STUDY ON *NDVI* OPTIMIZATION OF CORN VARIABLE FERTILIZER APPLICATOR
/
变量施肥机 NDVI 的优化研究

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ABSTRACT

The large error exists in Normalized Difference Vegetation Index (NDVI) data because of soil reflectance. An optimal corn canopy NDVI data processing method was proposed in this study. The method was employed to reduce the effect of soil reflectance error under different leaf areas on corn canopy NDVI. First, an experiment was established using different plant spacings to obtain different canopy leaf area treatments. Then, the average NDVI of the largest leaf area (dense plant spacing) was used as the evaluation standard value. The NDVI mean values
after error elimination by Box-plot, Dixon rule and Pauta criterion were obtained under other leaf area treatments. The difference between the NDVI mean and the standard value, the R2 of the regression model between the NDVI mean value of each algorithm with corn parameter were used to evaluate the performance of the algorithm. Results demonstrate that the difference between the NDVI mean of the Box-plot and the standard control value is the smallest at 9% and 16% under normal plant spacing and sparse plant spacing, respectively. The R2 between the NDVI mean of the Box-plot and corn plant height has the best effect, increasing to 0.7676 and 0.5966 under normal plant spacing and sparse plant spacing, respectively. The R2 between the NDVI mean of the Box-plot and the nitrogen content of corn has a similar result, increasing to 0.7154 and 0.5739, respectively. These findings indicate that the Box-plot reduces the interference of soil background on corn canopy NDVI and improves the estimation ability of corn parameters.

摘要

土壤反射对冠层 NDVI 造成较大的干扰。本研究提出了一种最佳的玉米冠层 NDVI 数据处理方法。该方法用于降低不同叶面积下土壤反射率误差对玉米冠层 NDVI 的影响。首先，使用建立差异性的玉米株距处理得到不同的叶面积。随后， NDVI 平均值和标准值之间的差异及 NDVI 平均值与玉米参数（株高，氮含量）之间的回归模型的 R2 来评估各算法的性能。结果表明，在正常植物间距和稀疏植物间距下，箱图的 NDVI 平均值与标准对照值之间的差异最小，分别为 9%和 16%。箱形图的 NDVI 平均值与玉米株高之间的 R2 达到最大值，在正常植物间距和稀疏植物间距下分别增加至 0.7676 和 0.7154。箱形图的 NDVI 平均值与玉米氮含量之间的 R2 具有相似的结果，分别增加至 0.5966 和 0.5739。这些结果表明，箱形图减少了土壤背景对玉米冠层 NDVI 的干扰，提高了玉米参数的估算能力。

INTRODUCTION

Top-dressing, which is among the available measures of increasing corn production, is popular in agricultural practices. The amount of fertilizers received in several regions is uneven because of crop growth or spatial differences in soil nutrient (*Chen P. et al, 2010*). Fertilizer cycle exhibits dynamic changes, and predicting the supply of various nutrients to plants is difficult. Therefore, the unified quantitative fertilization method results in low fertilizer use efficiency (*Fangfang Zhang et al, 2017*). China' s comprehensive fertilizer utilization rate was 34% in 2017 (*Sun S.K. et al, 2018*).

Previous studies have shown that a variable fertilizer applicator for corn top-dressing can effectively improve fertilizer utilization (*Torsten I., 1982*). The variable decision of the fertilizer applicator in previous studies was based on the normalized difference vegetation index (NDVI) (*Geipel J., Link J., 2014*). Commercialized products have been introduced for variable fertilizer applicators based on this approach, and examples include the Case 3230, which is equipped with Greenseeker to detect crop canopy NDVI and thus reflect differences in growth. Greenseeker has been employed to control the motor and adjust the flow of liquid fertilizer in real time for variable fertilization (*Cicek H. et al, 2010*). However, corn top-dressing in China uses solid fertilizer, the variable fertilizing device is mechanical and the speed of variable fertilization regulation is limited. A variable fertilizer application machine adopts a uniform fertilizer amount on a fixed area. The average method is employed to express the overall situation of the fixed area' s NDVI (*Ali A.M. et al, 2015*). This process has become a great challenge in the accurate assessment of NDVI because of numerous influencing factors, such as leaf shape difference, corn canopy difference, and soil reflection. On the basis of the analysis above, this study examines a core problem in the improvement of NDVI' s detection accuracy.

