*Retraction*

# Retracted: Monitoring and Analysis of Cotton Planting Parameters in Multiareas Based on Multisensor

## Mathematical Problems in Engineering

This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope

(2) Discrepancies in the description of the research reported

(3) Discrepancies between the availability of data and the research described

(4) Inappropriate citations

(5) Incoherent, meaningless and/or irrelevant content included in the article

(6) Peer-review manipulation

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

## References

[1] Z. Fan, N. Zhang, D. Wang, J. Zhi, and X. Zhang, "Monitoring and Analysis of Cotton Planting Parameters in Multiareas Based on Multisensor," *Mathematical Problems in Engineering*, vol. 2022, Article ID 7013745, 8 pages, 2022.

*Research Article*

# Monitoring and Analysis of Cotton Planting Parameters in Multiareas Based on Multisensor

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In order to realize cotton growth monitoring, a cotton planting monitoring system based on image processing technology was proposed. The system requires camera to collect cotton canopy images, leaf areometer to detect the leaf area index, and spectrometer to detect the normalized vegetation index (NDVI) and the vegetation index (RVI). Due to different types of data, based on the establishment of the output transmission system, the canopy coverage was calculated by the image processing method, and there was a linear relationship between canopy coverage NDVI and RVI. The leaf area index (LAI) of $N$ content was established, and the model of dry matter accumulation and canopy coverage was exponential. The experiment result shows that the linear and exponential coefficients of the model $k$ and $b$ increased with the increase of the nitrogen application rate. The fitting determination coefficient remained high under different nitrogen application rates. The fitting coefficient $R2$ of the three models in the two test fields ranged from 0.83 to 0.923, which also met the needs of model evaluation. The system was used to detect the cotton field with good accuracy.

## 1. Introduction

Agriculture is the basic industry of a country. It is the basic principle and law of agricultural production to develop agriculture according to local conditions, rationally utilize agricultural resources, and give play to regional advantages according to the regional distribution law of agriculture. Precision agriculture represents the direction of agricultural development and is also the focus of agricultural research. Compared with traditional agriculture, precision agriculture is characterized by the maximum saving of natural resources and the minimum pollution of the ecological environment in exchange for high-tech and scientific management [1]. Its core is to divide the whole field appropriately into a number of small pieces, timely access to small pieces of land information. Decisions are made on a plot basis, taking into account differences in natural conditions, and farming operations are carried out accurately on each plot, that is, real-time diagnosis of spatial differences in soil properties and crop growth conditions. On this basis, the timed, positioned, and

prescription farming can be achieved to make full use of modernized and mechanical technique to achieve intensive farming and obtain high economic benefits [2, 3].

At present, due to the lack of farmland information acquisition technology with low cost, high density, high accuracy, and high reliability, field information acquisition has become a bottleneck restricting the development of precision agricultural technology. Remote sensing technology, with its macrocharacteristics of rapid, real-time, accurate, and economical, provides the possibility to solve this problem.

Remote sensing technology is an important key technology to implement precision agriculture, which can obtain accurate information of crop growth and development, disease, insect, grass, water, and fertilizer, and corresponding environmental conditions in real time. It is an important tool to obtain field information of precision agriculture. In recent decades, remote sensing technology has made an important contribution in monitoring crop yield and forecasting crop conditions in large areas of agricultural resources.

