PREDICTION OF DRY MATTER AND YIELD OF SPRING MAIZE (*ZEA MAYS* L.) IN NORTHWEST CHINA BASED ON LOGISTIC MODEL

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(Received 25th Jun 2022; accepted 14th Oct 2022)

Abstract. Water and nitrogen are vital factors limiting dry matter accumulation (DMA) and yield formation of spring maize. Simulation of DMA in spring maize under different irrigation and nitrogen application levels is conducive to better field management. Logistic model is a simple and effective measure to simulate the DMA. However, the coupling effect of water amount and nitrogen rate on logistic model parameters for spring maize in Northwest China has received little attention thus far. In this study, regression equations between logistic model parameters, water amount (i.e. irrigation plus rainfall), and nitrogen application rate were established and validated using independent data sets from three experiment sites (Wuwei in Gansu Province, Guyuan in Ningxia Province and Bayannur in Inner Mongolia Autonomous Region). Similarly, the empirical model of harvest index was established and validated. The results showed that these regression equations can accurately predict the dry matter accumulation and yield of spring maize. Therefore, this study can provide an alternative simple method to predict DMA and yield of spring maize under various water and nitrogen treatment in this area.
Keywords: *irrigation amount, nitrogen application rate, growing degree days, harvest index*

Introduction

Spring maize (*Zea mays* L.) is the main cereal crops in northwest China, which plays an important role in ensuring food security (Li et al., 2017). In 2017, spring maize planting area has reached 3.58 million ha, accounting for 12.5% of the national maize cultivate area (China Statistical Yearbook, 2018). Due to mainland arid and semi-arid climate conditions in this region, irrigation is a vital agricultural management measure in maize production (Wang et al., 2016; Niu et al., 2019; Zhang et al., 2019; Chen et al., 2020). Furthermore, nitrogen fertilizer rate is also a crucial factor that limits yield of maize due to poor soil nutrients in northwest drylands (Liu et al., 2013). Reasonable irrigation and nitrogen management are of great significance to the high yield and high efficiency of agricultural industry in northwest China.

With the rapid growth of global population, accurate analysis and forecast of food production have attracted increasing attention (Deryng et al., 2011; Wan et al., 2020). Dry

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2101_189206

matter accumulation (DMA) is an important agronomic indicator to reflect the harvest yield of crops (Yin et al., 2011; Ning et al., 2013) because the formation of yield depends on the accumulation, distribution and transfer characteristics of dry matter (Ferrise et al., 2010). Since water and nitrogen fertilizer are two of the most important factors affecting supply of assimilation products (Mokhele et al., 2012). Hence, it is essential to grasp dynamic change of dry matter accumulation during crop production under various water and nitrogen regimes.

At present, the simulation of dynamic changes of the dry matter accumulation can usually be divided into two types: mechanism models and empirical models. The mechanism models quantitatively describe the crop growth from the perspective of plant photosynthesis, which is highly explanatory. The commonly used mechanism models include CERES-Maize, AquaCrop, APSIM, STICS and WOFOST models (Otter et al., 1985; Ritchie et al., 1985; van Diepen et al., 1989; Brisson et al., 2002). However, mechanism models usually require a lot of parameters and some parameters are difficult to determine (Makowski et al., 2006). Instead, the empirical models are widely used because of the process of the parameter determination is relatively simple. The common empirical models used to describe crop growth include Logistic, Gompertz and Richards equations (Gompertz, 1825; Verhulst, 1838; Richard, 1959). Among these models, Logistic model is most frequently used in crop dynamic simulation because of its biological significance. Logistic model was originally proposed by ecologists to describe the laws of biological population growth and were subsequently widely used in biomass accumulation, plant height, leaf area expansion and grain filling (Koesmarno et al., 1994; Zahedi et al., 2003; Bagheri et al., 2014; Hirooka et al., 2016; Liu et al., 2019). The logistic growth equation is a sigmoid curve, which initially increases gradually, then rapidly in the middle and slowly towards the end.

Many investigators have applied logistic models to simulate the accumulation processes of crop dry matter under different agronomic measures. Khan established a series of regression equations of cotton plant biomass, vegetative organ biomass and reproductive organ biomass using logistic function under different sowing dates and plant densities (Khan et al., 2017). Ma et al. (2013) and Wang et al. (2014) severally used logistic model to simulate dry matter accumulation of spring wheat and winter wheat under different irrigation regimes. Shabani et al. (2014) severally established two sets of regression equations of logistic model parameters under water salinity and deficit irrigation based on date after planting (DAP) and growing degree days (GDD). This study suggests that the performance of logistic model based on GDD is better than logistic model based on DAP under different planting dates (Shabani et al., 2014). Similarly, Rafiee et al. (2020) developed a function of irrigation amount and electrical conductivity of irrigation water in order to simulate eggplant DMA and yield under different water and salt stress in green house and outdoor conditions.

Among the field management measures, water and nitrogen are the two most critical factors for agricultural production in arid areas. However, so far little attention has been paid to the coupling effect of water amount and nitrogen rate on logistic model parameters for spring maize in Northwest China. Thus, it is significative to consider water and nitrogen coupling effect on logistic model parameters in order to make it easier to predict DMA in maize. Therefore, the objective of this study was to (1) quantify the relationship between water and nitrogen and logistic model parameters (2) establish and evaluate prediction model of dry matter and yield spring maize in northwest China.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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Materials and methods

Site description

In this study, three independent experiment data were used to establish and evaluate dry matter accumulation and yield prediction model for spring maize. These experiment sites located in northwest China, including Wuwei in Gansu Province (latitude 37°50′N, longitude 102°50′E, altitude 1581 m), Guyuan in Ningxia Province (latitude 35°79′N, longitude 106°45′E, altitude 1800 m) and Bayannur in inner Mongolia Autonomous Region (latitude 40°43′N, longitude 107°13′N, altitude 1039 m). All three sites belong to typical temperate continental arid or semi-arid climate, which is characterized by four distinct seasons, strong solar radiation and sufficient sunlight. The annual mean temperatures were 7.7, 6.1 and 6.8°C, respectively. And frost-free periods were about 171, 150 and 140 d. The annual average sunshine hours were 2876.9, 2518.2 and 3254 hours. The annual average evaporation was 2163.6, 1753.2 and 2605 mm and average precipitation was 212.2, 492.2 and 140 mm. The weather conditions of growing seasons were summarized in *Table 1*. The soil properties of these study sites were summarized in *Table 2*. Three experiment sites were shown in *Figure 1*.

