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Growth Indexes and Yield Prediction of Summer Maize in China Based on Supervised Machine Learning Method

Lijun Su [1,2,*], Tianyang Wen [3], Wanghai Tao [1,*], Mingjiang Deng [1,3], Shuai Yuan [3], Senlin Zeng [3] and Quanjiu Wang [1,3]

[1] State Key Laboratory of Eco-hydraulics in Northwest Arid Region, Xi'an University of Technology, Xi'an 710048, China
[2] School of Sciences, Xi'an University of Technology, Xi'an 710054, China
[3] Institute of Water Resources and Hydro-Electric Engineering, Xi'an University of Technology, Xi'an 710048, China
* Correspondence: sljun11@xaut.edu.cn (L.S.); xautsoilwater@163.com (W.T.)

Abstract: Leaf area index and dry matter mass are important indicators for crop growth and yields. In order to solve the problem of predicting the summer maize growth index and yield under different soil quality and field management conditions, this study proposes a prediction model based on the supervised machine learning regression algorithm. Firstly, the data pool was constructed by collecting the measured data for maize in the main planting area. The total water input (rainfall plus irrigation water), fertilization, soil quality, and planting density were selected as the training set. Then, the maximum leaf area index (LAI_{max}), maximum dry material mass (D_{max}), and summer maize yields (Y) in the data pool were trained by using Gaussian regression (rational quadratic kernel function and Matern kernel function), support vector machine (SVM) and linear regression models. The training models were verified with the data-set not included in the data pool, and the water and fertilizer coupling functions were developed. The prediction results showed that compared to the support vector machine models and the linear regression models, the Gaussian regression prediction models comprising the rational quadratic and Matern kernel functions had good prediction accuracy. The coefficients of determination (R^2) of the prediction results were 0.91, 0.89 and 0.88; the root-mean-square errors (RMSEs) were 0.3, 1138.6 and 666.16 kg/hm^2; and the relative root-mean-square errors (rRMSEs) were 6.3%, 5.94% and 6.53% for LAI_{max}, D_{max} and Y, respectively. The optimal total water inputs and nitrogen applications indicated by the prediction results and the water and fertilizer coupling functions were consistent with the measured range from the field tests. The supervised machine learning regression algorithm provides a simple method to predict the yield of maize and optimize the total water inputs and nitrogen applications using only the soil quality and planting density.

Keywords: summer maize; yield prediction; machine learning; Gaussian regression

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1. Introduction

Corn is one of the most widely grown crops in the world, accounting for 37% of the world's total crop production [1]. As the second largest corn producer in the world, China accounts for 21% of the world's total corn output. The levels of corn production and economic benefit directly affect China's food security and the development of agricultural production [2]. The growth of corn is closely related to the environment [3]. Different environmental conditions bring changes to corn characteristics, affect the overall development of corn and result in great fluctuations in annual yields of corn. Based on the requirement for national food security, research on increasing summer corn yields is growing, but it mainly focuses on cultivation techniques [4], land betterment [5] and the physiological characteristics of corn [6]. Furthermore, most of the studies are limited to specific spatial

conditions, so the relationship between yields of summer maize under different spatial distributions has not been explained. Therefore, it is of great theoretical and practical significance to improve the grain output for summer corn in China under different growth conditions and water and with difficult fertilizer treatments [7–9].

There are two traditional ways to explore how to achieve optimal crop yields. One is to obtain the water–nitrogen production function by setting up different regulation treatments in the field [10]. However, this method requires the design of many water–nitrogen coupling tests in the field and their implementation over least two years; furthermore, the irrigation and fertilization amounts for the optimal yield are often only applicable under local soil and meteorological conditions. Ma et al. [11] carried out field experiments over two years by setting three drip irrigation quotas and four nitrogen applied levels and determined the optimal water–nitrogen coupling treatments for dry matter accumulation and yield with summer maize in arid regions on silt loam soil. Using field experiments over two years, Momen et al. [12] evaluated the dry matter yield of maize using different levels of irrigation water, nitrogen and phosphorus. The other method is to use a crop growth model to predict the yield [13], such as DSSAT-CERES-Maize [14], AquaCrop [15] or WOFOST [16]. As the crop growth model needs to fully consider the physiological process of crop growth and development, a large amount of experimental data must be used as the basis for the adjustment of the model parameters before localized application. Crop models have some significant limitations, such as yield-limiting soil nutrients, physical limits in the soil and other stresses that reduce production in farmers' fields but are not currently taken into account in models [17]. Moreover, if a model has too many parameters, such as parameters relating to climate, soil, and hydrology, they are hard to obtain and limit practical applications [18].

Machine learning is the science of designing and applying algorithms that can be learned and predicted from data [19]. Compared with the two traditional methods, the prediction method based on machine learning is more concise, efficient and widely applied. In recent years, Chinese and international scholars have conducted series of studies on the agricultural applications of machine learning algorithms, such as for the prediction of soil carbon content [20] and forecast models of crops [21,22]. The agricultural production elements, such as soil, weather, management methods, and environmental effects, are considered as the input parameters through which the connection with the crop yield is learned. With the development of and innovations in machine learning methods, the improvement of computer hardware and software and the gradual application of cloud computing [22], the application prospects for machine learning in big data analysis and prediction of maize yields have also become broader [23]. The training data can be collected from field test results from different regions to learn a prediction model; the prediction results will thus be representative and accurate across the whole maize production area.

The main goal of this study was to develop a machine learning method to predict the leaf area index, dry matter mass, and yield of summer maize. Based on the comprehensive consideration of the key influence factors, the field-test data, such as the total water input, fertilizer quantity, soil quality, and planting density, were collected as the training set. The learning regression prediction models were proposed using the training set. Moreover, the optimal total water input and nitrogen application for the dry mass and yield for summer maize were obtained based on the soil quality and plant density. The proposed method fully develops the advantages of machine learning for crop growth prediction [24,25].

2. Materials and Methods

2.1. Data Source

The summer maize growth data used in this study were derived from 45 published studies (1998–2019) covering 35 sites in 13 provinces in China. The meteorological data were obtained from the China Meteorological Data Network. Studies were first searched for with keywords, such as "summer corn", "fertilizer coupling", and "yield ". Then, we selected from amount the available studies using two principles. One was that the test

design contained the different total water input and fertilization or planting density. The other one was that no other dependent variables (such as irrigation or fertilization methods, etc.) affected the test results.

Figure 1 shows the summer maize planting areas used in this study, which were mainly distributed in the east, central and northwest regions. The soil texture in the planting areas was loam soil, and the fertility was uniform. The sowing time and harvest time for the different varieties of summer corn were concentrated in the periods from mid-May to late May and late September to early October, respectively. During the growth period, the soil water contents could reach about 80% of the field moisture capacity because it the temperature was high and the climate rainy. The test fields were mostly fertilized with urea (nitrogen fertilizer), K_2O (potassic fertilizer) and P_2O_5 (phosphate fertilizer). The numbers of samples used for each growth index are shown in Table 1.