## 2. Literature Review

Remote monitoring technology of crop growth monitoring mainly uses CCD camera to collect remote image data and transmits the remote image captured by the camera to the control center through the wired wireless network or the mobile network. The control center processes the image and extracts relevant variable parameter values, currently uses CCD camera remote monitoring plant growing appearance information study which is also less and mostly uses the crop remote physiological monitoring technology PRPMT (plant remote physiological monitoring technique), through the various sensors installed in the plant body probes, monitoring of environmental factors, and crop. Changes in physiological indicators, soil moisture content, etc. [4, 5], Fouzi et al. developed a static image network real-time acquisition system, which consists of a camera support system and two subsystems. The camera support system enables network users to control the camera orientation and focal length and obtain a still image in real time [6]. Database support system server is to provide users with collected images. Database support system and camera support system work in coordination, regularly automatically obtained field images in the form of remote database provided to users, and users can retrieve the collected images according to the shooting time. Küük and Öveçoğlu monitored the environmental factors such as atmospheric temperature, humidity, soil humidity, light intensity, atmospheric vapor pressure difference, and tree physiological indexes such as fruit growth and leaf temperature in litchi orchard by using the plant dialogue monitoring system [7]. Moraes et al. studied the greenhouse environmental information acquisition system based on GPRS and WEB, and successfully realized the remote detection of the temperature, humidity, $CO_2$ concentration, and light intensity of the air and soil in the greenhouse by using ASP.NET technology and the B/S mode. It is pointed out that the accuracy and deviation of detection data mainly depend on the accuracy and error of sensors [8]. Caro-Ruiz et al. studied a static image acquisition technology based on WEB and built a crop image acquisition and a management system based on WEB [9]. Wang et al. combined the idea of network technology, computer vision technology, image processing, and data analysis technology to establish the prototype of the corn growing information remote monitoring system based on the B/S mode [10]. At present, the mainstream cotton growth monitoring methods are laboratory spectral analysis and image analysis [11].

On the current basis of this article in laboratory spectral analysis, NDVI and RVI were detected by spectrometer, and then the growth status model was established to evaluate the growth status. Image analysis is to establish the cotton growth model, with the characteristics of fast detection speed, but the model establishment process did not consider many factors, the accuracy is often poor that this system uses image processing and a spectral analysis method, establishes the cotton growth model, while introducing spectral analysis and leaf analysis, and improves the accuracy of the model. Because of the difference between cotton image acquisition, incoming spectral analysis, and leaf analysis data acquisition, IMS technology is adopted to establish a network system that can realize the transmission of various data types. The test results show that the system has higher detection accuracy.

## 3. Research Method

*3.1. System Composition.* In order to realize the real-time evaluation of cotton growth status, the leaf area index (LAI) of surface plant $N$ content and dry matter accumulation of surface plant were used as standards to establish the cotton growth status model based on IMS multiarea technology [12]. The system collects cotton canopy images by the camera and transmits them to the application service layer through the IMS system for canopy image processing and canopy coverage calculation. Then, with canopy coverage as the variable, the leaf area index (LAI) of $N$ content and dry matter accumulation on the surface as the stress variables, three growth index models were established. The leaf area index (LAI) was collected by the LAI instrument, and the normalized vegetation index (NDVI) and the vegetation index (RVI) were collected by the spectrometer to test the feasibility of the model. After the growth model was established, the camera collected the canopy image of the cotton field to be tested, calculated the canopy coverage, and then calculated the three growth model indicators of the cotton field to be tested to evaluate the growth status of the cotton field. The system terminals include cameras, leaf areometers, and spectrometer. The output of the camera is image continuous data, and the output of leaf areometers and spectrometer is Atlas data, as shown in Figure 1 [13].

Application services include canopy image processing, growth model establishment, target cotton field canopy image detection, and other functions in the process of transmitting detection data from system terminals to application services. Due to different data forms at the terminal layer, the IMS system should be used to build models. MRCF and MRPF are relay servers and control servers, respectively. MPT-SCF is the execution point of the media multipath transmission function supported by IMS and can complete tasks such as registration session establishment and multipath transmission service authorization, and complete the allocation and release of the relay path in the interaction with the relay server control server.