Table 1. *Weather conditions for each site and growing seasons*

Experimental site	Year	Rainfall (mm)	Daily average temperature (°C)
Wuwei City, Gansu Province	2015	120	20.1
	2016	86	21.09
Guyuan City, Ningxia Province	2015	335.2	16.72
	2016	251.6	17.74
Bayannur City, Inner Mongolia Autonomous Region	2013	40.2	21.59
	2014	42.5	20.52

Table 2. *Soil physical properties in the experimental area*

Experimental site	Soil particle distribution			Soil texture	Soil bulk density ($g \cdot cm^{-3}$)
	Clay(%)	Silt(%)	Sand(%)		
Wuwei City, Gansu Province	56	24	20	clay soil	1.52
Guyuan City, Ningxia Province	60	26	14	clay soil	1.31
Bayannur City, Inner Mongolia Autonomous Region	22.9	69.6	7.5	silt loam	1.33

Experimental design

Experiment 1 was conducted at the experimental station of Agricultural and Ecological water saving of Agricultural University of China in Shi yang River Basin during 2015 and 2016.The spring maize variety is Qiang sheng 51 and plant density is 76500 plants/ha. The experiment design consisted of four fertilizer rates and four irrigation amounts with three replications. The four fertilizer treatments were 60, 120, 180 and 240 N kg/ha in the two maize growing seasons. And four irrigation levels were 60%, 75%, 90% and 105% of actual crop evapotranspiration (242.06, 307.13, 372.2 and 437.26 mm) in 2015 and 60%, 80%, 100% and 120% (289.51, 369.35, 449.19 and 529.03 mm) of actual crop

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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evapotranspiration in 2016. And the amount of effective rainfall was 141 mm in 2015 and 115 mm in 2016. All treatments were carried out based on a random block design with three replications. Spring maize were sown on April 14 2015 and April 22 in 2016 and were harvested on September 5 2015 and September 10 2016. Calculation process of actual crop evapotranspiration was described by Zou et al. (2020).

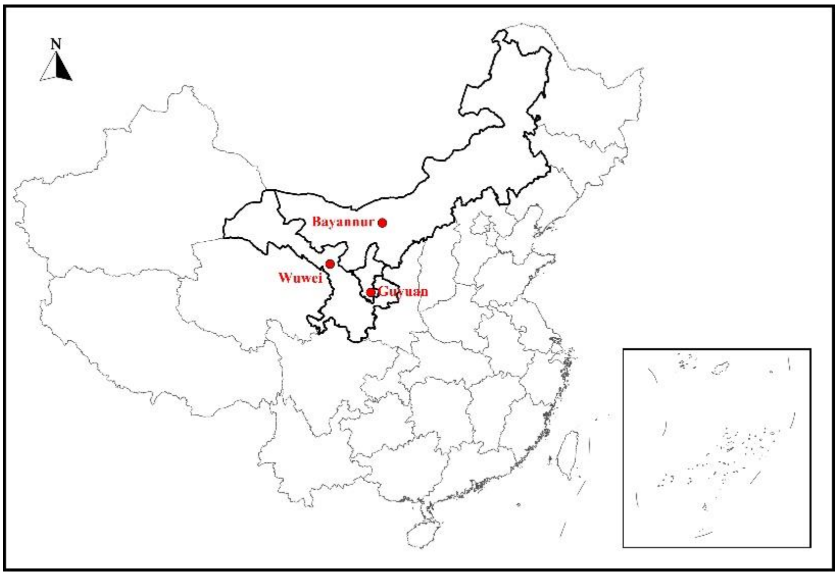

Figure 1. *The location of the three experimental sites (Wuwei in Gansu, Guyuan in Ningxia and Bayannur in Inner Mongolia Autonomous Region)*

Experiment 2 was carried out at the Dry-land Agricultural Experiment Station in Guyuan city during 2015 and 2016. The spring maize variety is Dafeng 30. This experiment design including three plant densities (52500 plants/ha, 75000 plants/ha and 97500 plants/ha) and four limited irrigation patterns (0 mm, 37.5 mm at vegetative stage, 37.5 mm at silking stage and 75 mm at the vegetative and silking stages). The amount of effective rainfall was 335.2 mm in 2015 and 251.6 mm in 2016. We only collected data on dry matter accumulation of spring maize at medium density (75000 plants/ha) as model validation data. The 300 $kg \cdot ha^{-1}$ N fertilizer rate was applied as urea (46% N), with half applied as base fertilizer and the remainder applied at top fertilizer. All treatments were carried out based on a random block design with three replications. Spring maize was sown on 23 April 2015 and April 21 2016 and were harvested on 10 October in 2015 and 5 October in 2016. Details of the experiment were described by Jia et al. (2018).

Experiment 3 was performed at Shuguang Experimental station in Hetao Irrigation District, Inner Mongolia Autonomous Region. Maize variety is Ximeng 6 and plant density is 75000 plant/ha. Five irrigation depths were used in 2013 (77.4, 131.9, 186.3, 240.8 and 295.2 mm) and in 2014 (134.5, 190.1, 245.6, 301.1 and 356.6 mm), respectively. The amount of effective rainfall was 40.2 mm in 2013 and 42.5 mm in 2014. All treatments were carried out based on a random block design with three replications. According to local practice, nitrogen application rate was 363 N kg/ha consisting of urea of 75 kg/ha, diammonium phosphate of 600 kg/ha for all treatments. Spring maize was severally sown on April 23 and 22, and were harvested on September 11 and 12 in 2013 and 2014. More details about the experimental station were described in Liu et al. (2017).

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
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In this study, prediction model was established using the data of experiment 1, and then the established model was validated using data of experiment 2 and experiment 3.

