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Remote Sensing Monitoring Data of Soybean Growth in Ecosystem

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Abstract: The time series images obtained by remote sensing can reflect the spectral characteristics of farmland soils and crops affected by the environment, thus providing the variation information of crop growth. In crop growing season, the dynamic changes of crop growth can be determined by different time series images. Therefore, remote sensing technology has the advantages of fast, accurate and strong current situation, it has increasingly become an important means of monitoring the dynamic changes of crop growth in a large area. Monitoring crop growth by remote sensing is of great significance for dynamic perception of food security. The purpose of this paper is to analyze the monitoring data of soybean growth under ecosystem by remote sensing technology. On the soybean scale, based on the difference of reflectance caused by the change of water structure, a method for screening and monitoring the sensitive characteristics of soybean growth was proposed. By measuring the spectral data of soybean growth potential samples, based on the characteristics of surface albedo, vegetation index and detail, and combined with correlation analysis and SVM and GASVM, the growth monitoring model on soybean scale was established. The characteristics of sensitivity to soybean growth and significant difference were screened out, it includes three characteristic bands of 340-380, 480-580 and 750-1000 nm, and three vegetation indices of MSR, NDVI and SIPI, WF01 and WF02 are two wavelet features. The experimental results show that in all models, the monitoring model established by MSR and GASVM has the highest monitoring accuracy, which is 75%.

1. Introduction

Ecosystem observation and experimentation are important means of obtaining ecological data. The proper integration of remote sensing technologies into the concepts and practices of ecosystem services has potential practical benefits for conserving biodiversity and promoting the sustainable use of the Earth’s natural assets [1]. The rapid expansion of remote sensing data, long-term positioning observation data, experiments and model simulation data has strongly promoted the development of ecological data mining and analysis technology. Multi-source, multi-scale integrated mining and simulation prediction have become important tools for ecological research in the era of big data. The ecological data integration mining method supported by big data includes three categories: (1) Meta analysis method; (2) Data-driven data mining method; (3) Process mechanism-based model-data fusion method. Although the amount of ecological observation data is increasing, the uncertainty of model simulation is still significant, and the model data fusion method based on process mechanism provides a new way to apply the massive data for model evaluation, benchmarking and constraints to reduce uncertainty. These methods are timely and effective integration of observations and experimental data of different sites, regions, time series, ecosystem processes and elements, revealing the general laws of ecosystem process mechanisms, variation laws, responses to environmental factors, and serving the ecology. System management and decision making provide an important means.

Crop growth, is the status and trend of crop growth, can be described as individual and group characteristics of the object, and a reasonable group of well-developed individuals is a good crop area. Crop growth monitoring is an important research area for agricultural remote sensing. Crop growth monitoring can obtain crop growth information in a timely manner, which is of great significance for crop management [2]. The United States was the first country to conduct remote sensing monitoring and research in agriculture. In the last century, its research focus was mainly on crop yield estimation. At the beginning of this century, the research focus has gradually turned into real-time monitoring and fine management of the crop growth process, thus opening the prelude to precision agriculture research [3]. The monitoring of crop growth is mainly to provide timely information for field management and to provide a basis for early estimation. Crop growth monitoring can provide information for field management and provide a basis for early estimation of production, which has become an important part of precision agriculture research. The traditional methods of monitoring the growth are mostly field surveys, which not only consume a lot of manpower, material resources, and financial resources, but also make it difficult to obtain large-scale crop growth information in time [4]. Remote sensing technology can acquire large-scale surface information, and it has real-time dynamics. It is increasingly used in agricultural production and management, and has made great progress in crop identification, area extraction, growth monitoring, production estimation, and disaster assessment. The monitoring of crop growth by remote sensing has become a hot spot in agricultural remote sensing research at home and abroad [5]. The rapid development of remote sensing technology has made it possible to monitor the growth and growth of large-scale crops around the world, and is the main means of dynamic perception of food security [6]. In recent years, image data of satellites such as Landsat, SPOT, MODIS and CBERS have been successfully used for planting area extraction and growth monitoring of wheat, corn, rice and other crops on a macro scale and have obtained satisfactory accuracy, but rarely used for Soybean planting distribution extraction and growth monitoring, and facing the tight supply of domestic soybeans and their products, the changes in international soybean cultivation will directly affect China's soybean import prices. Therefore, the research and development of methods and technical processes for remote sensing identification and growth monitoring of soybean planting are of great significance for analyzing the global soybean market.

Crop biomass plays an important role in food security and the global carbon cycle. The timely and accurate monitoring of biomass is essential for the precise and rational management of agriculture. Undoubtedly, remote sensing technology has been proven to be biomass estimation. Effective tool [7]. The traditional method is used to reduce the actual operation and investigation of the ground survey, in order to accurately estimate the above-ground biomass of the crop at the field scale, and improve the accuracy and stability of the on-ground biomass inversion model of soybean.

