ORIGINAL ARTICLE

Predicting time trend of dry matter accumulation and leaf area index of winter cereals under nitrogen limitation by non-linear models

Ali Rahemi-Karizaki[1] · Nabi Khaliliaghdam[2] · Abbas Biabani[3]

Abstract Physiological importance of some non-linear regression models parameters (Beta 1, Beta 2, Logistic, Richards, Gompertz, Symmetrical sigmoid pattern, cut linear exponential, and Weibull) were studied in describing the time trend of accumulated dry matter and LAI of winter cereals under two nitrogen levels. Thus, a factorial experiment based on Randomized Complete Block design with four replications was performed. Treatments were zero, and optimum nitrogen levels (150, 120, 150, 120, 210 and 240 kg/ha for bread wheat, durum wheat, hull less barley, two-rowed barley, six-rowed barley and triticale, respectively), and winter cereals including durum and bread wheat (cv. Koohdasht), barley (*Hordeum vulgare* L.), two-rowed barley (cv. Khorram), six-rowed (cv. Sahra), hull less barley (line 17), and triticale (*Triticum wittmak* L.). The experiment was performed during the 2013/2014 and 2014/2015 seasons at the research field of Gonbad Kavous University, Iran. Results revealed for LAI that in Koohdasht cultivar, according to MAE, the prediction of both Logistic (0.32) and Beta (0.38) models in the zero nitrogen was better than nitrogen consumption while in wheat drum, no difference was observed between the models in both conditions. All models could describe time trend of accumulated dry matter under both fertilizer levels, but Gompertz, symmetrical expo linear models shown slightly better than others. Enhancement estimation of parameters of these models (maximum accumulated dry matter, RGR in linear phase, RGR in Expo linear phase, lost time to beginning of Expo linear phase, slope of dry matter and time of CGR max) are very crucial in modelling studies, cultivars comparison, growth analyses and simulation of growth and production of winter cereals.

Keywords Cultivar · Fertilizer · LAI · Non-linear regression models · Triticale

✉ Ali Rahemi-Karizaki
   alirahemi@yahoo.com

1 Department of Plant Production, Faculty of Agricultural Sciences and Natural Resources, Gonbad Kavous University, Golestan, Iran

2 Department of Agriculture, Payame Noor University, Tehran, Iran

3 Department of Plant Production, Faculty of Agricultural Sciences and Natural Resources, Gonbad University, Golestan, Iran

Introduction

Nitrogen (N) is one of the most important limiting factor after water deficit that limits growth and yield of cereals (Xiao-jun, 2018). Nitrogen fertilizer consumption is the most widely used in cereals in the past decades (FAO-STAT, 2020). Indeed previous studies have shown a significantly positive correlation between plant nitrogen and leaf area index and total dry matter accumulation (Xiao-jun et al., 2018). Total dary matter and Leaf area index (LAI) are important determining factors of growth and yield- in cereals; According to Amanullah et al. (2014), LAI is very important variable in agronomic research and that is used for crop growth modeling, dynamic simulations of carbon and water, and is promising to diagnose the nitrogen (N) status of crops; because it is determinant light interception, evapotranspiration and photosynthesis.

There is a close relationship between biomass production and light interception, a parameter that is mainly determined by LAI (Portes & Melo, 2014; Weraduwage et al., 2015). Total crop dry matter is the spatial and

temporal integration of all plant processes and, therefore, crop dry matter is the most relevant parameters in the study of crop canopies. Dry matter production is the balance between photosynthesis and respiration. The rates of these physiological processes differ among organs, ages, cultural conditions, etc. (Akira & Junichi, 1972). Estimation of dry matter accumulation can be modified from leaf photosynthesis to canopy radiation use efficiency approach (Brankovic et al., 2018). The functional leaves, dry matter production, and leaf area index are the main growth factor which may directly reflect the grain yield production (Archana et al., 2017).

Monitoring biological growth of crops is important for planning and timing agricultural practices (Hocaoglu & Coskun, 2018). Also, plant growth analyses are able to generate information on plants requirements for optimum growth at each development stage. Non-linear regression models are appropriate quantification tools to describe the plants growth, since these models include parameters with practical biological interpretation (Puiatti et al., 2018). Crop models are used for an increasingly broad range of applications, with a commensurate proliferation of methods (Challinor et al., 2018). A major limitation of crop growth models is the lack of spatial information on the actual conditions of each field or region (Kasampalis et al., 2018).

Traditionally, mathematical models have been applied to describe growth-age relationship in crops (Betty et al., 2017). Many non-linear theoretical models (e.g., the Logistic, the Gompertz, the Bertalanffy-Richards and the Schnute models) rather than empirical models (e.g., polynomial model) have been used in growth modelling, dry matter accumulation and yield (Prasad et al., 1992; Lei & Zhang, 2004). An appropriate growth function should summarize the information provided by experimental observations into a small set of parameters with biological meaning (Jhony et al., 2017). Usually, these models consist of non-linear functions including Logistic, Beta1, Beta2, Richards, Gompertz, Weibull, Symmetrical sigmoid pattern and Cut linear exponential models (Jhony et al., 2017; Timmermans et al., 2007). Non-linear models have been used in several studies about dry matter accumulation and growth in different cropping systems like cassava (Silva et al., 2014), and garlic (Puiatti et al., 2018; Reis et al., 2014), which showed the good performance of the Logistic model. Some researchers studied curves of plant growth using quantile regression models (Fig. 1). Hence, Sorrell et al (2012), who used quantile regression and non-linear regression to evaluate the growth of three species of humid area plants in response to the water depth. Khamis and Ismail (2004) compared fourteen non-linear growth models for tobacco leaf data. They reported that Richards, Inverse power, Transformation and Simple Logistic models significantly outperformed parameters of non-linear models in

comparison to the other growth models. Karadavut et al. (2010) evaluated Richards model, Logistic model, Weibull model, MMF model and Gompertz models to demonstrate leaf are time trend in five maize cultivars. They used coefficient of determination (R^2), Sum Squares Error (SSE), Root Mean Squares error (RMSE) and Mean Relative Error (MRE) for models fitting performance evaluation. Their results indicated that Richards, Logistic and Gompertz models were more suitable than other non-linear models to estimate maize leaf area. A similar study was also carried out for triticale growth analysis. The study revealed that models such as Gompertz, Logistic, Logistic Power and Richards described the time trend changes of dry matter accumulation over 98% R^2 values and low RMSE. Also, Richards model had the best fitted for two years with 99% as R^2 value (Hocaoglu & Coskun, 2018). Shi et al (2013) evaluated some growth models including von Bertalanffy, Logistic, Gompertz and ontogenetic growth model in sunflowers, legume crops and some cereals. They reported that all the aforementioned four models based on the coefficient of determination (R^2) values could fit the data very well. However, the predicted values of asymptotic maximum body mass by Gompertz, von Bertalanffy and ontogenetic growth model were too high. Only the Logistic model predicted the reliable values of asymptotic maximum body mass. In another study in maize production reported that the exponential model as a function of light intercepted was the best model to estimate LAI and dry matter accumulation. Exponential, Logistic and linear models were good to predict the grain yield as a function of the light intercepted, and quadratic, the exponential straight line and modified logarithm were the best equations for predicting grain yield as a function of plant density (Portes & Melo, 2014).

The objective of this study was to evaluate the widely used non-linear regression models with meaningful physiological parameters such as LAI and dry matter accumulation for winter cereals growth analyses and find the best model that is able to be fit for various cereals. In this study, 8 nonlinear models to predict dry matter accumulation was used which were more comprehensive than previous studies, and 2 models to predict LAI.