Model description

The formula of the logistic growth function is as follows:

$$Y = \frac{K}{1+ae^{-bt}} \tag{Eq.1}$$

where Y is dry matter accumulation, K is the upper limit of the dry matter accumulation, t is the number of days after planting (DAP), a and b are coefficients of the equation.

Considering the effect of different weather conditions and plating dates, some reports have shown that GDD can be used instead of DAP in the logistic function.

Thus, logistic model can be expressed as follows:

$$Y = \frac{K}{1+ae^{-bGDD}} \tag{Eq.2}$$

where GDD is the difference between the average daily temperature and the minimum temperature required for crop activity, as shown below (McMaster et al., 1997):

$$GDD = \sum(T_{avg} - T_{base}) \tag{Eq.3}$$

where T_{avg} is average daily temperature; T_{base} is minimum temperature required for crop activity. T_{avg} is calculated as follows:

$$GT_{avg} = \begin{cases} T_{avg} = \frac{T_x+T_n}{2} \\ T_{avg} = T_{base} \quad if\ T_{avg} \leq T_{base} \\ T_{avg} = T_{upper}\ if\ \ T_{avg} \geq T_{base} \end{cases} \tag{Eq.4}$$

where T_x is daily maximum temperature; T_n is daily minimum temperature; T_{upper} is the maximum temperature required for crop activities. T_{upper} and T_{upper} are 40°C and 7°C for maize, respectively.

Water and nitrogen alter the values of *K*, *a*, and *b*, thus affecting the shape of the logistic growth curve. Water-nitrogen-*K* function, water-nitrogen-*a* function, water-nitrogen-*b* function during growth period of spring maize were expressed in the quadratic form, which can be obtained by regression. The fitting equation can be expressed as:

$$y = c(I+R)^2 + dN^2 + e(I+R)N + f(I+R) + gN + h \tag{Eq.5}$$

where y is logistic model parameter (*K*, a and *b*); *I* is irrigation amount; *R* is effective rainfall; *N* is nitrogen application rate. *c*,*d*,*e*,*f*,*g* and *h* are empirical coefficient

The data of dry matter accumulation was extracted from papers already published using the GetData Graph Digitizer software (http://getdata-graph-digitizer.com/). The meteorological data are obtained from the China Meteorological Data Network (http://data.cma.cn), including the daily maximum temperature and the daily minimum

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temperature during the crop growth period. The distribution of rainfall and mean air temperature in spring maize growing season is shown in *Figure 2*.

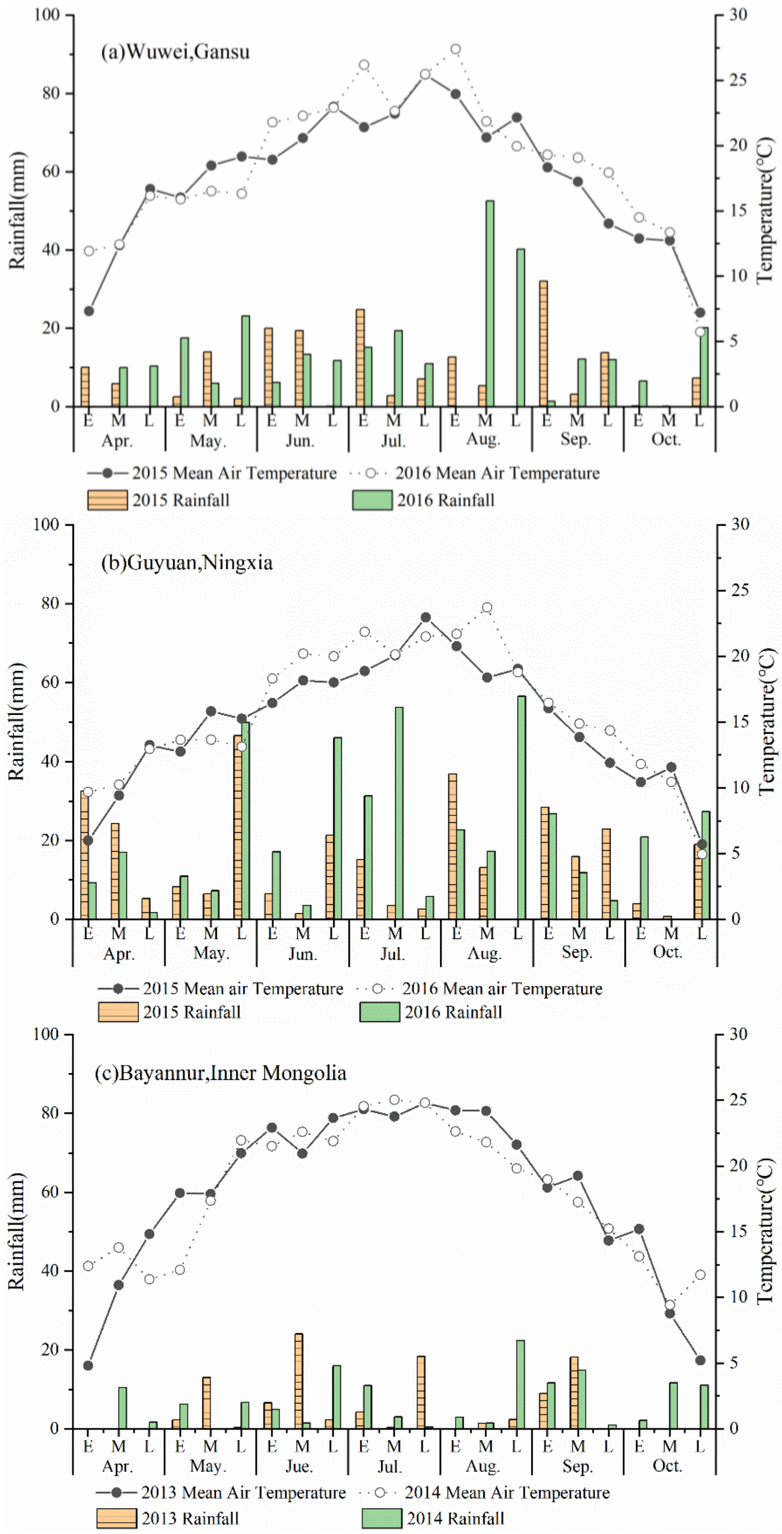

Figure 2. *Daily mean air temperature and rainfall during growing season of spring maize at Wuwei, Guyuan and Bayannur experiment stations in northwestern China*

The harvest index (HI) is defined as the ratio of yield to total dry matter, which is often used to predict crop yield (Donald et al., 1976). In this study, the relationship between HI and irrigation plus effective rainfall and N fertilizer rate can be obtained based on binary quadratic regression analysis. Then spring maize yield can be predicted by multiplying the harvest index by finial DMA.

