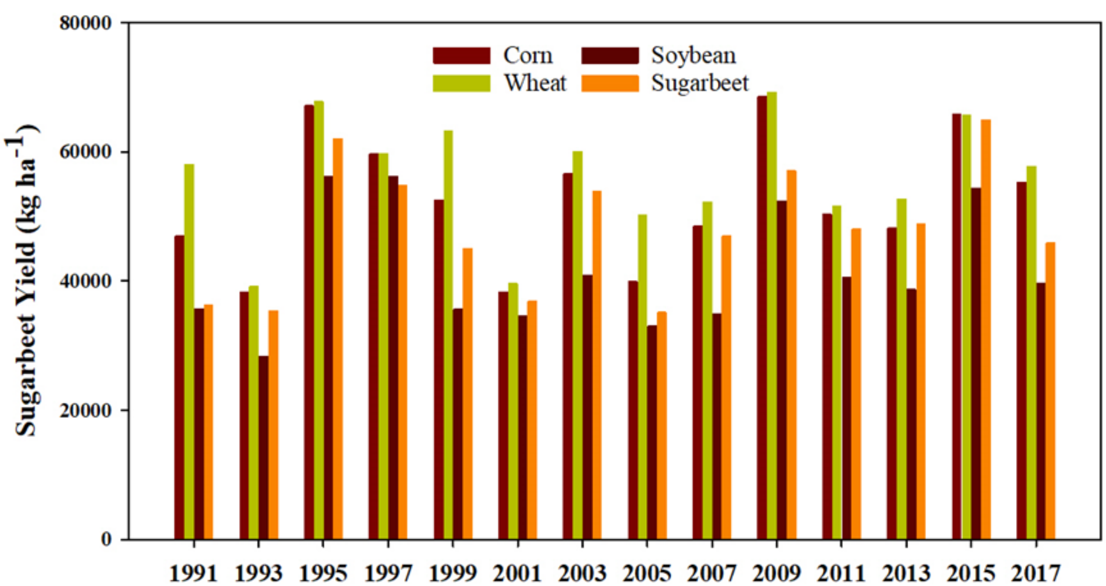


Figure 5.5. Sugarbeet yields following different crops (corn, wheat, soybean, and sugarbeet) in five hypothetical crop rotation scenarios.

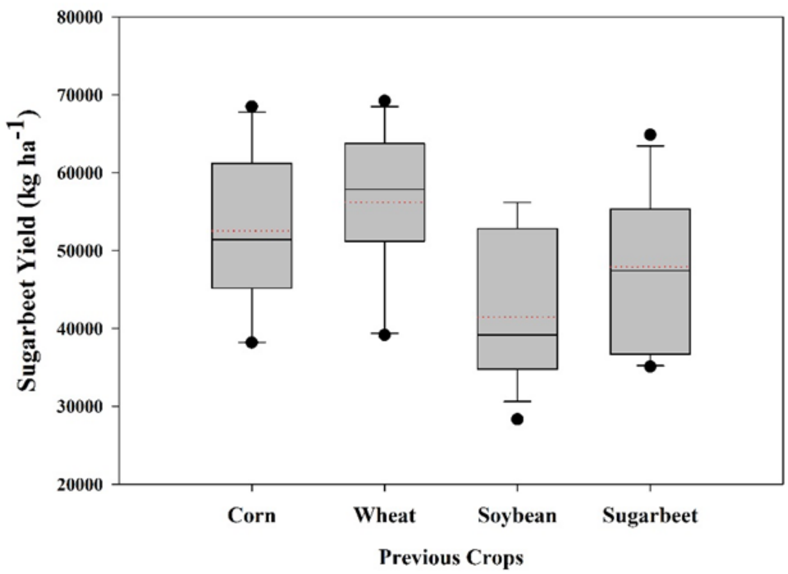


Figure 5.6. Effects of previous crops on sugarbeet yields.

Figure 5.7 compares the soil profile NO_3-N contents in the top 60 cm in sugarbeet plots where sugarbeet was planted after four different previous crops. It suggests that when sugarbeet followed soybean in crop rotation, the plot would have highest NO_3-N contents in all layers and for almost the entire growing season, except in the 45-60 cm layer during the early growing season (Fig. 5.7d). In the top two layers, soil NO_3-N content dynamics in the sugarbeet plots are very similar throughout the entire growing season when sugarbeet followed corn, wheat, or continuous beet (Fig. 5.7a and 5.7b). However, in the deeper two layers, NO_3-N contents in the continuous beet plots were much lower compared to other crops (Fig. 5.7c and 5.7d). Sims (2009) also observed higher NO_3-N content in the first two layers when sugarbeet followed soybean in the crop rotation.

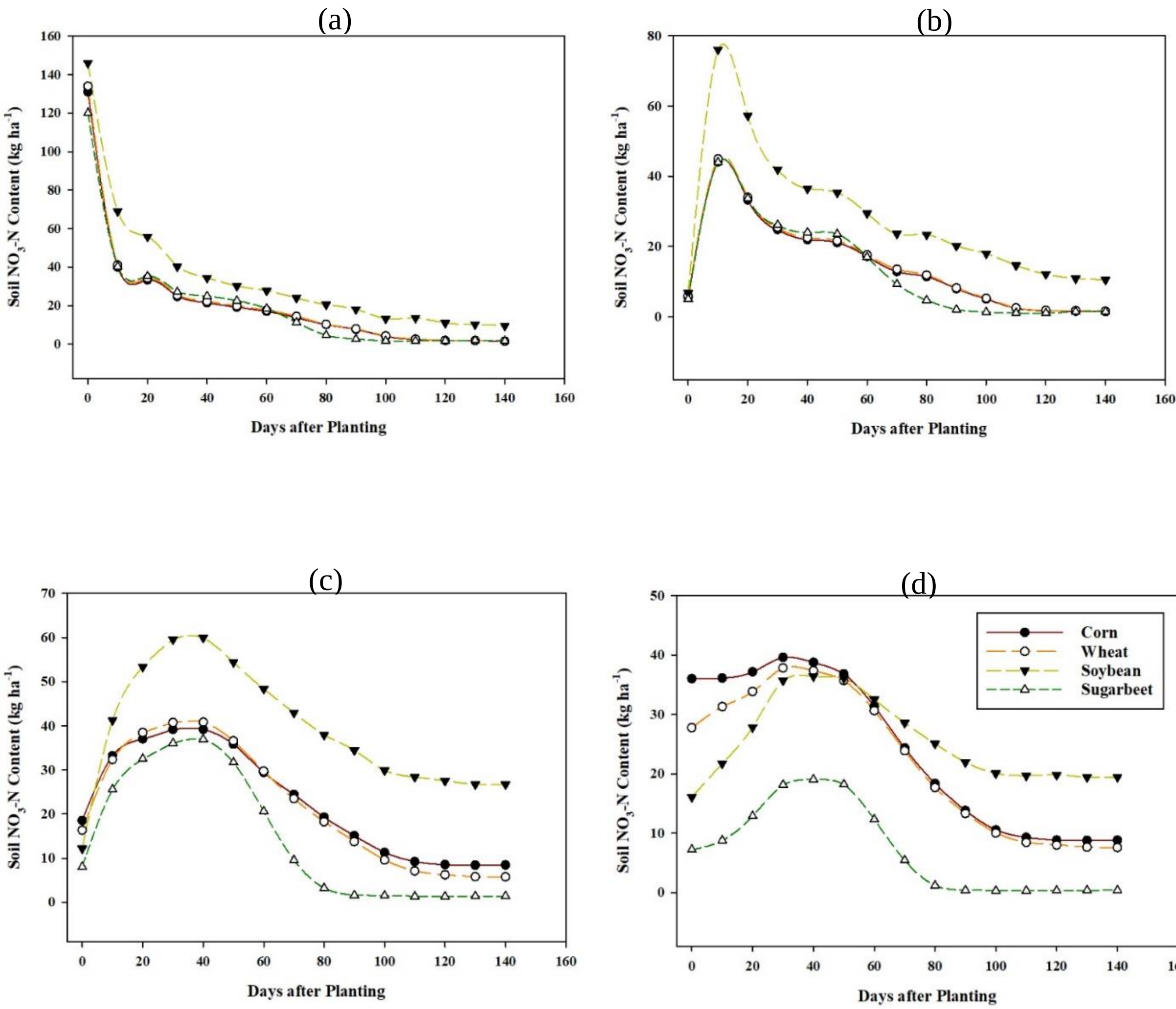


Figure 5.7. Comparisons of soil profile NO_3-N within sugarbeet plots following corn, wheat, soybean, and sugarbeet in the five hypothetical crop rotation scenarios within a) 0-15 cm, b) 15-30 cm, c) 30-45 cm, and d) 45-60 cm layers.