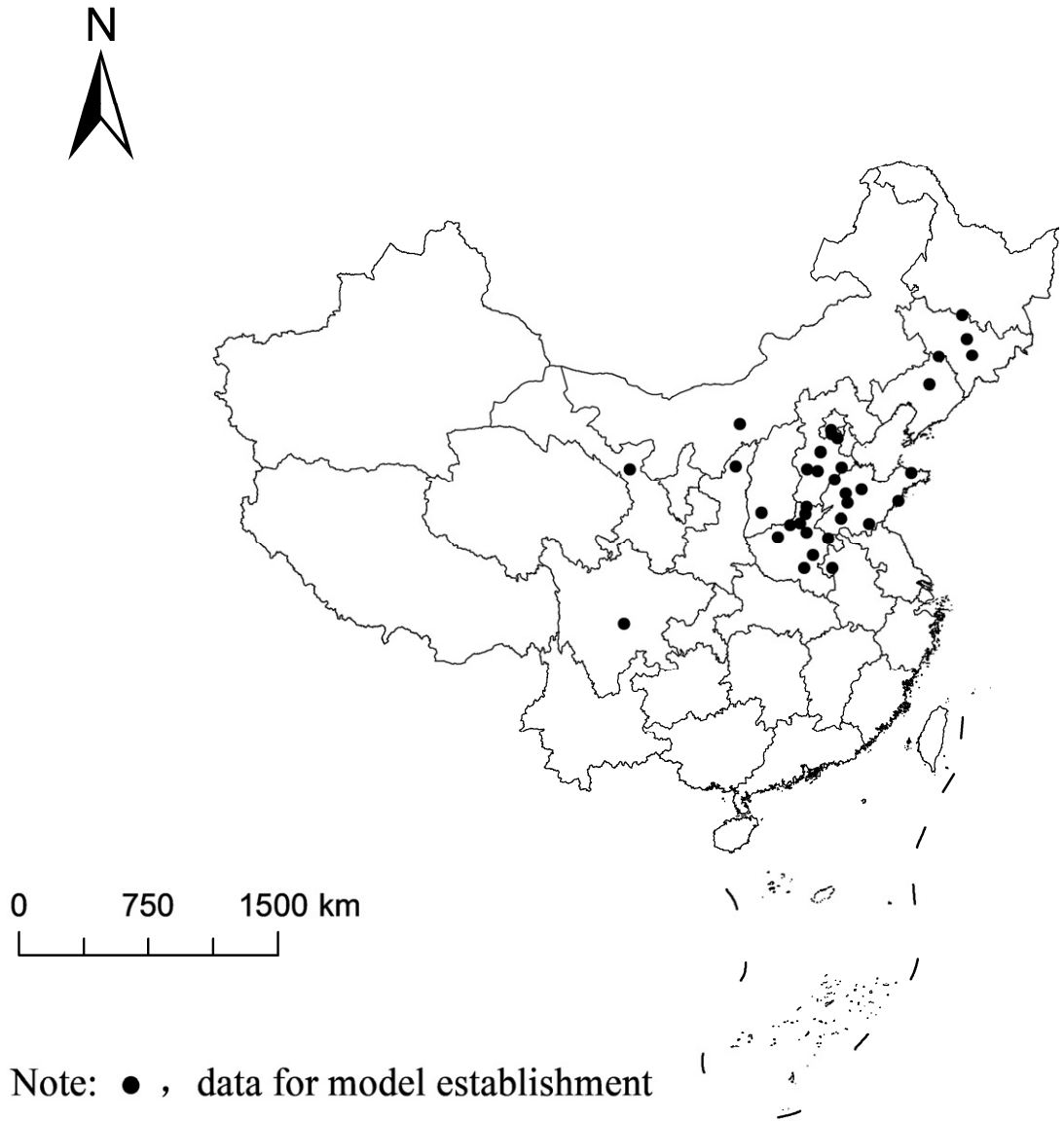


Figure 1. Regional distribution of summer maize data sources. Note: This drawing was produced based on the standard map no. GS(2020)3183 downloaded from the standard map service website of the National Administration of Surveying, Mapping and Geographic Information, without modification of the base map.

Table 1. Data sources and sample size.

District	Yield		Leaf Area Index		Dry Matter Accumulation	
	Sample Size	Data Source	Sample Size	Data Source	Sample Size	Data Source
Shandong	78	[26–34]	73	[26–33]	60	[26–31]
Hebei	44	[35–41]	24	[35–37,41]	30	[35–38]
Jilin	13	[42–44]	10	[43,44]	3	[42]
Sichuan	12	[45,46]			12	[45,46]
Henan	52	[47–57]	36	[47–55]	42	[47,49–53,57,58]
Gansu	3	[59]	3	[59]		
Heilongjiang	9	[60]			9	[60]
Shaanxi	34	[61,62]	39	[61–63]	34	[61,62]
Nei Monggol	30	[64]	30	[64]		
Liaoning			12	[65]		
Beijing	14	[66,67]	7	[67,68]		
Anhui	2	[69]	2	[70]		
Shanxi	12	[70]			12	[70]
Total	303		236		202	

2.2. Research Methods

2.2.1. Method Introduction

The harvest index (HI) and the leaf area index (LAI) are key indicators of crop growth characteristics not only for estimating the crop growth status but also for calculating the yields indirectly [71]. Therefore, the intrinsic link between LAI_{max}, D_{max} and Y were investigated based on machine learning methods.

By consulting a large number of Chinese studies on the growth characteristics of maize, the main indexes affecting the crop growth such as the rainfall, irrigation quantity, fertilization (nitrogen, phosphorus, and potassium content), soil quality (organic matter (g/kg), nitrogen (g/kg), alkali-hydrolyzable nitrogen (mg/kg), phosphorus (g/kg), valid phosphorus (mg/kg), valid potassium (mg/kg) and pH), planting density, LAI_{max}, D_{max}, and Y were collected first. Then, the total water input (rainfall plus irrigation quantity), fertilization, soil quality, and planting density were defined as independent variables, and the LAI_{max}, D_{max} and Y were defined as response variables. Finally, the LAI_{max}, D_{max} and Y were used for training and learning to build regression prediction models with the supervised regression machine learning.

We use MATLAB's Regression Learner toolbox to construct prediction models with the collected data, including the linear regression model, SVM model, and Gaussian process regression model. The linear regression model has outstanding performance in rapid modeling and is easy to understand. The SVM model has strong generalization performance and high-dimensional spatial mapping. The Gaussian process regression model has good performance in explaining variable relationships. Based on the results of the machine learning, the regression models with the best-fitted results were considered for the prediction. Test data not included in the data pool from Lu et al. [71] and Yang et al. [72] were randomly selected for validation. The total water input, fertilization, soil quality and planting density were transferred into the regression prediction models to calculate the predicted values for LAI_{max}, D_{max}, and Y, and the effects of the regression models were tested by comparing the predicted value with the measured value.

2.2.2. Gaussian Process Regression Model

A GPR model, a form of Bayesian non-linear regression, was trained using the Gaussian Processes of Machine Learning (GPML) library in MATLAB [73,74]. It was defined primarily by the selection of a covariance function, which describes how the expected value of the target variable changes as values change across the input space.

GPR uses the Gaussian process as a prior process; that is, it assumes that the learning sample is sampled by the Gaussian process. Thus the estimation results are closely related

to the kernel function. The choice of kernel functions should satisfy the Mercer theorem, that an arbitrary kernel matrix in a sample space is a positive semidefinite matrix [75]. The kernel functions commonly used in GPR are the Matern kernel and rationalof the prediction results were 0.9 quadratic kernel.

