Journal of Sugar Beet
http://jsb.areeo.ac.ir/
Journal of Sugar Beet 2015, 31(1)

Simulation of sugar beet growth and yield under different nitrogen levels

S. Khayamim(1)*, M. Banayan Aval(2), H. Noshad(2) and F. Rouzbeh(4)

(1) Assistant Professor, Sugar Beet Seed Institute (SBSI), Agricultural Research, Education and Extension Organization (AREEO), Karaj, Iran.
(2) Associate Professor, Agriculture and Plant Breeding Group, Faculty of Agriculture, Ferdowsi University, Mashhad, Iran.
(3) Lecturer, Sugar Beet Seed Institute (SBSI), Agricultural Research, Education and Extension Organization (AREEO), Karaj, Iran.
(4) Lecturer, Seed and Plant Improvement Institute, Agricultural Research, Education and Extension Organization (AREEO), Karaj, Iran.

Khayamim S, Banayan Aval M, Noshad H, Rouzbeh F. Simulation of sugar beet growth and yield under different nitrogen levels. J. Sugar Beet. 2015; 31(1): 1-9.

Received October 8, 2014; Accepted March 2, 2015

ABSTRACT

Models can be used to forecast crop yield and the consumption of inputs such as fertilizer, and thereby we can plan and manage the likely crises that may arise in near future. The present study used a model to estimate the effect of N fertilization on dry matter partitioning between sugar beet shoot and root. To construct the model, data collected during an experiment in Karaj, Iran in 2001 were used. The model was inputted with solar radiation, consumed N and some morphophysiological traits of sugar beet such as radiation use efficiency (RUE), specific leaf area (SLA), and the coefficient of assimilate partitioning between root and shoot. For this model, 11 variables were defined including six independent parameters and five parameters with interactions. This is the fewest among similar models. RUE and SLA were calibrated for the region of Karaj. The model was validated using the results of a three-year experiment in Karaj across 2001-2003 and another experiment in 2009. The model estimations of total dry matter, root dry matter, and plant cover fitted well with the observed values, and the effect of nitrogen was identified on the partitioning of assimilate among different parts of the plants. The model, also, estimated sugar yield by nitrogen amount properly. Root-mean-square error between the estimated values of root and total dry matter and sugar yield with their observed counterparts were 12.86, 17.57, and 20.62%, respectively. This supports the adaptability of the model to root and total dry matter as well as sugar yield for the studied N rates.

Keywords: solar radiation, dry matter partitioning, growth simulation, sugar yield

INTRODUCTION

Crop simulation models are increasingly used in agricultural science with varying applications in plant physiology, soil science, agro-climatology, plant diseases, and so on. Simulation models are used to determine the relationship among different growth processes in a certain plant species. Then, these processes are quantified and their relationship is included in a computer program. These programs contribute to variation anticipation of a system (Nasiri Mahalati, 2000).

The significance of sugar beet for sugar production has prompted modeling researchers to develop growth models for this species, starting from 40 years ago (Fick et al. 1973). The initial models focused on various research topics such as the impact of year on early growth, yield prediction by physiological traits, sugar beet growth cost, and improvement of crop management practices among sugar beet farmers in terms of nitrogen fertilization rate, plant density, harvest date, and duration of the crop delivery to the factory (Weeden 2000).

Dry matter and plant canopy are two major parameters estimated by the agronomic models as a function of radiation/temperature. Growth is the result of a cumulative increase in solar radiation and radiation use efficiency (RUE). The resources

*Corresponding author's email: samar.khayam@gmail.com

that are absorbed by a plant on a single day make a small but valuable contribution to the final yield (Jaggard et al. 2009). Most of the models apply radiation to simulate cumulative dry matter. In SUBEMOpo model, which is composed of one main program and 11 sub-programs, dry matter and sugar content are simulated in terms of carbon balance; in other words, respiration maintenance and growth respiration are subtracted from total CO_2 assimilation (Vandendriessche 2000a,b). In the SBEET model, phenological growth, development, and leaf senescence are simulated as a function of temperature, and dry matter accumulation is simulated as a function of radiation, temperature, CO_2, and soil water balance (Soltani et al. 2005).

In addition to cumulative sunlight, RUE is important for estimating dry matter production. Radiation use efficiency varies with environment and variety so that sugar beet experience fewer sunny days in temperate climate (e.g. in Europe), such that their canopy is not saturated by radiation for an extended period. Therefore, total biomass production is closely associated with radiation interception. In adjacent to equator, radiation becomes more intense and as a result canopy is saturated by radiation (Anonymous, 1998). Iran is exposed to high-level radiation so the fraction of the equation is greater and RUE is smaller (Soltani et al. 2005). The application of different cultivars is useful for RUE study. Radiation use efficiency is about 0.0014 kg MJ^{-1} for Iranian cultivars whilst it is about 0.0019 kg MJ^{-1} for foreign cultivars (Hemayati, 2009).