Greenseeker is the most widely utilized near-surface plant canopy spectral detection sensor. The direction of Greenseeker measurement for corn canopy spectral reflectance detection has been tested, and results showed that the variation in the crop nutritional parameters of the output value of longitudinal measurement is higher than that of transverse measurement (*Ali A.M. et al, 2014*). The optimal height for Greenseeker measurements is 70–110 cm and sunlight exerts a minimal effect on Greenseeker' s performance (*Enciso J. et al, 2017*). A previous study added an adjustment factor based on NDVI to establish a soil-adjusted vegetation index (SAVI) and showed that corn nitrogen content prediction improves when the corn canopy coverage is 50% of the leaf area (*Chua T. et al, 2003*). Another study used mathematical iteration methods to perform an infinite number of iterations for removing the adjustment factors and established a modified SAVI (MSAVI); However, the feasibility of the index was not further verified (*Gianquinto G. et al, 2011*). Currently, NDVI is still the most widely used parameter in the estimation of plant nitrogen content. Using statistical methods to optimize NDVI can also effectively reduce the interference of background factors. For example, the maximum method has been applied to perform noise reduction processing on cotton canopy NDVI data and obtain the average NDVI of the detection area, thus reflecting the overall NDVI trend in the detection area (*Ramirez M.B., Schjoerring J K, 2015*). The following problems are encountered under actual production conditions. First, the corn leaf area cannot be obtained in real time. Second, a difference exists between cotton and corn canopy, and the application of the maximum method in the NDVI quantification of the corn canopy has not been verified.

A method of evaluating four types of algorithms for error culling to reduce the error data of NDVI by Greenseeker under different leaf areas was proposed. The NDVI of the optimal algorithm has the highest correlation with the plant height and nitrogen content of corn. The applicability of the maximum method to the NDVI of corn was also verified.

MATERIALS AND METHODS

The study area is located at the Heilongjiang Bayi Agricultural University research base in Daqing City, with latitude 46°63'–46°64'N and longitude 125°20'–125°21'E. The area of the research base is 50 hm^2. The soil type is chernozem, in which the thickness of the black soil layer is 25–40 cm and the organic matter mass fraction is high at 3.0%–4.0%. The basic conditions of the soil are shown in Table 1 (tested using the soil nutrient status system research method).

Table 1

The basic characteristics of the soil

Definition of the parameter	Parameter values
A. PH	6–7
B. Electrical Conductivity	232 μs/cm
C. Available Nitrogen	50 ppm
D. Total Nitrogen	32 ppm
E. Organic content	22 g/kg
F. Soil type	Chernozem

The research data were acquired using a ground-based remote sensing platform. The Greenseeker plant canopy spectral detector mainly obtains NDVI data of the corn canopy and its own narrow-band light emitting diode with red light at 660 nm and near-infrared light at 770 nm is used as the active light source. The second-generation optical sensor (N Tech) is used as a detection sensor to acquire plant spectral information under two bands. It has a measurement area of 61 cm ± 10 cm (width) × 1.5 cm ± 0.5 cm (length). The RT100 GPS (Trimble Company) obtains position information with an error of 1 cm.

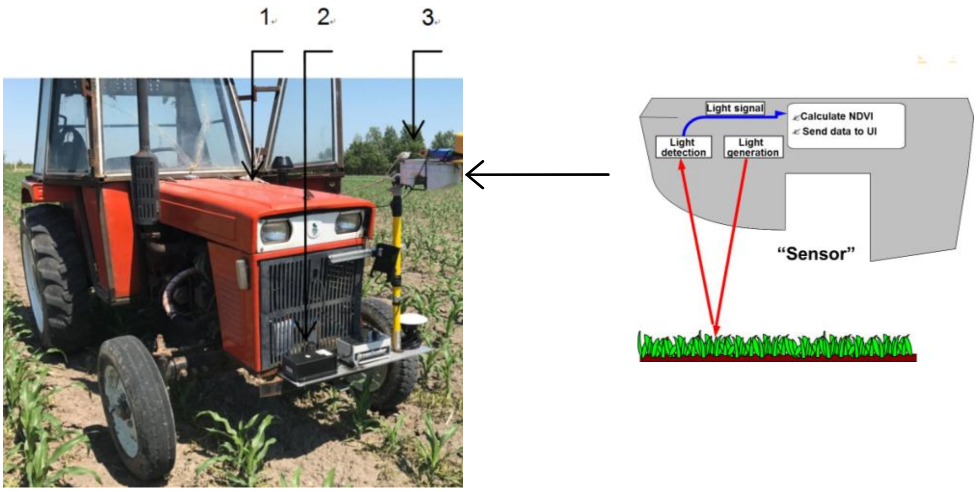


Fig.1 - Test data acquisition platform
1 – Tractor of 405; 2 – GPS; 3 – Greenseeker sensor

Test Design

Three different plant spacings of corn were set (Fig. 2): dense plant spacing (N1: 12 cm), normal plant spacing (N2: 18 cm) and sparse plant spacing (N3: 22 cm). Each plot area was 1.3 m × 100 m. Fertilizer was applied as urea, P_2O_5 and K_2O, in the ratio of 3:1:1 to give a total fertilizer application rate of 250 kg/hm^2.