Model performance criteria

Model accuracy was assessed by calculating coefficient of determination (R^2), Root Mean Square Error (RMSE), Normalized Root Mean Square Error (NRMSE), Nash-Sutcliffe efficiency coefficient (EF) and Willmott's index of agreement (d-index). These formulas for these statistical indicators are as follows (Nash et al., 1970; Heinemann et al., 2012; Yang et al., 2014; Archontoulis et al., 2014)

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(M_i - P_i)^2}{\sum_{i=1}^{n}(M_i - \bar{M})^2} \quad \text{(Eq.6)}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - M_i)^2}{n}} \quad \text{(Eq.7)}$$

$$NRMSE = \frac{1}{\bar{O}}\sqrt{\frac{\sum_{i=1}^{n}(P_i - M_i)^2}{n}} \cdot 100 \quad \text{(Eq.8)}$$

$$EF = 1 - \frac{\sum_{i=1}^{n}(P_i - M_i)^2}{\sum_{i=1}^{n}(M_i - \bar{M})^2} \quad \text{(Eq.9)}$$

$$d\ index = 1 - \frac{\sum_{i=1}^{n}(P_i - M_i)^2}{\sum_{i=1}^{n}(|P_i - \bar{M}| + |M_i - \bar{M}|)^2} \quad \text{(Eq.10)}$$

where M_i is measured data, $\bar{M}$ is mean value of measured data, P_i is predicted data, $\bar{P}$ is mean value of predicted data, n is number of data.

As the value of R^2 is closer to 1 and RMSE is closer to 0 the predict accuracy is higher. In general, model accuracy was excellent if NRMSE＜10%, good if 10%＜NRMSE＜20%, acceptable if 20%＜NRMSE＜30% and poor if NRMSE＞30%. The range of EF is -∞ to 1. EF=1 indicates a perfect match of predicted and measured data. And 0＜EF＜1 indicate model is acceptable, while EF≤0 shows no agreement. The range of d-index is 0 to 1. The d parameter is 1 indicates that perfect agreement between measured and predicted data, while 0 shows no agreement.

Results

Model establishment

Taking the input amount of irrigation plus effective rainfall and N fertilizer rate as the independent variable, *K*, *a*, and *b* were employed as the response variables. The data were analyzed using Matlab R2018b, and a series of binary quadratic regression equations were established (*Table 3*). *Figure 3(a)-(c)* shows the relationships between irrigation plus rainfall and nitrogen fertilizer rate and logistic parameters (*K*, *a* and *b*), respectively. The

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DOI: http://dx.doi.org/10.15666/aeer/2101_189206

coupling effects of irrigation plus effective rainfall and N fertilizer rate on *K*, *a* and *b* exhibited convex shape.

Table 3. *Regression equations for the K, a and b of Logistic model parameters under different water and nitrogen levels*

Regression equations	
$K = -7.094 \cdot 10^{-5}(I+R)^2 - 9.37 \cdot 10^{-6}N^2 + 2.602 \cdot 10^{-5} \cdot (I+R)N + 0.1045 \cdot (I+R) + 0.03114N - 5.895$ R^2=0.80	(Eq.11)
$a = -0.0008242 \cdot (I+R)^2 - 1.86 \cdot 10^{-4}N^2 - 1.333 \cdot 10^{-3}(I+R)N + 1.27 \cdot (I+R) + 0.7518 \cdot N - 314.7$ R^2=0.79	(Eq.12)
$b = -1.196 \cdot 10^{-8}(I+R)^2 - 4.034 \cdot 10^{-9}N^2 - 1.5 \cdot 10^{-8}(I+R)N + 1.542 \cdot 10^{-5}(I+R) + 8.64 \cdot 10^{-6}N - 9.061 \cdot 10^{-3}$ R^2=0.78	(Eq.13)

Note: $I + R$ is the irrigation plus rainfall amount (mm), N is the nitrogen rate (kg/ha)