Plant canopy is an important parameter which should be estimated by the models and is mostly measured as a function of radiation absorption (Kropff and Vanlaar 1993, Soltani et al. 2005). Recently, novel methods have been introduced for canopy area estimation such as Normalized Difference Vegetative Index (NDVI) which builds on the difference between red and far-red reflection. The obtained value at harvest stage is related to sugar yield and total shoot N content (Gehl and Boring 2011).

The first attempt in Sugar Beet Research Institute started with the INTERCOM model (Kropff and Vanlaar 1993). By adopting the INTERCOM model and using the raw data for Karaj and Kermanshah regions, in a clean area of weeds, it was observed that the curve of leaf area index estimated by the model does not differ from the observed data considerably (Gohari 2001, Gohari and Khayamim 2006). Also, the fitting of the INTERCOM model with data from UK showed that the model was efficient and accurate enough to predict the variation in leaf area index and dry weight of sugar beet. However, leaf area was predicted with a one-week delay (Abdollahian Noghabi and Khayamim 2008); in other words, canopy area was not estimated accurately. Given the difference in Iran climate from Europe as well as the difference in the simulation of plant canopy, it is important to perform a research on the better compatibility of the INTERCOM model and estimating parameters more accurately (Mohammadian 2010).

Nitrogen fertilizer plays an important role in the development of plant canopy. Nitrogen application may influence the RUE in the first half of sugar beet growth (Jaggard et al. 2009). The first nitrogen fertilization model for sugar beet in Iran was an empirical model developed as a comprehensive computerized model on the basis of soil data only (Khademi et al. 2001). However, the descriptive model accounted for the effect of soil mineral nitrogen on photosynthate distribution among plant organs using linear and quadratic regression equation (Soltani et al. 2006).

In sugar beet, the effect of photosynthate partitioning among shoot and storage root over the growing season was simulated by a simple nonlinear function. The model calculated radiation penetration using non-destructive measurement and then, result was used to estimate total photosynthates available to the crop. Leaf area was also specified by Mitscherlich function. In other words, photosynthate production rate was dependent on radiation, RUE and canopy cover (fraction of radiation absorbed by plant canopy). Radiation was derived from 30-year meteorological data, canopy cover was obtained from fitting to experimental data for data series on canopy cover, and photosynthate partitioning was estimated by fitting descending logistic function with soil N data (Webb et al. 1997). Khayamim (2001) used the suggested model by Webb et al. (1997) to simulate the effect of N on shoot and root dry matter in a single year. She focused on the effect of N on one of the partitioning coefficients (b) and assumed the other coefficients of assimilate partitioning among different organs to be constant. Since the model was calibrated by data for a single year, the effect of N on yield was estimated properly. On the other hand, sugar yield was not estimated by the model. So, it seems necessary to make re-simulation by this model and calibrate it more accurately. The present study calibrates and develops the model

Table 1. General specifications of the studies' results used in the model

Experiment	Year	Sowing date	No. of days since Jan. 1	Harvest date	No. of days since Jan. 1	Number of sampling	Cultivar	Source
1	2001	Apr. 28	118	Nov. 28	332	10 times	BR1	(Gohari and Kayamim 2006)
	2002	May 18	138	Oct. 30	303	5 times	BR1	
	2003	May 11	131	Nov. 6	310	3 times	BR1	
2	2009	Apr. 23	113	Oct. 27	300	1 time	Zaragan	(Noshad 2012)

for root and sugar yield anticipation in sugar beet at different N fertilization levels.

Materials and Methods

Using data collected from the first year of a three-year trial (Table 1, Gohari and Khayamim 2006), sugar beet growth and sugar production were simulated by Webb et al. (1997) model under optimal nutritional condition in a medium free of pest, disease, and weed with a few changes as described below. The main inputs of the revised model of Webb et al. (1997) are daily radiation and N rate applied for sugar beet, and the output is shoot and root dry matter, and also sugar yield. In other words, the model estimates sugar beet growth with respect to the amount of N applied in which the plant growth is influenced by climate and physiological factors as well as N fertilization level. The effect of soil N content on photosynthate partitioning among shoot and storage root is examined using a simple nonlinear function. The simulation was run at 100,000 plants ha^{-1} density, which is known as the optimal population, in Microsoft Windows-based Model Marker Ver. 3.0.3 (Figure 1). At the first stage, meteorological data collected from Meteorological Station in Karaj including growing degree days based on 1st January and solar radiation (MJ m^{-2} day^{-1}), were inputted into the model as a text file. Total produced photosynthate (biomass) was calculated as the total radiation (derived from daily data of the Meteorological Station) multiplied by the fraction of radiation absorbed by the plant canopy (Table 2) and RUE (Table 3).