Fig. 2 - Experimental setup for different plant spacing

Data Detection Methods

The data processing interval was 3 s, according to the operating speed (1.4 m/s) and separation of Greenseeker from the tailstock spreader (4.1 m). The Greenseeker vertical distance was 70 cm from the canopy and the detection direction was consistent with the ridge. The NDVI and GPS output frequencies were 26 times/s and 5 times/s, respectively.

Data Processing Methods

The error based on experience was an abnormally low value. First, the maximum method was used for data pre-processing. The 24 maximum values were selected based on the data processing interval (3 s), operating speed (1.4m/s) and standard plant spacing (18cm). Further error elimination of pre-processed data used the following methods:

Pauta criterion: If the difference between the measured value (x_n) and the average value ($\overline{x_n}$) is greater than N times the standard deviation (σ), then (x_n) will be eliminated. In this study n was 1 based on experience (*Cheng Shen et al, 2017*).

$$\alpha = \left| x_n - \bar{x} \right| > n\sigma \tag{1}$$

Dixon criterion: Calculates the *r* values in different orders according to formula (2) after arranging the data by size. This method compares the difference between the *r* value and the Dixon criterion test critical value; the data are eliminated when r_{max} and r_{min} are greater than the corresponding critical value *F* (0.05, m), or less than the corresponding critical value *F* (0.05, m) *(Grubbs F., 2012; Serth R.W. et al, 1986; Özyurt D., Pike P., 2004)*.

$$\begin{cases} r_{max} = \dfrac{x_n - x_{n-1}}{x_n - x_1}, r_{min} = \dfrac{x_2 - x_1}{x_n - x_1} (3 \le n \le 7) \\ r_{max} = \dfrac{x_n - x_{n-1}}{x_n - x_2}, r_{min} = \dfrac{x_2 - x_1}{x_{n-1} - x_1} (8 \le n \le 12) \\ r_{max} = \dfrac{x_n - x_{n-1}}{x_n - x_3}, r_{min} = \dfrac{x_3 - x_1}{x_{n-2} - x_1} (13 \le n) \end{cases} \quad (2)$$

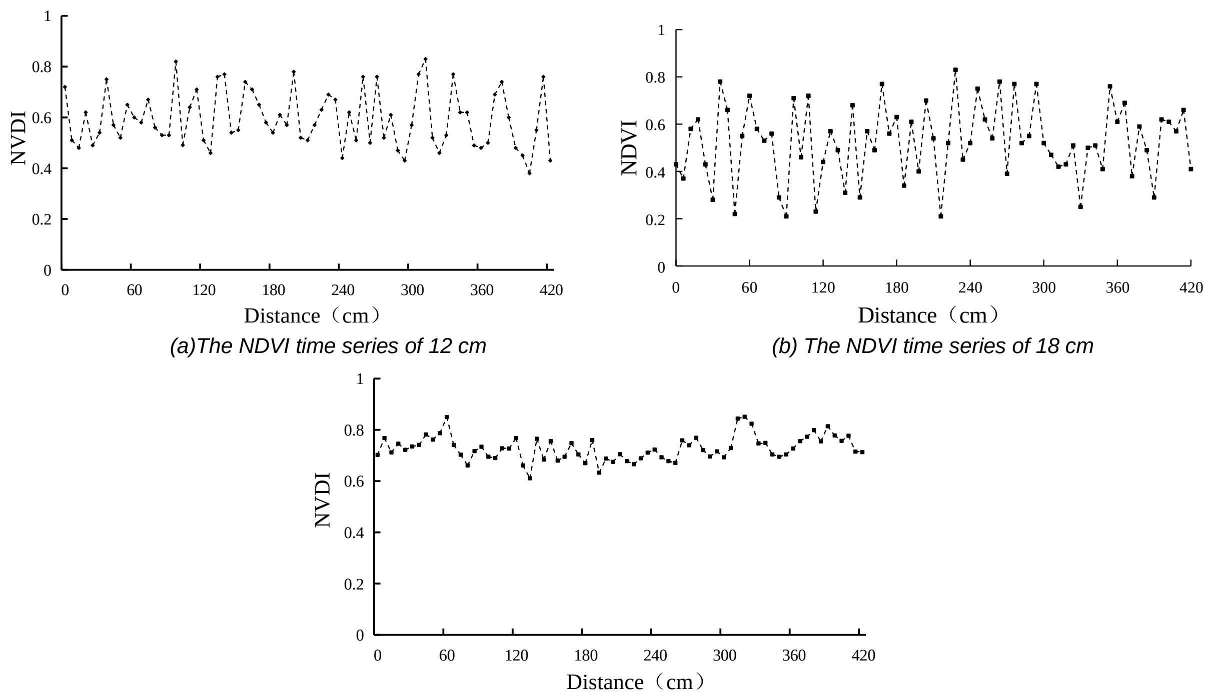
The Box-plot method: The 25% quantiles, 75% quantiles, top borders and bottom borders were obtained after sorting the data by size to create a Box plot, which describes the overall distribution of the data. The box contains most of the normal data, with outliers outside the upper and lower boundaries of the box (*Zhengjiang Zhang et al, 2014*).