ZhangXinle obtained 6-meter multi-spectral data of spot-6 in July and August of 2016 in the study area, as well as above-ground biomass of soybeans with different terrain slopes. At the same time, the topographic data of the study area were measured, and the topography and elevation were obtained. factor. The slope and aspect are extracted, and the traditional linear regression model, multiple regression model and neural network model are established by using the above measured data [8]. With the continuous innovation of remote sensing technology, remote sensing data sources are becoming more and more abundant. Lin Gao analyzed the inversion accuracy of soybean leaf area indexbased on multi-source remote sensing data such as terrestrial hyperspectral, unmanned multispectral, and high score 1 (gf-1) wfv. The lai inversion model was established by using the ratio vegetation index, the normalized difference vegetation index , the soil regulation vegetation index, the difference vegetation index and the triangular vegetation index . The model with the highest calibration accuracy was used in the verification. According to the estimation accuracy of the model, the lai inversion ability of these three kinds of remote sensing data is evaluated [9]. Using the spectral reflectance characteristics of plants to estimate the damage of soybean aphids, the reconnaissance-based integrated pest management (IPM) scheme can be applied more effectively and widely. Alves established early, late and non-destructive treatment to establish a soybean aphid pressure gradient. The soybean aphid density was recorded weekly. Plant spectral reflectance is measured on two sampling days per year. The effects of aphid accumulation days (cad) on spectral reflectance, normalized difference vegetation index (ndvi) and relative chlorophyll content of 680 nm (red) and 800 nm (near infrared) plants were studied using a simple linear regression model. The results show that cad has no effect on the red reflectance of the canopy, but reduces the near-infrared reflectance and ndvi of the canopy.[10].

Based on the measured surface reflectance data, the change of surface reflectivity is studied to carry out the growth monitoring of soybean scale, and attempts to provide a theoretical basis for regional scale research. The sensitive features of soybean growth were extracted through correlation analysis. The selected features were sensitive reflectivity, vegetation index and detail features, including the original bands 340nm-380nm, 480-580nm and 750-1000nm. MSR, The three characteristic vegetation indices of NDVI and SIPI, and the two wavelet features of WF01 and WF02. Using these three characteristic variables as input variables, combined with SVM and GASVM classification algorithms, the soybean growth monitoring model was established. The monitoring model based on vegetation index MSR and GASVM has the highest monitoring accuracy and monitoring accuracy. Up to 75%, basically achieve monitoring data on the growth of soybeans.

2. Proposed Method

2.1. Processing of Remote Sensing Images

(1) Remote sensing image enhancement

Remote sensing image enhancement is a key step in remote sensing image preprocessing. Its purpose is to improve the visual interpretation performance of remote sensing images, to highlight the overall or local characteristics of remote sensing images, and to enhance the target features for subsequent processing of remote sensing images. The analysis lays a good foundation. At present, remote sensing image enhancement methods can be basically divided into two types: spatial domain based methods and transform domain based methods.

1) Remote sensing image enhancement method based on spatial domain. The basic idea of the remote sensing image enhancement method based on spatial domain is to operate the gray level of the original remote sensing image pixel according to certain criteria in the airspace, thereby realizing image enhancement, which can be mainly divided into gray level transformation and

histogram processing. And spatial domain filtering, including grayscale stretching, unsharp masking, logarithmic image processing, histogram equalization, and guided filtering. This kind of method can improve the contrast of remote sensing images to a certain extent, but there is often a phenomenon of amplifying noise, and the enhancement effect of the detail information of remote sensing images is not ideal.

2) Remote sensing image enhancement method based on transform domain. The remote sensing image enhancement method based on transform domain generally decomposes the remote sensing image by wavelet, Curvelet, Contourlet, non-subsampled Contourlet, Shearlet, and then uses the spatial domain-based image enhancement technology to enhance the decomposed high and low frequency components respectively. The inverse transform yields the final enhanced result. The subsampling Shearlet transform is an improvement on Shearlet, which can describe image features more accurately. In recent years, it has also been introduced into the field of remote sensing image enhancement. This kind of transform domain-based enhancement method can not only enhance the edge and other detailed information, but also suppress the interference information such as noise, and improve the interpretability of the remote sensing image. Compared with the spatial domain-based method, the detailed information of the remote sensing image can be enhanced more effectively, but the subjective visual effect may be unsatisfactory, and the subjective and objective evaluation may be inconsistent.

(2) Remote sensing image segmentation and edge extraction

Due to the complexity of remote sensing images, most remote sensing image segmentation methods are proposed in combination with the characteristics of certain types of targets. Generally, they are not universal, that is, they cannot obtain satisfactory segmentation results for different types of remote sensing images. Rivers are an important type of ground object in remote sensing images. This paper focuses on river remote sensing images and studies suitable segmentation methods according to their characteristics. At present, there are two major difficulties in the research of related fields. The first is that the data of remote sensing images of rivers is large, and the accuracy and speed of segmentation often cannot be achieved. Second, the remote sensing images of rivers generally contain more noise and need to be segmented simultaneously. To suppress noise interference. In recent years, river remote sensing image segmentation methods are basically divided into the following two categories:

1) Region-based river remote sensing image segmentation method. Among such segmentation methods, threshold segmentation is fast, efficient, easy to implement, and common, and the entropy-based approach is the most concerned. The method calculates the corresponding criterion function according to the probability distribution of the histogram, and uses the optimization algorithm to speed up the threshold search speed, and then selects the appropriate threshold to segment the river remote sensing image. Commonly used are the maximum entropy method, the minimum cross entropy method, the Tsallis cross entropy method, the reciprocal cross entropy method, the reciprocal gray entropy method, but since only the gray information is used, the segmentation precision needs to be improved.