Materials and methods

This research was carried out in 2013–2014 and 2014–2015 growing seasons in Gonbad Kavous region (37°15´ N and 45°46´ E), Golestan Province, Iran. Winter cereals including durum and bread wheat (cv. Koohdasht), barley (*Hordeum vulgare* L.) include two-rowed barley (cv. Khorram), and six-rowed barley (cv. Sahra), and triticale (X Triticosecale Wittmack) were investigated at two

Fig. 1 Meteorological information of the experimental site in two cropping years 1392–1393 and 1393–1394
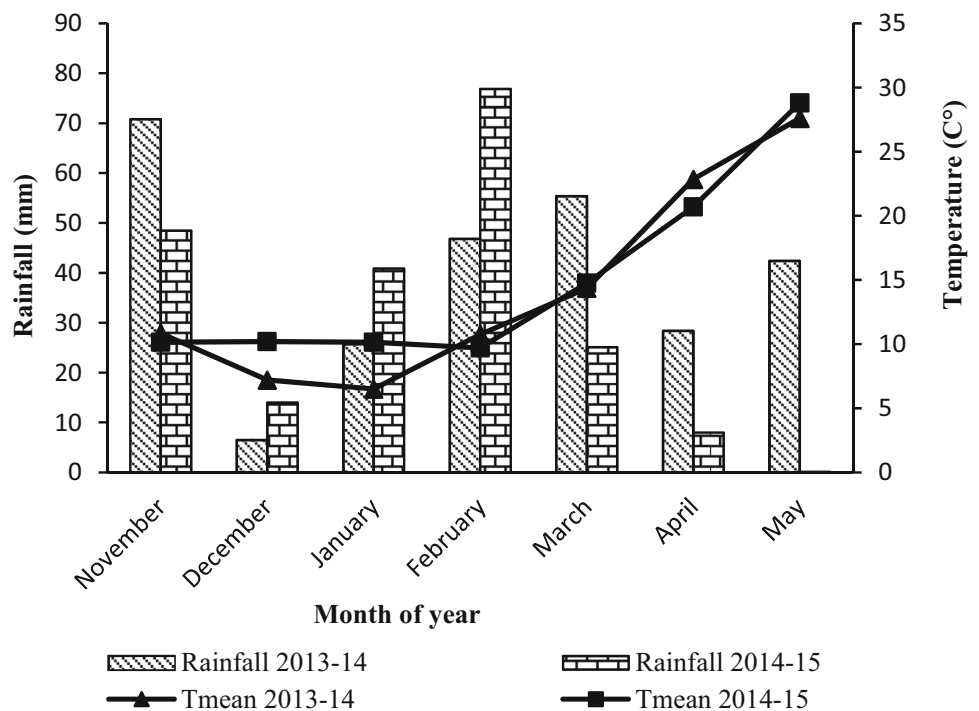
nitrogen fertilizer consumption rates, zero and optimum in a factorial completely randomized block design with four replications. Fertilizer N, P and K were applied at autumn season according to soil analysis (Table 1). The optimum nitrogen level was determined as 150 kg/ha for bread wheat, 120 kg/ha for durum wheat, 150 kg/ha for hull less barley, 120 kg/ha for two-rowed barley, 210 kg/ha for six-rowed barley and 240 kg/ha for triticale, based on the soil analysis. The basis of nitrogen levels selecting in each cereal was the expected yield and recommendations of Soil laboratory and Cereal Research Center in Iran. The plots were sown on 7 December 2013 and 9 December 2014 by hand with plant density of 270 per square meter for barley and 350 per square meter for wheat and triticale. This experiment was carried out under rain-fed conditions. In

Table 1 Physico-chemical properties of the soil (0–30 cm)

Characteristics	2013–2014	2014–2015
EC (dS/m)	1.19	1.21
pH	7.9	7.99
Total carbon (%)	0.68	0.76
Total nitrogen (%)	0.117	0.112
P (PPM)	13.4	14.2
K (PPM)	356	310
Clay (%)	15	25
Loam (%)	64	60
Sand (%)	21	15

both years, weeds were hand-controlled and Tilt pesticide was used to control the rust and mildew diseases at two per thousand concentration during two stages after stem elongation and three weeks after the first spraying with amount of 0.5 L per hectare.

Leaf area was measured by a leaf area meter (Delta-T area meter, Delta-T Devices, England) during the growing season at different times and regular intervals. Different parts of the plant including leaves, stems, and inflorescences were separated and dried separately at 70° C until reaching a constant weight in each sampling. TDM was calculated from the sum of different parts dry matter in each samples.

Two nonlinear regression models were used to describe the LAI changes trend during plant growth using the following two models:

1. Beta 1 model (Yin et al., 2003):

$$y = l_{max}\left[\left(\frac{t_e - x}{t_e - t_m}\right)\left(\frac{x - t_b}{t_m - t_b}\right)^{\frac{t_m - t_b}{t_e - t_b}}\right]^{\delta} \qquad (1)$$

where y is LAI; x is the day after planting; the l_{max} is maximum LAI; t_m when maximum LAI is achieved; t_e is the time at the end of the growth period, t_b: the time of LAI starting.

2. Logistic model (Rahemi-karizaki, 2005):

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$$y = \frac{ae^{-a(x-b)(c)}}{\left(1 + e^{-a(x-b)}\right)^2} \tag{2}$$

where x is the day after planting; a is a constant that determines the curvature of the growth pattern; b when maximum LAI is achieved; c is a constant.

The following nonlinear regression were used to describe the dry matter accumulation changes trend over time:

3. Beta1 model (Yin et al., 2003):

$$w = w_{max}\left(1 + \frac{t_e - x}{t_e - t_m}\right)\left(\frac{x}{t_e}\right)^{\frac{t_e}{t_e - t_m}} \tag{3}$$

where w is the dry matter; x is the day after planting; the W_{max} is maximum dry matter; t_m when maximum growth rate is achieved; t_e is the time at the end of the growth period.

4. Beta2 model (Yin et al., 2003):

$$\begin{array}{lll} x < t_b & if & w = w_b \\ t_b < x < t_e & if & w = w_b + (w_{max} - w_b)\left(1 + \frac{t_e - x}{t_e - t_m}\right)\left(\frac{x - t_b}{t_e - t_b}\right)^{\frac{t_m - t_b}{t_e - t_b}} \\ x > t_e & if & w = w_{max} \\ & & t_b < t_m < t_e \end{array} \tag{4}$$

where W_b is the dry matter during initial growth phase, t_m when maximum growth rate is achieved; t_e is time at the end of the growth period, and t_b is time at the beginning of the growth period.

5. Logistic model (Yin et al., 2003):

$$w = \frac{w_{max}}{1 + e^{-k(x - t_m)}} \tag{5}$$

where K is a constant that determines the curvature of the growth pattern, t_m when maximum growth rate is achieved.

6. Gompertz model (Yin et al., 2003):

$$w = w_{max}e^{-e^{-k(x - t_m)}} \tag{6}$$

where x is day after planting; W_{max} is maximum dry matter; K is a constant that determines the curvature of the growth pattern, t_m when maximum growth rate is achieved.

7. Richards model (Richards, 1959; Yin et al., 2003):

$$w = \frac{w_{max}}{\left[1 + ve^{-k(x - t_m)}\right]^{\frac{1}{v}}} \tag{7}$$

where is V deals with the asymmetric growth (if $v = 1$, then Richards' equation becomes Logistic.

8. Weibull model (Weibull, 1951; Yin et al., 2003):

$$w = w_{max}\left(1 - e^{-ax^b}\right) \tag{8}$$

where a and b are empirical constants, defining the shape of the response.

9. Symmetrical sigmoid pattern model (Yin et al., 2003):

$$w = \frac{c_m}{r_m}\ln\left[\frac{1 + e^{r_m(x - t_o)}}{1 + e^{r_m\left(x - t_o - \left(\frac{w_{max}}{c_m}\right)\right)}}\right] \tag{9}$$

where W_{max} is maximum of dry matter; t_o is the moment at which the linear phase effectively begins, c_m is maximum growth rate in the linear phase, r_m is maximum Relative Growth Rate (RGR) in the exponential phase (where maximum growth is seen in a short period).