Evaluation Methods

The NDVI of 42 meters (10 intervals) in the middle area was selected under each plant spacing. The dense plant spacing was basically free of soil exposure, so the NDVI mean value was employed as the evaluation standard value. Using different algorithms to eliminate the outliers of NDVI in each interval and obtain the overall mean at different plant spacings. The performance of different algorithms was evaluated by comparing the differences between the mean and the standard values. Five corn plants with uniform growth were selected in each interval to measure the mean value of nitrogen content and plant height under each plant spacing. The regression equations of NDVI, nitrogen content and plant height were established, and the fitness (R^2) was employed as the evaluation standard for each algorithm performance.

RESULTS

In Fig. 3, *a*, *b*, and *c* are the NDVI time series data obtained by the plant spacing of 12 cm, 18 cm and 22 cm, respectively. The change in NDVI data was gradual with the change in plant spacing because the area of corn canopy leaf increased and the soil background had less influence on the detection of crop canopy reflectance with the increase in plant spacing. When the plant spacing increased from 12 to 18 cm, the mutual shielding effects of the leaves became smaller, and the exposed area of the soil background increased. This led Greenseeker to integrate the measured values of the soil into the measured values of the crop canopy NDVI, resulting in a smaller NDVI detection value. Significant surface exposure was observed between plants, and the lowest value of canopy NDVI was detected when the maximum distance between rows was the largest. The NDVI continuous data obtained from the mean value of the largest plant spacing could not accurately describe the overall NDVI trend.



(a)The NDVI time series of 12 cm
(b) The NDVI time series of 18 cm
(c) The NDVI time series of 22 cm

Fig. 3 - Change of NDVI data with different plant distance within a certain distance

The mean after pre-processing the NDVI data of each plant spacing using the maximum value method increased significantly, but there was still a large difference between the mean and the standard control value (Table 2). Therefore, the NDVI maximum value needs to be further processed to reduce the error rate.

Table 2

Maximum value processing mean

Treatment	Plant spacing (cm)	The mean of NDVI	Mean value of NDVI processed by the maximum value
N1	12	0.781	0.786
N2	18	0.51	0.66
N3	22	0.42	0.53

Data Processing Algorithm Performance

Pauta criterion: After the elimination of data by comparison of the standard deviation of pre-processed data using formula (1). As shown in Fig. 4, the mean of Pauta criterion for N2 and N3 were 0.709 and 0.657, respectively. The average N2 data processed by Pauta criterion was not significantly different from the mean of Maximum method and the difference from the standard value was 11%. The average N3 data processed by Pauta criterion was no significantly different (F >0.05) from the mean of Maximum method and the difference from the standard value was 18%.