2) Edge-based remote sensing image segmentation method for rivers. The edge-based river remote sensing image segmentation method finds the segmentation boundary according to the discontinuity of pixel points in different regions. According to the characteristics of high-resolution remote sensing image river targets, a complete regular river region is segmented by using the regularization level set evolution model. Although this type of method guarantees high segmentation accuracy, it runs for a long time.

On the other hand, the edge is one of the important features of the target in the remote sensing image. Edge extraction of the target region in the remote sensing image is the premise and basis of subsequent remote sensing image description, feature extraction and classification recognition. At present, remote sensing image edge extraction usually adopts a spatial domain or transform domain based method.

1) Remote sensing image edge extraction method based on spatial domain. The spatial domain-based remote sensing image edge extraction method mainly uses Sobel, Prewitt, Laplacian of Gaussian (LoG), Canny and other differential operators and morphology to extract the edges in the remote sensing image. Due to the poor anti-interference ability of the differential operation, the extracted edges are missing, false alarm and broken. In contrast, the edge extraction results obtained by mathematical morphology methods have certain advantages. The corrosion and expansion operations commonly used in this method can ensure that the extracted edges are smoother, but the edge signals obtained by the corrosion operation are stronger and the anti-interference is not strong; while the expansion operation is weak due to the obtained edge signals, which tends to cause the edges to be unclear.

2) Remote sensing image edge extraction method based on transform domain. The transform domain based remote sensing image edge extraction method usually extracts the detail edge of the high frequency component and the contour edge of the low frequency component in the transform domain, and organically combines it to obtain the final result. Among them, the method based on wavelet transform and the multi-scale geometric analysis based on Contourlet, NSCT and Shearlet are widely used in remote sensing image edge extraction. Due to the weak directionality of the wavelet transform, the ability of the edge extraction method based on wavelet transform to extract the edge of the detail is limited. The edge extraction method of remote sensing image based on Contourlet transform compensates for the above defects to a certain extent, but it is easy to cause pseudo-Gibbs effect because it needs to perform downsampling operation.

(3) Remote sensing image matching

The remote sensing image matching methods in the past can be roughly divided into two types: gray-based methods and feature-based methods.

1) Remote sensing image matching method based on gray scale. The similarity measure of the gray-based remote sensing image matching method is generally established based on the gray level information of the image, such as entropy value, cross-correlation, mutual information, and the like. Generally, the amount of information of remote sensing images is large, and due to the complex shape of the landform, there is a certain degree of shape distortion and gray scale difference. Although this method is simple to implement, it has a large amount of calculation and is susceptible to interference such as illumination, noise, and distortion.

2) Feature-based remote sensing image matching method. The feature-based remote sensing image matching method can largely avoid the above problems and has certain robustness to changes such as gray scale and shape. In this kind of method, the remote sensing image features commonly used for matching have some features, edge features and regional features.Remote sensing image matching method based on point feature; Remote sensing image matching method based on edge features; Remote sensing image matching method based on regional features. Moment feature is an important regional feature and is widely used in remote sensing image matching. Commonly used moments include histogram invariant moment, line moment, Zernike moment, and Krawtchouk moment.

(4) Remote sensing image fusion

Research on effective remote sensing image fusion methods has important practical significance for land use survey, vegetation cover statistics, and urban/building extraction. The existing remote sensing image fusion methods can basically be divided into two categories:

1) Remote sensing image fusion method based on spatial domain. The spatial domain-based remote sensing image fusion method is directly based on the pixel information of the original remote sensing image, mainly including compressed sensing, principal component analysis, Brovey

transform, pulse coupled neural network, non-negative matrix factorization, luminance-chroma-saturation conversion, etc. . Among them, the IHS transform method is simple to use and can effectively preserve the spatial information of the image, which is common, but at the same time, it is easy to cause serious spectral distortion.

2) Remote sensing image fusion method based on transform domain. In order to effectively improve the comprehensive performance of the image after fusion in maintaining spatial information and spectral characteristics, a remote sensing image fusion method based on wavelet domain has been proposed and achieved certain effects, but this method can only capture point singularity and poor direction selectivity. The description of spatial details is limited.