10. Cut linear exponential model (Yin et al., 2003):

$$\begin{array}{ll} x\langle t_o + \dfrac{w_{max}}{c_m} & if \\ x \geq t_o + \dfrac{w_{max}}{c_m} & if \end{array} w = \left(\begin{array}{c} \dfrac{c_m}{r_m}\ln\left[1 + e^{r_m(x - t_o)}\right] \\ w_{max} \end{array}\right. \tag{10}$$

Extracting the coefficients of all models was performed using iterative optimization using Proc NLIN procedure in the SAS software (SAS Institute, 1992). Standard deviation (SD) and MAE (Yin et al., 2003) were used as criteria to detect best estimates of parameters by non-linear models:

$$MAE = \left|\sum_{I=1}^{n}(P_i - O_i)/n\right| \tag{11}$$

where P_i and O_i indicate predicted and observed values data and n is numbers of observation. The model with lower Mean Absolute Error (MAE), higher R^2, and lower bias of linear regressed line between observed versus predicted values from the 1:1 line, and lower coefficient of variance (CV) was selected as the best model to estimate dry mater. Parameters a and b (as intercept and slope values of linear regression between observed versus predicted values of dry matter) were compared with zero and 1 (intercept and slope of line 1:1). A closer a to 0 and b to 1 indicate better estimates of models.

Results

Climate conditions

As can be seen in comparison between the two cropping years, the rainfall of the 2013–2014 crop year with a total rainfall of 276 mm was wetter than the 2014–2015 crop year with a total rainfall of 213 mm. The monthly total rainfall of the experimental period was 39.42 and 30.5 mm in the first and the second years, respectively. The distribution of rainfall varied in different years. The highest rainfall (70.2 mm) was recorded in December in the first

year, and in March (76.9 mm) in the second year. However, no significant differences were observed in terms of average temperature between most months during the two crop years, only in January and February in 2013–2014 crop year. Also, the average air temperature was lower than 2014–2015 crop year.

The analysis of variance results showed that the interaction of cereal type and nitrogen consumption on leaf area index and total dry matter were significant at the level of 1 and 5%, respectively, While the effect of other factors on these two traits were not significant. These two traits are tested at the level of each species with different levels of nitrogen. Therefore, nonlinear models on these two traits are investigated at the level of each species with different levels of nitrogen.

LAI prediction in bread and durum wheat

The results of analysis of LAI trend in Koohdasht cultivar and Durum wheat at both levels of N consumption during two years and using two Logistic and beta1 models showed that the intercepts and regression slopes were not significant in both models. The MAE values of two models were acceptable. Also, the coefficients of variation had the appropriate range for both models (Table 2).

It is noteworthy that MAE decreased and R^2 increased in each cultivar and each model by N consumption. Results revealed that in Koohdasht cultivar, according to MAE, the prediction of both Logistic (0.32) and Beta (0.38) models was better in the zero nitrogen than nitrogen consumption, while in wheat drum, no difference was observed between the models in both conditions. Also, the estimated parameters using these models showed that the maximum LAI (LAI_{max}) in Koohdasht cultivar was higher than Durum wheat in both fertilizer levels.

The LAI_{max} occurred at Koohdasht cultivar later than durum wheat with one day difference at each fertilizer level. The results also showed that the time at the end of the growth period (T_e) in Koohdasht cultivar was later than Durum wheat at two N consumption levels. It indicates the long leaf growth period in Koohdasht cultivar. The important point about fertilizer application was that it delayed the end of leaf growth even though it led to earlier leaf growth (Table 3). The results of Logistic model showed that this model was significant in describing the LAI trend changes. In the Logistic model, the time to reach the LAI_{max} (b) at the two fertilizer levels in both cultivars also had a one day time difference and was not significant.

Dry matter accumulation prediction in bread (Koodasht) and durum wheat

The proper distribution of observed data along with the predicted data by models indicated that these models are good fitted to the data (Table 4). The values of the regression line intercepts and the slopes fitted to the observed data versus the predicted data were not significant, indicating that the deviation value of regression lines from origin and bias value of regression line from 1:1 line were not significant in all of models. Therefore, models should be chosen whose coefficients a and b (intercepts and slopes) are not significant.

The results showed that CV and MAE of all models performance were acceptable and R^2 was above 97% that indicating the good fitting of all models was based on dry matter accumulation in two cultivars at two fertilizer levels. Therefore, non-linear regression models can be used successfully to predict cumulative dry matter of bread and durum wheat, but the results demonstrated that Richard, symmetrical sigmoid and cut linear exponential models were superior to other models in both consumption and non-consumption of nitrogen in Koohdasht cultivar according to MAE≤ 63. In wheat Durum, the cut linear exponential and symmetrical sigmoid models (MAE≈ 28) were superior to other models in nitrogen consumption treatment, while Gompertz and Richard models (MAE≈ 32) were superior to other models in non-consumption of nitrogen (Table 3). Moreover, the obtained parameters in these models have great importance in simulation studies, comparison of different cultivars and treatments (Table 4).

Table 2 MAE, R^2, CV coefficients and regression coefficients for non-linear regression models in descrbing the LAI trends in studied bread and Durum wheat at zero and desirable nitrogen levels during growing seasons of 2013–2014 and 2014–2015

Wheat	Model	n	Nitrogen	a ± SE	b ± SE	MAE	R^2	CV
Koohdasht	Logistic	9	Zero	−0.088 ± 0.24	1.02 ± 0.093	0.32	0.95	19.7
		9	150 kg	−0.0508 ± 0.22	1.01 ± 0.065	0.61	0.97	15.52
	Beta	9	Zero	0.130 ± 0.22	0.98 ± 0.087	0.38	0.95	19.21
		9	150 kg	−1.05 ± 0.36	1.27 ± 0.093	0.77	0.95	16.97
Durum	Logistic	9	Zero	−0.101 ± 0.27	1.03 ± 0.11	0.37	0.92	15.55
		9	120 kg	−0.181 ± 0.24	1.06 ± 0.095	0.31	0.95	18.21
	Beta	9	Zero	−0.080 ± 0.23	0.97 ± 0.101	0.45	0.93	22.29
		9	120 kg	−0.083 ± 0.16	0.99 ± 0.064	0.26	0.97	13.29

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Table 3 Regression coefficients for non-linear regression models in describing the LAI trends in studied bread and Durum wheat at zero and desirable nitrogen levels during growing seasons of 2013–2014 and 2014–2015

Wheat	Model	n	Nitrogen	LAImax ± SE	T_b ± SE	T_m ± SE	T_e ± SE	Delta ± SE	Pmodel
Koohdasht	Logistic	9	Zero	4.59 ± 0.46	73 ± 33.56	119.5 ± 2.92	174 ± 49.88	3.87 ± 7.76	0.001
		9	150 kg	5.52 ± 0.95	73 ± 22.8	118.6 ± 7	176 ± 25.4	2.93 ± 4.39	0.001
	Beta	9	Zero	4.04 ± 0.44	73 ± 31.47	117.8 ± 3.36	167.6 ± 37.79	3.05 ± 5.47	0.002
		9	150 kg	4.10 ± 0.29	73 ± 17.79	116.5 ± 2.31	161.1 ± 10.97	1.97 ± 1.53	0.0004
				a ± SE	b ± SE	c ± SE	P_{model}		
Durum	Logistic	9	Zero	0.09 ± 0.008	118.5 ± 1.39	213.4 ± 15.58	0.001		
		9	120 kg	0.103 ± 0.006	116.7 ± 1.73	252.1 ± 13.93	0.001		
	Beta	9	Zero	0.089 ± 0.009	117.6 ± 1.73	189.1 ± 16.83	0.001		
		9	120 kg	0.083 ± 0.007	117.8 ± 1.50	209.1 ± 15.18	0.001		

In Richards model, the highest cumulative dry matter (W_{max}) was higher in Koohdasht cultivar than durum wheat in both N treatments, but the increases in cumulative dry matter due to N consumptions in Durum wheat was significantly higher than Koohdasht cultivar. Although, increasing the dry matter slope over time (k) was not affected by N consumption in Koohdasht cultivar, however, N consumption decreased this slope in Durum wheat. Finally, time to maximize of crop growth rate (t_m) in Durum wheat was increased to 10 days by non-fertilizer treatment (Table 5).