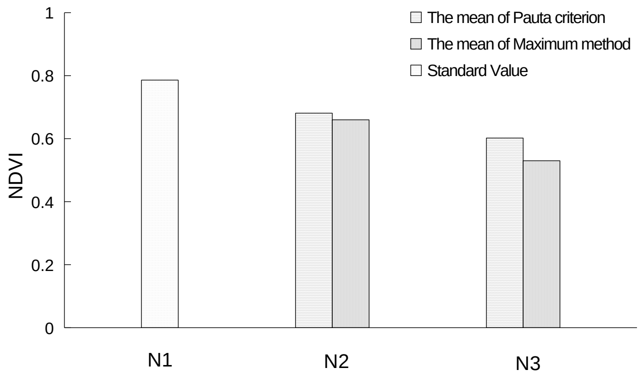
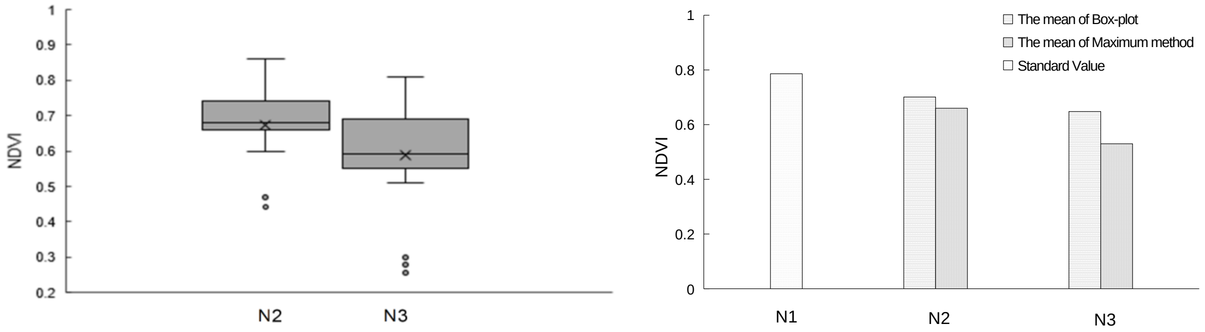


Fig. 4 - The treatment of NDVI mean by Pauta criterion

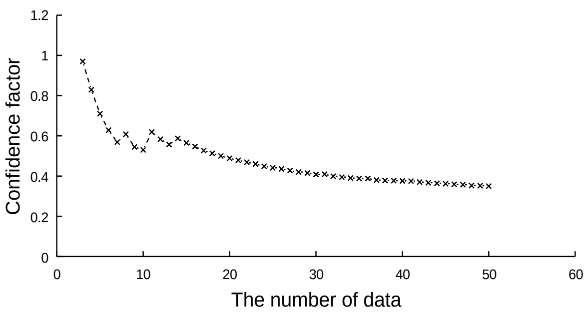
The Box-plot method: As shown in Fig. 5-a, there were two error points and three error points for N2 and N3 which were eliminated by Box-plot, respectively (Fig. 5-a). The mean of Box-plot for N2 was 0.722; its difference with the standard values was 9% and it had no significant difference (F>0.05) with the mean of Maximum method (Fig. 5-b). The mean of Box-plot for N3 was 0.689, its difference with the standard values was 16% and it had no significant difference (F >0.05) with the mean of Maximum method (Fig. 5-b).



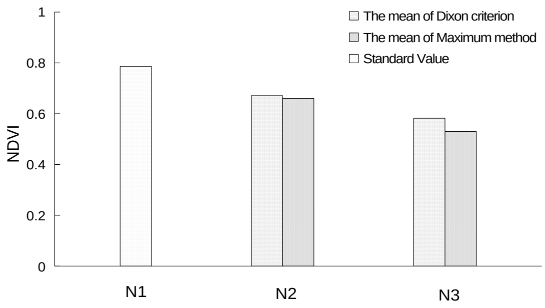
(a) The error values of Box-plot *(b) The average value of Box-plot*

Fig.5 - Line map box of different plant distance processing

Dixon criterion: The r_{max} and r_{min} for all data were calculated according to the Dixon criterion confidence factor (as shown in Fig. 6-*a*) and formula (2). The mean of Dixon criterion *for N2* was 0.693, its difference with the standard values was 12%. The mean of Dixon criterion *for N3* was 0.649, its difference with the standard values was 19%. At same time, the mean of Dixon criterion for N2 and N3 had no significant difference with the mean of Maximum method (Fig. 6-b).



(a) The eigenvalues of Dixon criterion

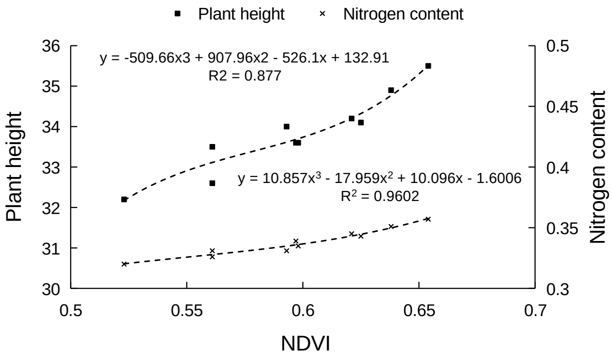


(b) The average value of Dixon criterion

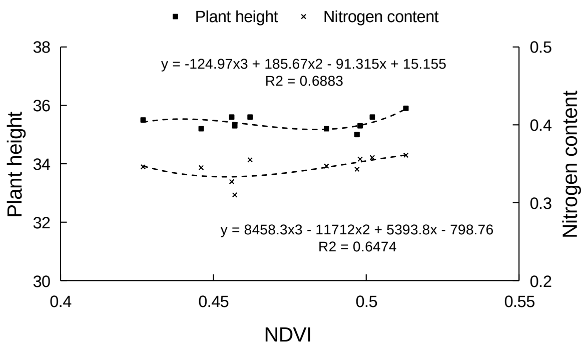
Fig 6 -Different plant distance processing of Dixon criterion