5.4.3. Effects of Tillage Operations on Sugarbeet Yield and Soil Nitrate

Effects of different tillage operations on sugarbeet yields are plotted in Fig. 5.8. Among these four tillage methods, sugarbeet field tilled with the MP method would produce slightly higher yield compared to those tilled using other tillage methods. Tarkalson et al. (2009) observed a slightly higher sugarbeet yield with MP compared to CP at a nitrogen fertilization rate of 112 kg ha^{-1}. However, the differences in yield resulted from the different tillage methods are not significant. Non-significant effects of different tillage operation methods on sugarbeet yields were also observed by some other studies conducted by Hao et al. (2001), Jabro et al. (2010), Tarkalson et al. (2012), and Larney et al. (2016).

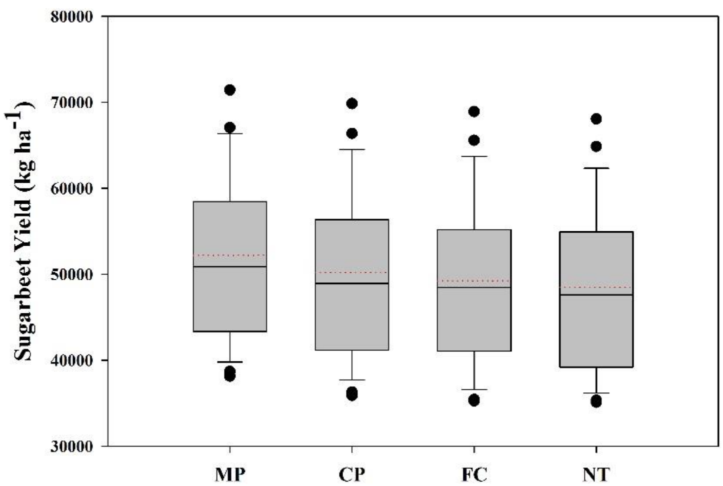


Figure 5.8. Effects of different tillage operations on sugarbeet yields. Notes: MP- Moldboard Plow, CP- Chisel Plow, FC- Field Cultivator, and NT- No Tillage.

The difference observed in the sugarbeet yields under different tillage operation scenarios may be due to soil NO_3-N availability (Hansen and Djurhuus, 1997; Catt et al., 2000; Mitchell et al., 2000; Thomsen, 2005; Askegaard et al., 2011). A comparison of the model simulated NO_3-N content in the top 60 cm are plotted in Fig. 5.9. Fig. 5.9a and 5.9b show that the sugarbeet field that was tilled by MP, which reaches up to 15 cm, had the highest NO_3-N contents in the upper two layers compared to those tilled by other methods (CP, FC, and NT) during the first 60-100 days after planting. For the bottom two layers, there was no difference in soil NO_3-N contents in the sugarbeet fields tilled using the four different tillage methods (Fig. 5.9c and 5.9d).

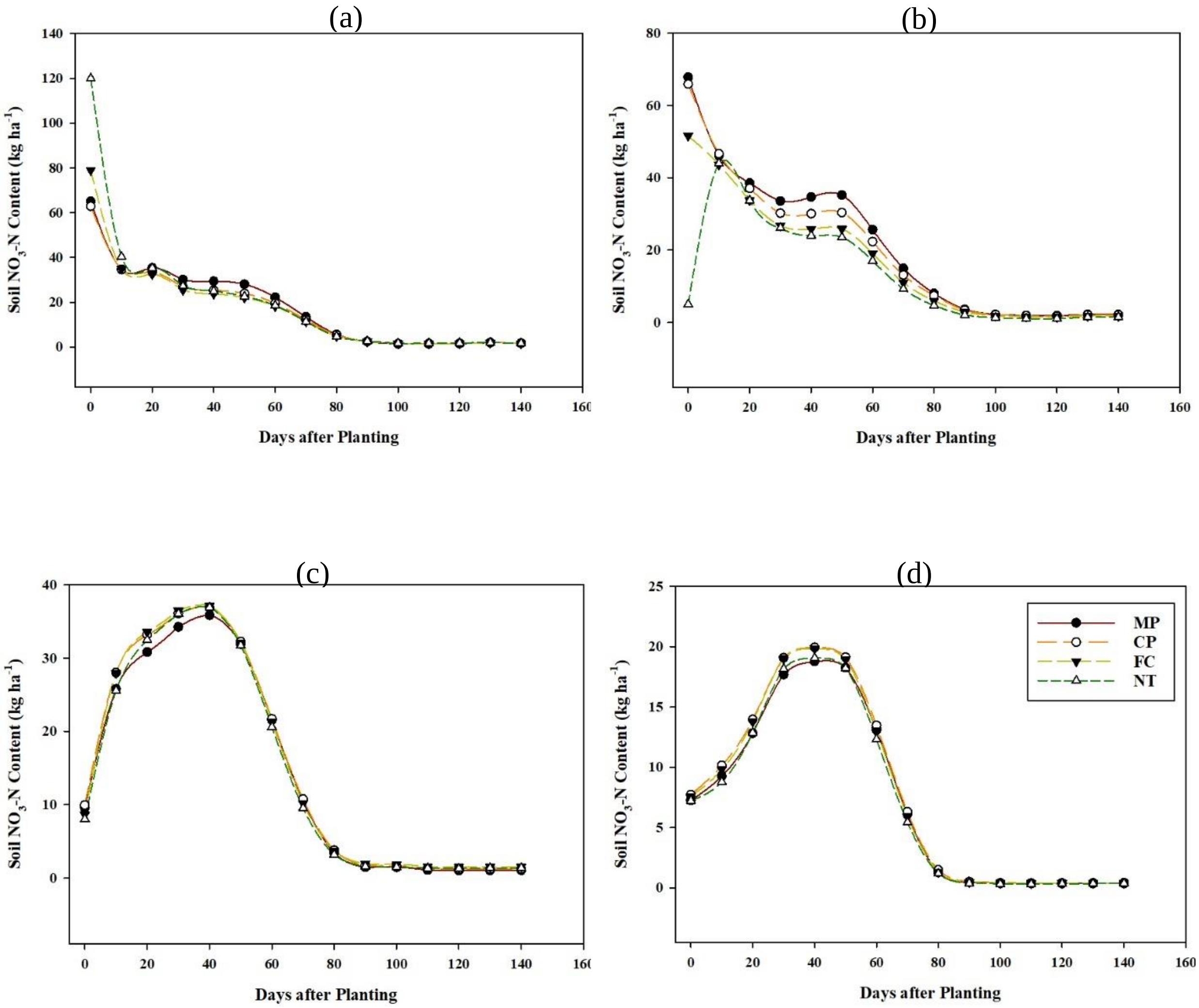


Figure 5.9. Comparisons of soil profile NO_3-N within sugarbeet plots under four different hypothetical tillage operation scenarios within a) 0-15 cm, b) 15-30 cm, c) 30-45 cm, and d) 45-60 cm layers. Notes: MP- Moldboard Plow, CP- Chisel Plow, FC- Field Cultivator, and NT- No Tillage.