Table 3 presents all parameters which were used in the model as well as all equations. At the second stage of the model, shoot dry matter (CWS) in kg m^{-2}, storage root dry matter (CWR) in kg m^{-2}, and dry matter allocated to sugar (Sugar Yield) were calculated (Table 2). *TotalDM* denotes total shoot dry matter (CWSSUM) and total root dry matter (CWRSUM), which are calculated based

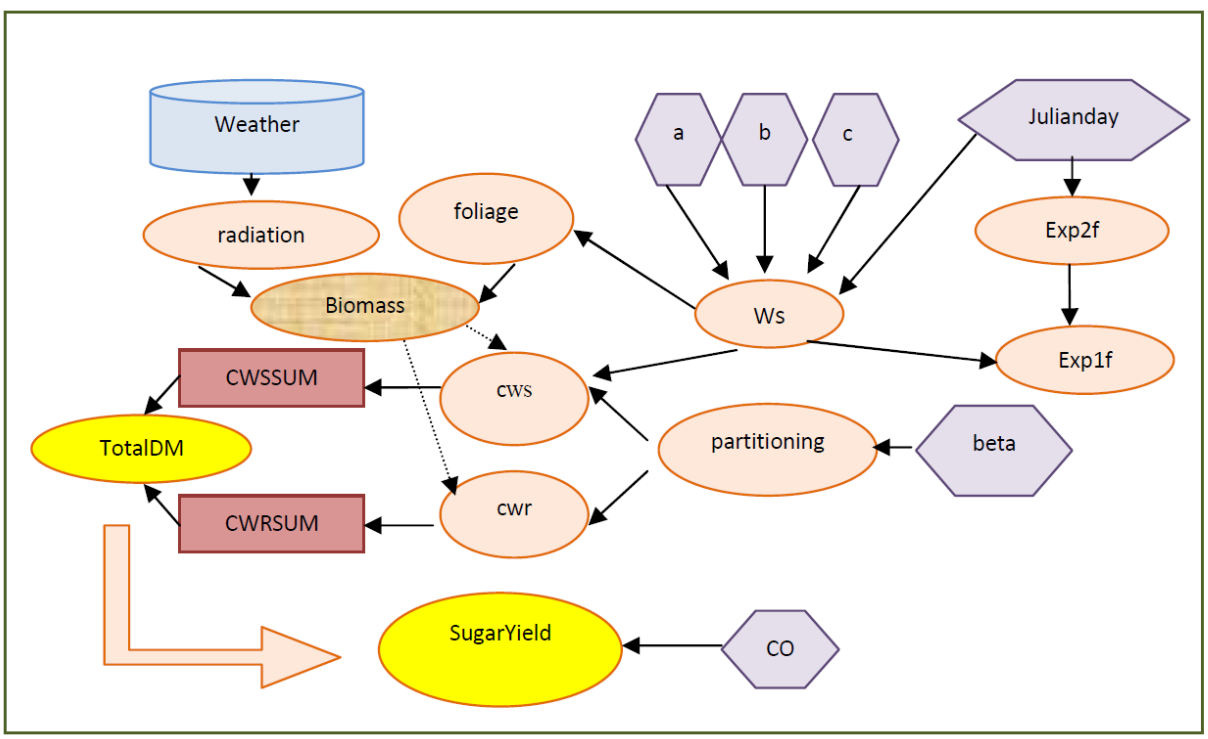

Figure 1. The flowchart of model running steps by the Model Maker Ver. 3.0.3 Software Package

Table 2. The variables included in the model

Variable	Description	Unit	Equation
Julain day (JD)	Time (2001 = 118, 2002 = 138, 2003=131)	Number of days since January 1	-
Radiation	Solar radiation	MJ m^{-2} d^{-1}	-
Biomass	Net photosynthate production	kg m^{-2} d^{-1}	RUE × foliage × radiation
Shoot weight (Ws)	Leaf dry matter	kg m^{-2}	-
Foliage	Plant canopy (leaf coverage)	-	Fmax (1-exp 1f) exp 1f = exp (-Ws × SLA × exp 2f) exp 2f = exp (-kf × (t – JD))
Partitioning	Photosynthate partitioning among different organs	-	-
N	Soil N content (100, 200, 300)	kg ha^{-1}	-
CWS	Shoot dry matter	kg m^{-2}	$Partitioning^2$ × Biomass – (Vs × Ws)
CWR	Root dry matter	kg m^{-2}	(1 – Partitioning) × Biomass
TotalDM	Total dry matter	kg m^{-2}	CWSSUM + CWRSUM
Sugar Yield	Sugar yield	t ha^{-1}	TotalDM × Co

Table 3. Parameters and estimated values used in the model

Parameter	Description	Unit	Valued used in model	Values in references
RUE	Radiation use efficiency	kg MJ^{-1}	0.0012	0.0008 (Khayamim 2001) 0.0012 (Gohari and Khayamim 2006) 0.0013 (Soltani et al. 2005) 0.0014-0.0019 (Hemayati 2008) 0.0015-0.0023 (Yousefabadi 2010) 0.0018 (Webb et al. 1997) 0.0017-0.0019 (Anonymous 1998)
Fmax	Maximum coverage	m^2 leaf per m^2 land	0.95	
SLA	Specific leaf area	m^2 kg^{-1}	10.69	10.69 (Gohari and Khayamim 2006) 13.21 (Shokuhfar 2001) 21.75 (Webb et al. 1997) 20 (Kropff and Vanlaar 1993)
Kf	SLA degradation rate	d^{-1}	0.014	0.07 (Webb et al. 1997) 0.014 (Gohari and Khayamim 2006)
Ts	Sowing date	Days from Jan. 1		
Vs	Leaf senescence rate	d^{-1}	0.001	0.0006 (Kropff and Vanlaar 1993) 0.24 (Mohammadian 2009)

on the model equations integrating against time and their cumulative values were estimated.