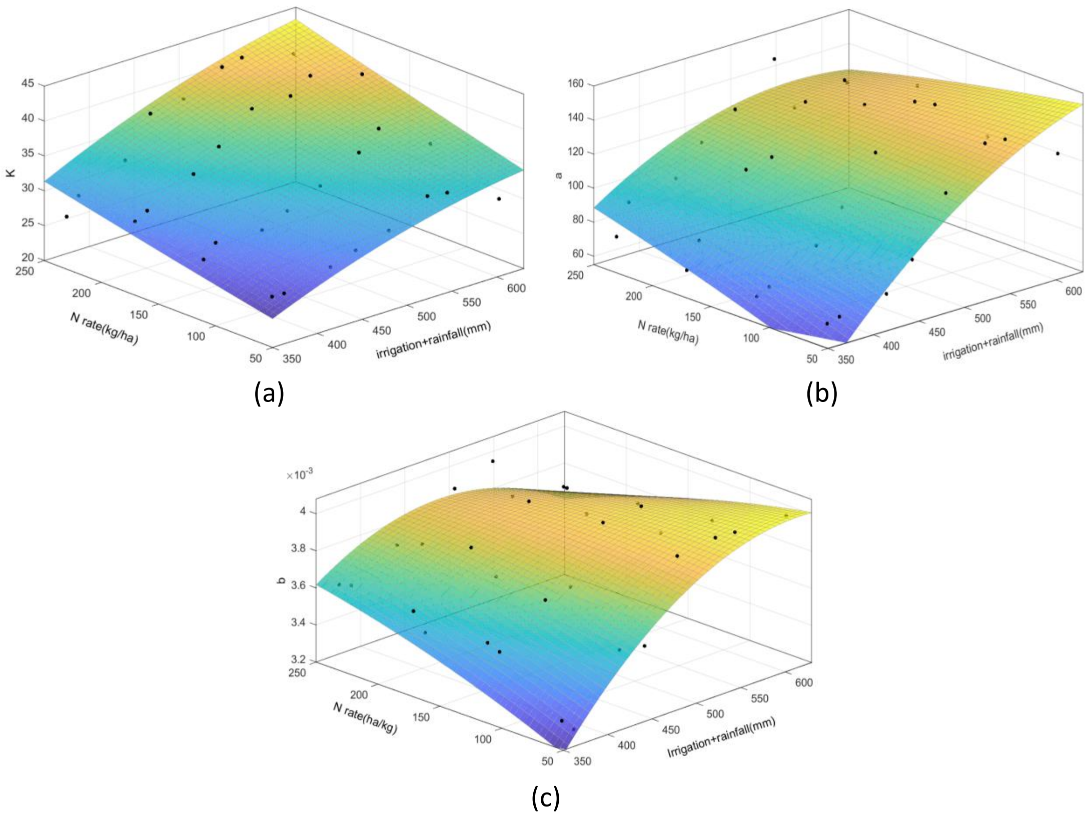

Figure 3. *Relationship between K, a and b and irrigation plus rainfall (I+R) and nitrogen fertilizer rate*

At a given *I*+*R* amount, the variation trend of logistic model parameters (*K*, *a* and *b*) increased first and then decreased with the increase of N fertilizer rate. And at a given N fertilizer rate, the variation trend of logistic model parameters (*K*, *a* and *b*) increased first and then decreased with the increase of *I*+*R* rate.

The regression equation of HI and irrigation plus rainfall and nitrogen rate is obtained as follows:

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$$HI = -9.102 \cdot 10^{-7}(I+R)^2 - 1.677 \cdot 10^{-6}N^2 - 2.498 \cdot 10^{-8}(I+R)N + 5.495 \cdot 10^{-4}(I+R) + 7.103 \cdot 10^{-4} \cdot N + 0.3983 \quad \text{(Eq.14)}$$

Then then yield of spring maize can be calculated through predicted dry matter accumulation multiply predicted HI. The formula is as follows:

$$Yield = DMA * HI \quad \text{(Eq.15)}$$

Model validation

In order to evaluate the performance of prediction model, the data of experiment 2 and experiment 3 were used to validate the performance of prediction model. Firstly, *K*, *a* and *b* were severally obtained using the above regression equations and values are shown in *Table 4*. Then predicted dry matter values are calculated based on logistic equation using growing degree days as independent variable. *Figure 4* and *Figure 5* show the comparison of predicted and measured dry matter accumulation under water and nitrogen treatments for experiment 2 and experiment 3, respectively. There was a good correlation between the measured and predicted dry matter for validation data of experiment 2 and experiment 3. The statistical indices of all treatments are shown in *Table 5*. It can be seen that the established models reasonably describe the relative dry matter accumulation process of spring maize. The ranges of R^2, RMSE, NRMSE, EF and d index were 0.9766 to 0.9879, 1.5586 to 2.8759 t/ha, 13.7858 % to 23.0055 %, 0.9120 to 0.9863 and 0.9750 to 0.9927 for experiment 2, respectively. The ranges of R^2, RMSE, NRMSE, EF and d index were 0.9544 to 0.9977, 0.8237 to 2.8732 t/ha, 4.5000% to 31.5684%, 0.6387 to 0.9962 and 0.9880 to 0.9962 for experiment 3, respectively. These results indicated that the established predicted model performed well in modeling DMA for spring maize under different water and Nitrogen regimes.

Table 4. *Logistic parameters calculated by established binary quadratic equations*

Validation data	Year	I+R (mm)	N rate (kg/ha)	K	a	b
Experiment 2	2015	335.2	300	32.3679	93.1512	0.003639
		372.7	300	34.6962	103.9005	0.003731
		372.7	300	34.6962	103.9005	0.003731
		410.2	300	36.8245	112.3318	0.003790
	2016	251.6	300	26.4592	60.8432	0.003313
		289.1	300	29.2323	76.7603	0.003480
		289.1	300	29.2323	76.7603	0.003480
		326.6	300	31.8058	90.3593	0.003614
Experiment 3	2013	117.6	363	16.7019	14.74371	0.002706
		172.1	363	21.7919	44.5743	0.003061
		226.5	363	26.4523	69.4675	0.003344
		281	363	30.7002	89.5147	0.003557
		335.4	363	34.5200	104.6425	0.003699
	2014	177	363	22.2289	47.0164	0.003090
		232.6	363	26.9487	71.9546	0.003372
		288.1	363	31.2225	91.7659	0.003580
		343.6	363	35.0594	106.4997	0.003714
		399.1	363	38.4592	116.1560	0.003775

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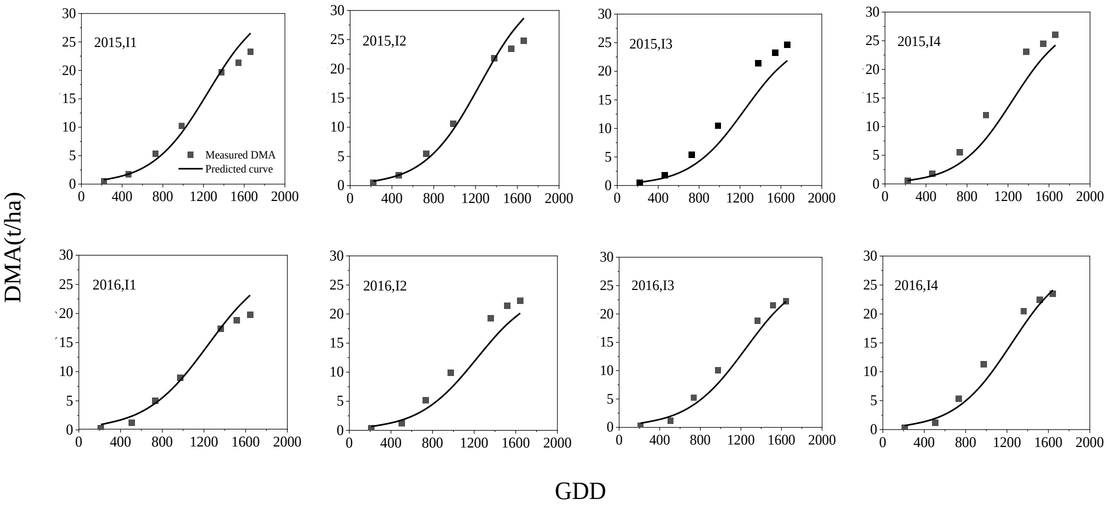