5.5. Conclusions

Sugarbeet as an alternative biofuel source is getting popularity and its production within the RRV are increasing. A prudent crop rotation and tillage operation is essential for economic production of deep-rooted sugarbeet. Both crop rotation and tillage operation can significantly affect soil organic C and N accumulation and thus may affect sugarbeet productivity. A sound crop rotation is also the key component of effective pest management and stabilization of sugarbeet yields. For these reasons, modeling the impacts of different crop rotation and tillage operation scenarios on sugarbeets production are very essential for prudent decision makings. In this research, four crop growth models from RZWQM2 v. 4.0 (CSM-CERES-Beet for sugarbeet; CSM-CERES-Maize for corn; CROPSIM-Wheat for wheat; and CROPGRO-Soybean for soybean) were used to assess the impacts of crop rotation and tillage operations on sugarbeet production.

The crop growth modules for the four crops were first calibrated for field data in 2014 and evaluated for 2015-2016 crop rotation sequences. Hypothetical crop rotation and tillage operation scenarios identified wheat most suitable crop before sugarbeet in the crop rotation scenarios. Among the tillage operations, moldboard plow (MP) at a depth of 15 cm performed much better compared to other tillage operations of chisel plow (CP), field cultivator (FC), or no tillage (NT).

In future RZWQM2 model may be used for different soil and climatic conditions under different management scenarios in the Red River Valley for longer periods of observed data for better evaluation of the model performances. As the sugarbeet production may also be expanded into the nontraditional planting areas in the region due to potential demand for biofuel production, RZWQM2 can also be used to assess the associated environmental impacts and suitability for different crop rotation and management scenarios.

CHAPTER 6. CONCLUSIONS

Greenhouse gas (GHG) emissions in the US have increased by approximately 1% each year in the last decade (USDOE/EIA, 2005). Renewable biofuel energy sources are getting popular because of their potential to reduce net GHG emission. The Energy Independence and Security Act (EISA) of 2007 classified biofuels into three categories called conventional, advanced, and cellulosic biofuels, offering 20%, 50%, and 60% reduction in GHG emission respectively. Currently, 97% of the biofuels produced in the US are corn-based ethanol, which can offer up to 40% reduction in GHG emissions. Sugarbeet is currently being considered to be uniquely qualified as “advanced biofuels” under the EISA.

Modeling sugarbeet growth can be very useful for the sugarbeet growers and sugarbeet industries for predicting the yields and total acreage required to reach their production goals. At the same time, models that can simulate the effects of crop growth on soil and water quality will be helpful in predicting their impacts on soil health and environment, thus can play an important role in prudent decision makings. We first developed a sugarbeet model to be included in DSSAT (Decision Support System for Agrotechnology Transfer) by adopting and modifying the CERES-Beet model. The new sugarbeet model is named CSM-CERES-Beet, which was calibrated and evaluated against the available field data from Carrington Research Extension Center, North Dakota and Bucharest, Romania. The model did reasonably well in simulating LAI, top and root weight. Transferability of the model was also assessed applying the model to simulate the yields for five different sugarbeet cultivars grown in North Dakota, USA in 2016. 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 calibrated CSM-CERES-Beet model was then linked to RZWQM2 for the assessment of sugarbeet growth on soil and water quality. The model was applied to evaluate it for sugarbeet production at Carrington, ND study sites. The model was able to closely simulate the sugarbeet growth variables, and soil water and nitrate contents within 0-60 cm. The identifiability and sensitivity of the model parameters were also analyzed. RZWQM2 was also used to simulate the effects of crop rotation and tillage operations on sugarbeet production. The model was able to closely simulate the yields of the crop rotation scenarios studied at Carrington, ND. Hypothetical crop rotation and tillage operation scenarios identified wheat as most suitable previous year crop and moldboard plow as the best tillage operation method compared to other scenarios.

One limitation of the model is that uncertainty analysis revealed that the calibrated CSM-CERES-Beet consistently over-predicted leaf numbers with false confidence (i.e., small confidence intervals), although it did not affect the model's capabilities in simulating sugarbeet's yield. In future, works can be carried out to improve the leaf number equations in the developed CSM-CERES-Beet model for better simulations. In the future, the developed model will be applied to simulate sugarbeet production under different management scenarios for different soils and under different climatic conditions in the Red River Valley. As the sugarbeet production may be expanded into the nontraditional planting areas in the region due to potential demand for biofuel production, both the DSSAT and RZWQM2 model enhanced with the new sugarbeet module can be used to assess the associated environmental impacts. The developed models can also be used to assess the associated environmental impacts and suitability for different crop rotation and management scenarios.

REFERENCES

Ahuja, L.R., Rojas, K.W., Hanson, J.D., Shaffer, M.J., Ma, L., 2000. Root Zone Water Quality Model: Modeling Management Effects on Water Quality and Crop Production. Water Resources Publications, LLC, Colorado, U.S.

Anar, M.J., Lin, Z., Teboh, J., Ostlie, M., 2015. Modeling energy beets using the Decision Support System for Agrotechnology Transfer. 2015 ASABE North Central Intersectional Conference, Fargo, ND. Available online at http://elibrary.asabe.org/azdez.asp?JID=8&AID=45608&CID=smpnc&T=1 (Accessed on 27 January, 2017).

Anar, M.J., Lin, Z., 2016. Developing sugarbeet growth model for soil & water quality assessment. 2016 Annual International Meeting Proceedings, Orlando, Florida. Available online at http://elibrary.asabe.org/azdez.asp?JID=5&AID=46869&CID=orl2016&T=1 (Accessed on 27 January, 2017).

Anar, M. J., Lin, Z., Ma, L., Bartling, P., Teboh, J. M., Ostlie, M., 2017. Analysis of parameter sensitivity and identifiability of Root Zone Water Quality Model (RZWQM) for dryland sugarbeet modeling. Trans. ASABE, 60(6), 1995-2010.

Askegaard, M., Olesen, J.E., Rasmussen, I.A., Kristensen, K., 2011. Nitrate leaching from organic arable crop rotations is mostly determined by autumn field management. Agric. Ecosyst. Environ. 142, 149-160.

Aster, R.C., Borchers, B., Thurber, C.H., 2005. Parameter Estimation and Inverse Problems. Elsevier Academic Press, Amsterdam.

Baey, C., Didier, A., Lamaire, S., Maupas, F., 2014. Parametrization of five classical plant growth models applied to sugarbeet and comparison of their predictive capacity on root yield and total biomass. Ecol. Model. 290, 11–20.

Bangsund, D.A., Hodur, N.M., Leistritz, F.L. 2012. Economic contribution of the sugarbeet industry in Minnesota and North Dakota. Report no. 688, Feb. 2012. North Dakota State Univ. Agribusiness and Applied Economics, Fargo. Accessed online at: https://www.crystalsugar.com/media/42851/impact2012.pdf (accessed April 16, 2017).

Belmans, C., Wesseling, J.G., Feddes, R.A., 1982. Simulation model of the water balance of a cropped soil: SWATRE. J. Hydrol. 63: 271-286.

Biemond, T., Greve, H.J., Schiphouwer, T., Verhage, A.J., 1989. PIEteR: Semi green-box produktiemodel suikerbieten. LU Wageningen, Vakgroep Agrarische Bedrijfseconomie, 31 p.

Boote, K.J., Minguez, M.I., Sau, F., 2002. Adapting the CROPGRO-legume model to simulate growth of faba bean. J. Agronomy. 94: 743-756.

Breda, N.J.J., 2003. Ground-based measurements of leaf area index: a review of methods, instruments, and current controversies. J. Experi. Bot. 54 (392), 2403-2417.

Brisson, N., Mary, B., Ripoche, D., Jeuffroy, M.H., Ruget, F., Nicoullaud, B., Gate, P., Devienne-Barret, F., Antonioletti, R., Durr, C., Richard, G., Beaudoin, N., Recous, S., Tayot, X., Plenet, D., Cellier, P., Machet, J.M., Meynard, J.M., Delécolle, R., 1998. STICS: a generic model for the simulation of crops and their water and nitrogen balances. I. Theory and parametrization applied to wheat and corn. Agronomie, 18 (5–6), p.36

Burke J.I., 1992. A Physiological Growth model for Forecasting Sugar Beet Yield in Ireland. Proceedings of the IIRB 55th Winter Congress, 239-251.

Canter, C.E., Dunn, J.B., Han, J., Wang, Z., Wang, M., 2016. Policy implications of allocation methods in the life cycle analysis of integrated corn and corn stover ethanol production. BioEnergy Research, 9: 77-87.