In symmetric exponential model, both fertilizer treatments increased the maximum cumulative dry matter (W_{max}) in both cultivars. Totally, in symmetric exponential model, the cumulative dry matter was estimated higher than Richards model, and its amount in Durum wheat was higher than Koohdasht cultivar in both N treatments (Table 5).

Analysis of cut exponential model parameters also showed that Koohdasht cultivar had higher RGR in linear phase (c_m) than Durum wheat in both fertilizer treatments. Conversely, the RGR in exponential phase (r_m) was higher in Durum wheat than Koohdasht cultivar, and this postponement in reaching the maximum RGR in linear phase in Durum wheat increased lost time to exponential phase (t_o). However, fertilizer applications in both cultivars reduced this time period. In this model, the estimated maximum cumulative dry matter (W_{max}) was also higher in Koohdasht at both N treatments (Table 5).

In the Weibull model, only the maximum cumulative dry matter parameter is important in comparative studies between treatments. And its value in Koohdasht was higher than that of durum wheat as in other models. In addition, N consumption increased the cumulative dry matter in both

cultivars. However, the response of Durum wheat was higher than that of Koohdasht (Table 5).

Dry matter accumulation prediction in barely and triticale

Estimated parameters for different models have been presented in Table 4. The results showed that the deviation of the regression line from origin and bias of regression line from 1:1 line were not significant in all of models (Table 6). The model with lower MAE, higher R^2, and lower bias of linear regressed line between observed versus predicted values from the 1:1 line, and lower CV was selected as the best model to estimate dry matter.

The results showed that CV and MAE of all models were acceptable and R^2 was above 98%. Therefore, non-linear regression models can be used successfully to predict the cumulative dry matter in barely and triticale. In triticale, symmetrical sigmoid model (MAE = 59.15), cut linear exponential (MAE = 58.03) and Gompertz (MAE = 55.61) were superior to other models in nitrogen consumption treatment, and Richard (MAE = 72.10) was superior to other models in non-consumption of nitrogen. In Sahra cultivar, the MAE value was much lower than other cereals, so that it can be said that the models explained the accumulation of dry matter in this cultivar well. However, with the exception of beta 2 (MAE = 10.04), which was superior to other models in nitrogen consumption treatment, the symmetrical sigmoid pattern, cut linear exponential, and Richard (Table 4) models were superior in both consumption and non-consumption of nitrogen. In line 17, with the exception of the Gompertz model (MAE = 17.80), which was superior to other models in nitrogen consumption treatment, the symmetrical sigmoid pattern, cut linear exponential and Richard (Table 4) models were superior in both consumption and non-

Table 4 MAE, R^2, CV coefficients and regression coefficients for non-linear regression models in describing of cumulative dry matter trends in studied cereals at zero and desirable nitrogen levels during growing seasons of 2013–2014 and 2014–2015

Cereals	Model	n	Nitrogen	a ± SE	b ± SE	R^2	MAE	CV
Koohdasht	Beta1	9	Zero	−49.41 ± 91.24	0.099 ± 1.04	0.94	144.30	23.80
		9	150 kg	−48.93 ± 65.38	0.055 ± 1.03	0.98	109.95	12.87
	Beta2	9	Zero	−46.77 ± 81.85	0.09 ± 1.07	0.95	151.77	21.41
		9	120 kg	−62.75 ± 59.14	0.05 ± 1.21	0.98	193.70	11.56
	Gompertz	9	Zero	−3.59 ± 76.60	0.08 ± 1.002	0.95	93.64	20.31
		9	150 kg	7.80 ± 38.22	0.03 ± 0.99	0.99	59.14	7.83
	Logistic	9	Zero	−31.48 ± 84.69	0.09 ± 1.02	0.94	106.55	22.47
		9	210 kg	−25.26 ± 49.84	0.04 ± 1.01	0.98	81.13	9.99
	Richards	9	Zero	10.80 ± 22.01	0.02 ± 1.01	0.99	62.45	5.57
		9	150 kg	15.05 ± 37.27	0.03 ± 0.99	0.99	59.63	6.67
	Weibull	9	Zero	−22.96 ± 39.95	0.03 ± 1.02	0.99	66.10	10.16
		9	120 kg	−32.97 ± 54.57	0.04 ± 1.02	0.98	92.88	10.87
	Symmetrical sigmoid pattern	9	Zero	−8.91 ± 31.67	0.03 ± 1.00	0.99	45.41	8.1
		9	150 kg	5.08 ± 20.58	0.02 ± 0.99	0.99	63.04	5.97
	Cut linear exponential	9	Zero	13.13 ± 27.67	0.02 ± 0.99	0.99	42.12	7.24
		9	150 kg	11.74 ± 45.05	0.03 ± 0.99	0.99	62.93	9.26
Durum	Beta1	9	Zero	−47.23 ± 55.06	0.062 ± 1.04	0.97	91.18	13.54
		9	240 kg	−32.42 ± 39.28	0.046 ± 1.03	0.98	63.84	10.65
	Beta2	9	Zero	−17.62 ± 58.31	0.075 ± 1.04	0.97	96.78	14.70
		9	210 kg	−34.56 ± 29.07	0.037 ± 1.03	0.99	44.52	7.88
	Gompertz	9	Zero	7.80 ± 38.22	0.03 ± 0.99	0.99	59.14	7.83
		9	150 kg	6.56 ± 22.63	0.02 ± 0.99	0.99	31.42	5.87
	Logistic	9	Zero	−17.84 ± 32.43	0.04 ± 1.01	0.99	46.55	8.22
		9	120 kg	−23.08 ± 33.59	0.03 ± 1.01	0.99	58.37	9.20
	Richards	9	Zero	11.47 ± 21.83	0.02 ± 0.98	0.99	32.74	5.69
		9	120 kg	5.58 ± 19.87	0.02 ± 1.07	0.99	39.14	5.60
	Weibull	9	Zero	−26.49 ± 39.46	0.04 ± 1.02	0.99	75.00	9.92
		9	120 kg	−25.07 ± 34.06	0.04 ± 1.02	0.99	57.89	9.30
	Symmetrical sigmoid pattern	9	Zero	13.65 ± 27.85	0.02 ± 0.98	0.99	47.90	7.25
		9	120 kg	4.10 ± 43.34	0.02 ± 0.99	0.99	27.79	8.85
	Cut linear exponential	9	Zero	8.47 ± 36.11	0.04 ± 0.98	0.99	60.07	9.37
		9	210 kg	5.85 ± 20.68	0.02 ± 1.07	0.99	27.53	5.82
Triticale	Beta1	9	Zero	−71.32 ± 93.41	0.079 ± 1.04	0.96	118.87	17.97
		9	150 kg	1.02 ± −45.23	0.050 ± 1.02	0.98	101.88	12.78
	Beta2	9	Zero	114.77 ± 156.26	0.11 ± 1.08	0.94	187.00	19.50
		9	120 kg	59.53 ± 29.53	0.057 ± 1.01	0.98	156.31	10.54
	Gompertz	9	Zero	46.32 ± 13.87	0.03 ± 0.99	0.99	79.96	9.51
		9	150 kg	31.48 ± 7.10	0.02 ± 0.99	0.99	55.61	7.03
	Logistic	9	Zero	59.29 ± −22.38	0.05 ± 1.14	0.98	86.35	11.86
		9	240 kg	45.65 ± −25.87	0.03 ± 1.01	0.99	94.44	10.02
	Richards	9	Zero	40.14 ± 48.47	0.044 ± 1.04	0.99	72.10	10.18
		9	150 kg	−5.31 ± 31.10	0.027 ± 1.03	0.99	68.95	6.92
	Weibull	9	Zero	−25.98 ± 57.79	0.05 ± 1.08	0.99	116.60	12.33
		9	120 kg	−31.26 ± 49.42	0.04 ± 1.02	0.99	86.99	10.80
	Symmetrical sigmoid pattern	9	Zero	15.81 ± 46.62	0.04 ± 0.98	0.99	85.28	10.13