Figure 4. *Comparison of predicted and measured DMA of spring maize in experiment 2. GDD is growing degree days, DMA is dry matter accumulation. I1, I2, I3, and I4 in 2015 represent irrigation amount of 0, 37.5, 37.5 and 75 mm, respectively. I1, I2, I3, and I4 in 2016 represent irrigation amount of 0, 37.5, 37.5 and 75 mm, respectively*

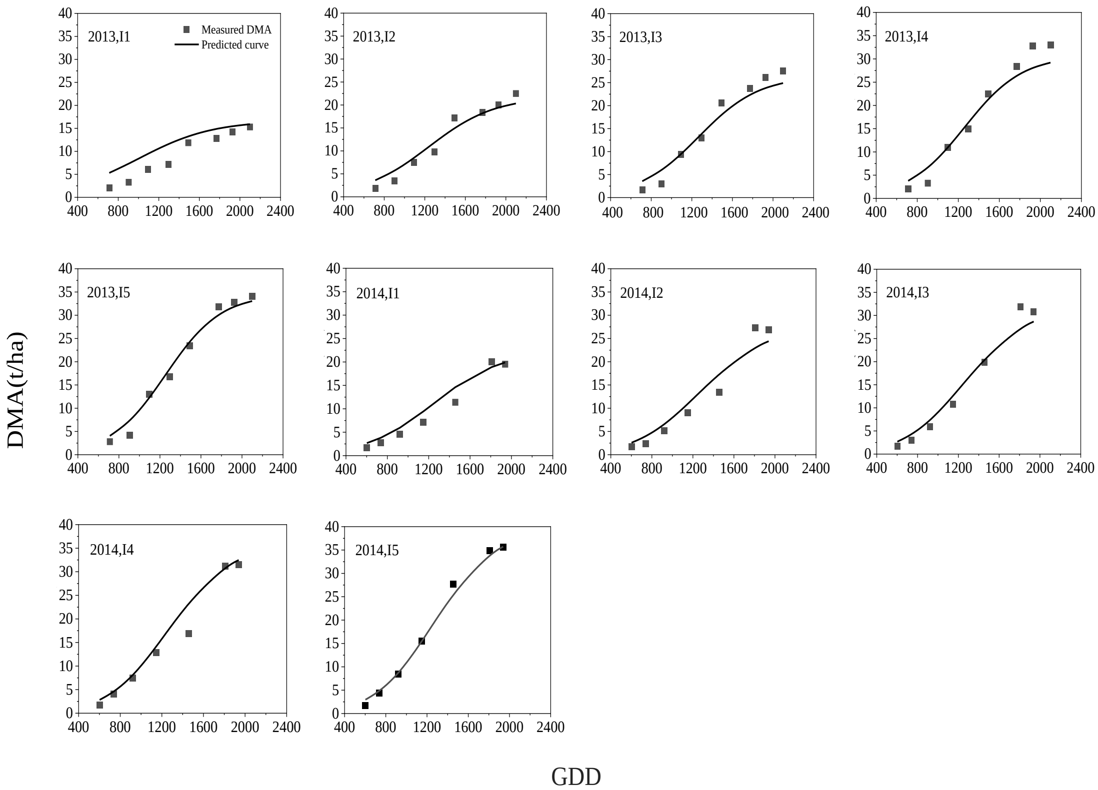

Figure 5. *Comparison of predicted and measured DMA of spring maize in experiment 3. I1, I2, I3, I4, and I5 in 2013 represent irrigation amount of 77.4, 131.9, 186.3, 240.8 and 295.2mm, respectively. I1, I2, I3, I4, and I5 in 2014 represent irrigation amount of 134.5, 190.1, 245.6, 301.1 and 356.6mm, respectively*

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***Table 5.** Statistic index of different water and nitrogen treatment of experiment 2 and experiment 3*

I+R (mm)	N rate (kg/ha)	R^2	RMSE	NRMSE	EF	d-index
335.2	300	0.9876	1.7561	14.9591	0.9612	0.9916
372.7	300	0.9862	1.8693	14.7963	0.9863	0.9921
372.7	300	0.9879	2.8759	23.0055	0.9120	0.9750
410.2	300	0.9804	2.7536	20.6238	0.9285	0.9805
251.6	300	0.9841	1.5586	15.2416	0.9602	0.9910
289.1	300	0.9867	2.4193	21.2649	0.9255	0.9785
289.1	300	0.9850	1.4556	12.8333	0.9726	0.9927
326.6	300	0.9766	1.6652	13.7858	0.9682	0.9918
117.6	363	0.9669	2.8732	31.5684	0.6387	0.9880
172.1	363	0.9744	1.7202	13.6552	0.9463	0.9923
226.5	363	0.9886	2.0863	13.3523	0.9530	0.9943
281	363	0.9909	2.7151	14.6796	0.9464	0.9953
335.4	363	0.9887	1.6281	8.1966	0.9811	0.9955
177	363	0.9710	1.7152	17.8704	0.9411	0.9926
232.6	363	0.9544	2.6265	21.3938	0.9322	0.9948
288.1	363	0.9867	2.1514	14.4939	0.9669	0.9956
343.6	363	0.9629	2.7043	17.9166	0.9428	0.9959
399.1	363	0.9977	0.8237	4.5000	0.9962	0.9962

The measured and predicted values were plotted 1: 1 line to verify the simulation performance of the model in *Figure 6*. It can be seen that the scattered points are evenly distributed around the 1: 1 line. The value of R^2 and RMSE are 0.9573 and 2.214. Therefore, the empirical model had a satisfactory precise simulating the dry matter accumulation of spring maize.