Estimation of corn nitrogen content and plant height at different plant spacings

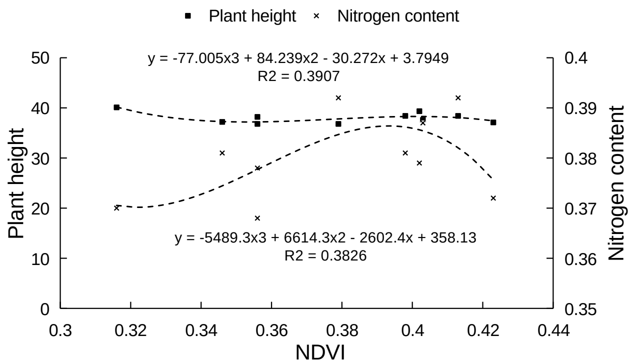
As shown in Fig.7*a*, at the close planting distance, the R^2 between NDVI and plant height was of plant height and nitrogen content 0.877, and the R^2 between NDVI and nitrogen content was 0.8134. At this time, it accurately inverted the growth state of corn. With the increase of plant spacing, the soil background interference existed under normal plant spacing, but the fitting degree R^2 of plant height and nitrogen content were greater than 0.6 (Fig.7-*b*), the NDVI could predict the growth parameters. At sparse plant spacing, the R^2 of plant height and nitrogen content were significantly lower than other plant spacing, indicating that NDVI could not be used for corn parameter estimation (Fig.7-*c*).



(a)The regression model of 12cm



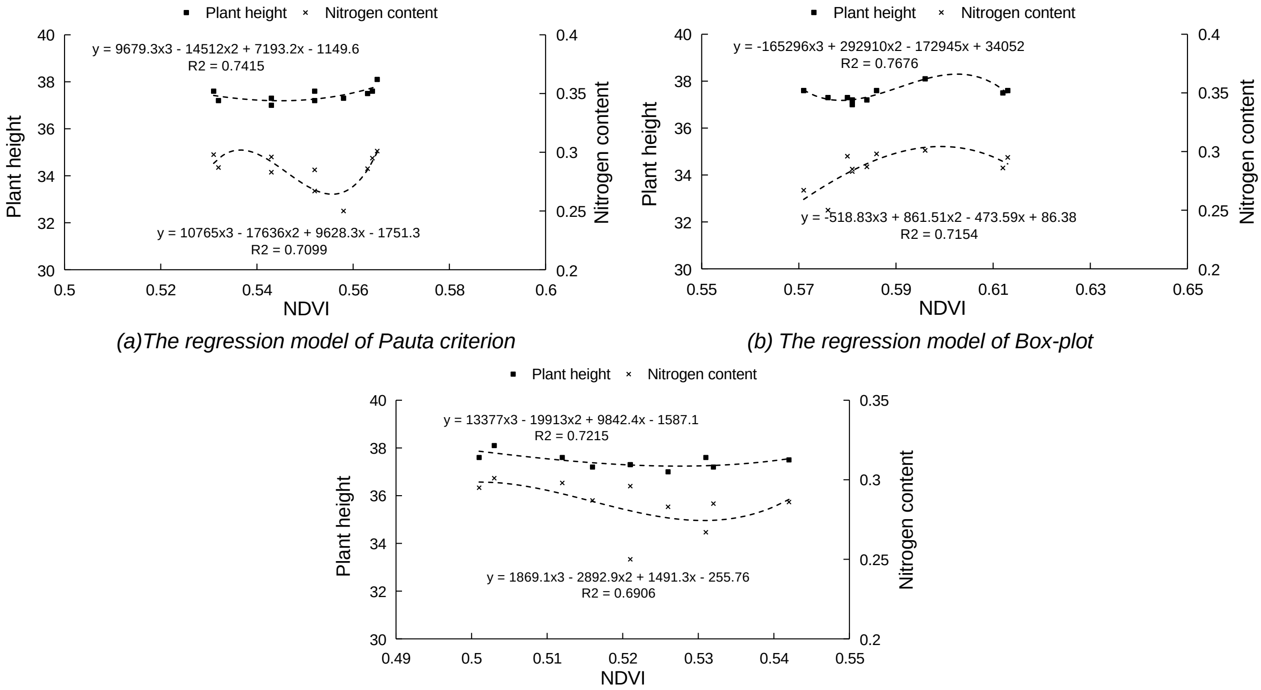
(b) The regression model of 18cm



(c) The regression model of 22cm

Fig 7 - Estimation of plant height and nitrogen content of original NDVI data with different row spacing