2.2. Soybean Growth Detection Model

Support vector machine (SVM) is a model builder based on statistical learning theory, which is usually used in pattern recognition, classification and regression analysis. Some scholars have used the particle group (Pso) optimized least square support vector machine (LSSVM) to establish a monitoring model for soybean growth (Pso-LSSVM). However, when using this algorithm, how to effectively select the kernel function and determine the parameters is still controversial. The traditional grid search (Grid Search, GS) algorithm is inefficient, computationally intensive, and takes a long time, and the effect is not satisfactory. The genetic algorithm (GA) is good at solving global optimization problems. The algorithm is robust and simple. It can be independent of the problem domain and has good scalability when performing fast search.

(1) Principle of support vector machine

The basic idea of SVM is to find an optimal hyperplane, so that the hyperplane maximizes the classification accuracy while maximizing both sides of the hyperplane. In the SVM classifier, an independent hyperplane can be defined as an $f(x)=\omega Tx+k$ representation vector in the ω style, which determines the direction of the hyperplane; x represents the feature vector; k represents the offset, which determines the distance between the hyperplane and the origin. Converting the expression into a regular optimization term and a relaxation variable ζ

$$\min\left(\frac{1}{2}\|\omega\|^2+C\sum_{i=1}^{n}\xi_i\right)\tag{1}$$

$$y_i(\omega\cdot x+k)\geq 1-\zeta_i\tag{2}$$

Where C is the penalty factor, n is the feature dimension, and y is the target category.

The Lagrangian multiplier is introduced to solve this constrained optimization problem. Finally, the decision function of the SVM is obtained.

$$f(x)=\mathrm{sgn}\left(\sum_{i=1}^{n}a_i y_i(x\cdot x_i)+k\right)\tag{3}$$

Where ai is a Lagrangian multiplier and $y_i(x\cdot x_i)$ is a kernel function. The radial basis kernel function has a good effect on nonlinear fitting. Therefore, the radial basis kernel function is chosen as the kernel function of SVM. The two model parameters that affect the accuracy of the monitoring model are the penalty factor C and the radial basis kernel function. Parameter y

(2) GASVM principle

At present, the grid search method is commonly used to obtain optimal parameters, but this method is inefficient and has a large workload. The advantage of the genetic algorithm is that it solves the global optimal problem and is robust. It can be independent of the problem domain when performing fast search, so the algorithm has good scalability. In this paper, the advantages of genetic algorithm are used to optimize the penalty factor and kernel parameters. The algorithm steps of using GA optimization SVM to establish soybean growth monitoring model are as follows:

First, initialize the population algebra

Second, the sample data filtered by the rdief+mRMR algorithm is divided into training samples and verification samples. There are 56 points in the field survey data. The sample data of 42 points are used as training samples to train each group of parameters, and the remaining 14 points are used as verification samples to calculate the average relative error between output value and expected value.

Third, the selection, crossover, and mutation operations of the population

Fourth, determine whether the maximum genetic algebra of the initial setting is satisfied, and obtain the optimal penalty factor and nuclear parameter when the condition is met.

Fifth, monitoring the growth of soybeans with the SVM model optimized by parameters

2.3. Construction of Soybean Scale Monitoring Model

The optimal original spectral features, vegetation index features and wavelet features were used as input variables of the monitoring model. The optimal feature variables were selected by the relief algorithm and mRMR algorithm, and the SVM (GASVM) classification model optimized by genetic algorithm was used to construct wheat wheat ear scale. Scab monitoring model. Among them, 48 samples were used for model construction, 24 samples were used for model accuracy verification, and the accuracy of the model was evaluated by the overall accuracy and Kappa coefficient.

(1) Relief feature dimension reduction algorithm

The Relief algorithm is a feature weighting algorithm that assigns different weights to features by calculating the correlation between features and categories. When the weight of features is less than the set threshold, they are removed. The Relief algorithm randomly selects a sample a from the primary feature set and then finds a nearest neighbor sample H in the same sample set, and finds a nearest neighbor sample M in the different class set. The weight w of the sample a in the feature $\int$ is expressed as:

$$w = diff(\int, a, M) - diff(\int, a, H) \quad (4)$$

$$diff(\int, a, b) = \frac{|a-b|}{\max(\int) - \min(\int)} \quad (5)$$

(2) The mRMR algorithm

The MRMR algorithm is a typical feature dimension reduction algorithm based on information theory. The algorithm mainly finds n features that have the greatest correlation with the growth category and the least redundancy between them from the features screened by the relief algorithm. Mutual information is used to measure the correlation between features and features in feature subsets and characteristics and soybean growth. Given two random variables x and y, the mutual information is:

$$I(x, y) = \int\int p(x, y) \log \frac{p(x, y)}{p(x)P(y)} dxdy \quad (6)$$

Where p(x) is the probability of the variable x, p(y) is the probability of the variable y, and p(x, y) is the joint probability of x, y. The correlation between feature features and features is:

$$R = \frac{1}{|S|^2} \sum_{xi,xj} \in sI(x_i, x_j) \quad (7)$$

In the formula, $|S|$ is a feature set, which is the number of samples of the feature, x_i and x_j

are feature variables in feature i and feature j, respectively, and $I(x_i, x_j)$ function is mutual information between feature i and feature j. The correlation between features and categories in a feature set is:

$$D = \frac{1}{|S|} \sum_{x_i \in s} I(x_i, z) \quad (8)$$

Where z is the target category and I(xi,z) is the mutual information between feature i and target category z. According to the difference criterion combination, the feature selection criteria of mRMR are obtained:

Max(D-R) (9)

3. Experiments

3.1. Collection of Experimental Data

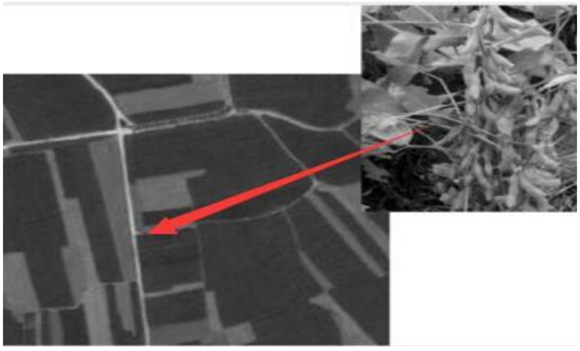


Figure 1. Remote sensing image

In this experiment, soybeans were selected as research objects, each with 30 test sites. In order to ensure that other research conditions are as consistent as possible, we have selected three MODIS data sets as the daily surface reflectance data (MOD09GQ), 8-day synthetic surface reflectance data (MOD09QI) and 16-day synthetic vegetation index. Product (MOD13QI). In view of the fact that MOD09QI does not have sufficient data quality information, it must incorporate a 500m resolution surface reflectance product (MOD09AI) during use. After the three data products are generated by NDVI and filtered with data quality information, the relationship between the three is obtained. The year-by-year comparison model is based on the local seedling situation. The current situation is compared with the growth of the same period last year. This model is mainly derived from traditional habits. The agricultural management and production departments are accustomed to carry out this year’s growth with the same period last year. In comparison, because of the growth situation and production knowing last year, this is convenient for early production estimates.Soybean growth monitoring by remote sensing is shown in Figure 1.

3.2. Experimental Environment

The research area of the soybean growth monitoring experiment belongs to the Yellow River Basin in the climate division. The terrain of the region is gently open and the whole territory is plain. Due to the flat terrain and small climate change, the main factors are warm and wet stuffing, combined with good local water and fertilizer conditions, high yield and high density of soybean population. Therefore, remote sensing satellite imagery can be considered to monitor the growth of soybeans.

3.3. Evaluation Model

The evaluation model can be further subdivided into year-by-year comparison model and grade model. The year-by-year comparison model is based on the local seedling situation. The current situation is compared with the growth of the same period last year. This model is mainly derived from traditional habits and agricultural management. And the production department is accustomed to compare this year's growth with the same period of last year, because last year's growth situation and production know, this is convenient for early production forecast, the model can be expressed as a mathematical formula:

$$\Delta = {(VI_C - VI_1)}/{\overline{VI}} \tag{10}$$

In the formula, VIc is the vegetation index of the current crop, VIl is the vegetation index of the crops of the same period last year, $\overline{VI}$ is the multi-year average, and Δ is the parameter reflecting the growth of the crop. According to the size of Δ, with reference to the results of ground monitoring, it is possible to judge the growth situation of the current crop, and the judgment process is as shown in Figure 2.

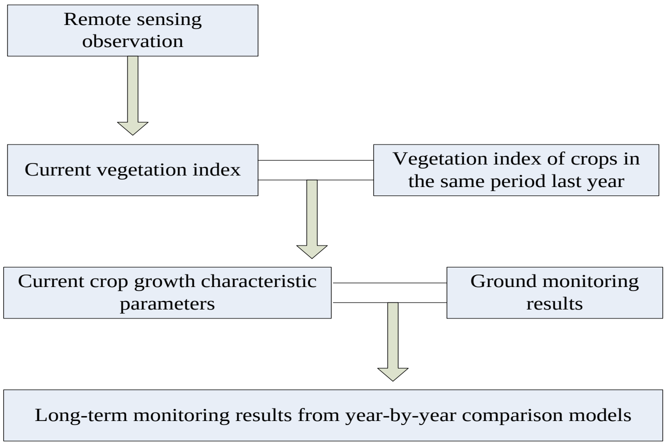


Figure 2. Performance of soybean vegetation index in different periods

The year-by-year comparison model can only produce relative results relative to the average level of last year or a few years ago, and cannot be graded. The grade model is designed to overcome this defect. According to the different calculation methods, the grade model can be divided into an anomaly model and an extreme model anomaly model. The vegetation index of the same period last year in the formula (10) is replaced with the average value of the vegetation index in the past many years, namely:

$$\overline{\Delta} = {(VI_c - \overline{VI})}/{\overline{VI}} \tag{11}$$

$\overline{VI}$ is the multi-year average. The calculation process of the anomaly model is similar to that of Figure 2. It is only necessary to replace the vegetation index of the same period last year with the multi-year average. One advantage of this replacement is that when the crop grew very well (very poor) in the same period last year, this year's results may be slightly worse (slightly better) than last year. If you use the year-by-year comparison model, you can only see that this year's crops are growing poorly.(Good), while the anomaly model can relatively objectively reflect that this year's growth situation is good (poor).