Catt, J.A., Howse, K.R., Christian, D.G., Lane, G.L., Goss, M.J., 2000. Assessment of tillage strategies to decrease nitrate leaching in the Brimstone Farm Experiment, Oxfordshire, UK. Soil Till. Res. 53, 185-200

Cattanach, A.W., Dexter, A.G., Oplinger, E.S., 1991. Sugarbeets. Alternative Field Crop Manual. Available online at: http://www.hort.purdue.edu/newcrop/afcm/sugarbeet.html (Accessed on March 18, 2014)

Church, B.M., Gnanasakthy, A., 1983. Estimating sugar production from pre-harvest samples. Br. Sugar Beet Rev, 51 (3): 9-11.

Confalonieri, R., Orlando, F., Paleari, L., Stella, T., Gilardelli, C., Movedi, E., Pagani, V., Cappelli, G., Vertemara, A., Alberti, L., Alberti, P., Atanassiu, S., Bonaiti, M., Cappelletti, G., Ceruti, M., Confalonieri, A., Corgatelli, G., Corti, P., Dell'Oro, M., Ghidoni, A., Lamarta, A., Maghini, A., Mambretti, M., Manchia, A., Massoni, G., Mutti, P., Pariani, S., Pasini, D., Pesenti, A., Pizzamiglio, G., Ravasio, A., Rea, A., Santorsola, D., Serafini, G., Slavazza, M., Acutis, M., 2016. Uncertainty in crop model predictions: What is the role of users? Environ. Model. Softw. 81, 165-173.

Congress, U.S., 2007. Renewable Fuels, Consumer Protection, and Energy Efficiency Act of 2007. Section 111, Subtitle A, H.R. 6 (EAS).

Cooke, D.A., Scott, R.K., 1993.The Sugarbeet Crop. 1st edition. Chapman & Hall, 2-6 Boundary Row, London, UK.

Cournede, P.H., Chen, Y., Wu, Q., Baey, C., Bayol, B., 2013. Development and evaluation of plant growth models: methodology and implementation in the PyGMAlion platform. Mathematical Model. Nat. Phenom. 8 (4): 112-130.

Day, W., 1986. A simple model to describe variation between years in early growth of sugarbeet. Field Crops Res., 14: 213-220.

de Reffye, P., Hu, B.G., 2003. Relevant qualitative and quantitative choices for building an efficient dynamic plant growth model: GREENLAB case. In: Hu BG and Jaeger M (eds.) Plant Growth Modelling and Applications. Proc. PMA03' Int. symp. on plant growth modelling, simulation, visualization and their applications, Beijing, China, October 13-16, 2003. Tsinghua University Press and Springer.

de Wit, C.T., 1965. Photosynthesis of leaf canopies. Versl. Landbouwk. Onderz., Wageningen, No. 663.

Doherty, J.E., 2005. PEST. Model-independent Parameter Estimation. User Manual, fifth ed. Watermark Numerical Computing, Brisbane, Australia.

Doherty, J.E., 2007. Use of PEST and some of its utilities in model calibration and predictive error variance analysis: a roadmap, Brisbane, Australia.

Doherty, J.E., 2010. PEST, Model-independent Parameter Estimation User Manual (fifth ed., with slight additions).Watermark Numerical Computing, Brisbane, Australia.

Doherty, J.E., 2013. Getting the most out of PEST. Available online at: www.pesthomepage.org/getfiles.php?file=pest_settings.pdf (Accessed 1.11.17)

Doherty, J.E., 2016a. PEST, Model-independent Parameter Estimation User Manual part I: PEST Utility Support Software (sixth ed.). Watermark Numerical Computing, Brisbane, Australia.

Doherty, J.E., 2016b. PEST, Model-independent Parameter Estimation User Manual part II: PEST Utility Support Software (sixth ed.). Watermark Numerical Computing, Brisbane, Australia.

Doherty, J.E., Hunt, R.J., 2009. Two statistics for evaluating parameter identifiability and error reduction. J. Hydrol., 366, 119-127.

Doherty, J.E., Hunt, R.J., 2010. Approaches to Highly Parameterized Inversion Guide to Using PEST for Groundwater-model Calibration. U.S. Geological Survey Scientific Investigations Report 2010-5169. USGS, Madison, USA.

Doherty, J.E., Welter, D., 2010. A short exploration of structural noise. Water Resour. Res. 46, W05525.

Duffy, J., Chung, C., Franklin, M., Boast, C., 1977. Reference manual for FIELD, a program for the simulation of nitrogen flow in a tile drained Corn Belt agricultural field. CBNS Washington University, Saint-Louis, Missouri. 103p.

El-Abyad, M.S., Hindrof, H., Rizk, M.A., 1988. Impact of salinity stress on soil borne fungi of sugar beet. II. Growth activities in vitro. Plant and Soil. 110: 33-37.

Fang, Q. X., Green, T.R., Ma, L., Malone, R.W., Erskine, R.H., Ahuja, L.R., 2010. Optimizing soil hydraulic parameters in RZWQM2 using automated calibration methods. SSSA J. 74(6): 1897-1913.

Farahani, H.J., Bausch, W.c., Aiken, R.M., Ahuja, L.R., 1996. Evapotranspiration in system-wide agricultural models. In Camp, C. R., E. J. Sadler, and R. E. Yoder (editors). Evapotranspiration and Irrigation Scheduling: Proceedings of the International Conference. ASAE, St. Joseph, MI.

Ferreira, V.A., Weesies, G.A., Yoder, D.C., Foster, G.R., Renard, K.G., 1995. The site and condition specific nature of sensitivity analysis. J. Soil & water Conserv. 50(5): 493-497.

Fick, G.W., 1971. Analysis and simulation of the growth of sugar beet (Beta vulgaris L.). Ph.D. thesis, University of California, Davis, 222 p.

Flerchinger, G.N., Caldwell, T.G., Cho, J., Hardegree, S.P., 2012. Simultaneous Heat and Water Model: Model use, calibration, and validation. Trans. ASABE. 55(4): 1395-1411.

Flugge, M., Lewandrowski, J., Rosenfeld, J., Boland, C., Hendrickson, T., Jaglo, K., Kolansky, S., Moffroid, K., Riley-Gilbert, M., Pape, D., 2017. A Life-Cycle Analysis of the Greenhouse Gas Emissions of Corn-Based Ethanol. Report prepared by ICF under USDA Contract No. AG-3142-D-16-0243.

Foteinis, S., Kouloumpis, V., Tsoutsos, T., 2011. Life cycle analysis for bioethanol production from sugar beet crops in Greece. Energy Policy 39, 4834-41.

France, J., Thomley, J.H.M., 1984. Mathematical models in agriculture. London: Butterworths, 335 p.

Frere, M.H., Jensen, M.E., Carter, J.N., 1970. Modeling water and nitrogen behavior in the soil plant system. Proceedings of the 1970 summer computer simulation conference, Denver, Colorado, 746-450.

Gholipouri, A., Sharifi, R.S., Sedghi, M., Heydari, A., 2009. A very simple model for simulating sugar beet yield for potential production. J. Phytology., 1(5): 277–284.

Goenaga, R., 1995. Accumulation and portioning of dry matter in Taro [Colocasia esculenta (L.) Schoot]. Ann. Bot. 76, 337-341.

Goudriaan, J., van Laar, H.H., 1994. Modelling potential crop growth processes. Kluwer Academic Publishers. Dordrecht, Netherlands.

Grahovac, J.A., Dodic, J.M., Dodic, S.N., Popov, S.D., Jokic, A.I., Zavargo, Z.Z., 2011. Optimization of bioethanol production from intermediates of sugar beet processing by response surface methodology. Biomass Bioenergy 35, 4290-4296.

Guerif, M., Duke, C., 1998. Calibration of the SUCROS emergence and early growth module for sugar beet using optical remote sensing data assimilation. Eur. J. Agron. 9: 127–136.

Hansen, S., Aslyng, H.C., 1984. Nitrogen balance in crop production. Simulation model NITCROS. Hydrotechnical laboratory, the Royal Veterinary and Agricultural University, Copenhagen, 113p.