It was assumed that soil N content and N up take by plants would influence leaf and root dry matter, sugar yield, and assimilate partitioning factor. To determine the partitioning factor during the vegetative period, shoot dry weight was divided by total dry weight in N fertilization treatments. Then, using the Slide Write software package, the best graph was fitted for the shoot and root dry matter and sugar yield. In other words, a relationship was established between N and the above-mentioned traits, and the best models of partitioning factor were derived for shoot and root dry matter and sugar yield (Table 4).

The model was tested and validated using data from Gohari and Khayamim (2006) and Noshad (2012, Table 1). To this end, it was necessary to statistically compare values estimated by the model with observed data. The comparison was made using root-mean-square error (RMSE) as described in equation 1 (Bannayan and Cruot 1999):

$$RMSE(\%) = \sqrt{\frac{\sum_{i=1}^{n}(S_i - O_i)^2}{n}} \cdot \frac{100}{\bar{O}} \qquad (1)$$

in which S_i represents the estimation by the model, O_i is the observed value, n is the number of observations, and $\bar{O}$ is the average of the observed values. The standard deviation was also calculated for the model prediction. If RMSE is <10%, the model estimation is excellent, in the range of 10-20%, the estimation is good, in the range of 20-30%, the estimation is relatively appropriate and it is poor if RMSE is >30% (Bannayan and Cruot 1999). As well, the linear regression curve was plotted between estimated values by the model and observations using Sigma Plot and MS-Excel software packages. In addition to RMSE, the coefficient of determination (R^2) was also calculated between observed and estimated data of the studied traits using SPSS (v. 16) software.

Table 4. Coefficients and equations used in the model (fitted by the Slide Write Software Package)

Coefficient	Description	Equation
beta	Coefficient pertaining to partitioning factor	0.22 (1.005^N*)(N^-0.16)
a	Coefficient pertaining to shoot dry matter share	0.0000045*.099^N*n62.83
b	Coefficient pertaining to shoot dry matter share	Exp (-53.17+(1458.075/N)+9.32*ln(N))
c	Coefficient pertaining to shoot dry matter share	1/(-11.59+0.5N-0.001N^2)
Co	Coefficient pertaining to sugar yield	4.29-0.01N+0.000028N^2

N* = the amount of nitrogen in kg ha^{-1} net nitrogen

Results and Discussion

Most parameters of the model, e.g. RUE, specific leaf area (SLA), and leaf senescence, were found to differ in Iran from Europe (Table 3). The average RUE in Iran was in the range of 0.0012 to 0.0014 kg MJ^{-1}. This is lower than the values used in the main model (Web *et al.* 1997, Anonymous 1998). This can be related to the fact that Iran is located in arid area with high number of sunny days, therefore plant canopy is saturated earlier which results in lower RUE (Soltani *et al.* 2005, Werker and Jaggard 1997).

Specific leaf area in Iran was about 10 m^2 kg^{-1} (Table 3) which was half the original value of the model (Webb et al. 1997). Specific leaf area is a measure of leaf specific weight or thinness. It can also be an indicator of leaf photosynthesis potential in which the higher the SLA, the thinner the leaf and the less efficient its photosynthesis (Karimi and Azizi 1994). This parameter is influenced by environmental factors so that leaves grown under shadow develop larger area, but they become thinner and photosynthesize less as per unit area under intense radiation. It can be inferred that in Europe, leaves have a larger area to weight ratio (higher SLA) and are thinner due to less intense radiation. Thicker leaves have higher photosynthesis efficiency but it seems that sugar beet may fall in short of a chance to realize their maximum photosynthesis potential due to their high degradation rate.

Model estimations of the shoot and root dry matter at diverse N rates were in good agreement with the observations in the first experimental year (Table 1, Figure 2). When the local coefficients of Iran were applied (Table 3), the model well-estimated canopy cover (Figure 3). Nonetheless, a previous study (Gohari and Khayamim 2006) found a significant difference between estimated and observed leaf area index since some coefficients were not precisely determined for Iran. Even when the values for parameters like relative leaf growth, CO_2 assimilation, and relative leaf senescence were changed, the model failed to provide a good estimation of leaf area index (Gohari and Khayamim 2006).