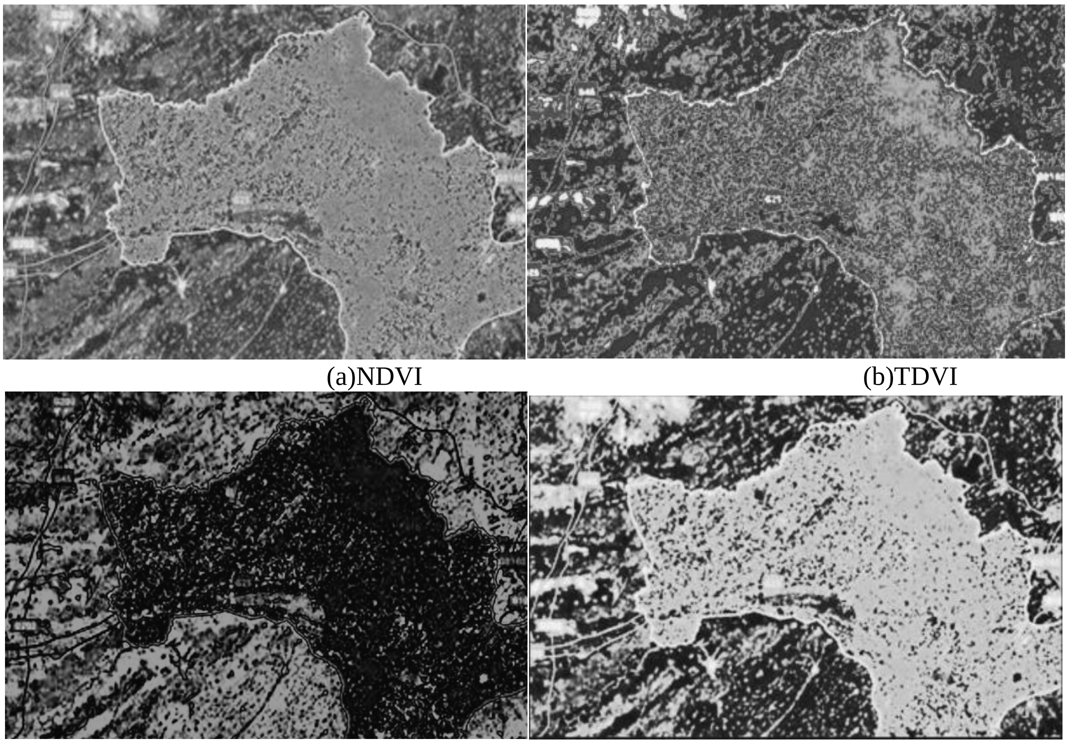
When the crop growth situation is not much different for many years, the vegetation index of the crop is difficult to obtain detailed grading results in the anomaly model. In this case, the extreme value model should be used. The extreme value model uses the maximum and minimum values of the vegetation index over a certain time horizon to establish a hierarchical model, which can be expressed as follows:

$$VCI = \frac{VI_{c} - VI_{\min}}{VI_{\max} - VI_{\min}} \tag{12}$$

$VI_{\max}$ and $VI_{\min}$ are the maximum and minimum values of the vegetation index in the same period, and VIc is the vegetation index value of the current crop. The judgment process of the hierarchical model is similar to that of Figure 2.

4. Discussion

4.1. Analysis of Vegetation Cover Period



(a)NDVI (b)TDVI

(c)SR (d)RNDVI

Figure 3. Performance of soybean vegetation index in different periods

After eliminating the effects of clouds and other noises, we compared the performance of the vegetation index during the low vegetation coverage period (day 140) and the high vegetation coverage period (day 200), as shown in Figure 3.

It can be seen from the figure that NDVI saturates during high vegetation coverage, but the difference between crops and soil and background is not seen from the performance of NDVI, and the influence of soil background on low vegetation coverage is eliminated. Not thorough enough, so that the soil-based surface should be characterized by higher vegetation coverage. Compared with NDVI, SR and TDVI have improved in soil background and NDVI saturation, reflecting the potential of these two vegetation indices to replace NDVI as a surface vegetation. In-depth comparisons show that SR is better than TD in eliminating soil background, and TDVI is slightly better than SR in combating saturation.

Taking the effect of NDVI as a reference, SR and GRNDVI performed well in eliminating the influence of soil background. Although TDVI was corrected, it was more effective than SR and GRNDVI; RNDVI and GRNDVI had better correction on saturation problem. SR is more effective than them; RNDVI is slightly over-corrected in terms of soil background and saturation due to the mathematical formula of quadratic calculation, and the improved GRNDVI is ideal in both aspects, and can be used as a remote sensing extraction crop. The replacement indicator of NDVI when growing information.