In Fig. 8, *a*, *b*, and *c* represent the regression model of the plant height and nitrogen content of the Pauta criterion, the Box-plot and the Dixon law under the normal plant spacing (N2), respectively. The R^2 of the plant height and nitrogen content were improved to different degrees by different algorithms. The R^2 of the Box-plot were processed having the maximum value. Compare with the dense plant spacing, the difference rates of R^2 were 10.6% and 13.7%, respectively. However, the R^2 change was not obvious compared to the original data, indicating that the abnormal value had no significant effect on the accuracy of corn canopy NDVI under normal plant spacing.

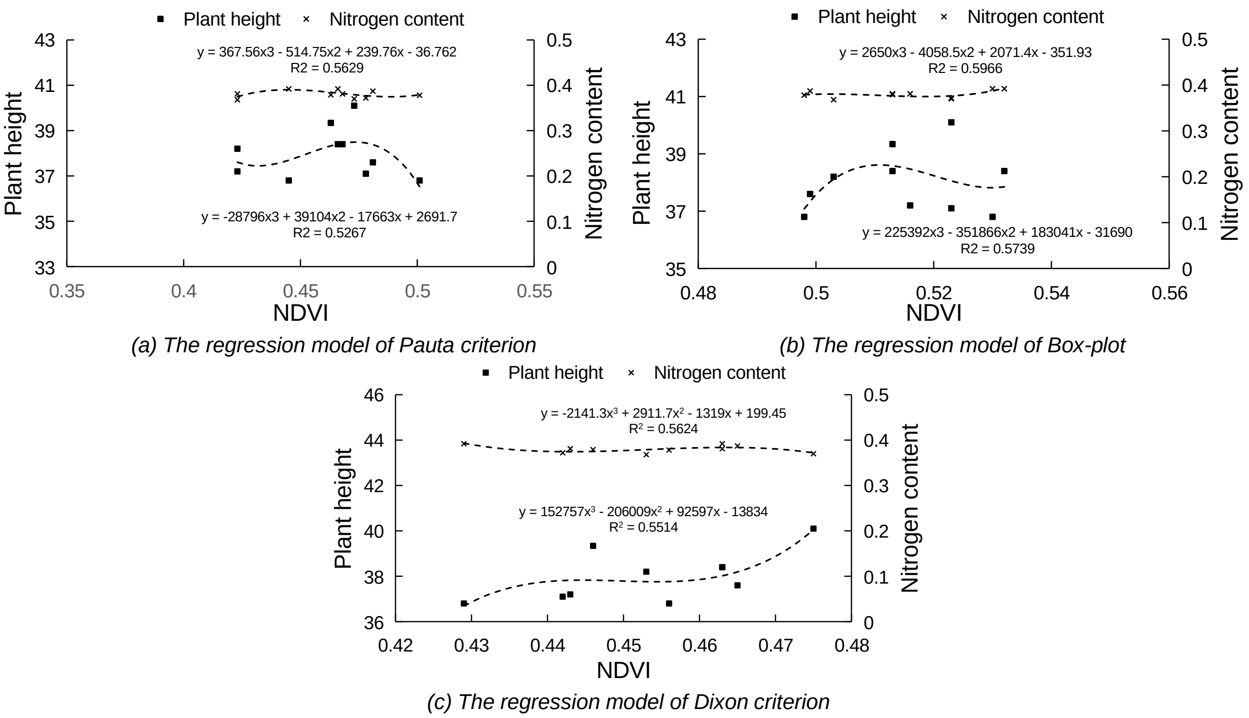


(a)The regression model of Pauta criterion *(b) The regression model of Box-plot*

(c) The regression model of Dixon criterion

Fig 8 - Estimation of plant height and nitrogen content of NDVI at normal plant spacing

Compared with the original data, the R^2 has been significantly improved by the data processed by different algorithms under the sparse plant spacing (N3). The Box-plot has the best results and the R^2 of the plant height and nitrogen content have maximum value, which are 36% and 30% higher than the original data, respectively. There was no significant difference between R^2 after treatment under normal plant spacing, indicating that the NDVI data processed by the Box-plot under sparse plant spacing significantly reduced the disturbance of soil background.