Hansen, E.M., Djurhuus, J., 1997. Nitrate leaching as influenced by soil tillage and catch crop. Soil Till. Res. 41, 203-219.

Hanson, J.D., Skiles, J.W., Parton, W.J., 1988. A multispecies model for rangeland plant communities. Ecological Modelling, 44, 89-123.

Hao, X., Chang, C, Conner, R.L., Bergen, P., 2001. Effect of minimum tillage and crop sequence on crop yield and quality under irrigation in a southern Alberta clay loam soil. Soil and Tillage Research, 59(1-2): 45-55.

Hartkamp, A.D., Hoogenboom, G., White, J.W., 2002. Adaptation of the CROPGRO growth model to velvet bean as a green manure cover crop: I. Model development. Field Crops Res. 78 (1): 9-25.

Havlin, J.L., Kissel, D.E., Maddux, L.D., Classes, M.M., Long, J.H., 1990. Crop rotation and Tillage effects on soil organic carbon and nitrogen. Soil Sci. Soc. Am. J. 54: 448-452.

Hemayati, S.S., Shirzadi, M.H., 2011. Study on radiation use efficiency of different sugarbeet cultivars. Plant Ecophysiol. 3, 5-13.

Hendrickx, G., 1986. Het water- en stikstofgedrag in het bodem-plantsysteem bij suikerbieten, simulatie en validatie. Eindwerk, K.U. Leuven, 145 p.

Hettinga, W.G., Junginger, H.M., Dekker, S.C., Hoogwijk, M., McAloon, A.J., Hicks, K.B., 2009. Understanding the reductions in US corn ethanol production costs: an experience curve approach. Energy Policy. 37: 190-203.

Hill, J., 2006. Inhibition of Vesicular-Arbuscular Mycorrhizae on Soybean Roots following Brassica Cover Crop. J. of Nat. Resour. Life Sci. Educ. 35: 158-160.

Hoogenboom, G., Jones, J.W., Porter, C.H., Wilkens, P.W., Boote, K.J., Hunt, L.A., Tsuji, G.Y. (Eds), 2010. Decision Support System for Agrotechnology Transfer Version 4.5. Volume 1: Overview. University of Hawaii, Honolulu, HI.

Hoogenboom, G., Jones, J.W., Traore, P.C.S., Boote, K.J., 2012. Experiments and data for model evaluation and application, In: p. 9-18. [J. Kihara, D. Fatondji, J.W. Jones, G. Hoogenboom, R. Tabo, and A. Bationo, editors] Improving Soil Fertility Recommendations in Africa using the Decision Support Systems for Agrotechnology Transfers (DSSAT). Springer, Dordrecht, the Netherlands.

Hoogenboom, G., Porter, C.H., Shelia, V., Boote, K.J., Singh, U., White, J.W., Hunt, L.A., Ogoshi, R., Lizaso, J.I., Koo, J., Asseng, S., Singels, A., Moreno, L.P., Jones, J.W., 2017. Decision Support System for Agrotechnology Transfer (DSSAT) Version 4.7 (www.DSSAT.net). DSSAT Foundation, Gainesville, Florida, USA.

Hunt, W.F., 1974. Respiratory control and its prediction by a dynamic model of sugar beet growth. Ph.D. thesis, University of California, Davis, 243 p.

Hunt, L.A., White, J.W., Hoogenboom, G., 2001. Agronomic data: Advances in documentation and protocols for exchange and use. Agricultural Systems 70:477-492.

International Benchmark Sites Network for Agrotechnology Transfer, 1993a. The IBSNAT Decade. Department of Agronomy and Soil Science, College of Tropical Agriculture and Human Resources, University of Hawaii, Honoluly, Hawaii.

International Benchmark Sites Network for Agrotechnology Transfer, 1993b. Research Report Series 02. A simulation model for potato growth and development: SUBSTOR-Potato Version 2.0. Department of Agronomy and Soil Science, College of Tropical Agriculture and Human Resources, University of Hawaii, Honoluly, Hawaii.

Jabro, J.D., Stevens, W.B., Iversen, W.M., Evans, R.G., 2010. Tillage Depth Effects on Soil Physical Properties, Sugarbeet Yield, and Sugarbeet Quality. J. Communictions in Soil Science and Plant Analysis, 41: 908-916.

Jackson, R. B., Schenk, H.J., Jobbágy, E.G., Canadell, J., Colello, G.D., Dickinson, R.E., Field, C.B., Friedlingstein, P., Heimann, M., Hibbard, M., Kicklighter, D.W., Kleidon, A., Neilson, R.P., Parton, W.J., Sala, O.E., Sykes, M.T., 2000. Belowground consequences of vegetation change and their treatment in models. Ecol. Appl., 10: 470 – 483.

Jaggard, K.W., 1992. Remote sensing to forecast yield in England. Proceedings of the IIRB 55th winter congress, 253-260.

Jaynes, D.B., Miller, J.G., 1999. Evaluation of the Root Zone Water Quality Model using field-measured data from the Iowa MSEA. Agron. J., 91(2), 192-200.

Jessen, H., 2012. RFS volume requirements released by EPA. Ethanol Production Magazine. Accessed online at: http://ethanolproducer.com/articles/8444/rfs-volume-requirements-released-by-epa. (Accessed 8.21.16).

Jones, C.A., Kiniry, J.R., 1986. CERES-Maize: a simulation of maize growth and development. Texas A & M University Press, College Station.

Jones, J.W., Tsuji, G.Y., Hoogenboom, G., Hunt, L.A., Thornton, P.K., Wilkens, P.W., Imamura, D.T., Bowen, W.T., Singh, U., 1998. Decision support system for agrotechnology transfer; DSSAT v3. In: Tsuji, G.Y., Hoogenboom, G., Thornton, P.K. (Eds.), Understanding Options for Agricultural Production. Kluwer Academic Publishers, Dordrecht, the Netherlands, pp. 157-177.

Jones, J. W., Hoogenboom, G., Porter, C.H., Boote, K.J., Batchelor, W.D., Hunt, L.A., Wilkens, P.W., Singh, U., Gijsman, A.J., Richie, J.T., 2003. The DSSAT cropping system model. European J. Agron. 18(3): 235-265.

Kakani, V.G., Godsey, C.B., Wagle, P., Foster, A.J., Kakani, A., Sripathi, R., Pandey, A., 2012. Energy Beets as a Bioenergy Feedstock in Southern Great Plains. Paper presented at the National Conference of Science for Biomass Feedstock Production and Utilization, New Orleans, LA, October 2-5, 2012.

Katerjii, N., van Hoorn, J.W., Hamdy, A., Mastrorilli, M., 2000. Salt tolerance classification of crops to soil salinity and to water stress day index. Agric. Water Manage. 43: 99-109.

Katupitiya, A., Eisenhauer, D.E., Ferguson, R.B., Spalding, R.F., Roeth, F.W., Bobier, M.W., 1997. Long-term tillage and crop rotation effects on residual nitrate in the crop root zone and nitrate accumulation in the intermediate vadose zone. Trans. ASAE 40, 1321–1327.

Khaembah, E.N., Brown, H.E., Zyskowski, R., Chakwizira, E., de ruiter, J.M., Teixeria, E.I., 2017. Development of a fodder beet potential yield model in the next generation APSIM. Agric Syst. 158, 23-38.

Khan, M., 2014. A1698 - 2014 Sugarbeet Production Guide. NDSU Extension Service and University of Minnesota Extension Service.

Knisel, W. G., 1980. CREAMS: a field-scale model for chemicals, runoff, and erosion from agricultural management systems, Conservation Research Report No. 26, USDA.

Kraalingen, D.W.G. van., 1995. The FSE system for crop simulation, version 2.1. Quantitative Approaches in Systems Analysis, No. 1, C.T. de Wit Graduate School for Production Ecology and Resource Conservation, Wageningen University, The Netherlands, pp. 58.

Kobayashi, K., Salam, M.U., 2000. Comparing simulated and measured values using mean squared deviation and its components. Agron J. 92, 345–352.