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Table 4 continued

Cereals	Model	n	Nitrogen	a ± SE	b ± SE	R^2	MAE	CV
	9		150 kg	21.82 ± 32.47	0.02 ± 0.98	0.99	59.15	7.35
Cut linear exponential	9		Zero	−19.73 ± 59.27	0.05 ± 1.01	0.99	77.36	11.88
	9		150 kg	16.19 ± 32.28	0.02 ± 0.98	0.99	58.03	7.28
Sahra	Beta1	9	Zero	18.87 ± −18.58	0.020 ± 1.01	0.99	34.87	6.05
		9	240 kg	31.34 ± −26.79	0.030 ± 1.02	0.99	45.33	8.54
	Beta2	9	Zero	6.92 ± −1.54	0.007 ± 1.004	0.99	10.04	1.77
		9	210 kg	21.17 ± 13.42	0.021 ± 1.03	0.99	38.71	4.56
	Gompertz	9	Zero	8.03 ± 9.16	0.08 ± 0.99	0.99	15.72	2.63
		9	150 kg	18.67 ± −2.48	0.01 ± 1.01	0.99	41.02	5.19
	Logistic	9	Zero	21.01 ± −9.95	0.01 ± 1.01	0.99	23.34	3.88
		9	120 kg	29.70 ± −22.37	0.03 ± 1.01	0.99	49.19	8.12
	Richards	9	Zero	2.70 ± 6.83	0.007 ± 0.99	0.99	12.72	11.77
		9	120 kg	13.29 ± 15.96	0.02 ± 1.26	0.99	15.63	8.45
	Weibull	9	Zero	−45.99 ± 23.25	0.02 ± 1.13	0.99	88.64	7.29
		9	120 kg	−11.48 ± 16.14	0.01 ± 1.008	0.99	28.48	4.71
	Symmetrical sigmoid pattern	9	Zero	5.37 ± 6.27	0.01 ± 0.99	0.99	10.28	2.05
		9	120 kg	2.27 ± 10.95	0.01 ± 0.99	0.99	16.38	3.23
	Cut linear exponential	9	Zero	4.67 ± 5.64	0.01 ± 0.99	0.99	10.86	1.84
		9	210 kg	1.55 ± 10.38	0.01 ± 0.99	0.99	17.64	3.06
Line17	Beta1	9	Zero	26.75 ± −24.28	0.030 ± 1.02	0.99	50.55	9.38
		9	150 kg	33.20 ± −17.75	0.030 ± 1.01	0.99	38.99	10.24
	Beta2	9	Zero	17.00 ± 26.94	0.020 ± 1.08	0.99	54.99	4.68
		9	120 kg	29.87 ± −6.79	0.03 ± 1.07	0.99	51.90	9.30
	Gompertz	9	Zero	10.05 ± 6.34	0.01 ± 0.99	0.99	17.80	3.62
		9	150 kg	29.98 ± −4.56	0.03 ± 1.003	0.99	37.41	9.35
	Logistic	9	Zero	18.15 ± −13.29	0.02 ± 1.01	0.99	33.10	6.43
		9	240 kg	34.84 ± −18.72	0.03 ± 1.01	0.99	50.71	10.74
	Richards	9	Zero	6.12 ± 10.07	0.01 ± 0.99	0.99	17.79	3.63
		9	150 kg	2.32 ± 15.96	0.01 ± 0.99	0.99	27.63	5.21
	Weibull	9	Zero	−39.40 ± 28.55	0.03 ± 1.10	0.99	77.25	9.88
		9	120 kg	−15.97 ± 19.84	0.02 ± 1.07	0.99	60.09	6.38
	Symmetrical sigmoid pattern	9	Zero	7.45 ± 12.55	0.01 ± 0.99	0.99	19.23	4.53
		9	150 kg	−1.49 ± 15.00	0.01 ± 1.01	0.99	26.47	4.88
	Cut linear exponential	9	Zero	4.70 ± 11.35	0.01 ± 0.99	0.99	21.66	4.09
		9	150 kg	−0.30 ± 15.97	0.01 ± 1.001	0.99	23.73	5.20
Khorram	Beta1	9	Zero	52.42 ± −42.50	0.053 ± 1.03	0.98	85.23	12.56
		9	240 kg	55.40 ± −48.23	0.055 ± 1.03	0.98	93.99	13.34
	Beta2	9	Zero	66.82 ± 103.93	0.07 ± 1.06	0.97	156.23	13.79
		9	210 kg	61.57 ± 88.33	0.07 ± 1.13	0.97	179.77	12.64
	Gompertz	9	Zero	23.41 ± 14.72	0.02 ± 0.98	0.99	37.89	5.90
		9	150 kg	24.05 ± 3.23	0.02 ± 0.99	0.99	44.08	6.05
	Logistic	9	Zero	30.06 ± −11.44	0.03 ± 1.01	0.99	47.53	7.41
		9	120 kg	37.68 ± −24.66	0.03 ± 1.01	0.99	68.12	9.26
	Richards	9	Zero	10.70 ± 23.57	0.02 ± 0.99	0.99	37.63	6.92
		9	120 kg	10.81 ± 22.01	0.02 ± 1.01	0.99	42.34	5.57
	Weibull	9	Zero	−19.78 ± 36.77	0.04 ± 1.01	0.99	60.40	9.00

Table 4 continued

Cereals	Model	n	Nitrogen	a ± SE	b ± SE	R^2	MAE	CV
		9	120 kg	−32.01 ± 43.57	0.04 ± 1.02	0.99	79.71	10.65
	Symmetrical sigmoid pattern	9	Zero	−11.30 ± 38.11	0.03 ± 0.99	0.99	47.04	9.56
		9	120 kg	−10.93 ± 33.30	0.03 ± 0.99	0.99	52.52	8.41
	Cut linear exponential	9	Zero	−3.23 ± 29.27	0.03 ± 1.00	0.99	54.25	7.27
		9	210 kg	−0.96 ± 31.64	0.03 ± 0.99	0.99	53.14	7.94

n number of sampling

consumption of nitrogen. In Khorram cultivar, in both consumption and non-consumption of nitrogen treatments, according to MAE ≤ 45, Gompertz and Richard models were superior to other models (Table 4). In total Gompertz and symmetrical sigmoid pattern models were superior compared to other models.

Symmetrical sigmoid pattern model showed that the maximum cumulative dry matter increased in the N consumption compared to the lack of N consumption treatments. Also, the increase in cumulative dry matter due to N consumption in Sahara cultivar was significantly higher than other cultivars. However, N consumption decreased the RGR in linear phase (c_m) on 17 line, while there was an increasing effect on other cultivars (Table 4). The maximum RGR in the exponential phase (r_m) was higher in triticale and cultivar Khorram than other cultivars and also the use of N increased the RGR in the exponential phase (r_m), while there was a decreasing effect on other cultivars. Specifically, the cultivars with maximum RGR in the exponential phase (r_m) had shorter time when the linear phase effectively begins (t_o). In others words, r_m and t_o have inverse relationship and this relationship is very important in selecting cultivars in different studies under different treatments. The effect of fertilizer application on t_o was not significant (Table 4).