(a) The regression model of Pauta criterion *(b) The regression model of Box-plot*

(c) The regression model of Dixon criterion

Fig 9 - Estimation of plant height and nitrogen content of NDVI at sparse plant spacing

Discussion

In this study, the NDVI of corn canopy obtained from Greenseeker was used to study the effects of different NDVI data error elimination algorithms to reduce the interference of soil background under different leaf area. The NDVI mean after error elimination was used to accurately describe the overall trend of NDVI in the detection area.

The corn canopy spectral reflectance is the key to real-time monitoring of corn nitrogen status. The canopy reflectance of plants is measured by satellite, aircraft and ground equipment equipped with spectral image sensors or plant spectral detectors. Satellite and aircraft remote sensing platforms have limited application in crop management because of their own operational cycles and cloud, weather and low resolution *(Cicek H. et al, 2010; Geipel J., Link J., 2014).* Ground remote sensing is a good way to overcome the above problems, as it is conducted close to the plants (50– 150 cm) and can be used in conjunction with variable-rate fertilizer applicators for real-time variable fertilization *(Nakajima Teruyuki T. et al, 1996; Michael T et al, 2016)*.

The bare soil light reflectance is the main problem that affects the accuracy of NDVI of corn canopy. It is difficult to strip soil reflectance from NDVI data. Statistical methods are employed to reduce the interference of soil background on NDVI. For example, the Curve fitting *(Bradley et al, 2007; Chen J., Per J., 2004)*, asymmetric Gaussian function fitting *(Nan Cong, 2012; Zhuokun Pan et al, 2015)* and Fourier transform *(Quiroz R. et al, 2011; Yang Shao et al, 2016; Du Ming Tsai and Wan-Ling Chen, 2017)* methods were employed to reconstruct NDVI data and reduce outliers. The appeal methods are based on the least-squares method and the time-frequency conversion principle, which are limited in real-time applications because of computational complexity. The experimental design was based on the work of *(Ramirez M., Schjoerring J.K, 2015)* and verified the efficiency of the algorithm in corn applications. The results showed that the optimal algorithm reduced the influence of soil light reflectance on corn canopy NDVI to a certain extent, but the large errors in the NDVI data after processing because the canopy is different between cotton and corn *(Atanassov R. et al, 2009)*. Alternative data processing methods, such as Pauta criterion and Dixon criterion are tested because they are simple to calculate and can be applied under actual production conditions. All of the data processing methods remove outliers based on their particular threshold values. The Dixon criterion automatically set the threshold according to the amount of data. In this study, The Box-plot determines the threshold according to the characteristics of the data. It does not require prior knowledge and accurately removes outliers of NDVI data when compared with other algorithms. Simultaneously, the correlation between the mean value of NDVI by the Box-plot and the nitrogen content is 0.94. Accuracy of nitrogen content estimation is improved compared to other studies *(Scharf P.C et al, 2002; Kyle W et al, 2007)*. Application of the Box-plot effectively improved the accuracy of the NDVI-based variable fertilization model.

The test plant spacing, evaluation criteria and area of the test space are set according to the characteristics of the fertilizer application or for a certain purpose. With the development of the electronically controlled fertilization device, the NDVI method for a smaller area can be studied to further improve the refinement of corn canopy growth and further reduce the amount of fertilizer applied. At the same time, the applicability of this method can be studied in other crops such as rice, wheat, soybean, and cotton. The method can be applied to forestry surveys, land use monitoring *(Michael T et al, 2016)* and other applications, to improve the popularization of the method and to be able to use remote sensing error analysis, remote sensing applications in statistical techniques and for other applications.

CONCLUSIONS

To reduce the interference of soil reflection on corn canopy NDVI under different leaf areas, a case study was made to compare the performance of three types of error culling algorithms. A novel method based on the Box-plot method was developed to reduce the effect of soil background on corn effective NDVI and improve the accuracy of NDVI estimation of corn plant height and nitrogen content. The following conclusions were obtained.

(1) The NDVI error depends on the leaf area. When the leaf area is small, NDVI has a large error.

(2) Under a different leaf area, the Box-plot method exhibits the best performance. When NDVI has a large error, the Box-plot method considerably improves the estimation of NDVI, corn plant height and nitrogen content.

(3) Although the maximum method improves the effectiveness of NDVI compared with the averaging method, a large error is observed when the leaf area is small. The method is suitable for small leaf crops, such as cotton.

The resulting method considers the variation in leaf area to achieve a highly accurate simulation of the actual application. However, leaf area is affected by many factors and the proposed method is limited to considering the influence of plant spacing. Future research should consider other influencing factors.

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