Land, F.M., Fausey, N.R., Nokes, S.E., Hanson, J.D., 1999. Evaluation of the root zone water quality model (RZWQM3.2) at the Ohio MSEA. Agron. J., 91, 220-227.

Larney, F.J., Nitschelm, J.J., Regitnig, P.J., Pearson, D.C., Blackshaw, R.E., Lupwayi, N.Z., 2016. Sugarbeet response to rotation and conservation management in a 12-year irrigated study in southern Alberta. Can J. Plant Sci. 96: 776-789.

Lee, G.S., 1983. Conceptual Development of a sugar beet crop growth model. Ph.D. thesis, Colorado State University, Fort Collins, Colorado, 265 p.

Legates, D.R., McCabe, G.J., 1999. Evaluating the use of “goodness-of-fit” measures in hydrologic and hydroclimatic model evaluation. Water Resour. Res. 35, 233–241.

Leonard, R.A., Knisel, W.G., Still, D.A., 1986. GLEAMS: Groundwater Loading Effects of Agricultural Management Systems. Presented at American Society of Agricultural Engineers Winter Meeting, Chicago, 16–19 December, 1986.

Leviel, B., 2000. Evaluation des risques et maîtrise des flux d’azote au niveau d’uneparcelle agricole dans la plaine roumaine et bulgare. Application aux cultures demais, blé, colza et betterave. Institut National Polytechnique de Toulouse (Ph.D.Thesis).

Leviel, B., Crivineanu, C., Gabrielle, B., 2003. CERES-Beet, a model for the production and environmental impact of sugar beet. A proceeding of the joint colloquium on sugar beet growing and modelling. Sept. 12th, 2003. Lille, France.

Lemaire, S., Maupas, F., Cournède, P.H., de Reffye, P., 2008. A morphogenetic crop model for sugar-beet (Beta vulgaris L.). In International Symposium on Crop Modeling and Decision Support: ISCMDS 2008, April 19-22, 2008, Nanjing, China, 2008.

Li, Z.T., Yang, J.Y., Drury, C.F., Hoogenboom, G., 2015. Evaluation of the DSSAT-CSM for simulating yield and soil organic C and N of a long-term maize and wheat rotation experiment in the Loess Plateau of Northwestern China. Agric Syst. 135, 90-104.

Li, Y, Zu, Y.K., Chen, J.J., Chen, H.Y., 2002. Intraspecific responses in crop growth and yield of 20 soybean cultivars to enhanced ultraviolet-B radiation under field conditions. Field Crops Res. 78, 1–8.

Ma, L., Ascough II, J.C., Ahuja, L.R., Shaffer, M.J., Hanson, J.D., Rojas, K.W., 2000. Root Zone Water Quality Model Sensitivity Analysis Using Monte Carlo Simulation. Trans. ASABE. 43(4), 883-895.

Ma, L., Hoogenboom, G., Ahuja, L.R., Nielsen, D.C., Ascough II, J.C., 2005. Development and evaluation of RZWQMCROPGRO hybrid model for soybean production. Agron. J. 97(4): 1172-1182.

Ma, L., Hoogenboom, G., Ahuja, L.R., Ascough II, J.C., Anapalli, S.S, 2006. Evaluation of RZWQM-CERES-Maize hybrid model for maize production. Agric. Systems. 87(3): 274-295.

Ma, L., Malone, R.W., Heilman, P., Ahuja, L.R., Meade, T., Saseendran, S.A., Ascough II, J.C., Kanwar, R.S., 2007. Sensitivity of tile drainage flow and crop yield on measured and calibrated soil hydraulic properties. Geoderma. 140, 284–296

Ma, L., Hoogenboom, G., Saseendran, S.A., Bartling, P.N.S., Ahuja, L.R., Green, T.R., 2009. Effect of estimating soil hydraulic properties and root growth factors on soil water balance and crop production. Agron. J. 101.

Ma, L, Ahuja, L.R., Nolan, B.T., Malone, R.W., Trout, T.J., Qi, Z., 2012. Root Zone Water Quality Model (RZWQM2): Model Use, Calibration, and Validation. Trans. ASABE. 55(4): 1425-1446.

Mailhol, J.C., Revol, P., Ruelle, P., 1996. Pilote: un modèle opérationnel pour décelerl'apparition de stress hydrique. In: ICID 16th International Congress on Irrigationand Drainage: Workshop on Crop-Water-Environment Models, Cairo, Egypt,July.

Mailhol, J.C., Olufayo, A., Ruelle, P., 1997. Sorghum and sunflower evapotranspira-tion and yield from simulated leaf area index. Agricultural Water Management35, 167–182.

Malnou, C.S., Jaggard, K.W.,Sparkes, D.L., 2008. Nitrogen fertilizer and the efficiency of sugar beet crop in late summer. Eur. J. Agron. 28:47-56.

Malone, R.W., Jaynes, D., Ma, L., Nolan, B.T., Meek, D., Karlen, D., 2010. Soil-test N recommendations augmented with PEST-optimized RZWQM simulations. J. Environ. Qual., 39(5), 1711-1723.

Marin, F.R., Thorburn, P.J., Nassif, D.S.P., Costa, L.G., 2015. Sugarcane model intercomparison: Structural differences and uncertainties under current and potential future climates. Environ. Model. Softw. 72, 372-386.

Martin, D.L., Watts, D.G., 1999. Application of the root zone water quality model in central Nebraska. Agron. J., 91, 201-211.

Maung, T.A., Gustafson, C.R., 2005. The economic feasibility of sugar beet biofuel production in central North Dakota. Biomass and Bioenergy. 35: 3737-3747.

McNider, R.T., Handyside, C., Doty, K., Ellenburg, W.L., Cruise, J.F., Christy, J.R., Moss, D., Sharda, V., Hoogenboom, G., Caldwell, P., 2015. An integrated crop and hydrologic modeling system to estimate hydrologic impacts of crop irrigation demands. Environ. Model. Softw. 72, 341-355.

Milford, G., Pocock, T., Riley, J., 1985. An analysis of leaf growth in sugar beet. II. Leafappearance in field crops. Annals of Applied Biol. 106: 173–185.Milford, G.F.J., Travis, K.Z., Pocock, T.O., Jaggard K.W., Day W. (1988). Growth and dry matter partitioning in suger beet. Journal of Agricultural Science, Cambridge 110, 301-308.

Mitchell, R., Harrison, R., Russell K.J., Webb, J., 2000. The effect of crop residue incorporation date on soil inorganic nitrogen, nitrate leaching and nitrogen mineralization. Biol. Fertil. Soils 32, 294-301.

Miyake, S., Smith, C., Peterson, A., McAlpine, C., Renouf, M., Waters, D., 2015. Environmental implications of using ‘underutilised agricultural land’ for future bioenergy crop production. Agric Syst. 139, 180-195.

Modig, S.A., 1992. Swedish Forecasts of sugar beet yields -Some Regression Models. Proceedings of the /IRB 55th winter congress, 189-210.

Moore, C., Doherty, J.E., 2005. Role of the calibration process in reducing model predictive error. Water Resour. Res. 41 (5), W05020.

Nahar, N., Pryor, S.W., 2013. Enzymatic hydrolysis and fermentation of crushed whole sugar beets. Biomass Bioenergy 59, 512-519.

Necpálová, M., Anex, R.P., Fienen, M.N., Grosso, S.J.D., Castellano, M.J., Sawyer, J.E., Iqbal, J., Pantoja, J.L., Barker, D.W., 2015. Understanding the DayCent model: Calibration, sensitivity, and identifiability through inverse modeling. Environ. Model. Softw. 66, 110-130.Nolan, B.T., Malone, R.W., Ma, L., Green, C.T., Fienen, M.N., Jaynes, D.B. (2011). Inverse modeling with RZWQM2 to predict water quality. In: Ahuja, L. R., Ma, L., (Eds). Methods of introducing system models in agricultural research, Advances in agricultural systems modeling series 2. pp. 349.

Nordgaard, J.T., Hemb, R., Hughes, M., 1982. Sugarbeet yield and sugar content as influenced by previous crop and soil organic matter. 1981 Sugarbeet Res. Ext. Rept., Coop. Ext. Serv., North Dakota State Univ. 12:129-132.