*3.2. Canopy Image Coverage Calculation.* Timely intervention is very important to improve cotton quality and yield when cotton growth is not good. Canopy area is closely tied to the cotton growth state, the cotton canopy image captured by the camera, and image processing calculation of cotton coverage $C$, and then set up on the Earth's surface and plant $N$ content of the leaf area index, dry matter accumulation of cotton plant growth parameters, and model between cotton canopy coverage, an effective evaluation of the current cotton growth situation.
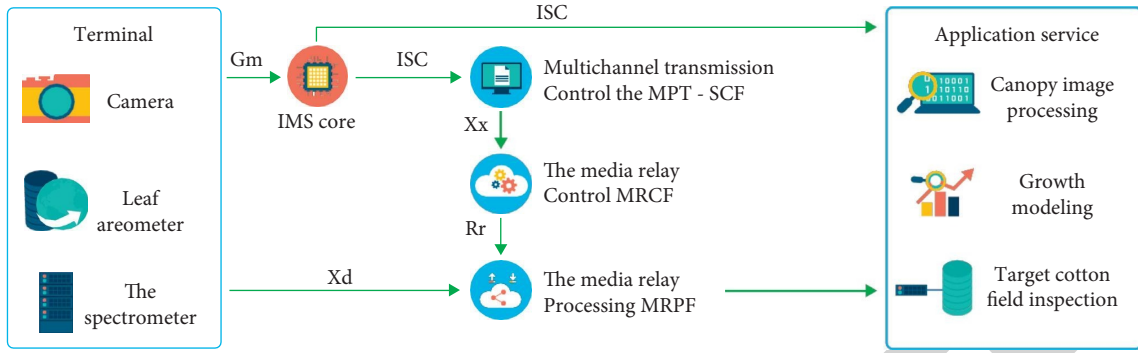
Figure 1: System composition.

*3.2.1. Picture Processing.* The image of the cotton canopy is collected by the camera, and the binary image of the cotton canopy is obtained by image enhancement processing to realize the calculation of the cotton coverage rate [14]. Image processing includes the following steps: canopy image enhancement. When the camera is collecting the cotton canopy image, it is affected by light intensity at different times, so it is necessary to suppress the influence of light conditions on the cotton canopy image. Image gray processing combines the information of $R$, $G$, and $B$ channels into the same gray intensity. Binary processing: the pixel value of cotton canopy leaves is 255, and the rest is 0. Image filtering processing is carried out for the spot-like salt and pepper clutter in the binary image, and finally a clear cotton canopy binary image is obtained.

When the camera head shoots the cotton canopy image, it will be affected by different environmental light, resulting in different image clarity. In order to effectively eliminate the influence of illumination and other environmental factors on the image, an algorithm is designed to suppress stray light [15]. Cotton canopy image is taken at 7:00 and it is known that the image $I(x, y)$ obtained includes cotton canopy $R(x, y)$ image and stray light. Now, the stray light is suppressed, and formula (1) can be obtained as

$$R_{n,i}(x, y) = \log \left[ \frac{I(x, y)}{I(x, y) * N e^{-(x+y)^2/\delta_i^2}} \right], \quad (1)$$

$N$ is the normalized parameter of Gaussian function; $\delta$ is the Gaussian standardization deviation, which affects the local contrast of the image. Three scales, 15, 90, and 250, are used for calculation $\delta$.

In the three channels, the intensity of the first channel is

$$R_{\text{MSR},i}(x, y) = \sum_{n=1}^{3} W_n R_{n,i}(x, y). \quad (2)$$

$w_n$ is the weight coefficient of three scales.

The intensity of the three channels is adjusted again, and the final intensity $R_{\text{MSR},i}(x, y)$ of the three channels is calculated as

$$R_{\text{MSRCR},i}(x, y) = C_i R_{\text{MSR},i}(x, y). \quad (3)$$

$C_i$ is the secondary adjustment coefficient of 3 channels.

$$C_i = \log[\alpha I_i(x, y)] - \log \sum_{i=1}^{3} I_i(x, y). \quad (4)$$

Among them, the value range of $\alpha$ is 0.5~2. After image enhancement, the edge of ridges and cotton leaves becomes clear.

Grayscale processing and binary processing are carried out on the image after enhanced processing. The grayscale processing adopts index $\text{MExG} - \text{ExR}$, then, formula (5) is obtained as

$$\text{MExG} - \text{ExR} = 2G - 1.9R - B. \quad (5)$$

$G$, $B$, and $R$ are the three channel intensities of the enhanced images, respectively, which are transformed into gray images, and then binarization processing is carried out by the maximum variance method. There are discrete interference points in the ridge of the cotton field, and there are also discrete interference points in the leaf area. Now, the median filtering method is used to remove the interference points in the binary image.