(1) Rational quadratic kernel function

The general form of the rational quadratic kernel function is:

$$K_{RQ}(r) = \left(1 + \frac{r^2}{2\alpha l^2}\right) \tag{1}$$

where α and l are parameters. This kernel function is infinitely differentiable.

(2) Matern class kernel function

The general form of the Matern class kernel function is:

$$K_{Matren}(r) = \frac{2^{1-v}}{\Gamma(v)}\left(\frac{\sqrt{2v}r}{l}\right)^{v} K_v\left(\frac{\sqrt{2v}r}{l}\right) \tag{2}$$

where v and l are the positive real parameters, and K_v is a modified Bessel function. Note that when the parameter v tends to infinity, the Matern kernel function becomes the square exponential kernel function. The Matern kernel function is particularly simple when v is a half-integer ($v = p + 1/2$, where p is a non-negative integer). In this case, the kernel function is the product of the exponential function and the p-order polynomial. In this case, the kernel function is p-order derivable, and the general expression is as follows:

$$K_{v=p+1/2}(r) = \exp\left(-\frac{\sqrt{2v}r}{l}\right)\frac{\Gamma(p+1)}{\Gamma(2p+1)}\sum_{i=0}^{p}\frac{(p+i)!}{i!(p-i)!}\left(\frac{\sqrt{8v}r}{l}\right)^{p-i} \tag{3}$$

Moreover, it is the most meaningful kernel function for machine learning whenof the prediction results were 0.9 $v = 5/2$, which can be defined as:

$$K_{v=5/2}(r) = \left(1 + \frac{\sqrt{5}r}{l} + \frac{5r^2}{3l}\right)\exp\left(-\frac{\sqrt{5}r}{l}\right) \tag{4}$$

2.3. Error Analysis

The data collected were all processed in Excel2020. The rainfall for summer corn not given in the references was obtained by consulting the monthly rainfall data for the same year in the China Meteorological Data Network. The soil nutrient status values not given in the data articles were obtained by consulting studies or other data for the same year and location. We deduced the model parameters with MATLAB 2019 and used the R^2, root-mean-square error (RMSE) and relative root-mean-square error (rRMSE) as feature evaluation indicators for the error analysis.

The root-mean-square error (RMSE), relative root-mean-square error (rRMSE) and coefficient of determination (R^2) were used for the statistical analyses to investigate the simulation accuracy and applicability of the approximate analytical solutions. The specific expressions are as follows:

$$R^2 = \frac{\sum_{i=1}^{n}(x-\overline{x})^2(y-\overline{y})^2}{n\sum_{i=1}^{n}(x_i-\overline{x})^2 n\sum_{i=1}^{n}(y_i-\overline{y})^2} \tag{5}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - x_i)^2} \tag{6}$$

$$\text{rRMSE} = \frac{\text{RMSE}}{\overline{x}} \times 100\% \quad (7)$$

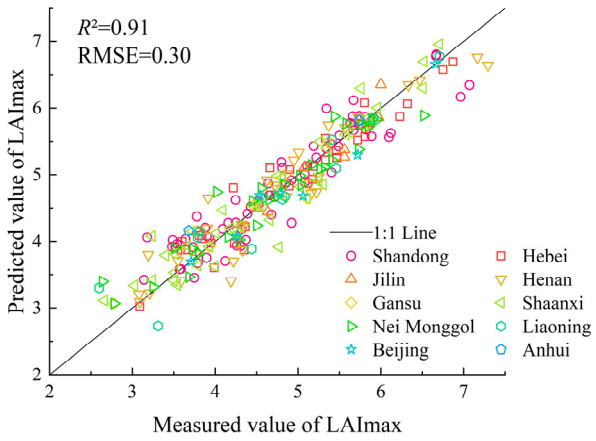
where x_i is the true value of the ith sample point, y_i is the predicted value of the i sample point, $\overline{x}$ is the average of the true values, $\overline{y}$ is the average of the predicted values, n is the total number of test samples.

3. Result

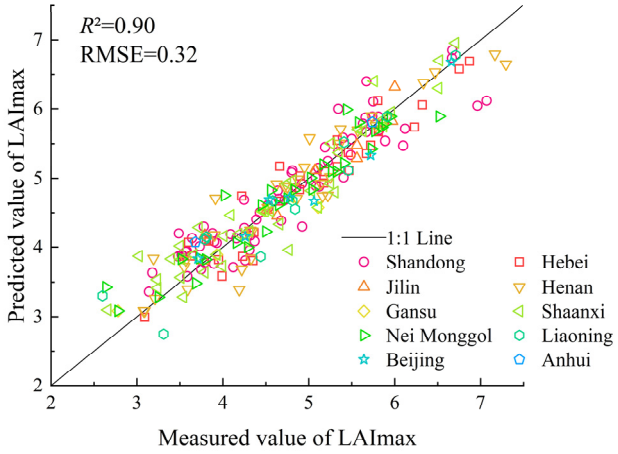
3.1. Prediction Model for Maximum Leaf Area Index

3.1.1. Model Comparison

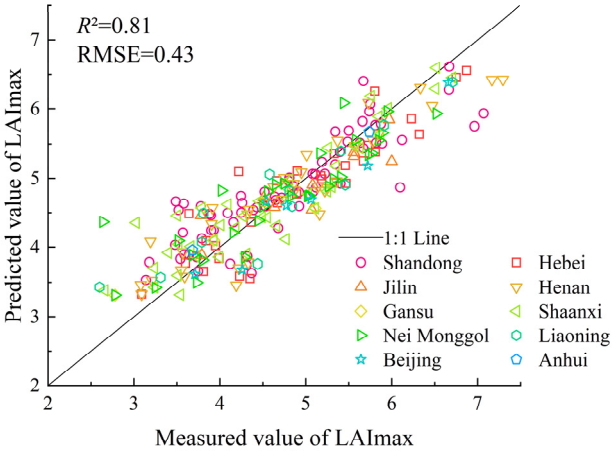
Gaussian process regression models (Matern kernel function and rational quadratic kernel function), a support vector machine model and a linear regression model were applied to learn the training set and maximum leaf area index. Figure 2 showed the learning results for LAI_{max} with four regression models. The R^2 value of the four models were 0.91, 0.90, 0.81 and 0.53; the RMSE values were 0.30, 0.32, 0.43 and 0.68; and the rRMSE values were 6.30%, 6.72%, 9.02% and 14.27%, respectively. It was obvious that the Gaussian process regression models with the Matern 5/2 kernel function and rational quadratic function had better fitting accuracy than the support vector machine model and linear regression model. Thus, the Gaussian process regression models were used to predict the LAI_{max} based on the machine learning method.