Overstreet, L.F, Cattanach, N.R., Gegner, S., Franzen, D., 2007. Crop sequence effect in sugarbeet, soybean, corn, and wheat rotations. Sugarbeet Research and Education Board. Accessed online: http://www.sbreb.org/research/soil/soil08/CropSequenceEffect.pdf (Accessed November 28, 2017)

Panella, L., Kaffka, S.R., Lewellen, R.T., McGrath, J.M., Metzger, M.S., Strausbaugh, C.A., 2014. Sugarbeet. Yield Gains in Major U.S. Field Crops. CSSA Special Publication 33: 357-395.

Patefield, W.M., Austin, R.B., 1971. A model for the simulation of the growth of Beta vulgaris L. Ann. Bot., 35, 1227- 1250.

Pates, M., 2011. Energy beets touted as fighting salty soils. Ag week (August, 2011). Available online at. http://www.agweek.com/event/article/id/18833/.Poeter, E.P., Hill, M.C. (1997).

Inverse models: a necessary next step in ground-water modeling. Ground Water., 35 (2): 250-260.

Qi, A., Kenter, C., Hoffmann, C., Jaggard, K.W., 2005. The Broom's Barn sugar beet growth model and its adaptation to soils with varied available water content. Europ. J. Agronomy. 23: 108–122.

Rawls, W. J., Brakensiek, D.L., Saxton, K.E., 1982. Estimation of soil water properties. Trans. ASAE 25(5): 1316-1328.

Rinaldi, M., Ventrella, D., Gagliano, C., 2007. Comparison of nitrogen and irrigation strategies in tomato using CROPGRO model. A case study from Southern Italy. Agric. Water Manage. 87, 91–105.

Rosenzweig, C., Parry, M.L., 1994. Potential impact of climate change on world food supply. Nature, 367: 133-138.

Saseendran, S.A., Ma, L., Malone, R.W., Heilman, P., Ahuja, L.R., Kanwar, R.S., 2007. Simulating management effects on crop production, tile drainage, and water quality using RZWQM-DSSAT. Geoderma. 140(3): 297-309.

Scholberg, J.M.S., Boote, K.J., Jones, J.W., McNeal, B.L., 1997. Adaptation of the CROPGRO model to simulate the growth of field-grown tomato. In: Kropff, M.J., et al. (Eds.), Systems Approaches for Sustainable Agricultural Development: Applications of Systems Approaches at the Field Level. Kluwer Academic Publishers, Dordrecht, The Netherlands, pp. 133-151.

Seligman, N.G., van Keulen, H., 1981. PAPRAN: a simulation model of annual pasture production limited by rainfall and nitrogen. In: N.H. Frissel and J. A. Van Veen (eds.), Simulation of nitrogen behavior of soil-plant systems. Wageningen: Pudoc, 27p.

Shaffer, M.J., Halvorson, A.D., Pierce, F.J., 1991. Nitrate leaching and economic analysis package (NLEAP): model description and application. R.F. Follett, et al. (Eds.), Managing Nitrogen for Groundwater Quality and Farm Profitability, SSSA, Madison, WI (1991), pp. 285-322.

Sharpley, A.N., Williams, J.R., 1990. EPIC — Erosion/Productivity Impact Calculator: 1. Model Documentation, USDA Technical Bulletin No. 1768.

Shapouri, H., Salassi, M., Fairbanks, J.N. 2006. The Economic Feasibility of Ethanol Production from Sugar in the United States. Accessed online at: http://www.usda.gov/oce/reports/energy/EthanolSugarFeasibilityReport3.pdf. (Accessed March 23, 2017)

Sims, A.L., 2004. Nitrogen management in sugarbeet grown in spring wheat and corn residue. 2003 sugarbeet res. Ext. rept., Coop. Ext. Serv., NDSU.

Sims, A.L., 2009. Sugarbeet production after previous crops of corn, wheat, and soybean. Sugarbeet res. Ext. rept., NWROC, UMN. http://www.sbreb.org/research/prod/prod07/SugarbeetProduction.pdf

Singh, U., Matthews, R.B., Griffin, T.S., Ritchie, J.T., Hunt, L.A., Goenga, R., 1998. Modeling growth and development of root and tuber crops. In: Tsuji, G.Y., Hoogenboom, G., Thornton, P.K. (eds). Understanding options for agricultural production, 129-156.

Smit, A.B., van Niejenhuis, J.H., Struik, P.C., 1993. Introduction to a bio-economic production model for sugar beet growing. In: Proceedings of 'Plant Production on the threshold of new century'. Wageningen June 28-July 1 1993.

Smith, R.E., 1992. Opus, an integrated simulation model for transport of non-point source pollutants at the field scale: Vol. I, Documentation USDA, ARS. ARS-98.

Smith, L.J., Dexter, A.G., 1988. Sugarbeets following soybeans in a crop rotation. 1987 Sugarbeet Res. Ext. Rept., Coop. Ext. Serv., North Dakota State Univ. 18:54-57.

Soine, O.C., Severson, R.K., 1975. Sugarbeet research-1974. 1974 Sugarbeet Res. Ext. Rept., Coop. Ext. Serv., North Dakota State Univ. 5:80-90.

Spitters, C.J.T., van Keulen, H., van Kraalingen, D.W.G., 1989. A simple and universal crop growth simulator: SUCROS87. In: Rabbinge, R., Ward, S.A., van Laar, H.H. (Eds.). Simulation and Systems Management in Crop Protection. Simulation Monographs 32, PUDOC, Wageningen, 434 pp. Goudriaan, J. & H.H. van Laar, 1994.

Spitters, C.J.T., Kiewiet, B., Schiphouwer, T., 1990. A weather-based yield-forecasting model for sugar beet. Neth. J. agric. Sci. 38: 731-735.

Sugarbeet Production Guide, 2013. University of Nebraska-Lincoln Extension, EC 156.

Taky, A., 2008. Maîtrise des excès d'eau hivernaux et de Iirrigation et de leurs con-séquences sur la productivité de la betterave sucrière dans le périmètre irriguédu Gharb (Maroc). Analyse expérimentale et modélisation. AgroParisTech (Ph.D.Thesis).

Tanaka, K., Takizawa, H., Kume, T., Xu, J., Tantasirin, C., Suzuki, M. (2004). Impact of rooting depth and soil hydraulic properties on the transpiration peak of an evergreen forest in northern Thailand in the late dry season. J. Geophys. Res., 109, D23107.

Tarkalson, D.D., Bjorneberg, D.L., Moore, A., Beutler, B., 2009. Effects of tillage methods, tillage timing, and nitrogen fertilizer application rate on sugarbeet production: year 1 summury. Conference Preccedings. Snake River Sugarbeet Conference, January 09, 2009.

Tarkalson, D.D., Bjorneberg, D.L., Moore, A., 2012. Effects of tillage system and nitrogen supply on sugarbeet production. J. Sugar Beet Res. 49 (3&4), 79-102.

Thomsen, I.K., 2005. Crop N utilization and leaching losses as affected by time and method of application of farmyard manure. Eur. J. Agron. 22, 1-9.

Thornley, J.H.M., Johnson, I.R., 1990. Plant and crop modelling. A mathematical approach to plant and crop physiology. Oxford; Clarendon press, 669 p.

Timsina, J, Humphreys, E., 2006. Performance of CERES-Rice and CERES-Wheat models in rice-wheat systems: a review. Agric Syst. 90, 5–31.

Tonkin, M.J., Doherty, J., 2005. A hybrid regularized inversion methodology for highly parameterized environmental models. Water Resour. Res. 41 (10), W10412.

Tsuji, G.Y., 1998. Network management and information dissemination for agrotechnology transfer. In: Tsuji, G.Y., Hoogenboom, G., Thornton, P.K. (Eds.), Understanding Options for Agricultural Production. Kluwer Academic Publishers, Dordrecht, The Netherlands, pp. 367-381.