Linear regression curve for the values estimated by the model against observations across the three years of experiment 1 (Table 1) demonstrates that the model provided a good estimation

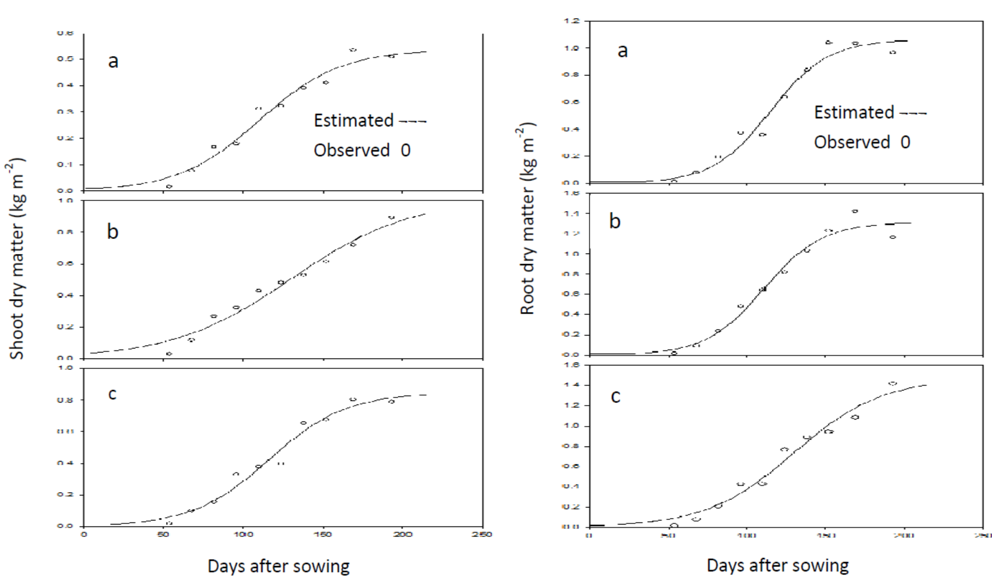

Figure 2. Comparison of shoot dry matter (left) and root dry matter (right) between estimated values and observations at different levels (a: 100, b: 200, and c: 300 kg ha^{-1}) in 2001

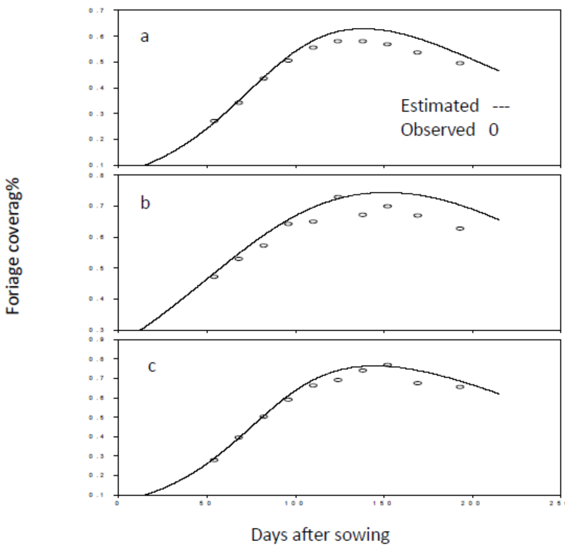

Figure 3. Comparison of canopy cover percentage between estimated values and observations at different levels (a: 100, b: 200, and c: 300 kg ha^{-1}) in 2001

of shoot, root and total dry matter and sugar yield (Figure 4 and 5). Root-mean-square error between the observed and estimated values were found to be 19.57, 19.08, 16.54, and 17.33 for root, shoot, and total dry matter and sugar yield, respectively (Table 5). These coefficients are in a good range (i.e. 10-20%) for all traits confirming good estimation of the model. With respect to the estimated and observed values of sugar yield, a deviation was observed for 100 kg ha^{-1} N level (Figure 5). This is likely to be associated with the fact that the model has some deviations at low levels of soil N content (without N fertilization and on the basis of soil N content). Same results were observed when the model was validated against experiment 2 (Figure 6, Table 5). Thus, it is necessary in future models to pay more attention to estimations under no fertilization condition or sugar is estimated

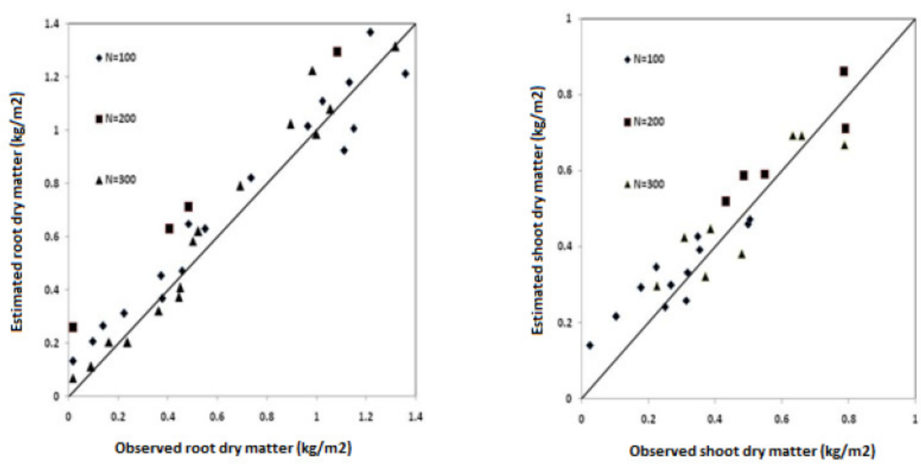

Figure 4. The 1:1 linear curve between estimated and observed values of shoot dry matter (right) and root dry matter (left) across three years of experiment 1 at different N rates of 100, 200, and 300 kg ha^{-1}