4.2. Selection of Feature Variables

(1) Analysis of feature weight distribution

By calculating the weight of features, it assigns higher weight to the features with strong classification ability. However, the relief algorithm does not consider the correlation between features, so the redundancy between features cannot be removed. mRMR algorithm It is possible to obtain a feature subset with minimal redundancy between features and maximum correlation between features and targets, but the weight size cannot be calculated. Therefore, feature reduction is achieved by combining the relief algorithm and the mRMR algorithm. A certain threshold is used to improve the weight of the feature with good discrimination, and the optimal feature subset is obtained. The specific operation process is to first calculate the weight distribution between the first eight features and categories through the relief algorithm as shown in Figure 4:

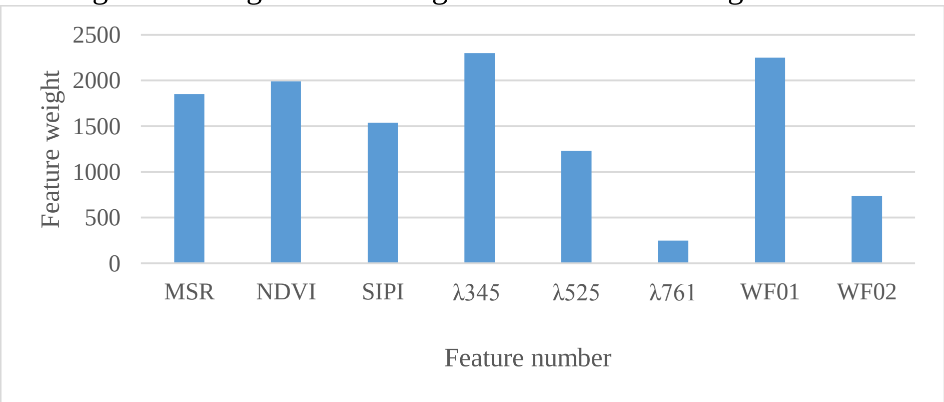


Figure 4. Different features weight values based on relief algorithm

Analysis of different feature weight values

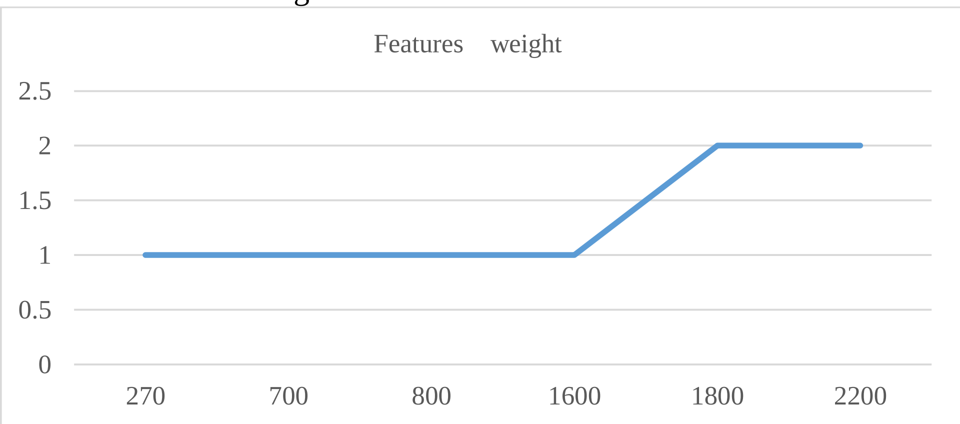


Figure 5. Distribution of feature weight values based on relief algorithm

The threshold is set to 1000, and the five features satisfying the condition are selected as the primary features of the mRMR algorithm. Then the optimal feature variable set is obtained by the mRMR algorithm: MSR, NDVI, SIPI, $\lambda 354$ and WF01, and MSR is selected as the first. Set the feature variable Feature l, select MSR and NDVI as the second set of feature variable Feature2, select MSR, NDVI and S1PI as the third set of characteristic variable Feature3, select MSR, NDVI, SIPI and $\lambda 354$ as the fourth set of characteristic variable Feature4, select MSR , NDVI, SIPI, $\lambda 354$, and WF01 as the fifth set of feature variables Feature 5. The different feature weight values based on the relief algorithm are shown in Figure 5.

The monitoring results, overall accuracy and Kappa coefficient of the five monitoring models established by the five sets of characteristic variables GASVM, the accuracy of the optimal model variable MSR combined with the relief-mRMR algorithm combined with GASVM and the Kappa coefficient are higher than other characteristics. The established monitoring model showed consistency. As the input variables increase, the accuracy of the model decreases due to the influence of redundancy between the characteristic variables. Soybean-scale growth monitoring model was established by field investigation and experimental determination of soybean growth spectrum data using original spectral features, vegetation index features and wavelet transform features combined with correlation analysis and SVM and GASVM classification methods. Screening for growth-sensitive and significantly different features, including 350nm-400nm, 500-600nm and 720-1000nm.