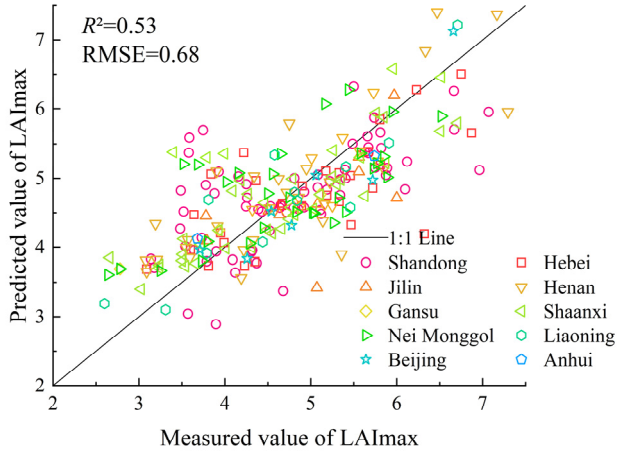
a. Gaussian process regression (Matern 5/2 GPR)



b. Gaussian process regression (rational quadratic GPR)



c. Support vector machine



d. Linear regression

Figure 2. Regression model for maximum leaf area index for summer maize.

3.1.2. Model Verification

The field-test data from Lu et al. were used to verify the availability of the Gaussian process regression models. The experiment station was the water-saving irrigation station of Northwest A&F University, and 12 groups of water–fertilizer coupling treatments were applied, as shown in Table 2. The rainfall during the growth period of summer maize was 434 mm in the test year. The maize variety was *Zhengdan* 958, the soil pH was 8.14, the organic content was 12.02 mg/kg, the alkali-hydrolyzable nitrogen content was 17.02 mg/kg, the valid phosphorus content was 20.47 mg/kg, the valid potassium content was 164.5 mg/kg, the phosphorus fertilizer (P_2O_5) applied over the whole growth period was 90 kg/hm^2, the potassic fertilizer (K_2O) applied over the whole growth period was 60 kg/hm^2, and the planting density was 70922 plants/hm^2. Taking the Matern 5/2 kernel function as an example, the LAI_{max} of the maize in the test station was predicted by the Gaussian regression model for different water and nitrogen treatments. The prediction results are shown in Figure 3.

Table 2. Relative leaf area index (*RLAI*) values for the six treatments at different points in time and mean *RLAI* values for all treatments in 2009.

Treatment	Total Water Input (mm)	Nitrogen Application Rate (kg·hm^{-2})	Measured Value of LAI_{max}	Predicted Value of LAI_{max}	Relative Error (%)
1	434	0	2.79	4.63	65.95
2	434	90	3.27	4.74	44.95
3	434	150	3.87	4.78	23.51
4	434	210	4.04	4.81	19.06
5	659	0	3.35	5.10	52.24
6	659	90	3.98	5.23	31.41
7	659	150	5.08	5.28	3.94
8	659	210	5.16	5.30	2.71
9	734	0	3.52	5.16	46.6
10	734	90	4.26	5.28	23.94
11	734	150	5.13	5.33	3.9
12	734	210	5.21	5.35	2.69

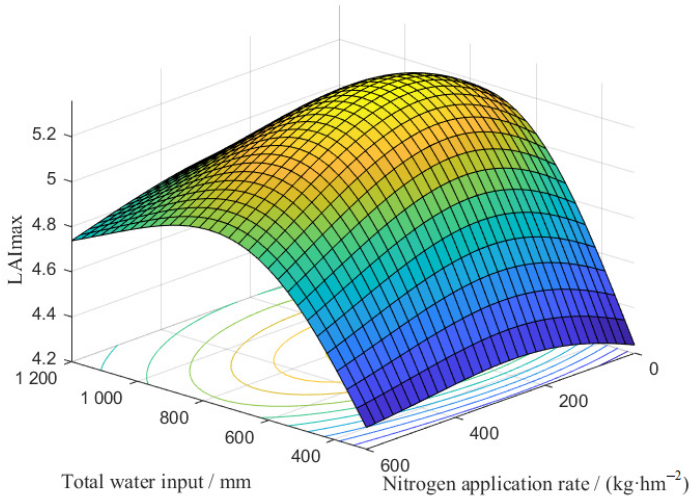


Figure 3. LAI_{max} prediction results with Gauss regression model under water and nitrogen coupling.

The measured and predicted LAI_{max} values are shown in Table 2. In the experimental results published by Lu et al., irrigation was found to significantly increase the LAI of the maize compared to treatments depending only on rainfall. There was no significant difference in the LAI between the deficient-irrigation and the adequate-irrigation treatments, but nitrogen fertilizer amounts ranging from 0 to 150 kg/hm^2 significantly affected the LAI.

The LAI values increased with the amounts of nitrogen applied, and stopped increasing when the amounts of nitrogen applied exceeded 150 kg/hm^2. It can be seen from Figure 3 and Table 2 that the predicted value for LAI_{max} of 5.36 was optimal when the intervals of total water inputs and nitrogen fertilizer amount ranged from 650 to 850 mm and 150 to 300 kg/hm^2, respectively. Moreover, the optimal value for LAI_{max} measured with different irrigation treatments was 5.21 when the total water inputs was 734 mm and the nitrogen fertilizer amount was 210 kg/hm^2. The predicted value for the optimal LAI_{max} was in agreement with the measured value, and the total water input and nitrogen fertilizer amount at the optimal measured value were within the ranges of predicted value. However, large errors appeared with lower total water inputs or nitrogen fertilizer amounts because the data pool was insufficient and these data points were concentrated at the boundaries of intervals [76].

3.1.3. Water and Nitrogen Coupling Function

The models obtained with the machine learning had no specific functional expressions and thus could not describe the relationship among the variables. To determine the water and nitrogen application amounts and estimate the LAI_{max}, the predicted values of LAI_{max} were simulated with the Gaussian process regression models for total water input and nitrogen application ranges from 650 mm to 850 mm and 150 kg/hm^2 to 300 kg/hm^2. Then, the quadratic polynomial was used to fit the water-nitrogen coupling function of LAI_{max} in the Yangling area:

$$LAI_{max} = 2.643 + 6.701 \times 10^{-3} W_a + 1.828 \times 10^{-3} N_r - 4.422 \times 10^{-6} {W_a}^2 - 2.346 \times 10^{-7} \cdot W_a \cdot N_r - 3.881 \times 10^{-6} {N_r}^2 \quad (8)$$

where W_a is the total water input in mm and N_r is the nitrogen application in kg/hm^2. The fitting results are shown in Figure 4. It can be seen form Figure 4 that the water-nitrogen coupling function had outstanding fitting accuracy for the predicted yields with $R^2 = 0.9971$ and RMSE = 0.00087. Letting $dLAI_{max}/dW_a = 0$ and $dLAI_{max}/dN_r = 0$, we obtained the following equation set:

$$\begin{cases} 6.701 \times 10^{-3} - 8.844 \times 10^{-6} W_a - 2.346 \times 10^{-7} N_r = 0 \\ 1.828 \times 10^{-3} - 2.346 \times 10^{-7} W_a - 7.762 \times 10^{-6} N_r = 0 \end{cases} \quad (9)$$

Then, the extreme point of the water–nitrogen coupling function (Equation (9)) could be calculated, and the optimal water input, nitrogen application and LAI_{max} were 750 mm, 210 kg/hm^2 and 5.36, respectively.