USDA Economic Research Service, 2016. Commodity Costs and Returns Documentation. Available online at http://www.ers.usda.gov/data-products/commodity-costs-and-returns/documentation.aspx (Last accessed online on October 10, 2016).

USDA Economic Research Service, 2018. Table 14—U.S. sugar beet crops: area planted, acres harvested, yield per acre, and production, by State and region. Available online at http://www.ers.usda.gov/data-products/sugar-and-sweeteners-yearbook-tables.aspx (Accessed 01.10.18).

USDOE/EIA, 2006. Emissions of greenhouse gases in the United States 2005, U.S. Department of Energy, Energy Information Administration. Report No.: DOE/EIA-0573.

USEPA, 2010. Regulation of Fuels and Fuel Additives: Changes to Renewable Fuel Standard Program; Final Rule. Federal Register, 5, 14670–14904.

Vandendriessche, H., 1989. Het suikerbietenmodel SUBEMO. In: Simulatie als lwlpmiddel bij het stikstojbemestingsadvies voor de tee/tell willfertarwe en suikerbieten, I. W.O.N.L., 83-l 08.

Vandendriessche, H.J., Ittersum, van M.K., 1995. Crop models and decision support systems for yield forecasting and management of the sugarbeet crop. Eur. J. Agron. 4(3): 269-279.

van der Beek, M.A., 1993. Groeiverlooponderzoek, met Speciale aandacht voor het suikergehalte. I.R.S.-dag, 3 juni 1993. Bergen op Zoom I.R.S.

van Laar H.H., Goudriaan, J., van Keulen, H., 1992. Simulation of crop growth for potential and water limited production situations. Simulation Reports, 27, p. 76.

Vargas-Ramirez, J.M., Haagenson, D.M., Pryor, S.W., Wiesenborn, D.P., 2013. Determination of suitable storage conditions to preserve fermentable sugars in raw thick beet juice for ethanol production. Biomass Bioenergy 59, 362-369.

Vos, J., Marcelis, L., De Visser, P., Struik, P., Evers, J. (Eds.), 2007. Functional-StructuralPlant Modelling in Crop Production. Springer, Dordrecht (Chapter 1).

Wang, M.Q., Han, J., Haq, Z., Tyner, W.E., Wu, M., Elgowainy, A., 2011. Energy and greenhouse emission effects of corn and cellulosic ethanol with technology improvements and land use changes. Biomass Bioenergy. 35: 1885-1896.

Webb, C.R., Werker, A.R., Gilligan, C.A., 1997. Modelling the dynamical components of sugar beet. Annals of Botany. 80: 427-436.

Werker, A.R., Jaggard, K.W., 1997. Modelling asymmetrical growth curves that rise then fall. Ann. Bot., 79: 657-665.

Wilhelm, W., McMaster, G.S. (1995). Importance of the Phyllochron in Studying Development and Growth in Grasses. Crop Sci. 35 (1): 1-3.

Yang, J.M., Yang, J.Y., Liu, S., Hoogenboom, G., 2014. An evaluation of the statistical methods for testing the performance of a crop simulation model with observed data. Agricultural Systems 127(1):81-89.

Ziska, L.H., Runion, R.B., Tomecek, M., Prior, S.A., Torbet, H.A., Sicher, R., 2009. An evaluation of cassava, sweet potato and field corn as potential carbohydrate sources for bioethanol production in Alabama and Maryland. Biomass and Bioenergy, 33 (11), 1503-1508.

APPENDIX. MATERIAL FOR CHAPTER 3

Table A1. Field management for 2015 sugarbeet experimental plots at 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: 112.08 kg ha^{-1} (100 lbs ac^{-1}) P: 22.42 kg ha^{-1} (20 lbs ac^{-1}) S: 11.21 kg ha^{-1} (10 lbs ac^{-1})
Fertilizer application date	May 31
Harvesting	October 17

Table A2. CSM-CERES-Beet model validation using the CREC (USA) 2015 dataset.

Observation Group	Index of agreement (*d*)	Relative root mean square error (*rRMSE*)
Leaf area index	0.931	0.444
Leaf number	0.842	0.243
Top weight	0.822	0.534
Root weight	0.953	0.396

Note: CREC – Carrington Research and Extension Center.

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. A1). 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.

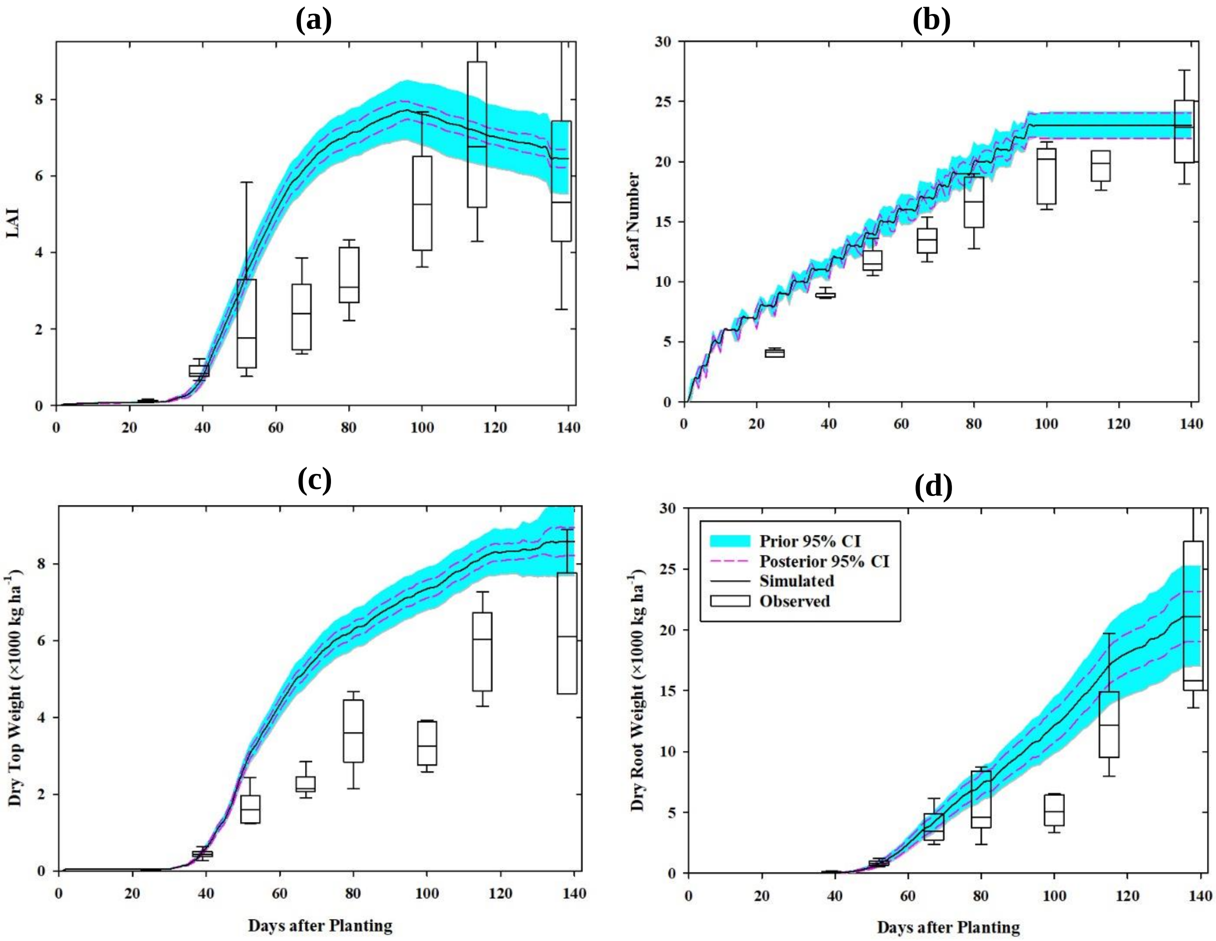


Figure A1. Model-simulated and observed values of (a) leaf area index (LAI), (b) leaf number, (c) top weight, and (d) root weight for model validation (2015) and their 95% confidence intervals (CI's). Notes: Observed values are plotted in the boxplots with the medians shown as the lines within the boxes, 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.