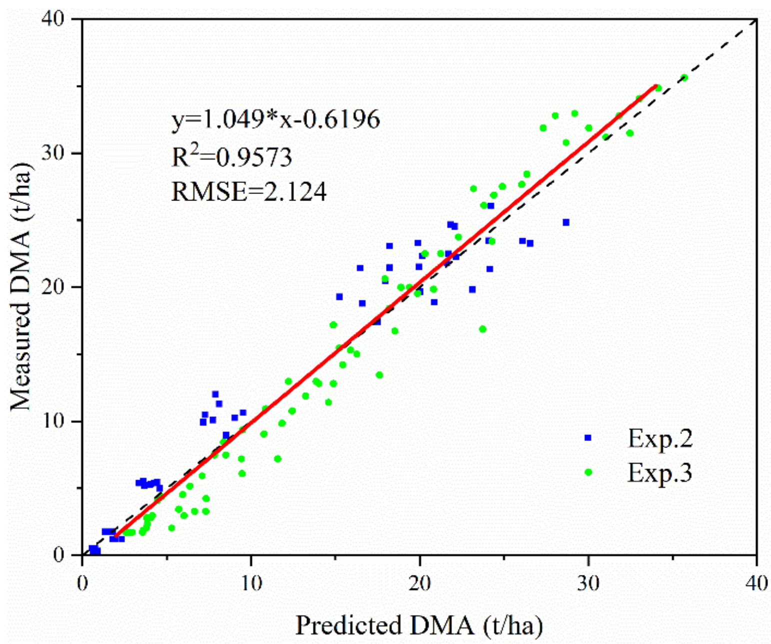

***Figure 6.** Correlations between measured DMA and predicted DMA. DMA is dry matter accumulation*

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DOI: http://dx.doi.org/10.15666/aeer/2101_189206

Using the above developed binary quadratic equations, the HI of experiment 2 and experiment 3 were calculated. The results are shown in *Table 6*. It can be seen that when I+R is small (117.6 and 177 mm), the simulation error of HI is large. This indicated that the constructed harvest index model can not accurately predict the harvest index under drought stress. The relationship between measured and estimated HI values was compared with 1:1 line in *Figure 7*. It can be seen that the value of R^2 is 0.0354 and RMSE is 0.0175. Here the reason for the low R^2 also reflects the lower prediction accuracy when the I+R is small.

Table 6. *Comparison of predicted and measured harvest index of spring maize under various treatments from experiment 2 and experiment 3*

Validation data	year	I+R (mm)	N rate (kg/ha)	Measured HI	Predicted HI
Experiment 2	2015	335.2	300	0.4938	0.5434
		372.7	300	0.5072	0.5399
		372.7	300	0.5253	0.5399
		410.2	300	0.5173	0.5339
	2016	251.6	300	0.4818	0.5418
		289.1	300	0.5054	0.5441
		289.1	300	0.5457	0.5441
		326.6	300	0.5422	0.5438
Experiment 3	2013	117.6	363	0.3987	0.4877
		172.1	363	0.5055	0.5036
		226.5	363	0.5607	0.5140
		281	363	0.5018	0.5190
		335.4	363	0.5187	0.5186
	2014	177	363	0.6017	0.5047
		232.6	363	0.5287	0.5148
		288.1	363	0.5148	0.5192
		343.6	363	0.5488	0.5181
		399.1	363	0.4958	0.5113

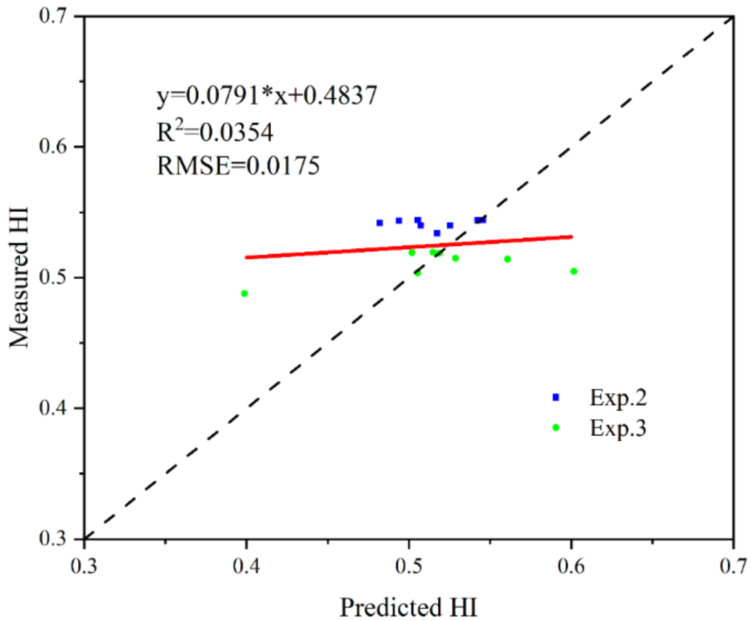

Figure 7. *Correlations between measured HI and predicted HI of spring maize (Validation data). HI is harvest index*

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DOI: http://dx.doi.org/10.15666/aeer/2101_189206

Spring maize predicted yield can be obtained through predicted dry matter multiplying predicted harvest index. The measured and simulated spring maize yield were compared with 1:1 line in *Figure 8*. The values of R^2 and RMSE are 0.6948 and 1.735, which showed that established model predicted spring maize dry matter accumulation with good accuracy.