*3.2.2. Calculation of Canopy Coverage.* After image enhancement, the binary image of separation between the cotton canopy and the field ridge was obtained, and the canopy coverage was calculated by the statistical method to prepare for the establishment of cotton growth parameters and the canopy coverage model, such as surface plant $N$ content, leaf area index, and surface plant dry matter accumulation.

Canopy coverage is the ratio of the canopy leaf area to the area of the whole image. It is known that the size of the canopy binary image is $m \times n$ pixel and the gray scale $R(i, j)$ is 255 pixels, so canopy coverage $C$ is the following formula:

$$C = \frac{\sum_{j=1}^{m} \sum_{j=1}^{n} R(i, j)}{m \times n}. \quad (6)$$

*3.3. Model of the Cotton Growth State.* $N$ is an important component of chlorophyll, which determines the photosynthetic capacity of plants. Leaf growth is also related to photosynthesis and transpiration of nutrient elements transport. Material accumulation can indicate the current

plant material accumulation degree. Normalized vegetation index (NDVI) and the vegetation index (NDVI) of the cotton canopy are the current mature evaluation parameters of the cotton growth state, which can be detected by the spectrometer. The research ideas are as follows: to explore the relationship between canopy coverage $C$,NDVI, and RVI, and to determine the feasibility of using canopy coverage $C$ to characterize the cotton growth state; leaf area index (LAI) $C$ and canopy coverage $N$ were used to model dry matter accumulation of plants on the surface [16].

*3.3.1. The Relationship between CC, NDVI, and RVI.* Vegetation index RVI has been widely used to evaluate the growth condition of vegetation qualitatively and quantitatively, and NDVI can represent the content of $N$ elements in vegetation, and then evaluate whether plants need to apply nitrogen fertilizer. The two parameters are mature and can be detected by the spectrometer. The relationship between canopy coverage rate $C$ and canopy coverage rate RVI, NDVI is studied, and the feasibility of the canopy coverage rate to characterize the plant growth state is discussed [17].

The relationship between different canopy coverage rates and their corresponding NDVI relationships is established, as shown in Figure 2. On the whole, canopy coverage rates and NDVI show a linear distribution.

$$\text{NDVI} = 0.91C + 0.093. \tag{7}$$

The linear determination coefficient is 0.95, indicating a good linear correlation between the canopy coverage rate and canopy coverage rate NDVI, and the linear fitting performance is high in the range [0.3–0.6]. With the increase of canopy coverage, the accuracy of the model decreased, indicating that canopy coverage can effectively represent the $N$ element content in plants.

The relationship between the canopy coverage rate and RVI is also linear, showing that the canopy coverage rate RVI gradually decreases with the increase. The linear fitting result is shown in the following equation

$$\text{RVI} = -0.736C + 0.664. \tag{8}$$

The linear correlation coefficient $R2$ was 0.96, and the fitting degree was the best in the range [0.45–0.7]. The results showed that both canopy coverage and RVI, NDVI had good linear correlation, so it was feasible to characterize the growth state of cotton by canopy coverage $C$.

*3.3.2. Establishment of the Cotton Growth Model.* Leaf area index (LAI) of plant $N$ content and dry matter accumulation on the ground surface were selected as the growth characteristic parameters of cotton. The $N$ content of plant could effectively represent chlorophyll content, the leaf surface index could represent the growth state of plant leaves, and dry matter accumulation on the ground surface could represent the matter accumulation of cotton. Canopy coverage was used as a variable; the leaf area index (LAI) of plant $N$ content and dry matter accumulation on the ground were used as stress variables to establish models [18, 19].
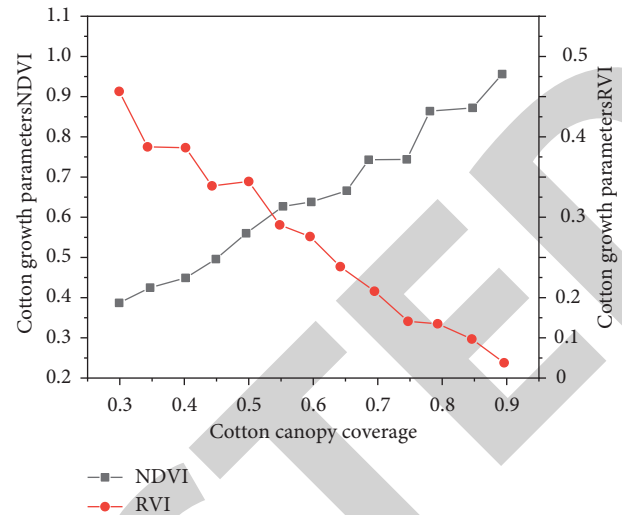