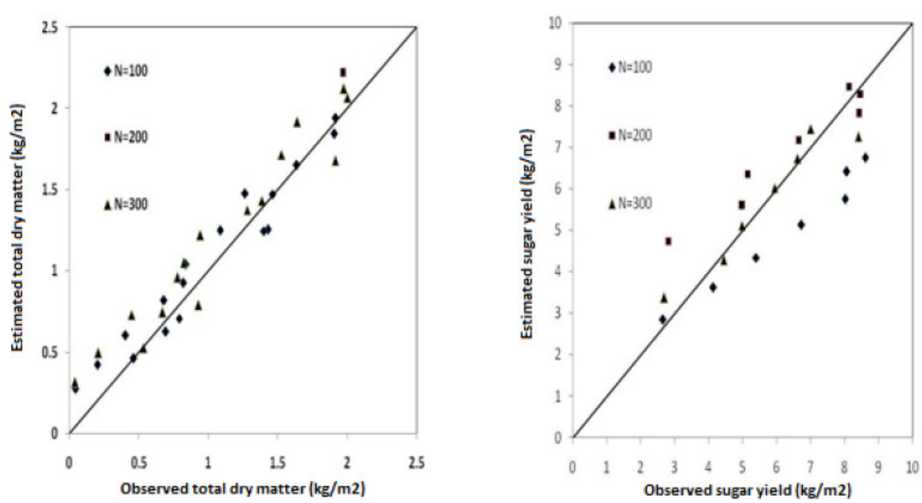

Figure 5. The 1:1 linear curve between estimated and observed values of total dry matter (right) and sugar yield (left) across three years of Experiment 1 at different N rates of 100, 200, and 300 kg ha^{-1}

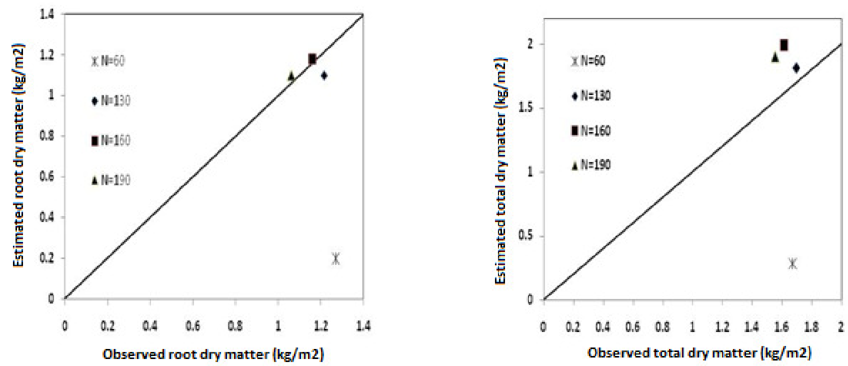

Figure 6. The 1:1 linear curve between estimated and observed values of total dry matter (right) and root dry matter (left) in experiment 2 at different N rates of 60, 130, 160 and 190 kg ha^{-1}

Table 5. Model specifications and their confidence level for the traits studied in the model

Experiment	Trait	RMSE (%)	R^2 (%)	Sample number	Model sensitivity
1	Shoot dry matter	19.08	0.92	27	Good
	Root dry matter	19.57	0.95	39	Good
	Total dry matter	16.54	0.95	36	Good
	Sugar yield	17.33	0.83	23	Good
2	Shoot dry matter	63.43	0.81	3	Poor
	Root dry matter	6.15	0.99	3	Excellent
	Total dry matter	18.59	0.96	3	Good
	Sugar yield	23.91	0.92	3	Acceptable

by model through placing the relationship in the model and not merely a specific coefficient.

In addition to RMSE, the coefficient of determination (R^2) was also calculated for all studied traits between the estimated and observed values. The coefficient of determination was 0.95, 0.92, 0.95, and 0.83 for shoot, root and total dry matter and sugar yield, respectively (Table 5). In other words, the model captured at least 83% and at most 95% of the variance, and just 5-20% (of shoot dry matter) was related to the error.