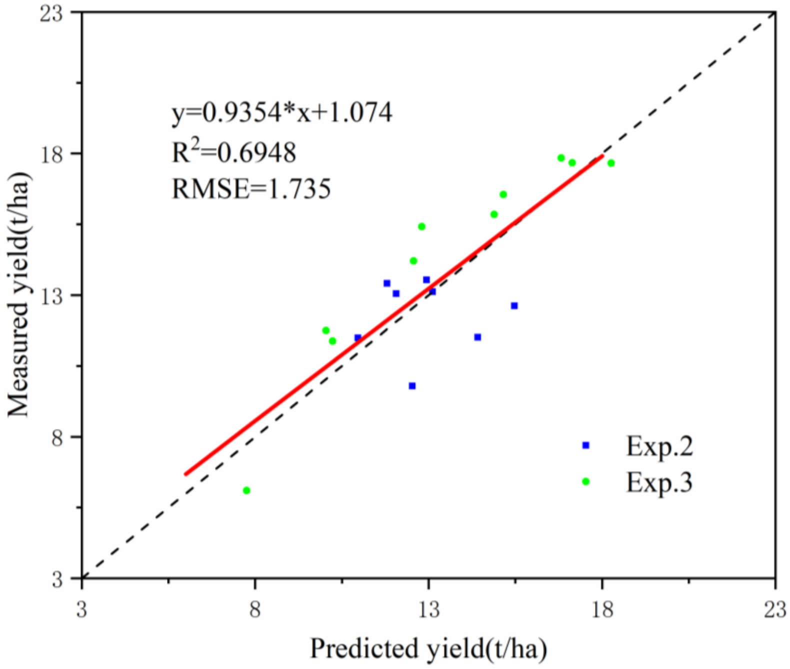

Figure 8. *Correlations between measured yield and predicted yield of spring maize (Validation data)*

Discussion

DMA is an important indicator reflecting spring maize yield formation (Arduini et al., 2006; Fang et al., 2010; Rebetzke et al., 2011; Jiang et al., 2020). In the arid and semi-arid region of Northwest China, water and fertilizer are the two most important factors that limit the yield formation of spring maize because of the shortage of water resources and poor soil nutrients in this region (Liu et al., 2013; Niu et al., 2019; Chen et al., 2020). Simulating DMA of spring maize under different irrigation and nitrogen application levels is of great significance to optimize water and fertilizer management and ensure high yield of maize (Ma et al., 2021; Zhu et al., 2022). Logistic model is a simple and effective measure in modeling the DMA process of crop (Liu et al., 2020; Zhu et al., 2022). Thus, it is essential to understand water and nitrogen coupling effect on Logistic model parameters in the process of simulating DMA under various water and irrigation.

GDD refers to the effective temperature accumulated by crops in a certain growth stage, which reflects the amount of heat required by crops in this growth period (Hou et al., 2014). Generally, the GDD required by the same crop to complete its growth period is relatively stable, so it is more accurate to use GDD to predict crop growth (Liu et al., 2020). Recently, there is growing interest in using GDD to develop general logistic model suitable for different regions. For example, Liu et al. (2020) and Wang et al. (2021) developed a universal logistic model for predicting the growth indexes of winter wheat

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2101_189206

and cotton in different regions based on the GDD, respectively. Compared with the DAP as an independent variable, the logistic model based on GDD can weaken the impact of climate differences in different regions on crop growth characteristics.

The difference of dry matter accumulation and yield formation of spring maize in the three experimental sites was mainly caused by the difference of water, nitrogen, temperature. Thus, based on GDD, we established the regression equations considering the influence of water and nitrogen on the parameters (*K*, *a* and *b*) of logistic model. In the present work, data from experiment 1 was used to establish the prediction model, and then data from experiments 2 and 3 were used to validate the model's accuracy. The variation trend of Logistic model parameters is that: at a given irrigation level, *K*, *a* and *b* initially increased and then decreased with Nitrogen rate. At a given Nitrogen rate, *K*, *a* and *b* initially increased and then decreased with with *I+R*. And these established regressions equation can accurately predict the dry matter accumulation and yield. Ma et al. (2013) also found variation trend of Logistic model parameters *K* (maximum DMA) and a of spring wheat increased initially and then decreased with the increase of irrigation amount. But parameter b did not change obviously. Wang et al. (2014) also reported similar variation of logistic parameters (*K*, *a* and *b*) of winter wheat under different irrigation levels in China's Loess Plateau. Liu et al. (2011) and Yan et al. (2019) reported that different nitrogen rates had significant effects on the parameters of the logistic model. However, previous studies did not deeply analysis the response of logistic model parameters to different irrigation and nitrogen rates. Logistic model parameters cannot be directly calculated according to the amount of irrigation water and nitrogen application. In this paper, the binary regression equation of logistic model parameters and different water and nitrogen application amounts in northwest China was constructed. Therefore, after knowing the amount of irrigation and fertilization, we can calculate the parameters of the logistic model according to the binary regression equation, and then get the dry matter accumulation and yield. The model proposed in this study is simple in calculation and convenient for farmers to use.

In addition, *Figure 8* suggests that simulation error of harvest index is large when irrigation plus rainfall is small (117.6 and 177 mm). This means the established empirical model can not accurately reflect the effect of drought stress on harvest index. Ran also pointed out that simulating harvest index under severe drought stress was still a challenge (Ran et al., 2019).

The above-mentioned results showed that established prediction model performed well in modeling dry matter accumulation and yield of spring maize in northwest China. It should be noted that the conclusions of our study were obtained under a certain range of planting density. According to our field survey, the planting density of spring maize in these areas was about 75000 plants per hectare, so we mainly developed and verified the model under this planting density. Considering that higher density planting may be encountered, we will further collect data, divide multiple planting density intervals, and build corresponding models respectively to improve the simulation accuracy and application scope of the model.

Conclusions

In this study, we developed an empirical prediction model of DMA and yield based on logistic growth function under different water and nitrogen regimes in northwest China. The model was established and validated using data of three independent experiment sites.

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DOI: http://dx.doi.org/10.15666/aeer/2101_189206

Results showed that the model are acceptable to model dry accumulation process and yield prediction. Therefore, the prediction model can be recommended for of DMA and yield of spring maize. The newly established empirical model provides a simple method to predict DMA and yield under various water and nitrogen treatment in northwest China.

Acknowledgments. This work was supported by the National Natural Science Foundation of China (41830754, 52179042), Major science and technology projects of the XPCC (2021AA003-2) and Major Science and Technology Projects of Autonomous Region (2020A01003-3).

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DOI: http://dx.doi.org/10.15666/aeer/2101_189206