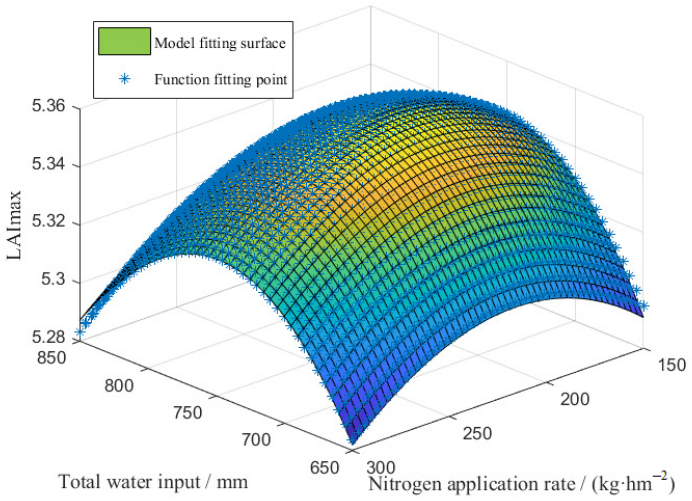
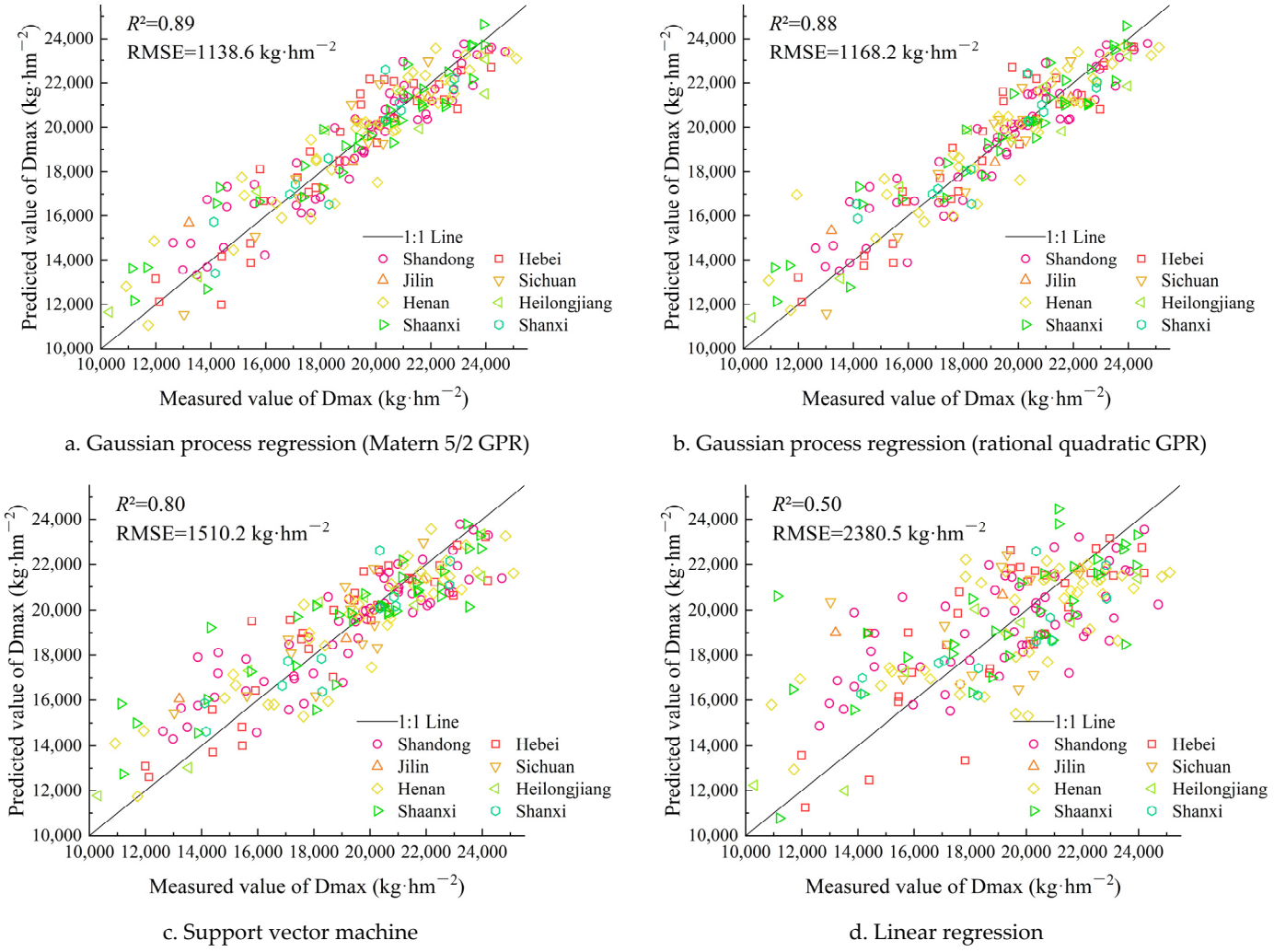


Figure 4. Fitting results for LAI_{max} with the quadratic polynomial based on the values predicted by Gaussian regression model.

3.2. Prediction Model for Maximum Dry Matter Mass

3.2.1. Model Comparison

Four models were used for learning the training set and the maximum dry matter mass D_{max} based on the machine learning method, and the learning results are shown in Figure 5. The R^2 value of the four models were 0.89, 0.88, 0.80 and 0.50; the RMSE values were 1138.6, 1168.2, 1510.2 and 2380.5; and the rRMSE values were 5.94%, 6.09%, 7.88%, and 12.42%, respectively. As with the results for LAI_{max}, the Gaussian process regression models showed good performances in learning the D_{max} compared to the other regression models. Moreover, the GPR with the Matern 5/2 kernel function was the most effective learning model among the involved models. Therefore, based on the training set data and machine learning methods, we were able to use the Gaussian process regression model to predict the maximum dry matter mass.



a. Gaussian process regression (Matern 5/2 GPR)

b. Gaussian process regression (rational quadratic GPR)

c. Support vector machine

d. Linear regression

Figure 5. Regression models for maximum dry material mass for summer maize.

3.2.2. Model Verification

The field-test data were collected from the study by Yang et al. and used to verify the accuracy of the models. The experiment station was located in Wenxian county, Jiaozuo city, Henan province, and the maize variety was *Zhengdan* 958. By applying different combinations of water and fertilizer, 12 water–fertilizer coupling treatments were carried out, as shown in Table 3. The organic content, nitrogen content, phosphorus content, alkali-hydrolyzable nitrogen content, valid phosphorus conten and valid potassium content in the soil were 18.82 g/kg, 1.18 g/kg, 1.14 g/kg, 112.71 mg/kg, 37.13 mg/kg, and

89.69 mg/kg. The phosphorus fertilizer (P_2O_5) and potassic fertilizer (K_2O) applied across the whole growth period were 120 kg/hm^2 and 200 kg/hm^2. The planting density was 75,000 plants/hm^2. The Gaussian regression model with the Matern 5/2 kernel function was used to predict the D_{max} of maize in the test station by with different water and nitrogen coupling treatments. The prediction results are shown in Figure 6.

Table 3. The measured and predicted values of yields and D_{max}.