The Gompertz model parameters showed that the maximum and lowest cumulative dry matter (W_{max}) were observed in treatment of 150 kg in 17 Line and treatment control (zero of nitrogen) in cultivar Khorram, respectively. Fertilizer application increased the maximum cumulative dry matter (W_{max}) of all cultivars, however, W_{max} of 17 line was more than other cultivars. It is noteworthy, N Consumption reduced the slope of dry matter increase over time (k) in all cultivars and the highest increase in dry matter slope over time (k) was observed in the zero N Consumption in triticale. Maximum crop growth rate (t_m) of triticale was higher than cultivars and fertilizer

application increased t_m of all cultivars (Table 4). The parameter t_m is important in cultivar selection because it indicates when the cumulative dry matter reaches half of its maximum.

Discussion

Based on the results of LAI trends, MAE was low and R^2 was high in Logistic and Beta1 models, indicated that models superiority in describing the process of trait variations more appropriately. Considering the proximity of the MAE and R^2 values indicated that both models were able to describe LAI changes well with no relative superiority over the other. Results revealed that in Koohdasht cultivar, according to MAE, the prediction of both Logistic (0.32) and Beta (0.38) models was better than nitrogen consumption in the zero nitrogen, while in wheat drum, no difference was observed between the models in both conditions. Kiynaz et al (2016) reported that the accuracy of non-linear regression models such as Logistic, Richards, and Gompertz models were more than linear regression models such as simple linear and polynomial models in predicting sugar beet LAI trend. Also, in prediction of cotton LAI trend were indicated that Gaussian and cubic polynomial models had higher MAE and correlation coefficients (R^2) or the relationship between predicted and experimental results than did the modified Logistic, modified Gaussian, and log normal models (Su et al., 2015). Although in a research was evaluated that Logistic model was more acceptable than Beta1 model in predicting of maize LAI trend (Karadavut et al., 2010).

Among fitted models such as Beta1, beta2, Logistic, Gompertz, Richards, Weibull, symmetrical sigmoid pattern and cut linear exponential model to cumulative dry matter versus days after planting, all models had good predictions for wheat cultivars, and Gompertz and symmetrical

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Table 5 Regression coefficients for non-linear regression models in describing the process of cumulative dry matter trends in studied cereals at zero and desirable nitrogen levels during growing seasons of 2013–2014 and 2014–2015

Model	Cereals	n	Nitrogen	$W_{max} \pm SE$	$t_e \pm SE$	$t_m \pm SE$	P_{model}	–
Beta1	Koohdasht	9	Zero	1830.4 ± 519.3	164.8 ± 25.12	13.1 ± 13.58	0.0001	–
		9	150 kg	2148.0 ± 101.9	153.1 ± 4.21	128.7 ± 2.32	0.0001	–
	Durum	9	Zero	1508.5 ± 75.31	157.4 ± 6.42	125.1 ± 2.37	0.0001	–
		9	120 kg	1550.1 ± 93.64	151.0 ± 4.84	130.2 ± 3.10	0.0001	–
	Triticale	9	Zero	2026.3 ± 130.7	151.0 ± 4.84	126.2 ± 3.3	0.0001	–
		9	240 kg	2149.4 ± 102.1	154.1 ± 4.20	130.9 ± 2.27	0.0001	–
	Sahra	9	Zero	1754.7 ± 36.73	154.2 ± 1.56	134.6 ± 0.88	0.0001	–
		9	210 kg	1940.4 ± 102.1	158.7 ± 4.59	135.2 ± 2.45	0.0001	–
	Line17	9	Zero	1590.0 ± 52.6	154.5 ± 2.6	134.5 ± 1.44	0.0001	–
		9	150 kg	1792.4 ± 124.3	159.7 ± 5.75	136.4 ± 3.13	0.0001	–
	Khorram	9	Zero	1704.6 ± 76.45	150.8 ± 3.01	127.2 ± 1.99	0.0001	–
		9	120 kg	1798.9 ± 87.91	153.1 ± 4.18	129.1 ± 2.34	0.0001	–

Model	Cereals	n	Nitrogen	$W_{base} \pm SE$	$W_{max} \pm SE$	$t_m \pm SE$	$t_b \pm SE$	$t_e \pm SE$	P_{model}
Beta2	Koohdasht	9	Zero	31.88 ± 231.60	181.5 ± 587.8	129.5 ± 18.4	73 ± 95.09	161.5 ± 42.3	0.015
		9	150 kg	41.43 ± 268.9	211.7 ± 638.9	128.9 ± 18.5	73 ± 91.36	161.2 ± 40.4	0.01
	Durum	9	Zero	30.19 ± 261.60	150.5 ± 619.6	128.4 ± 57.5	73 ± 120.4	161.3 ± 55.6	0.03
		9	120 kg	30.33 ± 173.1	153.9 ± 506.0	128.8 ± 16.8	73 ± 79.45	161.9 ± 42.99	0.007
	Triticale	9	Zero	31.60 ± 343.60	2060.1 ± 806.6	129.0 ± 24.1	73 ± 120.70	161.1 ± 52.1	0.0100
		9	240 kg	51.32 ± 195.20	2115.3 ± 458.6	129.2 ± 13.4	73 ± 68.36	161.0 ± 29.03	0.0300
	Sahra	9	Zero	21.90 ± 45.50	1720.4 ± 96.8	129.6 ± 3.7	73 ± 20.09	160.02 ± 7.51	0.0001
		9	210 kg	27.70 ± 72.42	1927.6 ± 197.4	129.6 ± 5.4	73 ± 27.90	162.1 ± 13.16	0.0010
	Line17	9	Zero	14.26 ± 42.6	1606.5 ± 96.5	129.5 ± 3.7	73 ± 19.80	160.7 ± 7.92	0.0010
		9	150 kg	10.13 ± 78.81	1990.7 ± 785.2	132.4 ± 8.5	73 ± 30.40	176.1 ± 44.8	0.0010
	Khorram	9	Zero	41.12 ± 229.6	1704.8 ± 509.2	128.8 ± 19.6	73 ± 97.30	160.7 ± 40.7	0.0100
		9	120 kg	30.93 ± 203.4	1811.5 ± 481.8	129.0 ± 16.3	73 ± 35.45	161.1 ± 35.4	0.0070

Model	Cereals	n	Nitrogen	$W_{max} \pm SE$	$k \pm SE$	$t_m \pm SE$	P_{model}	–	–
Gompertz	Koohdasht	9	Zero	2008.2 ± 465.4	0.04 ± 0.015	114.8 ± 7.72	0.0001	–	–
		9	150 kg	2435.9 ± 183.5	0.045 ± 0.006	112.1 ± 2.38	0.0001	–	–
	Durum	9	Zero	1570.9 ± 66.46	0.054 ± 0.005	106.4 ± 1.28	0.0001	–	–
		9	120 kg	1943.9 ± 167.8	0.035 ± 0.004	115.6 ± 3.13	0.0001	–	–
	Triticale	n	Zero	2037.9 ± 119.7	0.062 ± 0.010	106.9 ± 7.72	0.0001	–	–
		9	240 kg	2498.4 ± 178.2	0.044 ± 0.005	115.1 ± 2.38	0.0001	–	–
	Sahra	9	Zero	2325.2 ± 89.8	0.040 ± 0.002	123.6 ± 7.72	0.0001	–	–
		9	210 kg	2832.2 ± 271.5	0.032 ± 0.003	126.31 ± 2.38	0.0001	–	–
	Line17	9	Zero	2011.7 ± 90.6	0.042 ± 0.0002	122.1 ± 7.72	0.0001	–	–
		9	150 kg	2987.1 ± 662.7	0.028 ± 0.005	132.6 ± 2.38	0.0001	–	–
	Khorram	9	Zero	1818.1 ± 84.3	0.053 ± 0.005	109.5 ± 7.72	0.0001	–	–
			120 kg	1988.1 ± 104.2	0.040 ± 0.005	111.8 ± 2.38	0.0001	–	–