To supplement model calibration, linear regression curve was drawn for the values estimated by the model against the observations made in experiment 2 (Table 1). Since sampling was not carried out over the growth period, the curve was just fitted for the values obtained at harvest. Results indicated that the model estimation was excellent for root dry matter at N rates of 130, 160 and 190 kg ha^{-1} and it was good for the total dry matter, but the model did not make a good estimation of soil N content at 60 kg ha^{-1} level (Figure 6). Root-mean-square error was found to be 6.15 and 18.59 for root and total dry matter at N fertilization rates of 130, 160, and 190 kg m^{-2}. The model estimation for sugar yield was appropriate given its RMSE of about 24% (Table 5). Also, significant R^2 of 0.99, 0.96, and 0.92 for root dry matter, total dry matter, and sugar yield, respectively was observed (Table 5).

Sugar yield used to be rarely estimated by sugar beet models (Vandendriessche 2000a, b). This highlights a major difference of our model with previous models (Khayamim 2001, Webb et al. 1997) so that our model simulates sugar yield on the basis of N rate in addition to simulating dry matter. Sugar yield was predicted through the relationship with total dry matter, and not just root yield, and on the basis of N rate. In other words, sugar yield is predicted by intercepted radiation across the year via its influence on photosynthesis and total biomass production and also by N rate through its influence on assimilate partitioning among different organs and total dry matter. The comparison of estimated values with observations revealed that this estimation was good for experiment 1 and relatively good for experiment 2 (Table 5). Root-mean-square error is a good measure for comparison of estimated and observed values as it has been used in different modeling studies (Soltani et al. 2005, Richter et al. 2001); For example, it was about 11.7 for sugar yield estimation by model SBEET implying its appropriate estimation (Soltani et al. 2005).

Fewer parameters were included in this model compared with other sugar beet models. Eleven variables were defined for this model – six independent parameters and five interaction parameters. In the SUBEMOpo model (Vandendriessche 2000a), there is a primary program with 11 subprograms and a lot of parameters. The SUCROS model (Spitters et al. 1989) needs 15 parameters, 12 experimental functions, and 9 initial data for model definition. There are 16 parameters with interactions, 20 variables, and 880 sub-variables in the SUBGRO model (Fick et al. 1973). More comprehensive models have more parameters. For example, given that it has been developed by data from Iran, the SBEET model (Soltani et al. 2005) includes 18 parameters with 23 experimental functions. In addition to the production and partitioning of dry matter in sugar beets, plant phenology, and leaf area loss, the model is based on a function of phenology and soil water balance. In other words, the SBEET model explores the effect of soil moisture, but our model considers the influence of N rate on sugar beet growth. When compared to the comprehensive computerized model of sugar beet fertilization recommendation (Khademi et al. 2001) which is a model based on experimental relationships without their impact on plant, our model can be known as the first model describing the effect of nitrogen on sugar beet growth. In practice, nitrogen is influenced by various factors, e.g. time and rate of fertilizer application as well as fertilizer type. Therefore, more study is required to estimate the effect of these factors on sugar so that, in addition to shoot, root and sugar yield, it is necessary to monitor and control soil and plant N status over the growing season in order to develop a more comprehensive computerized model.

The calibration of most coefficients under Iranian condition considerably contribute to the better fitness of the model. The results reveal that the local coefficients employed in the model remained unchanged for three year assessment. On the other hand, one of the most difficult fittings in model is the fitting of canopy cover. The present model fitted canopy cover percentage well using the coefficients, whereas remarkable differences were observed between the estimated values of the model and observations in previous studies since some coefficients could not precisely be specified for Iran.

The fitting of the model to root and total dry matter data in two experiments of validation and studied N levels (100-300 kg ha^{-1}) was found to be good. Root-mean-square error between the estimated and observed values varied in the range of 6.15% (for root dry matter) to 24% (for sugar yield). The average of these coefficients for two validating experiments was about 12.86, 41.56, 17.57, and 20.62% for root, shoot, and total dry matter and sugar yield, respectively. Values were in a good range for root and total dry matter and in an appropriate range for sugar yield. Similarly, the coefficient of determination in two validating experiments was over 95% for root and total dry matter and 80-90% for shoot dry matter and sugar yield. In other words, the model produced a good estimation of root and total dry matter and acceptable estimation of sugar yield at the studied N levels. One of the differences of our model with previous models is the prediction of sugar yield. The model anticipates sugar yield as a relationship with total dry matter, and not just root yield, and on the basis of nitrogen. However, further studies are required with more comprehensive data and assessment over numerous years for the overall conclusion.

Finally, we can conclude that despite its simplicity (due to less number of parameters and variables compared with similar models), this is the first model that describes the effect of nitrogen on sugar beet growth and yield. Given the very good fitting of canopy cover percentage, total dry matter, and root dry matter as statistical indicators, the model can be considered for further and more comprehensive examination. The estimation of sugar yield by the model is another advantage compared with similar models.

REFERENCES

AbdollahianNoghabi M, Khayamim S. Application of the INTERCOM model to predict the changes of leaf area index and total dry weight of sugar beet. Iran second weeds science congress, Mashhad, Iran. 2008

Anonymous. Sugar Beet: Science in to Practice. Agriculture Science Publisher. 1998. Pp.656 (Translated in Persian).