Treatment	Total Water Input (mm)	Nitrogen Application Rate (kg·hm^{-2})	Measured Yield (kg·hm^{-2})	Predicted Yield (kg·hm^{-2})	Relative Error (%)	Measured D_{max} (kg·hm^{-2})	Predicted D_{max} (kg·hm^{-2})	Relative Error (%)
1	593.5	0	10,169	10,518	3.43	16,830	18,479	9.8
2	593.5	180	11,712	12,199	4.16	18,592	20,597	10.79
3	593.5	240	11,986	12,351	3.05	19,859	20,940	5.44
4	593.5	300	10,124	12,321	21.69	18,567	20,966	12.92
5	790.2	0	9956	10,777	8.25	19,115	19,456	1.79
6	790.2	180	11,622	12,325	6.05	20,023	21,551	7.63
7	790.2	240	12,338	12,543	1.67	21,388	21,874	2.27
8	790.2	300	10,448	12,615	20.75	20,006	21,893	9.43
9	987	0	9931	10,610	6.84	18,896	19,901	5.32
10	987	180	11,265	11,899	5.63	18,865	21,707	15.06
11	987	240	11,722	12,142	3.58	21,437	21,957	2.42
12	987	300	11,679	12,281	5.16	22,089	21,948	0.64

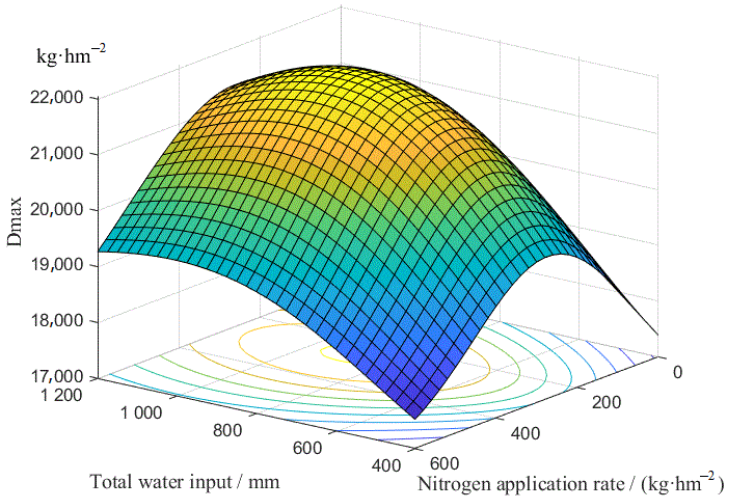


Figure 6. Prediction results for D_{max} with Gaussian regression model for water and nitrogen coupling.

According to Table 3, the cumulative amount of dry matter for all nitrogen treatments was significantly higher than that for the treatment without nitrogen under the same irrigation quota condition. In the mature period, the cumulative amount of dry matter was the maximum with the nitrogen applications of 240 kg/hm, 240 kg/hm and 300 kg/hm when the total water inputs were 593.5 mm, 790.2 mm and 987 mm, respectively. For the same nitrogen level, the dry matter accumulations with different total water inputs were as follows: 987 mm treatment > 790.2 mm treatment > 593.5 mm treatment. The measured optimal D_{max} was 22,089 kg/hm^2 for the total water input amount of 987 mm and the nitrogen application amount of 300 kg/hm^2. It can be seen from Figure 6 that the predicted value of D_{max} was optimal at 22,054 kg/hm^2 when the total water inputs and nitrogen fertilizer amounts ranged from 800 to 1000 mm and 150 to 350 kg/hm^2, respectively. Moreover, the predicted optimal D_{max} and the optimal ranges for water–nitrogen application were in accordance with the maximum measured values.

In the test treatments of described by Yang et al., the optimal D_{max} was obtained with the treatment with the maximum total water input and the maximum nitrogen application.

It is unknown whether the maximum dry matter mass would continue to increase if the amounts of irrigation water or nitrogen continued to increase. However, the machine learning method could effectively solve this problem with enough test data. As can be seen from Figure 6 showing the water–nitrogen coupling prediction results, the tests with the higher amounts of irrigation water or nitrogen did not cause the values of D_{max} continue to increase.

3.2.3. Water and Nitrogen Coupling Function

In order to predict the dry matter mass from the amounts of irrigation water and nitrogen, the water and nitrogen coupling function was fitted with the predicted results obtained with machine learning method for total water inputs ranging from 800 to 1000 mm and nitrogen ranging from 200 to 350 kg/hm^2. The quadratic polynomial was used to obtain the water and nitrogen coupling function for the maximum dry material mass of summer corn in Wenxian county, Jiaozuo city, as follows:

$$D_{max} = 1.108 \times 10^4 + 17.58W_a + 22.68N_r - 9.479 \times 10^{-3}{W_a}^2 - 2.02 \times 10^{-3} \cdot W_a \cdot N_r - 3.849 \times 10^{-2}{N_r}^2 \quad (10)$$

The fitting results are shown in Figure 7, with R^2 = 0.9975 and RMSE = 3.778. The water–nitrogen coupling function was used to estimate the D_{max} of the summer maize in the same way as the machine learning method. To obtain the optimal water and nitrogen, let $dD_{max}/dW_a = 0$ and $dD_{max}/dN_r = 0$ based on Equation (10). Then,

$$\begin{cases} 17.58 - 1.8958 \times 10^{-2}W_a - 2.02 \times 10^{-3}N_r = 0 \\ 22.68 - 2.02 \times 10^{-3}W_a - 7.698 \times 10^{-2}N_r = 0 \end{cases} \quad (11)$$

By solving Equation (11), the extreme point of the water-nitrogen coupling function (Equation (10)) can be found, and the optimal water input, nitrogen application and D_{max} were 895 mm, 272 kg/hm^2, and 22,054 kg/hm^2, respectively.