Model	Cereals	n	Nitrogen	$W_{max} \pm SE$	$K \pm SE$	$t_m \pm SE$	P_{model}
Logistic	Koohdasht	9	Zero	1717.6 ± 247.6	0.076 ± 0.023	119.0 ± 6.21	0.001
		9	150 kg	2175.9 ± 128.9	0.081 ± 0.011	117.4 ± 2.53	0.001
	Durum	9	Zero	1459.7 ± 59.61	0.091 ± 0.011	112.0 ± 1.74	0.001
		9	120 kg	1642.7 ± 91.18	0.068 ± 0.009	120.2 ± 3.25	0.001
	Triticale	9	Zero	1914.6 ± 247.6	0.102 ± 0.017	112.0 ± 2.15	0.001
		9	240 kg	2214.7 ± 128.9	0.087 ± 0.011	120.3 ± 2.59	0.001

Table 5 continued

Model	Cereals	n	Nitrogen	$W_{max} \pm$ SE	$K \pm$ SE	$t_m \pm$ SE	P_{model}
	Sahra	9	Zero	1905.9 ± 247.6	0.081 ± 0.004	126.8 ± 1.06	0.001
		9	210 kg	2190.5 ± 128.9	0.067 ± 0.007	128.1 ± 3.14	0.001
	Line17	9	Zero	1691.2 ± 247.6	0.083 ± 0.006	125.7 ± 1.63	0.001
		9	150 kg	2130.8 ± 128.9	0.064 ± 0.009	131.5 ± 4.8	0.001
	Khorram	9	Zero	1669.6 ± 247.6	0.091 ± 0.009	114.9 ± 1.55	0.001
		9	120 kg	1795.9 ± 128.9	0.085 ± 0.011	117.1 ± 2.17	0.001

Model	Cereals	n	Nitrogen	$W_{max} \pm$ SE	$k \pm$ SE	$tm \pm$ SE	$v \pm$ SE	P_{model}
Richards	Koohdasht	9	Zero	2100.4 ± 303.5	0.038 ± 0.017	110.4 ± 9.80	0.236 ± 0.43	0.0001
		9	150 kg	2548.7 ± 463.3	0.038 ± 0.021	110.4 ± 6.02	0.198 ± 0.56	0.0001
	Durum	9	Zero	1612.3 ± 135.1	0.047 ± 0.016	104.7 ± 4.51	0.193 ± 0.42	0.0001
		9	120 kg	2453.7 ± 251.8	0.018 ± 0.030	110.7 ± 15.08	0.461 ± 1.08	0.0001
	Triticale	9	Zero	2117.1 ± 548.8	0.045 ± 0.044	107.9 ± 11.55	−0.205 ± 1.08	0.0001
		9	240 kg	2669.2 ± 742.6	0.032 ± 0.023	113.1 ± 6.79	−0.207 ± 0.606	0.0001
	Sahra	9	Zero	2124.6 ± 107.5	0.052 ± 0.007	124.6 ± 1.02	−0.298 ± 0.17	0.0001
		9	210 kg	2997.6 ± 123.6	0.018 ± 0.123	128.9 ± 6.02	0.364 ± 0.15	0.0001
	Line17	9	Zero	2005.2 ± 197.1	0.043 ± 0.011	122.0 ± 1.90	−0.009 ± 0.25	0.0001
		9	150 kg	2991.9 ± 78.9	0.026 ± 0.016	131.0 ± 6.17	−0.100 ± 0.40	0.0001
	Khorram	9	Zero	1785.6 ± 132.5	0.058 ± 0.019	110.4 ± 3.64	−0.137 ± 0.47	0.0001
		9	120 kg	2074.3 ± 300.7	0.038 ± 0.017	109.2 ± 5.07	−0.251 ± 0.44	0.0001

Model	Cereals	n	Nitrogen	$W_{max} \pm$ SE	$a \pm$ SE	$b \pm$ SE	P_{model}	–
Weibull	Koohdasht	9	Zero	1812.6 ± 391.8	$8.18 \times 10^{-13} \pm 6.06 \times 10^{-12}$	5.71 ± 1.89	0.0001	–
		9	150 kg	1852.7 ± 106.8	$2.68 \times 10^{-15} \pm 1.0 \times 10^{-14}$	6.92 ± 0.79	0.0001	–
	Durum	9	Zero	1432.2 ± 63.86	$2.96 \times 10^{-15} \pm 1.23 \times 10^{-14}$	7.00 ± 0.88	0.0001	–
		9	120 kg	1600.1 ± 124.0	$7.30 \times 10{-13} \pm 2.2 \times 10^{-12}$	5.75 ± 0.67	0.0001	–
	Triticale	n	Zero	1977.2 ± 212.0	$3.80 \times 10{-14} \pm 2.18 \times 10^{-13}$	56.37 ± 1.22	0.0001	–
		9	240 kg	2145.8 ± 131.8	$3.58 \times 10{-15} \pm 1.41 \times 10^{-14}$	6.86 ± 0.83	0.0001	–
	Sahra	9	Zero	1857.0 ± 395.2	$4.15 \times 10{-14} \pm 2.48 \times 10^{-13}$	6.25 ± 1.28	0.0001	–
		9	210 kg	2076.2 ± 88.08	$3.01 \times 10{-15} \pm 5.14 \times 10^{-15}$	6.81 ± 0.36	0.0001	–
	Line17	9	Zero	1740.3 ± 336.2	$3.80 \times 10{-13} \pm 2.06 \times 10^{-13}$	2.26 ± 1.15	0.0001	–
		9	150 kg	1900.1 ± 253.6	$1.81 \times 10{-14} \pm 7.01 \times 10^{-14}$	6.41 ± 0.83	0.0001	–
	Khorram	9	Zero	1627.4 ± 64.96	$5.60 \times 10{-16} \pm 2.10 \times 10^{-15}$	7.32 ± 0.78	0.0001	–
			120 kg	1765.9 ± 99.93	$4.77 \times 10{-15} \pm 1.92 \times 10^{-14}$	6.83 ± 0.85	0.0001	–

Model	Cereals	n	Nitrogen	$W_{max} \pm$ SE	$cm \pm$ SE	$rm \pm$ SE	$to \pm$ SE	P_{model}
Symmetrical sigmoid pattern	Koohdasht	9	Zero	1460.1 ± 71.74	23.96 ± 1.72	0.13 ± 0.10	90.8 ± 13.88	0.0001
		9	150 kg	1670.7 ± 183.8	22.49 ± 1.44	0.23 ± 0.19	84.17 ± 2.44	0.0001
	Durum	9	Zero	1871.9 ± 96.17	32.36 ± 3.92	0.22 ± 0.19	91.04 ± 3.61	0.0001
		9	120 kg	2180.1 ± 146.9	37.08 ± 7.50	0.17 ± 0.15	83.97 ± 2.3	0.0001
	Triticale	9	Zero	1915.8 ± 124.3	94.49 ± 6.21	0.11 ± 0.12	102.10 ± 4.43	0.0001
		9	240 kg	2199.7 ± 127.1	36.02 ± 3.52	0.25 ± 0.24	90.07 ± 3.12	0.0001
	Sahra	9	Zero	1889 ± 31.90	37.63 ± 2.72	0.12 ± 0.01	101.30 ± 1.86	0.0001
		9	210 kg	2307.7 ± 131.9	37.31 ± 3.83	0.11 ± 0.01	100.20 ± 3.08	0.0001
	Line17	9	Zero	1685.8 ± 63.23	30.84 ± 2.85	0.16 ± 0.04	98.34 ± 2.61	0.0001
		9	150 kg	2117.0 ± 253.8	32.25 ± 4.45	0.18 ± .03	98.74 ± 4.44	0.0001
	Khorram	9	Zero	1666.6 ± 74.08	42.19 ± 3.70	0.12 ± 0.07	95.25 ± 4.54	0.0001
		9	120 kg	1810.3 ± 99.06	31.45 ± 5.04	0.19 ± 0.16	89.26 ± 4.71	0.0001