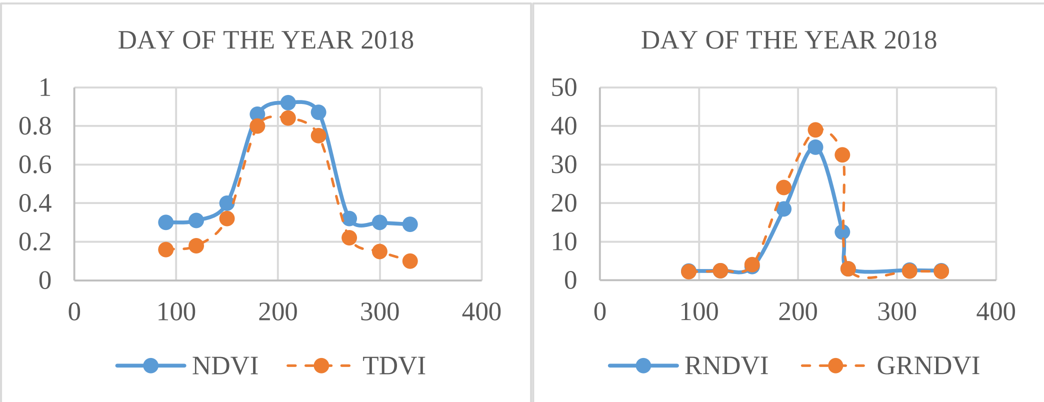


Figure 6. Pixel level vegetation index changes

4.3. Vegetation Index Changes

From the point of view of eliminating the saturation of NDVI, as shown in Fig. 6, the change of the pixel level vegetation index is between 186th and 233 days, and the crop growth is in the lush vegetative growth/reproductive growth transition period. High, NDVI is more prone to saturation. Similarly, whether it is corn or soybeans, the left curve is flatter than the right curve during this period, NDVI and TDVI are generally more prone to saturation than RNDVI and GRNDVI pairs. This phenomenon confirms our improvement of the saturation problem of NDVI for RNDVI and GRNDVI. For NDVI and TDVI, soybeans show little difference between the two during this period, RNDVI and GRNDVI during this period. The level of change is rich, soybeans reach a maximum in the middle of this period, and the whole curve appears symmetrical. This indicates that RNDVI and GRNDVI are indeed sensitive to changes in canopy structure during high vegetation cover, and can reflect the trend of leaf area index LAI during high vegetation coverage.

5. Conclusion

The research focused on crop soybeans, using MODIS dataset as the main data, and proposed a soybean growth evaluation method based on NDVI and phenological correction. Based on the NDVI time series data of soybean growth period, the criteria for soybean growth evaluation in the study area were established. Aiming at the spatial difference of phenology, the soybean podging period was monitored by remote sensing, and the phenological information was used to correct the soybean growth. Finally, the soybean growth evaluation results before and after the phenological correction were compared. The study reached the following conclusions.

During the growth of soybean, the pod-forming period is an important stage in which soybeans enter reproductive growth, corresponding to the date when the soybean NDVI growth curve appears to be the maximum. The time distribution of soybeans entering the pod-forming period in the study area. The monitoring results showed that the date of soybean entering the pod-forming period in the study area was the most common in 201~215 Julian days, during which the pixels entering the pod-forming period accounted for 89.2% of the total pixels. The pod-forming period of soybeans is consistent within the plot, and the phenological differences between the plots are more obvious. However, due to the small scope of the study area and the lack of obvious north-south climate differences, the soybean pod formation period did not show obvious spatial differentiation. Different crops and the same crop have different physiological characteristics at different growth and development stages. These characteristics can be expressed to some extent through their spectral reflection and absorption characteristics. Therefore, the difference in spectral reflectance and its combination can be used as crop type identification. Important reference. Vegetation index uses the contrast combination of green plant leaves in different spectral segments to quantitatively describe vegetation characteristics. It is the most effective method to distinguish different land types or vegetation types and monitor vegetation growth status so far. During the whole development of soybean emergence, flowering, pod formation, blasting and maturation, NDVI will show corresponding increase and decrease. When the leaf area of the crop increases, the NDVI increases, and the vegetation index reaches the maximum when the leaf area is maximum. When the crop enters the mature stage, the photosynthesis decreases, the chlorophyll decreases, and the NDVI value decreases accordingly. The development of harvesting activities will cause a sharp decline in vegetation cover.

Time series remote sensing data can effectively extract crop phenology, and the key phenological period of soybean was monitored by fitting method. The monitoring results were combined to correct the soybean growth. After the phenology correction, the consistency of growth and yield increased to 75.6%, and the consistency increased to 95.1% when the tolerance was 1 grade, indicating that the use of phenological information can improve the evaluation of growth. The method proposed in this paper can greatly reduce the influence of subjective factors and phenological differences on the growth assessment, and can provide an important reference for the growth monitoring of other crops. When conducting further research, the growth assessment method should be applied to other crops to verify the applicability of the method.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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