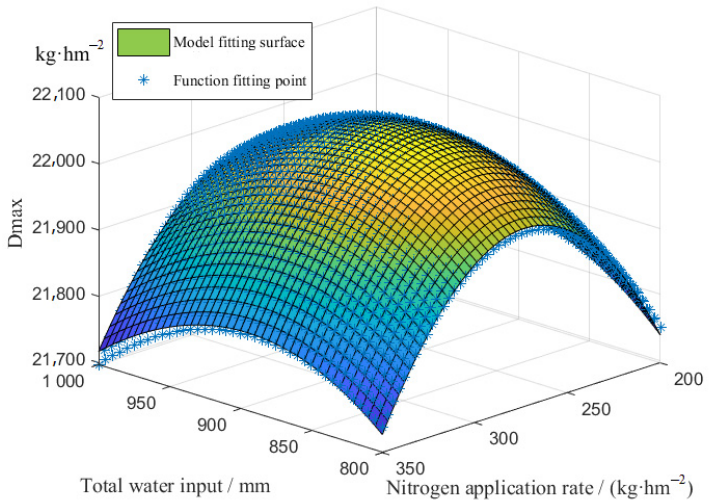


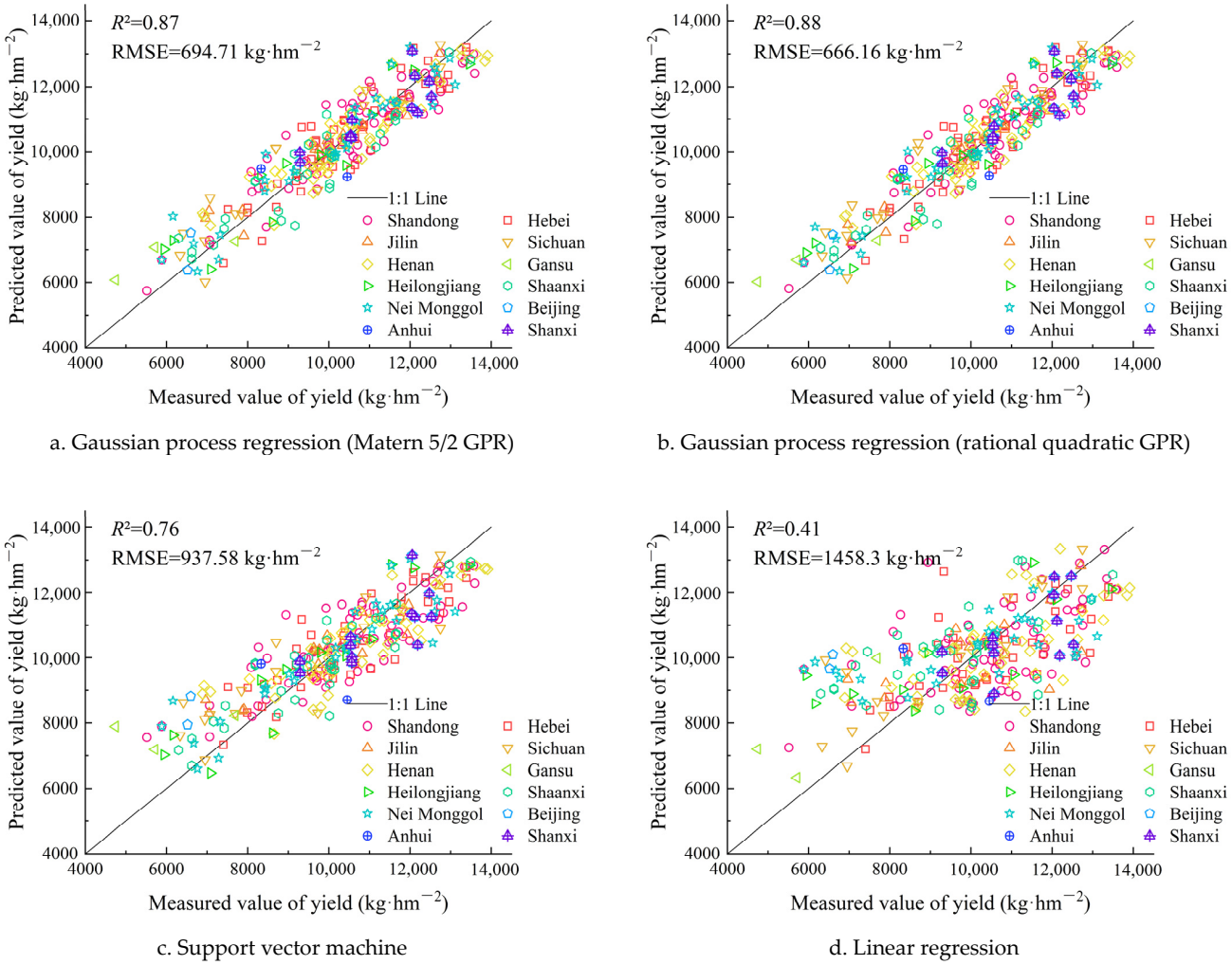
Figure 7. Fitting results for D_{max} with the quadratic polynomial based on the values predicted by the Gaussian regression model.

3.3. Prediction Model for Yield

3.3.1. Model Comparison

Yield is the most important indicator in agriculture, and its accurate prediction can guide water and fertilizer management in fields. The learning results for four models based on the training data set and collected yield data are shown in Figure 8. The R^2 values of the four models were 0.87, 0.88,0.76 and 0.41; the RMSE values were 694.71, 666.16, 937.58 and 1458.3 kg/hm^2; and the rRMSE values were 6.81%, 6.53%, 9.19%, and 14.30%, respectively. The Gaussian process regression models with both the rational quadratic kernel and Matern

5/2 kernel functions had good fitting results, and the rational quadratic kernel function was the best in the four models. Therefore, the Gaussian process regression model could be used to predict summer maize yield based on the data for the total water input (the sum of irrigation and rainfall), fertilization (nitrogen, phosphorus, potassium), soil mass (organic matter, total nitrogen, alkali-hydrolyzable nitrogen, valid phosphorus, valid potassium, pH) and planting density.



a. Gaussian process regression (Matern 5/2 GPR)

b. Gaussian process regression (rational quadratic GPR)

c. Support vector machine

d. Linear regression

Figure 8. Regression model for summer maize yield.

3.3.2. Model Verification

The training data and yield were also collected from the field experiments described by Yang et al. as shown in Table 3. The results predicted for the yield by the Gaussian process regression model (taking the rational quadratic kernel function as an example) are shown in Figure 9 for different water and nitrogen treatments. In the field experiments, the yields increased first and then decreased with the increase in the application of nitrogen when the total water inputs were 593.5 mm and 790.2 mm. However, the yields no longer changed obviously with the increase in the application of nitrogen when the total water input was 987 mm. The measured optimal yield for summer corn was 12,338 kg/hm^2 for a total water input of 790.2 mm and nitrogen application of 240 kg/hm^2. As shown by the water–nitrogen coupling prediction results in Figure 9, the predicted optimal yield was 12,639 kg/hm^2 for a total water input range from 600 to 800 mm and nitrogen range from 200 to 400 kg/hm^2. As shown in Table 3, the ranges for the total water input and nitrogen for the measured optimal yield basically coincided with the predicted ranges.

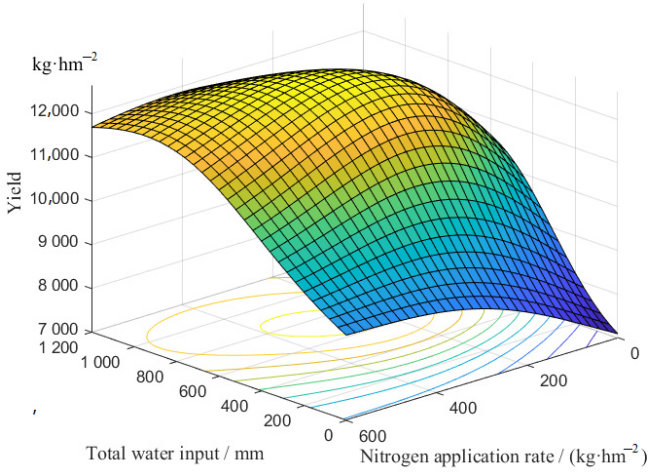


Figure 9. Yield prediction results with Gauss regression model for water and nitrogen coupling.