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Table 5 continued

Model	Cereals	n	Nitrogen	$W_{max} \pm SE$	$cm \pm SE$	$rm \pm SE$	$to \pm SE$	P_{model}
Cut linear exponential	Koohdasht	9	Zero	1843.1 ± 66.41	31.68 ± 2.29	0.23 ± 0.17	90.46 ± 2.67	0.0001
		9	150 kg	2159.0 ± 102.6	34.34 ± 3.01	0.24 ± 0.28	86.66 ± 3.40	0.0001
	Durum	9	Zero	1432.3 ± 55.5	26.21 ± 3.01	0.29 ± 0.46	8487. ± 3.61	0.0001
		9	120 kg	1576.8 ± 42.25	22.34 ± 1.26	0.25 ± 0.22	83.97 ± 2.3	0.0001
	Triticale	9	Zero	2029.6 ± 106.8	33.85 ± 3.05	0.29 ± 0.45	86.67 ± 2.67	0.0001
		9	240 kg	2175.6 ± 79.33	35.24 ± 2.34	0.33 ± 0.44	89.52 ± 3.40	0.0001
	Sahra	9	Zero	1756.6 ± 16.41	33.86 ± 1.01	0.14 ± 0.01	99.00 ± 2.67	0.0001
		9	210 kg	1945.0 ± 27.03	35.13 ± 1.90	0.11 ± 0.01	98.67 ± 3.40	0.0001
	Line17	9	Zero	1601.8 ± 32.21	39.02 ± 1.52	0.19 ± 0.06	96.86 ± 2.67	0.0001
		9	150 kg	1753.3 ± 36.82	32.29 ± 2.71	0.11 ± 0.02	99.09 ± 3.40	0.0001
	Khorram	9	Zero	1681.1 ± 86.22	28.09 ± 2.46	0.26 ± 0.34	86.46 ± 2.67	0.0001
		9	120 kg	1817.4 ± 77.31	29.08 ± 2.10	0.33 ± 0.49	87.36 ± 3.40	0.0001

Table 6 Analysis of variance for leaf area index and total dry matter of cereals during the two cropping years 2013–2014 and 2014–2015 under different amounts of nitrogen

Treatments	df (LAI/TDM)	LAI	TDM
Year	1(1)	17.18	80025984
Error	6(6)	1.59	1235183
Cereal	1(1)	0.02	7130862
Nitrogen	1(5)	12.94	5619763
Cereal × nitrogen	1(5)	33.16**	1204069*
Year × cereal	1(5)	8.49	1194606
Year × nitrogen	1(1)	1.46	3222627
Year × cereal × nitrogen	1(5)	1.59	1484563
Error	18(66)	1.24	9973113
C.V	–	2.81	18.6

sigmoid pattern models were the best compared to others for triticale and barely cultivars.

Parameters a and b (as intercept and slope values of linear regression between observed versus predicted values of dry matter) were compared with zero and 1. A closer a to 0 and closer b to 1 indicated the better estimations in models (Ghadirian et al., 2011). In addition, the parameters obtained in these models are very important for use in simulation studies and comparison of different cultivars and treatments.). In relation to the mentioned linear relationship, it should be stated that the regression line slope is close to 1, indicating the greater conformity of the observed and predicted values of the cumulative grain dry matter. On the other hand, the lack of difference in zero intercept indicated that the intercept of the regression line

from the intercept of line 1:1 was not significant (Sabouri & Alipour Estakhri, 2014).

Lithourgidis et al (2011) found that quadratic equation had the best fit for dry matter accumulation across time in cereal productions. In contrast, the linear equation had the best fit for pea dry matter accumulation in the intercropping and monoculture across time. In fact, the cereals show a determinate growth pattern during from 3 to 9 weeks after tillering, whereas legumes such as pea and fababean reveal an enhancing growth pattern. Also, a single second-degree expo-polynomial model were fitted for dry matter prediction in soybean production, and single-degree models, such as the Gompertz or the Logistic model had the lower significance and quality (Montoya et al., 2017). Pirmoradian and Sepaskhah (2006) also, revealed that simple models with fewer and readily available inputs are preferred for crop yield prediction. In another study, Sepaskhah et al (2011) reported that the Logistic model was fitted to dry matter yield prediction for different times at different irrigation water and nitrogen application in maize production over the time. They suggested that the use of Logistic model base on cumulative heat units is better than calendar days after sowing, because it can be applicable for different weather conditions and sowing dates. Beta-function was the most suitable model to describe the growth and daily partitioning differences in cotton in relation to plant density. Logistic and Richards functions underestimated the maximum values of organ biomass and overestimated the time reaching it due to the lack of considering the high organ shedding rate in the final stages of the cotton crop (Mao et al., 2018). So, According to the phenology, morphology and physiology of different crops, different models can be fitted with the highest R^2.

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In present study, symmetrical sigmoid pattern model indicated that the maximum cumulative dry matter increased in the fertilized compared to non-fertilized treatments. In a study, wheat accumulated more dry matter and N accumulation during the vegetative period. High nitrogen application caused larger canopy, accumulated more dry matter and N concentration during grain filling than low nitrogen application, resulting in higher grain yield and protein concentration at harvest (Ferrise et al., 2010). Therefore, it is useful to know the time of occurrence of crop growth stages for crop management such as selecting the planting date (Khan et al., 2019), water and nitrogen application (Sepaskhah et al., 2011).

Khamis and Ismail (2004) compared fourteen non-linear growth models for tobacco leaf data. They reported that Richards, Inverse power, Transformation and Simple Logistic models significantly outperformed parameters of non-linear models in comparison to the other growth models. Yin et al. (2003) in a study on grain filling in 208 soybean genotypes in three regions found that the logistic model was the best to predict the grain dry matter accumulation. It was also reported that the correlation coefficient in the three regions ranged from 0.95 to 0.97. On the other hand, there were significant differences between environment and genotype and the interaction of genotype in the environment was very significant. Karadavut et al (2010) evaluated Richards, Logistic, Weibull, MMF and Gompertz Models to demonstrate the leaf are time trend of five maize cultivars. The results showed that, R^2, SSE, RMSE and MRE were estimated for models fitting performance. The results indicated that Richards, Logistic and Gompertz models are more suitable models than other nonlinear models to estimate maize leaf growth. A similar study was also carried out by Ghadirian et al (2011) on wheat growth analysis. Their study revealed that all of the fitted models well described the time trend of dry matter accumulation and LAI. These models can be used in the growth analysis studies.

Conclusion

The result indicated that Logistic and Beta1 models were good predictors for LAI. Also the results revealed that all non-linear models could describe changing trend of accumulated dry matter under either fertilizer level, but Gompertz, Symmetrical Expo linear models performed better than others. Therefore, nonlinear regression models and estimated parameters can be used in the preparation and evaluation of models for predicting yield of cereals in the field. Finally it can be said that, the use of non-linear models varies depending on genetics and growth environment, so that depending on the species or genetics, the efficiency of the model may vary in favourable or unfavourable conditions, so the use of models in predicting dry matter accumulation and leaf area index should be done with caution

Declarations

Conflict of interest The authors have declared that no competing interests exist.

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