BannayanM,Cruot NMJ. A stochastic modeling approach for real time forecasting of winter wheat yield. Field Crops Research.1999; 62: 85-95.

Fick GW, Williams WA, Loomis RS. Computer simulation of dry matter distribution during sugar beet growth. Crop Science.1973; 13: 413-417.

Gehl RJ, Boring TJ. In-Season prediction of sugar beet yield, quality and nitrogen status using an active sensor. Agronomy Journal.2011; 103: 1012-1018.

Gohari J, Khayamim S. Determination of leaf extinction coefficient and potential sugar beet production under plant densities and nitrogen fertilizer. Sugar Beet Seed Institute.2006.38 p. Report No.8/296. (In Persian, Abstract in English)

Gohari J. Rules and guidelines of sugar beet growth model adaptation and its calibration (Appendix 1 and 2). Agronomy Department Sugar Beet Seed Institute. 2001. (In Persian, abstract in English)

Hemayati SS, Evaluation of light use efficiency (LUE) in different cultivars of sugar beet. Sugar Beet Seed Institute. 2008. 92p.Report No. 31688. (In Persian, abstract in English)

Jaggard KW, Qi A, Ober ES. Capture and use of solar radiation, water and nitrogen by sugar beet (*Beta Vulgaris* L.). Journal of Experimental Botany. 2009; 1-7 Doi: 10.1093/jxb/rep 110.

Karimi M, Azizi M. Crop Growth Analysis. Jihad Daneshgahi Mashhad. 1994. Pp.111 (Translated in Persian).

Khademi Z, Mohajer Milani P, Balali MR, Dorodi MS, Shahbazi K, Malakouti MJ.A Comprehensive computer model for fertilizer recommendation towards sustainable agriculture Sugar Beet. Soil and Water Research Institute. 2001. 67 p. Report No. 2178. (In Persian, Abstract in English)

Khayamim S,Sugar beet simulation under different plant densities and nitrogen fertilizers (Ms Thesis). University of Tehran. 2001. (In Persian, abstract in English)

Kropff MJ,Vanlaar HH. Modeling crop-weed interactions. CAB International. 1993; P.273.

Mohammadian R.Study of important agronomical, physiological and ecological characteristic of sugar beet crop in Iran. Sugar Beet Seed Institute. 2010.Report No. 89/704. (In Persian, abstract in English)

Mohammadian R.Study of leaf appearance and leaf senescence rate and dry matter partitioning in sugar beet varieties.Sugar Beet Seed Institute. 2009.Report No. 88/1468. (In Persian, abstract in English)

NasiriMahallati M. Modeling potential crop growth processes. Jihad Daneshgahi Mashhad.2000. Pp. 280. (Translated in Persian)

Noshad H. Effect of Amino acids and Humic components on the Nitrogen Use Efficiency (NUE), and Quantity and Quality of Sugar Beet in Karaj. Sugar Beet Seed Institute. 2012.Report No. 91/42589 (In Persian, abstract in English)

Richter GM, Jaggard KW, Mitchell RAC.Modeling radiation interception and radiation use efficiency forsugar beet under variable climatic stress. Agricultural and Forest Meteorology.2001; 109:13-25.

Soltani A, Gholipur M, Hajizade AH. SBEET, A simple model for sugar beet growth and yield simulation. Agric Science and Technology. 2005;19(2): 1-26(In Persian, abstract in English)

Soltani A, Robertson MJ, Manschadi AM. Modeling chickpea growth and development: Nitrogen accumulation and use.Field Crop Research.2006; 99:24-34.

SpittersCJT, Van Keulen H, Van Kraalingen DWG. A simple and universal crop growth simulator: SUCROS87.In: Rabbinge R, Ward SA,Van Laar HH, Eds. Simulation and system management in crop protection. Simulation Monographs 32 Pudoc, Wageningen. 1989.pp.147-181.

Vandendriessche HJ. A model of growth and sugar accumulation of sugar beet for potential production conditions: SUBEMOpo. II. Model performance. Agricultural Systems. 2000 b; 64:21-35.

Vandendriessche H J. A model of growth and sugar accumulation of sugar beet for potential production conditions: SUBEMOpo. I. Theory and model structure. Agricultural Systems.2000 a; 64:1-19.

Webb CR, Werker AR, Gilligan CA. Modeling the dynamical components of sugar beet crop. Annals of Botany.1997; 80: 427-436.

Weeden BR. Potential of sugar beet on Atherton Tableland.A report for Rural Industries Research and Development Corporation RIRDC publication. 2000.

Werker AR, Jaggard KW. Modeling asymmetric growth curves that rise and then fall: Application to foliage dynamics in sugar beet (*Beta vulgaris L.*). Annals of Botany. 1997; 79: 657-665

Yousefabadi V. Effect of irrigation and planting date on radiation use efficiency. Sugar Beet Seed Institute. 2010. Report No. 89/704 (In Persian, abstract in English)