3.3.3. Water and Nitrogen Coupling Function

The water and nitrogen coupling function was similarly considered to estimate the yield. For a total water input range from 800 to 1000 mm and nitrogen application range from 200 to 350 kg/hm^2, the quadratic polynomial was used to fit the predicted values of the Gaussian process regression. Then, the water and nitrogen coupling function for the summer maize yield in Wenxian county, Jiaozuo city was as follows:

$$Y = 8123 + 10.54W_a + 4.05N_r - 8.721 \times 10^{-3}{W_a}^2 + 8.314 \times 10^{-3}W_a{\cdot}N_r - 1.743 \times 10^{-2}{N_r}^2 \quad (12)$$

The fitting results for the coupling function are shown in Figure 10. The R^2 and RMSE of the fitting results were 0.9957 and 5.93. It can be seen from Figure 10 that the water and nitrogen coupling function simulated the predicted data obtained with machine learning very well. To obtain the optimal water and nitrogen, we let $dY/dW_a = 0$ and $dY/dN_r = 0$ based on Equation (12). Then,

$$\begin{cases} 10.54 - 1.7442 \times 10^{-2}W_a + 8.314 \times 10^{-3}N_r = 0 \\ 4.05 + 8.314 \times 10^{-3}W_a - 3.486 \times 10^{-2}N_r = 0 \end{cases} \quad (13)$$

By solving Equation (13), the extreme point of the water-nitrogen coupling function (Equation (12)) could be found, and the optimal water input, nitrogen application, and yield were 730 mm, 285 kg/hm^2, and 12,639 kg/hm^2, respectively.

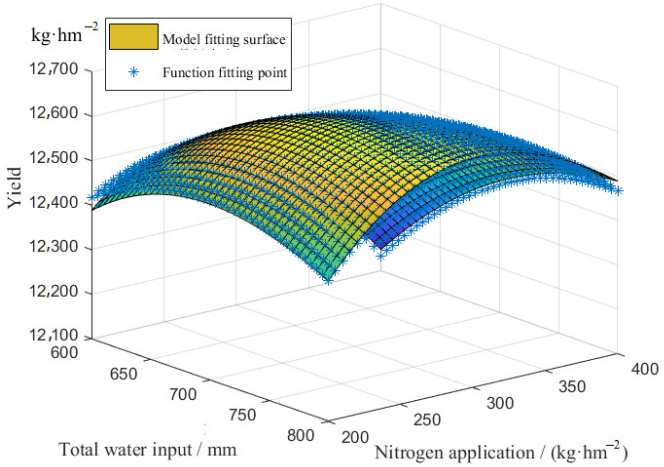


Figure 10. Fitting results for yield with the quadratic polynomial based on the values predicted by the Gaussian regression model.

4. Discussion

In this study, the LAI_{max}, D_{max}, and Y of summer maize in 35 main growth areas were predicted and verified with machine learning methods. The total water input (rainfall and irrigation), fertilization amount, soil quality and planting density were chosen as the independent variables, and the Gaussian process regression models with the rational quadratic kernel function and the Matern kernel function obtained good accuracies ($R^2 > 0.87$ and RMSE < 7%) for the predicted results. The total water input and nitrogen application for the optimal growth indexes were consistent with the measured ranges from the field tests. The main advantage of machine learning in yield prediction is the ability to build low-cost and non-destructive prediction models based on massive, complex, nonlinear agricultural data.

Most current research on summer maize yields had focused on ndividual regions and specific water and fertilizer conditions. However, farmers are concerned not only with irrigation and fertilization but also with soil quality and planting density in actual field management. Moreover, the multi-variable and multi-dimensional regression model of yield hardly fit the limited field-test data. However, the machine learning method can solve this problem effectively because it can learn the mapping relationship between the dependent variable and the characteristic variables based on the mass data [77]. Thus, the machine learning method was applied to explain the relationship between the yield, irrigation amount, fertilizer application, soil quality and planting density using data collected from the main maize planting areas in China.

In addition to the growth indexes used in the training data set, many factors affect the growth of summer maize, such as meteorological factors. However due to the limitations of the data collection, the important meteorological data, such as temperature and effective radiation, could not be collected from the literature directly. Most of the crop growth models used commonly worldwide, including AquaCrop [78], DSSAT [79], and EPIC [80], consider the meteorological factors as the primary parameters. Growing degree days (GDD) is a crucial meteorological factor for the explanation of the development of growth indexes in crop growth models, but few studies have introduced it. The meteorological indicators only consider the rainfall when constructing the training set, and it causes obvious deviations between the predicted values and measured values.

Moreover, crop management (crop varieties, irrigation and fertilization ranges and organic fertilizer) and mechanization and other technologies also affect crop growth [81,82], resulting in large errors in this study, as shown in Table 2. The mechanization index (MI) is defined as the ratio of the energy used by machinery to the total energy used by humans and animals [83], and it has a notable relationship with crop yield [81]. A high MI means a high crop yield. The reason is that farmers with high MIs use more advanced technologies to manage crop cultivation compared to farmers with small MIs. The lack of consideration of key factors affecting crop yield reduced the model accuracy obviously, as shown in Figures 2, 5 and 8. Thus, the more key factors are considered, the higher the prediction accuracy will be.

The water–fertilizer coupling function proposed in this paper invovled the application of machine learning methods but was limited to merely applying the local conditions. However, we can collect the data on local soil quality and set up different water and fertilizer coupling schemes as the training data set for different maize production areas. Then, the Gaussian process regression models can be used to predict the yields with the training data set. Using the predicted values and the water and fertilizer coupling schemes, a water–fertilizer coupling function suitable for local conditions can be obtained to guide local maize production with the quadratic polynomial fitting.

The prediction of maize yield can provide support for farmers in arranging production plans, improving yield production levels and developing reasonable irrigation and fertilization. The prediction idea proposed in this paper not only has reference significance for the problem of predicting summer maize yields but can also be applied in the prediction of other crops. To further optimize the model, the training data should take into account

meteorological indicators, such as GDD, to expand the data capacity, and batter machine learning algorithms can be used to predict the crop growth.

5. Conclusions

Four different machine learning prediction methods were developed for predicting growth indexes and yield based on linear regression, support vector machine and Gaussian process regression models (rational quadratic kernel function and Matern kernel function). The most effective prediction model was chosen to predict the LAI_{max}, D_{max}, and yield of summer maize and verified with the measured data from field tests. In order to make the prediction simple, water and fertilizer coupling functions were proposed. The main conclusions are as follows:

(1) Based on the prediction model accuracy, the Gaussian process regression model was the best for the summer maize LAI_{max}, D_{max} and yield. The models with the rational quadratic kernel and Matern kernel had similar performance and good fitting effects. The R^2 values of the models were larger than 0.87, and the rRMSE values were lower than 7%. The SVM model was the second best model, and the linear regression model was the worst;

(2) In this study, the measured optimal values for the LAI_{max}, D_{max} and Y of summer maize used for verification were 5.21, 22088.92 kg/hm^2 and 12337.5 kg/hm^2, respectively. The corresponding optimal values obtained with the machine learning model were 5.36, 22054.0 kg/hm^2 and 12639 kg/hm^2, respectively. Moreover, the corresponding total water input and nitrogen application amount were basically consistent with the measured ranges from the field experiments;

(3) Based on the prediction model, a water–fertilizer coupling scheme suitable for local conditions could be obtained from the field soil quality data and plant density in different regions. This scheme is significant for guiding summer maize production. The water-fertilizer coupling functions for the LAI_{max}, D_{max} and Y of summer maize were constructed with the validation data-set for the experimental area. The values of R^2 were 0.9971, 0.9975 and 0.9957, respectively.

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