Figure 2: Relationship between canopy coverage and RVI, NDVI.

In the experiment, plant $N$ content was detected by the Kjeldahl nitrogen determination method. Leaf area index was determined by the digital leaf area meter to measure the leaf area index (LAI) of a single cotton plant [20]. The cotton leaf area index (LAI) per plant was multiplied by the number of cotton plants per unit area to determine the cumulative amount of dry matter on the surface of the plant: separate the single cotton sample, dry it in 105°C oven for 30 min, dry it in 80°C oven until the quality is not reduced, and then weigh it. The dry matter mass per plant was multiplied by the number of plants per unit area to obtain the dry matter mass of the upper part of the ground.

Figures 3(a)–3(c) were, respectively, used to fit the canopy coverage with the plant $N$ content and the leaf area index (LAI) with the plant dry matter accumulation on the surface.

Figure 3(a) shows the fitting results of canopy coverage and plant $N$ content, which are distributed in exponential form, and the fitting determination coefficient is 0.94, i.e.:

$$y = 0.712e^{4.187C}. \tag{9}$$

Figure 3(b) shows the fitting results of canopy coverage and the leaf area index, the distribution is exponential, and the fitting determination coefficient is 0.89, i.e.:

$$y = 0.462e^{2.564C}. \tag{10}$$

Figure 3(c) shows the fitting results of canopy coverage and cumulative dry matter amount of plants on the surface, which are distributed in an exponential form, and the fitting determination coefficient is 0.92, i.e.:

$$y = 0.769e^{4.245C}. \tag{11}$$

Comprehensive analysis showed that the growth index and canopy coverage of three kinds of cotton were exponential distribution. And the lowest model fitting determining coefficient is 0.89, showing that the fitting model has high precision.
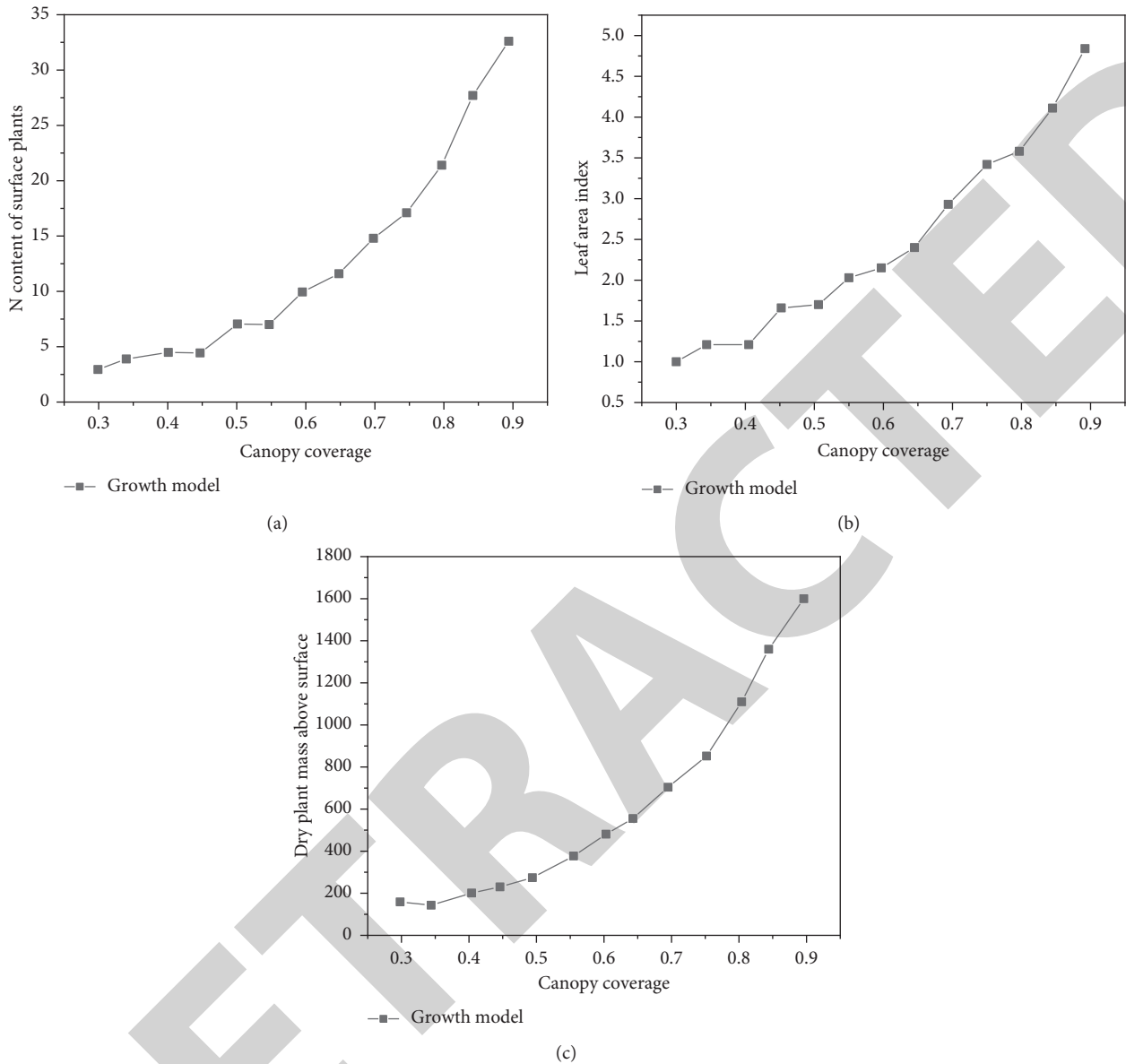
(a)



(b)



(c)

Figure 3: (a–c) Cotton growth model.

3.4. Effect of N Fertilizer Dosage on Cotton Growth. Nitrogen is a component of chlorophyll, under the action of chlorophyll plants will be water and $CO_2$ into sugar; sugar is the plant growth and accumulation of raw materials. At the same time, the effect of nitrogen on plant growth and development is very obvious, plants can use nitrogen to synthesize more protein, promote cell division and growth, and then grow more leaves, generate more chlorophyll, to achieve stable and sustainable growth of cotton. In this paper, cotton images with different nitrogen application rates were tested to calculate canopy coverage, and then the leaf area index (LAI) of plant N content and dry matter accumulative amount of plants on the surface were calculated through the model to evaluate the current growth status of cotton and guide nitrogen topdressing.

3.4.1. N Fertilizer Dosage and the Cotton Growth Index Model. According to the cotton growth model, the leaf area index (LAI) of plant N content and the cumulative dry matter amount of plant on the surface are both exponential relationships with canopy coverage, i.e.:

$$y = ke^{bC}. \qquad (12)$$

The effects of N fertilizer dosage on the leaf area index of plant N content and dry matter accumulation of plants on the ground surface were analyzed. The method was to fit the cotton canopy coverage and growth index $k$ under different N fertilizer dosage, and the linear coefficient is shown in Figure 4. In general, the linear coefficient of the fitting model of the three indexes increased with the increase of nitrogen
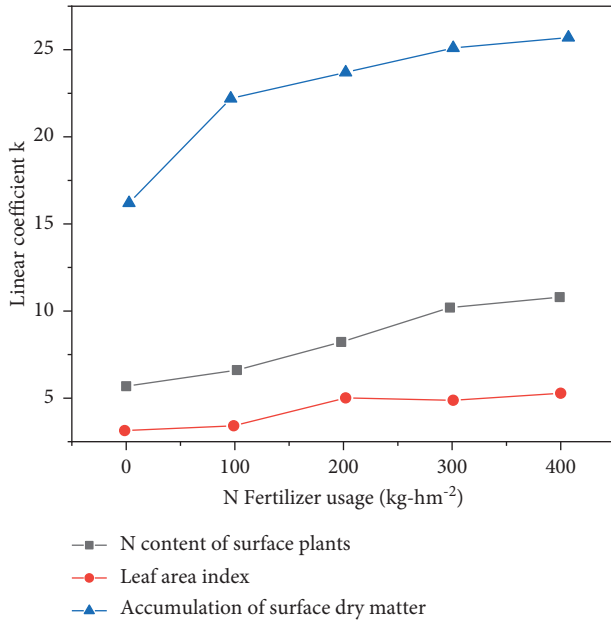
Figure 4: Effects of nitrogen dosage on cotton growth.



Figure 5: Effect of $N$ fertilizer dosage on model accuracy.



Figure 6: System testing.

content: the linear coefficient $k$ of the plant $N$ content model increased from 0.49 to 0.8. The linear coefficient of the LAI model increased from 0.385 to 0.481. The linear coefficient $k$ of dry matter accumulation model increased from 23.5 to 28.74. The effects of nitrogen application rate on the three growth indexes from high to low were dry matter accumulation and leaf area index, respectively.

*3.4.2. Effect of N Fertilizer Dosage on Model Fitting Accuracy.* Nitrogen application is ranged from 0 to 400 kg/hm$^2$. The fitting accuracy of three growth models under different nitrogen application rates was tested, and the changing trend of model accuracy under different nitrogen content was tested. Under different nitrogen application rates, the models between plant $N$ content, leaf area index (LAI), plant dry matter accumulation on the surface, and canopy coverage were fitted, and the corresponding fitting determination coefficients were calculated. As shown in Figure 5, the fitting determination coefficients $R2$ of the three models were all greater than 0.84, indicating that the above three models had high reliability [21]. Among them, the fitting accuracy of $N$ content in surface plants was the highest, and the distribution range was 0.949–0.978, which showed a trend of increasing first and then decreasing, and reached the maximum value when the $N$ application rate was 300 kg/hm$^2$. The fitting accuracy of the foliar index was next, with a distribution range of 0.846~0.938, which increased first and then decreased, and reached the maximum value at 300 kg/hm$^2$. The fitting determination coefficient of plant dry matter accumulation on the surface was the lowest, which showed a trend of increasing first, then decreasing and then increasing, and also reached the maximum value when the $N$ fertilizer amount was 300 kg/hm$^2$. The analysis of fitting determination coefficient showed that nitrogen fertilizer dosage had a certain influence on the model accuracy and
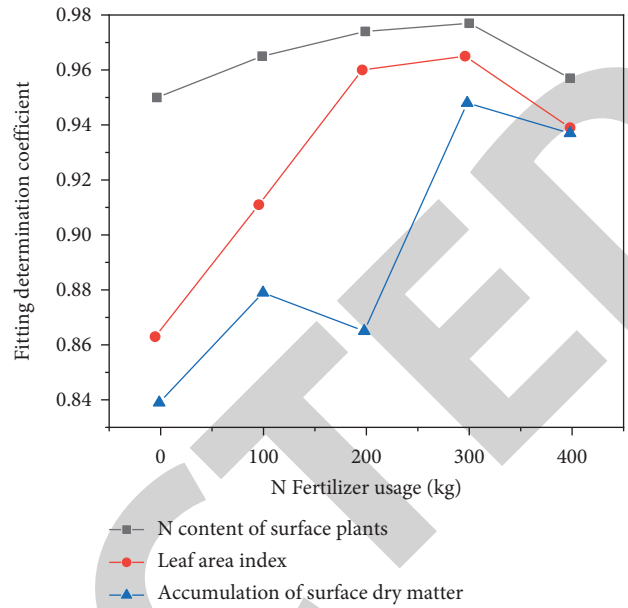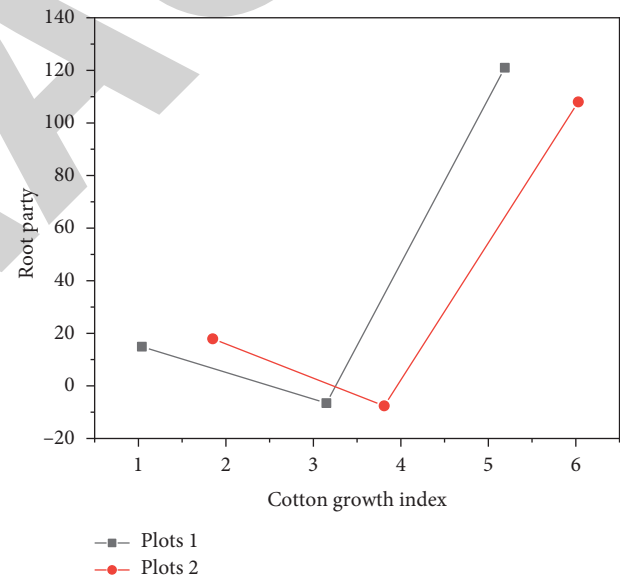
reached the maximum value when $N$ fertilizer dosage was 300 kg/hm$^2$, and the whole model met the accuracy requirement [22].

## 4. Interpretation of Result

The leaf area index (LAI) of plant $N$ content and dry matter accumulation on the ground surface were used as plant growth parameters. The cotton canopy image was extracted by the image analysis method, and the canopy coverage was calculated, as shown in Figure 6. The cotton growth model with canopy coverage as independent variable and three growth parameters as dependent variables was established [23]. In the collection of cotton growth data, the camera leaf

area and spectral analyzer are used, and the data collection forms are different. Therefore, the IMS data transmission system is adopted to realize data transmission. Now, this system is used to establish the cotton growth model, and the growth state of the two test fields is analyzed, and RMSE of root square difference between the two test fields is tested [24]. The $N$ content and the RMSE value of surface plants in the two experimental fields were 1.62 and 1.7, leaf area indexes were 0.675 and 0.65, and dry matter accumulative amounts of surface plants were 170 and 168, respectively. Therefore, the system could effectively evaluate the current growth status of cotton [25].

## 5. Conclusion

In order to realize the monitoring of cotton growth condition, a monitoring system was designed based on IMS network technology and image processing technology. The image processing technology was used to extract cotton canopy coverage, and the spectrometer collected the normalized vegetation index (NDVI) and the vegetation index (RVI) to test the feasibility of the model. Leaf area meter was used to detect the leaf area index. Firstly, the relationship between cotton canopy coverage and the normalized vegetation index (NDVI) and the vegetation index (RVI) was linear, and the fitting determination coefficient was greater than 0.95, indicating the feasibility of establishing the cotton growth model based on cotton canopy coverage. Secondly, the leaf area index (LAI) and dry matter accumulation of surface plants were established as dependent variables. Taking cotton canopy coverage as an independent variable, a cotton growth model was established. All three models are exponential and the fitting determination coefficient $R^2$ are all above 0.89. The effects of $N$ fertilizer dosage on three growth indexes were discussed: with the increase of $N$ fertilizer dosage, the linear coefficient $k$ and exponential coefficient $b$ of the three models showed an increasing trend, and the three models had high precision under different $N$ fertilizer dosage. Two experimental fields were tested by using this system. RMSE of root square mean difference of three index models met the design requirements, and $R^2$ of the fitting determination coefficient was between 0.83 and 0.923, indicating that the system can effectively evaluate cotton growth status.

## Data Availability

The data used to support the findings of this study are available from the corresponding author upon request.

## Conflicts of Interest

The authors declare that there are no conflicts of interest.

## Acknowledgments

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